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Land Suitability Evaluation for Agricultural Cropland in Mongolia Using the Spatial MCDM Method and AHP Based GIS

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Abstract

The purpose of this study was to prepare a cropland suitability map of Mongolia based on comprehensive landscape principles, including topography, soil properties, vegetation, climate and socio-economic factors. The primary goal was to create a more accurate map to estimate vegetation criteria (above ground biomass AGB), soil organic matter, soil texture, and the hydrothermal coefficient using Landsat 8 satellite imagery. The analysis used Landsat 8 imagery from the 2016 summer season with a resolution of 30 meters, time series MODIS vegetation products (MOD13, MOD15, MOD17) averaged over 16 days from June to August 2000-2016, an SRTM DEM with a resolution of 30 meters, and a field survey of measured biomass and soil data. In total, 6 main factors were classified and quality evaluation criteria were developed for 17 criteria, each with 5 levels. In this research the spatial MCDM (multi-criteria decision-making) method and AHP based GIS were applied. This was developed for each criteria layer's value by multiplying parameters for each factor obtained from the pair comparison matrix by the weight addition, and by the suitable evaluation of several criteria factors affecting cropland. General accuracy was 88%, while PLS and RF regressions were 82.3% and 92.8%, respectively.

Keywords

Land Suitability, MCDM, Boolean and Fuzzy Analysis, AHP, RF and PLS Regression

1. Introduction

Science-based agricultural production has been developing intensively in Mongolia since 1960 [1]. Between 1960 and 1989 the total sown area increased from 267.1 to 846.1 thousand hectares. From 1989 the total sown area fell, reaching 165.0 thousand hectares in 2006 [2]. The sown areas rose steadily by 440.6 thousand hectares between the years 2006 and 2016. However, cropland remains 405.5 thousand hectares less than in 1989. In this same time period, the total population increased 3.19 times while the amount of sown area declined by half as compared with the population growth. There is a significant difference in vegetable consumption between the urban and rural population. Urban population vegetable consumption is double that of the rural population [3].

In 1960, 40.2% of the total population lived in settled areas. This increased to 66.4% by 2016. Population increase coupled with consumption increase resulted in an intensified demand for food. On the other hand, agricultural products, especially wheat and potato production, increased as a result of the national government crop development program. Nowadays, potato and wheat consumption needs can be fulfilled by domestic production. However, of the total vegetable consumption (not including potato), 40% - 45% were imported [4].

The main vegetables imports (onion, garlic, cabbage, turnips and other root seed vegetables) increased from 5438.4 tons in 1995 to 64,107 tons in 2016, an increase of 11.7 times. Of these, 96% - 99% were imported from China. Mongolia remains strongly dependent on food security from neighboring countries. In addition, soils of currently cultivated areas are degrading. The country is facing challenges (especially local governments and community groups) to identify new crop areas with enough capacity for cultivation.

We have previously studied this topic: "Land suitability evaluation for cropland based on GIS between 2014 and 2016", was funded by the Mongolian Agency of Administration of Land Affairs, Geodesy and Cartography. In our preliminary study we used small and medium scale digital thematic maps to analyze and assess land suitability for cropland. During the study it was recognized that there was a need to improve the accuracy of input data using high-resolution satellite imagery for future research [5].

Geographic information system (GIS) and remote sensing (RS) techniques have been broadly used in agricultural studies. Remote sensing can provide a timely and accurate picture of the agricultural sector, as it is very suitable for gathering information over large areas with frequency and regularity [6]. The derived information is used for qualitative and quantitative analysis within near real-time production forecasts as well as for the anticipation of food security problems within the framework of monitoring agriculture [7].

2. Objectives

The purpose of this study is to identify new crop areas with enough capacity for cultivation across the entirety of Mongolia. The specific objectives are as follows:

- Identify a methodology for land suitability evaluation for agricultural cropland.
- Develop criteria parameters for land suitability evaluation for agricultural cropland.
- Prepare more accurate input data using high-resolution satellite imagery.
- Use the spatial MCDM method and the AHP GIS for land suitability evaluation for agricultural cropland.

3. Methods

A combination of Boolean and Fuzzy logic theory, the spatial multi-criteria decision-making method, the analytical hierarchical process (AHP), expert knowledge analysis, random forest (RF) and partial least square (PLS) regression were used.

The study's general procedure for land suitability evaluation had several phases (Figure 1). The first phase was to define the objectives. The second phase was to select criteria, for which there are two kinds of factors and constraints [8]. The third phase was standardization of the criteria; the fourth phase was assessing the ranking and weights of the criteria; the fifth phase was to overlap the map layers; the sixth phase was accuracy assessment.

3.1. Creation of Constraint Map Using Boolean Logic Theory

Constraints can be expressed in the form of a Boolean (logical) [8]. Boolean logic can have only two outcomes, true (1) or false (0). A constraint factor is a discrete

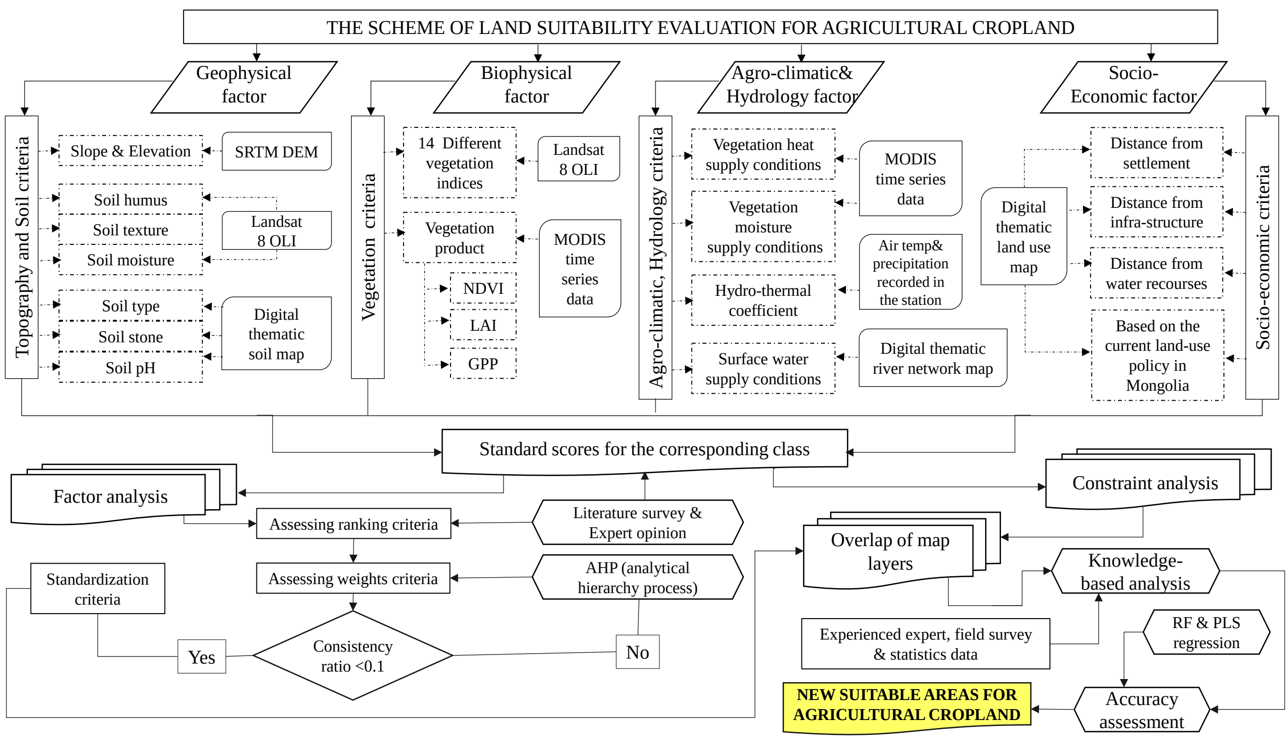


Figure 1. The approach of land suitability evaluation for agricultural cropland.

metric that can represent a true or false condition [9]. Zero values are prohibited conditions, and 1 values are permitted conditions. Constraints in this particular study often include legal restrictions. These are current land-use policy restrictions. Condition assessments and prohibitions can be factors as well.

The Boolean logic method must assume there is a definite cut-off point, because there is no flexibility for assessing real uncertainty [10]. Boolean logic can't be used when environmental and socio-economic factors are imprecise and incomplete. Under uncertain situations, fuzzy (probabilistic) logic comes in handy [11].

3.2. Creation of Factor Map Using Spatial Multi-Criteria Decision-Making (MCDM) Method

A factor is a criterion that can determine the suitability of specific outcomes for activities under consideration [8]. In this study, the spatial MCDM method was used in the creation of factor maps. Suitability levels for each of the factors were defined; these levels were used as a base to generate the factor maps (one for each factor [12]. Land suitability evaluation is expressed by qualitative and quantitative parameters.

In this section a combination of the spatial MCDM-, and the Fuzzy method was used. The main objective of land suitability analysis is to select the most optimal areas for a specific purpose. Land suitability analysis is a multi-criteria decision-making process [11]. Land suitability analysis is an interdisciplinary approach that includes information from different factors such as environmental and socio-economic. A main advantage of the MCDM procedure is the decision rule relationship between the input and output map. The MCDM method is divided into 4 groups and 7 classes [13].

- Multi-attribute and multi-objective decision making methods based on an objective or attribute.
- Individual and group decision making methods based on the number of people involved in the decision making process.
- Decision making under certainty and uncertainty methods based on the situation under which decision-making is being done and the nature of the criteria.
- Spatial MCDM based on spatial data.

From these, multi-attribute, multi-objective and spatial multi-criteria decision-making methods have been widely used in land-use suitability analysis. The multi-objective methods are based on mathematical programming models, and the multi-attribute methods are data oriented [14]. Spatial MCDM is a process where geographical data can be combined and transformed into a decision [11].

The main purpose of the spatial MCDM is to solve spatial decision-making problems originating from multiple criteria. The integration of spatial MCDM techniques with GIS has considerably advanced conventional map overlay approaches with regard to land-use suitability analysis [11] [13] [15] [16] [17] [18]. Land suitability analysis involves the incorporation of expert knowledge at various levels of decision-making. Experts however, cannot be certain all the time, there is still uncertainty and imprecision.

The MCDM method contains many different theories on how to improve the algorithm for processing imprecise or uncertain information, such as Fuzzy set theory, ELECTRE, PROMOTHEE, MAUT, and Random set theory. Many studies have recommended as such [8] [19]-[24]. The fuzzy set theory technique is one of the most commonly used techniques for improving upon imprecise, incomplete and vague information [25]. Fuzzy logic is like Boolean logic but more fuzzy. Mathematician Lofti Zadeh presented fuzzy set theory in 1965, illustrating a mathematically meaningful method to quantify the degree of uncertainty and imprecision of non-discrete data [26]. The main point was that fuzzy data are obtained using an array of fuzzy membership functions with values that range from "0" to "1" [27].

3.3. Standardization of Criteria

All criteria used in the analysis were measured with different measurement values. Different values of criteria needed to be transformed into common values [28]. In order to implement this objective, we used a criteria standardization procedure. We used a simple linear scaling equation based on the fuzzy set method.

$$E_i = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

where: E_i is value of standardized in pixel *i*, $X_{\min}$ is the minimum value criteria, $X_{\max}$ is the maximum value.

3.4. Assessing Ranking and Weights of Criteria

In land suitability analysis there must be an evaluation that ranks the relative importance of the criteria. In this evaluation many different factors such as geophysical, biophysical, climate, and socio-economic were ranked. We ranked each criterion based on conclusions from literature from professional experts. Next, came the important step of determining the weighting values for each criterion. There are many different approaches for assessing the weight of criteria based on MCDM techniques such as ELECTRE-TRI [29], ordered weighted averaging [30], compromise programming [31], analytical hierarchy process (AHP) [32] [33] [34] and Fuzzy AHP [11] [24]. Sensitivity analysis [35] includes 3 different approaches such as one-dimensional weights, random weights and selected weights [36]. From these, the most widely used method in spatial multi-criteria decision analysis for land suitability evaluation is the GIS-based AHP because it calculates weight values associated with criteria maps through a pairwise comparison matrix. Moreover, the weighting values of each of the criteria can be compared against each other with an index consistency. AHP has been calculated by weighting values of the criteria, and it is expressed with the following equation.

$$W_{ij} = \frac{\sum X(ij)}{n} \tag{2}$$

where: X_{ij}—normalized value of a pairwise comparison matrix; n—the order of the matrix; W_{ij} —weight of the criteria.

The consistency ratio (CR) indicates the probability, and that the matrix ratings were randomly generated. The consistency of the pairwise comparison matrix is expressed by the consistency ration index. When the CR exceed 0.1 the weighting value is disagreeable, and when the index value is estimated below 0.1, the weighting value is agreeable.

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{3}$$

where: CI—consistency index; RI—random index; CR—consistency ratio.

Herein, calculating the consistency index was applied to the following common equation.

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n-1} \tag{4}$$

where: CI—consistency index; $\lambda_{\max}$ —maximum eigen value, and n is the order of the matrix

3.5. Overlap of Map Layers

After describing weights values of the criteria concerning their importance for land suitability analysis, all criteria maps have been overlaid using suitability index. The formula used for calculating the suitability index of each layer was as follows:

$$S_i = \sum X_i * W_i \tag{5}$$

where,

X_i—values of the each criterion,

W_i—weight values of the each criterion,

S_i—suitability index.

3.6. Accuracy Assessment

Accuracy assessments for random forest (RF) and partial least square (PLS) regression were calculated and compared with field survey biomass and soil archive data obtained from the Information and Research Institute of Hydrology, Meteorology and Environment. The Institute is authorized to provide qualified nationwide data sets.

4. Study Area

The study area covers the entirety (1566.6 × 10^3 square kilometers) of Mongolia (**Figure 2**). Mongolia is comprised of 73% agricultural land, 0.5% villages and other settlements, 0.35% land under roads and networks, 9.2% forest and forest resources, 0.4% water and water resources and 16.1% land for special needs.

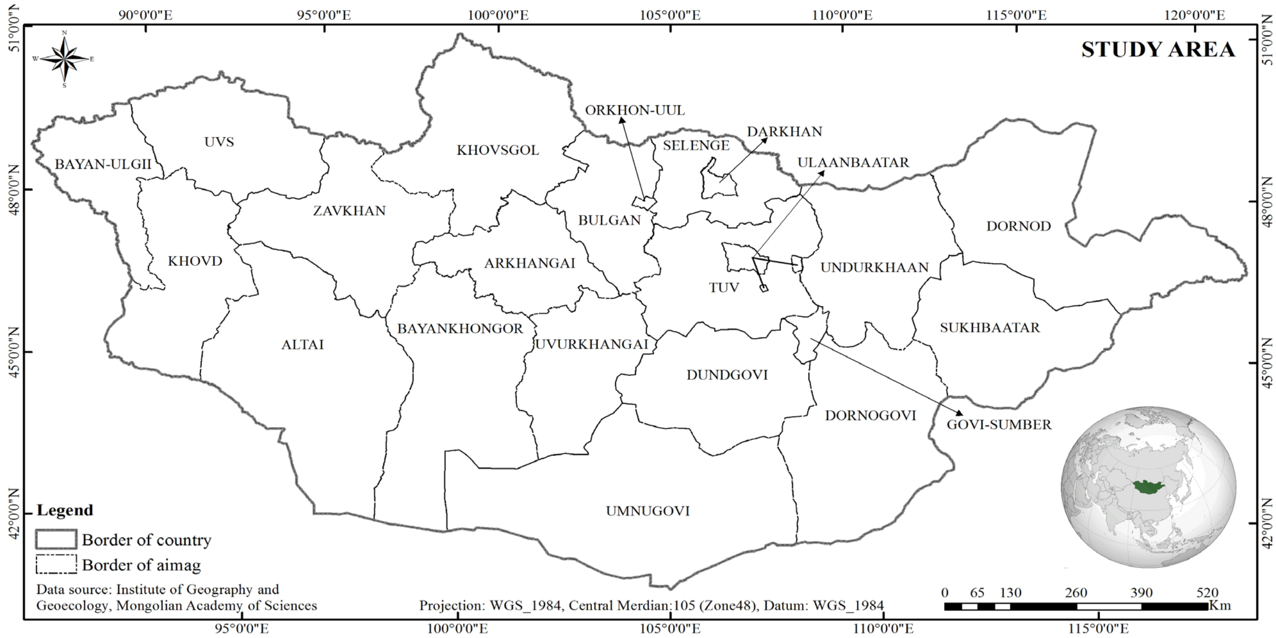


Figure 2. Location of the study area.

There are 21 administrative units, a population of over 3.0 million, and more than 52 million livestock in the country. The country is located in the continental temperate zone with an arid climate and variable topography. Annual average precipitation is 50 - 500 mm, annual average air temperature is −1.27˚C - 2.22˚C, and average wind speed is 5 - 10 m/s.

5. Data Used and Pre-Processing

5.1. Data Used

The main goal of the study was to create more accurate input maps using satellite imagery and ground measurement data such as soil humus, soil texture, soil permeability, agro-climate condition, and hydrothermal in land suitability evaluation for agricultural cropland. In order to implement this three different datasets were used; satellite data, biomass data from field surveys, and field survey soil data (Table 1). In the subsequent analysis Random forest (RF) and Partial least square (PLS) regressions were used.

5.2. Data Pre-Processing

The first step in processing the Landsat 8 satellite imagery was to calibrate the radiometric and atmospheric correction. Radiometric calibration is used to calibrate radiance, reflectance or brightness temperature in imagery analysis. Atmospheric correction was applied to eliminate the impact of the atmosphere, such as the amount of water vapor, distribution of aerosols, and scene visibility. In other words, eliminating the impact of the atmosphere is a pre-processing step for analyzing images of surface reflectance. Atmospheric correction was implemented in the QGIS 2.18 SCP plugin, parameterized with a tropical atmos-

Table 1. Used data.

Type of data	Path/Row	Bands	Resolution, m	Date	Source
			Raster data		
Landsat 8	123-143/ 24-31	2-7	30	Between on 1^{st} June and 31^{st} August, 2016	www.glovis.usgs.gov http://earthexplorer.gov
SRTM DEM	123-143/ 24-31	1	30, 90	Version 5.0	http://earthexplorer.gov
GLC product	-	LC type	30	03^{rd} July 2014	http://www.glcn.org/databases/
MODIS product	23-25/ 03-04 26/04	MOD13	250	Average 16 days, from 1^{st} June to 31^{st} August 2000-2016	www.ipdaac.usgs.gov
		MOD15	500		
		MOD17	1000		
			Field data		
Biomass data	969 sites	1 hectare	100 centner/ha	1^{st} August 2016	IRIMHE
Field survey soil data	137 sites	501 plots	1*1	2013-2016	
			Vector data		
Land use data	-	-	Scale 1: 100,000	-	AALAGC
River Network	-	-		-	
Soil humus, soil stone, soil pH	-	-	Scale 1: 5,000,000	-	National Atlas of Mongolia, 2009, IGG, MAS
Distribution permafrost	-	-	-	-	www.eic.mn IGG, MAS
Sum of daily rainfall and mean the temperature in summer season			-	-	IRIMHE

SRTM—Shuttle radar topographic mission; DEM—digital elevation model, MODIS—moderate-resolution imaging spectroradiometer; GLC—global land cover; LC—land cover; IGG—Institute of Geography and Geoecology; MAS—Mongolian Academy of Sciences; IRIMHE—Information and Research Institute of Meteorology, Hydrology and Environment; AALAGG—Agency of Administration of Land Affair, Geodesy and Cartography.

pheric model, a rural aerosol model, no aerosol retrieval and 40 km initial visibility. These were generated from the six bands of the surfaces' reflectance images. In this study 104 scenes of Landsat 8 satellite were analyzed, and the primary difficulty was the associated color balance. In order to address this we used the MOSPREP algorithm with the bundle color balancing method in PCI GEOMATICA. The bundle color balancing method applies a global adjustment of the mean and sigma of each image using a "block-bundle" method between it and each of its overlapping images, and then, using dodging points, makes smaller local adjustments between pairs of images once they have been mosaicked (www.pcigeomatics.com).

For MODIS satellite image processing the first step was to convert the input file format and coordinate system, and then apply the atmospheric correction. Using MRT (MODIS re-projection tools) we can read input datasets in HDF-EOS, which were then converted to the UTM coordinate system with a changed file format (*.tiff). The generated surfaces' reflectance images each used atmospheric correction as implemented in the QGIS2.18 SCP plugin. All image pre-processing used QGIS 2.18, ArcMap 10.4, PCI, Geomatica, ENVI v5.1, and RStudio.

Data validations accuracy assessment RF and PLS were calculated to compare with field survey soil and biomass data. RF regression was chosen because RF is a statistical algorithm that is capable of synthesizing regression or classification functions based on discrete or continuous datasets [37]. RF and CDT regression analyses were performed in Salford predictive Modeler 8.0 software. We also used PLS regression because the main goal of PLS regression is to predict or analyze a set of dependent variables from a set of independent variables or predictors [38]. PLS can easily treat data from a large number of variables in each factor that is identified [39]. Finally, all vector data were converted to raster format and then, all raster format data were transformed to the same geographical coordinate system and spatial resolution (30 m). Thereafter, each criterion map was classified into five suitability classes applying the classification threshold values of each criteria and standard scores for the corresponding class obtained in **Table 2**.

6. Analysis

The analysis comprised of three phases; the development of criteria parameters in land suitability evaluation for agricultural cropland; the preparation of more accurate input data using high-resolution satellite image, and an integrated evaluation.

6.1. Develop Criteria Parameters for Land Suitability Evaluation for Agricultural Cropland

6 main factors and 17 criteria for land suitability evaluation for agricultural cropland were selected. A criteria evaluation schema was then developed based on our own, and other countries practices, literature and expert knowledge (**Table 2**, **Table 3**). The criteria evaluation were divided into two types, multi-variables (factor) and constraint criteria parameters.

A constraint is restraint criteria and it serves to limit the alternative. The constraint can also be often represented the legal restriction. That will be the decision based on the current land-use policy. It can apply for land use constraints condition assessment such as determined by the sum of factors prohibiting the use. In this study, 9 constraints have been chosen and there are obtained range values 0 and 1. The land use constraints condition assessment determined by the sum of factors prohibiting the use. The constraint factor assessment of land use is true or false condition represent. Zero value is impossible, and 1 value is possible.

Table 2. Evaluation of the multi-variable (factor) criteria parameters.

Factor	Criteria	Unit	Standard scores for the corresponding class				
			Highly suitable (5 scores)	Suitable (4 scores)	Moderately suitable (3 scores)	Unsuitable (2 scores)	Highly unsuitable (1 score)
Topography	Slope	Degree	<3	3 - 6	6 - 9	9 - 12	>12
	Elevation	Meter	<1000	1000 - 1500	1500 - 2000	2000 - 3500	>3500
Soil	Soil humus	(%)	>4	3 - 3.9	2 - 2.9	1 - 1.9	<0.9
	Depth soil humus	(cm)	>20.1	15.1 - 20	10.1 - 15	5.1 - 10	<5
	Soil texture	-	Light clay (21 - 30), Sandy (10 - 20)	Mid-siltstone (31 - 45)	Sand (<10)	Heavy clay (45 - 60)	Clay (>60)
	pH	-	6.5 - 7.0	7.1 - 7.5 6.1 - 6.5	7.6 - 8 5.6 - 6.0	8.5 - 9 5.1 - 5.5	>9 <5
	Soil stone	%	<5.0	6 - 20	21 - 35	36 - 50	>50
Vegetation	Estimated soil organic C	-	>0.50	0.35 - 0.50	0.25 - 0.35	0.15 - 0.25	<0.15
	Estimated AGB	%	>75	55 - 75	30 - 55	10 - 30	<10
	NDVI	-	>0.50	0.35 - 0.50	0.25 - 0.35	0.15 - 0.25	<0.15
	LAI (MODIS)	m^2 plant/ m^2 ground	>60	40 - 60	20 - 40	10 - 20	<10
	GPP (MODIS)	kg C/m^2	>0.035	0.02 - 0.035	0.01 - 0.02	0 - 0.01	3.0 - 3.27
Climate	Mean temperature summer season	(˚C)	19 - 22	15 - 19	>22	13 - 15	<13
	Sum of rainfall summer season	(mm)	>200.1	150.1 - 200	100.1 - 150	50.1 - 100	<50
	Estimated Hydro-Thermal coefficient	-	1.5 - 2.0	1.0 - 1.5	0.5 - 1.0	>2.0	<0.5
Hydrology	River density	km/km^2	>0.4	0.2 - 0.4	0.1 - 0.2	0.05 - 0.1	<0.05
	Permafrost distribution	-	Region of seasonal freezing	Sporadic & Prelatic	Island	Dis-continuous	Continuous
	Water index	-	>0.50	0.35 - 0.50	0.25 - 0.35	0.15 - 0.25	<0.15
Socio-economic	Distance from settlement area	km	<100	100 - 200	200 - 400	400 - 800	>800
	Distance from infrastructure	km	<50	50 - 100	100 - 300	300 - 500	>500
	Distance from surface water resources	km	<3	3 - 6	6 - 12	12 - 15	>15

Table 3. Evaluation of the constraint criteria parameters.

Constraint criteria	Standard scores for the corresponding class		Requirement
	Prohibit land	Other land	
Forest land	0	1	Forest land for natural resources not be in used for cropland purposes
Urban land	0	1	Not be located in near settlement and in the settlement areas
Roads, high-voltage electricity transmission network areas	0	1	Avoid roads, high-voltage electricity transmission network areas
Cropland	0	1	Not be located cropland areas
Mining land	0	1	Not be located mining areas
Historical and cultural monuments areas	0	1	Not be located historical and cultural monuments areas (buffer zone with 500 m radius)
Archaeological sites	0	1	Not be located archaeological sites (buffer zone with 500 m radius)
River, lake, ponds	0	1	Be near to water reserve, but not in buffer zone
Springs, wells and water points	0	1	Be near to water reserve, but not in buffer zone (buffer zone with 500 m radius)

6.2. Prepare More Accurate Input Data Using High-Resolution Satellite Image

Complex natural factors are nearly impossible to express by quantitative and qualitative values with 100 percent conviction. In order to improve accuracy, various analytical methods and satellite images were used. In this section we attempted to estimate vegetation parameters, soil organic matter, soil texture, soil moisture, and agro-climatic conditions for the hydrothermal coefficient using Landsat 8 image and MODIS products (MOD11, MOD13, MOD15, MOD17) that used the follow indices (Table 4).

6.2.1. Topography Factor Analysis

Topography is important for maintaining slope stability and is critical to the distribution of other variables at a regional and local scale (e.g. a steep terrain should not be tilled to prevent soil erosion). The factors of slope and elevation were chosen for analysis of the contribution of topography to land suitability. The analysis used STRM DEM with a spatial resolution of 30 meters, which can be inverted from the remote sensing data. This was then classified into five map classes for slope and elevation by land suitability level (Table 2).

Table 4. Vegetation & other indices used in this study.

Vegetation index	Abbr	Formula	Reference
Green Normalized Difference Vegetation Index	NDVI green	$\frac{(NIR - Green)}{(NIR + Green)}$	[40]
Simple Ratio	Simple Ratio	$\frac{NIR}{Red}$	[41]
Green Chlorophyll Index	Cl green	$\frac{NIR}{Red} - 1$	[42]
Normalized Difference Vegetation Index	NDVI	$\frac{(NIR - Red)}{(NIR + Red)}$	[43]
Enhanced Vegetation Index	EV_1	$2.5 * \frac{(NIR - RED)}{(1 + NIR + 6 * Red - 7.5 * Blue)}$	[44]
Enhanced Vegetation Index 2	EV_2	$2.5 * \frac{(NIR - Red)}{(1 + NIR + 2.4 * Red)}$	[45]
Wide Dynamic Rage Vegetation Index	WDRVI	$\frac{(\alpha * NIR - Red)}{(\alpha * NIR + Red)}$	[46]
Green Wide Dynamic Rage Vegetation Index	WDRVI green	$\frac{(\alpha * NIR - Green)}{(\alpha * NIR + Green) + \frac{(1-\alpha)}{(1+\alpha)}}$	[47]
Modified Soil Adjusted Vegetation Index 2	MSAVI2	$\frac{NIR + 1 - \sqrt{(2 * NIR + 1)^2 - 8 * (NIR - RED)}}{2}$	[48]
Colorations Index	CI	$\frac{(Red - Green)}{(Red + Green)}$	[49]
Hue Index	HI	$\frac{(2 * Red - Green - Blue)}{(Green + Blue)}$	[50]
Brightness Index	BI	$\frac{\sqrt{Green^2 + Red^2 + NIR^2}}{3}$	[51]
Redness Index	RI	$\frac{Red^2}{(Blue + Green)}$	[52]
Top Grain Size Index	GSI	$\frac{(NIR - Blue)}{(NIR + Blue + Green)}$	[53]
Normalized Difference Water Index	NDWI	$\frac{(NIR - SWIR)}{(NIR + SWIR)}$	[54]
Moisture Stress Index	MSI	$\frac{SWIR}{NIR}$	[55]
Soil Organic Carbon Concentration	SOC	$EXP(a + b * Red + c * Green + d * Blue)$	[56]
MODIS (MOD13)	NDVI		
MODIS (MOD15)	LAI	-	www.ipdaac.usgs.gov
MODIS (MOD17)	GPP		

NIR—near infrared wavelength, Red—red wavelength, Green—green wavelength, Blue—blue wavelength, SWIR—short wavelength infrared, α a value of 0.3, a, b, c and d are coefficients where a = 1.71499, b = −0.01576, c = 0.01281, d = −0.0113.

6.2.2. Vegetation Factor Analysis

Stable natural vegetation growing areas can be represented as a habitat in areas with crop vegetation. Natural vegetation parameters can provide an additional source of information for regional agro-production use [43]. Therefore, in this study vegetation indices estimated from Landsat 8 satellite image were compared with the 969 sites' biomass data from the field survey. By comprehensively analyzing 553 sites of the biomass data, 416 sites' data were eliminated because 31 sites had no data, 21 were too biased, and another 365 sites' data depended on the temporal resolution of the Landsat 8 image.

1) Partial Least Squares (PLS) regression result

A total of 17 indices were selected to analyze the correlation between measured AGB and Landsat 8 images. There were 14 vegetation indices, 2 moisture indices and 1 soil index. PLS regression analysis was performed with SPSS software.

The strongest correlation between AGB and Landsat indices were detected in the Cl green (0.89), simple ratio (0.89), WDRVI (0.87), NDVI (0.84), EV1 (0.84), EV2 (0.80), and MSAVI2 (0.80) as a result of the PLS regression. Correlation between AGB and Landsat 8 indices showed 11 linear indices and 6 nonlinear indices. The general correlation between AGB and Landsat indices were defined by the result of the PLS regression at R^2 0.749, RMSE 1.011. In other words, AGB from Landsat 8 satellite image was estimated at 75% confidence and a linear regression was obtained.

In the four abovementioned analyses, we obtained the 6 most important variables to evaluate AGB, the Cl green, simple ratio, NDVI, EV_2, WDRVI and MSAVI2. We then calculated six vegetation indices using Landsat 8 to estimate AGB across the study area. The results are shown in Table 5.

We explored the relationship between estimated AGB and MODIS time-series vegetation products (NDVI, LAI, GPP), to understand the major controls of estimated AGB. Our country on average, has a 5-month natural growing season (April to August). At about the end of April and the start of May the grass turns green. June is the primary period of grass growth. The growth slows down toward the end of August, then the grass begins to fade. Therefore, in this study the MODIS vegetation products (NDVI, LAI, and GPP) covering the period from the beginning of June to the end of August was used, ranging from the year 2000 to 2016. The performed regression analyses were used to evaluate the relationship between estimated AGB and the 17-year average MODIS vegetation products.

Table 5. The result of regression models.

Correlation	Regression types	R^2	RMSE	MSE
Between measured AGB and estimated AGB	PLS	0.749	1.021	1.011
	Random forest	0.760	0.966	0.934
	CART decision tree	0.890	0.668	0.477

Equation: $$\begin{aligned} AGB = & -0.331 + 0.415 * \text{Cl green} + 2.125 * NDVI + 0.415 * \text{Simple ratio} \\ & + 3.860 * EV2 + 1.987 * WDRVI + 4.082 * MSAVI \end{aligned}$$

6.2.3. Soil Factor Analysis

Parameters of soil properties mirror the land suitability evaluation for agricultural cropland. The spectral response of soil is influenced by a number of soil related properties such as surface condition, particle size (texture), organic matter, soil color, moisture content, iron and iron oxide content and mineralogy [57]. It is also possible to obtain soil property estimations from remotely sensed images [58]. Several studies attempted to demonstrate the relationship between soil properties and reflectance data from satellite imagery [56] [58] [59] [60] [61] [62]. From these studies, a logarithmic linear relationship for organic C was developed by Chen *et al.* This linear equation utilizes image intensity in Red, Green and Blue bands and it is widely used to evaluate soil organic properties [58] [60]. In this study, Chen's equation was used for the evaluation of the soil's organic carbon.

$$SOC = \exp\left(a + b * R + c * G + d * B\right) \tag{6}$$

SOC is the surface organic C; *a*, *b*, *c* and *d* are curve fit parameters ($a = 1.71499$, $b = -0.01576$, $c = 0.01281$, $d = -0.0113$); *R*, *G* and *B* are wavelength ranges.

6.2.4. Agro-Climatic Factor Analysis

Agro-climatic factors establish a quantitative connection between vegetative processes of specific plants and their in situ atmospheric environment [63]. Mongolia has an extreme continental climate with great variation between the four seasons. It has long, cold winters and short summers, with more than 65% of its annual precipitation falling in the summer season. In the summer season, the precipitation amount and daily mean air temperature affect plant growth rate. Data from 55 meteorological stations between 1940 and 2013 show that annual precipitation averages 153 mm in the summer season (from June to August), and the mean air temperature is 17.5˚C (http://www.eic.mn/climate/). In Mongolia, the temperature threshold that allows growth and biomass production to begin is generally +5˚C. The time period with daily temperature means at or above this threshold is approximately 150 - 165 days. One of the most important parameters to evaluate agro-climatic conditions is the hydrothermal coefficient (HTK). HTK is the sum of precipitation compared with the sum of the daily temperature in the vegetation period. In this research HTK has been estimated based on Selyaninov's formula.

$$HTK_i = \frac{\sum P_i}{\left[0.1 * \sum T_{>X^\circ\mathrm{C}}\right]} \tag{7}$$

HTK_i —HydroThermal coefficient.

$\sum P$ —Sum of precipitation, mm.

$\sum T_{>X^\circ\mathrm{C}}$ —Sum of positive daily mean temperature, ˚C.

X —Threshold temperature, ˚C.

For the summer season, maps of total rainfall and geographical distribution of mean temperature in the study area were obtained from "Changes in event number and duration of rain types over Mongolia from 1981 to 2014" [64]. The maps were created in the 2010s, by the joint research efforts of the "Asia Research Center, National University of Mongolia (NUM)" and the Information and Research Institute of Meteorology, Hydrology and Environment (IRIMHE). This study used daily precipitation and temperature data recorded during the summer season (from June to August) between 1981 and 2014 from 55 meteorological stations throughout Mongolia. These maps were converted to thematic GIS layers.

7. Results

In this study a combination of constraint and factor analysis methods were used. There were nine constraint factors and 17 criteria factors. All constraints can be represented with values of 0 or 1. Suitability levels between 0 and 5 were obtained for each of the factors. The levels were 5—highly suitable, 4—suitable, 3—moderately suitable, 2—unsuitable and l—highly unsuitable (**Table 2**, **Table 3**).

7.1. Result of Constraint Factor Analysis Based on Boolean Logic Theory

Assessment of the land use constraint conditions was determined by the sum of factors restricting land usage. The constraint factor assessment of land use is represented by a true or false condition. A zero value means impossible, and a 1 value means possible. We defined the forest, urban area, roads, high-voltage electricity transmission network areas, mining areas, historical and cultural monument areas, archaeological sites, rivers, lakes, springs, wells and water points (near to water reserve, but not in buffer zone) as completely unsuitable for cropland based on current land-use policy in Mongolia. Using the weighted linear combination method all constraint factors were combined. The analysis demonstrated a 31.2% constraint factor for the entirety of Mongolia (**Figure 3**).

7.2. Result of Factor Analysis Based on the Spatial MCDM Method

A comprehensive analysis of the study area used six major factors (topography, soil, vegetation, agro-climate, hydrology and socio-economic) for land suitability evaluation at the primary level. There were a different number of criteria under each category totaling 22 at the secondary level (**Table 2**, column 2). In this analysis 5 factors and 17 criteria were applied. The topography factor was important for maintaining slope stability and was critical to the distribution of other variables at a local scale (e.g. a steep terrain should not be tilled to prevent soil erosion). Soil governed the type of vegetation that could grow most productively in a given area, and vegetation (e.g. its presence and health conditions) showed whether the land could be used productively. The agro-climatic factor was important because it affected the growth of vegetation and crops. The hydrology determined the amount of water available for plant growth. The role of these factors in the environment varied with land cover. Therefore, due to

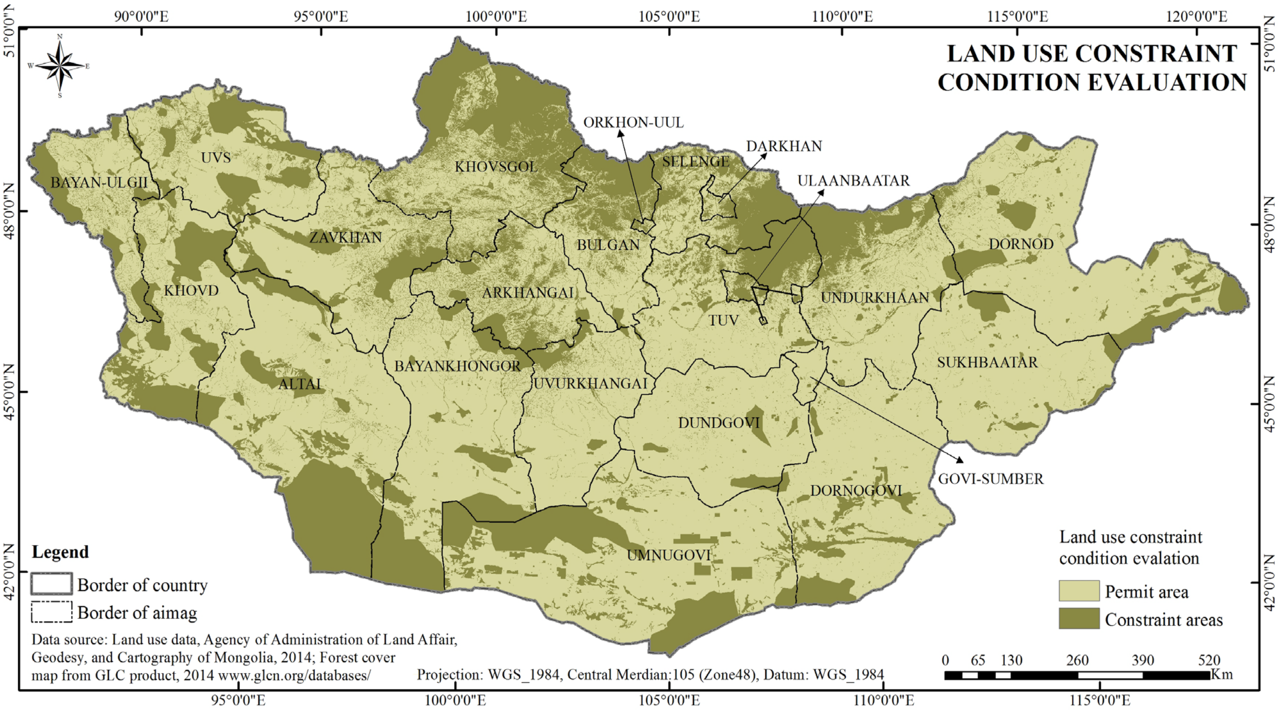


Figure 3. Land use constraint condition evaluation (Boolean map method).

changing dominance in different areas, the same environmental factors could have dissimilar influences.

Figure 4 shows the suitability value maps for 17 criteria, which represent the distribution of the suitability values within the study area using a continuous scale with values ranging from low to high.

7.3. Results of Ranking and Weights Analysis of the Criteria Based on the AHP Method

Table 6 shows the ranking of 17 factors based on a literature review and expert consultations, with the weights calculated using AHP based GIS. In this study we have estimated a CR = 0.089, suggesting that there was a reasonable level of consistency in judgement.

7.4. Result of Map Layer Overlay Analysis Based on Suitability Index

After weighing the importance of different criteria for land suitability analysis, seventeen criteria maps were overlaid using the suitability index.

$$\begin{aligned} S_i = {} & 0.142*\mathrm{S}+0.030*\mathrm{E}+0.142*\mathrm{H}+0.021*\mathrm{OC}+0.097*\mathrm{T}+0.014*\mathrm{P} \\ & +0.014*\mathrm{SS}+0.0142*\mathrm{A}+0.066\mathrm{N}+0.045*\mathrm{L}+0.030*\mathrm{G}+0.097*\mathrm{HT} \\ & +0.021*\mathrm{SR}+0.045\mathrm{MT}+0.069*\mathrm{R}+0.008*\mathrm{DP}+0.011*\mathrm{M} \end{aligned}$$

The results of the analysis show that 18.8% of the area studied was highly suitable, 20.2% was suitable, 19.0% was moderately suitable, 22.6% was unsuitable, and 19.3% was highly unsuitable (Figure 5).

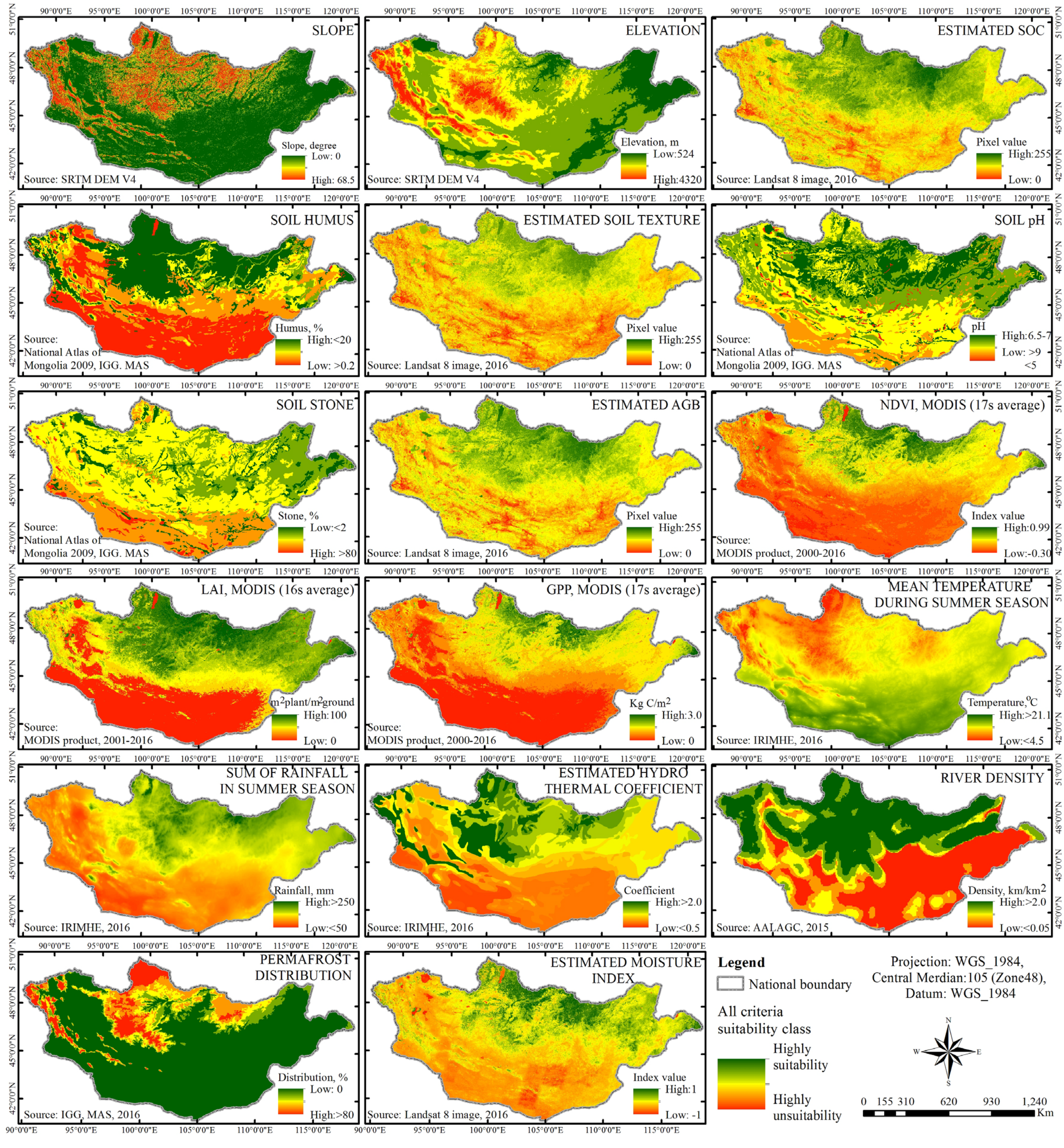


Figure 4. The main factors used in cropland suitability evaluation.

The results of the integrated assessment of constraint and factor analysis are shown in **Figure 6**, and **Table 7**. The integrated assessment shows that 10.1% of the area covered was highly suitable, 14.0% suitable, 15.5% moderately suitable, 16.3% unsuitable, 12.9% highly unsuitable and 31.2% was the constraint area.

7.5. Accuracy Assessment

Accuracy assessments used were the random forest (RF) and partial least square

Table 6. Defined ranking and weights of the criteria.

Factor	Weight	Criteria	Ranking	Weight	Function
Topography	0.172	Slope (S)	1	0.142	Linear
		Elevation (E)	5	0.030	Non linear
Soil	0.288	Humus (H)	1	0.142	Linear
		Estimated soil organic C (OC)	6	0.021	Linear
		Texture (T)	2	0.097	Linear
		pH (P)	7	0.014	Non linear
		Stone (SS)	7	0.014	Non linear
Vegetation	0.283	Estimated AGB (A)	1	0.142	Linear
		NDVI (N)	3	0.066	Linear
		LAI (L)	4	0.045	Linear
		GPP (G)	5	0.030	Linear
Agro-climatic	0.163	Estimated Hydro-Thermal coefficient (HT)	2	0.097	Linear
		Sum of rainfall in summer season (SR)	6	0.021	Linear
		Mean temperature in summer season (MT)	4	0.045	Linear
Hydrology	0.088	River density (R)	3	0.069	Linear
		Distribution permafrost (DP)	9	0.008	Non linear
		Estimated moisture index (M)	8	0.011	Linear

Consistency ratio (CR): 0.089.

Table 7. Suitability classification results for cropland in Mongolia.

Suitability classification	Preliminary study result (used thematic map)		Current study result (used satellite data)	
	Area, km^2	% of total area	Area, km^2	% of total area
Highly suitable	83,030	5.30	157,707.5	10.1
Suitable	222,457	14.2	219,716.4	14.0
Moderately suitable	452,747	28.9	243,498.4	15.5
Unsuitable	249,089	15.9	255,180.5	16.3
Highly unsuitable	65,797	4.20	201,514.7	12.9
Constraint area*	482,513	30.8	488,982.5	31.2

Constraint area* is unsuitable based on current land-use policy.

(PLS) regression. The general accuracy is 88%, while PLS and RF regression are 82.3% and 92.8%, respectively (Graphic 1, Graphic 2). The results were then compared with the current extent of sown area, and the results are shown in

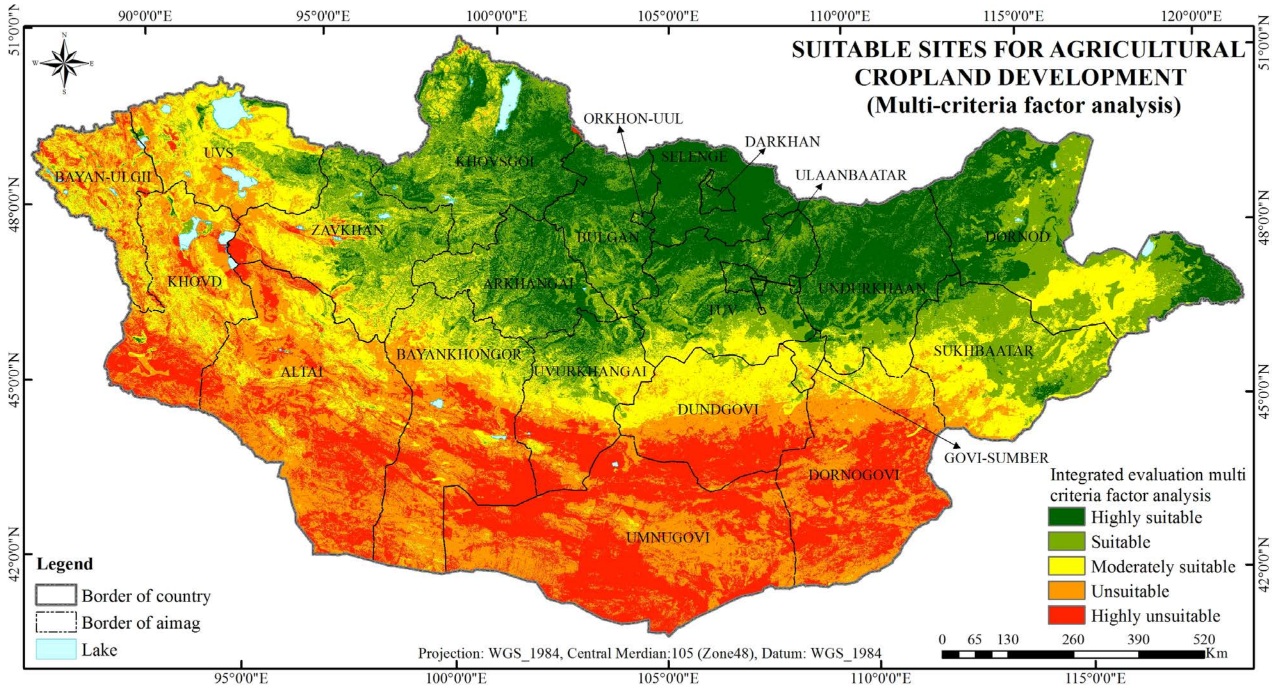


Figure 5. Suitable sites for cropland development (Multi-criteria factor analysis).

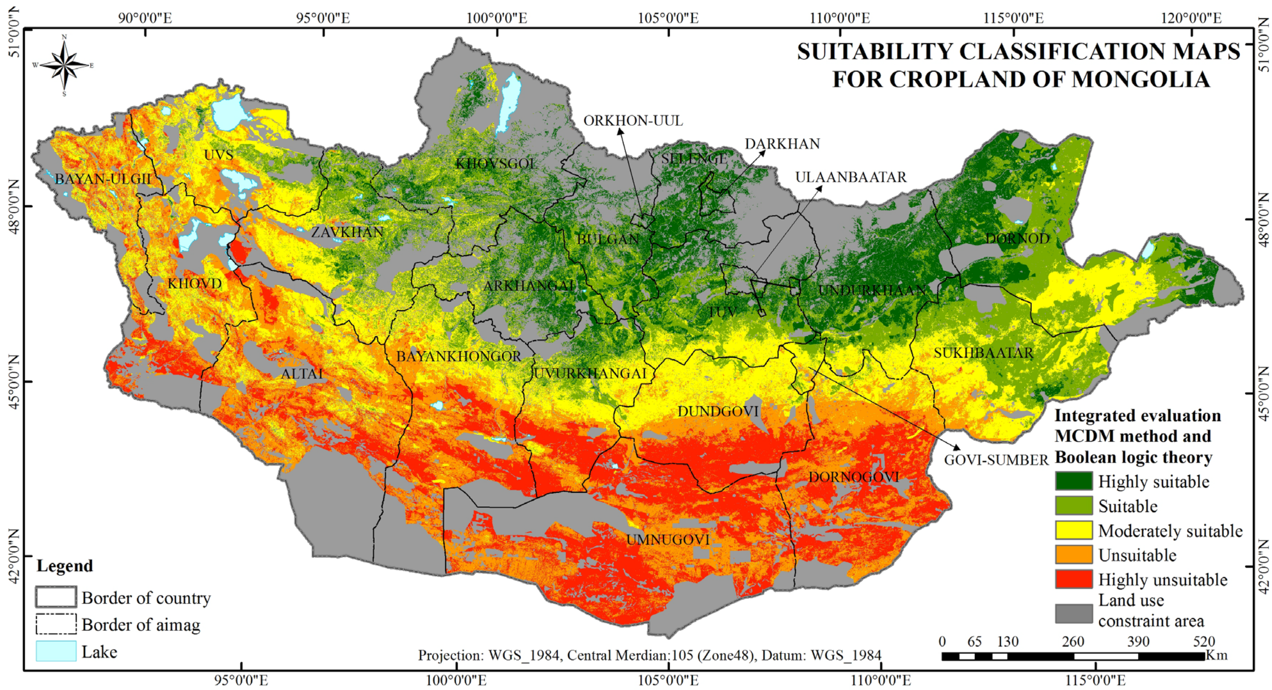
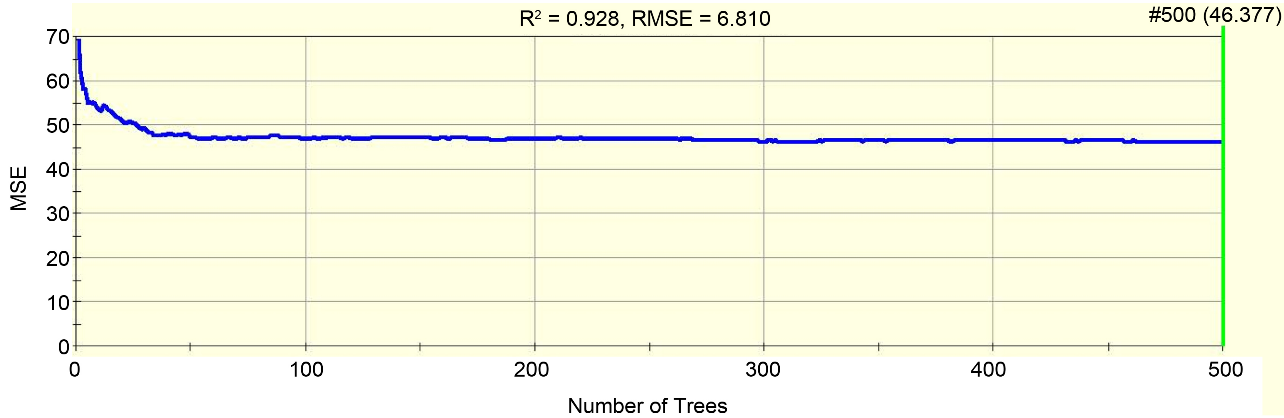


Figure 6. Suitability classification map for cropland in Mongolia.

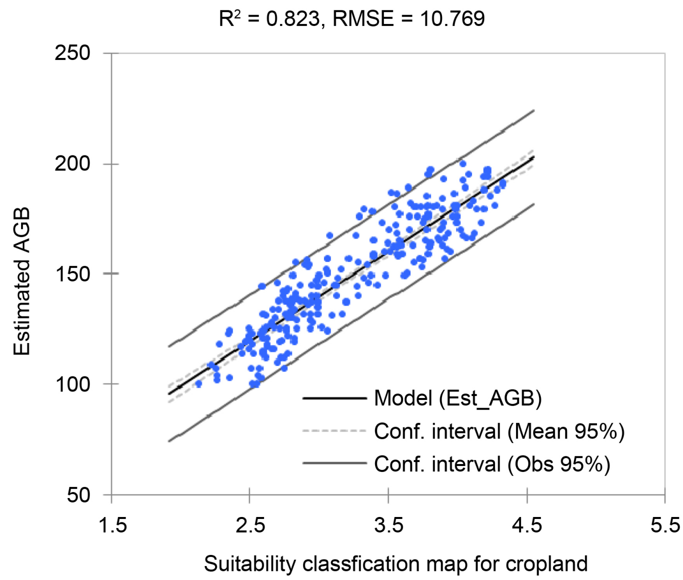
Figure 7 and Table 8.

8. Conclusion

Since 1960, the method of wholesale selection was used for cropland area. This was conducted based on a few parameters such as the general condition of the



Graphic 1. The relationship between AGB and suitability classification map for cropland by RF regression results.



Graphic 2. The correlation between AGB and suitability classification map for cropland and PLS regression results.

weather, the natural landscape, and the content of the soil. Our study, on the other hand evaluated the extent of cropland in Mongolia, examining the results of a land suitability multi-criteria evaluation based on multiple factors such as topography, soil, vegetation, agro-climatic, hydrology and constraints. Integrated assessment of constraint and factor analyses showed that 10.1% of the study area is highly suitable, 14.0% suitable, 15.5% moderately suitable, 16.3% unsuitable, 12.9% highly unsuitable for cropland, with 31.2% as the constraint area. General accuracy was 0.88, while PLS and RF regressions were 82.3% and 92.8%, respectively. As shown in the results land suitability evaluation for cropland is possible using GIS and remote sensing technology based on a combination of multi-criteria decision output and matrix. There is now the potential to evaluate other regions of Mongolia. The abovementioned method of land suitability evaluation for cropland can be used to save time for land management,

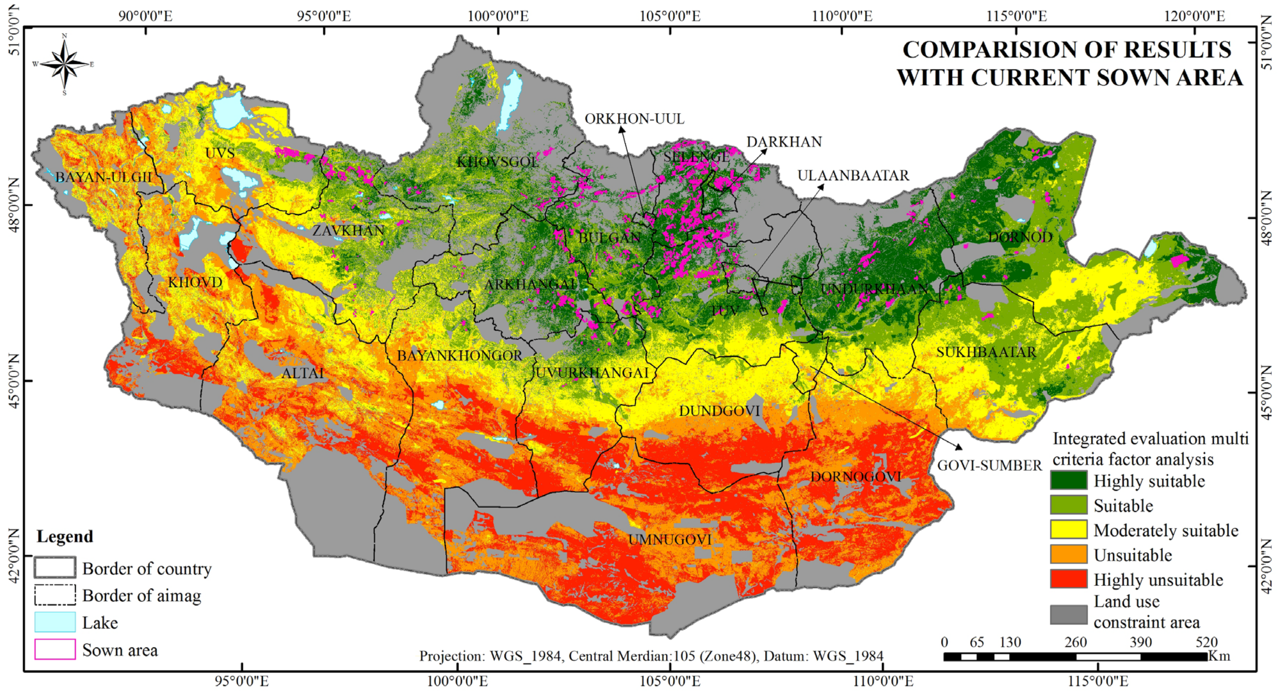


Figure 7. Evaluation validation.

Table 8. Comparison of results with sown area.

Suitability classification	Comparison of results (%)	
	Preliminary study result	Current study result
Highly suitable	30.0	82.4
Suitable	67.5	16.2
Moderately suitable	1.80	1.40
Unsuitable	0.40	-
Highly unsuitable	0.00	-

and it allows for the possibility of justifying policy decisions with science.

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Abbreviations

MCDM (Multi-Criteria Decision Method);
AHP (Analytical Hierarchy Process);
RF (Random Forest);
PLS (Partial Least Squares).