Exploring the Nexus of Topographical Factors and Agriculture: Identifying Suitable Land for Agriculture in Poonch District, Jammu and Kashmir

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Abstract

Agricultural land is essential for food production and income generation. The present study was conducted to understand the relationship between topographical factors and agricultural land and to identify suitable land for agriculture in the Poonch district. Eight topographical factors, such as elevation, slope, aspect, curvature, relief amplitude, standard deviation of elevation, topographical wet index, and solar radiation, were chosen for the study. Topographical information was extracted from the Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM), and agricultural land was digitized from ArcGIS Pro base map and Google Earth high-resolution satellite images. The location entropy technique was used to determine the relationship between topographical factors and agricultural land. Suitable land for agriculture was identified through fuzzy overlay analysis in ArcGIS Pro using chosen parameters by considering the threshold value obtained in the location entropy. The findings revealed 34.98 square kilometers of suitable agricultural land. The survey among local farmers shows profitable agriculture in the region, and utilizing this suitable land could significantly improve farmers' livelihoods and the production of food grains. This specific area offers a promising opportunity for advanced farming techniques. Harnessing the potential of this identified area can enhance agricultural production, resulting in higher crop yields and economic benefits for the local farmers.

Keywords: Agriculture, Entropy, Fuzzy Overlay, GIS, Topography.

Introduction

Agriculture is an essential component of India's economy, providing livelihoods to many. Around 70% of rural households depend primarily on agriculture for their income, and 82% of farmers work as small-scale or marginal producers (Deshmukh et al., 2023; Suryavanshi, 2023). Even though the country's large population is engaged in agriculture, demand for agricultural products is increasing steadily due to continuous population growth. Several factors influence agriculture activities and production, such as groundwater (Jain et al., 2021), climate change (Kumar et al., 2004), rural road infrastructure (Shamdasani, 2021), land degradation (Hossain A et al., 2020), water scarcity (Dinar A et al., 2019), deforestation (Leite-Filho et al., 2021), population growth (Maja & Ayano, 2021), flood (Antolini et al., 2020), pandemic (Gray, 2020), rainfall (Zhang, 2020) soil and topography (Franz et al., 2020), apart from these there are several natural and human-induced activities (Arora & Birwal, 2017; Elapata & Silva, 2021).

Studies conducted in Jammu and Kashmir illustrate lack of irrigation facilities, soil erosion, traditional mode of agriculture (Raina & Sharma, 2021), deforestation, land degradation (Rudiarto & Doppler, 2013), rainfall fluctuation, lack of surface water, sloping surfaces, water stagnation in flat areas, and gully erosion in high-elevated areas affects the agriculture (C-DAP, 2016). Agriculture is difficult in these mountains (Mehmood & Kumar, 2020), where topography significantly affects crop yield, soil, water quality, and field mechanization processes (Dada et al., 2013). Several constraints exist in the hilly regions, from technique adoption to agricultural product marketing (Joshi & Lohani, 2023). Most of the past farming development efforts made in the hills were based on a poor understanding of the hill conditions (Partap, 2011).

Topographical factors significantly influence agricultural land (Rabia et al., 2022). The relationship between topography and crop yield can be seen in several conditions (Guo et al., 2012). Rugged topography makes major areas inaccessible and makes it difficult to apply modern agricultural techniques and inputs required for agricultural development (Prabha & Kour, 2021). Crop production (Kumhálová & Moudrý, 2014; Persson et al., 2005) and potential productivity (Li, 2014) are observed to be decreased in the uneven landscape. Topographic factors like elevation and slope play a significant role in crop growth and the occurrence of ways to use land (Gong et al., 2022). It is evident that terrain and weather influence yield and should never be ignored in farming (Kumhálová et al., 2011). Topography affects agriculture by influencing environmental factors, soil conditions, and weather, ultimately impacting crop production and yield (Godwin & Miller, 2003). Topographic characteristics, such as altitude, slope, and curvature, can account for up to 50% of the variation in agricultural production (Nolan et al., 2000).

This present study was conducted to identify the relationship between topography and agriculture and the optimal place for agriculture in the Poonch district of Jammu and Kashmir. Topography determines agriculture in regions like Poonch, where the landscape is mainly hilly, with mountainous areas and a few low-lying valleys (Wani Z A, 2022). A significant number of the population relies primarily on agriculture as their source of livelihood, where minimum land is available for farming (Kumar et al., 2021). Thus, identifying even a small optimal agricultural area would benefit the inhabitants.

The complex topography in hilly areas leads to various challenges for farmers, including subsistence farming, limited land ownership (Shahbaz, 2010), inadequate public services and infrastructure, and limited market access and financial sources (Becirovic, 2017). Despite its challenging topography, agriculture should be pursued in this area to ensure food provision for the local population. Therefore, the relationship of agriculture with topographical factors was identified through the location entropy technique, and the suitable areas for agriculture were identified using Fuzzy logic by considering the threshold value obtained from entropy.

Study Area

Poonch is one of the isolated districts of Jammu and Kashmir (UT), also called "Mini-Kashmir" because of its climatic conditions (Kheraj et al., 2019). It is located between latitudes 33° 25' and 34° 01' north and longitudes 73°58' and 74° 35' east with an area of 1674 sq. km. (Sudan, 2022). According to the 2011 Census, the total population of the district is 4,76,835, which accounts for 3.8 % of the total Jammu and Kashmir UT population. It is surrounded by Kashmir Valley (Baramulla, Budgam, Shopian, and Kulgam Districts) in the northeast and east and Rajouri district in the south. Pir Panjal range of mountains separates Poonch from Kashmir valley (Suri, 2014).

The district boundary was obtained as vector data from the National Family Health Survey from the DHS program portal (https://dhsprogram.com/data/dataset-types.cfm). It includes 6 Tehsils (Haveli, Mandi, Mendhar, Surankote, Mankote, and Balakote) and 11 Blocks (Balakote, Bufliaz, Lassana, Loran, Mandi, Mankote, Mendhar, Nangali Sahib, Poonch, Sathra, Surankote). There are 228-gram panchayats in the Poonch district with two municipalities (Sudan, 2022). Cultivation is performed on a sloping valley within a tiny, fragmented terrace (Fig. 1), where the community grows maize as its main crop, followed by wheat and rice.

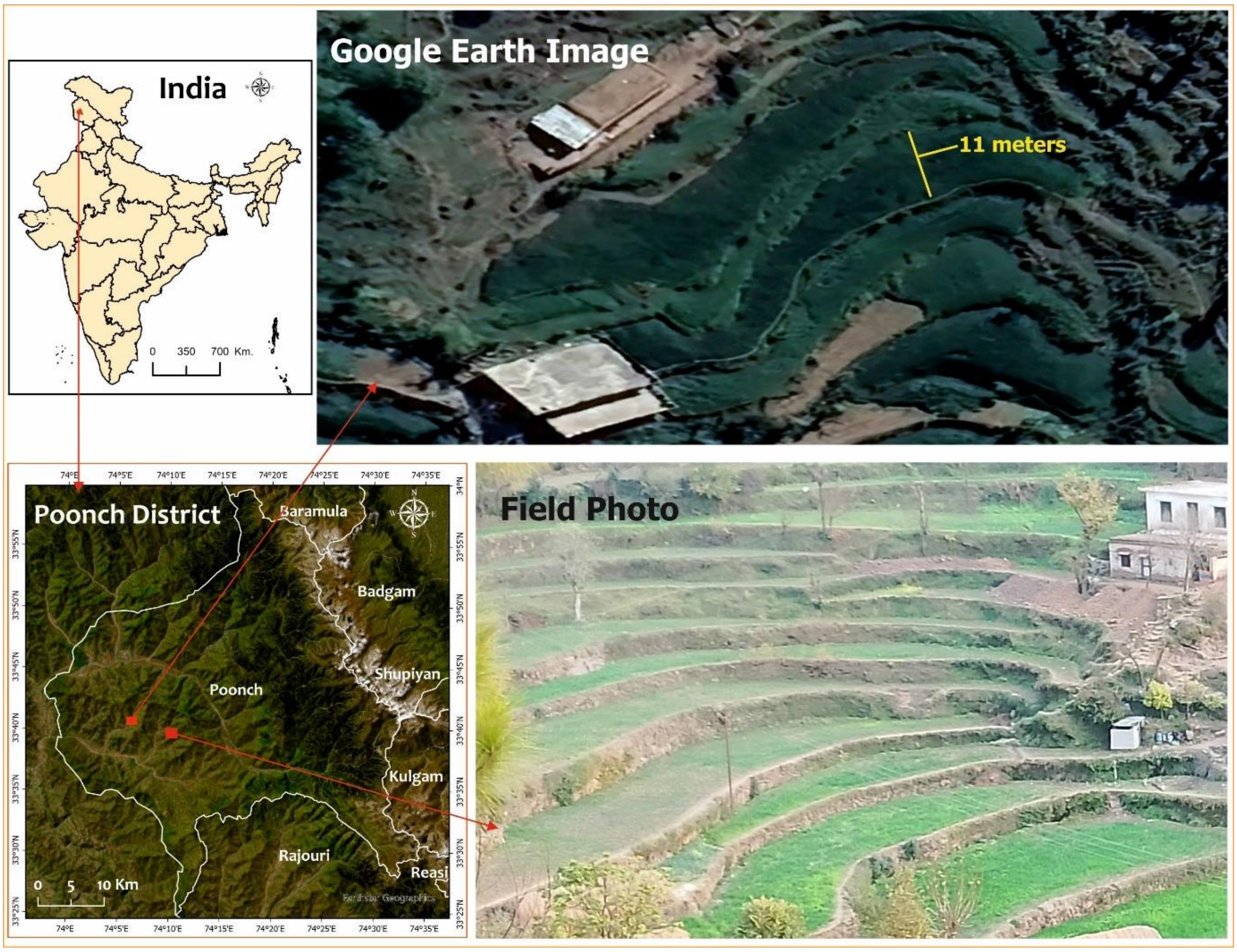

Figure 1 Location of Study Area with the Google Earth Image and Field Photo of Agricultural land in Poonch District.

Status of Agriculture

Field visits and a primary survey were carried out among 370 farmers to understand the status of agriculture in the Poonch. It is observed that the area cultivated under maize by the surveyed farmers is 2893.5 kanal (1 kanal is equal to 5,445 square feet), wheat is 2150.0 kanal, and rice is 667.5 kanal, with a total cultivation area of 5711 kanal (2.9 sq. km.), which illustrates maize is the main crop, followed by wheat, as it can be grown in slopy areas with step and terrace patches of land. A smaller area is used for rice cultivation in the low-lying areas as it requires a good water source. Small and scattered agricultural land and steep slopes are the significant difficulties farmers face. The cost of input and output per kanal for each crop is collected to understand the profitability of agriculture and presented in the table below.

Table 1 Input, output, and profit cost per kanal

S.No.	Crops	Cost in Rupees / Kanal		
		Average Input	Average Output	Average Profit
1	**Maize**	1170	1288	118
2	**Wheat**	801	1145	343
3	**Rice**	2201	2647	446
Total		1152	1393	241

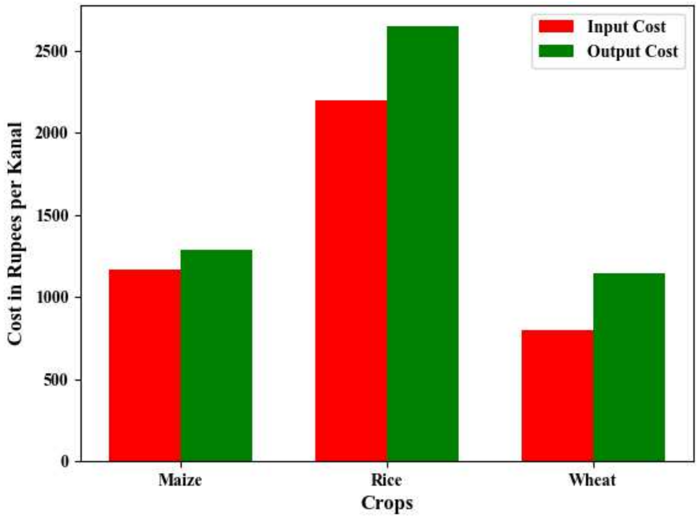

Figure 2 Comparison of Input and out costs per kanal

Table 1 and Figure 2 show that wheat is the most cost-effective crop. It has the lowest average total input and output costs per kanal. Even though rice has a higher input cost, it performs well financially, giving the highest profit per kanal among the three crops. Maize is economically viable but falls in the middle with moderate input and output costs. From this, it is clear that agriculture is profitable in Poonch, so understanding the influence of topography and identifying suitable areas for agriculture would benefit the farmers and increase their livelihood.

Materials and Methods

Topographical factors were derived from the Shuttle Radar Topographical Mission (SRTM) contours downloaded from OpenDEM (https://opendem.info/). A Digital Elevation Model (DEM) with a 10-meter spatial resolution was created using the topo-to-raster tool in ArcGIS Pro 3.2. This elevation data is used as a base to prepare other topographical factors chosen in the study. Subsequently, these topographical factors were classified into several classes and converted into vectors. Agriculture land was digitized using the high-resolution base map in ArcGIS Pro and Google Earth Pro. The entropy value was calculated using the total area and agriculture area in each class of chosen factor. Further, this entropy value was used as a threshold value to perform fuzzy overlay.

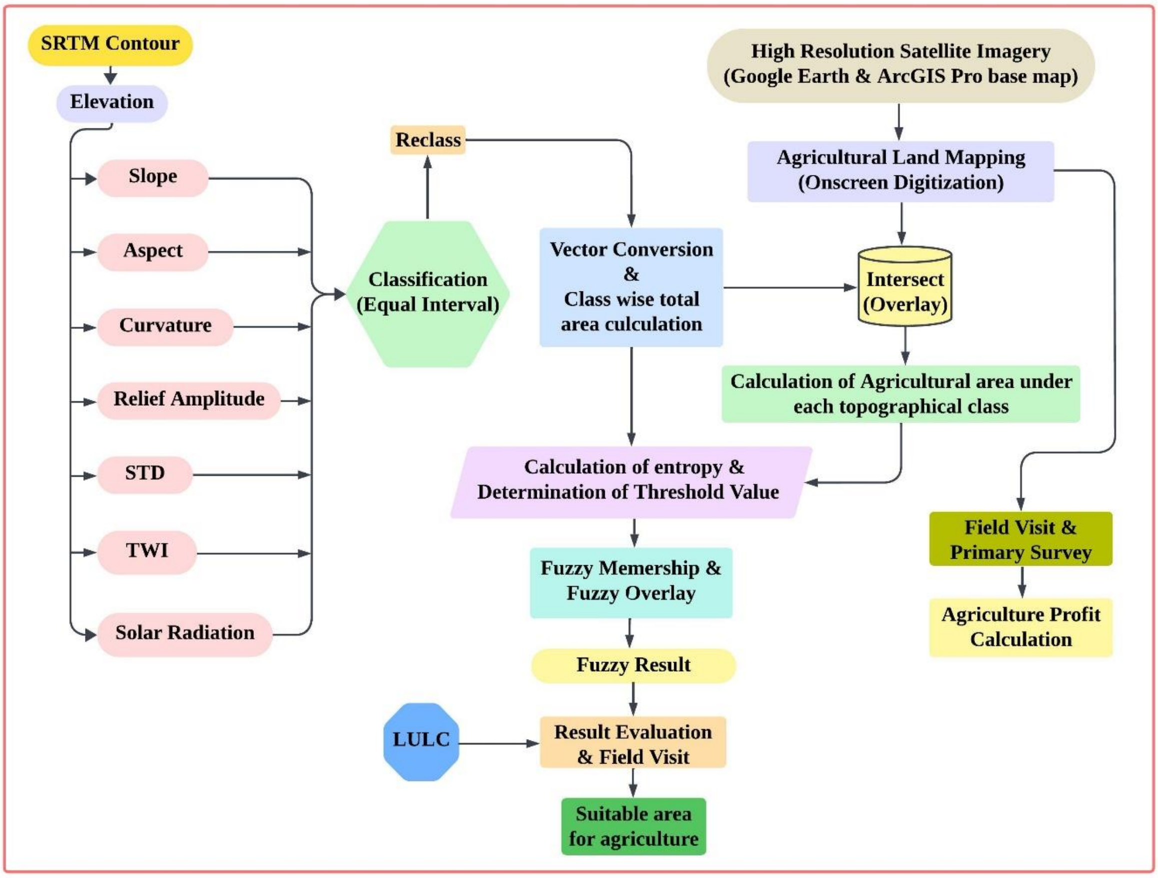

Figure 3 Methodology flowchart of study

Topographical Factors

Eight topographical factors, namely elevation, slope, aspect, curvature, relief amplitude, standard deviation of elevation, topographic wet index, and solar radiation, were selected as significant factors influencing agriculture (Ma et al., 2016; Maqsoom et al., 2023). Among the chosen factors, some are good at representing topography on a small scale, and some are good on a large scale (Tu et al., 1990). Considering this elevation, slope, aspect, curvature, topographical wet index, and solar radiation were performed at a micro-scale with a spatial resolution of DEM, 10 meters. The standard deviation of elevation was done at a 250-meter resolution scale, and relief amplitude was performed at a macro-scale with a grid of 1 km.

Location Entropy

Location entropy is a quantitative measure to assess the spatial distribution or concentration of activities, entities, or phenomena within a specific geographical area. It was used by Xi et al. (2018) to ascertain how the settlements are agglomerated in a particular location. However, we used the same location entropy to determine how agriculture activities are clustered within the Poonch district. The chosen topographical factors were categorized, and the distribution of agricultural land within these categories was used to calculate the location entropy. The following formula was employed to derive the location entropy (H):

$$H = \left(\frac{A_{ic}}{A_i}\right) / \left(\frac{T_c}{T}\right)$$

In the formula above, H indicates the measured location entropy for the topographical factors of specific category c at level i. A_{ic} denotes the area of the agricultural land at level i for category c, and A_i is the total agricultural land area of level i in the entire district. T_c is the total area of specific category c, and T is the district's total area. H value shows the agglomeration of the agricultural land for a particular topographical factor in each category. The areas with H values higher than 1 are suitable, while those with less than 1 are unsuitable for agriculture.

Fuzzy Overlay

Zadeh (1965) proposed the concept of fuzzy set theory to address situations when set membership is unclear. Fuzzy logic can represent the world using inaccurate terms and generate accurate actions in response (Gopal et al., 2016; Bartkova et al., 2017). Fuzzy logic utilizes a membership function to quantify the membership level of a specific property of interest (Park et al., 2014). The choice of an appropriate membership function for a fuzzy set is typically determined by the subjective judgment of the researcher (Jones et al., 1986).

The fuzzy overlay method utilizes mathematical or logical functions to rank and integrate data that is difficult to measure, leading to a scale of suitability (Mitchell, 2012). It enables the examination of the likelihood of a condition being part of various sets in a multicriteria overlay study (Hasanloo et al., 2019). The fuzzy overlay is utilized to ascertain the potential membership of the phenomenon in member sets (Vojteková & Vojtek, 2019), and it also examines the associations among the memberships of multiple sets (Baidya et al., 2014; Akgun et al., 2012). Fuzzy overlay analysis involves reclassifying or transforming data values to a standardized scale. However, the altered values indicate the likelihood of belonging to a particular category (Baidya, 2014). The process of fuzzy overlay analysis consists of two distinct stages. Initially, it is necessary to transform each criterion into fuzzy membership values by employing the fuzzy membership functions. Next, the data transformed into fuzzy form is superimposed using fuzzy overlay functions (Bamberger,2017).

Wang et al. (1990) suggested employing fuzzy sets in the assessment of land suitability, wherein the distinct boundary between the suitable and unsuitable categories was substituted with the notion of truth level. The study conducted by Breininger et al. (1998) exemplifies the integration of fuzzy overlay techniques with a site suitability analysis. Agricultural land suitability analysis aims to assess the appropriateness of agricultural land for growing crops, encouraging sustainable agriculture, and ensuring food security to eradicate hunger (Akpoti et al., 2019), and it is necessary to utilize available cultivable land for sustainable agricultural output effectively (Ahamed et al., 2000).

Analysis and Results

Agricultural Land Mapping

Agricultural land was mapped using the ArcGIS Pro base map in polygon. Further, these polygons were overlaid on the Google Earth Pro image to update the agricultural land using historical imagery. It was identified that 138.66 sq. km. of the area is under agriculture, mainly concentrated along the rivers in the central part (Fig. 4). While digitizing agricultural land, it is also observed that the region's dominant land cover is forest, with noticeable occurrences of built-up and water bodies. Seasonal snow cover near the eastern boundary, while the western boundary is predominantly forested, with scattered barren lands in the district.

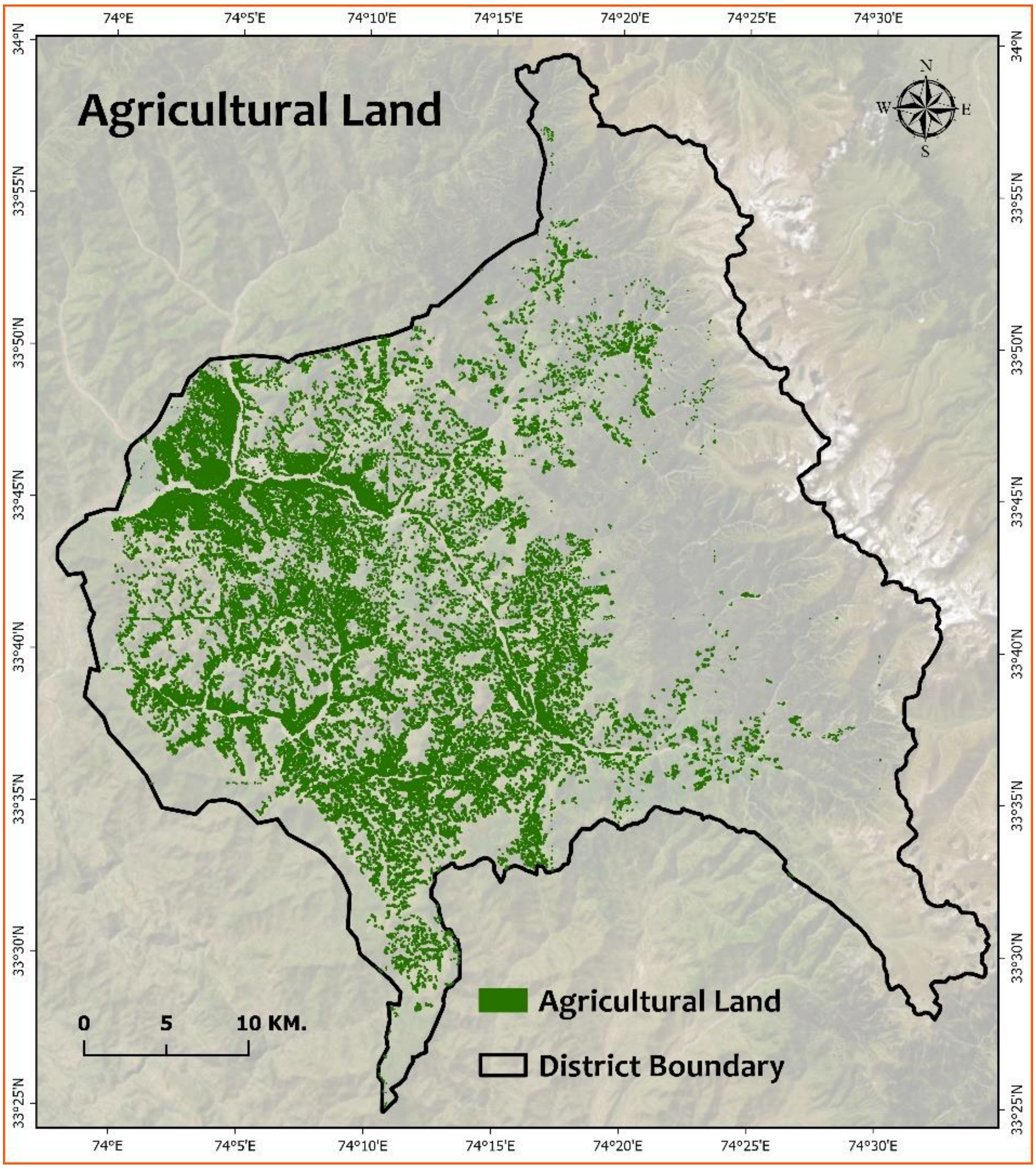

Figure 4 Agricultural Land

Elevation

The downloaded contour data had only a geographical coordinate system, so the data was projected using WGS84 - UTM zone 43N. DEM was prepared using a projected contour for the spatial resolution of 10 meters in ArcGIS Pro 3.2. Sink and peak errors in the DEM were corrected using the fill tool. The elevation ranges between 754 and 4687 meters; higher elevation is present in the eastern part of the district and decreases steeply towards the west. Elevation is classified into nine classes, starting from less than 1000 to more than 4500 meters, with a class interval of 500 meters (Fig. 5).

It is observed that less elevated areas generally have more significant agricultural land. As elevation increases, the agricultural land area tends to decrease, confirming that elevation considerably impacts crop cultivation and productivity (Ghosh et al., 2014). Elevations above 3500 meters have minimal to no agricultural land, indicating harsh conditions for agriculture at higher altitudes (Table 2). The most favorable terrain conditions for agriculture are at lower elevations, and agricultural productivity will be restricted at higher elevations (Li et al., 2014). The entropy value indicates the varying levels of disorder in the distribution of agricultural land over the different elevations. A higher value in lower elevations indicates higher concentrations of agricultural land suitable for agriculture, and values of 0 in higher elevations signify areas unsuitable.

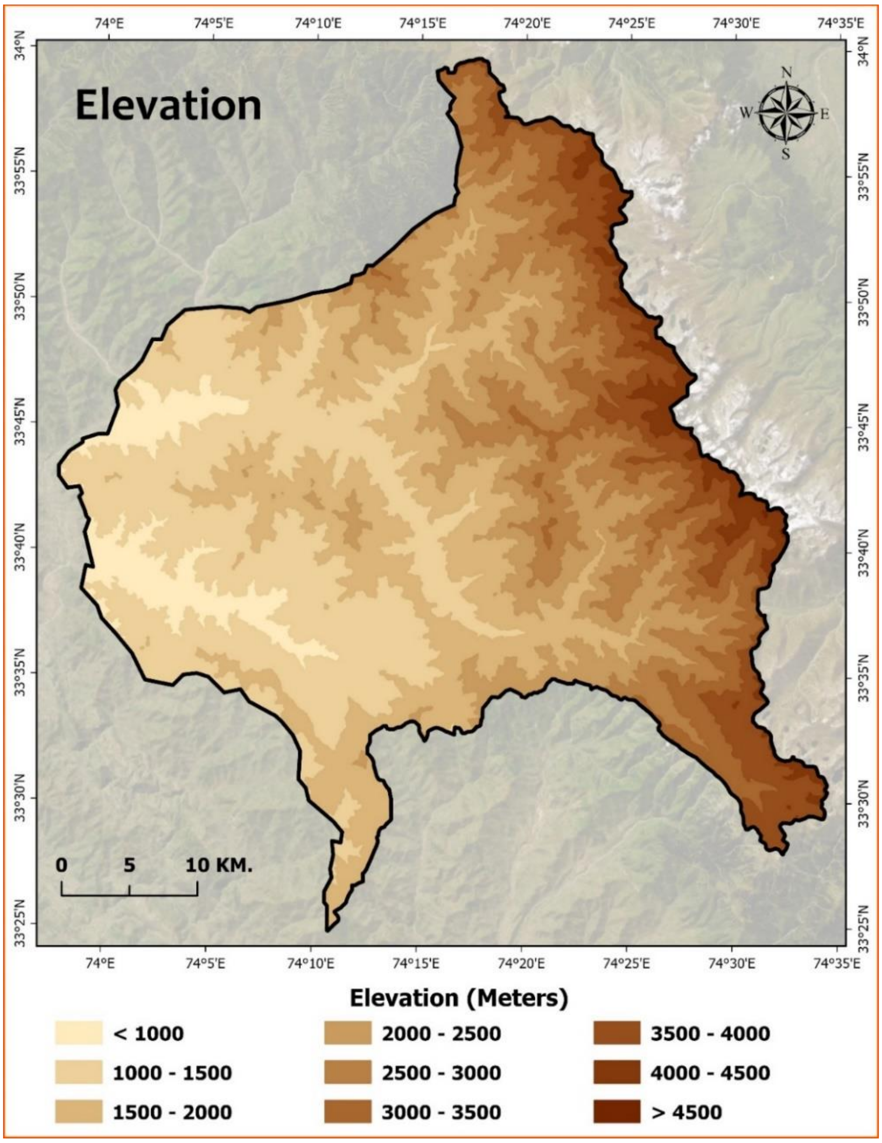

Figure 5 Elevation

Table 2 Class-wise extension of total and agriculture area and entropy value

S.No.	Factors	Class	Total Area	Agriculture Area	Entropy	S.No.	Factors	Class	Total Area	Agriculture Area	Entropy
1	Elevation in Mts.	< 1000	97.24	24.67	3.07	5	Relief Amplitude	< 110	30.08	11.09	4.47
		1000 - 1500	443.06	73.12	2.00			110 - 220	103.64	24.76	2.89
		1500 - 2000	363.92	34.33	1.14			220 - 330	314.93	39.63	1.52
		2000 - 2500	256.14	6.39	0.30			330 - 440	448.69	42.19	1.14
		2500 - 3000	203.23	0.19	0.01			440 - 550	381.95	16.84	0.53
		3000 - 3500	140.73	0.04	0.00			550 - 660	267.36	3.81	0.17
		3500 - 4000	124.63	0.00	0.00			660 - 770	112.27	0.38	0.04
		4000 - 4500	51.04	0.00	0.00			770 - 880	16.85	0.05	0.03
		> 4500	0.79	0.00	0.00			> 880	5.00	0.00	0.00
2	Slope in Degree	< 8	158.74	42.34	3.23	6	STD	< 14	173.29	47.55	3.32
		8 - 16	248.05	38.47	1.88			14 - 28	488.53	55.48	1.38
		16 - 24	391.24	36.03	1.12			28 - 42	592.47	30.62	0.63
		24 - 32	450.35	17.87	0.48			42 - 56	336.54	4.82	0.17
		32 - 40	321.53	3.75	0.14			56 - 70	78.66	0.27	0.04
		40 - 48	94.16	0.26	0.03			70 - 84	10.15	0.01	0.01
		48 - 56	15.32	0.01	0.01			84 - 98	0.95	0.00	0.01
		56 - 64	1.38	0.00	0.01			> 98	0.17	0.00	0.00
		> 64	0.01	0.00	0.00	7	TWI	< 3	21.24	0.35	0.20
3	Aspect	Flat	1.93	0.17	1.09			3 - 4	102.78	4.07	0.48
		North	190.17	12.75	0.81			4 - 5	307.06	12.43	0.49
		Northeast	174.88	16.41	1.14			5 - 6	516.16	27.36	0.64
		East	150.57	14.88	1.20			6 - 7	398.01	36.22	1.10
		Southeast	171.65	15.64	1.10			7 - 8	175.54	27.39	1.89
		South	229.67	20.04	1.06			8 - 9	74.18	15.09	2.46
		Southwest	289.89	24.66	1.03			> 9	85.81	15.84	2.24
		West	252.38	19.77	0.95	8	Solar Radiation	< 750	0.78	0.00	0.00
		Northwest	219.65	14.42	0.80			750 - 1000	24.85	0.07	0.03
4	Curvature	< - 2	6.68	0.10	0.17			1000 - 1250	186.41	5.27	0.34
		- 2 - -1.5	12.31	0.25	0.25			1250 - 1500	436.56	40.91	1.14
		- 1.5 - - 1	45.00	1.36	0.37			1500 - 1750	664.98	86.51	1.58
		- 1 - - 0.5	183.30	9.38	0.62			1750 - 2000	268.76	5.89	0.27
		- 0.5 - 0	641.36	71.11	1.34			2000 - 2250	95.32	0.00	0.00
		0 - 0.5	530.74	47.76	1.09			> 2250	1.96	0.00	0.00
		0.5 - 1	185.91	7.29	0.47						
		1 - 1.5	52.49	1.20	0.28						
		1.5 - 2	15.22	0.22	0.18						
		> 2	7.77	0.08	0.12						

Slope

The slope gradient directly influences agricultural productivity and determines the specific type of agriculture, yields, and cultivation methods used in a particular location (Fombe & Tossa, 2015). Due to the difficulty of agriculture on the steep slopes, most of these areas are used for grazing cattle, perennial bush growing, and timber production. The slope of the district is derived from DEM data in the units of degrees. The slope varies from 0 degrees to 61 degrees. These values were classified into nine classes, starting from less than 8 degrees to more than 64 degrees with a class interval of 8 degrees (Fig. 6). The calculation of the area under each class revealed a more extensive area under 24 to 32 degrees of slope (Table 2). The area under agriculture is high in the lower degree of slope, especially 97 percent of the land is located less than 32 degrees; agricultural land decreases while the degree of slope increases. The entropy value illustrates the variability in agricultural land distribution across the different degrees of slope. A higher entropy value in the gentle slope indicates a higher concentration of agricultural land and suitable for agriculture. Extremely low and zero entropy values in steeper slopes show unsuitable.

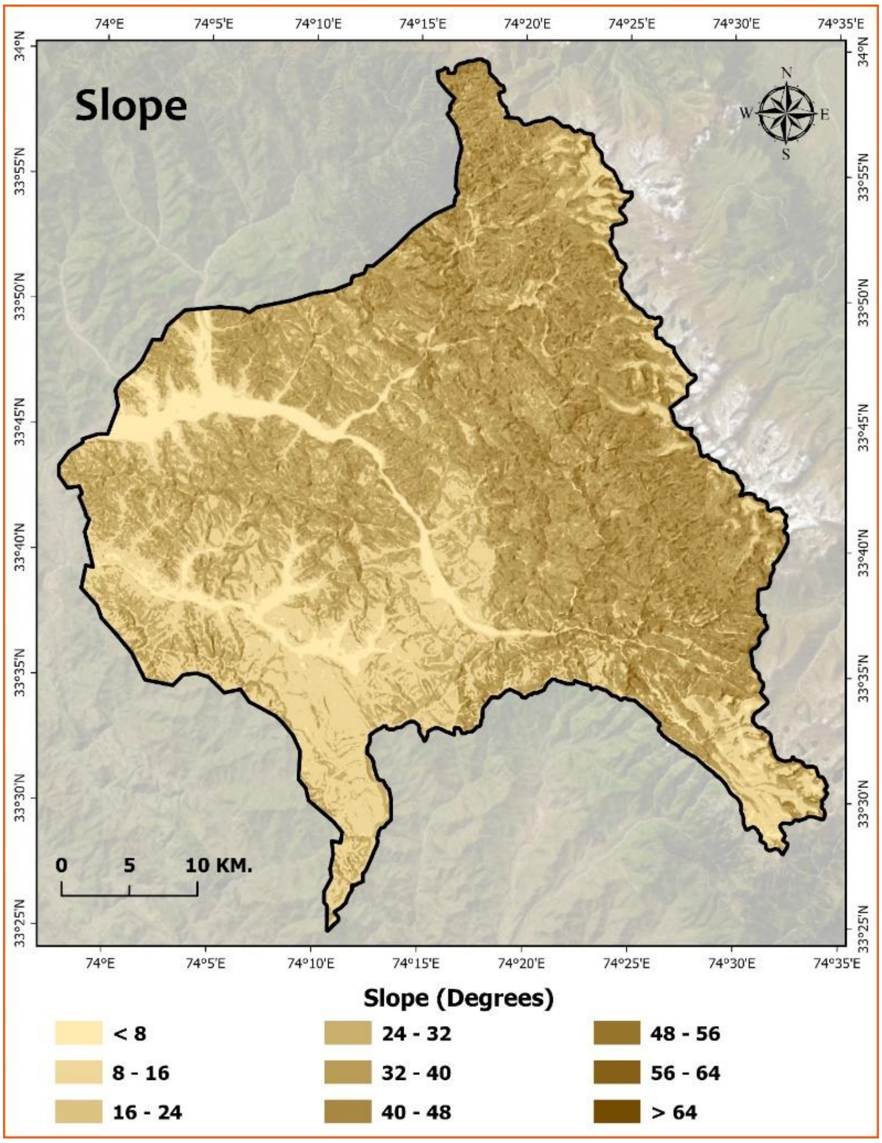

Figure 6 Slope

Aspect

The level of sunlight exposure on sloping terrain is closely tied to its aspect (Akbari et al., 2014), influencing the growth of crops. The aspect (direction of slope) is derived from DEM and classified into nine classes, including flat terrain. It is observed that slopes are present in all directions; a larger area is in the southwest direction, and a smaller area is in a flat area (Fig. 7). The rugged and highly undulated nature of the district contributes to the reduced extent of flat terrain. Agriculture land is present in all directions, including the flat area, but the area extension in each class varies. Like the total area, agricultural land also presents large in the southwest direction and least in flat terrain. A higher entropy value in flat terrain indicates a higher concentration of agriculture and suitable conditions (Table 2). The lowest values in the North and Northwest directions indicate unsuitable conditions for agriculture.

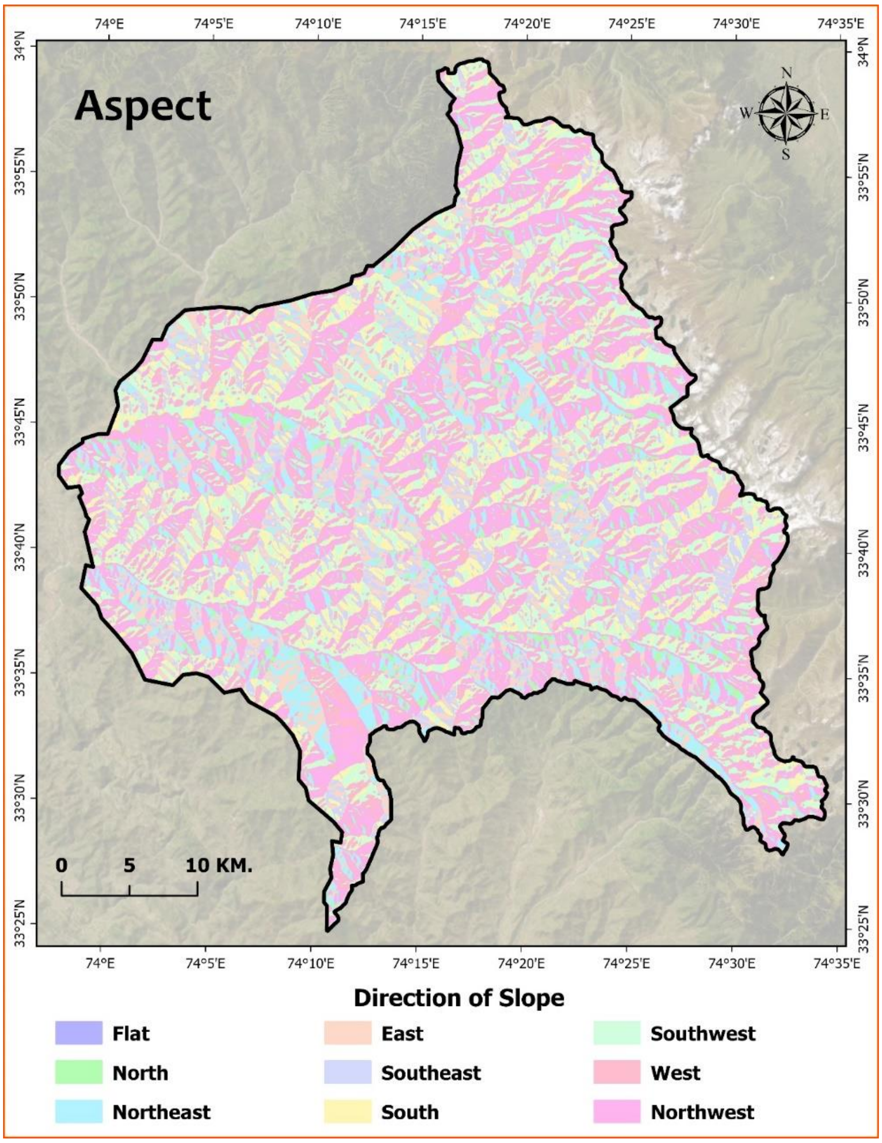

Figure 7 Aspect

Curvature

The magnitude of curvature seems to be a crucial determinant for achieving clearer demarcation of the converging and diverging regions (Girgin & Frazier, 1996). Convergent and divergent areas are essential in creating landscapes and can substantially impact agriculture, affecting water drainage, soil composition, and general terrain features.

The curvature of the terrain is obtained from DEM. The value of curvature ranges from – 4.5 to + 5.9. These values are classified into ten classes, from less than - 2 to more than 2, with an interval of 0.5 (Fig. 8). Positive curvature indicates the surface is convex, and a negative curvature value suggests the surface is concave. A value of 0 indicates that the surface is flat (Oueslati et al., 2013). Positive and negative curvature results indicate a mix of concave and convex landforms. Most of the total agricultural area is between – 1 and +1, encompassing relatively flat to gently sloping terrain (Table 2). The entropy value is high, between – 0.5 and +0.5, indicating areas with less curvature favor agriculture.

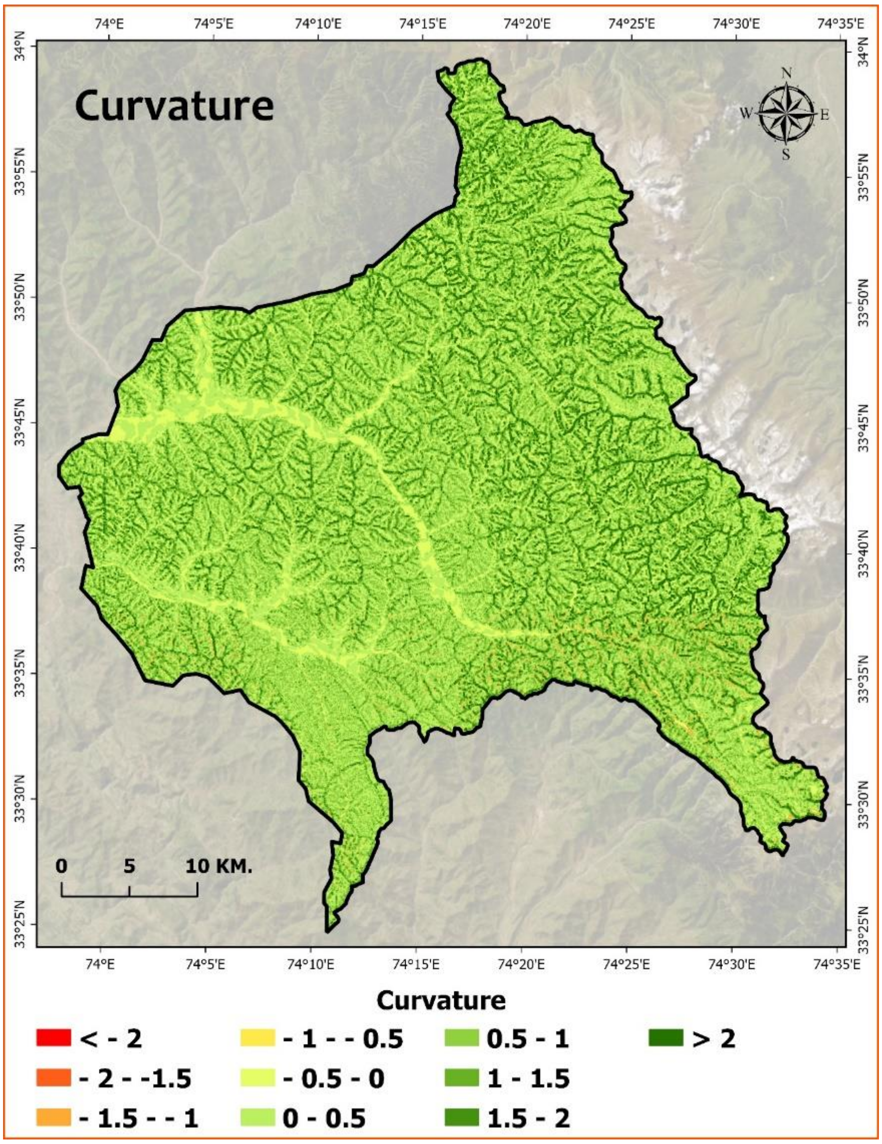

Figure 8 Curvature

Relief Amplitude

Relief amplitude represents the vertical difference in the elevation of an area, determined by computing the difference between the maximum and minimum elevation values. Calculating relief amplitude would provide meaningful information at a larger scale (Yang et al., 2018). Thus, one sq. km. grid covering the entire district was created using the fishnet tool in ArcGIS Pro 3.2, and the maximum and minimum elevation values within each grid are extracted using zonal statistics. Further, relief amplitude was calculated using the extracted values, which revealed a maximum of 914 meters and a minimum of 24 meters.

These values were classified into nine classes from less than 110 meters to more than 880 meters with a class interval of 110 meters (Fig. 9). Larger agricultural land is between 330 and 440 meters of relief amplitude. At the same time, other areas are relatively lesser (Table 2); the higher entropy values in the lesser relief amplitude indicate suitable conditions, and the lesser value in higher classes indicates unsuitable conditions for agriculture. Human activities, including agriculture, usually dominate in low-relief amplitude areas in influencing the distribution of landscape types, and natural factors usually dominate the higher-relief amplitude areas (Zhang et al., 2018).

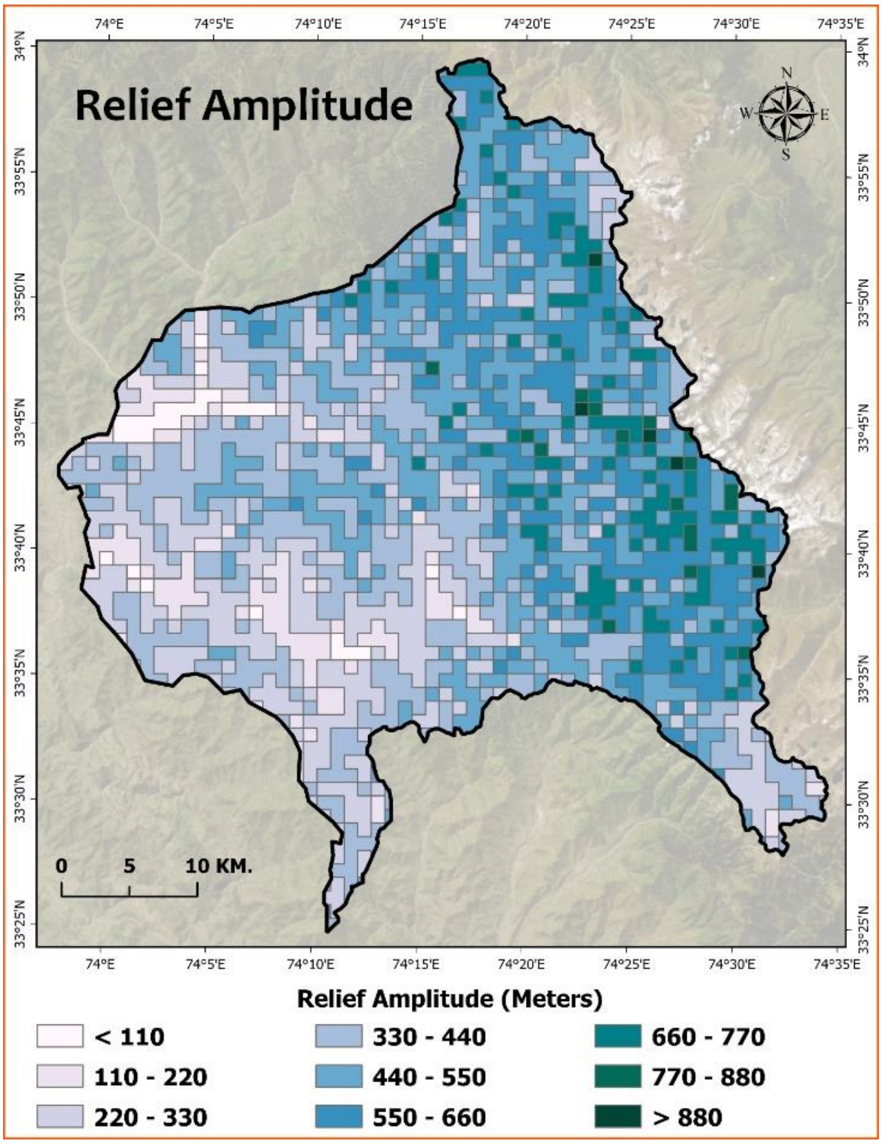

Figure 9 Relief Amplitude

Standard Deviation of Elevation (STD)

Standard Deviation of Elevation has greater significance in mountainous topography (Essery & Marks, 2007). An inverse relationship exists between the standard deviation of elevation and the percent covered by agriculture (Riera et al., 1998), impacting the appropriateness of crops and agricultural methods in a specific area. A fishnet covering 250 square meters was created for the entire study area, and the standard deviation of elevation was extracted using a zonal statistics tool. Higher values of STD indicate diverse topography, potentially with mountains or valleys, while lower values suggest a more uniform landscape. The computed STD value ranges between 0 and 121 meters; these values were classified into eight classes from less than 14 meters to more than 98 meters with a class interval of 14 meters (Fig. 10). Most agricultural land falls within the 42-meter standard deviation range. The smallest agricultural footprint is observed beyond this (Table 2). The entropy value decreases while the standard deviation class increases, indicating that lesser deviation areas are more suitable for agriculture.

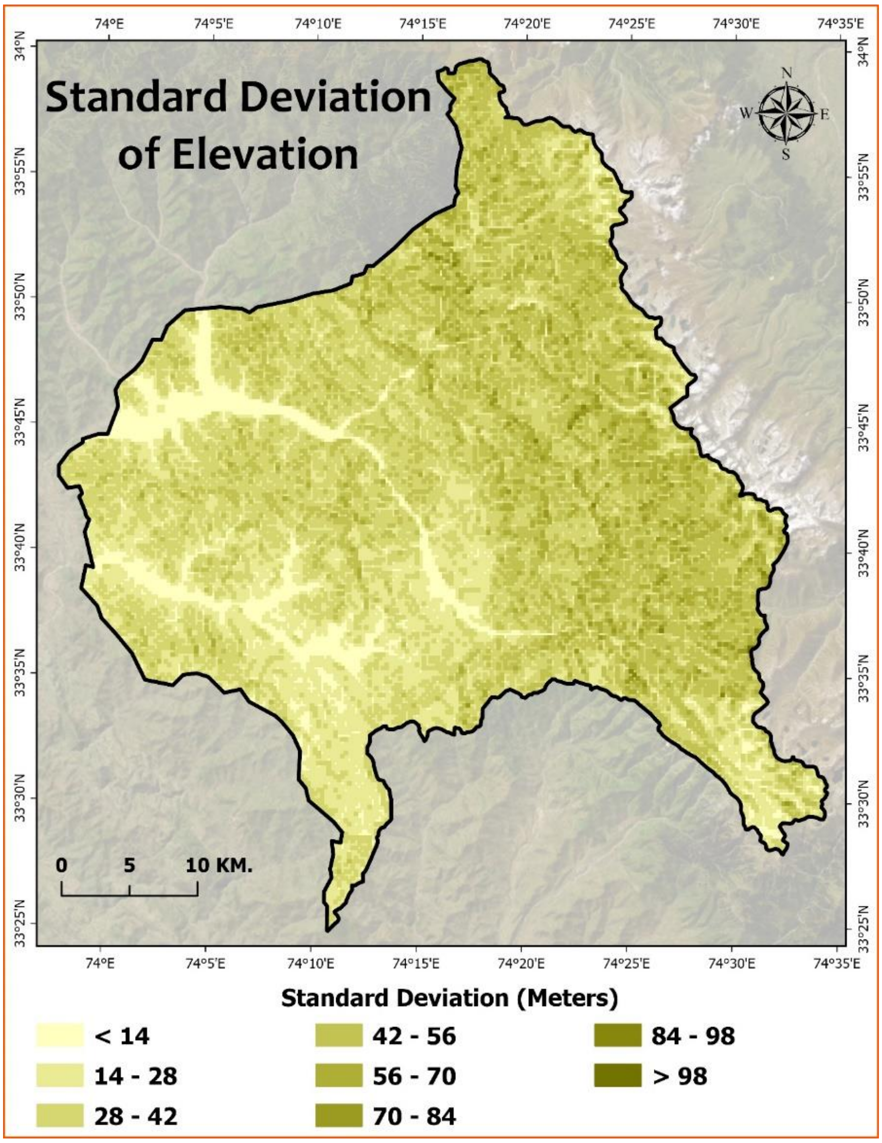

Figure 10 Standard Deviation of Elevation

Topographic Wetness Index (TWI)

The topographic wetness index is a significant topographic characteristic extensively utilized in precision agriculture to accurately measure the impact of regional terrain on hydrological events (Qin et al., 2011). It is also a secondary geomorphometric indicator to describe and quantify local relief (Różycka et al., 2016). The idea of TWI was initially proposed by Beven and Kirkby (1979). The TWI is calculated using DEM as a base based on the formula below.

$$TWI = ln\ (\frac{A}{tan\beta})$$

A denotes the area that contributes to the upslope, while tanβ represents the slope of the local area (Moore et al., 1991; Sorensen et al., 2006; Gruber & Peckham, 2009)

The result of TWI provides relative values in which lesser values indicate less water index and high values indicate high water index. The minimum of 1.6 and maximum of 32.2 was obtained as TWI for the entire district; these values were categorized into eight classes from less than 3 to more than 9 with the class interval of value 1 (Fig. 11). The highest agricultural area is observed in the TWI class of 6-7, covering 36.22 square kilometers (Table 2), indicating that this specific topographic wetness range is suitable for agriculture. The entropy value increases while the TWI class rises, suggesting that increasing the wetness index increases the suitability for agriculture.

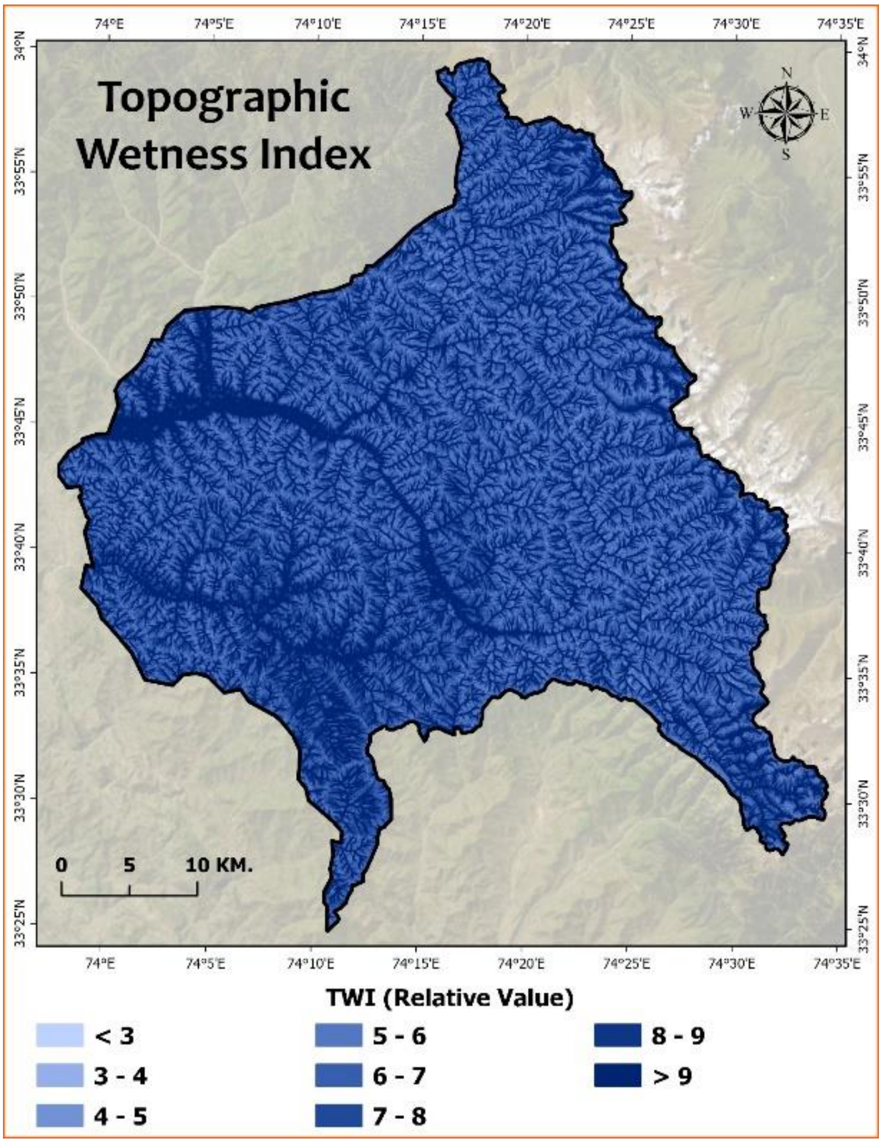

Figure 11 Topographic Wetness Index

Solar Radiation

Solar radiation serves as the primary source of energy equilibrium and is also a significant factor in water equilibrium. It plays a crucial role in all biological and physical processes in agriculture (Fu and Rich. 2002). Solar radiation is critical to agriculture as it directly influences plant growth (Duriyaprapan & Britten, 1982), photosynthesis (Moss et al., 1971), and overall crop development (Campillo et al., 2012). Annual solar radiation from January 1, 2023, to December 31, 2023, was calculated in ArcGIS Pro 3.2 using a raster solar radiation tool. The Solar Radiation tool in ArcGIS's Spatial Analyst Toolbox computes the solar radiation throughout a given geographical region or for specific point locations defined by latitude and longitude (Kausika & Sark, 2021). The resulting solar radiation is in the units of watt-hours per square meter (Wh/m^2), which revealed a minimum of 444 Wh/m2 and a maximum of 2374 Wh/m^2. These values were classified into eight classes, from less than 750 Wh/m^2 to more than 2250 Wh/m^2, with a 250 Wh/m^2 class interval (Fig.12). More than 90 percent of agricultural land is located between the classes 1250 – 1500 and 1500 – 1750. The entropy value is also higher in these classes (Table 2), indicating suitable conditions for agriculture.

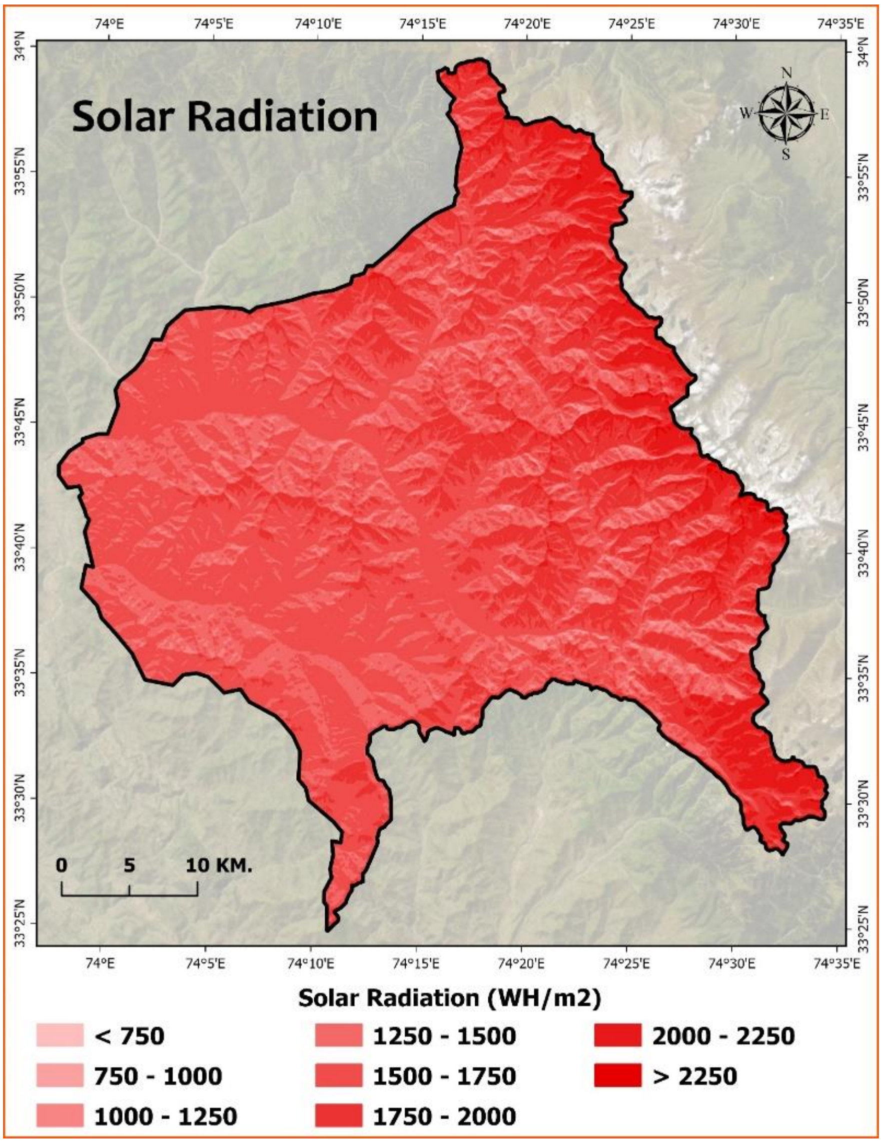

Figure 12 Solar Radiation

Identification of Suitable Area

The obtained entropy value indicates the suitable and unsuitable agricultural conditions for chosen factors. These values were considered input for the fuzzy overlay to identify the suitable areas for agriculture. The fuzzy overlay analysis model employs interval-valued fuzzy sets, allowing for the comprehensive execution of general and weighted fuzzy overlays (Yu et al., 2004). It performs based on various fuzzy membership types used to classify the data (Nedeljkovic, 2004). Fuzzy membership converts the input data between 0 and 1, in which one indicates high suitability and 0 indicates unsuitability, while a value approaching 0 shows a lower level of suitability. An analyst decides which value in the input data should be assigned with a higher value of 1 based on the nature of the data.

Three types of fuzzy membership, namely Small, Gaussian, and Large, were assigned to continuous data of DEM and other topographical factors to perform a fuzzy overlay. An entropy value of 1 was chosen as the threshold value as the suitability of agricultural land increases or decreases from this value (Xi et al., 2018). The pixel value of topographical factors that fall under the entropy value of 1 was considered as a mid-point value to perform fuzzy membership (Table 3).

A fuzzy small membership type was adopted for elevation, slope, relief amplitude, and standard deviation, with the mid-point threshold value of 2000 meters, 24 degrees, 440 meters, and 28 meters, respectively, as values smaller than the midpoint having a higher possibility of suitability and values above the midpoint having a decreasing suitability. A large membership type was adopted for the topographic wetness index, with the mid-point threshold value of 6 as values higher than this have higher suitability and less have lesser suitability.

Table 3 Chosen fuzzy membership type and the threshold value

S.No.	Topographical Factor	Fuzzy Membership Type	Threshold value (Mid-Point)
1	Elevation	Small	2000 Meters
2	Slope	Small	24 Degree
3	Aspect	Gaussian	90 Degree
4	Curvature	Gaussian	0
5	Relief Amplitude	Small	440 Meters
6	STD	Small	28 Meters
7	TWI	Large	6
8	Solar Radiation	Gaussian	1500 Wh/m^2

Gaussian membership is adopted for aspect, curvature, and solar radiation as suitability values are in the intermediate. The value of 90 degrees for aspect, zero for curvature, and 1500 Wh/m^2 for solar radiation was chosen as the mid-point threshold value for which the higher value of 1 is set, and the values reduce gradually to 0 for the increasing and decreasing pixel values. The fuzzy overlay was performed by using the generated fuzzy membership outputs. The result produced raster data having a value between 0 and 0. 97, where 0 is unsuitable, and suitability increases towards the higher value. It is observed that 44.91 sq. km. area resulted as a suitable area.

Evaluation of Result

The result obtained by a fuzzy overlay may include existing agricultural land and other unfavorable lands with similar characteristics of favorable topographical conditions, as the study has considered the entropy value of topographical factors derived from existing agricultural land to identify suitable land. Therefore, the result of the fuzzy overlay was converted into polygons and intersected with the Land Use and Land Cover (LULC) to determine the exact suitability of the land. LULC was prepared by onscreen digitization on the high-resolution image of Google Earth, which was captured in December 2022. Six LULC classes were mapped, namely, vegetation (all the greenery other than agriculture), barren land, agriculture, built-up, snow, and waterbody (Fig. 13). Since chosen classes can be identified clearly on the high-resolution imagery with the onscreen digitization itself, there was no need to conduct accuracy assessment.

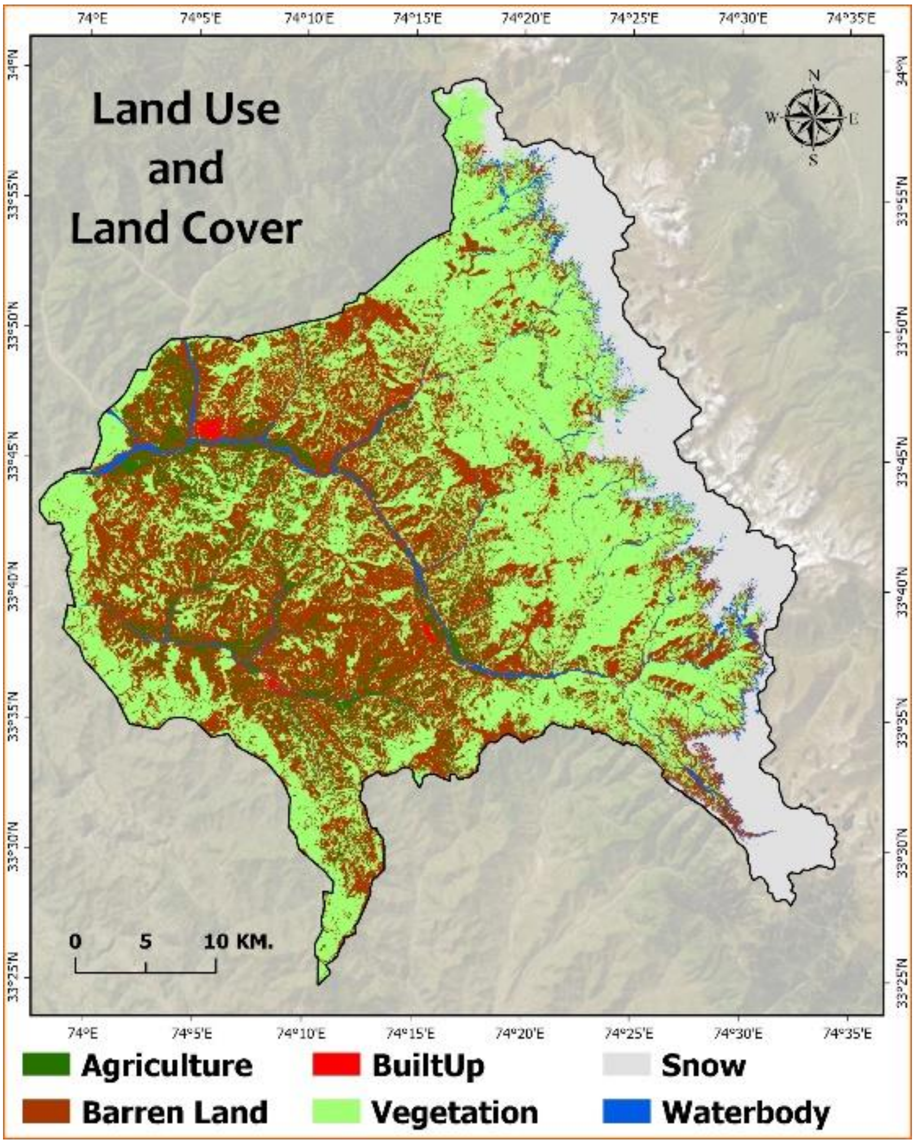

Figure 13 Land Use and Land Cover

The result illustrates that 19.03 sq. km. area falls in barren land, 15.95 sq. km area falls in vegetation, 6.21 sq. km. falls in existing agricultural land, 2.80 sq. km. falls in built-up land, 0.75 sq. km. falls in waterbody and 0.17 sq. km. falls in snow areas (Table: 4).

Table 4 Fuzzy overlay suitability under different Land Use and Land Cover

S.No.	LULC	Fuzzy result Area under different LULC (Sq. Km.)
1	**Barren Land**	19.03
2	**Vegetation**	15.95
3	**Agriculture**	6.21
4	**Builtup**	2.80
5	**Waterbody**	0.75
6	**Snow**	0.17
Total		44.91

It indicates that similar topography characteristics of existing agricultural land are present in different LULC areas. The land under the existing agriculture is excluded using the erase tool from the result as agriculture is already practiced on that land, and areas under built-up, water bodies, and snow are also excluded as these areas are unsuitable for agriculture. Thus, the barren land and vegetation area, consisting of 34.98 sq. km, is considered suitable for agriculture (Fig. 14). Validation techniques like Confusion Matrix and Receiver Operating Characteristics are not possible in this study since the identified suitable land falls on vegetation and barren land, which is decided based on the favorable condition of existing agricultural land. Therefore, a field visit was conducted randomly to verify the physical condition of the identified suitable land, and it was observed that the result obtained matched with the field in all the places visited (Fig. 15).

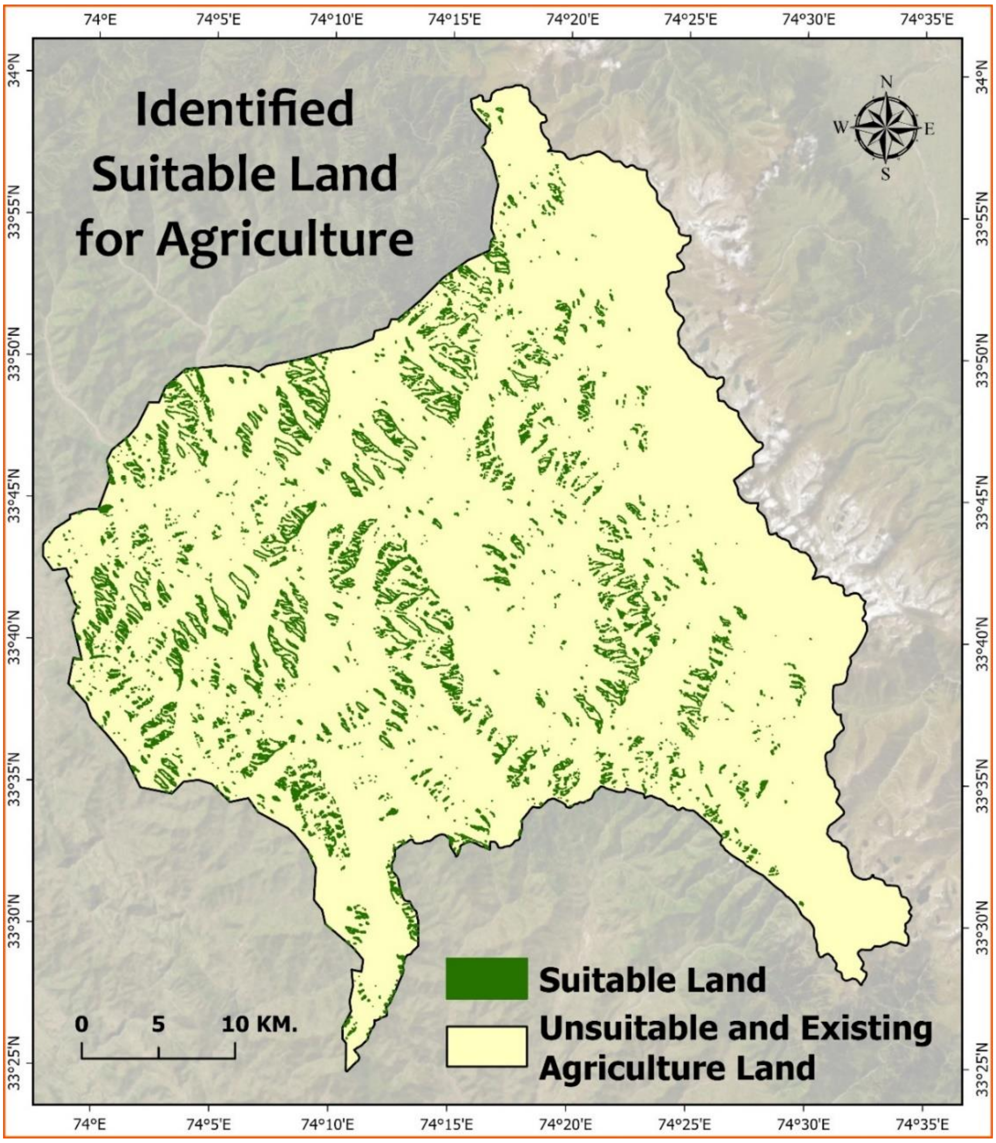

Figure 14 Identified Suitable Land for Agriculture

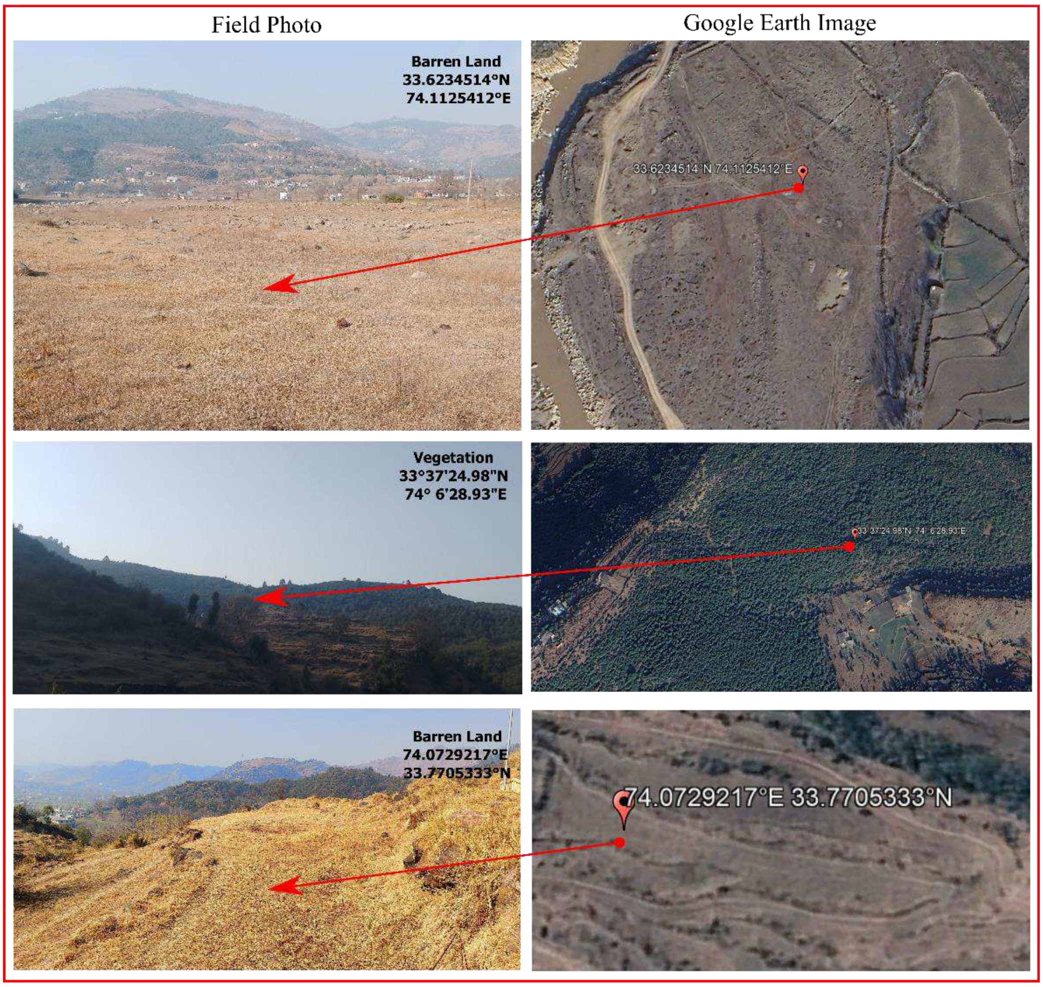

Figure 15 Field Photo and Google Earth Image of Identified Suitable Land

Conclusions

Topography is vital in agriculture, especially in hilly areas like Poonch. Thus, this study was conducted to identify the relationship between topography and agricultural land. It is observed that areas with higher topographical wetness index, lower elevation, flat or gentle slope, less relief amplitude and standard deviation of elevation, lower curvature, east direction of slope, and moderate solar radiation are more suitable for agriculture than other areas. The result obtained through fuzzy using entropy-derived threshold value was evaluated with LULC, which revealed that 34.98 sq. km. of vegetation and barren land is suitable for agriculture. This identified area may provide an opportunity for optimized agricultural practices. Utilizing this area can enhance agricultural productivity and sustainability, improving yields and economic benefits for local farmers. The study also demonstrated the application of entropy values as a threshold for identifying suitable agricultural land using fuzzy overlay, which may offer valuable understanding to the researcher interested in similar studies.

This study considered only topographical factors as this influence more than other factors in the study area. A study including other factors such as climate, soil quality, and water resources may provide more insight into the suitable area under agriculture. The identified suitable area may fall under different management types, such as private, public, and forest; thus, a collaborative effort may be required to appropriately utilize this land for agriculture.

Statements and Declarations

Competing Interest:

The authors have no competing interests to declare relevant to this article's content.

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All data supporting this study's findings are available from the author's side on reasonable request.

Author's Contribution Statement:

Mahalingam Bose: Conceptualization, Methodology, Software, Supervision, Interpretation, Writing and Final Revision of Manuscript. **Zaffar Iqbal:** Data Curation, Field Investigation, Validation, and Writing. **Tharayil Irshad:** Formal Analysis, Software, Visualization, Writing, Review, and Editing. All authors reviewed and approved the final manuscript.

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