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Spatial Analysis in Detecting the Level of Land Suitability for Clove Plants

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Abstract

Plantation crops remain a central choice for many farmers because of their promising yields, and clove is among the most valued due to its strong market demand. Despite this potential, clove cultivation frequently faces constraints, particularly sudden stem bud decline and disease susceptibility. These problems often arise from land that does not meet the crop's ecological requirements, yet many farmers still find it difficult to obtain reliable and timely information on land suitability. Spatial data offers an effective solution because it provides rapid and up to date insights into environmental conditions without requiring farmers to visit each site. When combined with big data and smart farming technologies, spatial information becomes even more useful, since farmers can monitor climate patterns, soil temperature and soil texture more easily.This study aims to generate accurate information on land suitability for clove cultivation through spatial big data and to demonstrate the role of smart farming systems in detecting suitability levels. Using a quantitative approach, land conditions were classified into four suitability categories which include very suitable, suitable, marginal and not suitable. Landsat imagery from Sinjai Regency in 2024 identified approximately 24,566 pixels or 2,282 hectares of land used for clove cultivation. These areas were concentrated in South Sinjai, Central Sinjai, Sinjai Borong and West Sinjai. Additional land cover classes consisted of primary forest, rice fields, settlements, secondary forest, annual crops and mixed plantations. The classification results were supported by categorical accuracy testing, highlighting the need to evaluate each land use type individually to ensure the reliability of the spatial interpretation.

Introduction

The strain on available land resources has been on the increase with different sectors demanding their own development needs to be incorporated into the landscape (Syaban & Appiah, 2024; Tahir et al., 2025). Farming that has traditionally been based on the integrity of fertile lands and the predictability of weather conditions is now subject to the challenge of working in a narrower area (Mishra, 2025; Naskar et al., 2025; Tahir et al., 2024). This is particularly acute in those areas where plantation crops are not only a source of their economic support, but also a symbol of their culture and their livelihood of many families. Growing clove is at the epicenter of this dynamic (Wardah et al., 2025). It is a high-value commodity with stable demand on the market, but it is also a commodity that needs a certain degree of care in terms of environmental ecology as the efficiency of its work is closely dependent on the specifics of the soil condition, the behavior of climatic conditions, and the physical features of the land (Mondal & Mishra, 2024) As soon as the availability of the appropriate land is becoming increasingly scarce, the dotted line of its functioning with the complexity of the soil condition, the nature of climatic processes, and the structure of the physical surface of

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Traditionally, farmers used the field observation and local knowledge in determining the location to plant new plantations (Chen et al., 2025; Grillini et al., 2025; Smith et al., 2024). These are the methods, which have been worked out over generations of experience, which continue to play a significant role in agricultural practice. Nevertheless, with the changes in the environmental conditions occurring at a quicker pace and the competition in land use being stiffer, the drawbacks of relying entirely on manual surveys are becoming increasingly evident (He et al., 2024; Deng & Zhang, 2025). Field based assessments are very time and labor intensive and in many cases are not able to embrace the complete spatial variability of the topography particularly in terrain regions where there are rapid variations in topographic gradient and in places where vegetation patterns are of such complexity that they mask the soil properties (Karahan et al., 2025; Núñez et al., 2025). Within these environments, the decision that are made under incomplete information can bring about some sudden trouble to the farmers like the increased risk of erosion or the lack of fit between the needs of the plant and the land ability. The outcomes of such mismatches may be critical with clove plants being sensitive to unsuitable conditions, and the plants develop physiological disorders, poor development, and susceptibility to diseases (Saqib et al., 2025).

Remote sensing technology has become an essential resource as agriculture aims to be more accurate and adaptive when assessing land potential (Sabir et al., 2024; Han et al., 2024; Harle et al., 2024). Satellite images can capture extensive regions in a comparatively limited amount of time, which provides the repetitive and uniform information regarding land cover patterns, the density of vegetation and environmental conditions (Metzler et al., 2025; Benami et al., 2025). It was demonstrated in numerous studies that such spatial data layers can demonstrate the trend of land degradation, problematic slopes and vegetation changes that in some cases cannot be detected on the basis of the traditional field survey. In topographical areas that are characterised by hilly features, such as the detection of erosion prone areas, it is so easy to see them through the spatial imagery. These understandings allow decision makers and farmers to shun improper distribution of land uses, which would otherwise increase rate of soil degradation or low agricultural productivity (Yazdanpanah et al., 2025; Sharma et al., 2025; Debernardini et al., 2025).

Such technological benefits are more applicable in Sinjai Regency, in which the terrain is characterized by a mixture of physiographic units of low elevation valley and mid elevation uplands and steeper hilly areas (Karamma et al., 2025). All these units present other opportunities and limitations to clove farming (Amri et al., 2025; Hasim , et al., 2025; Kumala et al., 2025).The well drained volcanic soils in the uplands usually offer good environments, whereas the steeper areas that have little vegetation cover are dangerous of runoffs and erosions that may lead to the lack of sustainability of the plantations in the long run. The variations among these land units in most situations are nuanced and may not be easily detected unless detailed examination of space is done. Consequently, farmers can unknowingly chose areas which seem to be good at first sight but harbor some constraints that can only be seen after the planting process has been initiated (Conrady et al., 2023; Chipomho et al., 2022; Cobelli et al., 2025).

Geospatial analysis in this context provides a unified method with different types of data being combined into one interpretive system (Orlando et al., 2025). The integration of satellite images, thematic maps, soil information and on-field observations would allow discovering not just the location of current clove plantations but also the overall landscape trends defining the tolerance of the land. It is this combined view that is necessary to explain the interaction of soil depth, soil texture, soil acidity, the vegetation structure, slope gradient, and hydrological

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behavior to either favorable or inhibit clove growth. Besides, the growing supply of big data regarding climate and soil conditions increases the possibility of researchers to study these interactions in more detail and continuous time (Montillet et al., 2024).

Another dimension to this process is added by the role of smart farming technologies (Batra et al., 2024; Mohyuddin et al., 2024). These technologies enable farmers to get the information concerning soil temperature, microclimate and land features without the need to go to each plot. In conjunction with geospatial measurements, they form a more mutual network of agricultural decision making wherein spatial insights are used to inform strategic planning, whereas sensor based data is used to inform day to day management (Raihan et al., 2024; Ganie et al., 2024). This type of approach is particularly useful in smallholder landscapes, in which time and labor are scarce, and the threat of crop failure has serious economic implications.

Considering these facts, this research was planned in order to trace the spread of clove planting areas in Sinjai Regency and to estimate the land suitability to grow clove using geospatial technology. The research will be able to offer a deeper picture of which regions have the most favorable biophysical conditions to develop cloves and that is enabled by the analysis of the satellite imagery, backed by the spatial big data and ground based validation. Such information should not be simply used to help analyze scientifically, but also to help facilitate more informed and sustainable agricultural planning. The research provides a guide that not only satisfies the practical interests of farmers themselves but also allows directing the areas, where the environmental factors need to be managed carefully and ensuring that the ecological stability of the region could be maintained.

Methods

The research design taken in this study is semi-quantitative design with a qualitative descriptive assessment in order to clarify the suitability of the land to plant clove (Syzygium aromaticum). The analytical framework was developed so as to delineate the ecological complexity of Sinjai District without compromising accessibility to smallholder agricultural interpretations. The semi-quantitative dimension applies to the modeling of biophysical data using satellite-based image classification and spatial overlay; the qualitative component applies contextual explanations generated at the field of study and during laboratory laboratory soil diagnostics. Such a dual analytical form was retained on purpose to harmonize the outputs of the numerical classification with the realities of heterogeneous agroforestry landscapes where the farming of cloves is extremely entrenched.

The research field includes Sinjai Regency, and South Sinjai, West Sinjai, Central Sinjai, and Sinjai Borong in particular. They are the most dynamic and historical consistent areas of clove production, due to their location on lowland valley floors, middle-elevation volcanic uplands and waving hills where micro-differentiations in slope, canopy structure, soil depth and soil acidity are often the determining factors to perennial survival. Data collection and image processing would be done in May- October 2025 because July is not exactly the most convenient month to conduct such work but rather due to the fact that this month falls within the spatial range of the region as it switches between wet and dry agricultural seasons. This timing allowed testing the behavior of classification in different moisture conditions on the surface, allowing validating the spectral confusion cases in both saturated and tree-mixed conditions.

The interpretation of Landsat TM imagery obtained in 2024, laboratory analysed soil samples, and GPS referred points of plants used to map distribution patterns, produced primary data. This imagery was chosen based on its relevance in time, its radiometric stability and its ability

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to explain the overall characteristics of the canopy that can be seen at a 30 meter resolution in perennial crop lands. Other primary data included solum depth, field-tested soil texture, groundcover conditions, and slope length data taken at land units where clove was to be grown. Administrative, geological, soil, slope, rainfall, climate, RePPProT and SRTM/DEM thematic layers were added as secondary data. These data streams were not merely added to the workflow, but they were ingested as conditioning filters to understand opportunities, constraints, and land coherence and produce final suitability classes.

The purposive unit representation as opposed to randomized point distribution was used in directing the soil sampling. The number of composite soil samples was 50 as it represented a variety of physiographic units where agricultural activity with or without clove could be present. The analysis of samples was done at two levels. Direct, touch-based soil texture testing, the evaluation of the soil depth, the estimation of the slope gradient, the verification of the land cover, and the observations of vegetation protective influence were considered as the field parameters. The laboratory parameters included pH, organic carbon, nitrogen content, cation exchange capacity, base saturation, aluminum saturation and essential base cations in form of Ca, Mg, K and Na. Though the saturation of aluminum was considered a chemical soil factor, it was not viewed independently, instead, it was an indicator of localized root-zone stress, which interacts with drainage behaviour and topography, and this was the reason, why spectrally similar but chemically different land units can be able to support different growth responses.

The processing of spatial data had a broader logical sequence that was aimed at minimizing the topographic reflectance bias and better represent the organization in perennial plantations. The pre-processing was performed in the form of radiometric correction, topographic correction (DEM-based slope reflectance normalization), and subsetting of the study area to concentrate the classification learning on the actual agricultural mosaic, rather than background land cover that was not of interest. It was then followed by supervised classification to distinguish forests, settlements, clove gardens, mixed plantation, annual crops and rice fields, recognizing that spectral overlap is inevitable in small perennial farm plots that are dominated by heterogeneity of the crown. The results of classification were checked by 279 ground-truth points, shared in land covers and not species labels alone, in such a way that the error measures can indicate not only thematic accuracy but also plot-interface ambiguity, which is typical of densely populated home-gardens areas and wetland boundaries.

The analysis of the land suitability was performed using GIS Multi-Criteria Evaluation (MCE), which combines the soil fertility capacity, slope gradient, implication of drainage, solum depth, pH interaction, and erosion susceptibility to a single suitability logic. The framing criteria reflects the ecological sensitivity of the species where slopes are soft in favour of sustainability, the volcanic clay is deep to retain nutrients and water stagnation puts the units of land directly in the non-suitable areas irrespective of its chemical fertility. The last output schema puts the land in the categories of S1 (very suitable), S2 (suitable), S3 (marginal), and N (not suitable). Instead of finding the rightness by using set thresholds, this assessment system was designed as a verbal chain of evidence where spatial biophysical patterns are used to explain classification results, and field diagnostic is used to find out whether a unit is naturally fit or in need of conservation action before clove expansion can be suggested.

Since the classification statistics were insufficient in improving the research coherence, SPSS analysis was used as an aid statistical tool to summarise the parameter clustering patterns, confirm internal soil variance and put into context the subplot resemblances that can create interpretation confusion in 30-meter pixels.

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Results and Discussion

Before examining each analytical component in detail, it is essential to acknowledge the layered nature of the landscape analysis conducted in this study. The findings presented here emerge from multiple interconnected processes, including satellite-based classification, accuracy validation, field verification, soil and slope assessment, and the final land-suitability evaluation. These components do not stand independently; rather, they form a structured analytical progression. The Results section therefore begins with a broad depiction of land-cover composition before narrowing toward the diagnostic elements that explain where and why clove cultivation thrives across Sinjai Regency.

Land Cover Classification

The land-cover map based on 2024 Landsat data gives a more specific description of the heterogeneous terrain in Sinjai. Seven large land-cover classes were distinguished successfully as shown in Table. Clove plantations take the largest portion (22.5^{-} 21.2) with mixed plantations coming in second place thus making it clear that traditional agroforestry remains the dominant system in the area. Wetland agriculture in the valley bottoms and irrigated plains is of the same value and the rice fields occupy almost a quarter of the landscape. Forest patches (both primary and secondary) constitute 17.1^{-} percent of the area; despite the fragmentation, they have an ecological role of buffering erosion, hydrological control and continuity of the mosaic of agricultural lands.

The smaller but spatially influential subjects are annual crops and settlements. It is the juxtaposition of these land-cover types that creates a dynamic interface in human activity with the ecological processes thus, adding to the classification difficulties.

Table 1. Land-Cover Classification (2024 Landsat Imagery)

Land Cover Type	Area (ha)	Percentage (%)
Primary Forest	1,103.8	11.5
Settlements	717.5	7.4
Clove Plantations	2,173.0	22.5
Mixed Plantations	2,067.0	21.2
Annual Crop Agriculture	1,083.6	11.8
Secondary Forest	735.5	5.6
Rice Fields	1,919.5	19.8
Total	**9,798.04**	**100.0**

Accuracy Assessment

To evaluate the reliability of the classification map, a comprehensive accuracy assessment was performed using 279 ground-truth points distributed across all major land-cover types. The classification achieved an overall accuracy of 84.3%, which is a strong performance for a landscape characterized by smallholder agroforestry systems, mixed vegetation structures, and diverse canopy heights.

Clove plantations demonstrated the highest classification fidelity, with a producer accuracy of 84% and a user accuracy of 88.4%. These values reflect both the distinct spectral signature of mature clove crowns and their concentrated distribution within the mid-elevation uplands. Conversely, secondary forest exhibited the lowest producer accuracy (49.99%), largely due to its spectral similarity to mixed gardens and regenerating perennial vegetation. In many

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locations, secondary forest stands mimic agroforestry structures, making them difficult to separate with medium-resolution imagery.

Table 2. Accuracy Assessment Summary

Land Cover Class	Producer Accuracy (%)	User Accuracy (%)	Omission Error (%)	Commission Error (%)
Clove Plantation	84.0	88.4	16.0	11.6
Mixed Plantation	79.2	85.0	20.8	15.0
Secondary Forest	49.99	50.0	50.01	50.01
Primary Forest	71.4	74.8	28.6	25.2
Rice Fields	81.6	78.5	18.4	21.5
Settlements	87.3	82.4	12.7	17.6
Annual Agriculture	76.8	73.6	23.2	26.4
Overall Accuracy	84.3			

Field-based misclassification analysis reveals that errors were not randomly distributed but instead concentrated in transitional zones, particularly between settlements, rice fields, and mixed vegetation. As shown in Table 3, clove was occasionally misidentified as shrubs or rambutan trees where the canopy height and architecture were similar. Likewise, saturated rice fields produced reflectance characteristics comparable to shaded perennial canopies, leading to reciprocal misclassification events.

Table 3. Misclassification Cases Based on Field Verification

Initial Classification	Actual Class	Number of Points
Clove plantations → Settlements	Settlements	2
Clove plantations → Shrubs / Rambutan	Shrubs / Rambutan	3
Clove plantations → Rice fields	Rice fields	1
Rice fields → Clove plantations	Clove plantations	5
Rice fields → Settlements	Settlements	6
Rice fields → Swamp forest	Swamp forest	2
Settlements → Secondary forest	Secondary forest	1
Settlements → Annual agriculture	Annual agriculture	2
Settlements → Bare soil / sand	Bare soil / sand	1

Pixel Distribution of Clove Plantations

The spatial distribution of clove pixels within the classified image provides insight into the structure of agricultural land use. Table 4 shows that the classification resulted in 24,566–24,834 pixels, equivalent to 2,282–2,872 ha of clove plantations. These plantations do not occur randomly; rather, they cluster in specific physiographic zones particularly in South Sinjai, Central Sinjai, Sinjai Borong, and West Sinjai.

These areas share environmental traits favorable to clove: well-drained volcanic soils, moderate slopes, and elevations that support stable microclimates. Such clustering reinforces the ecological coherence of the classification and supports the interpretation that clove

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cultivation is strongly shaped by biophysical preferences rather than random land-use expansion.

Table 4. Pixel Distribution of Clove Plantations

Parameter	Value
Total clove pixels	**24,566 – 24,834 pixels**
Equivalent area	**2,282 – 2,872 ha**
Spatial pattern	Clustered distribution
Dominant locations	South Sinjai, Central Sinjai, Sinjai Borong, West Sinjai

Comparison with Official Plantation Data

To contextualize satellite-derived estimates, clove area results were compared with official records from the Forestry and Plantation Agency (HUTBU). As shown in Table 5, satellite classification detected 2,872 ha, whereas the official figure is 4,113 ha, implying a detection ratio of 69.8%. The difference of 1,241 ha is consistent with the known difficulty of detecting small, fragmented clove orchards often grown under partial shade within mixed perennial crop systems.

Table 5. Comparison of Clove Area: Satellite vs Official Data

Data Source	Area (ha)	Difference (ha)	Detection Ratio (%)
HUTBU Field Data (2024)	4,113	0	100
Landsat Classification	2,872	1,241 smaller	69.8%

The discrepancy underscores a common limitation of medium-resolution imagery in smallholder-dominated landscapes, where agroforestry plots may occupy narrow field margins, steep slopes, or shaded understories. These conditions often generate mixed pixels, reducing spectral separability.

Slope and Erosion Risk Analysis

Topography constitutes a major determinant of clove suitability, given the species' sensitivity to water stagnation and soil erosion. For this reason, the slope analysis plays a key role in interpreting both the distribution of existing plantations and the potential for expansion. The updated Table 6, now containing only precise numeric values, displays the actual slope and slope-length measurements for each land unit.

Table 6. Slope and Erosion Risk of Land Units

Land Unit	Slope (%)	Slope Length (m)	Erosion Risk	Notes
1	7	10	Very slight	Dense perennial cover stabilizing soil
2	9	11	Slight	Good vegetation, minimal runoff
3	12	10	Slight	Moderate slope, stable agroforestry
7	27	18	Moderate	Limited groundcover, higher runoff
10	13	10	Slight	Mixed vegetation buffers erosion

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13	11	9	Slight	Agroforestry structure protects soil
14	10	11	Slight	Consistent canopy cover
15	14	10	Slight–Moderate	Requires basic conservation treatment
16	32	19	Moderate	Steeper slope, erosion-prone
18	35	18	Moderate	High runoff, sparse vegetation
21	8	10	Slight	Stable groundcover conditions

These figures reveal a landscape where the majority of clove-growing zones fall within the 7–14% slope range, corresponding to low erosion risk and favorable drainage. In contrast, Units 7, 16, and 18 exhibit steeper slopes above 27%, indicating moderate erosion risk and a need for conservation measures before clove can be sustainably cultivated.

Soil Characteristics of Clove-Growing Areas

The soil characteristics measured from 50 sample points reveal a dominantly volcanic soil landscape composed of latosols, regosols, and andosols all conducive to clove cultivation due to their deep solum, high cation exchange capacity, and moderate organic matter levels. The slightly acidic pH observed across most samples aligns well with the optimum pH range for clove growth.

Table 7. Soil Characteristics Summary

Parameter	Observed Condition	Suitability Implication
Solum depth	Deep	Excellent rooting environment
Texture	ClayClay loam	High stability & retention
pH	Slightly acidic	Ideal for clove
Organic matter	Moderate	Supports nutrient cycling
CEC	High	High fertility potential
Base saturation	Moderate–High	Strong nutrient support
Aluminum saturation	Present	May reduce suitability in some units

While aluminum saturation is present in several land units, which may inhibit root development in localized areas, the broader soil environment remains supportive. These findings reinforce the suitability of Sinjai's upland soils for perennial spice crops.

Detailed Misclassification Patterns

To further understand the spectral ambiguities observed during classification, Table 8 synthesizes the specific environmental and structural factors driving misclassification. Many errors stem from similarities in canopy height, leaf structure, moisture conditions, or settlement adjacency.

For example, zinc-roofed dwellings can resemble bare soil under certain solar angles; swamp forests and waterlogged rice fields show similar moisture-driven spectral responses; and perennial agroforestry systems share canopy complexities with clove orchards.

Table 8. Detailed Misclassification Patterns and Causes

Misclassification Type	Likely Cause	Field Observation Notes
Clove ↔ Mixed plantation	Similar perennial canopy height	Rambutan & tall shrubs 4–6 m

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Clove ↔ Rice fields	Moisture reflectance	Waterlogged paddy near Apareng River
Rice fields ↔ Settlements	Mixed pixels	Houses close to riverbanks
Rice fields ↔ Swamp forest	Spectral similarity	Wetland–paddy overlap
Settlements ↔ Bare soil	Zinc roofs reflectance	Unpainted metal roofs
Settlements ↔ Secondary forest	Dense home-garden vegetation	High canopy density

These insights underscore that classification errors arise not from methodological shortcomings alone but from the inherent complexity of smallholder-managed tropical landscapes.

Field Error Summary

A broader quantitative overview of classification errors is presented in Table 9. Out of 279 ground-truth points, only six clove points were misclassified, indicating generally strong performance for this class. The highest error count occurred in rice fields (13 cases), particularly in areas experiencing seasonal inundation.

Table 9. Clove Pixel Classification and Field Error Summary

Category	Value
Total ground-truth points	279
Clove points misclassified	6
Rice-field errors	13
Settlement-related errors	4
Wetland / swamp errors	2
Primary cause of clove error	Agroforestry spectral overlap
Primary cause of rice-field error	Waterlogging reflectance

These findings confirm that most classification challenges are associated with hydrological variation or densely mixed vegetation, rather than with misidentification of core clove plantations.

Final Land Suitability Classification

The integration of land-cover, slope, soil, and erosion analyses culminated in a final land-suitability classification for clove cultivation. As shown in Table 10, the study area contains substantial zones classified as S1 (very suitable) and S2 (suitable), predominantly located in gently sloping uplands with fertile volcanic soils.

Table 10. Final Land Suitability Classification

Suitability Class	Criteria	Representative Units	Limiting Factor
S1-Very Suitable	Deep soil, stable texture, slope 5–8%	Units 1–3	None/minor
S2 -Suitable	Slope 8–15%, moderate erosion	Units 10, 13–15, 21	Slight erosion
S3-Marginal	Slope 15–40%	Units 7, 16, 18	Erosion risk
N-Not Suitable	Flooded or built-up	Rice-field edges, wetlands	Waterlogging

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Marginal areas (S3) correspond to steep slopes vulnerable to erosion, while non-suitable (N) areas include wetlands, saturated rice-field zones, and settlements. This suitability map provides actionable spatial guidance for both agricultural planning and sustainable resource management.

Challenges of Mapping Clove Suitability in Fragmented Agroforestry Landscapes

However, recent literature has always recognized that demarcation of perennial tree crops in fragmented tropical mosaics is still a methodologically challenging task because of spectral similarity of tree species, sub-pixel heterogeneity, and radiometric distortion as a result of topography. As part of a regional analysis, published by Nur and Astuti (2020) on the basis of 30 m Landsat data, they found that smallholder plots are often mischaracterized or ignored as single pixels combine mixed crown responses of spice tree, fruit trees, shrubs, and young secondary forest. They sampled large homogeneous patches of reference areas which enhanced the overall reliability of the general land-use/land-cover classes, but reduced the detection of heterogeneous interfaces. This observation supports a larger body of opinion that medium resolution is generally underrepresentative of complex tree-based agriculture.

Following the concept of landscape heterogeneity, Abram et al. (2021) proposed an object-based workflow on the Sentinel 2 images that subdivided canopies into significant spatial units. They make more of a contribution in showing that object-centred representations enable classifiers to encode contextual relations (e.g. the crown adjacency, plantation geometry, shade length etc.) which are inexpressible in pixel-wise semantics. The work was limited especially in mountainous shadowy areas where spectral distances are reduced but it is important in highlighting the logic of structural classification that is very important to archipelagic and hill spice producing areas.

Research adding the temporal dimension, like Aditya and Prasetyo (2024), solidifies the fact that long-term vegetation index patterns are used to help differentiate between perennials and mixed annuals, as well as opportunistic regrowth of shrubs. Multi-season multi-season NDVI/EVI dynamics with gradient boosting were their modeling of signal stability over the years, implying that permanence signatures are significant differentiators of clove zoning, which places the current study in the lineage of progression to temporally sensitive classification schemes.

Lastly, Descals et al. (2022) tested very high-resolution plantation map validation of spatial bias in 10-30 m validation through reference validation based on auditing. They are important not because they repeat thematic results but because they show that the probability of detection is negatively proportional to plot size and heterogeneity, particularly in tree-mixed agriculture less than 5ha. This mass of evidence justifies the structural difficulty as opposed to doubting study-specific results.

The rest of the supporting evidence is the OBIA- CNN benchmarks provided by Sulistyo et al. (2024) that reveal that deep-feature extraction significantly enhances semantic separability in perennial tree plantations because CNNs are capable of encoding the nuances of the crowns; and Wahyudi et al. (2025), which point to the use of DEM-based topographic correction to decrease slope-related reflectance bias. Combined, these essential interpretations of the literature confirm that mapping small fragmented agroforestry zones is necessarily susceptible to omission and spectral confusions unless multi- sensor, temporal, or object-level education is utilized.

Profile of Ecological and Agronomic Limiting Factors for Clove Growth

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An independent but overlapping set of investigation is a critical look at soil chemical stressors, nutrient buffering over time, and impediments around the roots of trees in spice systems in the tropics. In their study, Riza et al. (2020) utilized FAO-specific criteria in dryland spice gardens and found that the depth of the soil, pH, and retention capacity of nutrients are the main axes determining the suitability of trees to spices. Nevertheless, this exploration did not overtly include an element of saturation of aluminum as a spatial restriction instead, the element of acidity was handled as a single scalar value, therefore, leaving local Al stress areas unmapped. This factor has not been considered and this is reflected in the inclusion of multi-unit agronomic granularity of aluminum in the present study.

Firmansyah and Rahman (2021) have performed a comprehensive soil sampling in the mixed systems of clove-fruits and defined Al- as an inductor of root impedance as a subsurface physico-chemical stressor. Their input is fundamental in explaining the mechanistic foundation of Al binding to phosphorus which reduces proliferation of roots and causes vegetative stress over time. Notably, their study failed to conduct suitability mapping, which underlines the fact that often the studies focused on physico-chemical stress are developed without considering the studies of spatial zoning, which justifies the approach to bridging the methodological divide presented by the current study.

International synthetic research activities like Oliveira et al. (2021) and Suharto et al. (2022) suggest that high CEC soils tend to stabilize cation fertility and also have strong pH buffering capacity due to organic complexes. Though these studies did not identify clove in isolation, their methodological frameworks indicate that nutrient buffering, CEC interactions are general to the tree spices, but they do not show spatial site description.

Adams et al. (2023) have used the long-term monitoring of the soil of tropical agroforestry plots and have shown that SOC enrichment does not only buffer acidity but also over time suppresses Al activity. This confirms the fact that enhancing soil organic matter is one of the important long-term mitigation factors as opposed to a mapping parameter. Jiang et al. (2024) combined root-zone stress modeling of various tree perennials and showed a feedback synergistic effect steep slopes increase erosion, which repeatedly redefines the ameliorative value of organic matter and makes chemical stress and slope-erosion inseparable at the landscape level. This explanation is crucial in understanding the reason field S3 often coincides with slope stress areas despite high soil fertility.

Other references that justify the ecological framing are Hidayat et al. (2024) and Rahman et al. (2024), who used the fuzzy multi-criteria evaluation to the perennial suitability of Southeast Asia. Their models focused on pH, slope, and soil depth without combining concurrently Al-toxicity and disaster susceptibility which means that the current model belongs to the crossroad of soil chemical stress, topography risk, multi-criteria decision science at the spatial level.

Land Degradation Risk on Steep Slopes and Conservation Imperatives for Tropical Tree Spices

There exists a solid body of evidence that separates perennial tree suitability and perennial tree sustainability. Arsyad et al. (2021) simulated the RUSLE soil loss in tree-based plantations and found out that soil productivity decreases drastically in the long run when slope categories are steeper than 27% unless terraces are built using engines. The research did not observe species-specific reactions or give a conclusion in terms of suitability, but instead promoted an argument of the limiting-stress layer that slope -erosion instability occurred, which legitimized that the interpretation of soil-erosion class S3 should not be in the form of crop failure area but a high-intervention landscape.

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Hasan et al. (2023) quantified the ecological effects of terraces on small-scale tree-crops survival. Their longitudinal structure demonstrated that terracing enhances early growth environments, not due to its chemical fixation of the soil but by a systematic mechanism of greatest velocity of runoff, stabilisation of root-zone moisture changes and deceleration of nutrient exchanges. Even though the research made no attempt to combine remote sensing to it, it offers a theoretical explanation of why slope should always be a crucial decision filter in perennial allocation despite the soil being chemically fertile.

Improving conceptual models that show how hydrological bulk flow regimes are altered by ground-layer vegetative cover and engineered terraces are found in mitigation studies like Zaeem et al. (2022) and Putri et al. (2025). Specifically, Putri et al. (2025) developed spatial erosion -masking logic of perennial allocation policy, indicating that suitability maps should have explicit constraints layers, including slope -erosion controls, instead of basing on final class results. This provides a sharp policy reading that is in line with MCE -GIS appropriateness logic of the current study that argues that the new spatial allocation schemes should provide suitability result as well as constraint disentanglement.

Other articles favoring such a degradation-specific interpretation are Budiharjo et al. (2020), Prabowo et al. (2021), and Utami et al. (2023), who explored land-degradation thresholds of perennial spice allocation in agroforestry systems (insular and mountainous). All these studies together emphasize that slope-erosion vulnerability should never be construed as a sustainability limit, and not just a plantability threshold.

Smart Farming Integration and the Role of Ground-Data Densification for Scaling Perennial Tree Suitability

The conceptual change in tropical digital agriculture makes IoT and densification of ground sensors an instrument to provide contextual error-correction of the zone scale, but not as independent productivity estimators. In Kumar et al. (2020), the authors used the IoT soil sensors in spice gardens to record the micro-block diurnal variability. Their results are critical in illustrating that tree-spice smallholders have high intra-unit spatial variance of pH, moisture, and temperature resulting in dynamic boundaries of suitability within a single unit of mapped land. Even though it is not a direct analogy, this work offers methodological justification of dense lapangan data or hybrid spatiotemporal learning architectures.

It was pointed out in reviews by Mansoor et al. (2022) and Rai et al. (2025) that IoT nodes are not to replace remote sensing but serve as reference-based correction anchors, which correct spatial classifier decisions in small tree-based agriculture. Their theoretic value is to outline sensor cost and scalability limitation, and thus endorse the idea that IoT is to be implemented at the reference-grid scale at the chosen correction locations, but not throughout the area. This is in line with the focus of the current paper on hybrid ground-truthing and explaining a policy gap: smallholders need a tiered sampling of correction, and not densifying sensors uniformly.

Nugroho et al. (2023) and Phong et al. (2024) experimented with combining the IoT with the Sentinel data to correct the reliability of the perennial mapping. The design was crucial in the quantification of how reference-grid sensors enhance precision in training of canopy-mixed plantations, indicating that sensor-fusion scaling pathways can increase reliability of tree spices with stable phenological cycles, e.g. clove when remote signals interact.

Such studies combining ML/semantic scaling context are Li et al. (2022), Singh et al. (2023), Harahap and Lestari (2024), and Zhang et al. (2024). Together, these people claim that tropical perennial zoning at scale requires hybrid RS-plus-ground reference correction, spatial cross-validation, and temporal-stability signature extraction to alleviate geographic overfitting in

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patch-rich landscapes, which the current paper has already started to solve, albeit potentially enhancing with testing of spatial model-generalization.

Theoretical and Regional Research Gap Contribution Toward a Unified Perennial Tree-Spice Suitability Framework

The body of research on clove suitability studies over the last five years is more apt to be subdivided into silos of isolated specialization, such as nutrient sampling studies, slope-erosion modeling, land use/land cover (LULC) classification studies, fuzzy analytic hierarchy process (AHP) multi-criterion evaluation (MCE) decision-making zoning, and Internet-of-Things (IoT)-based microblock analyses, but in rare cases are combined into a singular framework.

Santosa et al. (2020), Hakim et al. (2021), and Cahyono and Lestari (2022) evaluated productivity or acidity mechanism of clove fields, but none of the studies generated zoning layers of space suitability, nor did they consider slope -erosion as masking filters. In the same way, Dewi et al. (2023) and Muhlis et al. (2023) used remote sensing categorization of small gardens, however, without large-scale stratified ground-validation points or clear limitations on the saturation of aluminium. Rahman et al. (2024) presented a fuzzy-MCE tree-crop suitability model, but it lacked chemical aluminium stress, slope sustainability, and high-density reference map in one series of algorithmic zoning.

Conclusion

This study successfully applied GIS and big-data-based remote sensing to detect the spatial distribution of clove plantations and evaluate land suitability in Sinjai Regency. Through 2024 satellite image classification, approximately 2,282–2,872 ha of clove plantations were identified, exhibiting a clustered spatial pattern across four key sub-districts: South Sinjai; Central Sinjai; Sinjai Borong; and West Sinjai.

The classification accuracy assessment, supported by 279 ground-truth points, achieved an overall accuracy of 84.3%, indicating strong interpretation reliability for a heterogeneous tropical landscape. Clove plantations recorded the highest class accuracy, with 84.0% producer accuracy and 88.4% user accuracy. In contrast, primary and secondary forest classes presented the greatest spectral ambiguity (49.99% accuracy), mainly due to similarities in perennial canopy structure and crown height within mixed smallholder agroforestry systems.

Topographic and erosion-risk analysis revealed that most existing clove cultivation occurs on land with 7–14% slope, corresponding to very slight to slight erosion risk, supporting suitable drainage and long-term sustainability. Meanwhile, land units with slopes above 27% (Units 7, 16, 18) were categorized as marginal (S3) and require prior soil-conservation measures due to increased surface runoff and erosion susceptibility.

Soil assessment from 50 samples confirmed that the region is dominated by volcanic upland soils (deep solum, clay to clay-loam texture, slightly acidic pH, high cation exchange capacity, and moderate-to-high base saturation), all of which are broadly favorable for clove growth. However, localized aluminum (Al) saturation was observed in several land units and constitutes a partial limiting factor for root development.

The final land-suitability synthesis demonstrated that the study area contains extensive suitable zones, dominated by S1 (very suitable) and S2 (suitable) land classes, particularly in well-drained upland physiographic positions. The primary constraint to spatial detection remains the fragmentation of small shaded orchards and overlapping mixed vegetation pixels, which reduce spectral separation at subplot scales.

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The integration of smart-farming field sensors for real-time soil microclimate, texture, and temperature observation proved valuable for ground validation and practical usability, enabling farmers to access up-to-date decision-support information without full field visitation. This supports more precise land-use planning and sustainable clove-cultivation development strategies for smallholder plantation systems.

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