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WEIGHTED OVERLAY BASED LAND SUITABILITY ANALYSIS OF AGRICULTURE LAND IN AZAD JAMMU AND KASHMIR USING GIS AND AHP

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Agriculture land suitability plays an important role in sustainable agriculture production by improving the use of current land resources and in the identification of new land that maybe prepare for agriculture. The present research aimed to focus on the agricultural land suitability of Azad Jammu and Kashmir (AJK), where the existing agriculture land is only 8% and dense forest and glaciers are covering 46.06% of the total area. Based on the literature review and local expert's knowledge, eight different criteria have been taken to scale the available land for the suitability of agriculture practices. These parameters are soil orders, soil pH, Land-use Land-cover (LULC), slope, elevation, temperature, precipitation, and Potential Evapotranspiration (PET). Analytical Hierarchy Process (AHP) technique in integration with Geographical Information System (GIS) and Weighted Overlay Analysis (WOA) had been incorporated to classify the land for agriculture production. In AHP, weights were determined with the use of pairwise comparison matrix based on expert opinions. According to the guidelines of the United Nations Food and Agriculture Organization (FAO), the land suitability map was divided into five zones. After subtracting the areas of permanent features like mountains, forest, and glaciers, it was estimated that a highly suitable area was 13.21%, moderately suitable area was 11.61%, marginally suitable area was 13.14% and 62.05% was not suitable permanently. It is concluded that the integration of GIS and AHP in land suitability, is efficient and it will help the policymakers to improve the management of their land resources.
Keywords: GIS (Geographic Information System), AHP (Analytical Hierarchy Process), WOA (Weighted Overlay Analysis), Remote Sensing, Land Suitability, Agriculture, Land Cover, Pakistan.

INTRODUCTION

The simultaneous increase in population and irregular urban spread has increased the pressure on the utilization of agricultural resources and that may leave the land in lack of nutrition (Elaalem *et al*., 2011; Hovhannisyan and Devadoss, 2020; Jonah and May, 2020). Thus, it is critical to prepare the land utilization plans for agriculture that empower the use of land assets according to their potential and use. Land suitability relates to sustainability (Taghizadeh-Mehrjardi *et al*., 2020). The World Commission on Environment and Development defined it as ''growth that meets present-day requirements, without jeopardizing future generation needs'' (Marrewijk, 2013). The principal prerequisite of land-use planning is land suitability evaluation. The land suitability technique determines the most suitable land-use with the consideration of land characteristics and user needs (Jamil *et al*., 2018; Purnamasari *et al*., 2019).

The significance of land suitability is decided by the number of criteria that influence the suitability of agrarian and farming practices (Al-shalabi *et al*., 2006). The suitability analysis becomes a complex process when multiple criteria are selected based on the inherent properties of the land unit, socio-economic, and environmental factors (Duc, 2006; Bandyopadhyay *et al*., 2009). There are no certain or fixed standards in the selection of criteria for agricultural land suitability. Generally, most of the researchers used different soil, climatic, and topographical parameters prior to the availability to determine the land suitability (Akinci *et al*., 2013).

Zengin and Yılmaz (2008) used soil depth, soil characteristics, water availability, erosion, slope, aspect, rainfall, temperature, vegetation cover, and road network in the assessment of land suitability for cultivation. Likewise, Akbulak *et al*. (2010) used slope, erosion, soil depth, elevation, and road access parameters. Bandyopadhyay *et al*. (2009) on the other hand, used soil texture parameters, organic matter content, soil depth, slope, and Land-use Land-cover (LULC) to determine appropriate soil for agriculture. Feizizadeh and Blaschke (2013) conducted a research in

Tabriz (Iranian city) for agriculture suitability analysis with the help of Weighted Overlay Analysis (WOA) based on Geographical Information System (GIS) and Analytical Hierarchical Process (AHP) techniques for soil information they used soil fertility and soil pH data, for topographical information they used elevation, slope and aspect data, for climatic understanding they used temperature and rainfall data along with the groundwater data.

The process of finding suitable sites depends on different variables or criteria. These criteria have a different level of importance and many techniques are used to determine the weights of criteria. It always remains the concern of researchers that how to combine different datasets to form a single index of assessment since 1960 (Yu *et al*., 2011). Saaty (1980) first introduced the AHP multi-criteria decision-making technique for suitability analysis. AHP calculates the weights of criteria using pairwise comparison matrix based on expert opinions and local knowledge (Wu, 1998; Zurayk *et al*., 2001; Cools *et al*., 2003; Oudwater and Martin, 2003; Ohta *et al*., 2007; Saaty and Vargas, 2008). The integration of Multi-Criteria Decision Making (MCDM) and GIS methods is more useful as compare to standard map overlay methods in many applications (Carver, 1991; Malczewski, 1999).

It has been utilized effectively in GIS-based MCDM for land suitability since the mid-1990s (Feizizadeh *et al*., 2017; Nouri *et al*., 2017; Jamil *et al*., 2018; Ebrahimi *et al*., 2019; Shokati and Feizizadeh, 2019). Kihoro *et al*. (2013) used GIS and AHP technique for the identification of suitable sites for rice crop. Feizizadeh and Blaschke (2013) established a land suitability assessment method based on GIS and AHP techniques to examine the land resources for agricultural production. Furthermore, Mokarram and Aminzadeh (1996) established agriculture suitability using multi-criteria, ordered weight averaging, and fuzzy quantifier methods. In recent studies, Muhsin *et al*. (2018) performed the land suitability evaluation for agriculture and industrial sites in Bangladesh using the integration of GIS and AHP. Purnamasari *et al*. (2019) have evaluated land suitability for explicit crop yield in Indonesia using different spatial datasets in the multi-criteria AHP technique. Furthermore, Masih *et al*. (2018) have assessed the ecological capability to support the tourism in mountainous area of Iran using AHP and GIS integration.

The primary goal of this research is to use GIS and AHP to categorize the available land into five suitability levels according to the guidelines of Food and Agriculture Organization FAO.

This study of finding suitable sites for agriculture will be completed by the use of eight variables representing the local topography, climate, and land-use land-cover. These variables are the soil orders, soil pH, (LULC), slope, elevation, temperature, precipitation, and Potential Evapotranspiration (PET) that have been playing the main role in controlling the local agriculture pattern and yield. The level of importance of each variable has been determined through the use of AHP and later WOA, was performed on these layers in a GIS environment.

***Study Area*:** Azad Jammu and Kashmir (AJK) frequently named 'Paradise on the Earth' by vacationers for its beautiful common magnificence and staggering scenes, snow-secured tops, timberlands, waterways, streams, valleys, and velvet green levels. Its charming climatic conditions and rich biodiversity may prompt the advancement of agriculture practices, tourism, and socio-economic improvement (Nadeem *et al*., 2017). The study area covers a range of latitudes from 32° 46' 2.23" N to 35° 8' 9.34" N and longitudes from 73° 23' 54.34" E to 74° 48'2.38" E, having 13,297 km^2 area (Figure 1). This region has a total population of 4,045,366 persons (AJK, 2017). The hilly terrain is dominated, and elevation varies from 205meters (m) to 6212meters, and the average elevation is around 1560m.The main sources of water are Jhelum, Neelum, and Poonch Rivers which support agriculture at stable slopes. Maize accounts for 41% of Kharif (May-November cultivation season) season's annual crop area in major crops. The overall economy of AJK depends vigorously on farming, domesticated animals, remittances, industry, and tourism (Hameed *et al*., 2020).

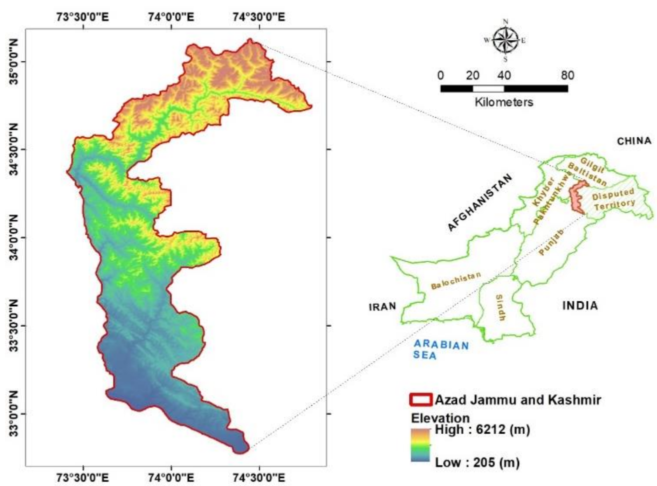

Figure 1. Azad Jammu and Kashmir (AJK) Location Map.

MATERIALS AND METHODS

AHP has been a great multi-criterion decision-making method used to generate the promising results for agriculture land suitability assessment together with WOA (Khahro *et al*., 2014). The methodology used in the current study is summarized in Figure 2. The following steps have been involved as performed by Elaalem *et al*. (2011) during the implementation of AHP.

- Selection of related factors or criteria
- The determination of weights or relative significance of all factors by using a pair-wise comparison matrix based

on the opinions of experts.
- The evaluation of the degree of consistency.

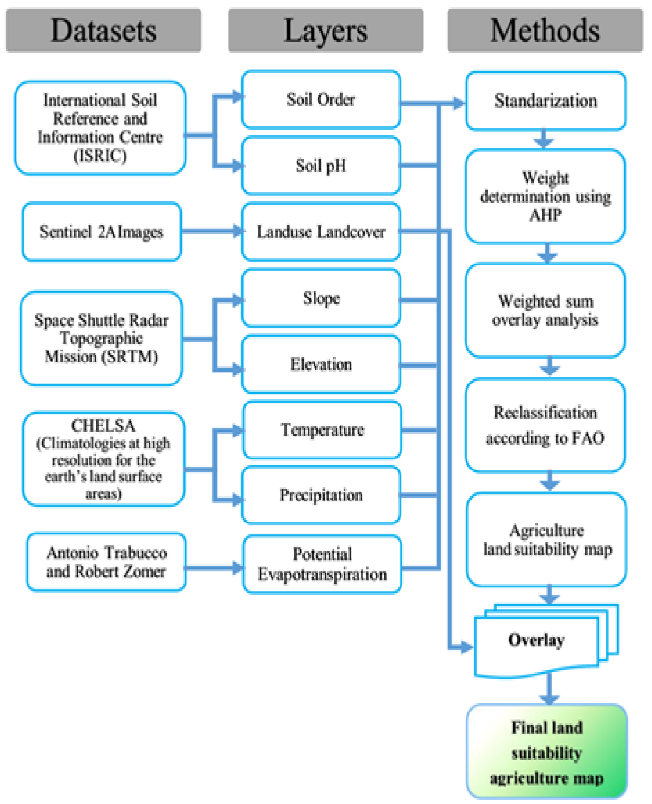

Figure 2. **Procedure followed in generating agriculture land suitability map.**

Preparation of Spatial Datasets**:** In this study eight criteria have been selected i.e. soil order (Figure 3a), LULC (Figure 3b), elevation (Figure 3c), slope (Figure 3d), temperature (Figure 3e), precipitation (Figure 3f), soil orders (Figure 3g) and PET (Figure 3h). These eight factors under consideration are chosen by means of literature inputs and the availability of data (Ayalew and Yamagishi, 2005). The details about data sources are written in Table 1.

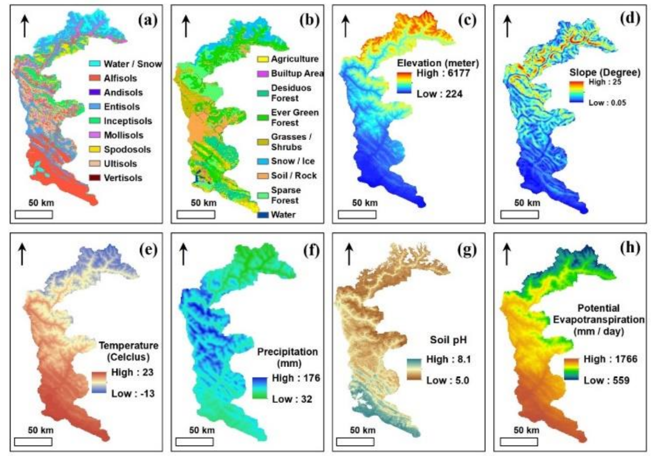

Figure 3. **GIS based criterion maps a) Soil Order b) LULC c) Elevation e) Temperature f) Precipitation g) Soil pH, h) PET.**

In this study, the thematic layer of LULC was developed by using the Sentinel 2A satellite images dated October2018 produced to compare it with suitability map, also to use in AHP. The Sentinel 2A images were used to produce the LULC by applying object-based classification technique in eCognition Developer Software by using the multi-resolution segmentation algorithm that grouped or formed the objects based on the spectral values, shape, and compactness of the pixels. The study area has been classified into Agriculture, Built-up Area, Deciduous Forest, Ever Green Forest, Grasses / Shrubs, Snow / Glaciers, Soil / Rock, Sparse Forest and Water.

The overall accuracy was determined to assess the results of classification that was 82.37% by taking the spatially well-distributed random samples. In the end, the results were compared with LULC to mask out the permanent features like forest and glaciers as our focus was to study agricultural land. Soil pH determines the amount of nutrient availability for plant growth and productivity (Mustafa *et al.*, 2011). According to FAO (2016) pH falls between 6.2 - 8.0 considered to be nominal for plant growth. In this research

Table 1. The data sources for various datasets used in the agriculture land suitability.

Parameter	Details or source	Period
Administrative Units	United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA), Type: Level-4	2011
Slope, Elevation	Space Shuttle Radar Topographic Mission (30m)	2014
LULC	Sentinel 2A Satellite images (10m)	10-24-2018
Soil Orders, Soil pH	International Soil Reference and Information Centre (ISRIC), Soil Grid 1km.	2014
Temperature, Precipitation	1 km resolution provided by CHELSA (Climatologies at high resolution for the earth's land surface areas) (Karger *et al.*, 2017).	1979 - 2013
PET	Antonio Trabucco and Robert Zomer global potential evapotranspiration data (Trabucco and Zomer, 2018)	2019

soil-order and soil-pH data sampled at a depth of 0.30 meters have been used. This data was acquired from International Soil Reference and Information Centre (ISRIC), a global 3D soil information system with 110,000 soil profiles worldwide, with 23-51% accuracy (Hengl *et al*., 2014).

The slope was calculated by using the Shuttle Radar Topographic Mission's (SRTM) Digital Elevation Model (DEM) (Farr *et al*., 2007).

The temperature and precipitation datasets were acquired from the CHELSA (Table 1) at the spatial resolution of 1 km in raster file format. The PET data was acquired from the Antonio Trabucco and Robert Zomer global potential evapotranspiration data (Trabucco and Zomer, 2018).

All the datasets had different spatial resolution. So, all the datasets were resampled to 10 m resolution to match with the Sentinel 2A data and to get a fine resolution at the end.

***Assessment of Weights*:** In the pairwise comparison matrix, criteria have been weighed on a scale of 1-9 where 9 indicates extreme importance and 1 indicates equal importance (Saaty, 1980; Leake and Malczewski, 2000; Feizizadeh *et al*., 2014). AHP simultaneously allowed consistency and inconsistent interactions in pairwise comparison matrix but it also measured the level of consistency or inconsistency as Consistency Ratio (CR) index (Forman and Selly, 2001; Chen *et al*., 2010; García *et al*., 2014). The value of CR depends on the Consistency Index (CI) and Ratio Index (RI) in the form of Equation 1.

CR=CI/RI

$$CI = \frac{\lambda_{\max} - n}{n - 1} \text{ …… (Equation 1)}$$

Where the highest eigenvector has been represented by λ_{max} and is equal to 8.29 and n represents the order of matrix and it is equal to 8. These RI values were given by Saaty (1977) and shown in Table 2. Saaty (1977) calculated the Random Index (RI) by taking the average of consistency index based on computed matrix order.

The value of CR less than 0.10 has been indicating that the pairwise comparison matrix holds an acceptable consistency. Else, CR value greater than or equal to 0.10 showed that there was a deficiency in consistency due to improper comparisons in the pairwise matrix, and there was a need to adjust the values in the matrix (Bodin and Gass, 2003; Chen *et al*., 2010). In this study the CR value was 0.029, confirming that weight values were logically valid as shown in Table 3 and Table 4.

***Standardization of Criteria*:** In the process of standardization, vector layers were converted to thematic layers by using a reclassify tool in ArcGIS software. After standardization, the resulted raster lost its dimension as well as measuring units (Effat and Hassan, 2013).

All parameters reclassified into five classes (Figure 4) or categories or sub-criteria and scored on a scale of 1-5 where 5 represent the greatest meaning and 1 has the least meaning. The aerial distribution, weights and score of each class have been given in Table 5.

Table 2. Random index (RI) values.

N	1	2	3	4	5	6	7	8	9	10
Random Index (RI)	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

Table 3. The pairwise comparison matrix.

	Soil	**Soil pH**	**LULC**	**Slope**	**Elevation**	**Temperature**	**Precipitation**	**PET**
Soil	1	2	3	4	5	6	7	8
Soil pH	1/2	1	2	3	4	5	6	7
LULC	1/3	1/2	1	2	3	4	5	6
Slope	1/4	1/3	1/2	1	2	3	4	5
Elevation	1/5	1/4	1/3	1/2	1	2	3	4
Temperature	1/6	1/5	1/4	1/3	1/2	1	2	3
Precipitation	1/7	1/6	1/5	1/4	1/3	1/2	1	2
PET	1/8	1/7	1/6	1/5	1/4	1/3	1/2	1

Table 4. The pairwise comparison matrix.

	Soil	**Soil pH**	**LULC**	**Slope**	**Elevation**	**Temperature**	**Precipitation**	**PET**	**Weight**
Soil	0.3679	0.4355	0.4027	0.3545	0.3109	0.2748	0.2456	0.2222	0.3268
Soil pH	0.1840	0.2177	0.2685	0.2659	0.2487	0.2290	0.2105	0.1944	0.2273
LULC	0.1226	0.1089	0.1342	0.1773	0.1865	0.1832	0.1754	0.1667	0.1569
Slope	0.0920	0.0726	0.0671	0.0886	0.1244	0.1374	0.1404	0.1389	0.1077
Elevation	0.0736	0.0544	0.0447	0.0443	0.0622	0.0916	0.1053	0.1111	0.0734
Temperature	0.0613	0.0435	0.0336	0.0295	0.0311	0.0458	0.0702	0.0833	0.0498
Precipitation	0.0526	0.0363	0.0268	0.0222	0.0207	0.0229	0.0351	0.0556	0.0340
PET	0.0460	0.0311	0.0224	0.0177	0.0155	0.0153	0.0175	0.0278	0.0242

Table 5. The aerial distribution, weights, and score.

Main criteria	Weight	Influence (%)	Sub-criteria	Score	Area (km^2)	Area (%)
Soil orders	0.3268	32.68	Mollisols	5	466.34	3.97
			Alfisols	4	3660.16	31.14
			Spodosols	3	432.75	3.68
			Entisols	3	3072.31	26.14
			Ultisols	3	1815.30	15.44
			Andisols	1	7.18	0.06
			Inceptisols	1	1508.59	12.83
			Water / Snow	1	792.45	6.74
Soil pH	0.2273	22.73	Water / Snow	1	792.45	6.74
			5 - 5.5	1	305.82	2.60
			5.6– 6	1	3592.05	30.56
			6.1 - 6.5	3	3856.38	32.81
			6.6 - 7.5	5	2342.20	19.93
			7.6 - 8.1	4	866.47	7.37
Land-use Land-cover	0.1569	15.69	Agriculture	5	954.92	8.12
			Grasses / Shrubs	4	1810.99	15.41
			Sparse Forest	2	1878.50	15.98
			Soil / Rock	2	1637.91	13.93
			Built-up Area	1	57.93	0.49
			Desiduos Forest	1	1119.39	9.52
			Ever Green Forest	1	2977.30	25.33
			Snow / Ice	1	1138.06	9.68
			Water	1	180.01	1.53
Slope (degree)	0.1077	10.77	0.005 – 3	5	3893.93	33.13
			3.1– 6	4	2965.33	25.23
			6.1– 9	3	2199.03	18.71
			9.1– 13	2	1747.30	14.86
			13.1– 26	1	949.41	8.08
Elevation (meter)	0.0734	7.34	205 – 980	5	3675.84	31.27
			981– 1779	4	2671.65	22.73
			1780– 2603	3	2129.33	18.11
			2604– 3550	2	1827.65	15.55
			3551– 6212	1	1450.54	12.34
Temperature ^oC	0.0498	4.98	-13.1 - -1	1	1273.38	10.83
			-1.1– 4	2	1372.86	11.68
			4.1– 10	3	2308.61	19.64
			10.1– 16	4	2851.46	24.26
			16.1– 23	5	3948.69	33.59
Precipitation (mm)	0.0340	3.40	32.44 - 65.07	3	1346.19	11.49
			65.08 - 87.57	5	3130.45	28.13
			87.58 - 107.82	4	3501.73	29.63
			107.83 - 132.01	2	2602.02	21.17
			132.02 - 175.89	1	1174.61	9.59
PET (mm / day)	0.0242	2.42	559 – 1252	1	2437.65	11.45
			1253– 1414	2	2315.82	26.63
			1415– 1513	3	2354.75	29.79
			1516– 1650	4	2334.56	22.14
			1651– 1766	5	2312.21	9.99

***Model for Land Suitability Using the Weighted Overlay Method*:** The weighted overlay analysis was applied by overlapping all thematic layers in GIS and by multiplying the weight value with the cell value of each raster in the ArcGIS model builder (Figure 5).

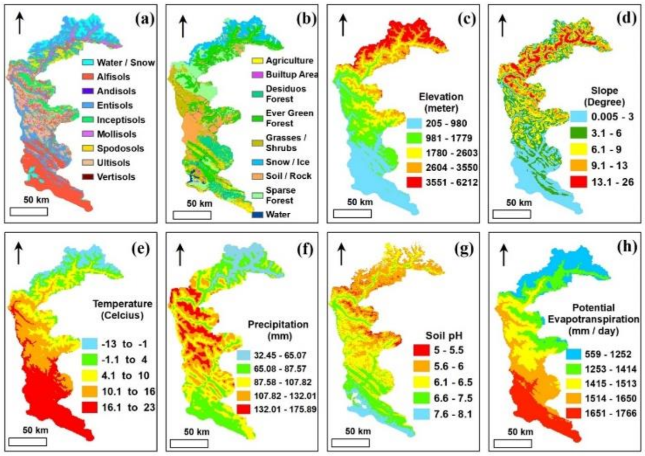

Figure 4. GIS based standardized criterion maps a) Soil Order b) LULC c) Elevation e) Temperature f) Precipitation g) Soil pH, h) PET.

RESULTS AND DISCUSSION

The determination of weights had been completed by the use of pair-wise cross-comparison matrix in the AHP technique and later these weights were utilized in the WOA method in ArcGIS to form the final suitability levels or zones.

The study area was divided into; 1. 'Highly suitable agricultural land', 2. 'Moderately suitable agricultural land', 3. 'Marginally suitable agricultural land', 4. 'Currently not suitable for agriculture' and 5. 'Permanently not suitable for agricultural activities'. It was determined with the help of suitability map (Figure 6a) that 14% (1704 km^2) of the study area would be highly suitable for agricultural production, 20% (2385 km^2) moderately suitable, 21% (2469 km^2) marginally suitable land, 18% (2188 km^2) currently not suitable land for agricultural production and in the end 25% (3007 km^2) area was found permanently unsuitable.

Figure 5. Land suitability model for agriculture.

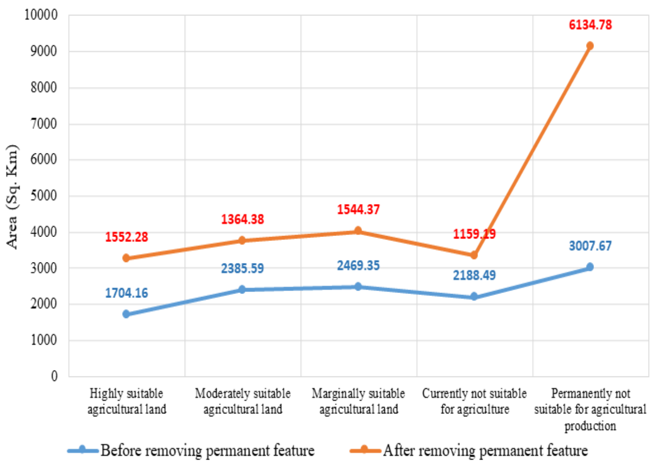

Figure 6. Suitability comparison before and after removing permanent features.

In a comparison between the suitability map (Figure 6a) and land-use map (Figure 4b), The features like an evergreen forest, deciduous forest, water bodies, and glaciers were permanently not suitable for agriculture and they affected each suitability zone. Evergreen forest, deciduous forest, water bodies, and glaciers were covering the 25% (2977 km^2), 9% (1119 km^2), 1% (180 km^2) and 9% (1138 km^2) of the total study area, respectively. The permanent features covered 9% (162 km^2) in highly suitable zone, 43% (1049 km^2) in the moderately suitable zone, 38% (955 km^2), and 50.76% (1113 km^2) was a marginally suitable zone in the agriculture suitability map. These regions were masked out from the suitability map (Figure 7a) and developed the final suitability map (Figure 7b). The comparison of the suitability map before and after removing permanent features has been presented in Figure 6 and Figure 7.

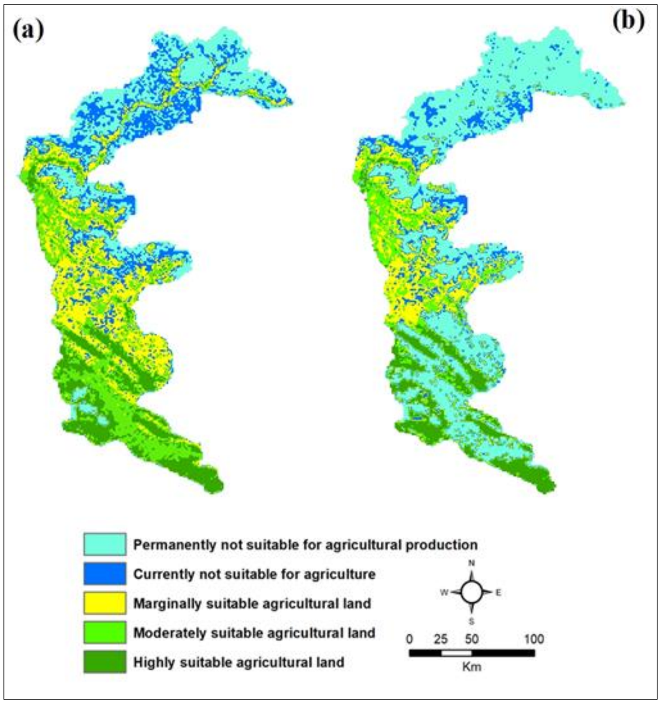

Figure 7. Suitability maps (a) before removing permanent features (b) after removing permanent feature.

It was investigated that approximately 33% (3893 km^2) area ranges from 0^o to 3^o slope, consist of permanent features like dense forests, water bodies and glaciers were covering ~46 % (~5414 km^2) land area, soil pH range 5.1-6.5 was 68% (2585

Table 6. Highly suitable land characteristics.

Criteria	Sub-criteria	Contribution in zone area (km^2)	Contribution in zone area (%)
Elevation	981 - 1779	84.77	5.46
	205 - 980	1467.51	94.54
LULC	Agriculture	520.54	33.53
	Grasses / Shrubs	745.37	48.02
	Sparse Forest	286.37	18.45
PET	1514 - 1650	465.06	29.96
	1651 - 1766	1087.22	70.04
Precipitation	87.58 - 107.82	689.63	44.43
	65.08 - 87.57	862.65	55.57
Slope	3.1 - 6	250.70	16.15
	0.005 - 3	1301.58	83.85
Soil Order	Entisols	159.13	10.25
	Alfisols	1393.15	89.75
Soil pH	6.6 - 7.5	858.14	55.28
	6.1 - 6.5	107.52	6.93
	7.6 - 8.1	586.62	37.79
Temperature	10.1 - 16	84.78	5.46
	16.1 - 23	1467.50	94.54

Table 7. Moderately suitable land characteristics.

Criteria	Sub-criteria	Contribution in Zone Area (km^2)	Contribution in Zone Area (%)
Elevation	1780 - 2603	110.25	8.08
	981 - 1779	772.52	56.62
	205 - 980	481.61	35.30
LULC	Agriculture	188.63	13.83
	Grasses / Shrubs	656.96	48.15
	Soil / Rock	296.38	21.72
	Sparse Forest	222.39	16.30
PET	1415 - 1513	582.40	42.69
	1514 - 1650	565.81	41.47
	1651 - 1766	216.17	15.84
Precipitation	65.08 - 87.57	229.53	16.82
	87.58 - 107.82	588.55	43.14
	107.83 - 132.01	417.69	30.61
	132.02 - 175.89	128.61	9.43
Slope	9.1- 13	114.65	8.40
	6.1 - 9	292.79	21.46
	3.1 - 6	497.51	36.46
	0.005 - 3	459.44	33.67
Soil Order	Mollisols	112.32	8.23
	Entisols	400.35	29.34
	Alfisols	465.72	34.13
	Ultisols	385.99	28.29
Soil pH	6.1 - 6.5	808.44	59.25
	6.6 - 7.5	449.29	32.93
	5.6 - 6	106.66	7.82
Temperature	10.1 - 16	805.47	59.04
	16.1 - 23	558.91	40.96

km^2), area with an elevation higher than 980 m was 68% (2019 km^2) and area under Spodosols, Entisols, Ultisols, Andisols, and Inceptisols was 58.16 % (6836 km^2). On lower elevations and gentle slopes, the most dominant soil order was Alfisols that was covering 31.14% (3660 km^2) with broad-leaved deciduous forest. It was important to note that the local people used to generate terraces on slopes and perform tiny rain-fed agriculture activities on the land that was presently and permanently unfit for agricultural activities.

***Highly Suitable Agriculture Land*:** That was a flat zone comparatively, in which 95% area was below 980 m, the slope was varying from 0.005° to 3° only, the most dominant land-cover was open fields consisted of grasses and shrubs, most of the agriculture part (54% of the total agriculture) was cultivating. In this zone, the most dominant soil order was Alfisols with ideal pH range of 6.6 to 7.5 with the availability of highest rate of potential evapotranspiration. In addition to it, Bong Canal originating from the Mangla Dam has been fulfilling the water needs for agriculture. The details are given in Table 6.

***Moderately Suitable*:** In this zone elevation was varying as 205 - 980 (57%), 981 - 1779 (35%) and 1780 - 2603 (8%), the slope was varying from gentle to stiff (0° - 13°), Alfisols and Entisols had been the most common with 6.1 - 6.5 pH. Furthermore, most of the agriculture had been found on the terraces. The other details of this zone are given in Table 7.

Marginally Suitable: The major part of this zone (63%) was above 1000 m with a dominated rocky surface and instable slopes ranging from 6.1° to 9°. The agriculture spread was over the 8.37% area (the least covered agriculture area) and mostly in the form of terraces. Ultisols had been covering 45% of the area with a 6.1 - 6.5 pH range, not favorable for agriculture (Table 8).

***Currently and Permanently Not Suitable*:** The land was not suitable for agriculture due to dense forest cover, glaciers, built-up, water bodies, and due to the dominant spread of not suitable soil order and soil pH. Mostly elevation was varying from 2604 - 3550 m with exposed rocky lands and precipitous slopes.

***Conclusion*:** The main objective of this research was to identify the appropriate land in support of sustainable agriculture growth in AJK which has been facing the low annual temperature range, rugged steep slopes, exposed rocky surface, dense forest cover, and permanent ice and snow cover in the form of glaciers. This technique has been recognized to

Table 8. Marginally suitable land characteristics.

Criteria	Sub-criteria	Contribution in Zone Area (km^2)	Contribution in Zone Area (%)
Elevation	1780 - 2603	408.72	26.47
	981 - 1779	973.31	63.02
	205 - 980	162.34	10.51
LULC	Agriculture	129.29	8.37
	Grasses / Shrubs	319.64	20.70
	Soil / Rock	780.79	50.56
	Sparse Forest	314.62	20.37
PET	1253 - 1414	204.80	13.26
	1415 - 1513	919.94	59.57
	1514 - 1650	419.63	27.17
Precipitation	87.58 - 107.82	455.12	29.47
	65.08 - 87.57	83.13	5.38
	132.02 - 175.89	279.94	18.13
	107.83 - 132.01	726.18	47.02
Slope	13.1 - 26	96.83	6.27
	9.1 - 13	323.81	20.97
	6.1 - 9	453.11	29.34
	3.1 - 6	459.57	29.76
	0.005 - 3	211.04	13.67
Soil Order	Entisols	382.14	24.74
	Inceptisols	122.12	7.91
	Alfisols	344.79	22.33
	Ultisols	695.32	45.02
Soil pH	5.5 - 6	287.57	18.62
	6.1 - 6.5	1112.90	72.06
	6.6 - 7.5	143.91	9.32
Temperature	4.1 - 10	269.68	17.46
	10.1 - 16	1058.36	68.53
	16.1 - 23	216.33	14.01

be very effective in identifying suitable land for agriculture. The most suitable area was only 13% (1552 km^2) and 52% (6134 km^2) area has been declared unsuitable for agriculture permanently. The permanently not suitable area was brought about by geomorphological features such as high elevations, sharp slopes, the existence of bare rocks, and poor accessibility of irrigation water. These threats led to the identification of small suitable land for agricultural activities. This research gives an insight into the suitability zones of agriculture and it could bring improvements in regional land-use policy.

This study only based on topographical, climatic, and soil properties and there is a need to include the socio-economic factors. The AHP should be applied carefully because any off-base judgment on any chosen parameter could affect the designated scores and weights. This is the main disadvantage of the AHP (Kritikos and Davies, 2011; Nefeslioglu *et al.*, 2013). There is a need to highlight the suitable land for some important species similar to Saffron (*Crocus sativus*) and some medicinal plants/species that have substantial financial worth. It will encourage the scope of tourism in the region. With the help of very high-resolution satellite images, the finer details can be identified in the region. During the final implementation at ground level, the other regional parameters should be taken into account.

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