# CROPLAND SUITABILITY ANALYSIS USING GIS TECHNIQUE

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**ABSTRACT:** This research aims at estimating best suitable area for crop production in the central region of Mongolia, using a GIS-based multi-criteria analysis (MCA) and remote sensing. In this study, the GIS-based spatial MCA among the Analytical Hierarchy Process (AHP) method was employed. Expert views of the leading agronomists and literature review were used to identify criteria (soil data, topography, water and vegetation data) that were necessary to recognize areas suitable for crops. Suitability classes were derived from the FAO land suitability analysis and ranged from highly suitable, moderately suitable and unsuitable to highly unsuitable. Findings of the study were compared with the crop cadastral map from the Administration of Land Affairs, Geodesy, and Cartography (ALAGAC) and ground truth data. Areas suitable for crop production amounted to 175200 hectares. The crop suitability method is capable of supporting significant decisions on different levels, and the findings may be used for optimizing cropland management in Mongolia.

## 1. INTRODUCTION

The studies on estimation of suitability for cropland are important in the Mongolian agriculture. Mongolia initiated a program called Atar 3, the 'Third Campaign to Reclaim Abandoned Agriculture Lands', which increased government spending between 2005 and 2009 in order to improve food security and prevent future food crises (Pederson, et al., 2012). Mongolian agriculture divided by five regions, namely, Khangai, West, East and Gobi. The total agricultural area of Mongolia is 1,269,498 ha of which 65 % is in Tuv, 11 % in Khangai, 10 % is in West, 13.97 % is in East and 0.03 % is in Gobi region (MFALI, 2018). Thus, we selected Tuv region as a study area with the largest area of agricultural lands. Mongolian agriculture produces more than 20 percent of Gross Domestic Product (GDP) and contributes 14 percent of the foreign currency revenues of Mongolia.

The goals of this program (Atar 3) are created favorable economic condition, increased agricultural production, ensured food safety, eliminated import dependence, increased self-reliance and intensified development of crop production. Mongolia has substantial potential for the improvement of agricultural production (Bat-Erdene, 2012). There have been several studies on Mongolian croplands and their suitability. The crop condition determinations are temporal tracking of changes in crop condition, quantitative estimation of production indicators such as Leaf Area index and biomass, identification of crop phenology and risk factors for crop disease (McNairn, Hochheim, & Rabe, 2004). Another research focused on cropland suitability based on natural and socio-economic factors and measures of adaptation to crops layout and farming system (Guobing & Jianping, 2011). Also, there was research for habitat suitability model for grassland restoration which applied GIS-based modeling to identify the landscape characteristics of calcareous grassland systems on the lowlands most suitable for the re-establishment and expansion of calcareous grasslands (Burnside, Smith, & Waite, 2002).. For this modeling, these researchers only used elevation, slope and aspect.

The Mongolian agricultural policy was designed to shift 15 million hectares of low-yield croplands to forest as well as the afforestation of barren hillsides by offering grain and cash to farmers as compensation for land conversion (Feng, Yang, Zhang, Zhang, & Li , 2005; Long, et al., 2006). Conversely, positive vegetation index anomalies (>1) for both desert and grassland biomes corresponded to negative albedo anomalies (<−1), which could be explained in part by irrigated agriculture in Inner Mongolia and cropland expansion in north-central Mongolia. This suggested that the vegetation anomalies were not false signals caused by clouds and/or aerosol-contaminated pixels (Ranjeet , et al., 2013). Many papers have emphasized the importance of the policy as the most important limitation affecting cropland suitability; relatively less attention has been paid to improving the policy in different land use regions (Wang, Lu, Fang, & Shen, 2007).

Mongolian agriculture needs satellite image processing for the soil moisture analysis, as it will be useful for agriculture and pasture management (Natsagdorj, et al., 2017). Mongolia also needs satellite image processing and monitoring for the long-term soil moisture analysis especially in agricultural areas. Soil moisture content methodology is suitable for using in agricultural areas and practical applications of drought and desertification monitoring in Mongolia (Natsagdorj, Renchin, De Maeyer, Dari, & Tseveen, 2018). According to the National development plan of 2040, north western soums (administrative Unit) of Tuv province were selected for the

agricultural production. The agriculture sector, including animal husbandry, has been the main source of income and practiced in almost all parts of this area. There are possibilities and advantages to use remote sensing and geographic information system in Mongolian agricultural studies (B. Batbileg, 2010). At present, the wide application of GIS in land suitable assessment makes land suitability assessment more flexible (Guobing & Jianping, 2011). Generally, Mongolian agriculture is divided into two main sub-sectors: livestock and crop production. Over the last century, crop production has always been an important but relatively small part of the Mongolian economy. Nowadays, there are about 1.2 million hectares of abandoned croplands in Mongolia. These abandoned croplands are filled with weeds and have caused land degradation and desertification. There is limited research on suitability for cropland in agricultural regions in Mongolia. Most croplands are situated in the Bulgan, Selenge and Tov aimags (first-level administrative subdivision) around the capital city of Ulaanbaatar (Pederson, et al., 2012). Therefore, there is a need for a regular analysis and monitoring to detect suitable croplands using remote sensing (RS) and geographic information system (GIS).
The main objective of this study is to develop approach to estimate suitability for cropland using geographic information system and remotely sensed data. Our research differs from previous studies on suitability. For instance, Guobing & Jianping, (2011); Burnside et al., (2002); McNairn et al., (2004) considered natural and socio-economic data and then converted values of data into the suitability index. In this study, we take factors for suitability such as moisture index, vegetation index, aspect, and slope and elevation. Evident novelty of the present research is its estimation approach of cropland suitability by means of both GIS and remotely sensed data in forested steppe region in Mongolia.

### 1.1 Study area

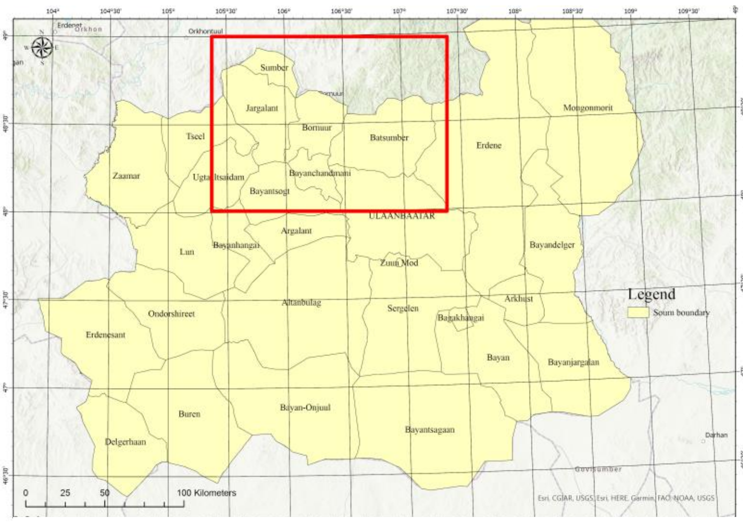


Figure 1. Study area in Tuv provinces
(E48°-49° and N105°-107°30')

The study area is characterized by agriculturally based economy, as it is the main crop area in Mongolia. It is located between E48°-49° and N105°-107°30' with average altitude of 1300 meters above the sea level (Figure 1). The study area included Bayanchandmani, Batsumber, Bornuur, Jargalant and Sumber soums. These soums are situated from 50 to 150 km from Ulaanbaatar city (capital city of Mongolia). Annual average precipitation ranges from 150 to 250 mm of which 85-95 percent fall in summer season (June to September). Soil remains frozen from October to May for 195-220 days a year. The elevation of the study area is 872~1821 m. The dominant plants are *Allium Mongolicum*, *Iris potaninii*, *Patriniasibirica and Scutellariabaicalensis* (Bayartogtokh B, 2015).

### 1.2 Dataset

In this research, we used crop cadastral map (from the ALAGAC of Mongolia), Landsat images and ASTER satellite data which were developed in our previous study (Natsagdorj, et al., 2017).

**Table 1.** Used data

| Data type | Data description | Data source |
|---|---|---|
| Soil data | Soil pH, soil humus, soil texture, soil type | ALAGAC |
| Digital Elevation Model | Aster GDEM V2 2011, the resolution is 30m | U.S Geological Survey (USGS) and Earth Remote Sensing Data Analysis Centre (ERSDAC) |
| Normalized Difference Vegetation Index (NDVI); Normalized Difference Moisture Index (NDMI) | *NDVI=(NIR-Red)/(NIR+Red)* *NDMI=(NIR-MIR)/(NIR+MIR)* | Landsat TM/OLI satellite images between 2014 and 2019 (McDonald, Gemmell, and Lewis 1998; Jin and Sader 2005; Woodcock et al. 1994) |
| Cropland cadastral map | Current cadastral survey | ALAGAC |

***Crop cadastral map***

The cadastral survey component comprised two major activities. The first one is the collection of geodetic field survey data to identify and record the location and area of all land parcels in both settlement (urban) and cropland areas. This component resulted in a digital cadastral map that allowed us to form the geographic foundation upon which additional land parcel information or attribute data could be layered. The cadastral surveys covered up to 3 million hectares (ha) of settlement land areas and farmlands (crop and intensive livestock farms, and livestock winter shelter sites), constituting about 2% of Mongolia. Outputs from the satellite image process provided cadastral survey and land registration with data for agricultural cropland areas at a scale of 1:50,000 (Asian Development Bank, 2010).

***Remotely sensed data***

*Landsat OLI8 satellite data:* Landsat 8 operational land imager (OLI) image (August 2015, path 132, row 26) was downloaded from the USGS earth resource observation and science center (EROS) website, and applied for this research (http://glovis.usgs.gov/). Landsat 8 measures different ranges of frequencies along the electromagnetic spectrum – a color, although not necessarily a color visible to the human eye. Each range is called a band, and Landsat 8 has 11 bands. For the predicted soil moisture index (PSMI) was used Landsat OLI8 August, 2015.

*ASTER satellite data:* In order to develop elevation, aspect, slope we used *advanced spaceborne thermal emission and reflection* radiometer (ASTER) satellite, global digital elevation model (GDEM) data with 30 m resolution. The ASTER GDEM covers land surfaces between 83°N and 83°S, and is composed of 22,600 1°-by-1° tiles. The ASTER GDEM is in GeoTIFF format with geographic Lat/Long coordinates and a 1 arc-second (30 m) grid of elevation postings. It is referenced to the WGS84/EGM96 geoid. Pre-production estimated accuracies for this global product were 20 m at 95% confidence for vertical data and 30 m at 95% confidence for horizontal data (http://gdem.ersdac.jspacesystems.or.jp).

## 2. METHODOLOGY

The multi-criteria analysis method (based on GIS) was applied to determine the cropland suitability. Based on literature review, we identified few scientific studies on land suitability evaluation in Mongolia (Otgonbayar et al. 2017; Purevtseren and Indraa 2018). Moreover, no reviews are available on the physical planning of croplands in the small regions of Mongolia using the spatial multicriteria analysis method. The process adopted for the crop suitability of the study area has applied the methodology illustrated in Figure 2.

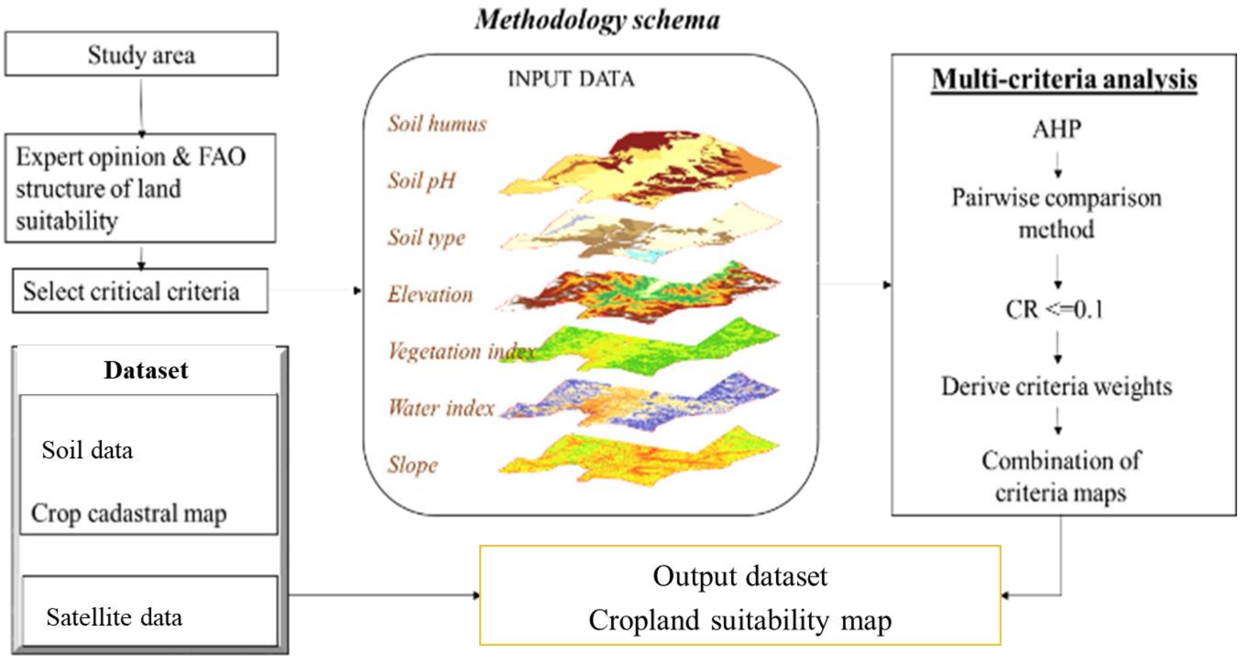


Figure 2. Flowchart methodology of the cropland suitability. FAO: Food and Agricultural Organization; AHP: Analytical Hierarchy Process; CR: Consistency Ratio

### 2.1 Selection of the suitability criteria

In the study area, the most important economic sector is agriculture, in particularly crop production sector. Literature review and consultations with local agricultural experts helped to identify the necessary criteria (soil texture, soil type, soil pH, soil humus, elevation (altitude), slope, vegetation and moisture) to estimate suitable areas for crop production. Suitability classes were identified based on classification from the FAO land suitability analysis and ranged from highly suitable, moderately suitable and unsuitable to highly unsuitable in the study area. These classes were estimated according to the FAO guideline and literature review (Table 2).

**Table 2.** Criteria for the cropland suitability

| Factor/Criterion | Highly suitable | Moderately suitable | Unsuitable | Highly unsuitable |
|---|---|---|---|---|
| **Soil texture (class)** | Light clay & mid-siltstone | Sand | Heavy clay | Clay |
| **Soil type** | Kastanozems, Gleysols, Gambisols and Leptosols etc. | | | |
| **Soil pH** | 5.5 – 7.5 | 5.2-5.5<br>7.5-7.8 | 4.5-5.2<br>7.8-8.5 | 8.5<<br>4.5> |
| **Soil humus (%)** | 3 < | 2.0 – 3.0 | 1.0 - 2.0 | 1 > |
| **Elevation (meter)** | 1,500 > | 1,500 – 2,000 | 2,000 – 3,500 | 3500 < |
| **Slope (degrees)** | 0 - 6 | 6 - 9 | 9 - 12 | 12 < |
| **NDVI (index)** | 0.35 < | 0.25 - 0.35 | 0.15 – 0.25 | 0.15 > |
| **NDMI (index)** | 0.35 < | 0.25 - 0.35 | 0.15 – 0.25 | 0.15 > |

*Source: based on the literature review and the FAO (1984)*

**2.2 MCA for assigning the weight to each criterion**

The Analytical Hierarchy Process (AHP) is a standard mathematical method introduced by Saaty (1977). Itis used when analyzing complex decision problems (Saaty 1977; 1990). The AHP, pairwise comparison matrix estimates the weights of each criterion ($w_i$).

Pairwise comparison matrixes involve the comparison of all possible pairs of criteria in order to estimate which of them are of a higher priority. Saaty (1980) suggests a scale from 1 to 9 where value 1 indicates that the criteria are equally essential and value 9 means that the considered criterion is superior to the other criteria (Table 3).

The crop suitability classes were assigned with the score 9, 7, 5 and 3, respectively. The classes with higher scores are highly suitable for crop production and by applying these scores, the estimated suitability classes and all thematic maps were reclassified.

**Table 3.** Scale concerning pairwise correlation

| Numerical expression | Comparative importance | Suitability rating |
|---|---|---|
| **1** | Equal importance | Unsuitable |
| **3** | Moderate importance of one factor covering another | Marginally suitable |
| **5** | Strong or crucial importance | Moderately suitable |
| **7 and 9** | Extreme importance | Highly suitable |
| **2, 4, 6, 8** | Moderate values | |

*Source: (Saaty 1990; Saaty and Vargas 2013; Burnside, Smith, and Waite 2002)*

**2.3 Weighted linear combination (WLC) estimation of the criteria**

In order to estimate the related criteria weight, the AHP method has been applied to compute every criterion weight. A pairwise comparison matrix (PWCM) was designed using information from the literature review and the local experts concerning the value of weights regarding each related criterion. In AHP method, a consistency index (CI) to calculate the Consistency Ratio (CR), has been applied to designate the possibility that matrix judgements obtained a randomly created by means of equation (1) (Hossain et al. 2013):

$$CR = \frac{CI}{RI} \qquad (1)$$

, where *RI* is mean of the resulting consistency index depending on the quantity of the matrix, given by Saaty (Hossain et al. 2013; Sanare and Ganawa 2015).

The *CR* index represents the consistency of the PWCM. If the *CR* exceeds 0.1, then weighting rate is unacceptable and if the ratio value is lower than 0.1, than weighting rate means acceptable (Hossain et al. 2013). The Consistency Index (*CI*) is described in equation (2):

$$CI = \frac{m_{\max} - n}{n-1} \qquad (2)$$

, where *CI* stands for the Consistency Index, $m_{max}$ is the maximum own value and *n* represents the matrix order.

After estimating the weights of the values of the criteria using the AHP tool, all criteria maps have been overlaid applying the cropland suitability (equation 3). Cropland suitability map could be calculated from the Weighted Linear Combination (WLC) of criteria used by the equation (3). The WLC method is one of the most commonly used in GIS-MCA (Malczewski 2000).

$$CS = \sum_i w_i * c_i \tag{3}$$

, where *CS* represents the final cropland suitability value, $w_i$ shows the weight of criterion *i* and $c_i$ demonstrates the standardized criterion score *i* (Gorsevski, Jankowski, and Gessler 2006).

The weights of seven criteria and ranks are presented in Table 4, according to the literature review and interviews with local experts. We have estimated CR = 0.091 and found that the judgement had a reasonable consistency. The $w_i$ is the weight value for each criterion and normalizes the amount of the sections facing unity while $\sum w_i = 1$ (Helmut et al. 2013).

**Table 4**. Defined ranking and weights of the criteria

| Id | Name of the criteria | Ranking | Weight |
|---|---|---|---|
| **1** | Soil texture (*ST*) | 2 | 0.191 |
| **2** | Soil pH (*pH*) | 7 | 0.221 |
| **3** | Soil humus (*SH*) | 1 | 0.130 |
| **4** | Elevation (*E*) | 5 | 0.157 |
| **5** | Slope (*Sl*) | 4 | 0.102 |
| **6** | NDMI (*NDMI*) | 6 | 0.106 |
| **7** | NDVI (*NDVI*) | 3 | 0.075 |
| **Consistency ratio (CR): 0.091** | | | |

## 3. RESULTS AND DISCUSSION

In order to obtain the weighted linear combination of different criteria for the cropland suitability in the study area, seven criteria images were overlaid applying the cropland suitability (equation 4).

$$CS = w_i * ST + w_i * pH + w_i * SH + w_i * E + w_i * Sl + w_i * NDVI + w_i * NDMI \tag{4}$$

, where: *CS* - Cropland Suitability, $w_i$ = j; $\sum w_i =$ 1.0, a weighted index for influencing criterion, *ST* - Soil Texture, *pH* - Soil PH, *SH* - Soil Humus, *Sl* - Slope, *E* - Elevation, *NDVI* - Normalized Difference Vegetation Index, *NDMI* - Normalized Difference Moisture Index

In this research, a multi-criteria analysis was applied to five soums of Tuv province using an ArcGIS weighted overlay tool. In the suitability analysis, weights measure the influence of the considered suitability criteria (Helmut et al. 2013), which are shown in Table 2. Multi-criteria analysis resulted in the equation (5) presented below. The tool works with multiple raster inputs, representing several criteria. In this suitability model, the output values from the approach could range from unsuitable to highly suitable. The $w_i$ stands for the weighted indexes (Table 4) for each criterion on cropland suitability in the study area. Thus, the weighted linear combination of criteria through equation (5) has been estimated.

$$CS = 0.19 * ST + 0.22 * pH + 0.13 * SH + 0.16 * E + 0.10 * Sl + 0.07 * NDVI + 0.11 * NDMI \tag{5}$$

In the present case, the cropland suitability classes consisting of four ranges applied in this research adjusted the FAO system (FAO 1976). They are specified as: highly suitable, moderately suitable, marginal suitable and not suitable. Seven criteria (soil texture, soil pH, soil humus, elevation, slope, NDVI and NDMI) were chosen based on the study objective and the data availability. The soil thematic data were converted into raster layers and processed in ArcGIS. The elevation and slope were produced from DEM. The NDVI and NDMI were calculated from the Landsat satellite images with a 30 m resolution during 2018-2021.

All selected criteria were classified into 4 classes as an integer raster displaying different cropland suitability set up on the origin rates in Table 2. The results of this study provide all criteria, as shown in Table 3.

The output map for suitability described four classes with the relative suitability for cropland. These classes are explained as follows: unsuitable in red, marginal suitable in light yellow, moderate suitable in light green and highly suitable in dark green (Figure 3). The output map from the cropland suitability area approach is demonstrated in Figure 3.

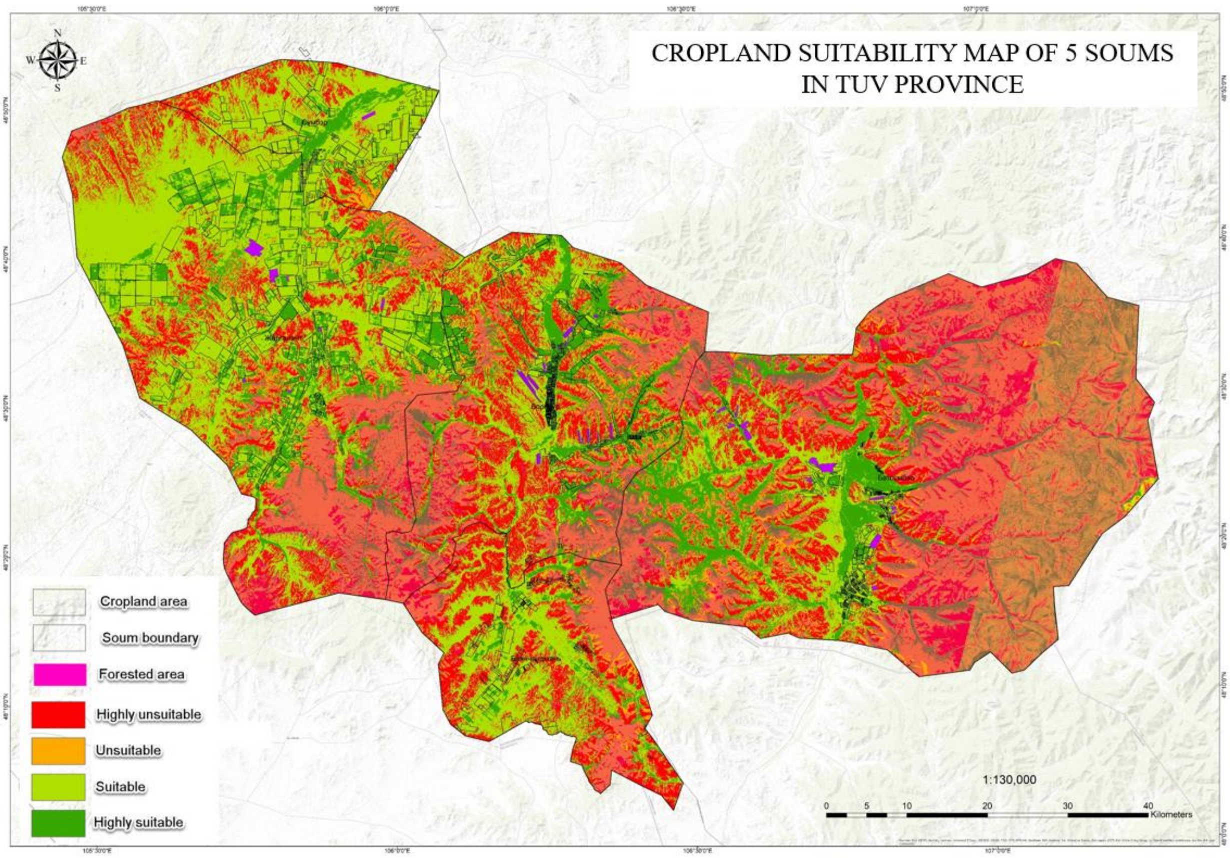

Figure 3. The output map of the cropland suitability in the study area

In order to make validations, the output map from the approach was compared with the crop cadastral map from the Agency for Land Administration and Management, Geodesy and Cartography and the field data from the field survey, respectively. The cropland cadastral map overlapped the output suitability map. Around 96% of the croplands are located in the highly suitable and suitable part of the output map of suitability.

The result of the cropland suitability analysis reveals that 18.6 % is highly suitable for crop production, 33.73% is moderate suitable, 24.3 % – unsuitable and 23.4 % – highly unsuitable (Figure 3).

Consequently, we overlapped constraint data for used area (forested, urban, mining, construction area etc) and protected area. Then, we obtained information on lands suitable for crop production in the study area that is shown in Figure 4. The total area reached 175200 hectares.

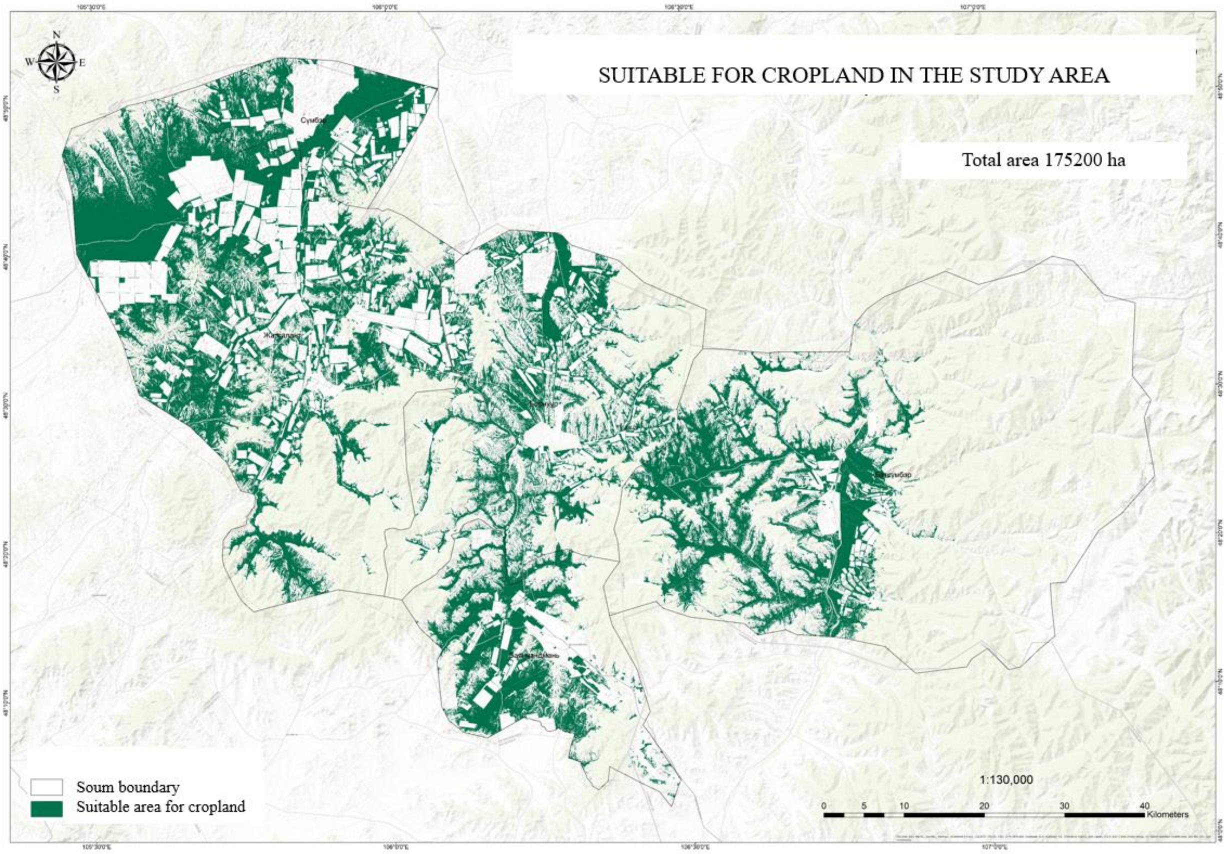


Figure 4. The suitable area for cropland in the study area

## 4. CONCLUSION

A GIS-based multicriteria analysis has recently been put into use for agricultural land suitability evaluation. The newly created area selection by means of the multi-criteria analysis method demonstrates high potential, especially for the small provinces. This method may enable more precise, rapid and low-priced environmental and agricultural management approach.

Recent agricultural studies have supported the idea of developing approach for the cropland suitability rating by means of the multi-criteria evaluation method. Mongolia also needs satellite image processing for the cropland studies, as it is valuable for agricultural and land management.

In the study area, all soil types are suitable for crop production. We selected other criteria such as soil parameters, topography, vegetation and moisture index. The multi-criteria analysis was applied for the cropland suitability approach based on GIS in the study area. GIS has proven to be an effective, operational tool for complex evaluation processes of cropland suitability (Pan and Pan 2012). We estimated the cropland suitability approach, using GIS in Tuv region of Mongolia.

The results shown in the output map are reasonable. Their consistency with the crop cadastral map reached approximately 96%. Developed cropland suitability maps confirmed that 18.6% of areas are highly suitable for cropland, 33.73% are moderate suitable, 24.3% are unsuitable and 23.4% are highly unsuitable.

The decision methods that are handled in the land-use evaluation problems cannot be randomly selected without appropriate justification (Dujmovic, Tré, and Dragicevic 2009; Chen, Yu, and Khan 2010; Zabihi et al. 2019). The novelty of this research is that it utilized both satellite images and GIS to identify suitable cropland regions. The study employed the elevation and slope factors for the forested mountainous and agricultural areas. It can be applied to various regions and climate zones. The additional factors should also be considered. The approach may function as a reliable indicator to inform further agricultural management decisions and support regional policymaking. The advantages of this approach allow researchers to determine new, suitable agricultural regions in various areas.

The result of this research could be used for the soum government in order to advise local farmers to choose suitable areas. In terms of practical application, this approach proves to be a useful tool to obtain reliable and reasonable data, thereby providing valuable information for the decision-makers and farmers. In the future, this study could be replicated to map the land suitability of other soums and countrywide with further and more processed parameters. The cropland suitability databases in the agricultural sector will ensure the essential reliability of the estimates and forecasts, which will be helpful in the process of planning and policy-making.

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