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ESTIMATION OF CROP SUITABILITY USING NDVI IN THE KHERLEN BASIN DORNOD PROVINCE, MONGOLIA

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Abstract: The Normalized Difference Vegetation Index (NDVI) is a graphical pixel indicator which used and analysed by remote sensing technology whether or not the target being observed contains live green vegetation. In this paper we estimated crop suitability using Normalized Difference Vegetation Index (NDVI) which depended on Land Surface Temperature (LST), The Normalized Difference Moisture Index (NDMI or water) from MODIS satellite data and Elevation, Slope form ASTER DEM satellite data. NDVI is used for several sector, especially in agriculture for cropland, precision farming and to measure biomass. Agriculture is one of the crucial and traditional sectors of Mongolia that produces approximately 15 % gross domestic production (GDP). This research focuses on estimation for crop suitability based on a statistical method and NDVI.
The study area is situated in the steppe region Dornod province, eastern part of Mongolia. NDVI MODIS data (April to September) from 2003 to 2018 were applied for the estimation. We used multiple linear regression analysis with python in order to develop crop suitability model using NDVI. The result of proposed model was compared with MODIS NDVI value. The agreement is positive which 71percent is.
Keywords: satellite data, remote sensing, multiple linear regression, vegetation index

1. Introduction

Agricultural activity and its economic importance in both national and international markets, the development and implementation of systematic crop area monitoring, and mapping tools are of fundamental importance for the country [1]. Most of the Mongolian territory is characterized by arid and semiarid climate, and over 70 % of Mongolia is covered by high-quality steppe grasslands [2]. In Mongolia, the total area is 1,565 million square kilometers, approximately 80 % of the total area could be used for agricultural activities (especially pasture) but only 1 % of the total area used for crop production [3]. At present, Mongolia has 15,000 square kilometers of arable land that produce agricultural production [4]. The Mongolian government has contributed several national programs to increase agricultural crop products and support agricultural equipment purchases [5]. Additionally, the national objectives to increase food security (agricultural production) could be achieved sustainably

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based on a national program in Mongolia. For that, there is a need to estimate newly suitable cropland using the science-based methodology.

Many researchers have been done with cropland suitability using remote sensing (RS) and geographic information system (GIS) techniques [6], [7], [8], [9], [10]. Cropland mapping through remote sensing could complement official statistics, generating annual cropland maps along with planted area estimates. Many applications are based on moderately high spatial resolution images, such as the Landsat TM with 30 m pixels, and are restricted to relatively small areas or demand a large amount of work. The moderate resolution imaging spectroradiometer (MODIS) produces near-daily images with 250, 500, 1000 m spatial resolution, suitable for identifying large crop fields in regions with the widespread use of mechanized agriculture [11], [12]. Information on spatial and temporal patterns of cropland use at multiple geographic scales is required to understand better the potential for intensification [13]. Unfortunately, existing data on cropland-use intensity are mostly coarse in scale, heavily rely on uncertain cropland maps [14]. To estimate suitable land for agriculture, [15] applied the variables of soil parameters including texture, organic matter, depth, slope, and land use/cover. Besides elevation, aspect, slope, soil pH, temperature, precipitation, and soil groundwater were used land suitability analysis for agricultural production [16]. Many criteria have to be considered to estimate the land suitability for agricultural production. Most of the previous studies have been used multi-criteria evaluation (MCE) and analytic hierarchy process (AHP) methods with GIS for land suitability. However, the estimation of the newly cropland area was investigated based on multiple linear regression (MLR) analysis using satellite images in a few studies [7]. Mongolia needs science-based satellite image processing and mapping on agricultural management in order to develop crop production.

The main objective of this research is to develop the cropland suitability model using NDVI analysis based on satellite images. A second goal is to make a cropland suitability map in Dornod province, Mongolia. To achieve these goals, we have used multiple linear regression analysis.

2. Study area

The study area is Dornod province which located in the eastern part of Mongolia (Figure 1). It covers east-central Asian grassland steppe. The total area of Dornod province is 123.5 thousand squares kilometers and geographically, it is mostly steppe, which situated in 560 – 1,300 m above sea level. The average annual rainfall is 150~300 mm, it occurs during summertime. Ten percent of the flora registered in Mongolia grow in Dornod province. Dornod is home to several globally rare or threatened bird species, and hosts typical Central Asia fauna and flora in relatively natural settings compared with other Asian steppe ecosystems [17]. The total cropland area is 117.0 thousand hectares, but 72.3 thousand hectares is an activity with 20 companies in 2019. The main cropland region is located in the south eastern part of the study area, Khalkhgol soum, it makes up 85 percent of the entire cropland.

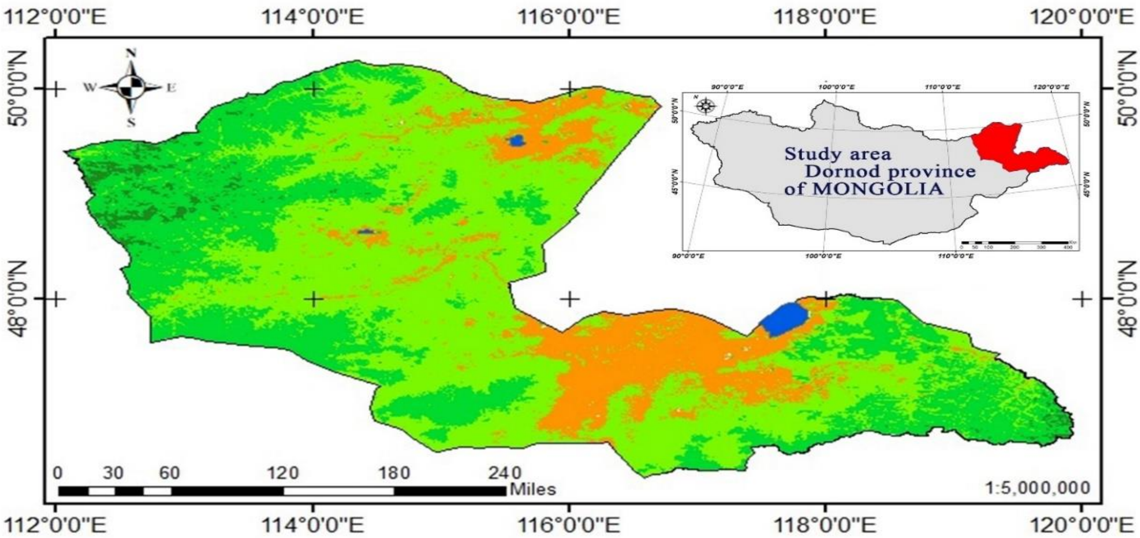

Figure 1. Study area: Dornod province

3. Data

In this paper, we used data for estimation crop suitability: MODIS and ASTER DEM. MODIS data is described in the Table 1. Moderate Resolution Imaging Spectroradiometer (MODIS) is a sensor operating on the Terra and Aqua satellites, which were launched by NASA in December 1999 and May 2002, respectively. Terra's orbit around Earth is timed so that it passes from north to south across the equator in the morning, while Aqua passes south to north over the equator in the afternoon.

Table 1. Spatial and temporal resolution of the MODIS products

MODIS product code	MODIS product name	Spatial resolution (m)	Temporal resolution (days)	Number of images
MYD13Q1.006	NDVI	*500*	*16*	*14*
MYD13Q1v006	NDMI	*500*	*16*	*14*
MOD11A2v006	LST	*1000*	*8*	*25*

MODIS vegetation indices, produced on 16-day intervals from 250-meter spatial resolution.

The red (RED) and NIR channels from MODIS Terra satellite applied in Equation (1) for NDVI calculation

$$\mathrm{NDVI} = \frac{\mathrm{NIR-RED}}{\mathrm{NIR+RED}} \tag{1}$$

We calculated Normalized Difference Moisture Index (NDMI) using equation 2. In here mid-infrared (MIR) and near-infrared (NIR) from MODIS Terra.

$$\mathrm{NDMI} = \frac{\mathrm{MIR-NIR}}{\mathrm{MIR+NIR}} \tag{2}$$

Finally, we used MODIS satellite data MOD11A2, which MODIS LST (land surface temperature) with 1000 m resolution, bundled for 8 days from 2003-2018.
LST is calculated the following equation:

$$LST = \left(BT + w * \frac{BT}{p}\right) * \ln(e). \tag{3}$$

where BT is satellite brightness temperature (K); w is the wavelength of emitted radiance (11.5 μm) ; $p = h * \frac{c}{s}$ ($1.438*10^{-2}$m K), h is the Plank's constant($6.626*10^{-34}$Js); s is the Boltzman's constant ($1.38*10^{-23}$J/K), c is the velocity of light ($2.998*10^{8}$ m/s), $e = 0.004 * P_v + 0.986$, $P_v = ((NDVI - NDVI_{min})/(NDVI - NDVI_{max}))^2$ is the proportion of vegetation [18].
We also used datasets of the elevation and the slope from ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) GDEM satellite datasets in this area. The ASTER is a 14-channel imaging instrument operating on NASA's Terra satellite since 1999. In 2009, the US/Japan Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) project released the first global high spatial resolution digital elevation model (DEM) available to all users. ASTER's GDEM was created by stereo correlation of more than 1.2 million individual ASTER stereo scenes contained in the archive. The GDEM had 1 arc-second latitude and longitude postings (~30 m), and vertical accuracy of approximately 10 [19].

4. Methodology

In this paper multiple linear regression (MLR) analysis was applied in order to develop a model for cropland suitability. Regression is a statistical method, which made a function that allows an analyst or statistician to make predictions about one variable based on the information that is known about other variables. MLR, also known simply as multiple regression, is a statistical technique that uses several (two or more) explanatory variables to predict the outcome (or function, or model) of a response variable. The goal of MLR is to model the linear relationship between the explanatory (independent) variables and response (dependent) variable. The formula for Multiple Linear Regression model is defined by the following equations:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + +\beta_n x_n + \varepsilon \quad (4)$$

Where: y - response (dependent) variable.

$x_1 x_2 \dots, x_n$ -explanatory (independent) variables

$\beta_0, \beta_1, \beta_2 \dots, \beta_n$ -slope coefficients for each explanatory variable

ε -the model's error term (also known as residuals)

The general structure of our model is given by the following equation:

NDVI =F (NDMI, LST, Elevation, Slope). (5)

and, linear form of the regression is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4$$

where: y -Normalized Difference Vegetation Index (NDVI), x_1-Normalized Difference moisture Index (NDMI), x_2 -Land Surface Temperature (LST), x_3 -Elevation and x_4 -Slope.

The result of the multi-linear regression, model for crop vegetation as follows:

$$\mathrm{NDVI} = 0.4\ \mathrm{NDMI} - 0.01\ \mathrm{LST} + +0.0006\ \mathrm{Elevation} + 0.243 \quad (6)$$

5. Analysis

We developed a model with multiple linear regression in Python. The result was R^2= 0.84 from the regression analysis (Table2). LST is the opposite relationship with NDVI and NDMI. Elevation is less dependency on NDVI but Slope is irrelevant

Table 2. Result of regression model from our developed model

OLS Regression Results						
Dep. Variable	NDVI		R-squared			0.84
Model	OLS		Adj.R-squared			0.83
Method	Least Squares		F-statistic			57.37
	coefficient	standard error	t	P>/t/	[0.025	0.975]
LST	-0.01	0.001	2.641	0.003	0.001	0.006
Elevation	0.0006	6.11E-05	5.362	0.000	0.000	0.000
Slope	1.8E-06	1.99E-07	5.362	0.000	6.69E-07	1.46E-06
NDMI	0.4	0.058	10.262	0.000	0.483	0.717

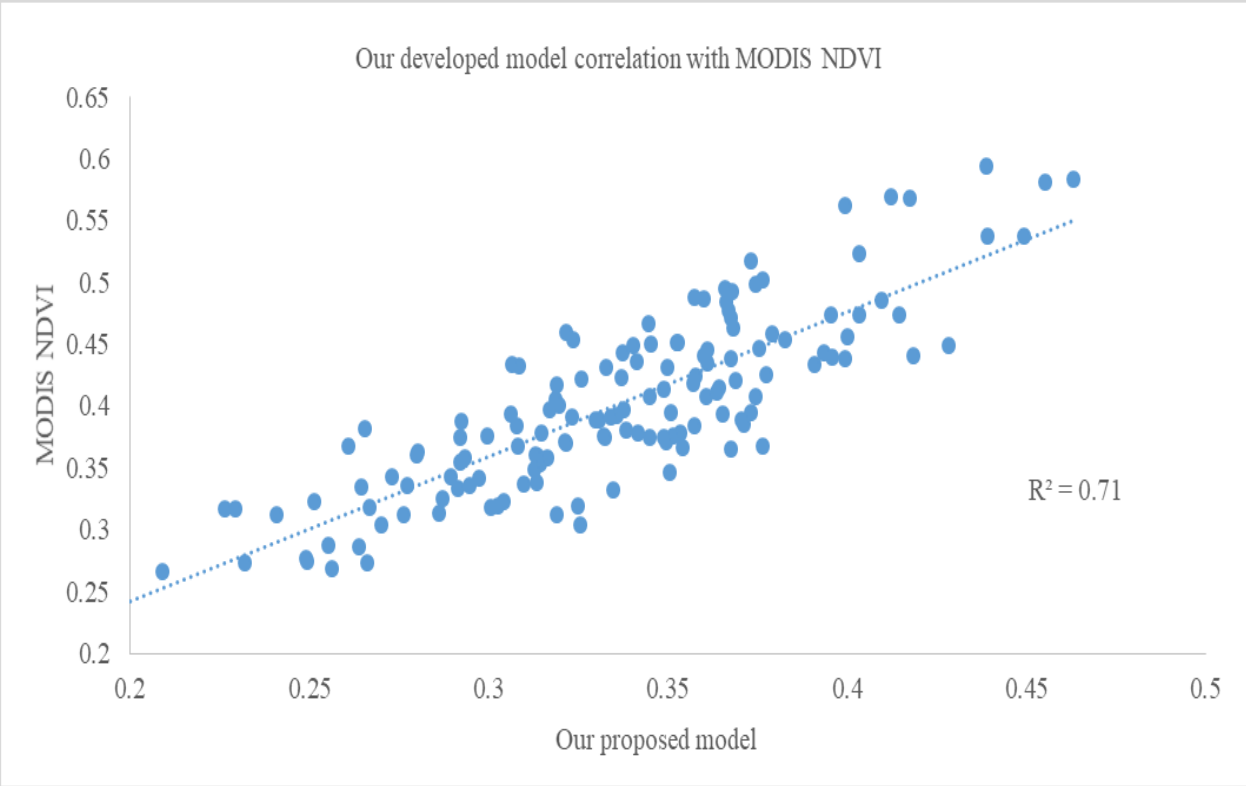

Figure 2. Validation the proposed model with standard MODIS NDVI from satellite data.

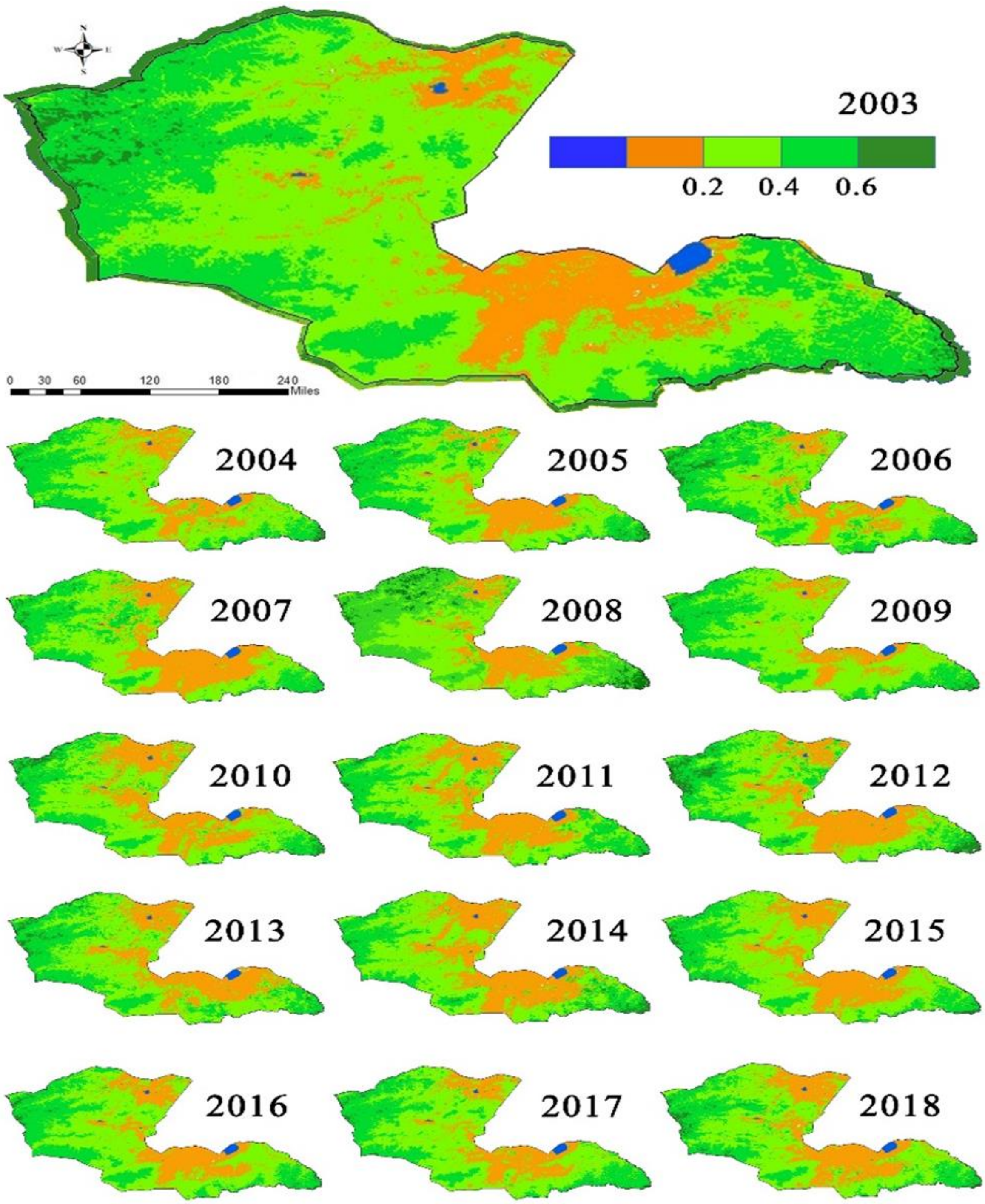

Figure 3. The result map of the proposed model from 2003 to 2018

5. Results

NDVI mainly is estimated by using channel NIR and RED by equation (1) for estimation crop production. There are different types of vegetation indices based on crop reflectance, the most commonly used NDVI. In this study, we developed a model to estimate crop suitability using NDVI. The vegetation index was related to NDMI, LST from MODIS data and, Elevation, Slope from ASTER data in the area of Dornod province over the years 2003 and 2018. According to the analysis, NDVI and NDMI values are increased while LST value is decreasing over years 2003 -2018.

The result is shown by equation (6), we classified the NDVI extent maps (Figure 3) from our developed models. We compared model result with standard MODIS NDVI. The correlation result between them is $R^2 = 0.71$. (Figure 2)

NDMI (also soil moisture) has an important effect on vegetation growth. Elevation and Slope had very little effect, which is specific characteristic of the steppe regions. The land surface temperature (LST) has the opposite of the vegetation index indicates that soil heating has a negative effect on vegetable growth.

The result of the map shows the highest NDVI values in the forested areas of the southeast (Khalkhgol) and northwest (Bayan-Uul) region of the study area, it indicates that the model is close to the ground truth. These places are the main agricultural regions in Dornod province. As shown in the map, the places with high NDVI values can be considered a high potential region for agricultural development. Finally, this model can be improved using logistics and nonlinear regression methods and other factors can be added.

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