Assessing land degradation using trend of MODIS NDVI time series and human influence

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Abstract

In the assessment of desertification and land degradation, the use of remote sensing is referred as an analysis of complex processes mainly based on vegetation density, and the most suitable index is NDVI. A continuously decreasing vegetation index along the year is a sign of degradation (Lantieri, 2003). Therefore, Sukhbaatar province was selected in our research, and the statistical analysis was made using the MODIS NDVI data of June, July and August of 2000-2014 time period determining the trend. Also, specific areas were selected and spatial analysis was conducted in each selected areas in order to assess human influence. The research result shows that 23.4% of the study area is degraded. With regard to the spatial zoning of human influence, areas surrounding 4 season camps of herders are degraded more than the settlement. Also, compared with state roads, local road areas are highly degraded.

Introduction

Desertification is defined in the UNCCD as involving "land degradation in arid, semi-arid and dry sub-humid areas resulting from various factors, including climatic variations and human activities" (UN, 1994) [1] where *land degradation* is defined as reduction or loss of biological or economic productivity. NDVI is biophysical indicator and it is selected by indicator of land degradation (FAO). A continuously decreasing vegetation index along the years is a sign of desertification (Lantieri, 2003) [5], and when vegetation at low cover is more than 40 % , NDVI is more convenient to use.

As NDVI is related to such a variety of vegetation properties, multiple explanations for a change in NDVI signals are possible. [3] Nevertheless, the NDVI from satellite observations is the only global vegetation dataset which continuously time series and thus allows the quantification and attribution of ecosystem changes as a result of ecosystem dynamics and varying climate conditions. Different ecosystem changes can be analyzed from NDVI time series. [3] NDVI data have been widely used in studies of land degradation from the field scale to the global scale (e.g. Tucker and others 1991, Bastin and others 1995, Stoms and Hargrove 2000, Wessels and others 2004, 2007, Singh and others 2006). Recently many researchers did statistical analysis for NDVI time series, and then detect land degradation by trend sign of NDVI. The patterns and trends of NDVI indicator each pixel, determined by the slope of the linear regression equation. (Bai ZG болон Dent DL) A negative slope of linear regression indicates a decline of green biomass and a positive slope, an increase – except for STD and CoV which indicate trends in variability. The absolute change (Δ in map legends, titled “changes in …..”) is the slope of the regression; the relative change (% in map legends, titled “trend in ….”) is 100 (slope of the regression/multi-year mean). Qingzhu Gao and Yunfan Wan estimated the trend of Pearson correlation for NPP within given time in Tibetan Plateau. [7]

M.Bayasgalan used 1982-2003 time series to identify the appropriate variables corresponding with each particular natural zone among the several scientists’ who used NDVI for their research work in Mongolia. [6] Scientists’ collaborated to develop the “Desertification Atlas of Mongolia” and “Desertification database” identifying the vegetation coverage transition, vegetation dynamics trend to assess the overall desertification.

We have selected Sukhbaatar province in our research, and the statistical analysis was made using the MODIS NDVI data of June, July and August of 2000-2014 time period determining the ups and down trend. As mentioned above, continued period's NDVI is one of the land degradation criterions. Therefore, we aimed to make the spatial analyses creating spatial zones on each parts how it impacted by the climate and human influence.

2. Study site, material and method

2.1. Study site

The study site is located in Sukhbaatar province, in the eastern part of Mongolia elevated 1000-1200m above the sea level, highest point is 1778 whereas 790m the lowest. The total area is 8240.6 thousand.ha and the province borders with China in the south, south west part with Dornogobi province, northwest with Khentii province and Dornod province in the northeast part respectively. Sukhbaatar province has 13 soums (smaller unit of the province) and 66 bags (smaller unit of the soum) and the number of population is 57423 with 2818181 animals. The natural zone is characterized by steppe since the land is continuation of the Dornod Mongol Plateau. The landscape of the province is dominant with mountain steppe, flat low land steppe, arid steppe and semi-arid steppe. Even though, it has harsh continental climate the weather is warm with low precipitation. The amount of the surface water source is considerably low and the river, streams dried up much.

2.2. Outlook of the study site

The total amount of the precipitation and NDVI's average mean distribution (Figure 1) shows less difference on the transition of arid steppe and the value distribution on dry steppe and arid steppe is similar in the study area. The highest value distribution of the precipitation and NDVI is mostly in arid steppe area.

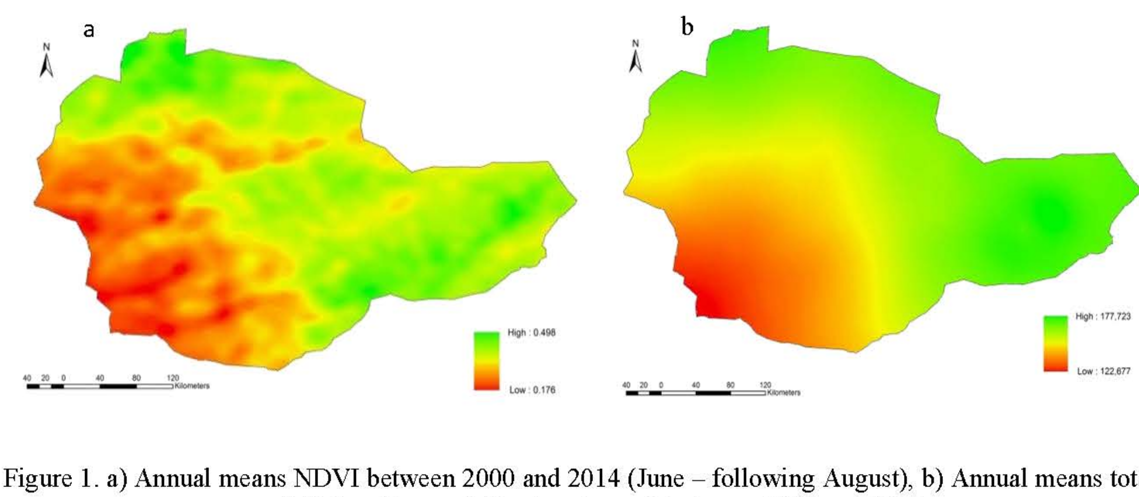


Figure 1. a) Annual means NDVI between 2000 and 2014 (June – following August), b) Annual means total precipitation (June – following August) between 2000 and 2014

The average of 96842 pixel points on the study site's (x;y) linear regression slope's correlation of precipitation and NDVI indicates the linear correlation.(Figure 2) Therefore, it's feasible to assess the study site's overall condition without any human influence.

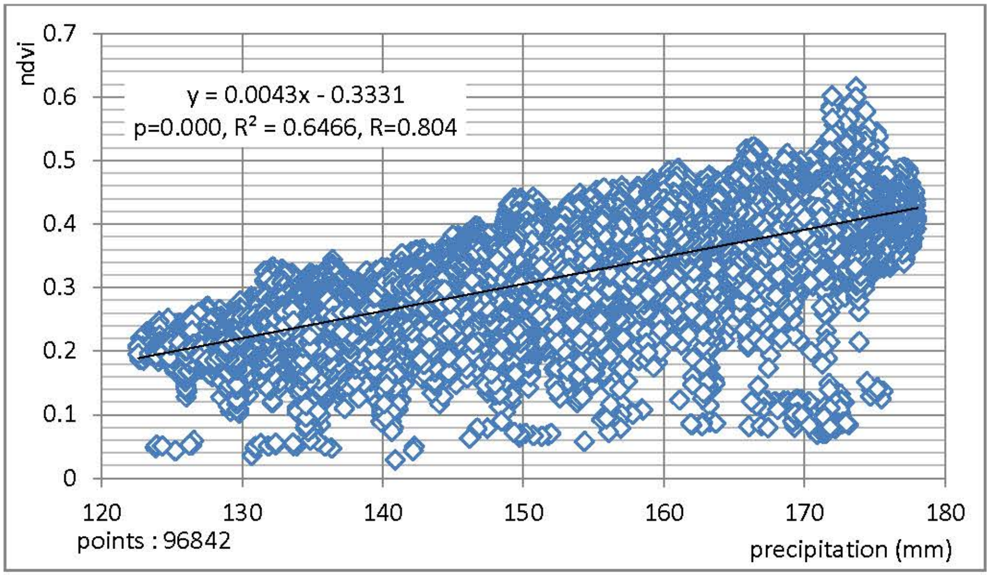


Figure 2. Scattered diagram of the correlation between annual sum NDVI (all pixels) and annual rainfall (all pixels), p=0.000. Years run from 1 June through the following August

However, research study result will show the different perception if considering to estimate the many years' spatial distribution trend.

2.2. Data and data processing

2.2.1. Data

Climate data: It includes total precipitation data and the average temperature of the June, July, and August of 2000-2014 years from the evenly distributed 60 weather stations' data in Mongolia. The weather station data on precipitation is not efficient to define the spatial analyses. Thus, during the study TRMM 3b43 surface precipitation data of TRMM satellite with 0.25^{o} grid resolution jointly fired by NASA and JAXA was used.

Normalized vegetation index /NDVI/: We used the MODIS satellite's with 1km resolution NDVI data of June, July and August for 2000-2014 time period.

Vector data: The vector data includes Sukhbaatar province's roads, settlement areas, and herders' four season camps' location, well, river and streams. The data sources provided from the "National Atlas" 2009.

2.2.2. Data processing

ArcGIS 10.2.1 program's Spatial analyst tools, Multidimension tools, Conversion tools were used for the data processing.

NDVI: Analysis was done extracting the study area by Mask clip using the overlay statistic mean estimation on each year of MODIS NDVI /June, July, August/ data.

Precipitation: TRMM 3b43 surface precipitation data of TRMM satellite with 0.25^{o} grid resolution installed by netCDF format and clipped accordingly with the border of Mongolia. The clipped pictures converted into (5341) point and integrated with weather station data in order to develop the each year's spatial distribution (1km accuracy) map trend.

Vector data processing: Buffer zone created in 2, 4 and 10 km respectively on roads, settlement areas, well, river and streams on study site. Vector data's' converted into raster format with 1km accuracy. Density analysis completed by 10km radius from the herders' four season camp location.

2.3. Analysis

2.3.1. Pearson correlation analysis

It is used to measure the degree of linear correlation between two variables. Given time and the variables' correlation presents the particular variables' trend. Coefficient in the given time and NDVI correlation characterized by Piao and Fang (2002) formation. [7]:

$$r_{xt} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(i-\bar{t})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(i-\bar{t})^2}} \quad (1)$$

Where, n- consecutive years, x_i –i- NDVI value of the year, $\bar{x}$ – mean value of the NDVI over the given period. $\bar{t}$ – $(n + 1)/2$- the average value of the consecutive years. This value assessed on 96841points with 1km accuracy (x;y) in study site. An estimated negative and positive value indicates the increased and decreased trend of NDVI between 2000-2014 years.

Precipitation for 2000-2014 years' total precipitation trend of June, July and August estimated similar to above approach. We used this approach to analyze how the precipitation trend affects the biomass production. The positive trend indicates the land improvement where the negative trend is for the land degradation. [9] In other words, precipitation is the main restriction factor for the biomass production and its long-term trend is the best indicator for the land improvement and degradation. (Houérou 1984, 1988, 1989; Snyman 1998; Illius and O'Connor 1999; O'Connor and others 2001).

Human influence analyzed by estimating the NDVI's Pearson correlation coefficient's increased and decreased value on each selected vector values in every spatial zone. The final analysis completed comparing two general human impact types in Mongolia. Herein:

- Human influence depending on the infrastructure /road system, urban area/
- Human influence depending on pasture use /herders' four season location, well, water points/.

2.3.2. Spatial distribution of human influence

In 2002 Sanderson et al produced human footprint through an overlay of a number pf global data layers that represents the location of various factors presumed to exert an influence on ecosystems by overlapping various factors (population distribution, population density, river basin and various agricultural land use). [8]

We have developed the spatial distribution of human influence based on above approach accordingly to Mongolian character. Spatial distribution of human influence's general map developed by giving 0-3 points on selected particular spatial creation of herders' four season location (density), water points, province and soum center, local and state roads (spatial zone created by 2, 4, 10 km). Impacts assessed as following:

0 – not influence
1 – low influence
2 – medium influence
3 – high influence

3. Results

3.1. Study site's NDVI trend and precipitation, 2000-2014

Trend of NDVI: Considering the average value's dynamic of the study site's NDVI between 2000-2014 years, it shows increasing trend within 15 years (Figure 3). However, the dynamic is less with slow movement but higher than many years' mean on given time.

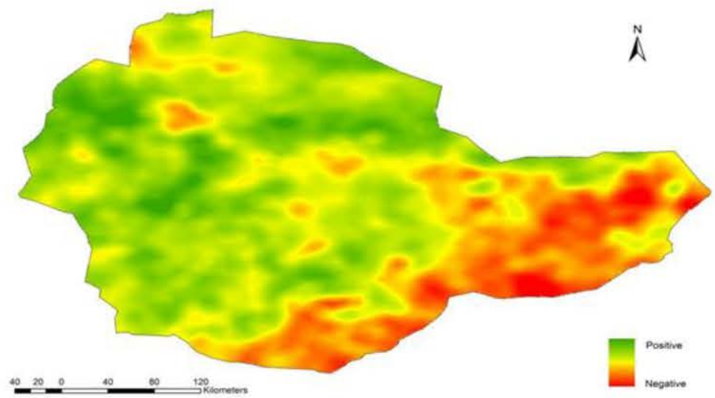
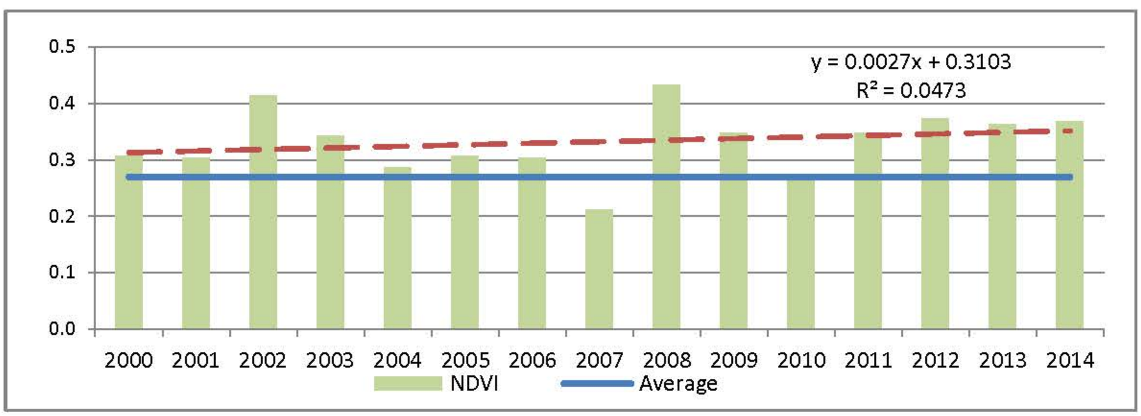


Figure 3. Annual average NDVI (all pixels) over study site, June – August

NDVI trend's spatial distribution estimated using the Pearson correlation coefficient in given time shown below. (Figure 4)

Figure 4. Spatial distribution trend of NDVI, 2000 - 2014



Along the border NDVI trend is negative or decreased while in other parts it increased or with positive trend. The positive/increased trend is 76.62 % where 23.38% is negative/decreased in total of 96842 points.

Trend of precipitation: The total precipitation dynamics in study site indicates the increasing trend with much variation within 15 years (figure 5).

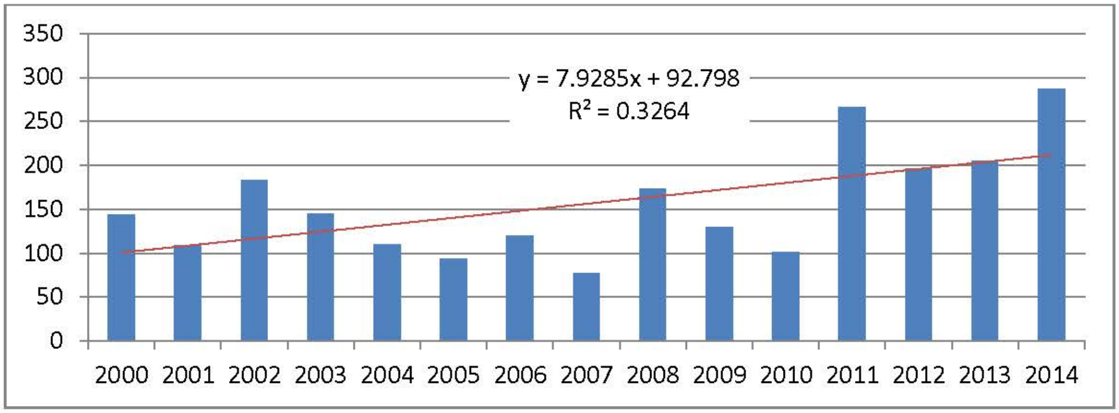


Figure 5. Annual means of total precipitation (June – following August) between 2000 and 2014, in all pixels

Total precipitation trend's spatial distribution unobserved decreased trend, along the border zone slightly but in other area shows highly increased trend. (Figure 6)

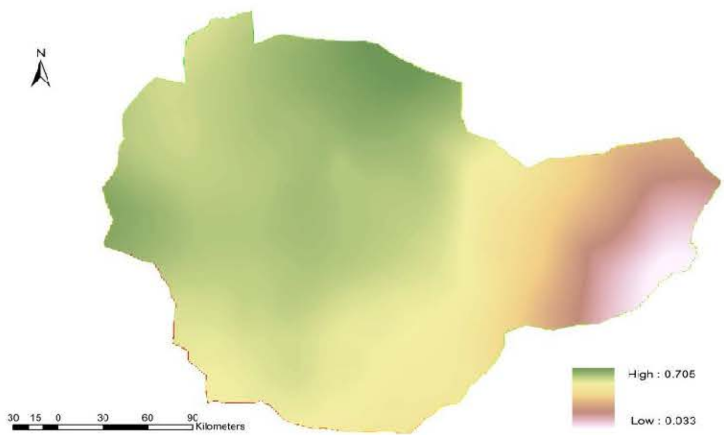


Figure 6. Trend of total precipitation, 2000 - 2014

3.2. **Human influence in NDVI trend**

3.2.1. Human influence depending on infrastructure

NDVI value trend in each spatial zone derived from human influence depending on infrastructure. (Table 1)

Table 1. NDVI trend in spatial zone human influence depending on infrastructure (%)

Spatial zone (км)		**2**	**4**	**10**
State roads		Pixel (%)	Pixel (%)	Pixel (%)
	Increased	95.3	95.2	94.6
	Decreased	0	0	0.9
	Unvaried	4.7	4.8	4.5
Local roads				
	Increased	83.2	82.9	81.8

	Decreased	15.9	16.2	17.4
	Unvaried	0.9	0.9	0.8
Province roads				
	Increased	100	100	100
	Decreased	0	0	0
	Unvaried	0	0	0
Soum roads				
	Increased	95.3	95	95
	Decreased	4.7	5	5
	Unvaried	0	0	0
Totally				
	Increased	92.62	92.14	91.54
	Decreased	4.64	4.6	5.24
	Unvaried	2.74	3.26	3.22

Table 1 indicates more or less value difference's on each spatial distribution. The total spatial distribution's 92.10 % positive, 4.823% decreased and 3.07 % with no difference. NDVI decrease is more or less in state and province roads based on their types. On the contrary, the NDVI decrease had high percentage in local area roads with 15.9-17.4% decrease in certain spatial zone's total pixel.

3.2.2. **Human influenced NDVI trend depending on pasture use**

NDVI value trend in each different spatial zone derived from human influence depending on pasture use or grazing shown below. (Table 2)

Table 2. NDVI trend in spatial zone from human influenced pasture use (%)

Spatial zone (км)		**2**	**4**	**10**
Near the river				
	Increased	73.9	78.4	84.3
	Decreased	24.7	19.6	13.1
	Unvaried	1.5	2	2.6
Near the well and stream				
	Increased	70.3	85.1	88.4
	Decreased	29.7	14.9	11.6
	Unvaried	0	0	0
Winter, winter spring camp				
	Increased	77.4	81.9	80.8
	Decreased	21.8	18	19.2
	Unvaried	0.9	0.1	0
Spring camp				
	Increased	77	83.8	78.8
	Decreased	22.2	16.1	21.2
	Unvaried	0.8	0.1	0

Summer, summer fall camp			
Increased	80.1	83.2	70.4
Decreased	19.3	16.6	29.6
Unvaried	0.6	0.2	0
Fall camp			
Increased	76.9	93.7	83.7
Decreased	22.6	6.1	16.3
Unvaried	0.5	0.2	0
Totally			
Increased	75.9	84.4	81.1
Decreased	23.4	15.2	18.5
Unvaried	0.7	0.4	0.4

Table indicates the spatial zone differences depending on pasture use impact. Herein, the percentage in within 2km decreasing value is higher than the spatial zone value in 4-10km, but the value in 10km spatial zone required more than 4km. Therefore, human impact has effects on vegetation coverage decrease. NDVI trend in spatial zone by human influence depending on pasture use shown 80.45 % positive, 19.03 % decreased, 0.53 % unvaried illustration.

3.2.3. Human influence's spatial distribution

We developed the influence's spatial distribution map integrating the herders' four season location (density), water points, province soum center, local and state road parameters by the human influence spatial zone. (Figure 7)

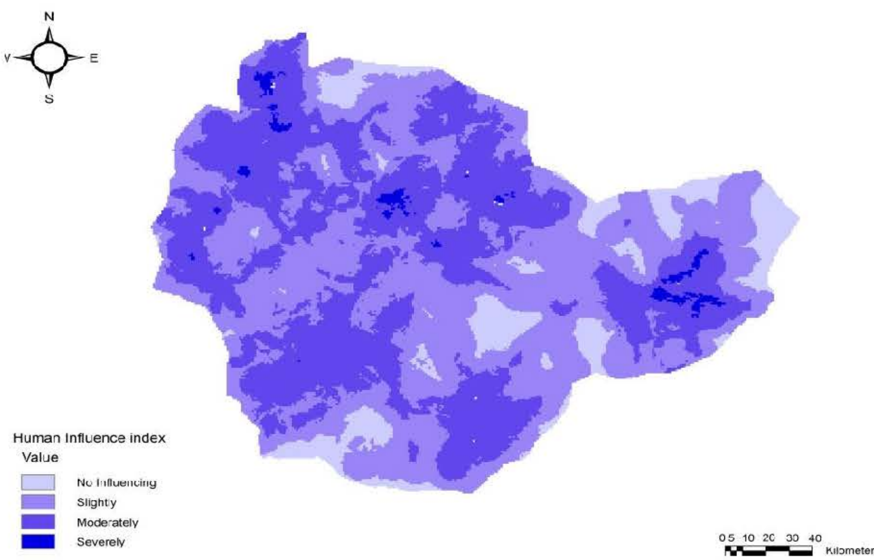


Figure 7. Spatial distribution of human influence

Total area's 10.1 % not impacted, 47.2% slightly, 41.47 % medium and 1.3 % severely impacted. The area with severe impact has the high risk for the land degradation process.

3.3. Accuracy of the study work

The research work aimed to state if the continuing decrease of vegetation biomass is the land degradation indicator then how it affected by comparing climate factors and human factors' spatial distribution. Correlation matrix estimated by spatial distribution and comparison estimation of human influence's spatial distribution, NDVI trend of spatial distribution and total precipitation trend's spatial distribution as well.

CORRELATION MATRIX

Parameter	**1**	**2**
Trend of NDVI	1.00000	0.65737
Trend of precipitation	0.65737	1.00000

Correlation matrix indicates the strong correlation between precipitation distribution and NDVI decrease spatial distribution but, human influenced factor has weak correlation with spatial zone. In other words, if the continuing biomass decreases for years indicating the land degradation then both climate and human impacts has effect too. The weak correlation with human influence approves our previous human influence's spatial distribution estimation meaning severely affected area by human influence has high chance of degradation (1.3 % in severely study site).

4. **Discussion**

- If many years' continuing decrease of NDVI is the land degradation indicator (Lantieri, 2003) then, 23.4% of the study site's NDVI trend decreased, estimated by the Pearson correlation coefficient trend. This means, 23.4% of the study site degraded in more or less level.
- Human influenced NDVI decrease for a long period considering the pasture use activity spatial zone's indicated 18.2 % decrease where 4.83% decrease in infrastructure influenced human impact. Based on this percentage human influence does not exceed their living environment while it maintains their active lives in infrastructure developed areas. In contrast, factory activities are the land degradation factors in an area with weak infrastructure development. NDVI decrease by the human influence type:
  - NDVI decrease indicted near the herders' four season location with 16-22 % in total pixels and 13-29% decrease in water points which means the water utilization is high. Decreasing percentage approves the land degradation is increasing due to the lack of natural pasture restoration with high pressure of animal numbers and lack of water points.
  - State road has not shown NDVI decrease in spatial zone however, in local roads NDVI decreased by 15.9-17.4%. This decrease related with creating new crossroads depending rough road condition in the countryside.
- It made possible to assess the influence for the degradation by integrating the human influence by creating certain spatial zone of human influence factors'. This will potentially help to assess the land use ideally for the countries with pasture animal husbandry practice. The overlaying of the influence in province and soum center are high in Sukhbaatar province's human influence but with small area. Impacted level of the herders' four season location comprises big area. This is not the degradation level it's only the level of potential spatial distribution of human influence in degradation.

- If many years' continuing decrease of NDVI is the land degradation indicator then, the study approved both climate and human influences estimated by the spatial correlation not by the numeral value have impact on land degradation too.
- In Mongolia, land degradation increases by the combined effect of climate and human influence.

Conclusion

The research study complimented the impact of the climate and human influence and how it depends on spatial zone identifying it by spatial distribution. The accuracy of the research study will improve in the further research study if consider to include more years' data.

Acknowledgement

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