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Multi-Criteria Land Suitability Analysis for Agriculture in Gundlupet Taluk: AHP and GIS Approach

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Abstract- This study aimed to assess suitable lands for agricultural purposes in the Gundlupet taluk of Chamarajanagar district. Leveraging the widely used Analytic Hierarchy Process (AHP) integrated with Geographic Information System (GIS), this research conducted a thorough land use suitability analysis. Key parameters including geomorphological and geological features, relief, slope, drainage density, rainfall, soil texture, and land use and land cover were considered in the analysis. Weights were assigned to these parameters based on their significance and importance, resulting in the generation of an agricultural land suitability map divided into three categories. Upon excluding forested and reservoir areas from the reclassified suitability map, the study estimated that 19.59% of the study area (266 sq. km) is highly suitable for agricultural production, 67.6% (918 sq. km) is moderately suitable, and 12.81% (174 sq. km) is unsuitable for agricultural production in this region. This framework facilitates the early zoning of agricultural land for protection, ensuring sustainable land use development in the future.

Keywords: Agricultural land suitability, Analytic Hierarchy Process, Weighted overlay analysis, GIS, Gundlupet.

I. INTRODUCTION

Lands represent crucial assets for nations, directly impacting agricultural progress and food security. Therefore, fostering sustainable agricultural practices stands as a paramount objective within both developed and developing countries' agricultural agendas. However, mounting population growth intensifies pressure on land resources MK Pramanik (2016). Particularly in developing nations, the socioeconomic demands of rapidly expanding populations compel the allocation of land for diverse purposes, primarily food production. Consequently, the socio-economic advancement of nations hinges upon the abundance of natural resources and the efficacy of resource management policies. Moreover, escalating population growth and competing land use necessitate enhanced efficiency in land utilization and administration.

Rational and sustainable land management emerges as a pivotal concern, benefiting both present and future populations, as well as stakeholders vested in land conservation. Nevertheless, the fertility of arable lands suffers from the adverse impacts of industrialization, urban sprawl, and improper land practices. Furthermore, these fertile lands endure excessive fertilization, and contamination from domestic and industrial waste, leading to irreversible soil degradation Recognizing the suitability and caliber of lands holds significant weight in determining their optimal usage and safeguarding natural resources for posterity. Particularly crucial is the identification of potential agricultural lands, necessitating meticulous land use planning (Mustafa et al., n.d.). This process involves conducting thorough analysis and assessment, leveraging contemporary technologies to access swift, precise, and comprehensive data on soil and land resources.

The primary aim of studies assessing land evaluation has been to develop methodologies that facilitate the quantification of land suitability (Panda, 2016). Generally, these methods fall into two categories: qualitative approaches based on expert knowledge and quantitative models relying on simulation methods. While quantitative models offer detailed insights into land performance, they often demand extensive data, time, and resources. Conversely, qualitative approaches express land and soil characteristics in mathematical formulas to identify agricultural land suitability. Consequently, evaluating land suitability for agricultural activities is recognized as a complex problem with multiple criteria, suggesting that a multi-criteria decision analysis approach would be more apt.

Today, with advancements such as remote sensing and Geographic Information Systems (GIS), challenges in land evaluation can be addressed using methods like Multi-Criteria Decision Analysis (MCDA) to facilitate rational analysis and evaluation. According to(Taherdoost, n.d.). The Analytic Hierarchy Process (AHP), a commonly employed MCDA method, assigns weights to evaluation criteria, capable of identifying and addressing inconsistencies in decision-making (Memarbashi et al., 2017). However, assigning explicit numerical values to evaluation criteria may prove challenging or imprecise in practice. Therefore, decision-makers often express their weights in linguistic terms. To accommodate uncertainties inherent in human cognitive processes, applying fuzzy logic provides a mathematical framework. (Risna et al., 2023) integrated fuzzy sets with AHP for uncertainty management (Ennaji et al., 2018)

According to (Bagheri et al., 2012), The process of identifying potential land suitability classes in the Multi-Criteria Decision Analysis (MCDA) approach typically involves a four-stage procedure. These stages encompass (i) indicator selection, (ii) indicator categorization and scoring, (iii) assigning weights to indicators based on their importance, and (iv) computing scores using a chosen model. However, the land quality indexes formulated through this process are generally tailored to specific purposes and environmental contexts, often limited in their applicability on a broader scale. Consequently, there is no universally applicable land quality index suitable for all geographical settings GB (Ahmed, 2022)(Rondhi et al., 2018).

Expecting indices to comprehensively assess land and soil properties, usage types, and plant species across all geographies is unrealistic. Additionally, developing a model capable of encompassing all ecological variables and socio-cultural practices is neither practically feasible nor economically viable in terms of time, labor, and cost.

This study aims to identify potential areas suitable for agricultural activities in the Central Anatolia Region, characterized by a semi-arid terrestrial ecosystem, using the Fuzzy Analytic Hierarchy Process (FAHP) within the Multi-Criteria Decision Analysis (MCDA) framework (Zolekar & Bhagat, 2018). Furthermore, the fundamental hypothesis of this research extends beyond the mere identification of suitable agricultural lands (Chen, 2014)(Bozdağ et al., 2016). It seeks to contribute to the sustainable use and management of lands by integrating soil characteristics, which are crucial in combating land degradation and desertification in arid and semi-arid terrestrial ecosystems.

Study area

Gundlupet taluk lies between 11°45' to 12°45' N latitude and 77°00' to 77°46' E longitude, covering an expanse of 1380.71 sq. km. With an average rainfall of 835 mm above mean sea level (MSL) as per District Glance (2020-21), Gundlupet sits adjacent to foothills, maintaining an elevation of about 835 MSL. Positioned on a plateau, it is enveloped by mountains from nearly all sides, except the northeast.

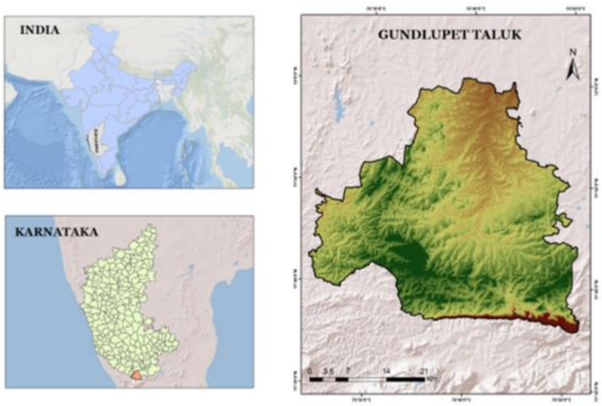

Fig 1: Location map of the Study area

Materials and methods

This study devised a multi-criteria site suitability modelling approach to determine suitable and potential locations for agricultural development, considering a set of constraints and criteria. Eight distinct constraints and criteria were chosen based on their significance and relevance to agriculture. The selection of various criteria relied on the maximum limitation method, which impacts agricultural productivity and encompasses factors such as geomorphological and geological features, soil texture, relief, slope, rainfall, drainage, and land use and landcover, among others. Furthermore, weights for each selected criterion were determined using the Analytical Hierarchy Process, followed by the adoption of the weighted overlay method to generate the suitability map.

Figure 2 illustrates the methodological flow of the current study. Criterion maps were generated employing geospatial techniques. Relief, slope, and drainage density maps were created using Digital Elevation Models (DEMs) with a resolution of 30 meters obtained from the Alos palsar Geology and geomorphology maps were derived from data provided by the Geological Survey of India (GSI). Soil maps were derived from the National Bureau of Soil Survey (NBSS). Land use/land cover (LULC) maps were generated using Landsat 8 satellite images with a spatial resolution of 10 meters. Rainfall maps were prepared using a Tropical rainfall measuring mission (TRMM-Nasa).

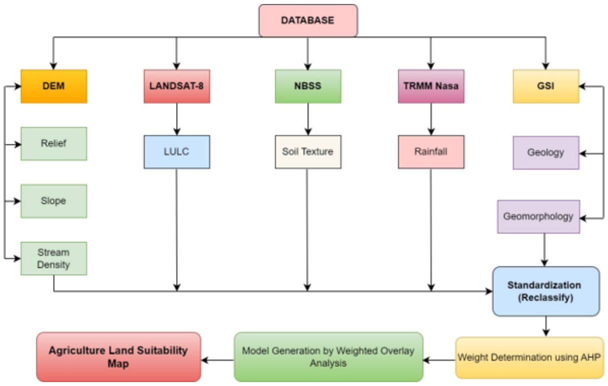

Fig 2: Flow chart of detailed methodology

II. METHODOLOGY: AHP AND GIS-BASED AGRICULTURAL LAND SUITABILITY ANALYSIS

Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is a mathematical technique utilized to address intricate decision-making dilemmas encompassing various scenarios, criteria, and factors (Saaty, 1977). Offering robustness and adaptability, the AHP aids in prioritizing tasks and making optimal decisions, particularly when both quantitative and qualitative factors are involved (Weerakoon, 2014). This method is applied to decision problems structured hierarchically across different levels, with each level comprising a finite number of elements. Introduced by Thomas L. Saaty in the 1970s, the Analytic Hierarchy Process (AHP) establishes a ratio scale to prioritize various items under consideration. In its conventional form, Saaty proposed a four-step methodology consisting of modeling, valuation, prioritization, and synthesis. Initially, a hierarchy representing the pertinent aspects of the problem (criteria, sub-criteria, attributes, and decision alternatives) is constructed. The primary objective or mission of the decision-making problem occupies the highest position in this hierarchy, with other relevant aspects (criteria, sub-criteria, attributes, etc.) arranged in subsequent levels (Arab & Ahamed, 2022)

Utilizing the Analytic Hierarchy Process as described earlier, the pairwise comparison matrix was computed using a scale ranging from 1 to 9, where 9 signifies extreme significance and 1 denotes equal significance between criteria within the matrix displayed in Table 4 (Saaty, 1977)(Feizizadeh et al., 2014). Notably, the comparison matrix inherently adheres to the criteria of reciprocity, expressed mathematically as $n(n-1)/2$ for n components in the pairwise comparison matrix (Saaty, 1977)(Akinci et al., 2013). Following the computation of the pairwise matrix, relative weights or eigenvectors are determined using Saaty's method (Saaty, 1977) (refer to Tables 5, 6). Furthermore, the Analytic Hierarchy Process is adept at identifying and quantifying inconsistencies among decision-makers, a significant feature of this method. The efficacy of the Analytic Hierarchy Process is gauged by the consistency ratio (CR), as calculated by Eq. 2.

$$CR = CI/RI \qquad 1$$

Equation 2 depicts the Consistency Ratio (CR), wherein CI denotes the Consistency Index and RI signifies the Random Index. The Consistency Ratio aids in identifying potential events and assessing logical inconsistencies in decision-making or judgments (Cengiz & Akbulak, 2009). It quantifies the probability of the matrix judgments being formed randomly The CR primarily relies on the Consistency Index and Random Index.

$$CI=(\lambda max - n)/(n - 1) \qquad 2$$

Equation 3 defines the Consistency Index (CI), where k max represents the principal or highest eigenvector of the computed matrix, and n denotes the order of the matrix. The Random Index (RI) is the average value of the consistency index based on the order of the computed matrix, as specified by (Saaty, 1977), as shown in Table 7. If the CR value is below 0.10, the weight values of the matrix indicate inconsistencies, and the Analytic Hierarchy Process (AHP) may not yield meaningful results (Saaty, 1977). In the present study, the calculated CR was 0.0669, which falls within acceptable limits, indicating the validity of the computed weight values. Furthermore, the computed weight values are converted into percentages for weighted overlay analysis (WOA) in GIS, as illustrated in Table 8.

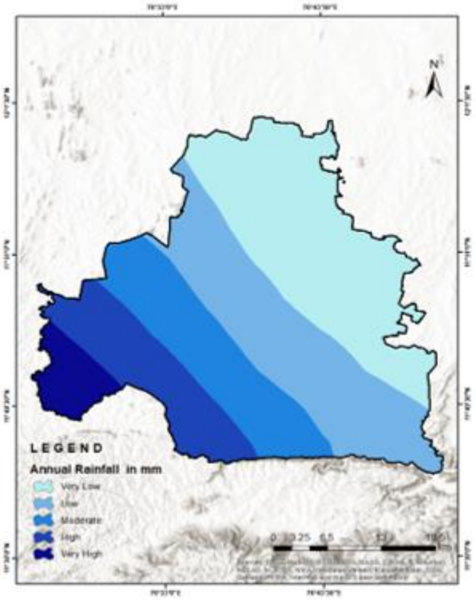

Fig 3: Rainfall map

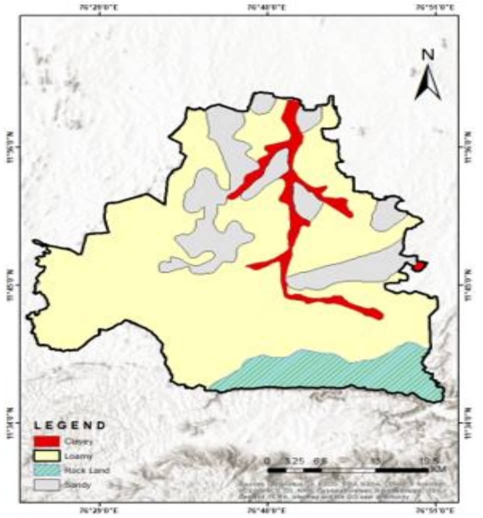

Fig 4: Soil texture map

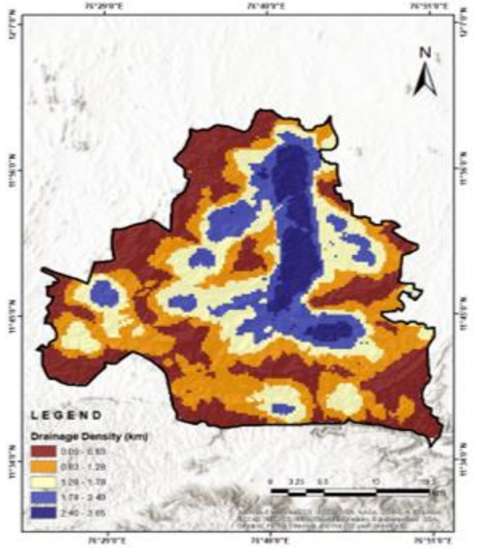

Fig 5: Drainage density map

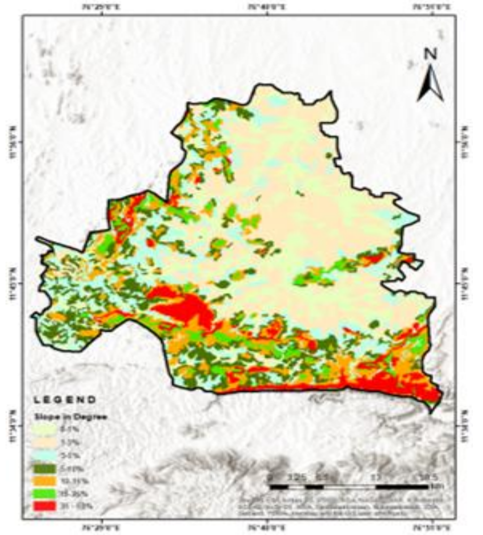

Fig 6: Slope map

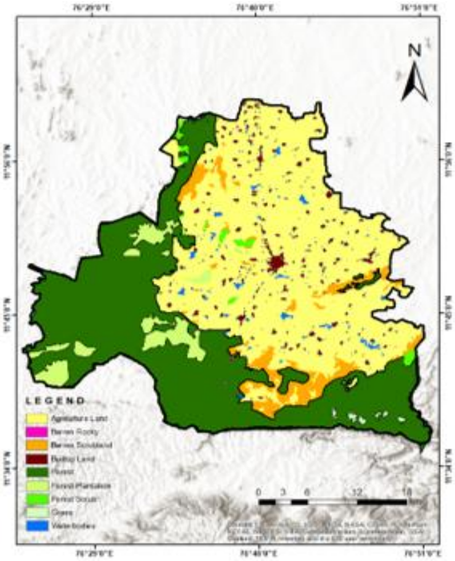

Fig 7: Landuse & Land cover map

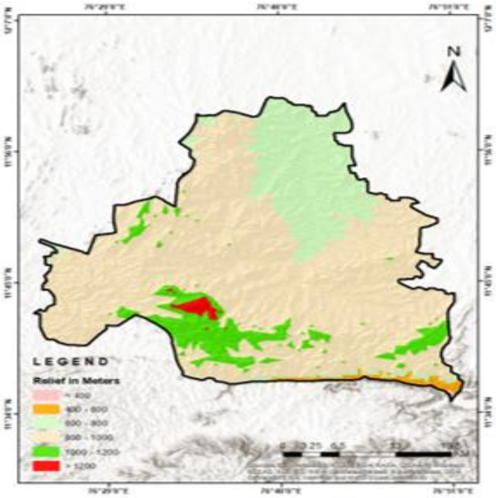

Fig 8: Relief map

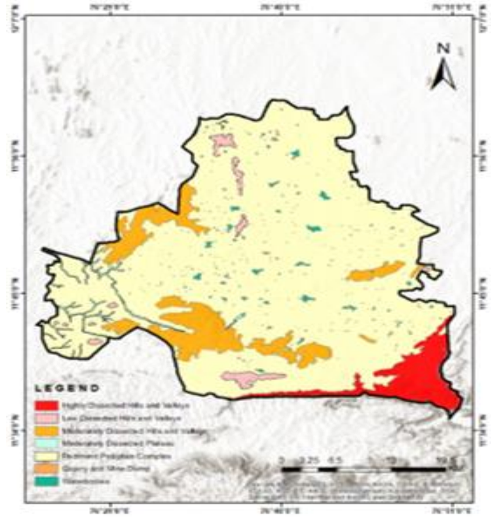

Fig 9: Geomorphology map

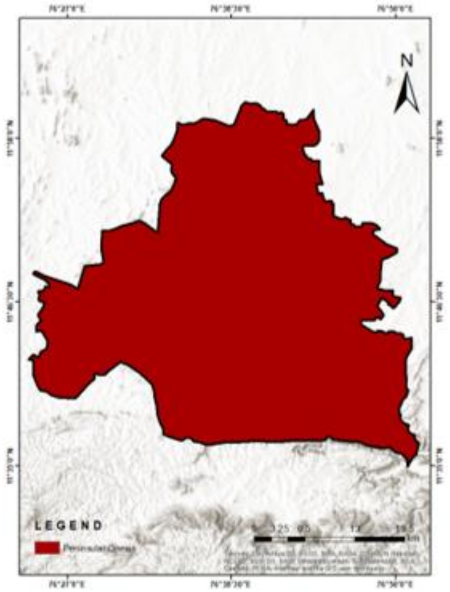

Fig 10: Geology Map

Tab 1: Landuse and land cover coverage and area of Gundlupet Taluk

S.N.	Classes	Area (Sq.km)	Percentage
1	Forest	530.36	38.40
2	Agriculture	676.98	49.02
3	Barren Scrubland	72.06	5.22
4	Forest Scrub	11.05	0.80
5	Forest Plantation	51.44	3.73
6	Waterbodies	10.58	0.77
7	Grass	2.89	0.21
8	Barren Rocky	0.08	0.01
9	Built-up Land	26.32	1.91
	Total	**1381**	**100**

IV. RESULTS AND DISCUSSION

Analytic Hierarchy Process (AHP)

The hierarchical structure of the Analytic Hierarchy Process (AHP) proves beneficial for tackling intricate spatial decisions with heightened confidence levels (Saaty, 1977). In this study, the AHP technique applied for Land Suitability Analysis (LSA) can be delineated into six sequential steps: (1) determining ranks, (2) conducting pairwise comparisons, (3) computing weights, (4) establishing scores, (5) performing weighted overlay analysis, and (6) conducting accuracy assessments.

Determination of Ranks

For this step, expert opinions and insights from the literature were utilized to assign ranks ranging from 1 to 9 to various criteria. Lower ranks signify lesser importance regarding suitability for agriculture, while higher ranks denote greater significance. Physiographic factors such as slope, relief, drainage density, rainfall, geology, geomorphological features, soil texture, and Land Use/Land Cover (LULC) were ranked and weighted based on their relevance and importance.

Pairwise Comparison Matrix

The Pairwise Comparison Matrix (PCM) was constructed to determine the weights of parameters using AHP techniques. Judgments within the PCM, reflecting the relative levels of importance of the parameters, were formulated based on expert opinions and existing literature. The Consistency Ratio (CR) was computed to assess the logical consistency of these judgments and to identify potential errors.(Saaty, 1977) suggested that a CR value of up to 0.1 is acceptable for PCM judgments. As the CR value for the PCM judgments was calculated as zero, the derived weights for the selected criteria are deemed acceptable for the LSA of agriculture. Sub-criteria were also assigned scores within the 1-9 range with the aid of a literature survey.

Determination of Score

Numerous researchers have utilized a scoring system ranging from 1 to 9 to evaluate sub-criteria based on land characteristics, favorable conditions, and limitations for agricultural practices. In this current study, scores were assigned according to favorable conditions for agriculture, fieldwork observations, expert opinions, land quality assessments, and a review of existing literature. Higher scores denote a greater influence of the sub-criteria, whereas lower scores indicate lesser suitability for agriculture (Zolekar & Bhagat, 2018).

Slopes exhibit a negative correlation with soil quality and agricultural productivity. Consequently, a maximum score of 1 was assigned to gentle slopes, while steep slopes received a minimum score of 9. Slopes categorized as stiff, with deep soils and slight erosion but less flat than gentle to moderate slopes, were assigned a score of 8 (Bandyopadhyay et al., 2009). A score of 6 was designated for slopes ranging from 6° to 12°, characterized by moderately deep soil and slightly undulating. Certain areas featuring very steep to extremely steep slopes (12° to 30°) exhibit potential for terracing, albeit with limitations such as difficult accessibility, shallow soils, low soil moisture, significant erosion, and high percolation rates. These classes were classified as "marginally suitable" and assigned a score of four.

V. DISCUSSION

The current research utilized an agriculture suitability map to conduct its investigation. Using Analytic Hierarchy Process (AHP) analyses, the weights of selected criteria were determined, and scores for sub-criteria were assigned within the Weighted overlay Analysis (WOA) method to delineate land suitability for agriculture. This categorization resulted in three classes for agricultural suitability: highly suitable, moderately suitable, and not suitable.

A. Highly Suitable:

Only 19.59% of the surveyed area was classified as "highly suitable" for agriculture (Figure 11). These lands exhibit gentle to moderate slopes, deep loam soils, and superior water retention capacities.

B. Moderately Suitable:

Approximately 67.6% of the surveyed lands fell into the category of "moderately suitable" (Figure 11). These lands typically feature steeper slopes, loam soils of moderate depth, and adequate water retention capacities. While suitable for agriculture, they may require additional interventions such as terracing, soil and water conservation, and irrigation due to the presence of grasslands and sparse forests.

C. Not Suitable:

An estimated 12.81% of the surveyed area was deemed "not suitable" for agriculture. These lands are characterized by steep slopes with rocky terrain, barren landscapes, and thin, dry soils. Additionally, agricultural lands and medium to dry deciduous forests are not recommended for agricultural use.

Tab 2: area and percentage distribution for selected criteria

Criteria	**Sub Criteria**	**area (ha)**	**area (%)**
Geomorphology	Highly Dissected Hills and Valleys	7400.28	5.39979204
	Low Dissected Hills and Valleys	2072.82	1.5124829
	Moderately Dissected Hills and Valleys	13122	9.57478247
	Moderately Dissected Plateau	1177.15	0.85893577
	Pediment Pediplain Complex	111725	81.5228297
	Quarry and Mine Dump	106.882	0.07798902
	Waterbodies-Other	1443.394	1.0532071
Relief	<400	92.7226	0.06371019
	400 - 600	1702.38	1.16971432
	600 - 800	25134.6	17.2701169
	800 - 1000	97908.7	67.2735868
	1000 - 1200	11265.9	7.74085961
	> 1200	9433.811	6.48202155
Rainfall	<600	5366.623	4.01804015
	600-800	31890.99	23.8770784
	800-1000	30759.48	23.0299064
	1000-1200	51488.56	38.5499599
	>1200	14057.58	10.5250398
Soil Texture	Clayey	7019.83	5.1279798
	Loamy	95418.7	69.7032786
	Rock Land	12756.5	9.31861231
	Sandy	21697.7	15.8501512
Drainage Density	0.05-0.83	51850.37	38.5131
	0.83-1.28	27772.93	20.6290
	1.28-1.78	26308.87	19.5416
	1.78-2.40	18487.55	13.7321
	2.40-3.65	10210.67	7.5842
Slope	0-1 (Nearly Level)	23904.7	17.5301309
	1-3 (Very Gentle Slope)	40078.1	29.3906361

	3-5 (Gentle Slope)	21434.1	15.7183557
	5-10 (Moderate Slope)	17989.2	13.1920932
	10-15 (Strong Slope)	17162.7	12.5859926
	15-35 (Moderate Steep Slope)	6412.77	4.7027027
	35 - 50% (Very Steep Slope)	9381.92	6.88008155
LULC	Forest	53036	38.6987936
	Agriculture	66565.99	48.5712253
	Barren Scrubland	7206.51	5.25837625
	Forest Scrub	1105.91	0.80694967
	Forest Plantation	5144.49	3.75378152
	Waterbodies	1058.62	0.77244356
	Grass	289.917	0.21154382
	Barren Rocky	8.76251	0.00639374
	Built-up Land	2632.01	1.9204995

Tab 3: pairwise comparison matrix

Decision Criteria	Geomorphology	Relief	Rainfall	Soil Texture	DD	Slope	Geology	LULC
Geomorphology	1	1	2	4	6	5	5	7
Relief	1	1	1	7	5	6	5	6
Rainfall	0.5	1	1	7	7	7	7	9
Soil Texture	0.25	0.14	0.14	1	1	2	4	6
DD	0.17	0.2	0.14	1	1	2	6	7
Slope	0.2	0.17	0.14	0.5	0.5	1	2	2
Geology	0.2	0.2	0.14	0.25	0.17	0.5	1	4
LULC	0.14	0.17	0.11	0.17	0.14	0.5	0.25	1

Tab 4: normalized weighted and pairwise comparison

Decision Criteria	Geomorphology	Relief	Rainfall	Soil Texture	DD	Slope	Geology	LULC	Nor weight
Geomorphology	0.2890	0.2577	0.4283	0.1912	0.2883	0.2083	0.1653	0.1667	0.2494
Relief	0.2890	0.2577	0.2141	0.3346	0.2403	0.2500	0.1653	0.1429	0.2367
Rainfall	0.1445	0.2577	0.2141	0.3346	0.3364	0.2917	0.2314	0.2143	0.2531
Soil Texture	0.0723	0.0361	0.0300	0.0478	0.0481	0.0833	0.1322	0.1429	0.0741
DD	0.0491	0.0515	0.0300	0.0478	0.0481	0.0833	0.1983	0.1667	0.0844
Slope	0.0578	0.0438	0.0300	0.0239	0.0240	0.0417	0.0661	0.0476	0.0419
Geology	0.0578	0.0515	0.0300	0.0120	0.0082	0.0208	0.0331	0.0952	0.0386
LULC	0.0405	0.0438	0.0236	0.0081	0.0067	0.0208	0.0083	0.0238	0.0219

Tab 5: random index value

N	1	2	3	4	5	6	7	8	9	10
R1	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.46	1.49

Tab 6: Sub-criteria of each parameter, C R and their weights

Criteria	Sub Criteria	**weight**	C R
Geomorphology	Highly Dissected Hills and Valleys	0.2944	0.82
	Low Dissected Hills and Valleys	0.2119	
	Moderately Dissected Hills and Valleys	0.1486	
	Moderately Dissected Plateau	0.1234	
	Pediment Pediplain Complex	0.0994	
	Quarry and Mine Dump	0.0696	
	Waterbodies-Other	0.0524	
Relief	<400	0.4155	0.42
	400 - 600	0.2368	
	600 - 800	0.1415	
	800 - 1000	0.0911	
	1000 - 1200	0.057	
	> 1200	0.0578	
Rainfall	<600	0.4228	0.52
	600-800	0.282	
	800-1000	0.1328	
	1000-1200	0.0794	
	>1200	0.0827	
Soil Texture	Clayey	0.412	0.26
	Loamy	0.2931	
	Rock Land	0.1872	
	Sandy	0.1074	
Drainage Density	0.05-0.83	0.3338	0.78
	0.83-1.28	0.2584	
	1.28-1.78	0.2111	
	1.78-2.40	0.1356	
	2.40-3.65	0.0609	
Slope	0-1 (Nearly Level)	0.2608	0.89
	1-3 (Very Gentle Slope)	0.2581	

	3-5 (Gentle Slope)	0.1905	
	5-10 (Moderate Slope)	0.1341	
	10-15 (Strong Slope)	0.0718	
	15-35 (Moderate Steep Slope)	0.0477	
	35 - 50% (Very Steep Slope)	0.0367	
LULC	Forest	0.2189	0.59
	Agriculture	0.1903	
	Barren Scrubland	0.1126	
	Forest Scrub	0.1179	
	Forest Plantation	0.0875	
	Waterbodies	0.11	
	Grass	0.0844	
	Barren Rocky	0.0458	
	Builtup Land	0.0321	

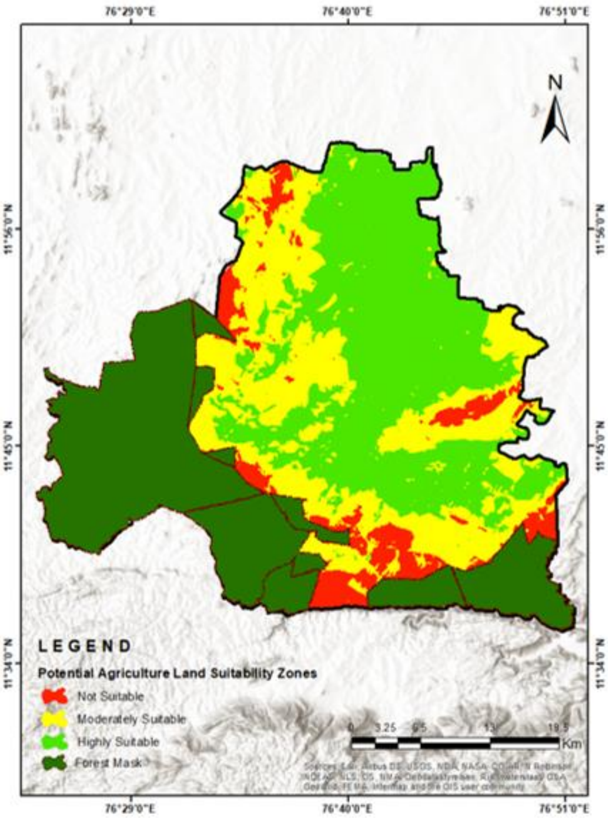

Fig 11: Agriculture land suitability map of Gundlupet taluk

VI. CONCLUSION

The primary objective of this study was to pinpoint suitable agricultural land within the Gundlupet taluk, a region largely dominated by agriculture and forest area. Utilizing a combination of the Analytic Hierarchy Process (AHP) and Geographic Information System (GIS), eight distinct criteria were chosen for evaluation. The integration of AHP with GIS proved highly effective in identifying appropriate agricultural sites. Upon completion of the assessment, it was revealed that only 19.59% (266 sq. km) of the study area was deemed most suitable for agricultural production, while 12.81% (174 sq. km) was classified as not suitable or currently not suitable for agricultural production. Challenges related to low production stemmed from various geomorphological characteristics, including high elevation, steep slopes, rainfall, and inadequate irrigation infrastructure. These factors significantly reduced the amount of land identified as suitable for agriculture within the study area.

The findings of this study offer valuable insights for decision-makers involved in agricultural production within the area, aiding in the identification of suitable sites amidst these challenges. Consequently, the resulting agricultural land suitability map: 1. Enhances comprehension of alternative agricultural land use suitability patterns for future development, facilitating decision-making in agricultural area development. 2. Direct agricultural activities to regions with favorable physical and environmental conditions, optimizing agricultural efficiency in rural areas. 3. Promotes non-agricultural uses in unsuitable areas with low efficiency, improving overall land utilization.

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