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EVALUATION OF LAND SUITABILITY FOR MAIN CROPS IN BAC SON DISTRICT, LANG SON PROVINCE USING MACHINE LEARNING AND ARTIFICIAL NEURAL NETWORK MODELS

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Abstract

This study evaluated land suitability for Golden Tangerine and Paddy Rice cultivation in Bac Son District, Lang Son Province, using Random Forest (RF) and Artificial Neural Network (ANN) models. Environmental factors, such as elevation, slope, aspect, NDVI, distance to streams and roads, rainfall, soil type, soil depth, and soil texture, were used as input variables. The results showed that both models effectively assessed land suitability, though their predictive performances differed by crop type. For Golden Tangerine, the ANN model predicted a higher mean suitability value (0.38313) and slightly better classification accuracy (0.7856) compared to the RF model (0.27367 and 0.7786, respectively). For Paddy Rice, the ANN model again estimated a larger suitable area (mean suitability: 0.38749), but the RF model outperformed the ANN in classification accuracy (0.6896 and 0.6663 respectively). Both models showed similar prediction variability, with only minor differences in standard deviations. These findings highlight the trade-off between the extent of suitable land identified by ANN and the higher classification accuracy achieved by RF, particularly for Paddy Rice. This study emphasized the need to consider both spatial distribution and accuracy.

Keywords: *: Land Suitability, Machine Learning, Artificial Neural Network, Paddy Rice, Golden Tangerine*

INTRODUCTION

Land evaluation plays a vital role in sustainable land-use planning and agricultural development. As a foundational tool for assessing the suitability of land for various uses, it contributes significantly to optimizing resource allocation, enhancing agricultural productivity, and ensuring environmental sustainability. Over the decades, land evaluation approaches have evolved, reflecting advancements in scientific methods, technological integration, and adaptation to local and global needs.

The 1970s marked a pivotal moment in land evaluation, as countries developed diverse systems for land assessment. However, the lack of standardization hindered the global exchange of evaluation results. To address this, the Food and Agriculture Organization (FAO) introduced a universal framework, detailed in "A Framework for Land Evaluation" (FAO, 1976). This systematic approach integrated biophysical, socio-economic, and technical criteria to determine land suitability for specific uses. The adoption of this framework revolutionized land evaluation practices, harmonizing processes across local and global scales. Subsequent updates and thematic extensions, such as guidelines for rainfed agriculture (1983) (Stewart, 1988), irrigated agriculture 1985 (FAO, 1985), and sustainable management (1993), further enhanced its relevance. Traditional methods of land evaluation were qualitative and labor-intensive, often leading to inconsistencies. The advent of Geographic Information Systems (GIS) and spatial modelling technologies marked a significant paradigm shift. Multi-Criteria Evaluation (MCE) techniques, combined with analytic hierarchy process (AHP) approaches, allowed for the integration of diverse factors like climate, soil properties, and topography, improving precision and objectivity (Ceballos-Silva & Lopez-Blanco, 2003; Chen, Yu, Khan, & software, 2010). More recently, Machine Learning (ML) (Giannarakis, Sitokonstantinou, Lorilla, & Kontoes, 2022; Mokarram, Hamzeh, Aminzadeh, & Zarei, 2015; Yang, Ma, Liu, & Li, 2023) and artificial intelligence (AI) (El Behairy et al., 2023; Farnood Ahmadi, Farsad Layegh, & applications, 2015; Li, 2022) have introduced transformative possibilities. These technologies utilize large datasets to identify patterns and relationships often overlooked by traditional methods. For instance, ML models have demonstrated superior accuracy in predicting natural hazards, such as landslides and floods, while applications in land evaluation have shown promise in mapping soil characteristics, modelling species distribution, and classifying land cover.

Case studies worldwide illustrated the diversity of land evaluation methodologies. Ceballos-Silva and Lopez-Blanco (2003) employed GIS-based MCE to assess land suitability for maize and potato cultivation in central Mexico, integrating climate, topography, and soil data to produce actionable maps (Ceballos-Silva & Lopez-Blanco, 2003). Similarly, Mulugeta (2010) used AHP and GIS-based linear weighting methods for wheat and maize suitability assessments in Ethiopia, addressing regional agricultural challenges (Mulugeta, 2010). The integration of socio-economic variables into land evaluation is also gaining traction. Studies such as those by Araya et al. (2010) and Purnamasari et al. (2018) emphasized incorporating economic and social factors alongside biophysical criteria to enable holistic land-use planning (PURNAMASARI, 2018). These advancements underscore the evolving nature of land evaluation, driven by scientific innovation and practical needs. Land Evaluation in Vietnam: Agriculture is a cornerstone of Vietnam's economy, contributing significantly to GDP and food security. Recognizing the importance of land resources, Vietnam has extensively adopted FAO's land evaluation methodologies. These methods have been instrumental in identifying land suitability for various crops and guiding sustainable practices. Historical studies laid the groundwork for Vietnam's contemporary land evaluation practices. Nguyen Khang and Pham Duong Ung (1995) produced a comprehensive land evaluation map at a scale of 1:250,000, classifying 372 land units and identifying 90 primary land-use types (Ưng, Khang, & Đài, 1995). Subsequent studies, such as those by Vu Cao Thai (1989) and Nguyen Cong Pho (1995), incorporated ecological and sustainable development perspectives, enriching the country's evaluation framework. Modern technologies have further enhanced land evaluation in Vietnam

(Pho, 1995; Thái, 1989). For example, Le Canh Dinh (2011) employed fuzzy GIS and multi-objective optimization to support sustainable land-use planning in Lam Dong Province (Dinh, 2011), demonstrating Vietnam's commitment to leveraging advanced methodologies.

Despite significant progress, challenges remain in addressing the complexities of modern land-use dynamics. Agricultural expansion, urbanization, and climate change exert increasing pressure on land resources, necessitating adaptive approaches. ML and AI technologies offer transformative potential, automating data analysis and enabling real-time decision-making. Moreover, integrating socio-economic considerations into evaluation frameworks is critical for equitable and sustainable outcomes. Studies, including those by Gardner et al. (2021) and Vasu et al. (2018), highlight the importance of accurate algorithms in influencing land-use decisions. These advancements, combined with a commitment to harmonized methodologies, technological innovation, and context-specific adaptations, will shape the future of sustainable land-use planning.

Land evaluation bridges the gap between science and practice, offering a robust tool for sustainable land management. By integrating traditional knowledge with modern technologies, it provides valuable insights for resource optimization and environmental sustainability. As challenges such as climate change and resource scarcity intensify, advanced computational techniques will play an increasingly pivotal role in shaping the future of land-use planning.

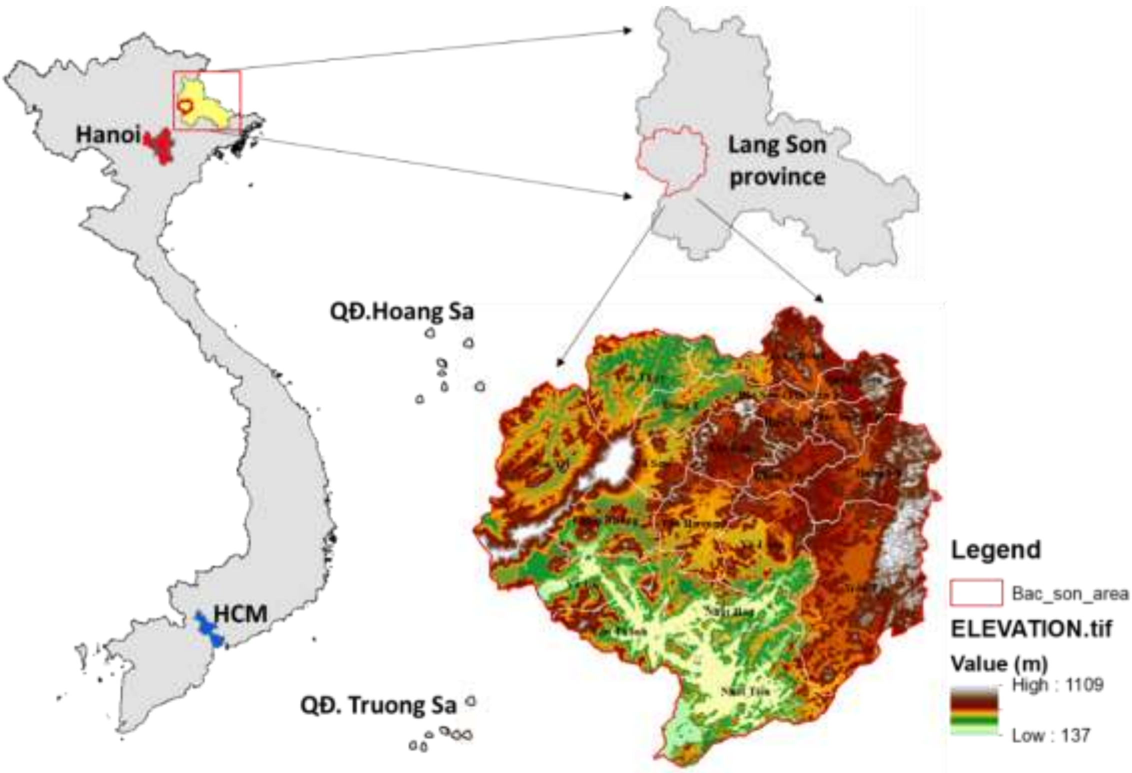

Figure 1. Location of study area

Bac Son, a mountainous district in Lang Son Province, holds significant potential for agricultural development oriented towards commercialization, linked with community-based and agro-ecotourism activities. In recent years, Bac Son has prioritized fostering key crops such as the golden-skinned Bac Son orange, tobacco, and red peanuts. These key agricultural products have contributed to the economic development of the locality. However, the production scale of these key crops remains fragmented, necessitating a comprehensive evaluation and strategic land-use planning to allocate suitable land for these crops. This would increase commodity production and enhance efficient land use. Thus, assessing the land-use efficiency of certain key crops in Bac Son District, Lang Son Province, is a critical task at present.

Table 1. Major crops cultivated in Bac Son District from 2019 to 2023 (Linh et al., 2024)

No.	Crops	Area (ha)					Area 2019/2023 (ha)	Yield 2023 (tons)
		2019	*2020*	*2021*	*2022*	*2023*		
1	Spring Rice	810,30	780,00	833,9	800	912,10	1,8	4.797,37
2	Summer Rice	3.722,91	3.500,00	3.596,03	3.500,00	3.675,67	-47,24	16.107,30
3	Maize (Corn)	4.149,25	3.720,39	3.909,36	4.271,42	4.291,36	142,11	19.783,27
4	Sweet potato	108,42	99,13	92,47	110,00	97,58	-10,84	432,8
5	Potato	12,68	4,46	4,54	3,72	3,72	-8,96	36,56
6	Vegetables	536,73	460,0	563,30	480,00	548,96	12,23	4.969
7	Beans	111,40	129,11	115,12	110,00	106,17	-5,23	140,95
8	Red peanut	1.076,27	1.159,03	1.126,23	1.125,53	1.122,13	45,86	1.222,28
9	Golden tangerine	450,34	510,23	520,43	447,57	490,00	39,66	1.350,00
10	Tobaco	1.140,68	1.073,58	1.215,82	1.328,17	1.516,16	375,48	3.416,63

Between 2019 and 2023, Bac Son District identified five primary crop groups with significant cultivation areas and yields: rice, corn, red peanuts, tobacco, and golden tangerine. Among these, golden tangerine and Bac Son red peanuts have emerged as prominent agricultural products, recognized for their contribution to the district's agricultural branding. Specifically, peanut oil was acknowledged as an outstanding provincial rural industrial product in 2021 and received a 3-star OCOP certification at the provincial level in 2022. Furthermore, golden tangerine orchards have been cultivated under stringent standards, including VietGAP and GlobalGAP, emphasizing sustainable and environmentally friendly agricultural practices. While rice and corn, particularly the "Nếp cái hoa vàng" variety, are predominantly grown for subsistence and encounter market volatility, they are prioritized for future development by Bac Son district, Lang Son Province. Considering these factors, tobacco, golden tangerine, and red peanuts are identified as the district's primary agricultural commodities for focused study and strategic planning (Linh et al., 2024).

In this study, the application of Artificial Neural network (ANN) and the Random Forest (RF) model will be conducted to evaluate and classify land suitability levels based on terrain, soil, and hydrological conditions for three primary land-use types that represent the strengths and characteristics of the locality: Paddy rice, and Golden tangerine. Based on the findings, we will propose agricultural planning strategies for these three key crops in Bac Son District, Lang Son Province.

DATA AND METHODOLOGY

Data preparation

In this study, ten environmental and geographical factors were selected as input variables to evaluate land suitability in Bac Son District, Vietnam. These factors were derived from various remote sensing and GIS data sources, ensuring a comprehensive analysis of land characteristics and their influence on land use potential.

Topographic factors such as Elevation, Slope, and Aspect were extracted from the Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM) and its derivatives. Elevation ranges from 137 m to 1109 m (Figure2g), while slope values vary between 0° and 72.39° Figure 2h). Aspect is classified into categories, representing the directional orientation of slopes, which can influence factors such as soil moisture and solar radiation exposure (Figure 2i). Vegetation and hydrological factors were included to assess ecological and environmental conditions. The Normalized Difference Vegetation Index (NDVI), derived from Sentinel-2 imagery, ranges from -0.114 to 0.583, providing insights into vegetation cover and biomass (Figure 2d). Distance to stream was calculated using stream networks, with distances ranging from 0 m to 5496.59 m, reflecting hydrological accessibility and potential water supply (Figure 2f). Annual rainfall, sourced from WorldClim data, ranges from 1498 mm to 1690 mm, representing climate variability that directly influences soil moisture and agricultural productivity (Figure 2j). Infrastructure and accessibility factors such as Distance to road were derived from the Bac Son road network map, with distances ranging from 0 m to 4915.25 m. This factor is crucial for determining the accessibility of agricultural land and potential transportation constraints (Figure 2e). Soil-related factors were obtained from the Soil Map provided by the Department of Natural Resources and Environment of Lang Son Province. These include Soil Type, Soil Depth, and Soil Texture, which were categorized based on soil properties. Soil depth ranges from 0 cm to over 100 cm, influencing root penetration and water retention capacity (Figure 2c). Soil texture was classified into distinct categories based on particle size distribution, affecting drainage and fertility (Figure 2b).

All spatial data were processed Geotiff file 10m resolution in the Universal Transverse Mercator (UTM) coordinate system, zone 48N, ensuring consistency in spatial analysis. These factors collectively provide a comprehensive framework for evaluating land suitability, integrating topographic, climatic, hydrological, infrastructural, and soil-related characteristics.

Table 2. Data used for Land suitability in Bac Son district (Vietnam)

<table>
<tr><th>Factor</th><th>Data source</th><th colspan="2">Min</th><th colspan="3">Max</th></tr>
<tr><td>ELEVATION</td><td>SRTM DEM (USGS)</td><td colspan="2">137 m</td><td colspan="3">1109 m</td></tr>
<tr><td>SLOPE (degree)</td><td>DEM - derived</td><td colspan="2">0</td><td colspan="3">72.39</td></tr>
<tr><td>ASPECT</td><td>DEM - derived</td><td colspan="5">Category</td></tr>
<tr><td>NDVI</td><td>Sentinel 2 - derived</td><td colspan="2">-0.114</td><td colspan="3">0.583</td></tr>
<tr><td>STREAM (Distance to stream)</td><td>Stream network extract from the Bac Son hydrology map</td><td colspan="2">0 m</td><td colspan="3">5496.59 m</td></tr>
<tr><td>RAINFALL</td><td>www.worldclim.org</td><td colspan="2">1498 mm</td><td colspan="3">1690 mm</td></tr>
<tr><td>ROAD (Distance to road)</td><td>Road network extract from the Bac Son road map</td><td colspan="2">0 m</td><td colspan="3">4915.25 m</td></tr>
<tr><td>SOIL</td><td rowspan="3">Soil map (province scale) provided by the Department of Natural Resources and Environment of Lang Son province</td><td colspan="5">Category
ATe – Eutric Anthrosols
FRd – Dystric Ferralsol
GLe – Eutric Gleysol
ATd – Dystric Anthrosols
AC – Haplic Acrisols
FLd – Dystric Fluvisol
LVst – Stagnic Luvisols
ACst – Stagnic Acrisol
LVe – Eutric Luvisols
ACf – Ferralic Acrisol
Rock – Rock Outcrops</td></tr>
<tr><td rowspan="2">SOIL_DEPTH</td><td>0</td><td>4</td><td>3</td><td>2</td><td>1</td></tr>
<tr><td>Unclassified</td><td><50 cm</td><td>50-70cm</td><td>70 - 100cm</td><td>>100cm</td></tr>
</table>

SOIL_TEXTURE		**Category** c. Light Loam d. Medium Loam e. Heavy Loam R* Rock

* All the data used the UTM coordinate system (zone 48N)

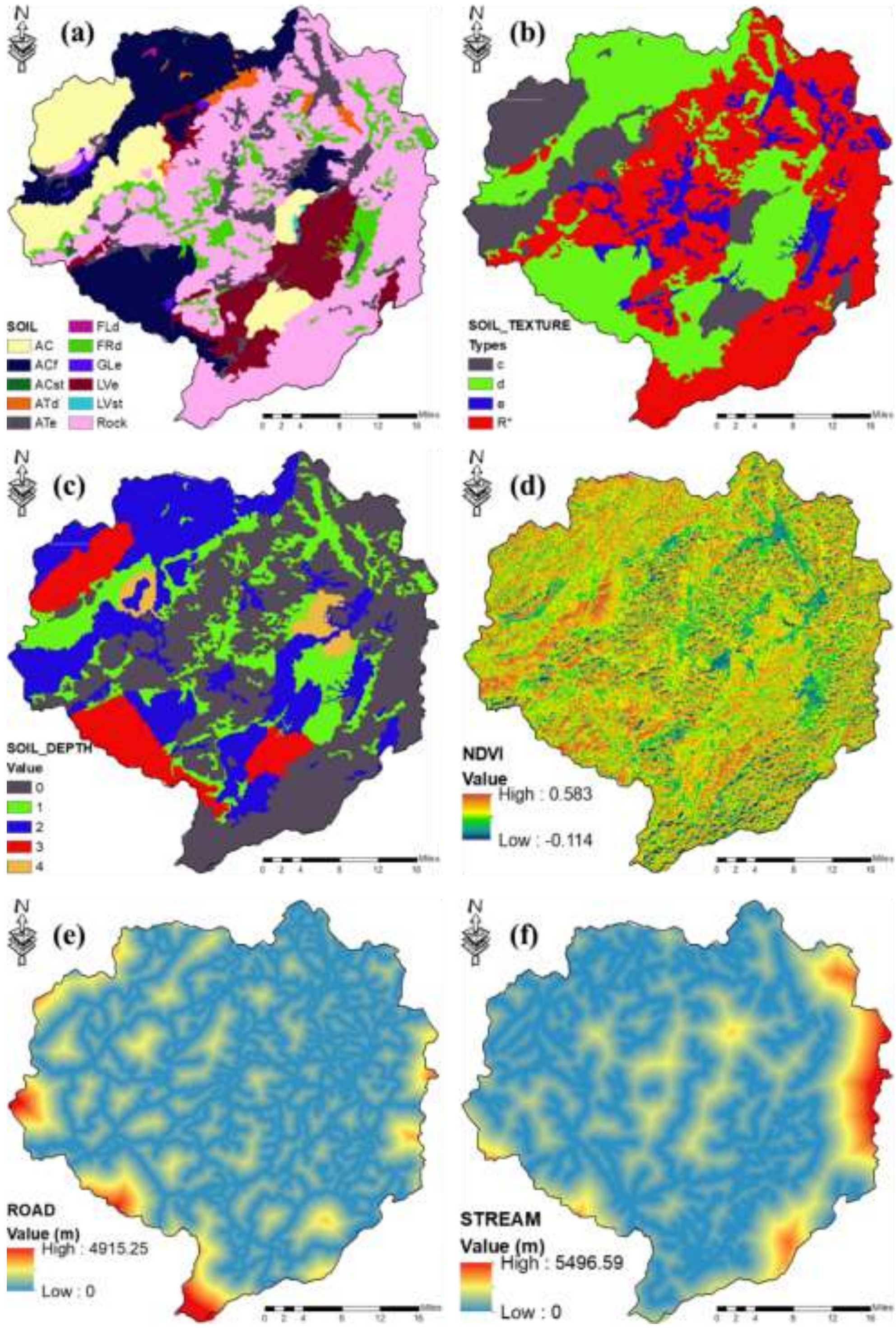

Figure 2. Slectected Factors: (a) Soil types, (b) Soil texture, (c) Soil Depth, (d) NDVI, (e) Distance to Road, (f) Distance to stream (continue)

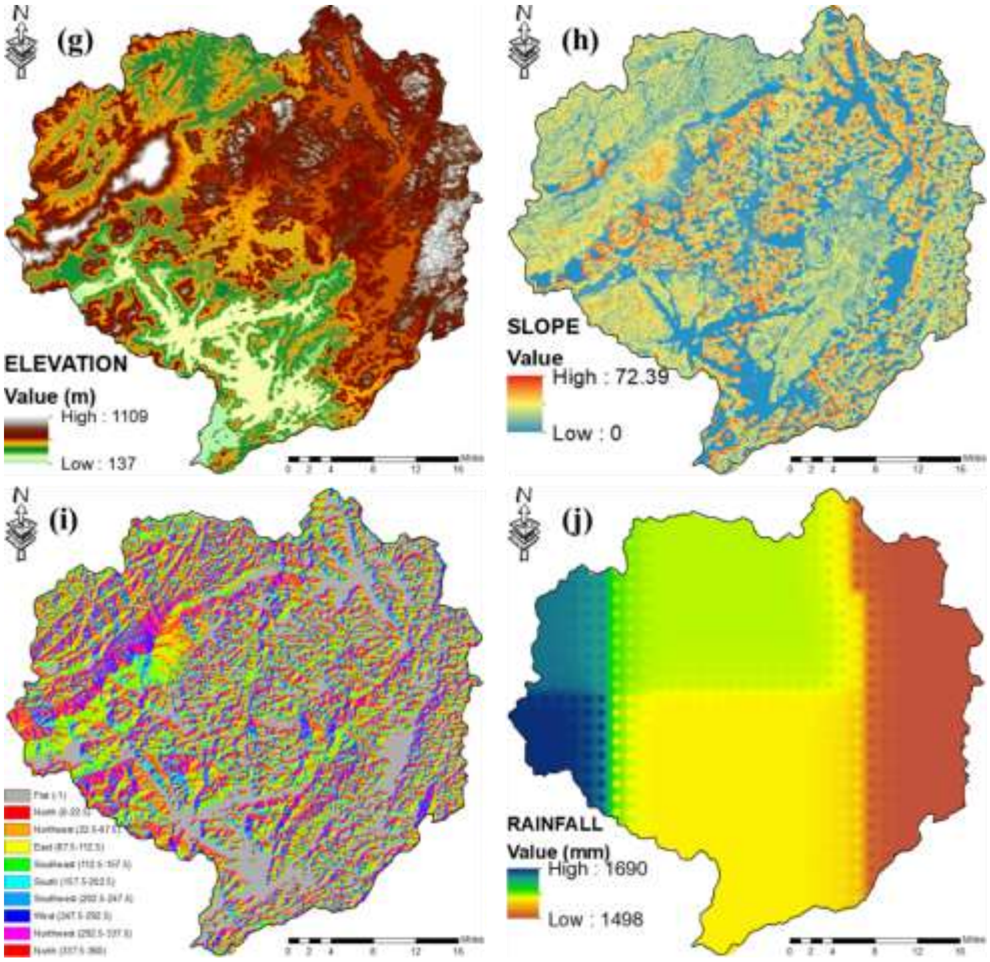

Figure 2. Selected factors: (g) Elevation, (h) Slope, (i) Aspect, (j) Rainfall

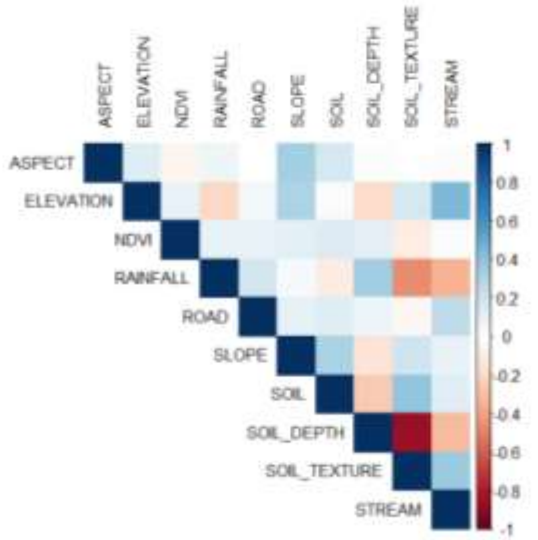

Figure 3. Pearson correlation coefficient between factors

The Pearson correlation matrix reveals the relationships among various environmental predictors. Most correlation values are relatively low, indicating weak linear relationships among predictors. However, a few notable correlations suggest potential interactions or dependencies. Soil Depth and Soil Texture exhibit a strong negative correlation (-0.86), indicating that as soil depth increases, soil texture values decrease significantly. Similarly, Rainfall and Soil Texture show a moderately strong negative correlation (-0.47), suggesting that regions with higher rainfall tend to have finer soil textures. Additionally, Elevation and Stream Density have a moderately strong positive correlation (0.45), which is reasonable given that higher elevations often contribute to stream formation and drainage patterns.

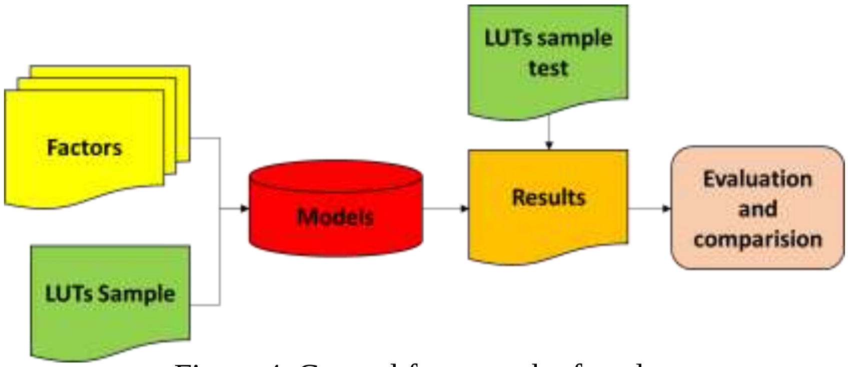

Figure 4. General framework of study

Methods of Model application and evaluation

Artificial Neural Network model

The Artificial Neural Network is a computational information processing model. Multilayer Perceptron (MLP) is the most popular ANN type, which is included an input layer, an output layer, and one or more hidden layers between them. The number of hidden layers and the number of nodes in a hidden layer required for a particular classification problem are not easy to deduce. However, according to the experience of experts, it can be defined by $2*Ni+1$, where Ni is the number of input factors (Hecht-Nielsen, 1987). The input factors were fed forward into the procedure as multiple notes, and their weights will compute the output in the hidden layer and from hidden layer nodes to the output layer with 70% of the training data by using a non-linear function.

Then, the multiple error units were determined based on the difference between computed output and the expected output (actual output). This error is distributed among the weights of the connection (back-propagation) in order to reduce the error. Subsequently, remained 30% of training data was used for testing and validation of the result of the training procedure. Suppose the result becomes significant with low mean square error (expected MSE<0.01), and the accuracy is acceptable, then the training step can stop. The completed network is used as a feed-forward structure to simulate for the entire study area. All of the training and simulation steps were performed in RStudio software.

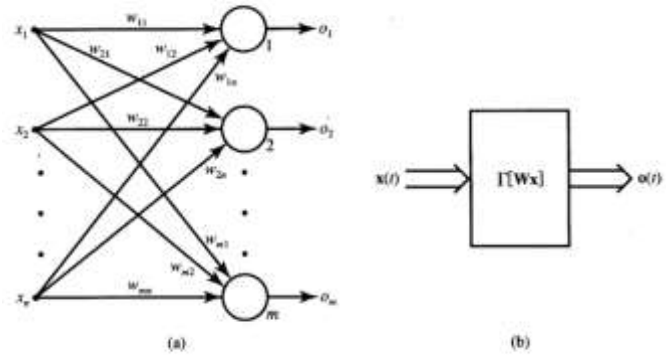

Figure 5. Single-layer feedforward network (a) interconnection scheme and (b) hidden diagram

The figure above represents the general schematic of ANN with the two directions. Training feedforward and backpropagation. The n is the number of inputs, and m is the number of output will be represented as a vector. The backpropagation algorithm will be given here in its final form as follows . The output to processing node net_{pj}, determined by computing the sums of the inputs i_{pi} multiplied by a set of associated weights w_{ji}, is used as input to the activation function f(.), as follows:

$$\mathrm{net_{pj}} = \sum_{j=1}^{n} \mathrm{w_{ij} i_j} \qquad (1)$$

The following nonlinear transformation involving the activation function $f(net_{pi})$, for pi=1,2,3,…,m), completes the processing of x. The transformation, performed by each of the *m* neurons in the network is a strong nonlinear mapping expressed as

$$\mathrm{o_{pi}} = \mathrm{f}(\mathrm{net_{pj}}) = \frac{1}{1+e^{-net_{pj}}} \qquad (2)$$

A sigmoid activation function is generally employed, in this case o_{pj} can be generated as above. The backpropagation algorithm computes the error signal Ep, which is a measure of the network's performance for one processing element in the output layer, using the following formula:

$$\mathrm{Ep} = \frac{1}{2}\sum(\mathrm{t_{pj}} - \mathrm{o_{pj}})^2 \qquad (3)$$

t_{pj} is the desired backpropagation output for j^{th} component of the output pattern for pattern p, and opj is the actual backpropagation output for j^{th} processing element. The total error for the network is given by the formula:

$$\mathrm{E} = \sum \mathrm{Ep} \qquad (4)$$

The new weights are estimated by using the modified delta rule:

$$\mathrm{wij'} = \mathrm{wij} + \Delta\mathrm{wij} \qquad (5)$$

$$\Delta wij = -\eta \frac{\delta E}{\delta wij} \quad (6)$$

Δwij is the incremental change in the weight and g is the learning rate controlling the update step size.

Random Forest model

RF is a powerful machine-learning technique that uses the Bootstrap sample approach to train many decision trees (DTs) with large depths. The RF ensemble model combines the results of the DTs by taking a majority vote for classification tasks or counting an average for regression tasks. This approach ensures that the model generalizes well and does not overfit the training data (Breiman, 2001). RF is suitable for continuous and categorical predictor variables and can minimize variance while maintaining the ensemble's bias. The unselected samples (out-of-bag) are used to evaluate the uncertainties of the model training. RF is widely used in various fields, due to its ability to generalize well. This study used RStudio software with updated packages to develop the RF model.

Model Performance

The performance of the land suitability models in this study was evaluated using the confusion matrix. To perform the reliability of the models, accuracy evaluation metrics was utilized with independent testing data for model performance and comparison. It assesses the accuracy with which a given area has been classified and the error of omission or the fraction of observable features on the ground that are not identified on the map. Overall accuracy represents the agreement of model prediction and reference data (Eq.7).

$$ACC = \frac{TP + TN}{TP + FP + TN + FN} \quad (7)$$

Where TP (true positive) and TN (true negative) are the numbers of correctly classified pixels. FP (false positive) and FN (false negative) are the numbers of incorrectly classified pixels,

RESULTS AND DISCUSSION

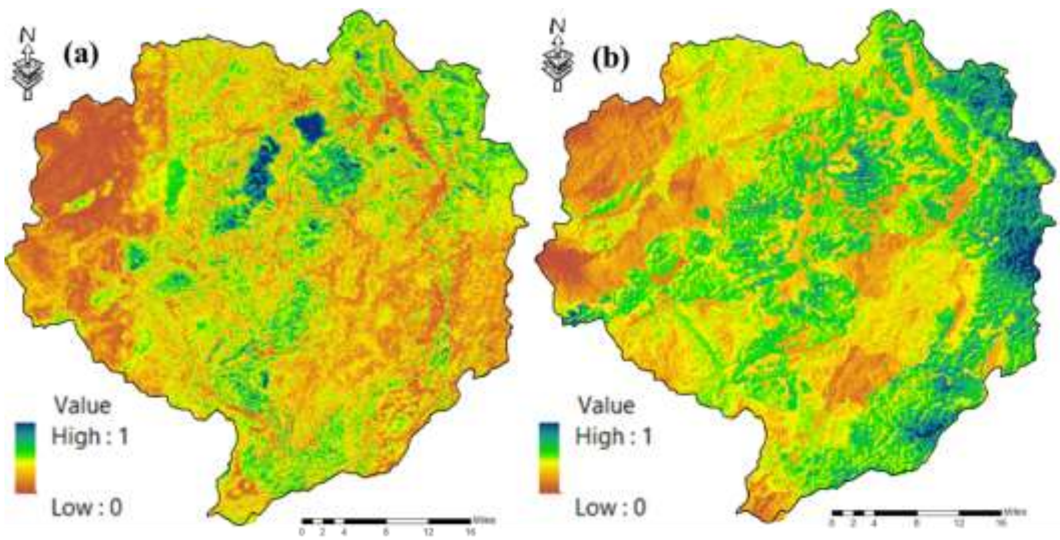

Figure 6. Land suitability for Golden tangerine: (a) Result of RandomForest model, (b) Result of ANN model

Table 3. Land suitability for Golden tangerine results

Value	Random Forest model	ANN model
Mean	0.27367	0.38313
Standard Deviation	0.13919	0.13804
Accuracy	0.7786	0.7856

Figure 6 illustrates the spatial distribution of the probability of land suitability for Golden Tangerine cultivation, where dark green areas indicate high suitability and brown areas represent low suitability. Table 3 summarizes the land suitability assessment results obtained from the Random Forest (RF) and Artificial Neural Network (ANN) models. The ANN model produced a higher mean suitability value (0.38313) compared to the RF model (0.27367), suggesting that it identified a larger proportion of the study area as suitable for cultivation. Both models exhibited comparable levels of variability, with standard deviations of 0.13919 for RF and 0.13804 for ANN. In terms of predictive performance, the ANN model demonstrated a slightly higher accuracy (0.7856) than the RF model (0.7786), indicating a marginally superior classification capability.

Overall, both RF and ANN model successfully evaluate land suitability for Golden Tangerine cultivation, meaning they can process input variables (such as climate, soil properties, and topography) and generate suitability maps. The ANN model is slightly superior in terms of both predictive accuracy and the ability to identify larger suitable areas. However, the small differences also indicate that RF remains a viable alternative, especially if computational efficiency or interpretability is a concern.

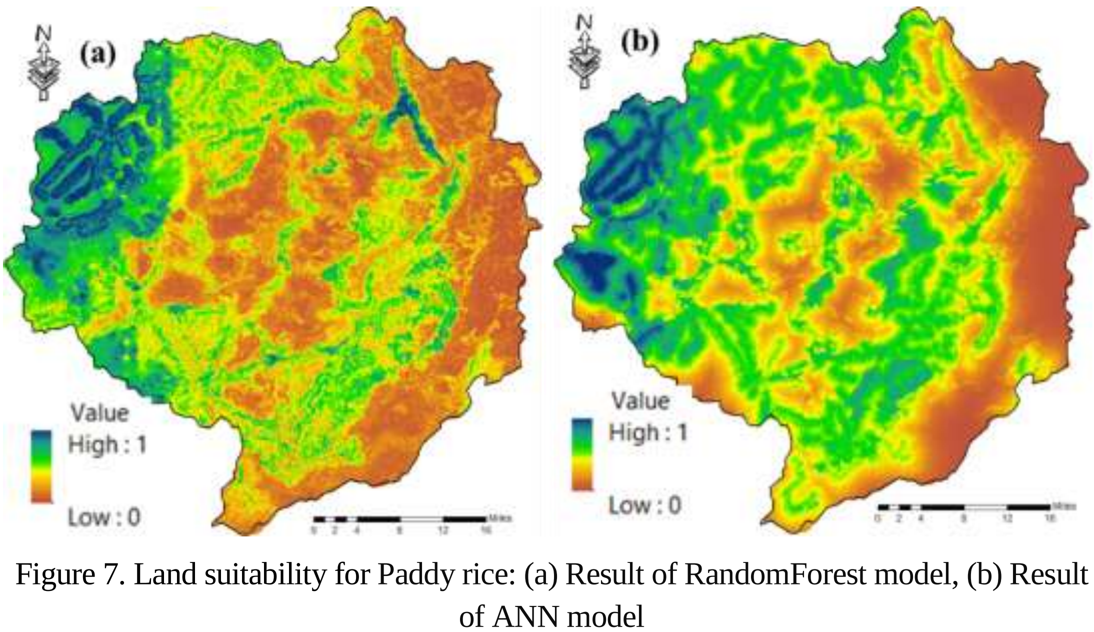

Figure 7. Land suitability for Paddy rice: (a) Result of RandomForest model, (b) Result of ANN model

Table 4. Land suitability for Paddy rice results

Value	Random Forest model	ANN model
Mean	0.34156	0.38749
Standard Deviation	0.2235	0.2118
Accuracy	0.6896	0.6663

Figure 7 illustrates the spatial distribution of land suitability probabilities for paddy rice cultivation in Bac Son district, Vietnam, as predicted by the Random Forest (RF) model (Figure 7a) and the Artificial Neural Network (ANN) model (Figure 7b). In both models, dark green areas represent regions with high suitability, while brown areas indicate low suitability. Table 4 summarizes the quantitative results of the suitability assessment, showing that the ANN model predicted a higher mean suitability value (0.38749) compared to the RF model (0.34156), suggesting that it identified a larger proportion of land as suitable for paddy rice cultivation. The ANN model also exhibited slightly lower variability in predictions, with a standard deviation of 0.2118 compared to 0.2235 for the RF model, indicating more consistent suitability estimations. However, in terms of classification accuracy, the RF model (0.6896) outperformed the ANN model (0.6663), suggesting that it provided more reliable classification results. Overall, while the ANN model predicted a broader suitable area, the RF model demonstrated higher classification accuracy, making it a more robust choice for paddy rice land suitability assessment.

CONCLUSION

This study assessed land suitability for Golden Tangerine and Paddy Rice cultivation in Bac Son District, Lang Son Province, using the Random Forest (RF) and Artificial Neural Network (ANN) models. Ten environmental and geographical factors were selected as input variables to evaluate land suitability in Bac Son District. The findings demonstrate that both models effectively evaluated land suitability; however, their predictive performance varied depending on the crop type.

For Golden Tangerine, the ANN model estimated a higher mean suitability value than the RF model, indicating that it classified a larger portion of the study area as suitable for cultivation. Additionally, ANN exhibited slightly higher predictive accuracy compared to RF model, suggesting a marginally improved classification performance. Both models showed similar prediction variability, as indicated by their nearly identical standard deviations.

For Paddy Rice, the ANN model also predicted a higher mean suitability value than the RF model, suggesting a broader distribution of suitable areas. However, the RF model demonstrated superior classification accuracy relative to the ANN model, implying a more reliable representation of actual land suitability. The RF model also exhibited slightly greater variability in suitability estimates, as reflected in its higher standard deviation.

Overall, while the ANN model identified larger areas as suitable for both crops, the RF model provided higher classification accuracy, particularly for Paddy Rice. These results highlight the importance of considering both predictive accuracy and spatial distribution when selecting models for land suitability assessments. The integration of machine learning techniques such as RF and ANN provides valuable insights into land suitability evaluation, supporting data-driven decision-making for sustainable agricultural planning in Bac Son District. Future research should explore the potential of hybrid modelling approaches and incorporate additional environmental and socioeconomic variables to enhance the precision and applicability of land suitability assessments.

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