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A GIS Framework to Demarcate Suitable Lands for Combine Harvesters Using Satellite DEM and Physical Properties of Soil

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Abstract

Rice harvesting in Bangladesh is impacted by the absence of advanced harvesting technologies, high labor costs, and natural calamities, which frequently interrupt the harvesting schedule. Mechanized harvesting methods, such as combine harvesters, could enable large-scale, efficient harvesting with reduced labor dependency. However, the use of such machinery is complicated by the varying and limited size of rice fields across the country. This research aimed to develop a suitable land classification map for combine harvester operations using satellite-derived digital elevation models (DEM) and soil physical property datasets at Kalikoir, Gazipur, Bangladesh, which will identify the most suitable rice fields for quick and efficient harvesting. The study considered eight thematic layers for developing the model, including sand, silt, clay, soil bulk density, soil moisture, dry density of soil, water holding capacity, and slope. The relative weight of selected layers was determined using the extra tree classifier machine learning algorithm within the Jupiter environment. The land classification map was subsequently generated using a weighted overlay analysis technique within the ArcGIS environment. The resulting map revealed that 1.88 km^2 (19.84%) was highly suitable for combine harvester use, 4.16 km^2 (43.53%) was moderately suitable, 2.67 km^2 (27.43%) had limited suitability, and 0.86 km^2 (9.19%) had very limited suitability. The classification map was validated using a ground truth dataset with several performance metrics, including overall accuracy, precision, recall, F1 score, and threat score. The model demonstrated robust performance with an overall accuracy of 71%, precision of 85%, recall of 79%, F1 score of 81%, and threat score of 69%. A further assessment of accuracy using area under curve (AUC) measures indicated a 60% success rate. The results provide valuable and precise insights that can benefit commercial combine harvester users, farmers, and policymakers, helping to identify optimal rice-harvesting locations in Bangladesh. This in turn can support more effective resource allocation, reduce costs, and ultimately enhance rice production yield in the country.

Keywords Combine harvester · GIS · Extra tree classifier · DEM · Soil physical properties

All authors guarantee that this research is their original work that has never been published previously.

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Introduction

Rice is a critical cereal crop both economically and in terms of national food security for Bangladesh. It comprises half of the nation's agricultural GDP and accounts for one-sixth of its overall income. Across the country, approximately 10.5 million hectares of land are dedicated to rice cultivation, maintained by 13 million farming families. Several challenges complicate the harvesting process, including shortages of workers, high labor costs, and the migration of agricultural workers to garment/textile or non-farm activities, which can delay harvest activities (Zhang et al. 2014). Furthermore, natural disasters and a lack of modern farming equipment often result in crop loss during harvest (Shelley et al. 2016). The combine harvester emerges as an effective solution to these issues, offering rapid, labor-saving, and efficient rice harvesting. It also has the potential to increase total production (Constable and Somerville, 2003). In addition to this, the use of a combine harvester can reduce harvest losses and cut production costs by as much as 52% (Hasan et al. 2019). However, the performance of combine harvesters is highly dependent on field conditions. Specifically, fields that are excessively wet, muddy, or waterlogged are not suitable for combine harvesters (Colton et al., 2021). In such circumstances, the efficiency of these machines diminishes, necessitating more time and labor for harvesting. Therefore, to circumvent these problems, it is crucial to establish an appropriate land assessment strategic plan. This plan would optimize the use of agricultural machinery and ensure that it is deployed in the most beneficial and efficient manner.

Over the past few decades, continuous agricultural land use without considering land evaluation assessments has led to significant land degradation. Land evaluation assessment involves the systematic process of determining the suitability of a piece of land for various uses, such as agriculture, forestry, urban development, conservation, or recreational purposes. In order to prevent further damage, it is essential to establish land suitability classification methods. These methods should consider water accessibility, soil management practices, and plant adaptability (Ziadat & Al-Bakri 2006). The soil condition plays a pivotal role in determining the efficiency of agricultural machinery (Abdel & Elzain 2007; Ohu et al. 1987). Key soil physical properties, including moisture, texture, structure, porosity, pore-size distribution, available water content, and bulk density, broadly influence the functioning of agricultural equipment (Lal 1995). Furthermore, other factors such as field size, shape, solid-continuous void organization, and pressure can also impact crop productivity. As agricultural technology becomes increasingly vital to securing an adequate food supply, identifying lands suitable for farm machinery becomes an important strategy. This approach is effective for promoting sustainable agriculture and critical for poverty reduction and ensuring food security by enhancing profitability of grain production (Yang et al. 2023). Therefore, developing and implementing strategies to detect and utilize suitable lands for farm machinery are a crucial step in promoting sustainable and profitable agricultural practices.

Land suitability assessment is a process that evaluates and classifies different areas of land based on its appropriateness for a particular purpose (Lee & Yeh 2009; Martin & Saha 2009; Yigeltu & Alemu 2022). This process plays an essential role in understanding the relationship between the characteristics of a land parcel and its potential usage (Beek 1980). Performing land suitability assessments can lead to improved land use planning, decrease soil degradation, and foster the design of land use structures that minimize environmental challenges by separating conflicting land uses like, land use zoning and land use segregation (Ziadat 2007). It also reveals existing constraints that may hinder land use, providing a comprehensive overview of the land's potential and limitations (Ziadat & Al-Bakri, 2015; Ziadat & Sultan 2011). Therefore, land suitability assessment is a critical tool for utilizing land resources effectively. By understanding the land's strengths and limitations, land managers can plan its use more wisely, mitigate potential environmental issues, and optimize its value for a specific purpose.

Land suitability evaluations have utilized a wide variety of factors, including slope, soil type, land use, land cover, drainage, soil texture, soil depth, soil electrical conductivity, calcium content, organic matter, and climate (Møller et al. 2021; Radocaj et al. 2020; Radocaj et al. 2021; Sultan 2013; Taghizadeh-Mehrjardi et al. 2020; Yigeltu & Alemu 2022). Moreover, numerous analytical methodologies have been employed by researchers to determine the most suitable land for agricultural machinery (AL-Taani et al. 2021; Mazahreh et al. 2019). Several techniques, such as spatial assessment, qualitative description, and advanced practices like hierarchical analytic procedures, dynamic system models, and other multi-criteria analysis techniques, have been used for land suitability assessments (Morales & de Vries 2021; Pilevar et al. 2020; Seyedmohammadi et al. 2019). However, traditional land suitability assessments often utilize limiting factors typically established by experts drawing on historical research and experience (Ziadat 2007). This conventional method, while thorough, often necessitates extensive computations and considerable time to produce reliable results (Mokarram et al. 2015). To overcome these limitations, some researchers have turned to machine learning algorithms, which can offer more efficient and scalable solutions compared to traditional methods (Almansi et al. 2021; Hernandez 2020; Møller et al. 2021; Radocaj et al. 2020; Radočaj et al. 2021; Taghizadeh-Mehrjardi et al. 2020). For instance, the study by Yang et al. (2023) employs a machine learning technique, specifically the extra trees classifier, to evaluate land suitability for combine harvesters. This machine learning technique represents a modern, data-driven approach to land suitability assessment that can potentially deliver more accurate results.

Bangladesh needs more land suitability analyses specifically for agricultural machinery (Binte Mostafiz et al. 2021; Haque et al. 2022; Hossen et al. 2021; Perveen et al. 2005). A key strategy for enhancing mechanization and consequently boosting agricultural production involves identifying well-suited lands for such machinery (Yang et al. 2023). Utilizing data on agricultural machinery usage, combined with spatial soil physical attributes, could provide information for such assessments. In this context, the primary aim of this study was to develop a suitable land classification map for the operation of combine harvesters at the Kalikoir, Gazipur, Bangladesh. Ultimately, this approach should identify the most suitable rice fields for efficient harvesting operations using a combine harvester and may result in substantial benefits, including reducing human drudgery and harvesting costs, saving time, and increasing crop productivity. Using this strategic approach to land suitability analysis, the effectiveness of mechanization in Bangladesh's agriculture sector can be optimized, and significant strides toward enhancing national food security will be made.

Materials and Methods

Study Area

The study area is Kaliakoir Upazila, Gazipur district, Bangladesh, which geographically lies between latitudes 24°15′ N and 90° 22′ E. The region comprises nine unions, 181 Mouza, and 283 villages (BBS 2020). The Kaliakoir rises 35 m above sea level (Fig. 1). The topography of the study area is lowland to medium plains, with gentle slopes along the northern part, moderately steep slopes in the western region, and steeper slopes in the center of the southeast parts. The major crops grown in this area include rice, wheat, jab, barley, cheena, maize, kaun, bajra, and joar, covering 233.19 km^2. The region experiences the effects of a monsoon climate, with average annual temperatures ranging from 12.7 to 36 °C and precipitation of 2376 mm (BBS 2011). The study area belongs to complex relief, and the soils developed over the Madhupur Clay. The region has eleven soil types, including deep red-brown, shallow red-brown, and acid basin clays. The terrace soils are well-drained, friable clay loams to clays over coarse clay with various depths. Red or brown top soils are mostly slightly acidic to very acidic, with moderate to low organic compounds, poor moisture retention ability, and low soil fertility. However, land degradation has become an urgent problem that limits production on soils with irregular and complex topography (Yang et al. 2023). Therefore, it is crucial to use land suitability classification techniques to increase agricultural productivity within the studied region.

Data Collection and Analysis

Soil Data Collection

The physical properties of the soil, such as sand, silt, clay, bulk density, soil moisture, dry soil density, and water holding capacity, were used to make a suitable land classification map for the combine harvester. The soil sample datasets were collected from selected fields in a soil container during the Boro rice harvesting season in 2022. A global position system (GPS) receiver (GPSMAP 64x, Garmin Ltd., Olathe, KS, USA) provided the latitude and longitude of the target fields. The Yanmar combine harvester (model AG600) was chosen based on the availability of combine harvesters in the study region. Soil samples were collected after the operation of the combine harvester in the field. Samples from each point were collected using a shovel, transferred to a container box, and labeled as suitable or not suitable based on the field condition after the combine harvester operation. When the combine harvester worked smoothly without any troubles, the samples were rated as suitable (1), and when it did not, they were rated as unsuitable (0). Each soil sample was marked with their respective latitude and longitude coordinates (Khatri 2019). Following soil sample collection, a standard laboratory procedure was used to analyze the soil samples at the Bangladesh Rural Advancement Committee (BRAC) Soil Analytical Lab.

Analysis of Soil

The details of the analysis of soil datasets are shown in Table 1. The soil physical property datasets comprised the combine harvester's land suitability classification map. The suitability map was generated using different soil datasets, including sand, silt, clay, bulk density, dry density, moisture content, and water holding capacity. By understanding soil formation, it is possible to improve the soil's health, the efficiency of land use, and the ecological sustainability of an area (Yan et al. 2019). The texture of the soil (sand, silt, or clay) affects the movement of water, the transformation and translocation of nutrients, and many other things. The soil texture also governs the soil water holding characteristics, which affects its workability and suitability for crop

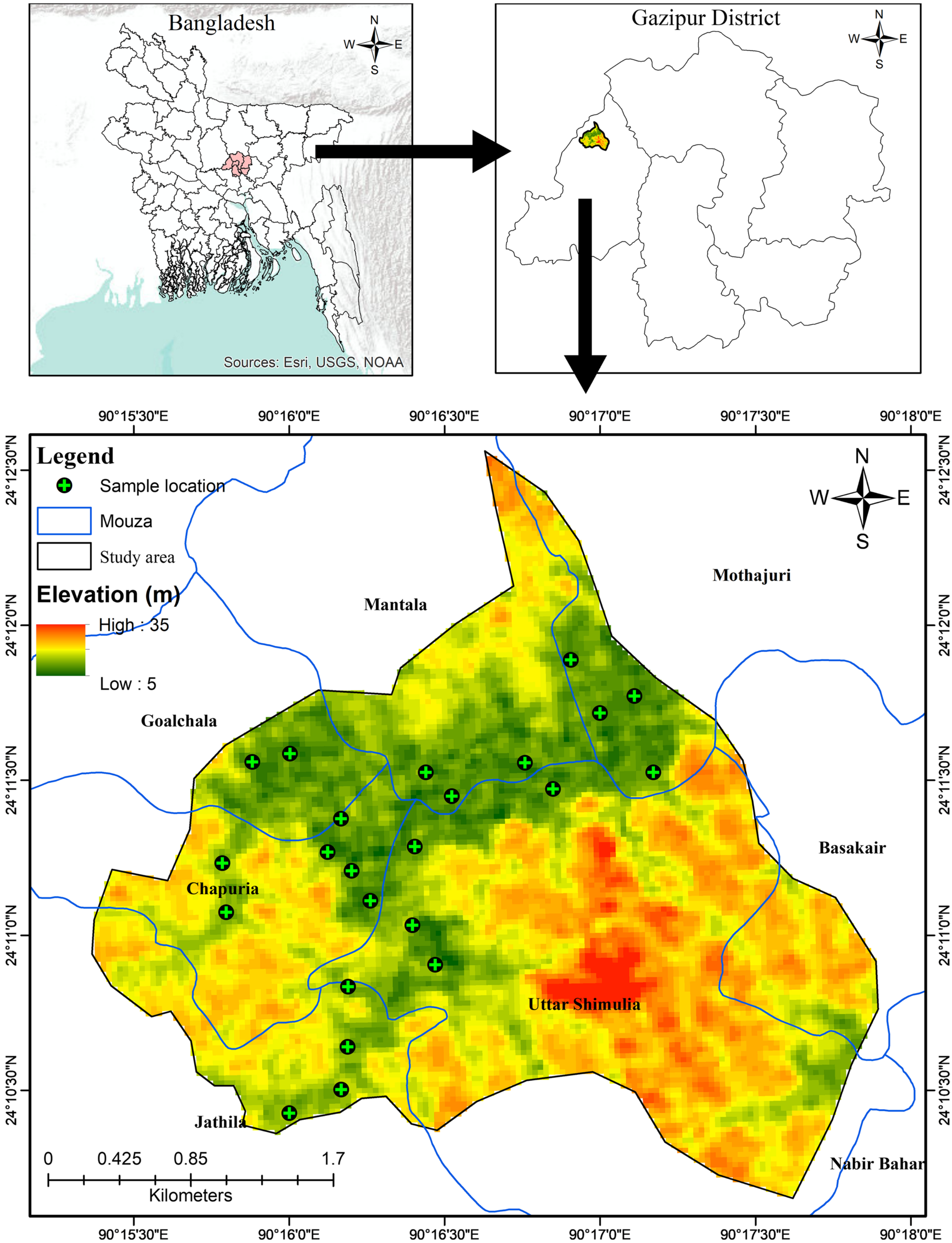


Fig. 1 Location map of the study area

Table 1 Details of soil datasets used in this study

Serial N	Sand (%)	Silt (%)	Clay (%)	Bulk density (g/cc)	Soil moisture (%)	Dry density (g/cc)	Water holding (%)	Remarks
1	35.67	51.33	13.00	1.69	29.91	1.30	74.00	S
2	33.50	50.83	15.67	1.44	38.28	1.04	76.00	S
3	34.75	47.75	17.50	1.53	28.92	1.18	68.00	S
4	38.43	43.28	18.29	1.61	32.33	1.22	71.00	S
5	34.38	50.94	14.69	1.75	22.23	1.43	72.00	S
6	33.33	51.28	15.38	1.57	26.88	1.28	74.00	S
7	35.79	44.47	19.74	1.68	27.45	1.31	72.00	S
8	37.26	46.41	16.32	1.61	29.43	1.25	72.14	S
9	37.97	46.64	15.39	1.55	32.37	1.17	72.00	S
10	36.73	48.54	14.79	1.62	27.92	1.28	72.71	S
11	36.03	47.85	16.12	1.61	29.23	1.25	72.38	S
12	37.28	46.65	16.08	1.61	29.57	1.25	72.19	S
13	36.17	47.23	16.60	1.67	25.52	1.34	72.67	S
14	37.19	46.70	16.12	1.61	29.23	1.25	72.23	S
15	37.40	45.53	17.07	1.47	44.10	1.02	68.00	N
16	35.00	45.50	19.50	1.56	28.75	1.21	72.00	N
17	39.24	41.77	18.99	1.53	42.47	1.07	66.00	N
18	36.25	43.75	20.00	1.40	50.82	0.93	67.00	N
19	36.97	45.89	17.14	1.49	41.54	1.06	68.25	N
20	37.12	45.66	17.22	1.45	48.34	1.07	68.34	N
21	36.96	45.87	17.17	1.48	42.67	1.06	68.27	N
22	38.98	42.78	18.24	1.52	43.67	1.09	67.67	N
23	37.35	45.37	17.30	1.49	42.79	1.06	68.19	N

S and N indicate the suitable and not suitable sample points after the combine harvester operation

production. This study used the hydrometer procedure for measuring particle size to determine the percentages of sand, silt, and clay. The standard method is more laborious but reliable than alternative approaches (Williams-caudle et al. 2003).

Bulk density is the ratio of the weight (Ws) and volume (Vs) of dry soil. The volume contains soil particles, organic materials, pores, and particle packing (Arshad et al. 2018). Loose and porous soils with high organic material have a lower bulk density. In contrast, increasing soil compression leads to higher bulk density, which can impede infiltration of water (Ohu et al. 1987). Greater soil bulk density also increases wheel slippage and fuel consumption of agricultural machinery, while reducing speed of operations (Abdel & Elzain 2007). However, agricultural equipment performs much better on solid soil than loose soil. Bulk density was calculated using the following formula:

$$\rho = \frac{Ws}{Vs} \tag{1}$$

where ρ is the soil bulk density and Ws and Vs refer to the weight and volume of dry soil, respectively.

The ratio of the mass of soil solids to the volume is called dry density when the soil is in a dry condition. The soil mass is typically composed of air, water, and solids from the soil. The dry density will vary with the classification and characteristics of the soil and indicate the soil's mineral properties and compaction (Lestariningsih et al. 2013). Higher compaction levels result in a higher dry density of the soil. In contrast, higher soil dry density corresponds to lower moisture content. The dry density was calculated using the below expression (2):

$$\gamma_d = \frac{M_s}{V_T} \tag{2}$$

Here, γ_d is the dry soil density, M_S is the mass of the soil solids, and V_T is the per unit volume of solid soil.

The ratio of the mass of water to the mass of solids in the soil sample is called soil moisture content. The amount of water in the soil dramatically affects the soil's physical properties. Although a higher soil moisture level often results in a lower specific draft demand and noticeable variances in traction performance across tested machinery, this condition may be ideal for particular crops and production technologies

(Salokhe et al. 1992). The oven drying method was used to identify the soil moisture content by following the Eq. (3):

$$\mathrm{MC} = \frac{M - D}{D} \tag{3}$$

where MC is the soil moisture content (%), and M and D indicate the weight of moist and dry soil, respectively.

The soil's ability to hold water against gravity is called its water holding capacity. A soil's water holding capacity depends on its texture and organic content. Medium-textured soils with silt, clay, and sand particles and excellent aggregation have many pores that retain water against gravity. Coarse soils, which are primarily composed of larger particles like sand, typically have larger pore spaces between particles. These larger pores allow for better drainage and lower water retention compared to finer soils (Oduma et al. 2018). Even though fine-textured clay soils have many smaller holes that hold much water, the water is often too tightly packed in the tiny pores for plant roots to access it. The soil water holding capacity was calculated in weight basis the following Eq. (4).

$$\mathrm{WC} = \frac{Ww - Dw}{Dw} * 100 \tag{4}$$

where WC is the water holding capacity of the soil, and Ww and Dw have indicated the wet soil and dry weight of the soil, respectively.

Topographic Slope Data

The topographic slope parameter significantly influences land use patterns and geographical variations (Gobin et al. 2004; Solaimani et al. 2009). Slope plays a vital role in determining the suitability and capability of land for agriculture (Lacko-Bartošová & Buday, 2013; Van Orshoven et al. 2008). Generally, a slope exceeding 3.60–6.72% is deemed unsuitable for farming activities (Andersen et al. 2003), as the topography of agricultural systems profoundly impacts management restrictions (van Asselen & Verburg 2012). In this study, the ALOS PALSAR derived Digital Elevation Model (DEM) with a spatial resolution of 12.5 m (ASF 2019) was used. For our analysis, slope was prioritized as the sole topographical criterion, due to its significant influence on the usage of agricultural machinery. Agricultural lands were characterized as having slopes less than 5%, and areas exhibiting slopes greater than 5% were excluded from our final map. Thus, the analysis focused on areas most amenable for agricultural use, as steeper slopes are generally impractical.

Generation of Thematic Layers

Thematic layer generation describes constructing geographical data layers that reflect distinct themes or subjects of interest. The soil datasets were used to generate continuous maps of each thematic layer. The inverse distance weighting (IDW) method was employed to interpolate the soil data and make predictions at unknown locations using the *Geostatistical Analyst* tool in ArcMap. The IDW method predicted each ground attribute at each position to create a continuous map (Khatri 2019). Generally, the IDW method performs better with enough sample locations and a good spread at local scale levels (Murmu et al. 2019). Finally, each thematic layer was converted to a raster format and projected with a spatial resolution of 10 m × 10 m to the WGS_1984_UTM_Zone_46N coordinate system. The continuous map of each thematic layer was classified into five subclasses using the natural breaks (Jenks) classification method using the reclassification toolset. This method generated geostatistical maps and contains precise estimates of the data patterns.

Features Relative Importance

Feature relative importance may give insight into the dataset by highlighting the most and least important features. A domain expert may analyze its relative importance and use it as the basis for gathering additional or alternative data. In this study, the extra tree classifier (ETC) machine learning algorithm was used to identify the relative importance of each feature. The extra tree classifier algorithm is an ensemble of binary decision trees where each tree uses its own technique to categorize new data (Melanson 2020). In previous studies, including land cover classification (Zafari et al. 2019), a multi-layer intrusion detection system utilizing Extra Trees (Sharma et al. 2019) used the extra trees classifier algorithm. Another study (Shafique et al. 2019) showed that the extra tree classifier was the best at predicting cardiovascular disease compared to logistic regression (LR), support vector machine (SVM), and naive Bayes (NB). The algorithm reduced the variance more than other methods (Geurts et al. 2006). The extra tree classifier differs from other machine learning algorithms because it separates nodes by selecting cut-points entirely at random and utilizes the whole training sample to construct the trees (Ampomah et al. 2020).

Delineation of Suitable Areas for Combine Harvester

A total of 23 soil properties were collected from the rice fields after the rice harvesting operation of the combine harvester. Seven thematic layers were generated from the soil property analysis: (1) sand, (2) silt, (3) clay, (4) bulk density, (5) soil moisture, (6) dry density of soil, and (7) water holding capacity. The raster values of the selected thematic layers were extracted from the sampling points using the extraction by mask technique. The relative importance of the thematic layers was identified based on the raster values of the selected thematic layers as input variables, and ground truth data (binary data) were used as target variables. The extra tree classifier algorithm was used to run the model based on the input and target variables in a Python Jupiter notebook environment. Finally, the weighted overlay analysis method was used to make the final map. The weighted overlay analysis reclassified the criteria of each thematic layer on the same scale according to the relative importance of land suitability. The values 1 to 4 were assigned to each class of the thematic layers, where 1 indicates the least suitable land, and 4 shows the most suitable land. The suitability index map was generated using the following formula:

$$SI = (Cc * Cw + Sc * Sw + Sic * Siw + Bc * Bw + Mc * Mw + Dc * Dw + Wc * Ww) \quad (5)$$

SI is the suitability index map, C is clay, S is sand, Si is silt, B is bulk density, M is soil Moisture content, D is dry soil density, and W is the water holding capacity, respectively. The w and c indicate the weight and subclass of each thematic layer, respectively. However, the final map was projected to the WGS_1984_UTM_Zone_46N coordinate system, with a pixel cell size of 10 m × 10 m. The majority filter was used to replace cells in a raster-based on most of the cells around them. The output raster data were reclassified into four suitability classes, including very low, low, moderate, and very high, using natural break classification techniques to produce the final land suitability map for the combine harvester. The overall methodology of the study is shown in Fig. 2.

Model Validation

The datasets were divided into training and testing at 70% and 30%, respectively (Almansi et al. 2021). There is no generally accepted mechanism for partitioning a sampling dataset. It usually depends on the quantity and quality of the sample data (Kalantar et al. 2020). This study evaluated the classification results by evaluating several performance metrics; overall accuracy, precision, recall, F1 score, and threat score. The receiver operating characteristics (ROC) were also used to check the model's performance. The ROC analysis measured the model's sensitivity, specificity, and area under the curve (AUC). The confusion matrix was used to predict binary scores for all selected parameters. Most of the time, the sensitivity, or true positive rate (TPR), and

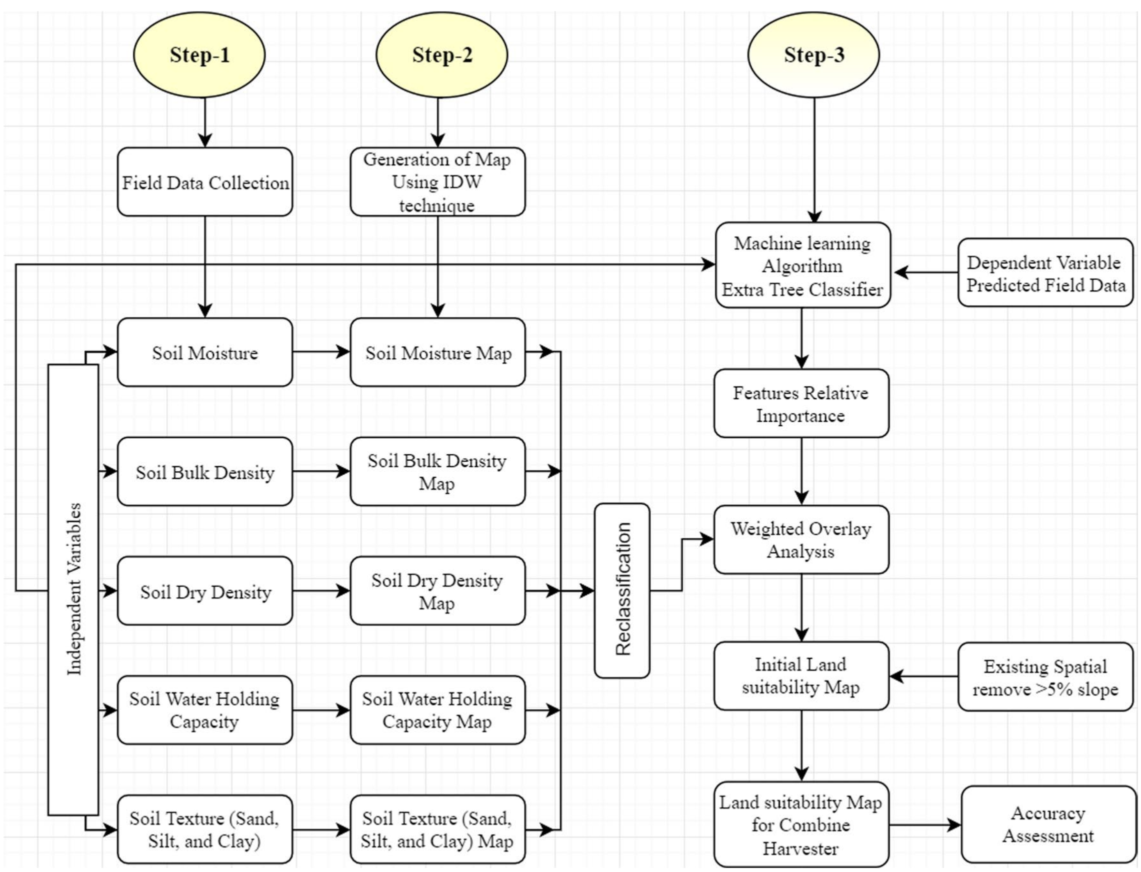


Fig. 2 Flow diagram of the method used in this study

specificity, or true negative rate (TNR), were used to sum up how well the confusion matrix predicts (Chicco et al. 2021). The function of the confusion matrix is shown in Table 2.

Tp is the true positive, Fp is the false positive, Fn is the false negative, and Tn is the true negative. The statistical values of interpolated rasters were helpful when figuring out how well the interpolation worked for soil thematic layers (An et al. 2016). The mathematical formula of the performance metrics is given below:

Overall Accuracy

The accuracy is the proportion of classified samples to the total number of samples in the assessment data. This accuracy measure is most commonly utilized in machine learning to get good precision. The accuracy is limited from 0 to 1, while 1 indicates correctly predicting all positive and negative samples, and 0 shows neither the positive nor negative samples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

Precision

Precision is the ratio of successfully predicted samples by the entire sample allocated to a class. The accuracy is limited from 0 to 1, where 1 indicates all accurately predicted samples and 0 indicates inaccurate predictions in the class.

$$Precision = \frac{TP}{TP + FN} \tag{7}$$

Recall

The recall is known as the sensitivity or true positive rate (TPR) and is computed as the proportion of identified positive samples and all samples allocated to the positive samples. The recall value is limited from 0 to 1, where 1 represents predicting a positive class, and 0 implies an inaccurate prediction of all positive samples.

$$Recall = \frac{TP}{TP + FP} \tag{8}$$

Table 2 An example of a confusion matrix

		Actual	
Predicted		Positive class	Negative class
	Positive class	Tp	Fp
	Negative class	Fn	Tn

F1 Score

The harmonic mean of recall and precision was used to get the F1 score. The F1 score depends on the positive and negative sample classes and helps to modify the sample classes. For instance, large negative samples are the majority, and the classifier is influenced by the negative sample class, resulting in a low F1 score. The F1-score ranges from 0 to 1, where 1 represents the most excellent recall and precision, and 0 illustrates no precision or recall.

$$\text{F1 score} = 2 \times \frac{PPV \times TPR}{PPV + TPR} \tag{9}$$

Threat Score

The threat score is the proportion of accurately positive samples to the total of accurately predicted positive samples and all wrong predictions. It balances false rates and missing events and eliminates only accurately indicated negative samples. The threat score ranges from 0 to 1, with 1 representing no error predictions in either class and 0 meaning no correctly predicted positive samples.

$$Threat\ score = \frac{TP}{TP + FN + FP} \tag{10}$$

Results

Features Relative Importance

Figure 3 shows the relative importance of selected thematic layers. Based on the analysis conducted using the extra tree classifier, the moisture content (25%) and dry density (19%) were the most critical factors affecting the harvesting operation of a combine harvester in the field. The results indicate that the amount of moisture in the soil and the soil's density are significant factors that affect the harvester's performance. The water holding capacity (15%), bulk density (12%), clay (11%), silt (10%), and sand (8%) were found to have varying levels of importance, with silt and sand having the lowest impact on the harvester's performance compared to other factors. Overall, the results suggest that understanding the soil's moisture content and density is essential to optimizing the performance of combine harvesters in the field. This information can help farmers and agricultural workers adjust their operations and optimize their harvesting processes to achieve better yields and productivity.

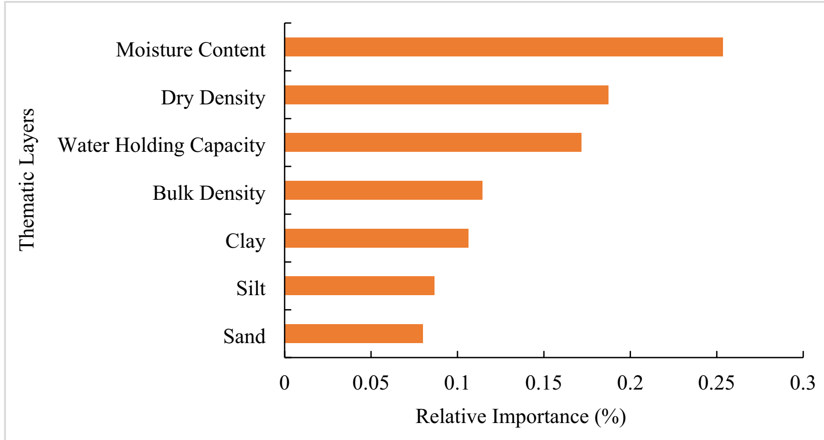


Fig. 3 Relative importance of selected thematic layers

Assessment of Soil Thematic Layers

Sand, Silt, and Clay

Table 3 provides information on the assigned rating and relative weight of soil physical properties used to create the land suitability map. The soil physical properties considered include clay, silt, and sand content, with variations ranging from 13.02 to 19.98%, 40.25 to 51.31%, and 33.38 to 39.23%, respectively. The fields with a higher proportion of clay and sand were deemed more suitable for combine harvester operations compared to fields with a lower ratio of these components. The findings suggest that a certain level of clay and sand content in the soil might provide better conditions for combine harvester operations. These soils might have characteristics that make them less prone to clogging or other operational issues that can arise with higher silt content or extremely fine-textured soils. The higher proportion of silt seems to have a positive effect on the operation of the combine harvester by potentially offering smoother conditions for the machinery. Overall, the assigned rating and relative weight of soil physical properties provide valuable information on the suitability of a field for combine harvester operations. Figure 4 shows the details of clay, silt, and sand in the study region.

Soil Bulk Density

The soil bulk density ranged from 1.34 to 1.75 (g/cc) and was categorized into five sub-classes: very low (1.34 to 1.47), low (1.48 to 1.53), moderate (1.54 to 1.56), high (1.57 to 1.61), and very high (1.62 to 1.75). The spatial distribution of these sub-classes revealed that 2.17% of the land (0.21 km^2) had very low bulk density, 8.68% (0.85 km^2) had low bulk density, 56.80% (5.54 km^2) had moderate bulk density, 29.72% (2.90 km^2) had high bulk density, and 2.63% (0.26 km^2) had very high bulk density. The study results suggest that lands with higher bulk density are suitable for combine harvester operations in fields, while lands with lower bulk density are unsuitable for such operations. The bulk density map of the study area is shown in Fig. 5(A). It can assist farmers and agricultural workers in making informed decisions about land suitability for combined harvester operations. Farmers can optimize their machine operations by understanding their fields' soil bulk density for better harvesting efficiency.

Soil Moisture Content

Figure 5(B) displays the moisture content map of the study area. The findings demonstrate that the soil moisture content significantly impacts the combine harvester's harvesting operation. The collected soil samples had a moisture content ranging from 22.48 to 50.74%. The spatial distribution of soil moisture content was categorized as very low 6.98% (22.25–30.99), low 28.59% (31.00–33.68), moderate 46.38% (33.69–36.48), high 14.15% (36.49–41.30), and very high 3.90% (41.31–50.82), respectively. The study revealed that most of the study area had low soil moisture content, particularly in the southeast, while regions with moderate soil moisture content were mainly in the northwest and center of the study area. The results suggest that higher moisture content makes the land unsuitable for smooth combine harvester operation during harvesting, while lower moisture content makes the land suitable. Thus, monitoring and managing soil moisture content is essential to optimizing combine harvester operations and achieving better productivity. The moisture content provides valuable information for farmers and agricultural workers to assess the suitability of their fields for combine harvester operations.

Table 3 The assigned weight and rank to different thematic layers and their sub-classes using natural breaks (Jenks) classification

Thematic layer	Break values	Sub-class	Assigned rank	Relative weight
Clay	13.02–15.75	Very low	5	
	15.76–16.52	Low	4	
	16.53–17.06	Moderate	3	11.76
	17.07–17.93	High	2	
	17.94–19.98	Very high	1	
Sand	33.38–35.24	Very low	5	
	35.25–35.97	Low	4	
	35.98–36.64	Moderate	3	8.70
	36.65–37.53	High	2	
	37.54–39.23	Very high	1	
Silt	40.25–44.72	Very low	1	
	44.73–46.11	Low	2	
	46.12–47.06	Moderate	3	9.72
	47.07–48.49	High	4	
	48.50–51.31	Very high	5	
Bulk density	1.34–1.48	Very low	1	
	1.49–1.54	Low	2	
	1.55–1.57	Moderate	3	12.41
	1.58–1.61	High	4	
	1.62–1.75	Very high	5	
Soil moisture	22.25–30.99	Very low	5	
	31.00–33.68	Low	4	
	33.69–36.48	Moderate	3	23.86
	36.49–41.30	High	2	
	41.31–50.82	Very high	1	
Dry density	0.93–1.06	Very low	1	
	1.07–1.14	Low	2	
	1.15–1.18	Moderate	3	17.66
	1.19–1.24	High	4	
	1.25–1.43	Very high	5	
Water holding capacity	61.37–65.79	Very low	1	
	65.80–68.82	Low	2	
	68.83–70.20	Moderate	3	15.88
	70.21–71.29	High	4	
	71.30–75.99	Very high	5	

Soil Dry Density

Figure 5(C) shows the soil dry density map in the study area. Soil dry density is essential when determining land suitability for combine harvester operations. The results show that the study area has a range of dry soil density from 0.93 to 1.42 (g/cc). The spatial distribution of dry density reveals that the areas with low and very low dry density are mainly in the southeast, covering 3.99% (0.39 km^2) and 13.88% (1.33 km^2) of the study area, respectively. The moderate dry density areas cover the most significant portion of the study area, 51.46% (4.96 km^2), mainly located in the northwest and central parts. The high and very high dry density areas cover 26.19% (2.52 km^2) and 4.48% (0.43 km^2) of the study area, respectively. The results suggest that the higher the soil dry density, the more suitable the land is for combine harvester operations, while lower soil dry density indicates unsuitability. Depending on other factors such as moisture content and bulk density, the areas with moderate to high soil dry density may be suitable for combine harvester operations. Therefore, the study area's dry soil density is crucial when assessing land suitability for combine harvester operations.

Soil Water Holding Capacity (WC)

Soil water holding capacity (WC) is a vital soil physical property for determining the land suitability for combine harvester operations. As shown in Fig. 5(D), the spatial

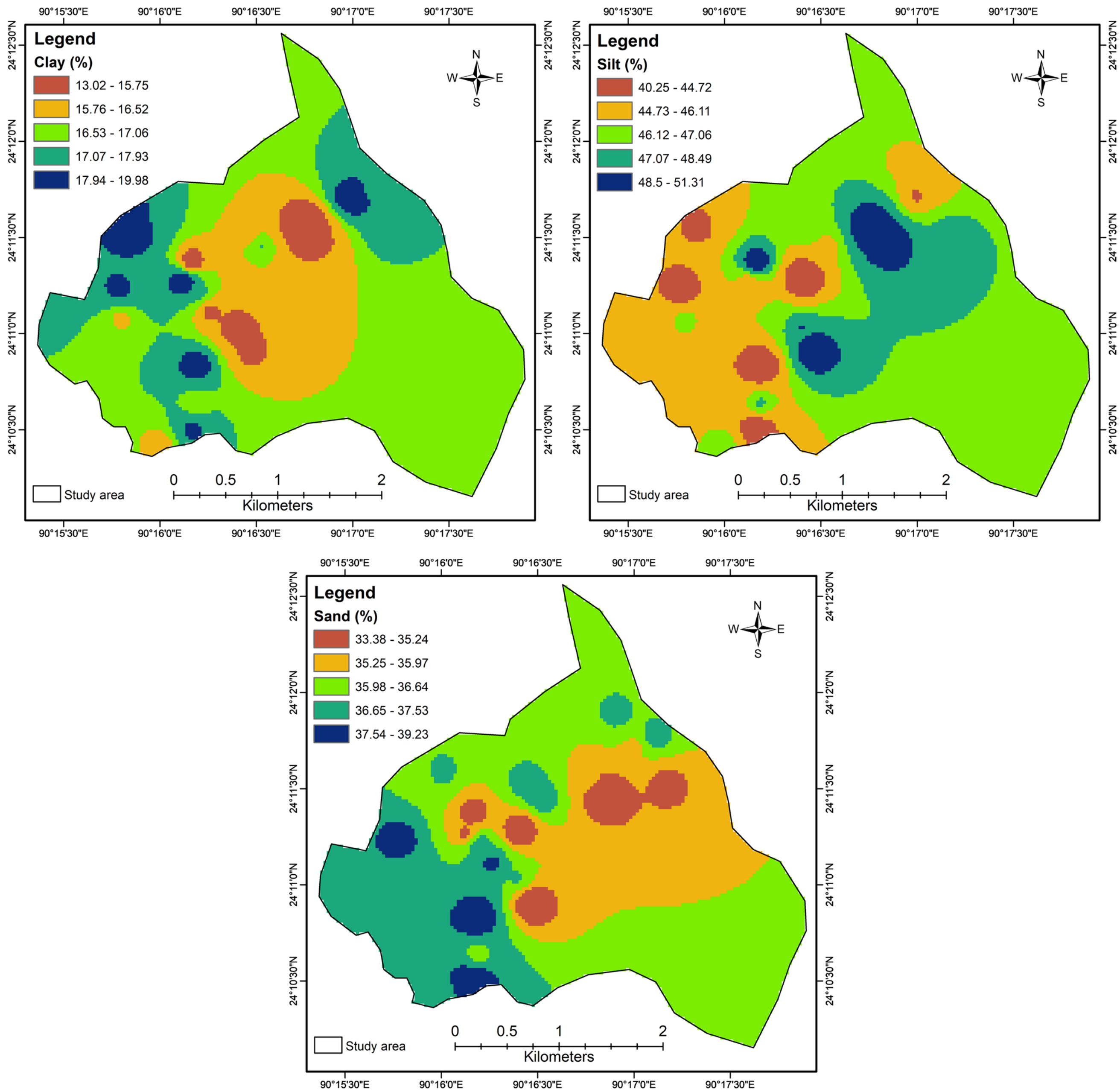


Fig. 4 Spatial distribution of the percentages of soil texture (clay, silt, and sand) in the study region

distribution of soil WC in the study area varied from 61.43 to 76.00%. The results indicated that a significant portion of the study area had very low WC, which covered 1.54% (0.15 km^2) of the site. The low WC covered 15.63% (1.51 km^2) of the area, and the moderate WC covered 63.78% (6.15 km^2). Additionally, high and very high WC covered 15.64% (1.51 km^2) and 3.41% (0.33 km^2) of the study area, respectively. The areas with higher WC were considered suitable for combine harvester operations, while those with lower WHC were unsuitable. The moderate WC was found in the northwest and central parts of the study area.

Assessment of the Topographic Slope

The slope distribution in the study area varied from 0 to 22.19%, as shown in Fig. 6. Based on the findings, the slope distribution was as follows: very low 27.08% (2.62 km^2), low 36.51% (3.53 km^2), moderate 23.84% (2.30 km^2), high 10.34% (1.00 km^2), and very high 2.23% (0.22 km^2). In this study, agricultural land was distinguished from other land uses by using gentle slope (<5%) areas, whereas lands with steeper slopes (>5%) were masked out from the analysis. The findings indicated that 65.40% (6.32 km^2) of the area was dominated by gentle slopes

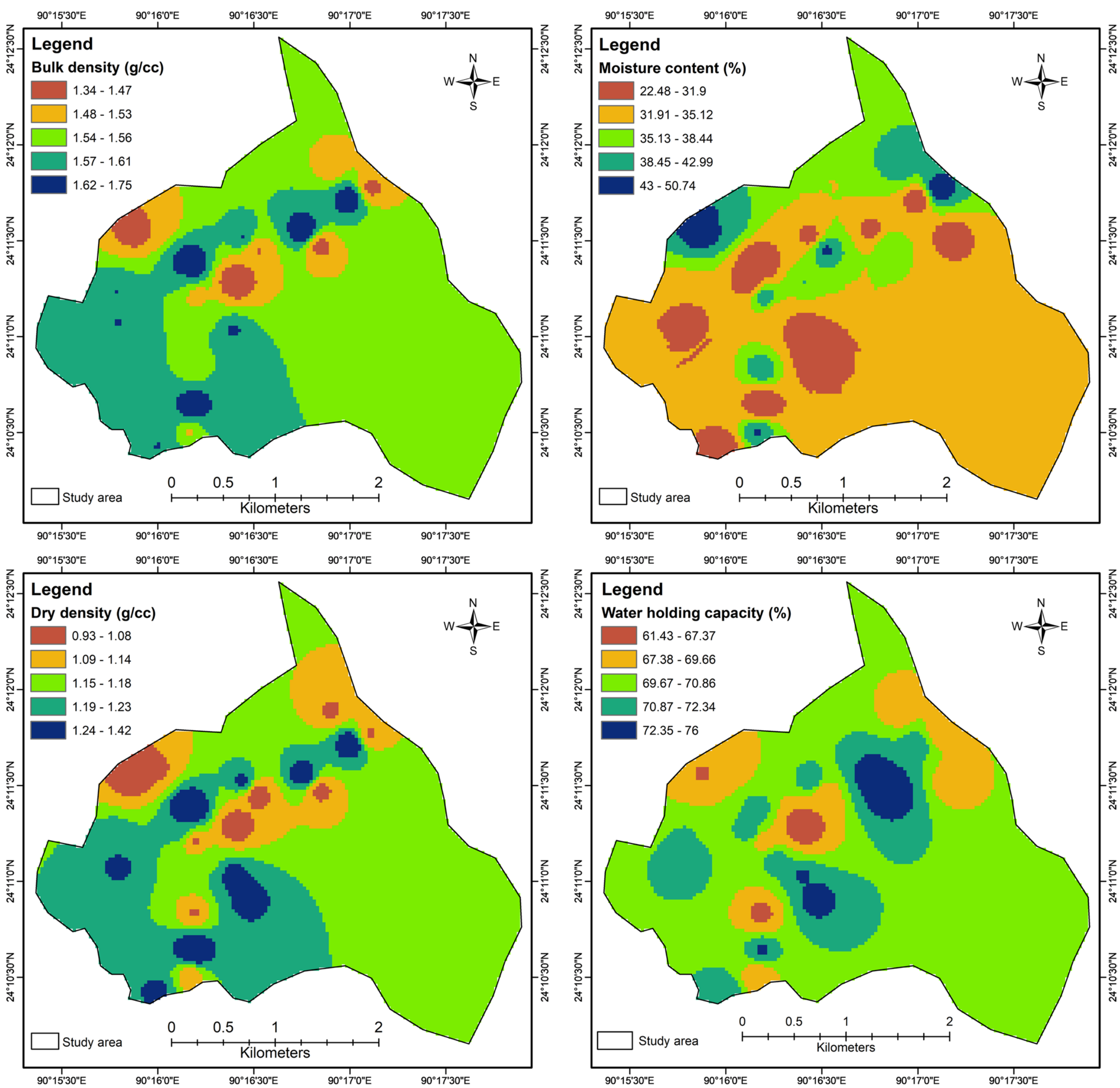


Fig. 5 Spatial distribution of soil bulk density, moisture content, dry density, and water holding capacity over the study area

(<5%). In comparison, 34.60% (3.35 km^2) of the study area was composed of steeper slopes (>5%), which were predominantly in non-agricultural areas such as settlements, forests, and other land covers. The higher slope areas were mainly in the southeast and central regions and some western parts of the study area.

Assessment of Land Suitability Map for Combine Harvester

Figure 7 shows the spatial distribution of the combined harvester's land suitability map. The land suitability map considered all the soil physical properties analyzed in the study, including soil texture, bulk density, moisture content, dry density, and water holding capacity. The resulting map showed the different levels of suitability for combine harvester operations. The land suitability map was divided into four groups: deficient, low, moderate, and very high. The map shows that a significant portion of the study area, 19.84% (1.90 km^2), is very high suitable for combine harvester operations. These areas are mainly located in the southwest and east, with dominant agricultural lands. The moderately suitable areas cover around 43.52% (4.17 km^2)

Fig. 6 Spatial distribution of slopes in the study area

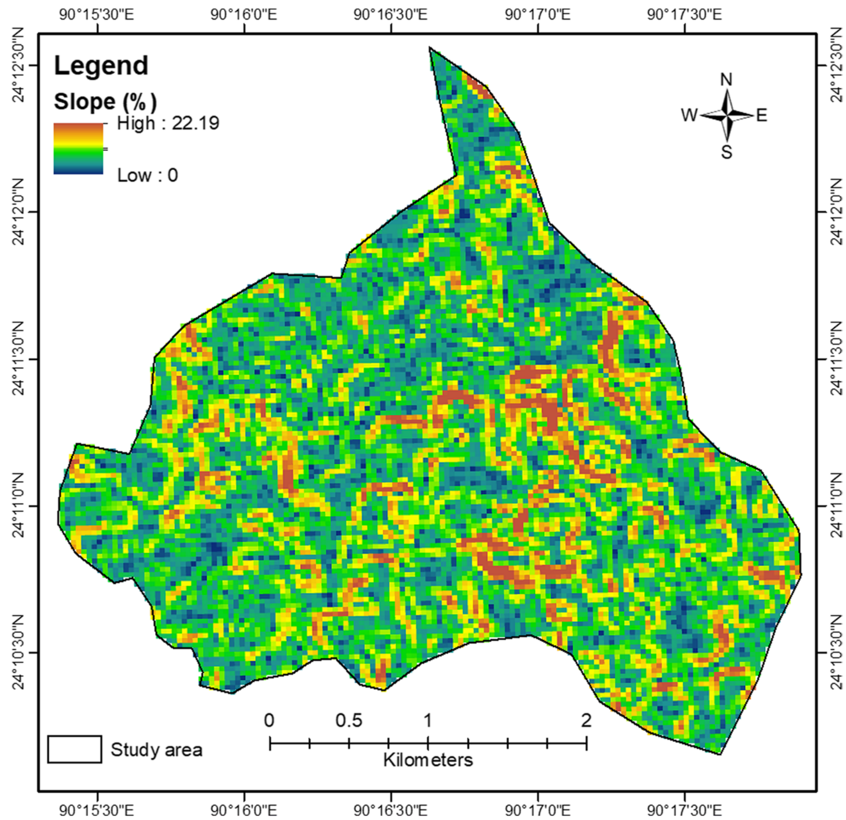
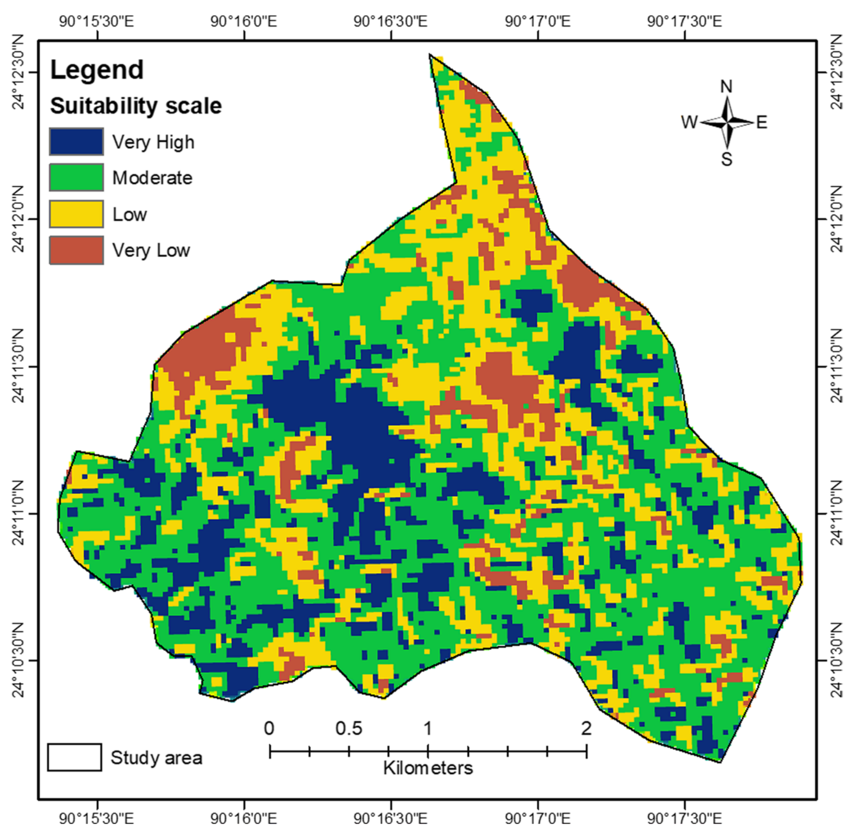


Fig. 7 Spatial distribution of land suitability classification map for combine harvester



of the study area, with scattered locations in the southeast and mainly in the northwest. The less suitable areas are concentrated in the study area's west, northeast, and central regions, covering around 27.42% (2.62 km^2). The significantly less suitable areas cover only 10% (0.88 km^2) of the study area. Overall, the land suitability map provides valuable information to farmers and land managers for optimizing the use of agricultural machinery in the study area. It can help them make informed decisions about crops, tillage practices, and other land management strategies based on the land's physical properties.

Model Validation

The overall accuracy, precision, recall, F1 score, and threat score were 71%, 85%, 79%, 81%, and 69%, respectively. The confusion matrix served as a pre-modeling evaluation that was utilized to forecast the appropriateness of the land using the conditioning factors. The actual positive and accurate negative rate graphs illustrated how well the models discriminated good locations from those that were not appropriate. Taking into account the ROC curve, the model had an accuracy of 60% (Fig. 8). The selected model demonstrated a strong correlation between the influencing factors and the locations determined to be appropriate. According to the findings, the method used to establish which fields would be suitable for a combine harvester would be beneficial. It could be used to increase agricultural production in Bangladesh. The confusion matrix, the ROC curve metrics, and the area under the curve (AUC) values were used to determine how well the model performed. Table 4 presents the results of a correlation analysis between the land suitability categorization map and the field conditions.

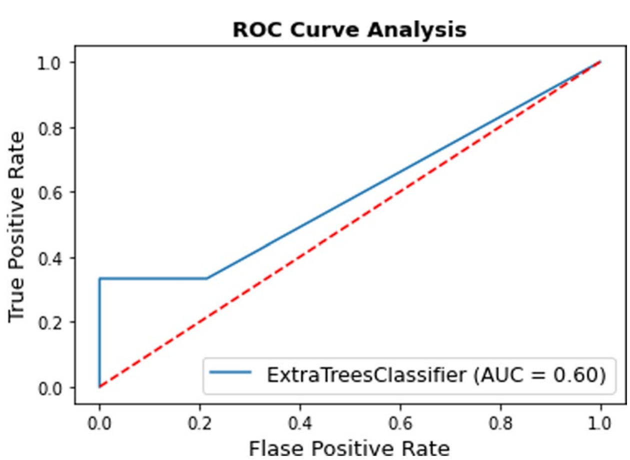


Fig. 8 ROC curve for validation of land suitability map for the combine harvester

Discussions

This study investigated the development of a land suitability classification map for the combine harvester at Kaliakoir, Gazipur district, Bangladesh. Eight thematic layers, including sand, silt, clay, soil bulk density, soil moisture content, dry soil density, soil water holding capacity, and topographic slope, were selected, and the weights of each parameter were calculated using a machine learning algorithm (i.e., extra tree classifier). The resulting output showed that selected parameters influence land suitability classification. However, the most significant were soil moisture content, dry soil density, soil water holding capacity, and soil bulk density. The results indicated that the study area has reasonable prospects for use of combine harvesters for rice harvesting. The study area was covered by moderate zone of 43.52% (4.17 km^2) for combine harvester operation.

A machine learning-based feature importance was used to identify and rank the most important features or variables that contributed to the performance of the model. The ranking can be based on a numerical score, a percentage, or a visual representation such as a bar chart or a heat map. The interpretation of feature importance depends on the specific model and the domain of the problem. In some cases, the most important features may be evident and intuitive, while in others, they may reveal unexpected or counterintuitive relationships between the features and the target variable. In this study, the soil moisture content (23.86%) was the most important factor, whereas sand (8.70%) was the least.

Soil moisture was the most important feature that affected the efficiency and effectiveness of combine harvesters, as it can influence the machine's ability to navigate the soil and harvest crops. Generally, areas with well-drained soils that maintain moderate moisture are considered the most suitable for combine harvester operation. This is because drier soils can become complex and compact, making it easier for the machine to navigate. At the same time, wetter soil can become muddy and boggy, causing the machine to become problematic due to trafficability issues when harvesting rice crops. Soil dry density (17.66%) was the second key feature for identifying areas suitable for combine harvester operation. The result indicated that the dry-density soils were too loose and prone to erosion. The soils with a higher dry density were compacted, and easy to harvest rice smoothly. The suitable dry density values ranged from 1.25 to 1.43 (g/cc) and were considered the most appropriate for the smooth operation of the combine harvester machine. Soil water holding capacity (15.88%) was the third most important feature for smooth combine harvester operation, as it can provide adequate moisture to crops even during harvesting. These soils are typically well-drained and have a high percentage

Table 4 Details of field observation and pixel correlation with resulting land classification map

Field condition					Classification map	
Site No	Latitude	Longitude	Suitability scale	Description	Suitability scale	Remarks
1	24° 11′ 33.40″ N	90° 16′ 45.47″ E	1	Suitable	2	Agree
2	24° 11′ 26.93″ N	90° 16′ 31.38″ E	0	Not suitable	3	Agree
3	24° 11′ 28.30″ N	90° 16′ 50.92″ E	1	Suitable	4	Disagree
4	24° 11′ 31.55″ N	90° 17′ 10.29″ E	1	Suitable	1	Agree
5	24° 11′ 37.92″ N	90° 16′ 59.36″ E	0	Not suitable	1	Disagree
6	24° 11′ 13.96″ N	90° 15′ 47.09″ E	1	Suitable	1	Agree
7	24° 11′ 22.56″ N	90° 16′ 10.01″ E	1	Suitable	1	Agree
8	24° 11′ 15.48″ N	90° 16′ 60.60″ E	0	Not suitable	2	Disagree
9	24° 11′ 30.71″ N	90° 16′ 22.71″ E	1	Suitable	1	Agree
10	24° 10′ 50.04″ N	90° 16′ 11.35″ E	0	Not suitable	3	Agree
11	24° 11′ 33.54 N	90° 15′ 52.87" E	0	Not suitable	4	Agree
12	24° 11′ 22.10″ N	90° 17′ 20.77″ E	1	Suitable	4	Disagree
13	24° 11′ 53.28″ N	90° 16′ 54.36″ E	0	Not suitable	3	Agree
14	24° 11′ 46.28″ N	90° 17′ 60.61″ E	0	Not suitable	4	Agree
15	24° 10′ 58.79″ N	90° 15′ 41.09″ E	1	Suitable	1	Agree
16	24° 10′ 53.49″ N	90° 16′ 43.68″ E	1	Suitable	2	Agree
17	24° 11′ 13.54″ N	90° 16′ 19.60″ E	1	Suitable	1	Agree
18	24° 11′ 37.27″ N	90° 16′ 10.24″ E	0	Not suitable	4	Agree
19	24° 11′ 32.85″ N	90° 16′ 26.55″ E	1	Suitable	1	Agree
20	24° 10′ 39.01″ N	90° 16′ 15.92″ E	1	Suitable	2	Agree
21	24° 10′ 27.58″ N	90° 15′ 56.24″ E	1	Suitable	1	Agree
22	24° 11′ 90.20″ N	90° 16′ 90.25″ E	0	Not suitable	4	Agree
23	24° 10′ 28.00″ N	90° 16′ 50.84″ E	1	Suitable	2	Agree

1, 2, 3, and 4 indicate the very high, moderate, low, and very low suitability land classes

of organic matter, which helps retain moisture and provides a favorable environment for plant growth. The soils with a lower water holding capacity were found unsuitable for the combine harvester operation, whereas higher water holding capacity indicated the most suitable.

Soil bulk density (12.41%) was the fourth most important feature for identifying suitable areas for combine harvester operation. Generally, soils with increased bulk density support the machine's wheels while allowing for efficient harvesting. The areas with low soil bulk density may not be suited since they are loose and prone to erosion, which may pose problems for combine harvester operation. The soils with high bulk density were well compacted and easy for the machine to operate. Therefore, identifying areas with a suitable range of soil bulk density is essential for efficient and effective combine harvester operation. The clay (11.76%), silt (9.72%), and sand (8.70%) were the fifth, sixth, and seven essential factors affecting the ability of a combine harvester to operate effectively. Soils with a high percentage of sand may not be suitable for combine harvester operation, as the soil may be too loose and prone to erosion. Similarly, soils with a high percentage of clay may need to be lighter and more accessible for the machine to navigate, especially in wet conditions. In contrast, soils with a low percentage of silt are often considered ideal for combine harvester operation, as they provide good support for the machine's wheels and allow for efficient harvesting.

Topographic slope can be important for identifying suitable areas for combine harvester operation. Soils with a topographic slope of less than 5% were considered the most suitable for combine harvester operation, because the machine can easily navigate flat or gently sloping terrain, which can help to enhance efficiency and reduce the risk of damage to the machine. However, soils with a slope greater than 5% may be less suitable for combine harvester operation, and the machine had trouble navigating steep or uneven terrain. Farmers may need to use lightweight harvesting machines in these areas to manage crops effectively.

The model prediction was verified by employing a ROC/AUC evaluation, which measured the accuracy of the model's predictions (Yamusa & Ismail 2023). The applied approach showed an overall accuracy of 71% when validated with ground truth data. On the other hand, the model led to a land suitability classification map with ROC values of 60%. The model's prediction accuracy can be categorized as satisfactory in both cases. Prediction accuracy was 81% for the threat score, 79% for the F1 score, 85% for precision, and 79% for recall, respectively. However, using the selected model, a robust association was found between the relevant parameters and the ground truth data. The GIS and machine learning-based feature importance techniques for delineating the land suitability classification map for combine harvesters were practical methods for sustainable agriculture and an essential strategy for reducing poverty, harvest time, and food insecurity by increasing profitability (Yang et al. 2023).

Conclusions

The land suitability map for rice harvesting was developed by taking into account various factors such as sand, silt, and clay content, bulk density, moisture levels, dryness, water holding capacity, and slope. The study found that 43.52% of the region was within the "moderately suitable zone" for using a combine harvester for rice harvesting. The effectiveness of a combine harvester in the studied region was primarily impacted by soil moisture and dry density. The accuracy of the land suitability classification map was ensured by employing a confusion matrix with conditional layers. The final output map yielded an accuracy score of 71%, a precision score of 79%, a recall score of 81%, an F1 score of 81%, and a threat score of 69%. Furthermore, according to receiver operating characteristic/area under curve (ROC/AUC) analyses, the research findings suggested an overall accuracy rate of 60%. Despite these encouraging results, the study had certain limitations including, lack of combine harvester, accessibility to fields, labor and time constraints, and costs. Future research will refine these results by considering additional factors such as soil depth, plow pan, and compaction. Regardless of its limitations, the proposed method provides valuable insight into the most effective locations for the use of a combine harvester for rice harvesting. This study has the potential to enhance mechanization and improve food security in Bangladesh. It can benefit stakeholders, farmers, and policymakers involved in the commercial use of combine harvesters across the nation by guiding strategic decision-making for future combine harvester operations.

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Author Contribution M.M.R designed, prepared, and wrote the manuscript; data collection was undertaken by H.R and M.M.S; D.H and AKMSI provided support in manuscript preparation and revisions; oversight of the study and comprehensive evaluation of the manuscript were conducted by S.S and M.K; K.R.T meticulously edited the entire manuscript, offering linguistic insights. All authors participated in the review process and granted their approval for the final version of the paper.

Data Availability Data will be prepared accessible on request.

Declarations

Ethics Approval This research is a response to a review and does not require Institutional Review Board Approval.

Informed Consent For this manuscript, formal consent is not necessary.

Conflict of Interest The authors declare no competing interests.

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