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CLIMATE-DRIVEN CHANGES IN VEGETATION DYNAMICS: KHANTAI NURUU, MONGOLIA PERSPECTIVE

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Article Info

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Abstract

Forests play a vital role in maintaining ecological balance and sustaining natural resources, yet the forests of Mongolia, covering 8% of its land area, are facing alarming decline due to an interplay of climate change-induced factors. This study addresses the pressing issue of declining forest cover by investigating the impact of climate change on Mongolia's forest ecosystems, with a focus on the Khantai mountain range. The study employs a multidisciplinary approach, integrating satellite remote sensing, multi-regression analysis, and simulation modeling to comprehensively assess the changes in forest dynamics.

Over the years, climate change-related factors, including droughts, forest fires, pests, and illegal logging, have collectively triggered a substantial reduction in forested areas. The study draws attention to significant events, such as the Khantai Mountains fires in 1990, 1996, and 1998, as well as recent deforestation incidents, which have negatively influenced forest ecosystems and natural resources. Utilizing data from the MODIS satellite, the research leverages long-term net primary production (NPP) and gross primary production (GPP) indicators based on normalized difference vegetation index (NDVI) trends. Remote sensing methodologies are employed to process multi-year data, facilitating the analysis and quantification of changes in vegetation. Incorporating the outcomes of a comprehensive nonlinear regression analysis, the study evaluates the relationship between NDVI and climatic variables, shedding light on how climate fluctuations affect vegetative transformations. The research extends beyond previous studies by encompassing the Khantai mountain range, where a detailed investigation had been lacking. This novel approach incorporates additional parameters, namely the Vegetation Index and soil moisture index, and employs simulation analysis to generate short-term predictions. The findings present a holistic understanding of the intricate interactions between climate change, NDVI fluctuations, and forest dynamics, ultimately contributing to the formulation of informed conservation strategies.

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Introduction

Forests, which cover 8% of Mongolia's territory, are declining year by year due to climate change-related droughts, droughts, intentional and unintentional forest fires, pests, and illegal logging. For example, large-scale fires in the Khantai Mountains in 1990, 1996, and 1998, and large-scale deforestation in recent years, droughts, and forest pests have negatively affected forest ecosystems and natural resources. In 2011, the German International Cooperation Agency (GIZ) estimated that the area covered by forests in northern Mongolia was 9,851.19 thousand hectares in 1999, up from 9,627.93 thousand hectares in 2009 to 223.25 thousand hectares which are a 2.27 thousand hectares % decreased. (GIZ, 2011)

The advantage of this study is to apply the results of a multi-regression analysis to calculate the NPP of NDVI and study how the climate affects changes in the normalized difference vegetation index. Multi-year data were processed by satellite remote sensing to analyze and quantify the data.

MODIS satellite has long-term net primary production (NPP) and gross primary production (GPP) based on long-term changes in vegetation index (NDVI). If remote sensing is planned, the methodology for performing the construction work on satellite data has been studied.

Between 1950 and 2016, a comprehensive analysis of climate change was conducted on the updated NDVI and calculating carbon cycle, which conducted a study on the state of the carbon cycle in Mongolia. (Mart Zaya*1).

Previous studies have been conducted nonlinear regression analysis of NPPs in the regions of Mongolia, but there is no detailed study in the Khantai mountain range. Vegetation Index and soil moisture index was added to this study, and we attempted to make short-term predictions through simulation analysis, which was a novelty of the study.

Study area

The study area is located in Bulgan province (Figure 1), Selenge, Khutag-Undur, and Teshig soum. According to the physical geography of Mongolia, they belong to the Orkhon-Selenge mountain range. Small mountains generally dominate the tops of the mountains with smooth peaks, the highest point of 2171 m above sea level at the top of the Khantai mountain. The forests of the Khantai Mountains belong to the Inner Natural Region and consist of pine, larch, spruce, and birch trees. (Tsogt.Z, 2018)

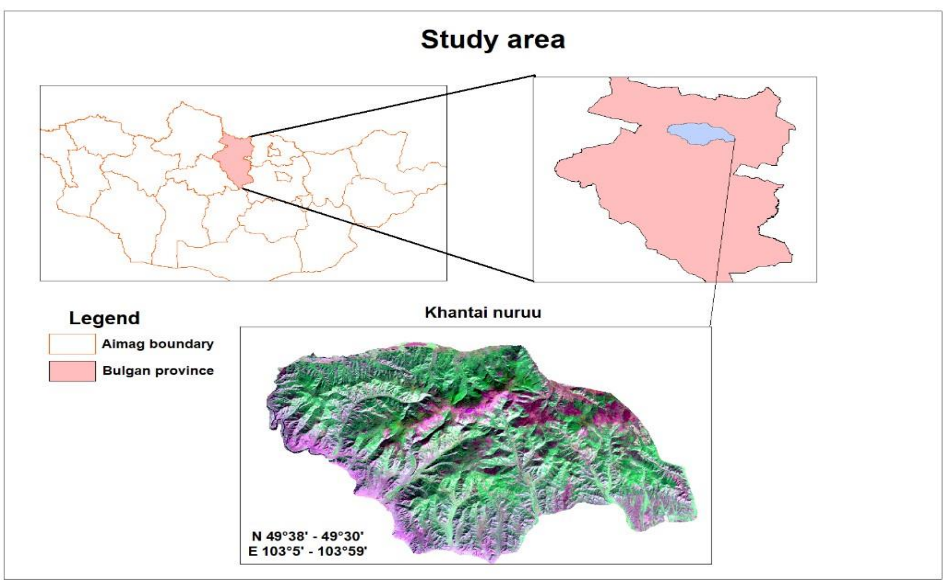

Figure 1. Location of the study area

Data

Several data was applied for this research in order to monitor NPP changes fpor the study are over years 2000-2019.

Climate station and CRU data: Rainfall and air temperature data from the climate station (19892019) is situated in the study area with coordinates (49.75 N and 103.25 E) in Bulgan province that will be used to calculate normalized vegetation difference index and NPP changes. (Harris, 2014) The station's meteorological data are insufficient to estimate the 30-year change.

Therefore, CRUTEM4 satellite data was downloaded in 0.50 grid resolution (KML) format and processed to produce an annual average. Normalized Different Vegetation Index: The MODIS satellite MOD13A3 product is the NDVI data, a spatial resolution is 500 meters, that we applied from April to September 2000-2019. (Didan, 2015)

Net Primary Productivity: The MODIS satellite MOD17A3HGF spatial resolution resampled an annual NPP average of 2000-2019 with an accuracy of 500 meters and compared it with climate data and NDVI data. (Running, 2019)

Methodology

The study was performed using the GIS and Remote Sensing method and regression analysis using several environmental factors.

Multivariate correlation and regression analysis were used in the study which is described by Makhgal.G, 2015:
The connections and dependencies of any natural phenomenon are complex and varied, but they are generally classified as dependent or irrelevant.

- If the co-distribution function of a random vector (X, Y) is equal to the product of the distribution functions for any number x and y, then the variables X and Y are irrelevant.
- Otherwise, they are called dependent variables.

Correlation analysis solves two main problems: measuring the strength of the relationship between random variables and determining the direction of the relationship.
(Makhgal.G, 2015)

The general model of linear regression

$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon$ Formula (1) Linear regression here:

y-dependent variable

x_1, x_2,, x_n are independent variables

β_0, β_1,…, β_n- unknown parameters of the model, ε- model error

The survey was conducted according to the following scheme (Figure 2).

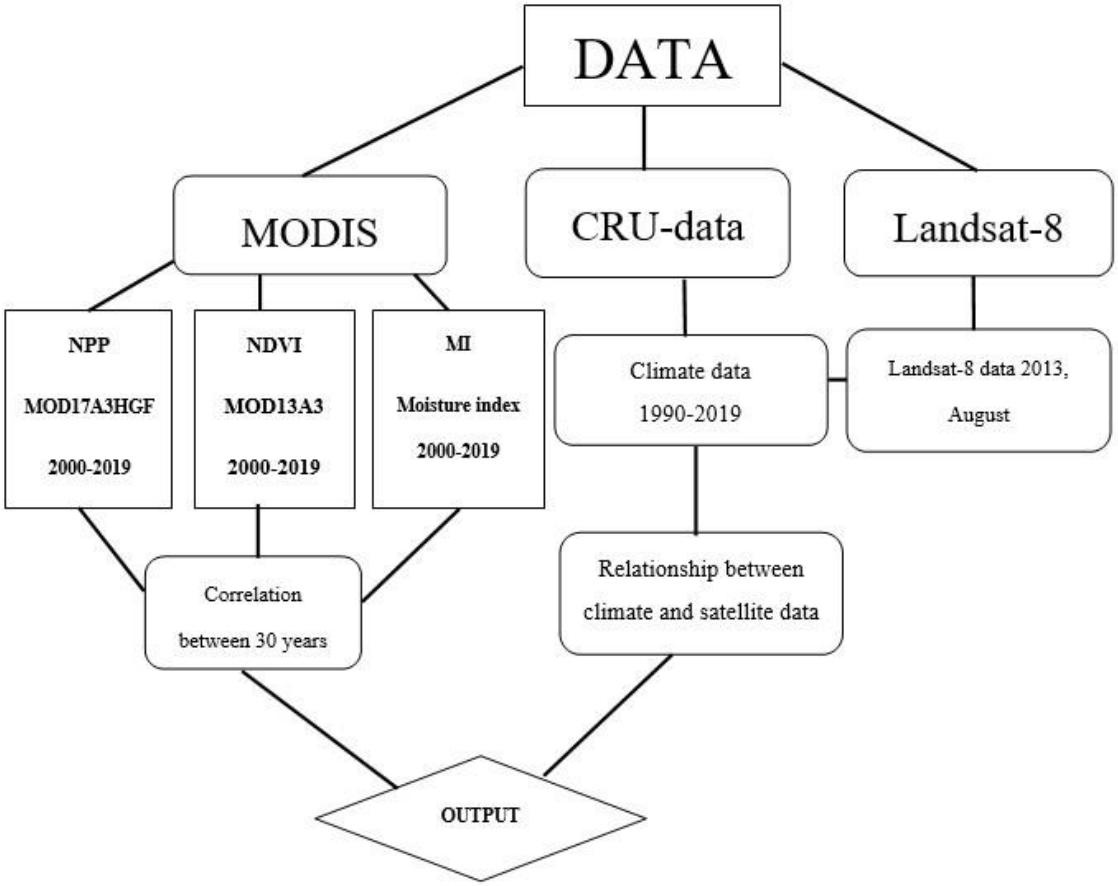

Figure 2. Research methodological scheme

Analysis

In order to find relationship between NPP and environmental factors such as moisture index, vegetation index and climate data we used linear regression model.

The table1 shows the correlations between the factors, such as the MI, NDVI, precipitation and temperature.

	MI	PRE	NDVI	TEMP
NPP	0.6307	0.5465	0.8664	0.2007

Table 1. Correlation matrix

From table-1, there is a strong linear relationship between NPP and NDVI. Therefore, the model was developed based on NDVI-dependent Cobb Douglas-type linear regression analysis of NPP. Output model in the formula 2 were developed using table 2. Figure 3 shows agreement for the theoretical value and NPP values.

$NPP = 0.668764 * NDVI^{1.360107}$ Formula (2)

Regression Statistics	
Multiple R	0.866483
R Square	0.750793
AdjustedRSquare	0.736949
Standard Error	0.057461

	Coefficients	*Standard*	*P-value*
Intercept	-0.40232	0.104307	0.001155
NDVI	1.360107	0.184696	7.81E-07
exp(intr)	0.668764		

Table 2 Output of the model

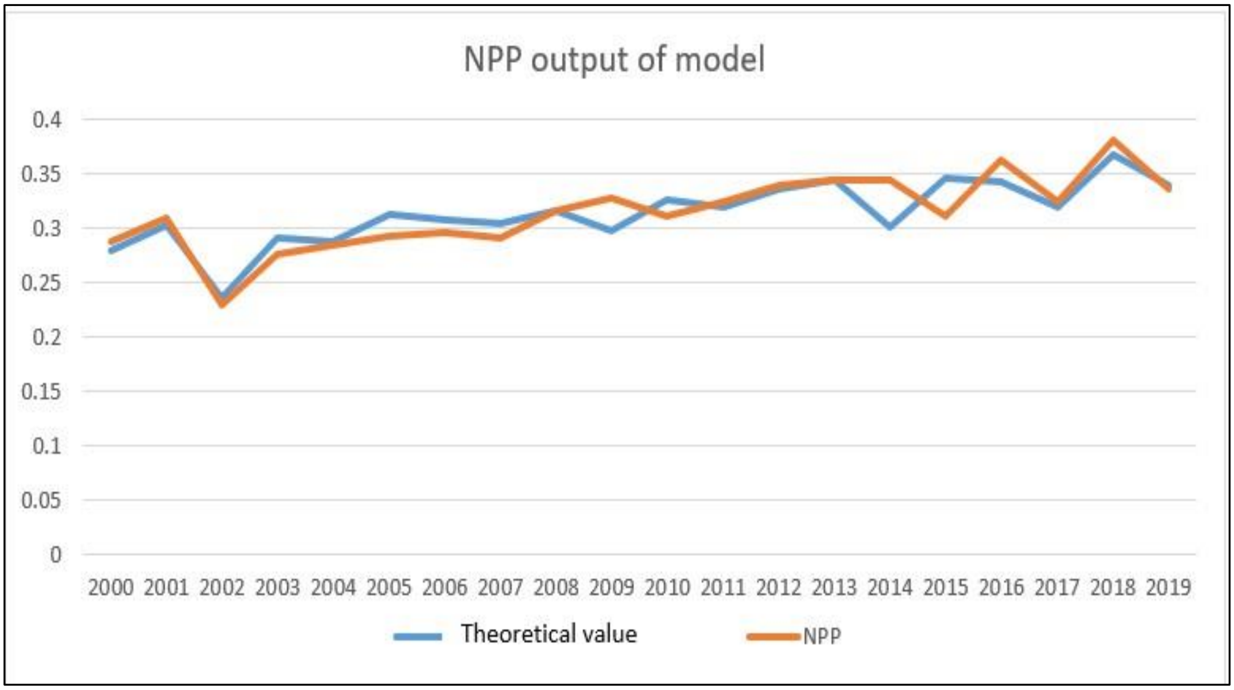

Figure 3. Theoretical value and actual value line plot

NDVI model

While the correlation is high, other factors may be highly correlated.

VIF = 1 means that the variable is orthogonal to other variables.

1 <VIF <5 Weakly related, VIF> 5 Depended (Dependency should be removed at this time) Therefore, to reduce the variable dependence on other variables, a regression analysis was performed on many factors minus the average. (Figure 4).

$$NDVI = 0.017 * TEMP + 0.001 * PRE + 0.016 * TEMP * MI - 0.187MI + 0.173$$

Formula (3)

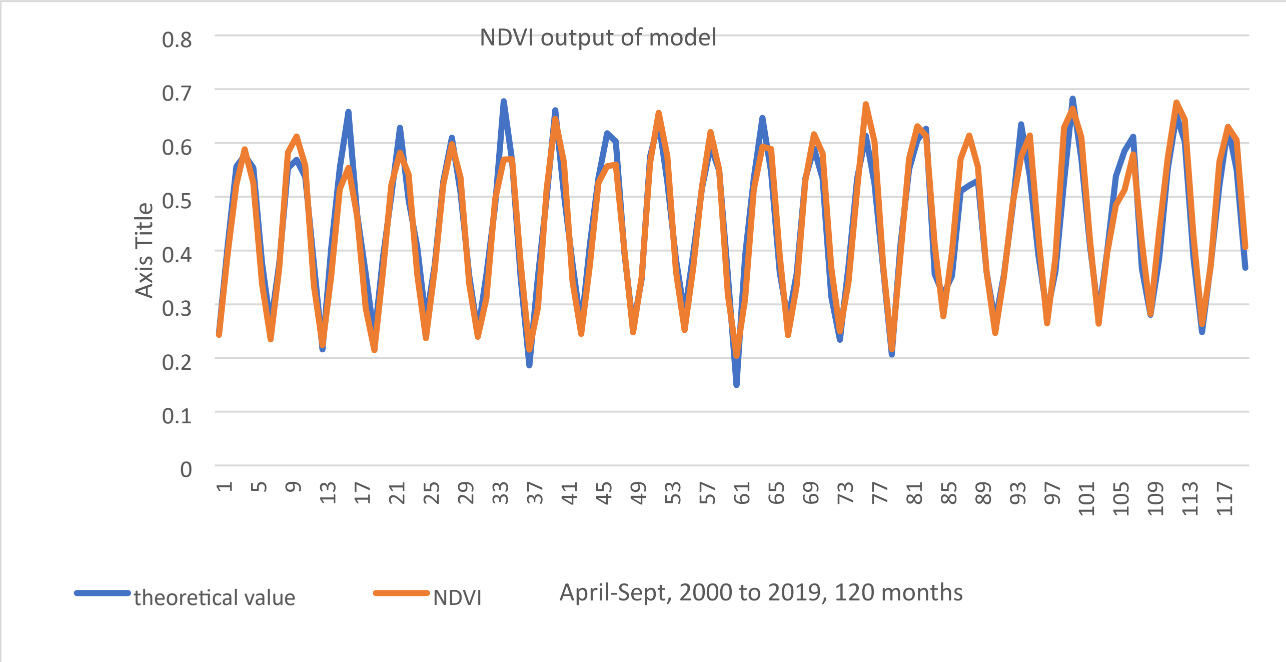

Figure 4. Line plot of the theoretical and actual value of NDVI

Combining the two basic formulas (2) and (3), the NPP can produce monthly values.

Formula5

$$\left\{ \begin{array}{l} NDVI = 0.017 * TEMP + 0.001 * PRE + 0.016 * TEMP * MI - 0.187MI + 0.173 \\ NPP = 0.668 * NDVI^{1.36} \end{array} \right. \quad (4)$$

$$NPP = 0.668(0.017 * TEMP + 0.001 * PRE + 0.016 * TEMP * MI - 0.187 * MI + 0.173)^{1.36}$$

Formula (5)

Using formula 5 we can estimate monthly net primary productivity as shown in figure 5

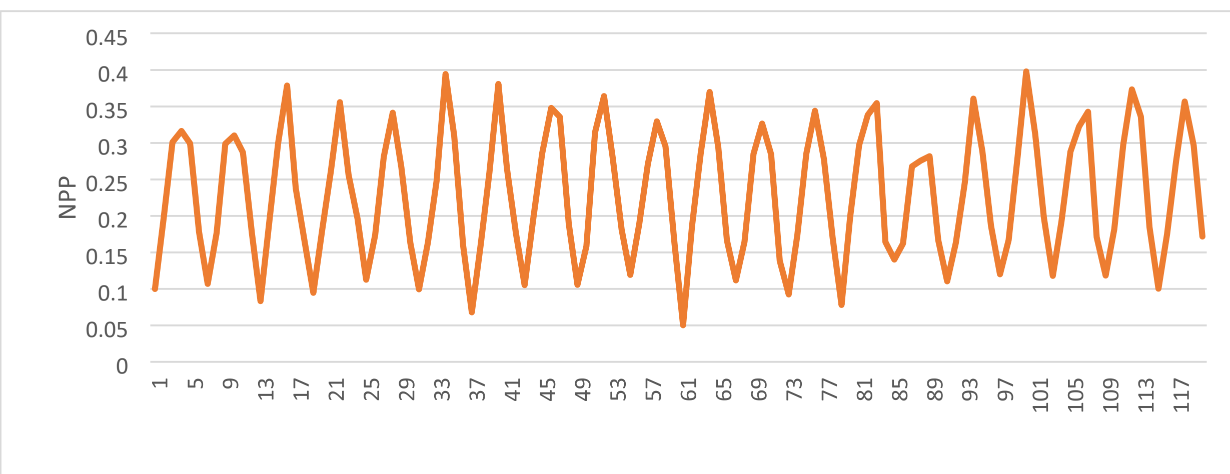

Figure 5. NPP monthly calculation

The annual average values of net primary productivity (NPP) and MODIS satellite data for 2000-2019 were processed and converted to units (g C / m2).

Results and Discussion

In this study, the NPP of NDVI changes in the Khantai Mountains were estimated by multiregression analysis using multiple factors, which is shown in the figure 6-7.

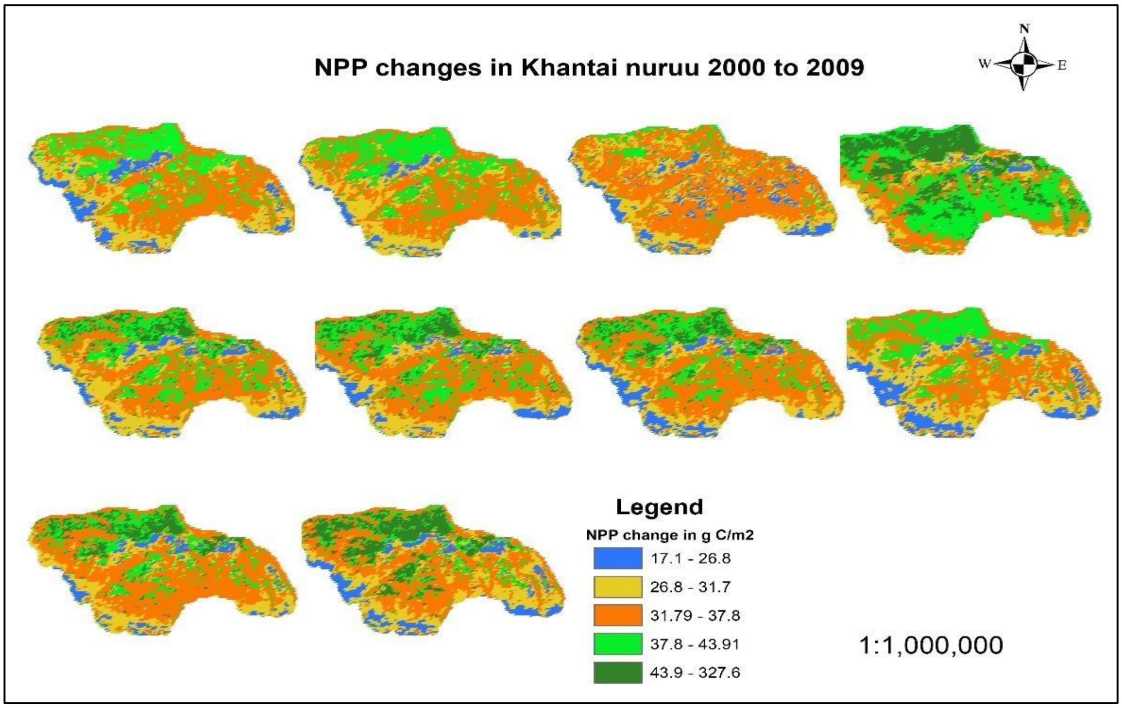

Figure 6.

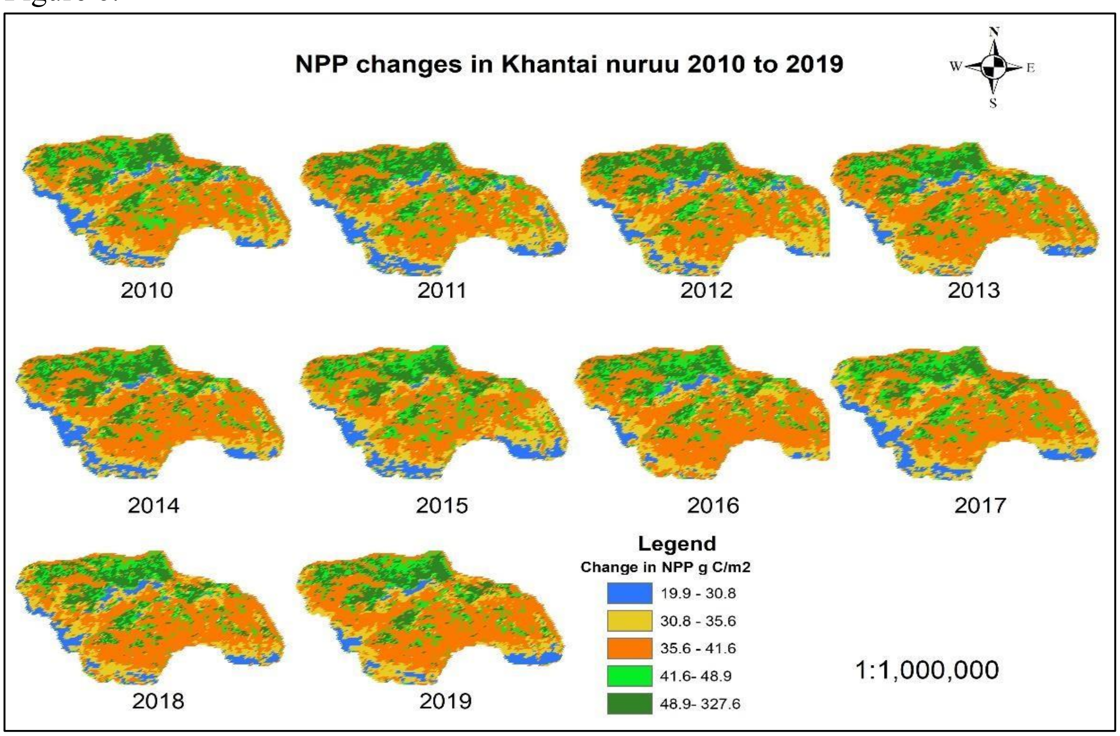

Figure 7.

The area that gives the highest value to the NPP is highlighted in green and the area is highlighted. The highest average values of net primary productivity were in 2003 and 2017, and the lowest values in 2000 and 2010 accounted for a large area.Formula (4) of net primary productivity related to meteorological data (precipitation, NDVI, air temperature) is modeled. As a result of short-term simulations, 0.081837 g/cm3 in April 2020, 0.16318 g/cm3 in May, 0.286011 g/cm3 in June, 0.341833 g/cm3 in July, 0.304491 g/cm3 in August, and 0.183605 g/cm3 in September trends to be. It shows that the maximum capacity is in July and the lowest in April and September. Vegetation index and soil moisture are important factors to estimate NPP in high mountain region.

Acknowledgements

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