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A GIS and remote sensing based multicriteria analysis for identifying potential agricultural land: A case study on Savar Upazila, Bangladesh

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ABSTRACT

Despite of gradually decreasing its contribution to gross domestic product (GDP), agriculture, however, is the backbone of the Bangladeshi economy. Farming is the primary mean of rural livelihoods in Bangladesh but agricultural land is slowly declining day by day. Although, at present, Bangladesh is self-sufficient in terms of producing food, especially rice and some other major agricultural products, it is predicted that, in near future, the country is going to face immense challenges due to climate related threats. The research aims to identify the potential lands for suitable farming in Savar Upazila (sub-district) under Dhaka district applying a geographic information system (GIS) and remote sensing (RS) based multicriteria analysis. Relevant biophysical characteristics of soil, terrain, and landuse and land cover (LULC) were considered. Soil and evelvation data was collected from Soil Resource Development Institute (SRDI)and Shuttle Radar Topography Mission (SRTM), respectively, whereas satellite images were collected from Landsat-8. The maximum likelihood supervised classification technique was used for LULC classification, and the multicriteria evaluation (MCE) and analytical hierarchy process (AHP) approach was employed to identify suitable areas for farming. The research finds the LULC classes are agricultural land, built-up area, fallow land, vegetation cover, waterbodies, and wetland are 12.42%, 31.01%, 25.69%, 25.98%, 4.81%, and 0.09%, respectively. This research also finds that agricultural land suitability was classified as highly suitable, moderately suitable, marginally suitable, and not suitable are 24.28%, 29.53%, 24.66%, and 21.53%, respectively. In contrast, the current agricultural land usage accounts for just 12.42% of the total land area in this research area. The Kappa accuracy has been measured at a value of 0.88 and an overall accuracy value of 0.90 which indicates that the LULC classification is done almost perfectly. This study offered information at the local level that farmers may utilize to decide on cropping patterns and appropriateness.

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Introduction

Bangladesh is a land of agriculture due to its soil characteristics and agro-climatic conditions. Agriculture is regarded as one of the most significant sustainable and progressive natural resources. Thorough, dependable, and accurate information on agricultural resources is critical for countries like Bangladesh since agriculture is the backbone of our economy (World Bank, 2016). The main employment sector is agriculture, which employed around 45.33% of Bangladesh's workers but contributed 11.22% of the national GDP (BBS, 2022). Using land most rationally and feasibly possible is imperative because existing land usage in Bangladesh, as in many developing countries is unsuitable (Barkat et al., 2007; Hasan et al., 2017; Parvin et al., 2017). According to the Sustainable Development Networking Programme (SDNP), land use in Bangladesh is incompatible with the country's overall social and economic goals (Bangladesh Planning Commission, 2013). It also states that fertile agricultural land which could be used to produce food is being lost to non-agricultural uses such as private development, housing facilities, brickfields, and so on (Sarak et al., 2013; Titumir, 2021).

The rapidly rising population of Bangladesh significantly strains the limited natural resources. According to BBS (2022), the population was 169.83 million in Bangladesh, accounting for 2.07% of the global population. However, it is under pressure from rapid population increase and natural disasters like floods, droughts, tropical cyclones, and soil erosion. As a result, land productivity is diminishing, and the country is unable to produce sufficient food to feed its growing population (Josephson et al., 2014). The reduction of agricultural land significantly impacts national food production and food security. Especially, the rapid urbanization and industrialization of Savar Upazila as the rural-urban fringe notably losses arable land, making the situation critical due to high population density and scarcity of agricultural suitable land. However, Bangladesh urgently requires more efficient and sustainable agriculture production techniques.

In this regard, GIS and RS technologies provide a dynamic instrument for a multidimensional landuse system. RS offers synoptic, repeated, and objective landscape observations, which is a valuable source of spatial data, including LULC, hydrology, and topography. GIS is useful for geological and environmental study and natural resource evaluation (Dai et al., 2001; Pourghasemi & Gokceoglu, 2019). It enables the user to merge databases created from multiple sources, including RS, on a single platform and evaluate them efficiently in a spatio-temporal dimension (Breunig et al., 2003). Especially, GIS and RS tools can robustly assess the potential agricultural suitable land using spatial and multicriteria approaches. In these circumstances, the broad aim of this research is to identify the potential agricultural land using geospatial technologies in Savar Upazila, Bangladesh.

Materials and methods

This research was conducted based on secondary data. Secondary data include soil and landform database, topography database, satellite imagery, and weather data. Soil and landform data were collected from SRDI, topography database, satellite imagery, and weather data were collected from SRTM, Landsat, and Bangladesh Meteorological Department (BMD), respectively. ArcGIS tools were used to georeferenced and digitized the soil base map at the 1:50,000 scale the SRDI gave. Also, a digital elevation model (DEM), slope, aspect, 3D and TIN with 90-metre spatial resolution were generated. In addition, LULC was conducted using Landsat8 imagery with 30-metre spatial resolution, along with the assessment of Kappa and overall accuracy. Finally, the analytical hierarchy process (AHP) and multicriteria evaluation (MCE) techniques were used to identify and assess potential agricultural land in the study area. The core methodological framework is demonstrated in the Figure 1.

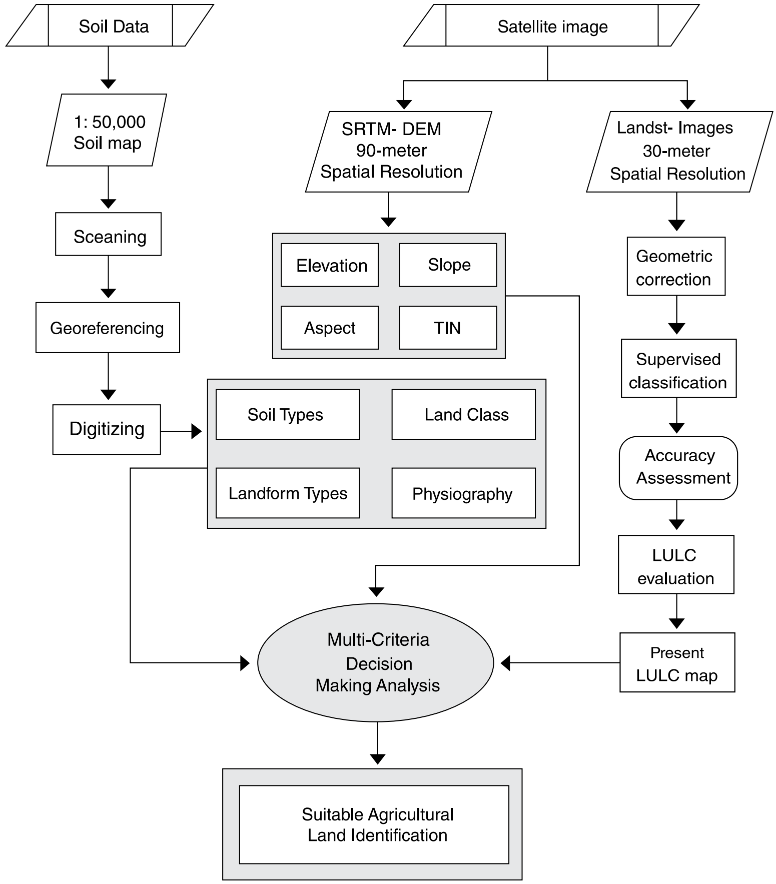

Figure 1: Methodological framework of this study.

Soil, landform, and physiography map preparation

Soil and landform classified images were collected from SRDI and employing ArcGIS tools to georeference the raster dataset. The georeferencing techniques are conducted step by step. To begin, raster image data has been integrated into the GIS programme. The Georeference tab is then used to generate control points that link the newly entered raster data to known positions on the map. Following that, the control points and errors were examined and eliminated. A control-point polynomial and the least-squares fitting (LSF) technique are used in the polynomial transformation. The polynomial transformation yields two formulas (ESRI, 2023): one for computing the output x-coordinate for an input (x,y) location and another for computing the output y-coordinate for an input (x,y) location (equations 1 and 2). Finally, the georeferenced image has been exported in .img (imagine image) file format. However, the georeferenced image has been digitized across the entire study area as polygon feature, and separate thematic maps were created based on soil category and landform types.

$$x^1 = Ax + By + C \qquad (1)$$

$$y^1 = Dx + Ey + F \qquad (2)$$

Where, x is the column count in image space, Y is the row count in image space, x^1 is the horizontal value in coordinate space, y^1 is the vertical value in coordinate space, A is the width of the cell in map units, B is a rotation term, C is the x^1 value of the center of the upper-left cell,

D is a rotation term, E is the negative height of the cell in map units, and F is the Y^1 value of the center of the upper–left cell.

Land use and land cover classification

LULC classification maps serve a significant and pivotal role in planning, managing, and monitoring programs at the local, regional, and national levels (Alshari & Gawali, 2021). Supervised image classification techniques were used for conducting LULC analysis in this study area using Landsat 8 images with 30-metre spatial analysis. Several training samples were taken for each LULC class. Following this approach, the output image is categorized according to each class, which is referred to as training. The maximum likelihood classifier calculates for each class the probability of the cell belonging to that class given its attribute values. The maximum likelihood classification techniques are used as (Richards, 1999)–

$$g_i(x) = 1np(w_i) - {}^1/_2\, 1n|\textstyle\sum_i| - {}^1/_2\,(x - m_i)^T \textstyle\sum_i^{-1}(x - m_i) \ldots\ldots\ldots\ldots (3)$$

Where, i is class, x is the n–dimensional data (where n is the number of bands), $p(c)$ is the probability that class w_i occurs in the image and is assumed the same for all classes, $|\sum_i|$ is determinant of the covariance matrix of the data in class $v_i, \sum_i$, is its inverse matrix, and m_i is a mean vector.

Confusion matrix

The efficiency of a classification system is described using a confusion matrix table. It exhibits and summarizes a classification algorithm's performance. Creating a confusion matrix is one of the most popular ways to represent classification accuracy. The first stage in generating an error matrix, which depends on the development of that matrix, is to locate ground reference test pixels or a sample collection. In this sense, there are several mathematical strategies. In general, it is advised that each LULC class should include at least 50 samples. This research has occupied 116 sample points for accuracy assessment. Data sampling was conducted using random procedures. An error matrix is used to compare the relevant classification result to known reference data (ground data).

Accuracy Assessment

Additionally, using accuracy evaluation point (AEP) tools, several points were constructed for the purpose of accuracy assessment. With a single band or integer data format, this tool primarily intends in order to determine the correctness of the characteristics found in the categorization pictures. Finally, according to the actual data, the accuracy evaluation divides the current class features into their original features. By calculating the confusion matrix from this procedure, an analysis of accuracy evaluation may be made. Confusion matrix tables allow analysts to see the precision of each feature used in SVM classification.

Overall accuracy

The entire classification accuracy is represented by overall accuracy (OA). The calculation is done by dividing the total number of correctly recognized pixels by the total number of reference pixels. This measure's limitation is not providing information on how accurately various groups are categorized. Producer and user accuracy are widely applied measures for class consistency depending on the omission and commission accuracy.

$$OA = \frac{Number\ \ of\ correctly\ \ classified\ \ samples}{Number\ \ of\ samples} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Producer's accuracy

The accuracy of the producer is the possibility that a certain feature of a location on the ground will be identified as such. It is computed by dividing the total correctly classified pixels by the total number of sample pixels for this class (column total).

$$PA = \frac{Number\ \ of\ correctly\ \ classified\ \ samples\ \ of\ spacific\ \ class}{Sum\ \ of\ classified\ \ samples\ \ of\ spacific\ \ class} \ldots\ldots\ldots\ldots (5)$$

User's accuracy

The likelihood that a map pixel labeled as a particular class is actually this class is known as the user's accuracy. It is derived by dividing the number of pixels properly recognized in this category by the total number of pixels correctly identified in this category. Usually, the accuracy of the producer and the user differ. For instance, water has a producer accuracy of 100% and a consumer accuracy of 93%.

$$PA = \frac{Number\ \ of\ correctly\ \ classified\ \ samples\ \ of\ spacific\ \ class}{Sum\ \ of\ reference\ \ samples\ \ of\ spacific\ \ class} \ldots\ldots\ldots\ldots (6)$$

Kappa coefficient

A distinct multivariate approach employed in accuracy evaluation is the Kappa coefficient. A proportion of correctly classified pixels will be generated through the classification process, in which classifications are randomly allocated to pixels. Although the assignment of pixels during image classification is not random, statistical techniques try to consider random chance when assessing categorization accuracy. The derived Kappa metric corrects for categorization chance agreement. It implies how much improved the categorization accuracy than the likelihood of allocating random pixels to the right categories. This is how the Kappa coefficient is written:

$$\widehat{K} = \frac{(P_o - P_e)}{(1 - P_e)} \ldots\ldots\ldots\ldots (7)$$

Where, $\widehat{K}$ indicates Kappa coefficient, P_o are relative observed agreement P_e among raters, and is hypothetical probability of chance agreement.

These can be calculated as:

$$\widehat{K} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+}.x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+}.x_{+i})} \ldots\ldots\ldots\ldots (8)$$

where, r is the number of rows in the error matrix, x_{ii} is the number of observations in the row i and column i, $x+i$, is total of observations in row i, $x+i$ is total of observations in column i and N is the total number of observations included in the matrix.

Topography, slope, aspect, and TIN generation

The DEM was derived from SRTM with a spatial resolution of 90-metre. Topography is crucial in agriculture because it directly affects food production. Water drainage, soil erosion, and crop suitability are all affected. It facilitates the planning of irrigation systems, the management of slopes, and the optimization of land use. The topographic map was generated using the SRTM database through ArcGIS. In this work, the geodesic approach was used to calculate the slope. It was carried out in a 3D Cartesian coordinate system with the earth's shape assumed to be an ellipse. The angle between the topographic surface and the referenced datum determines the slope value. It computes using a three-by-three cell neighbourhood (moving window). The geodesic computation employs an X, Y, and Z coordinate derived from its geodetic coordinates (latitude φ, longitude λ, height h).

The aspect tool was used to determine the direction of the downhill slope in Savar Upazila. The DN values of each cell in the resulting raster represent the compass direction that the surface faces at that point. It is measured in degrees clockwise from 0 (due north) to 360 (again due north), completing a full circle. Flat locations with no downslope direction are assigned the rating -1.

$$tan\ A = -\left(\frac{\partial Z}{\partial Y} \div \frac{\partial Z}{\partial X}\right) \ldots\ldots\ldots\ldots (9)$$

Where, A indicate slope aspect, $\frac{\partial Z}{\partial Y}$ is a rate of elevation change in Y direction, and $\frac{\partial Z}{\partial X}$ is a rate of elevation change in x direction. Further order methods are–

$$\frac{\partial Z}{\partial X} = \frac{(Z_4 - Z_8)}{2\Delta x} \qquad (10)$$

$$\frac{\partial Z}{\partial Y} = \frac{(Z_2 - Z_6)}{2\Delta y} \qquad (11)$$

Where, Z represents the elevation of a pixel, Δx is the pixel size in the x–diraction, and Δy is the pixel size in the y–diraction.

The surface morphology of Savar Upazila has been represented using triangular irregular networks (TIN). TINs are vector-based computational geographic data created by triangulating a collection of vertices (points). A network of triangles is formed by connecting the vertices with a set of edges. The TIN model for the investigation was created using the Delaunay triangulation method.

Weather and climate variability of Savar Upazila

Climate variability is a crucial contributor to the fall in agricultural production and significantly impacts agricultural productivity (Fischer et al., 2002; Rahman & Rahman, 2019). Agriculture is the most sensitive industry to the consequences of rapid wearther parameter fluctuations, such as temperature changes, changing rainfall, and flood and drought occurance patterns, and so on (EPA, 2017). Hence, the most significant concern is that Savar upazila has microclimatic variability, but this microclimatic variability database is unavailable. Also, there is no significant rapid weather variability, so this research considers the average monthly weather data

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Nov	Oct	Dec	Year
Record high °C (°F)	36.53 (97.75)	39.75 (103.55)	42.97 (109.35)	47.27 (117.09)	48.34 (119.01)	42.97 (109.35)	40.82 (105.48)	40.82 (105.48)	40.82 (105.48)	38.67 (101.61)	38.67 (101.61)	36.53 (97.75)	48.34 (119.01)
Average high °C (°F)	27.88 (82.18)	31.98 (89.56)	36.57 (97.83)	38.98 (102.16)	38.16 (100.69)	36.37 (97.47)	35.03 (95.05)	35.25 (95.45)	34.93 (94.87)	33.73 (92.71)	31.42 (88.56)	28.38 (83.08)	34.06 (93.31)
Daily mean °C (°F)	22.78 (73.0)	26.29 (79.32)	31.04 (87.87)	34.25 (93.65)	34.46 (94.03)	33.57 (92.43)	32.49 (90.48)	32.5 (90.5)	32.11 (89.8)	30.46 (86.83)	27.41 (81.34)	24.04 (75.27)	30.11 (86.2)
Average low °C (°F)	16.36 (61.45)	18.83 (65.89)	23.08 (73.54)	27.35 (81.23)	28.94 (84.09)	29.22 (84.6)	28.64 (83.55)	28.54 (83.37)	28.09 (82.56)	25.82 (78.48)	21.88 (71.38)	18.41 (65.14)	24.6 (76.28)
Record low °C (°F)	8.59 (47.46)	12.89 (55.2)	15.04 (59.07)	22.56 (72.61)	18.26 (64.87)	19.34 (66.81)	21.49 (70.68)	18.26 (64.87)	21.49 (70.68)	20.41 (68.74)	15.04 (59.07)	11.82 (53.28)	8.59 (47.46)
Average precipitation mm (inches)	1.4 (0.06)	12.14 (0.48)	24.58 (0.97)	111.9 (4.41)	140.82 (5.54)	139.24 (5.48)	135.29 (5.33)	102.64 (4.04)	120.11 (4.73)	77.53 (3.05)	18.14 (0.71)	5.5 (0.22)	74.11 (2.92)
Average precipitation days (≥ 1.0 mm)	0.48	1.46	5.47	14.85	17.88	18.17	17.29	16.8	16.21	8.98	1.56	0.98	10.01
Average relative humidity (%)	56.14	48.71	51.66	63.86	73.87	81.89	85.9	85.03	84.42	80.48	69.85	63.21	70.42
Mean monthly sunshine hours	9.26	9.44	12.46	13.38	13.63	12.98	12.4	12.56	11.77	10.78	9.13	9.15	11.41

Figure 2: Weather variability on a monthly basis in Savar Upazila.

Sources: Data collected from BMD and compiled by authors, 2023.

Assigning weight of factors and suitability analysis

The goal of weighting is to convey the relevance or preference of each component concerning the impacts on crop production and the growth rate of other factors. Suitability levels for each element were established, and these levels served as the foundation for creating the criterion maps (one for each factor). The appropriateness levels were as follows: according to the framework of the FAO land suitability classification, highly suitable (S1), moderately suitable (S2), marginally suitable (S3), and not suitable (N) (Makungwe et al., 2021). The framework of the FAO land suitability categorization is shown in Table 1.

Table 1: Structure of the FAO land suitability classification

Symbol	Suitability level	Description
S1	Highly suitable	Land without significant limitations. This land is not perfect, but it is the best to be hoped for appropriate use.
S2	Moderately suitable	Land that is clearly suitable has limitations that either reduce productivity or increase the inputs needed to sustain productivity compared with those needed on SI land.
S3	Marginally suitable	Land with limitations so severe that benefits are reduced and the inputs needed to sustain production are increased, so this cost is only marginally justified.
N	Not Suitable	Land that cannot support land use sustainably or land on which benefits do not justify necessary inputs.

Source: Guidelines for land-use planning. FAO, I 993.

MCE's overall method consisted of numerous stages. To begin, the pertinent were identified. A pair-wise comparisons matrix was created using the above-specified elements as the criterion. Although there are several ways for weight generation, one of the most promising is the pair-wise comparisons matrix (PWCM) created by Saaty (1980) in the framework of AHP (Saaty, 2008; Sepehrian et al., 2021). AHP adopts an inherent g scale with values ranging from 1 to 9 to score the comparative preferences for the two elements. Table 2 illustrates the numerical ratings proposed for the decision-spoken maker's preferences. This technique has been theoretically and experimentally evaluated for a wide range of decision-making circumstances, including spatial decision-making, and has been included in a GIS-based decision-making mechanism.

Table 2 : Numerical rating of the fundamental scale

Verbal Preference	Numerical Rating
Extremely preferred	9
Very strongly to extremely	8
Very strongly	7
Strongly to very strongly	6
Strongly	5
Moderately to strongly	4
Moderately	3
Equally to moderately	2
Equally	1

Source: Karayalcin, 1982.

The MCE approach (weighted linear combination) demands that all components be normalized or changed into units compared afterwards. In this research, the factor mappings were standardized/ranked via a conversation with a crop production specialist using Saaty's fundamental scale with values ranging from 1 to 9.

After obtaining the composite layer and their weights, the MCE technique in ArcGIS was used to generate the map of acceptable regions. Finally, the rice crop suitability map was created using ArcGIS spatial analyst tools and a weighted overlay. The land suitability assessment was completed in two stages. The initial stage was to divide the entire arable land into distinct suitability groups using AHP and MCE. The LULC map obtained from satellite data was superimposed in the second stage, and the extent of every suitability level per LULC class was computed.

Overlay existing LULC and the suitability map

The current LULC map and the agriculture suitability map were overlaid to find contrasts and similarities between existing and future land uses. A cross table between the map of appropriate areas and the LULC map was generated for crops. As a result, this research gathered helpful information on the geographical distribution of different appropriateness levels based on Landsat 8 data. Because the resulting layer offered information on how the agro crop was spread throughout the various land suitability zones, we could fine-tune results at this step. Weighted overlay has been incorporated in the spatial analysis tools in this research. Climate variable data, topographic data, soil classification data, and slope aspect data have been overlayed, and LULC data multiplied with the weighted overlay data using raster calculator tools.

Study area

Savar Upazila is located in the northeastern outskirts of Dhaka city. It is crossed by national highway N5, a major route that links Dhaka with northern Bangladesh (Figure 3). This sub-district is located between coordinates 23°44' and 24°02'N and 90°11' and 90°22'E and has an area of 283 km^2, including 20 km^2 of river and 8 km^2 of forest (Mahmudet al., 2021). According to the Bangladesh Bureau of Statistics (2011), the population in 2011 was 587,041 people, where Males constituted 54.20% of the population and females 45.80%. Savar Upazila has undergone a substantial population increase and changes in conventional agrarian land usage over the last several decades as a result of rapidurbanization and industrialization (Hassan et al., 2019; Mahmud et al., 2021).

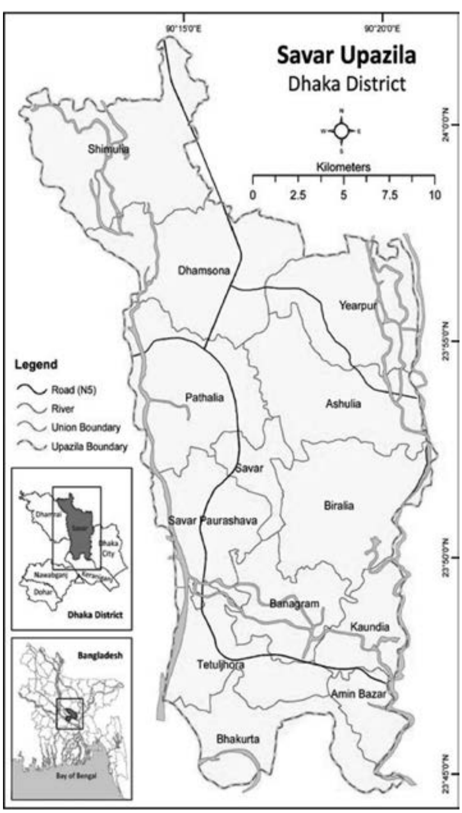

Figure 3: Location map of the study area (Savar Upazila, Bangladesh).

The main economic areas are agriculture and manufacturing in Savar Upazila.Rice, jute, peanut, onion, garlic, chilli, and other vegetables are the principal crops farmed here. Aus rice, sesame, linseed kaun, and Mas Kalai (black gram) are all extinct or virtually extinct crops in the region. Fruits grown here include jackfruit, mango, papaya, olive, guava, berry, kamranga, and banana. There are 181 total dairy, fisheries, and poultry operations, 209 poultry operations, five hatcheries, and 1319 fisheries. The garments industry, ceramic industry, beverage industry, foot ware, jute mills, textile mills, press and publication, printing and dyeing factory, automobile industry, transformer industry, pharmaceutical industry, biscuit and bread factory, soap factory, brickfield, cold storage, welding, plant nursery, and so on are examples of manufacturing facilities. The hydrological conditions are ideal for agricultural activity. Rivers, canals, and ponds are the supplemental groundwater sources for agricultural usage in Savar Upazila (Ahmedet al., 2017). However, there is a tremendous opportunity for enhanced cultivation from surface and groundwater resources. The depth of the inundation affects the type of crop and cropping strategy. The most incredible depth of flooding ranges between 30 and 180 cm (Mirza et al., 2003). Agriculture is performed in the study region using both rainfed and irrigated methods.

Result and discussion

LULC image processing of Savar Upazila

The LULC map derived from the Landsat 8 satellite image obtained from the supervised classification is shown in Figure 4(a). This LULC map shows six categories of LULC of Savar Upazila, which were produced from the combination of the multispectral bands corresponding to green (G), red (R), and near-infrared (NIR) that were found to be appropriate to identify the LULC types in the study area. The image processing and classification have been completed through the supervised classification

Table 3: Land use and land cover area of Savar Upazila

Type	Area (hectares)	Percentage
Agricultural land	3548.74	12.42
Built-up area	8861.39	31.01
Fallow land	7342.14	25.69
Vegetation cover	7424.13	25.98
Water bodies	1373.20	4.81
Wetland	26.60	0.09

approach and the maximum likelihood algorithm, ensuring that an acceptable percentage of the classified pixels were correctly classified. The LULC classification has been classified into six classes: agricultural land, built-up area, fallow land, vegetation cover, wetland and water bodies. The area-categorized classes have been extracted using ArcGIS tools shown in Table 3.

According to the current land use and land cover map, the agricultural land area was 3548.74 hectares, the built-up area was 8861.39 hectares, fallow land was 7342.14 hectares, vegetation cover was 7424.13 hectares, water bodies was 1373.20 hectares, and wetland was 26.60 hectares within the total area of 28576.20 hectares. The LULC classification is shown in Figure 4 (a), and the agricultural land of Savar Upazila was 12.42%, shown in Table 3 and Figure 4 (b). Most of the agricultural land was located rural fringe of Savar Upazila. The middle portion was industrialized, and the residential and middle-left portions were market.

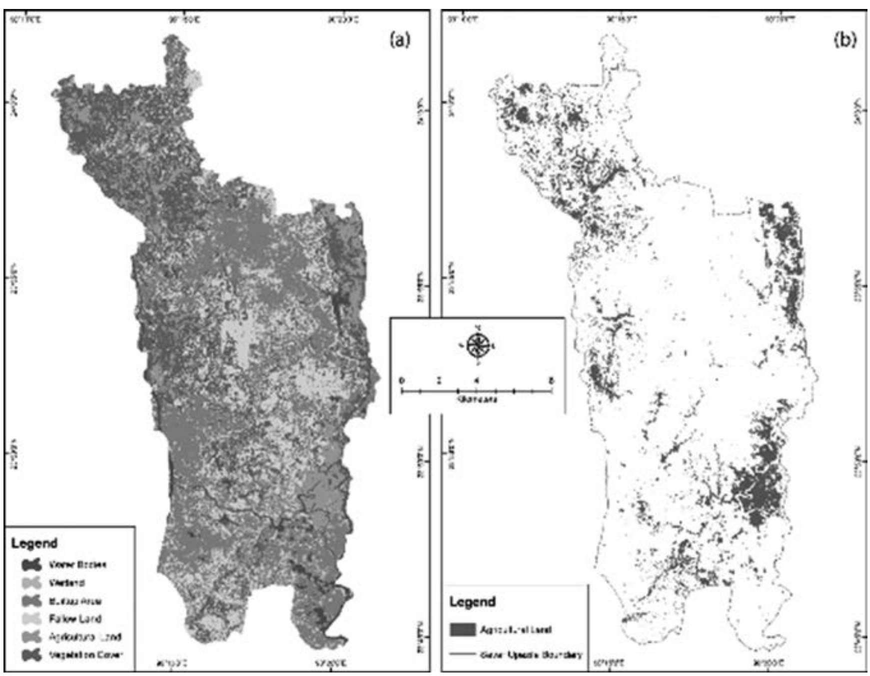

Figure 4: Land use and land cover of Savar Upazila (a) LULC map, (b) Spatial distribution of of existing agricultural land.

Agriculture (20.46%), non-agricultural laborer 3.09%, industry 2.82%, commerce 20.55%, transport and communication 5.75%, service 28.74%, construction 2.84%, religious service 0.18%, rent and remittance 2.67%, and other 12.90% are the major earning sources in Savar Upazila (Asian Development Bank, 2021). Important crops include rice, jute, groundnut, and vegetables. This extracted map (Figure 5) shows the agro-based land use of Savar Upazila, where positive value means highly agro-based land and negative value generated non-agro-based land use.

Accuracy assessment

Accuracy assessment is essential to the LULC categorization process connected with other assessments. The accuracy impacts the result of the entire suitability assessment directly. Accuracy

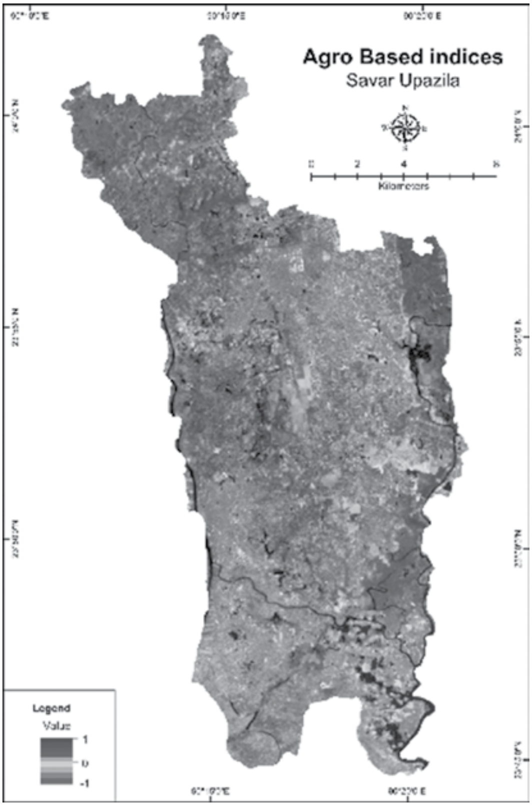

Figure 5: Agro-based indices for agricultural land use of Savar Upazila

evaluation aims to quantify how well pixels were sampled into the right land cover groups. In the study area, 116 points (locations) were formed and ground truthing was conducted by field verification. The Kappa accuracy has been measured at a value of 0.88 and an overall accuracy value of 0.90. Cohen suggested the Kappa result be interpreted as values 0.81–1.00, indicated as almost perfect agreement. This accuracy analysis demonstrates that the LULC classification is almost perfectly in agreement. The overall 116 points have been perfectly placed within 104 sample points. The overall producer accuracy of Agricultural Land, Built-up Area, Fallow Land, Vegetation, Waterbodies, and Wetland was 0.88, 0.94, 0.87, 0.89, 0.90, and 0.90, respectively; on the other hand, the overall used accuracy 0.91, 0.89, 0.87, 0.85, 0.95, and 0.90, respectively (Figure 6).

Topographic characteristics of Savar Upazila

The principal geomorphic units of Savar Upazila are the highland, also known as the Dhaka terrace, and the lowland, also known as floodplains, depressions, and abandoned waterways. Other significant topographic features in and around the Upazila are low-lying swamps and marshes. The topographic elevation, slope, and aspect map area are shown the Figures 7 (a-d).

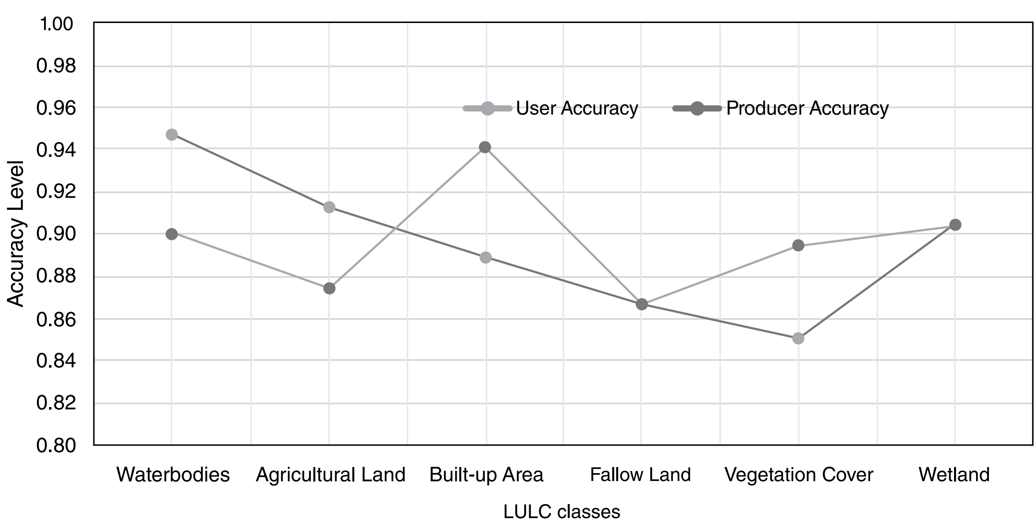

Figure 6: User and producer accuracy of LULC classification of Savar Upazila.

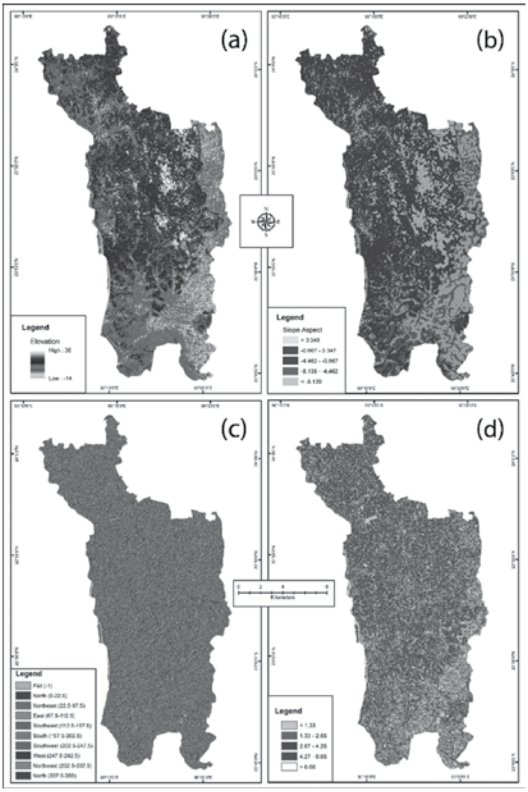

Figure 7: Topographic map of Savar Upazila (a) elevation map, (b) triangular irregular networks model, (c) aspect map, and (d) slope map.

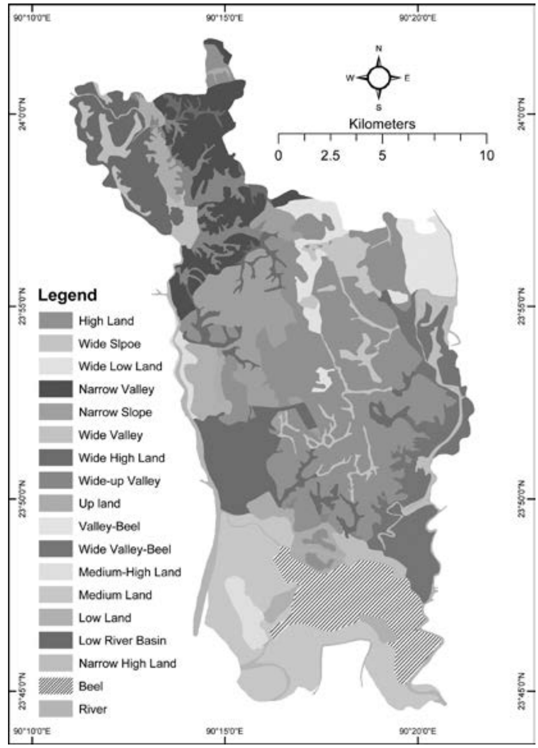

Figure 8: Figure 8: Soil map of Savar Upazila.

Soil of Savar Upazila

Agriculture disrupts the natural cycle of nutrients in the soil. Plant nutrients may be successfully mined from the soil by intensive crop production and harvesting for human or animal use. Soil additives are often necessary for conserving soil fertility for adequate agricultural yields. A fertile soil also offers crucial nutrients for plant development, producing healthful food containing all the substances required for human health. Furthermore, fertility influences economic activity and is thus linked to economic growth and poverty alleviation. However, SRDI of Bangladesh has designated 14 soil groups and 10 soil mapping units in Savar Upazila. Figure 8 shows the soil types, soil classes due to height, soil topography, soil physiography and landform types. A soil group comprises much identical soil series, generally 1-4, and is named by the dominating soil series (Islam, et al., 2017; SRDI, 2021). The soil mapping unit is a map-delineated region of land. This is a geographical entity whose land attributes are not always uniform. Soil mapping units (1–10) are identified based on landform, land type, and physical and chemical soil properties.

Multi-criteria evaluation and agricultural land suitability

Soil and topographic characteristics were investigated in this research to assess site suitability for Agricultural cultivation. After obtaining the factor maps and the weight of composite layers, the physical suitability mapping at four suitability classes (SI, S2, S3, N) for agricultural land was evaluated using a weighted overlay (Figure 9). Figure 9 (a) shows the number of hectares available for each suitability class: very suitable (S1) 6921.57 ha, moderately suitable (S2) 8419.38 ha, marginally suitable (S3) 7031.79 ha, and not suitable (N) 6139.98 ha (Table 4), and Figure

9 (b) shows the overlay of existing agricultural land in suitable land classes.

Table 4: Agricultural land suitability area calculation

Level of suitability	Area (ha.)	Percentage (%)
Highly suitable (S1)	6921.57	24.28
Moderately suitable (S2)	8419.38	29.53
Marginally suitable (S3)	7031.79	24.66
Not suitable (N)	6139.98	21.53

The findings revealed that highly suitable regions (S1) were predominantly identified in soil mapping units 3, 5, and 9. The soil mapping units 3, 5, and 9 (S1 areas) in Savar Upazila were characterized by: inundation land type high land, which is above regular flood level, soil drainage inadequately to imperfectly drained, soil moisture high, slope level (1%), and texture class clay; these values are consistent with those considered in the literature. In general, not suitable zones (N) were found along the industrial and built-up areas. Furthermore, significant components in unsuitable places included sandy soil, medium low land that is flooded to a depth of 90-180 cm for several months during the rainy season, and a slope of 5.00%. During the Rabi season, some of this land is planted with mustard and wheat, while most of it remains fallow or grassland the rest of the year. To enhance the LULC, the suitability mapping for agricultural cultivation was overlaid to highlight discrepancies and similarities between both current and future land uses for agricultural land. This was done because identifying and accurately describing present and future producing regions is critical for research and agricultural production.

Conclusion

This research used GIS and RS approaches to identify suitable areas for agricultural cultivation. The findings of this study suggest that integrating GIS-RS and utilizing MCE with AHP might

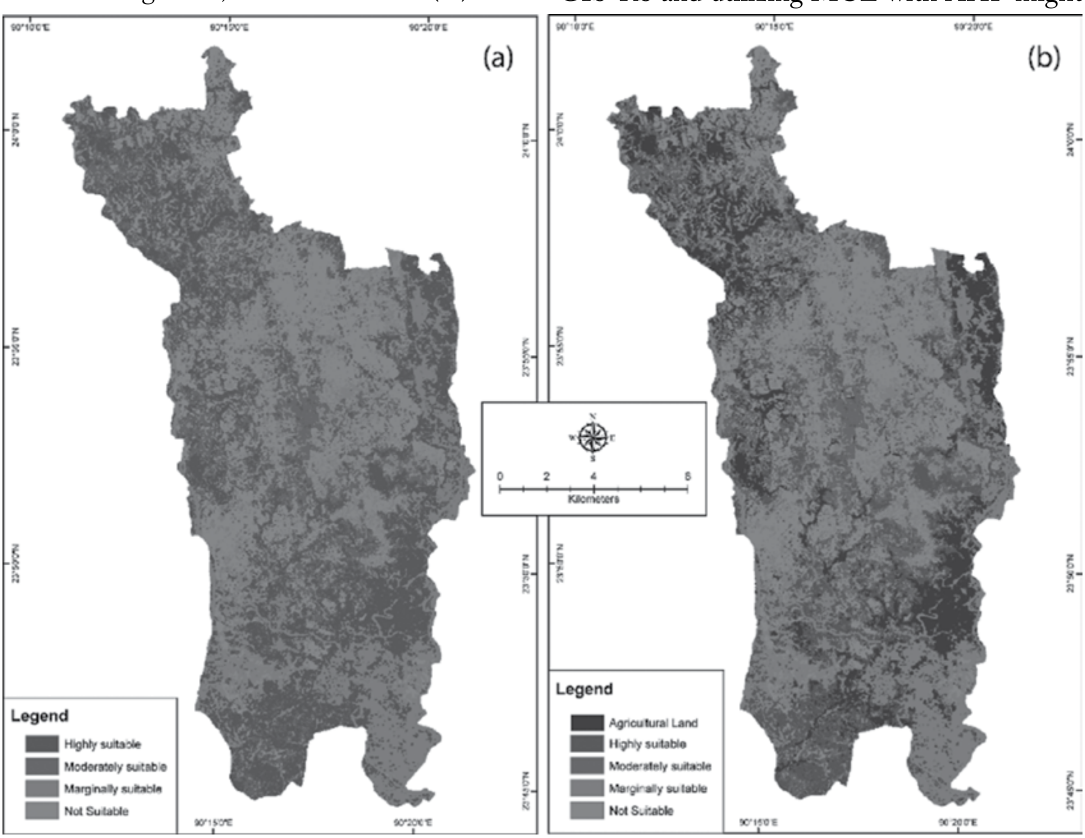

Figure 9:Land suitability of Savar Upazila (a) Suitable area of agricultural land, and (b) spatial distribution agricultural suitability and overaly of existing agricultural land.

give a superior database and guidance map for decision-makers contemplating agricultural harvesting substitution in order to improve agricultural productivity. The study demonstrated that the spatial distribution of agro-crops derived from RS data, in conjunction with the valuation of physical and biological variables of soil and topographic information in the GIS context, is beneficial in crop management options for intensification or diversification. Such an approach yielded excellent information about the relative relevance of the parameters under consideration and might serve as a beneficial model for future agricultural productivity research. This study also offers generic possibilities for local farmers in the context of agricultural land use planning for crop production. The findings of this study may be valuable to other researchers who may apply them in various investigations. This study considered present LULC, topography, and soil characteristics, all of which influenced the appropriateness categorization of land use categories. As a result, it produces main results. For further research, it has been advised to identify additional elements such as soil, climate, irrigation infrastructure, and socioeconomic aspects that impact land sustainability. In this circumstance, it needs to take the initiative to protect agricultural land, which is the recommendation based on this research assessment. The protection plans assist local governments in inventorying significant farmlands establishing goals for its conservation, and identifying implementation mechanisms.

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