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Extending NDVI time series in Mongolia using spatial correlation analysis between AVHRR-GIMMS and MODIS TERRA data

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ABSTRACT
Accurate and long-term monitoring of vegetation dynamics is critical for understanding how ecosystems respond to climate change and human-induced pressures, especially in environmentally sensitive regions like Mongolia. This study examined the relationship between the Normalized Difference Vegetation Index (NDVI) from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the third-generation Global Inventory Modeling and Mapping Studies (GIMMS) dataset to generate an extended NDVI time series for Mongolia. Spatial correlation analysis was performed for the growing season (April to September) from 2002 to 2015, with MODIS NDVI resampled to the 8 km resolution of the GIMMS dataset to ensure comparability. The results revealed a strong correlation between the two datasets, with the coefficient of determination (R^2) ranging from 0.776 to 0.905 and root mean square error (RMSE) values between 0.034 and 0.070. Higher agreement was observed in steppe and forest-steppe regions, while reduced consistency in mountainous and arid areas highlighted challenges in monitoring vegetation in complex or sparsely vegetated environments. The application of the Partial Least Squares Regression (PLSR) model demonstrated that MODIS NDVI could be reliably reconstructed from GIMMS NDVI values. This integration enables the extension of MODIS-like NDVI back to the 1980s, capitalizing on the longer temporal coverage of the GIMMS dataset for comprehensive vegetation monitoring and trend analysis. Overall, the study supports the combined use of MODIS and GIMMS NDVI for robust, long-term ecological assessments and provides a solid foundation for future research focused on cross-sensor harmonization using advanced statistical and machine learning approaches.

KEYWORDS

Vegetation index, Satellite imagery, Partial least squares Regression model, R package

1. INTRODUCTION

Vegetation plays a fundamental role in the global carbon and water cycles, influencing climate regulation, biodiversity, and land productivity [1]. In the context of global climate change and increasing anthropogenic pressure, continuous monitoring of vegetation dynamics is essential for understanding ecosystem responses and guiding sustainable land use policies [2].

The Normalized Difference Vegetation Index (NDVI), derived from satellite remote sensing data, is a widely used indicator to monitor vegetation health, greenness, and temporal trends [3]. NDVI is particularly useful for detecting seasonal and inter-annual changes in vegetation cover and identifying areas affected by drought, land degradation, or restoration [4].

A major limitation in analyzing long-term vegetation trends lies in the inconsistency of NDVI datasets due to differences in sensors, spatial resolutions, and processing methods [5]. The Global Inventory Modeling and Mapping Studies (GIMMS) NDVI dataset provides a long historical record from 1981 to 2015, while Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI offers higher spatial and spectral resolution but covers a shorter time span from 2000 onwards. Mongolia's diverse ecosystems, ranging from deserts to grasslands, are highly sensitive to climatic and human-induced changes. To accurately assess vegetation trends over the past four decades, integrating GIMMS and MODIS NDVI datasets is essential. Spatial correlation analysis offers a methodological approach to align and extend NDVI time series [6].

This study aims to extend the NDVI time series in Mongolia by conducting spatial correlation analysis between GIMMS and MODIS datasets. The specific objective is to create a consistent long-term dataset that can enhance the accuracy of vegetation trend analysis across Mongolia's varied landscapes.

2. STUDY AREA

The entire territory of Mongolia, covering approximately 1,566,000 km², is selected as the study area. Located in the temperate zone of Central Asia, Mongolia ranks as the 18th largest country in the world. It features a diverse landscape that includes snow-capped mountains, forests, steppe, taiga, the Gobi Desert, and cold desert regions. Elevation ranges from 524 to 4,320 meters above sea level, with an average altitude of approximately 1,488 meters (**Figure 1a**).

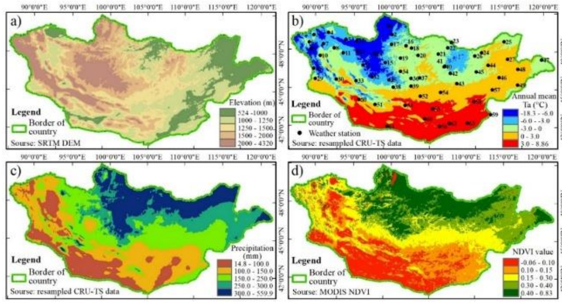

Figure 1. Study area and its natural characteristics: (a) land surface elevation; (b) annual mean air temperature, including the locations of 63 weather stations; (c) mean annual precipitation; and (d) mean NDVI of MODIS for the period 2002–2021

The western, central, and northern regions are predominantly mountainous, while the eastern and southeastern areas consist mainly of plains and depressions. Mongolia experiences a continental arid and temperate climate, characterized by long, harsh winters, short hot summers, and over 70% of days per year being clear. Between 1991 and 2021, annual mean temperatures ranged from -18.26°C to 8.86°C, with colder conditions in mountainous and river valley regions and warmer temperatures in the Gobi Desert (**Figure 1b**). Precipitation is highly seasonal, with approximately 85% occurring during the warm season (April–September) (**Figure 1c**), increasing from south to north and west to east, significantly influencing vegetation density across the country (**Figure 1d**).

3. METHOD AND DATA

3.1. Methods

Partial Least Squares Regression (PLSR) was employed to model the relationship between NDVI of MODIS and GIMMS. PLSR is a multivariate statistical method that reduces predictors to a smaller set of uncorrelated components while maximizing the explained variance in the dependent variables [7]. This technique is particularly suitable when predictor variables are highly collinear or when the number of predictors exceeds the number of observations.

In this study, PLSR was implemented using the "pls" package in the R program. It is an open-source programming language and software environment for statistical computing and graphics, developed by the R Core Team [8]. For the analysis, all variables were standardized (z-score normalization) to ensure comparability across different units. The optimal number of components was determined through leave-one-out cross-validation, based on the minimum Root Mean Square Error (RMSE) of prediction [9]. Model performance was evaluated using coefficients of determination (R^2), RMSE, and variable importance in projection (VIP) scores to identify the most influential predictors.

3.2. Data sources

For the analysis, NDVI data from MODIS TERRA and the third-generation GIMMS (gimmsNDVI3g) were used. GIMMS NDVI, derived from National Oceanic and Atmospheric Administration (NOAA) AVHRR data, has an 8 km spatial resolution and bi-monthly composites, covering 1982–2015 [10]. This study used data from 1982-2015, processed using the "GIMMS" R package [11].

The MODIS aboard National Aeronautics and Space Administration (NASA)'s Terra satellite provides comprehensive NDVI data through the MOD13 series of products. The MOD13Q1 product provides 16-day composite NDVI and Enhanced Vegetation Index (EVI) at a spatial resolution of 250 meters. It is a Level 3 gridded product in a Sinusoidal projection, designed to offer consistent vegetation indices over time. These datasets are instrumental in monitoring vegetation health, land cover dynamics, and ecological changes over time. For th analysis, NDVI of MODIS TERRA Collection 006 datasets for 2002–2021 were used. Data processing—download, mosaic, re-sampling, reprojection, masking, and cropping—was conducted using the "MODIS" R package [12], with data obtained from Land Processes Distributed Active Archive Center (LP DAAC).

4. RESULT

To assess the consistency and continuity between MODIS and GIMMS NDVI datasets, spatial correlation analysis was performed. Pearson correlation coefficients were calculated pixel-wise between the MODIS NDVI (MOD13Q1, 250 m resolution) and GIMMS NDVI (gimmsNDVI3g, 8 km resolution) monthly for the years 2002 to 2015. Prior to analysis, MODIS data were aggregated to match the coarser spatial resolution of GIMMS. This approach enabled the identification of spatial patterns of agreement and the potential for extending long-term NDVI time series using MODIS data.

In Table 1, both datasets show variation in NDVI, with the lowest mean values observed during the April and the highest during the summer growing season (June to August). MODIS NDVI values exhibit higher spatial resolution and slightly greater variability compared to GIMMS, which is reflected in generally higher standard deviations. Notably, peak NDVI values for both datasets occur in July and August, aligning with the peak of the vegetation growing seasons in Mongolia. Despite differences in spatial resolution, the seasonal trends between MODIS and GIMMS NDVI are consistent, supporting their comparability for time-series analysis and validation purposes.

Table 1. Summary statistics of monthly mean MODIS and GIMMS NDVI during the growing season (April to September) from 2002 to 2015

Variables	Minimum	Maximum	Mean	Std. deviation
MODIS NDVI Apr	-0.089	0.713	0.137	0.073
MODIS NDVI May	-0.113	0.763	0.182	0.113
MODIS NDVI Jun	-0.059	0.838	0.259	0.183
MODIS NDVI Jul	-0.052	0.897	0.318	0.223
MODIS NDVI Aug	-0.044	0.850	0.311	0.206
MODIS NDVI Sep	-0.048	0.804	0.238	0.139
GIMMS NDVI Apr	-0.045	0.638	0.109	0.068
GIMMS NDVI May	-0.001	0.681	0.226	0.129
GIMMS NDVI Jun	-0.006	0.879	0.296	0.204
GIMMS NDVI Jul	-0.001	0.922	0.352	0.247
GIMMS NDVI Aug	-0.003	0.897	0.362	0.242
GIMMS NDVI Sep	-0.003	0.769	0.300	0.182

Figure 2 shows the Pearson correlation matrix between monthly mean NDVI values from MODIS and GIMMS datasets during the growing season (April to September) from 2002 to 2015. MODIS NDVI shows strong inter-month correlations (r), especially between adjacent months like June–July (r = 0.98), indicating consistent seasonal vegetation patterns. Similarly, GIMMS and MODIS NDVI values for the same months have high correlations (r=0.91–0.95). Cross-month correlations are slightly weaker but still positive, showing coherence across the growing season. The uniformly strong positive correlations, with no negative values observed. This indicates a high level of agreement between the two datasets in capturing vegetation dynamics.

The PLS regression analysis results are illustrated in Figure 3 and Table 2. This figure displays the growing season (April to September) scatterplots comparing MODIS and GIMMS NDVI values from 2002 to 2015. Each panel corresponds, with MODIS NDVI values plotted on the vertical axis and GIMMS NDVI on the horizontal axis. Linear regression lines are included, along with 95% confidence intervals for both the mean prediction and individual observations. The coefficient of determination (R^2) in each panel indicates the strength of the linear relationship between the datasets. The results reveal a pronounced seasonal pattern in the agreement between MODIS and GIMMS NDVI values.

During the growing season, the datasets show strong correlations, with R^2 values ranging from 0.776 in April to 0.905 in August, demonstrating a high degree of consistency in capturing vegetation dynamics. The figure demonstrates a generally strong linear correlation between the two datasets across all months, indicating their mutual consistency in capturing vegetation dynamics over time. Overall, the results support the reliability and compatibility of MODIS and GIMMS NDVI products for long-term vegetation monitoring, particularly during periods of active plant growth.

Figure 2. Inter-correlations between the monthly mean NDVI values derived from the GIMMS and MODIS datasets during the growing season (April to September) from 2002 to 2015

Table 2. Results of a Partial Least Squares Regression (PLSR) model developed to estimate MODIS NDVI based on GIMMS NDVI during the growing season (April to September) from 2002 to 2015. The model performance is evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and the predictive equations

Month	R^2	RMSE	Formula generated by PLSR model
Apr	0.776	0.034	MODISNDVI04 = 0.034+0.942×GIMMSNDVI04
May	0.803	0.050	MODISNDVI05 = 0.003+0.790×GIMMSNDVI05
Jun	0.879	0.064	MODISNDVI06 = 0.009+0.845×GIMMSNDVI06
Jul	0.901	0.070	MODISNDVI07 = 0.016+0.858×GIMMSNDVI07
Aug	0.905	0.064	MODISNDVI08 = 0.064+0.905×GIMMSNDVI08

Sep	0.897	0.044	MODISNDVI09 = 0.021+0.724×GIMMSNDVI09
Yearly	0.809	0.020	MODISNDVIyr = 0.035+0.704×GIMMSNDVIyr

Figure 4 showed that a spatial correlation between yearly mean NDVI of MODIS and GIMMS across the study region for the period 2002-2015. The color gradient represents the strength and direction of the correlation between MODIS NDVI and GIMMS NDVI. High correlation values indicate strong agreement between the two datasets. This comparison is essential for evaluating data consistency, validating long-term vegetation trends, and identifying areas where the MODIS dataset (with higher spatial resolution) and the GIMMS dataset (with a longer temporal record) diverge. Such analyses are crucial for reliable ecological monitoring and for advancing climate change research.

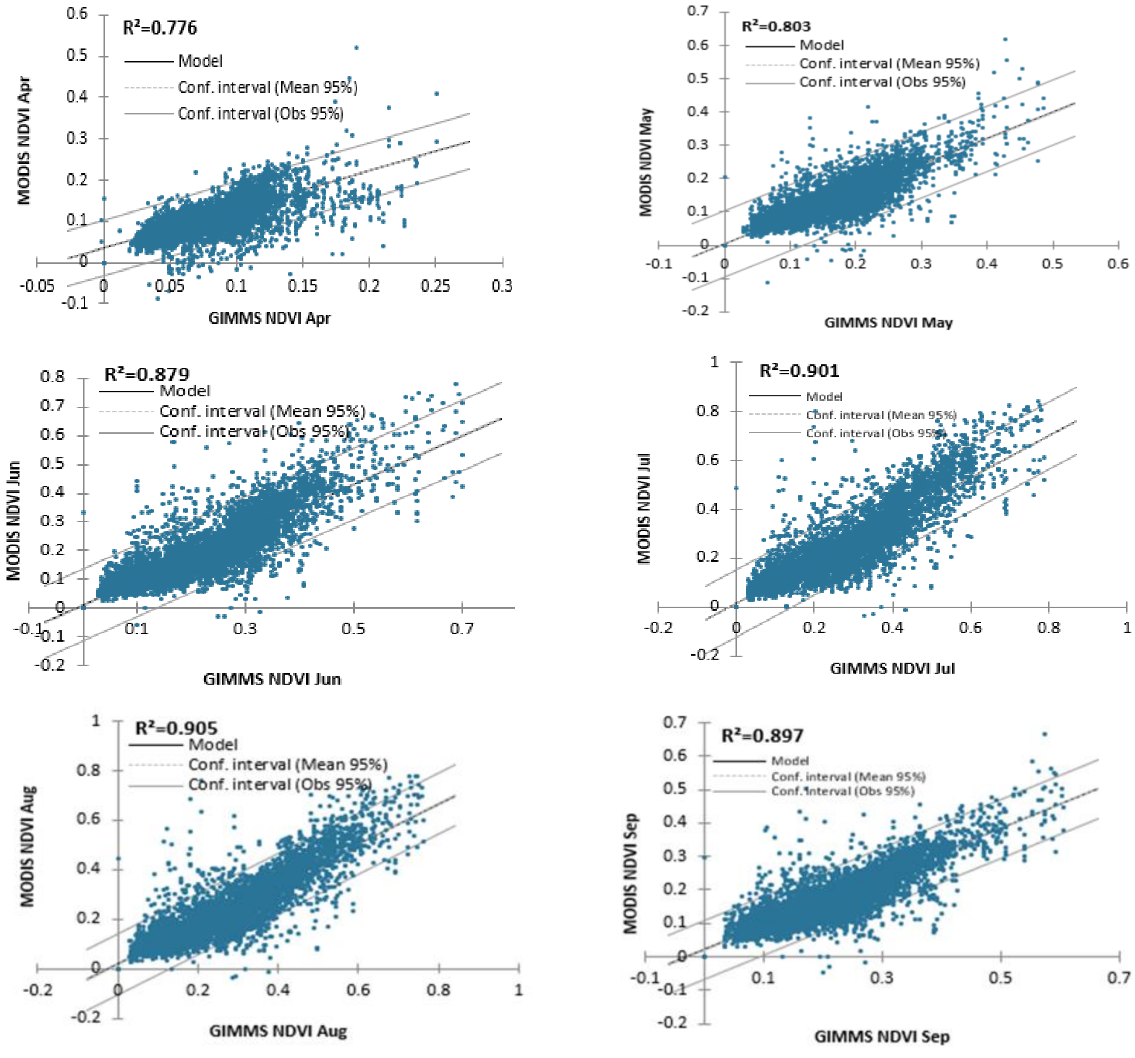

Figure 3. Relationships between the monthly mean NDVI values derived from the GIMMSand MODIS satellite datasets during the growing season (April to September) from 2002 to 2015

5. DISCUSSION

The results demonstrate that the MODIS and GIMMS NDVI datasets can be effectively integrated to support long-term vegetation monitoring in Mongolia. Spatial correlation analysis between NDVI of MODIS and GIMMS revealed strong seasonal coherence, particularly during the active growing season from May to September. These findings are consistent with earlier studies [13-14], which also reported high levels of agreement between NDVI products during periods of peak vegetation productivity.

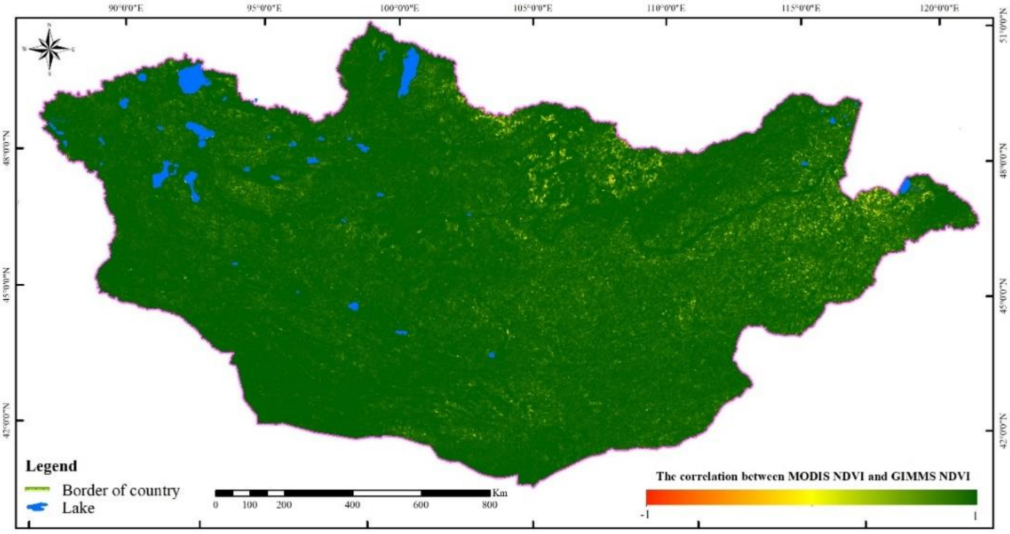

Figure 4. Spatial correlation between yealy mean MODIS and GIMMS NDVI for the period 2002-2015

Our results further corroborate the findings of Pinzon and Tucker [10], who highlighted the reliability of the GIMMS dataset for long-term trend analysis. By aggregating MODIS NDVI data to match the 8 km resolution of GIMMS, we minimized scale-related discrepancies and observed strong agreement during the summer months (e.g., $R^2 = 0.905$ in August), in line with the conclusions of Fensholt and Proud [15], who emphasized MODIS's effectiveness in capturing dense vegetation cover.

Similar seasonal reductions in NDVI reliability have been documented by Huete et al. [16] and Gonsamo et al. [17]. Spatially, high correlation values were observed across much of Mongolia, particularly in steppe and forest-steppe regions. However, lower agreement in arid and mountainous areas suggests the need for cautious interpretation in ecologically complex or sparsely vegetated zones, consistent with findings by Beck et al. [14] and Jiang et al. [18].

Future research should aim to refine cross-sensor calibration methods and incorporate in-situ validation to improve the accuracy of trend analyses. Additionally, the integration of NDVI data with ancillary climate and land-use datasets could further enhance our understanding of vegetation responses to environmental change in Mongolia's dynamic ecosystems.

6. CONCLUSION

This study confirms the feasibility and reliability of integrating NDVI of MODIS and GIMMS to construct a consistent, long-term NDVI time series for monitoring vegetation dynamics in Mongolia. Spatial correlation analysis for the period 2002–2015 revealed strong seasonal coherence between the two datasets, with particularly high agreement during the active growing season from June to August. The strongest correlation was observed in August ($R^2 = 0.905$), indicating the effectiveness of both datasets in capturing peak vegetation productivity.

Spatially, the datasets showed the highest levels of agreement in the steppe and forest-steppe regions, while reduced correlations in arid and mountainous areas underscore the complexity of monitoring vegetation in ecologically diverse or sparsely vegetated landscapes. These results are consistent with prior studies and reinforce the robustness of integrating MODIS and GIMMS NDVI for long-term ecological assessments.

The strong correlation and low errors observed across the growing season months suggest that the PLSR model provides a reliable approach for reconstructing MODIS NDVI values from GIMMS NDVI. This relationship is especially valuable for extending MODIS-like NDVI time series back to the 1980s, leveraging the longer temporal coverage of the GIMMS dataset for long-term vegetation monitoring and trend analysis.

The extended NDVI time series developed through this integration offers a valuable foundation for ecological research, climate change analysis, and sustainable land management in Mongolia. Future research should prioritize improving cross-sensor calibration methods, incorporating ground-based validation, and integrating NDVI with climate and land-use data. Such efforts will enhance our ability to assess vegetation responses to environmental change and support informed ecosystem management in this climatically sensitive region.

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