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Long-Term Sensitivity Analysis of Palmer Drought Severity Index (PDSI) Through Uncertainty and Error Estimation from Plant Productivity and Biophysical Parameters †

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Abstract: Palmer Drought Severity Index (PDSI) is the most effective and well-acknowledged drought severity index that particularly determines the long-term drought conditions over the forest and other terrestrial ecosystems. However, the sensitivity of PDSI has not been explored yet based on productivity (i.e. GPP), biophysical parameters (i.e. biomass- LAI, EVI; greenness content- NDVI), and absorbed solar radiation by plants (i.e. fAPAR) over humid-subtropical forest ecosystem. In this study, the sensitivity of PDSI was analyzed through uncertainty and error estimation modeling from long-term (2015-2019) MODIS GPP and reflectance data using Google Earth Engine (GEE) over a humid-subtropical forest region of Arunachal Pradesh, India. It was experimentally observed that EVI was the most sensitive parameter to PDSI in long-run observation based on low uncertainty (2.39%- 3.01%) and error (0.07-0.12) compared to the other parameters. Besides, EVI had a strong agreement with PDSI compared to GPP, NDVI, LAI, and fAPAR where Pearson's r was ranging from -0.87 to -0.63 except 2015. Hence it is stated that EVI is the simple, effective, and most complementary indicator for assessing PDSI over the forest regions of a tropical ecosystem. This study showed that EVI might be a promising tool for effectively evaluating long-term drought impacts on the forest ecosystem that indicates the actual water deficit induced stress conditions.

Keywords: Palmer Drought Severity Index; Enhanced Vegetation Index; Forest; Tropical Ecosystem; Google Earth Engine; India

1. Introduction

Drought is the dryness condition of the environment that creates ecological stress due to lack of precipitation and shortages in water supply for plant growth. The Palmer Drought Severity Index (PDSI) [1] is one of the most effective, well-acknowledged, and widely used drought severity index that particularly determines the long-term drought conditions over the forest and other terrestrial ecosystems.

The PDSI is based on the demand and supply concept of the water balance model, taking consideration not only precipitation deficit but also includes local temperature and soil moisture anomalies to assess relative dryness [2]. Several studies were already conducted on the application of PDSI, however, the sensitivity of PDSI has not been explored yet based on productivity (i.e. Gross

Primary Productivity or GPP), biophysical parameters (i.e. biomass- Leaf Area Index or LAI, Enhanced Vegetation Index or EVI; greenness content- Normalized Difference Vegetation Index or NDVI), and absorbed solar radiation by the plants (i.e. fraction of Absorbed Solar Radiation or fAPAR) over a humid-subtropical forest ecosystem. It was also observed that most of the existing literatures on drought severity preferred to use productivity, net photosynthesis (GPP, NPP,) [3–12] or NDVI or near-infrared (NIR) based vegetation indices [13–19] for long-term drought condition assessments. Hence, a true sensitivity analysis of all important vegetation parameters like GPP, NDVI, EVI, LAI, fAPAR was necessary to find out the most complimentary and effective PDSI indicator that shows the actual water deficit induced stress conditions over the vegetative areas of a sub-tropical humid ecosystem. In this study, the sensitivity of PDSI was analyzed through uncertainty and error estimation modeling from long-term (2015-2019) MODIS GPP and other reflectance products (NDVI, EVI, LAI) and fAPAR, using open source cloud-computing platform, Google Earth Engine (GEE).

2. Study Area

The study was carried out over the humid-subtropical forest region of Arunachal Pradesh, India, the Indian state that is enriched with the second largest forest cover spreading over 79.63% of the total geographical area of the state [20] (Figure 1). This north-eastern state lies at the eastern Himalayan region of the country coordinated between 26°28′ N to 29°30′ N latitude and 91°30′ E to 97°30′ E longitude, and shares international boundaries with Bhutan in the west, China to the north and north-east, and Myanmar to the east. The climate varies from temperate in the northern part and warm humid in the southern part having annual rainfall ranging between 2000 mm to 8000 mm and the annual temperature from <0°C to 31°C [21].

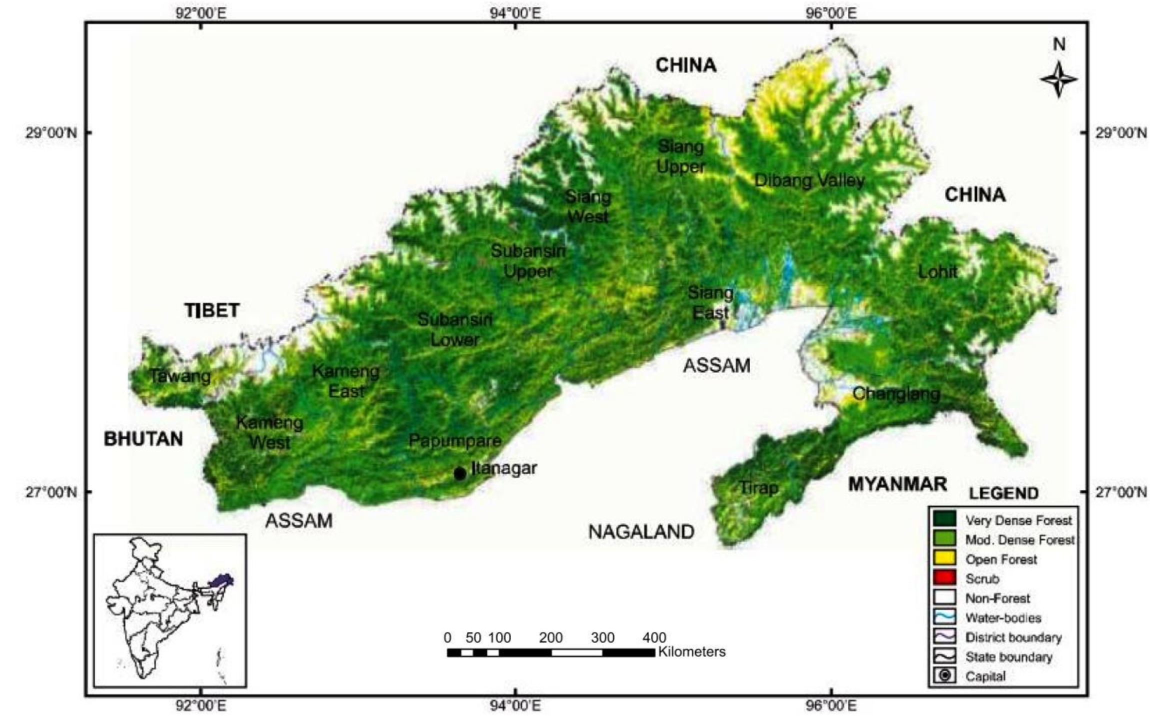

Figure 1. The Forest Cover map of Arunachal Pradesh, India (Source: India State of Forest Report 2019, Forest Survey of India, Ministry of Environment, Forest & Climate Change, Govt. of India).

3. Materials and Methods

3.1. Dataset

The monthly PDSI data (2015-2019) used in this study has been obtained from TerraClimate products that provide monthly climate and climatic water balance for global terrestrial surfaces developed by the University of Idaho, USA [22]. Similarly, long-term (2015-2019) GPP products (MOD17) have been obtained from MODIS Terra sensor with the temporal resolution of 8 days. Other required vegetation parameters such as NDVI (MOD13Q1), EVI (MOD13Q1), LAI (MOD15A2H), fAPAR (MOD15A2H) were also collected from MODIS Terra sensor with the temporal resolution of 16 days and 8 days respectively. The mean monthly products of GPP, NDVI, EVI, LAI, and fAPAR have been developed through cloud computing using GEE platform.

3.2. Methodology

3.2.1. Development of PDSI

PDSI was developed by Palmer in 1965 that uses readily available temperature and precipitation data as well as the locally available water content of the soil to estimate relative dryness. The step-wise retrieval of PDSI has been discussed by Palmer, 1965 [1]. It is a standardized drought index that spans -4 (extremely dry) to +4 (extremely wet). It has been reasonably successful at quantifying long-term drought, as it uses local temperature and rainfall data and a physical water balance model for estimation. It can also capture the basic effect of global warming on drought through changes in potential evapotranspiration. Monthly PDSI values do not capture droughts on time scales less than about 12 months.

3.2.2. Development of Vegetation Parameters

The sensitivity of five most commonly used vegetation parameters (i.e. GPP, NDVI, EVI, LAI, fAPAR) was tested with PDSI to understand the most sensitive parameter in reference to PDSI for long term under tropical or humid-subtropical climatic context. GPP is the rate at which chemical energy (typically expressed as carbon biomass or organic substances) is created by primary producers through capturing solar energy in a given unit of area and time during photosynthesis. GPP is considered as a very useful indicator of drought conditions in terms of productivity as reported by several studies that were mentioned before. LAI and EVI both indicate the biomass condition of vegetations. However, LAI (LAI = leaf area/ground area, m^2/m^2) typically characterizes plant canopies, whereas, EVI is highly responsive to plant physiognomy. EVI also indicates the water balance and atmospheric droughtiness of leaves that are the major eco-physiological parts of a plant that interact with the atmosphere. The formula used for computing EVI is-

$$EVI = G \times \frac{(NIR - RED)}{(NIR + C1 \times RED - C2 \times BLUE + L)} \quad (1)$$

Where, NIR/red/blue are atmospherically-corrected or partially atmosphere corrected (rayleigh and ozone absorption) surface reflectance, L is the canopy background adjustment that addresses non-linear, differential NIR and red radiant transfer through a canopy, and C1, C2 are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. The coefficients adopted in the MODIS-EVI algorithm are; L=1, C1 = 6, C2 = 7.5, and G (gain factor) = 2.5. The NDVI ($NDVI = NIR - RED/NIR + RED$) is a widely used greenness (chlorophyll content) indicator of vegetation, which is often used to assess the water deficit induced stress levels on plants. Lastly, fAPAR is one of the essential climate variables recognized by the UN Global Climate Observing System (GCOS) that has great potential to monitor and assess the drought impacts on vegetation. fAPAR monitors the greenness and health of vegetation by quantifying the fraction of the solar radiation absorbed by alive leaves for the photosynthesis activity.

3.2.3. Data Conversion

As the obtained data were having variations in terms of their temporal resolutions, data standardization was very much necessary for any kind of further analysis. ''naive'' method of conversion [23] was used to convert the NDVI, EVI, LAI, and fAPAR data into their average monthly values that facilitated comparability with the monthly PDSI information.

3.2.4. Statistical Measurements

Sensitivities of all five vegetation parameters were measured individually in respect to PDSI using three different statistical methods- 1. agreement between parameters using Pearson's r 2. error estimation between parameters and 3. uncertainty estimation through Root Mean Squared Error (RMSE). Pearson's r showed the relationship between the response variable (i.e. vegetation parameters) and the explanatory variable (i.e. PDSI), and helped to understand the agreement between response and explanatory variables ranging between -1 (negative agreement) to +1 (positive agreement). Standard Error of the estimate (SEE), derived from Pearson's simple linear regression analysis was used for error estimation between PDSI and the other vegetation parameters, as this statistic allows to construct a confidence interval within which the true population correlation will fall [24]. Hence smaller values indicate better sensitivity. Lastly, the Root Mean Squared Error (RMSE) was used to assess the standard deviation of the prediction errors and to measure the uncertainty between variables. The lower values of RMSE indicate the low uncertainty between variables and vice-versa. Open-source computing (R studio, version: 3.6.1) was used for statistical calculations.

4. Result and Discussion

4.1. Interpretation of Pearson's Correlation Analysis

In Pearson's correlation analysis (Figure 3), EVI showed as the most promising indicator in long term agreement between vegetation parameters and PDSI. Pearson r values for EVI was the highest negatively correlated parameter with PDSI ranging between -0.63 to -0.87 over the years (except 2015) in comparison to NDVI, GPP, LAI, and fAPAR. In 2015, EVI showed a surprisingly higher positive correlation with PDSI (0.50), which could be the result of the massive rainfall situation that hit the state of Arunachal Pradesh during that year [25]. Such a huge amount of rainfall effectively recharged the soil layers which helped the forest region to overcome water deficit conditions. Figure 2 shows the spatio-temporal distribution scenario of PDSI of the region over time (2015-2019).

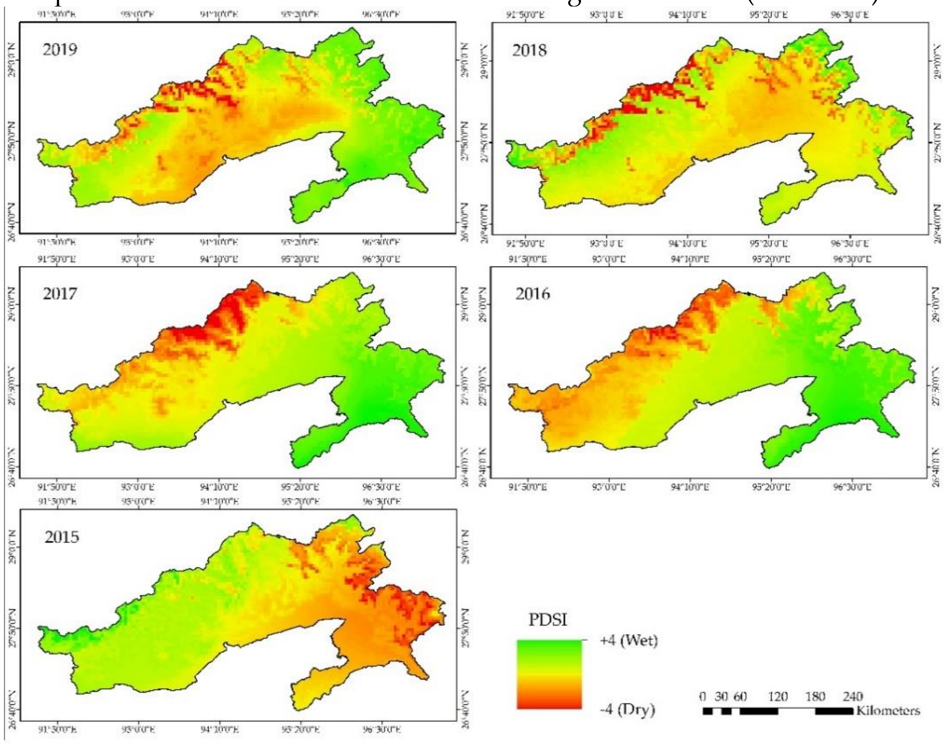

Figure 2. Temporal distribution (2015-2019) of PDSI over Arunachal Pradesh, India. PDSI value -4 represents the dry conditions and +4 represents the wet conditions.

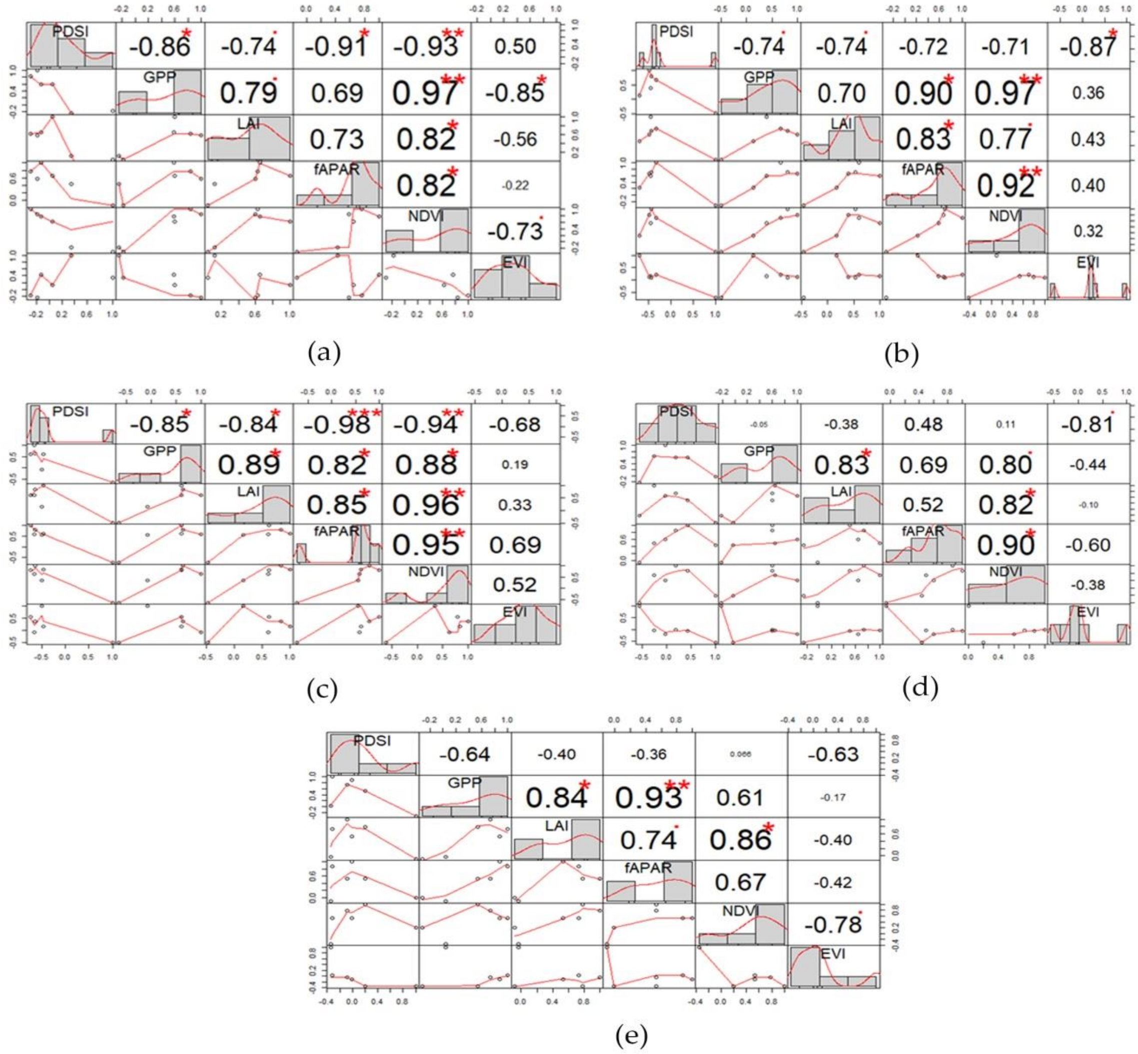

Figure 3. Correlation of the vegetation parameters with PDSI in the year 2015 (a), 2016 (b), 2017 (c), 2018 (d) and 2019 (e).

After EVI, the other vegetation parameters, i.e. LAI, NDVI, GPP, and fAPAR respectively were found to be having high negative agreement with PDSI.

4.2. Interpretation of Error Estimation Analysis

The following table (Table 1) shows the calculated standard error values between PDSI and vegetation parameters during 2015-2019 that were under consideration. The result showed that the estimated error ranged from 70.10 to 105.98 between GPP and PDSI, 11.23 to 18.01 between LAI and PDSI, 9.07 to 18.11 between fAPAR and PDSI, 0.18 to 0.26 between NDVI and PDSI, and 0.07 to 0.12 between EVI and PDSI. EVI continuously managed to show least estimated standard error values for all five years, clearly indicating the highest level of long-term sensitivity compared to the other parameters. The low error values between EVI and PDSI shows the most accurate negative agreement in all five years and also represents better sensitivity in compared to NDVI, LAI, GPP, fAPAR.

Table 1. Calculated Standard Error of the Estimate between PDSI and other vegetation parameters.

YEAR	PDSI-GPP	PDSI-LAI	PDSI- fAPAR	PDSI-NDVI	PDSI-EVI
2019	70.10047	11.23408	16.35537	0.22529	0.07128
2018	85.00281	14.707568	14.64304	0.26018	0.07962
2017	84.30856	14.99181	9.07160	0.18792	0.12114
2016	105.98472	18.01153	18.11280	0.21312	0.07426

2015	97.12000	12.47910	16.85542	0.21665	0.11117

4.3. Interpretation of Uncertainty Analysis

Both EVI and NDVI showed the least uncertainties compared to the other vegetation parameters in respect to PDSI for all five years (Figure 4). The RMSE values for both NDVI and EVI were found to be ranging from 2.39% to 3.01% during 2015-2018, which is overall the lowest among the others. However, in 2019 NDVI showed slightly lesser RMSE values than EVI, but in that year, it was fAPAR that actually showed the optimum sensitive condition to PDSI with a RMSE 1.89%. Overall, The estimated uncertainty (RMSE) between PDSI and EVI, and PDSI and NDVI were found to be 1% - 2% lower compared to the others, showing better sensitivity than the other four vegetation parameters in a long-term context.

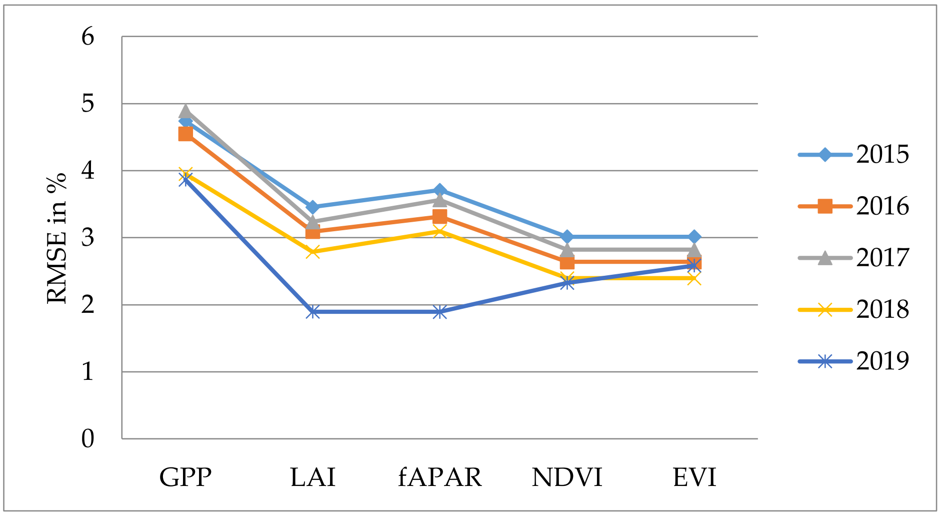

Figure 4. Uncertainty Analysis (RMSE) of vegetation parameters with PDSI.

4.4. Sensitivity Ranking for PDSI

In compilation of the overall statistical analyses such as agreement, error estimation, and uncertainty analysis, it was found that EVI, which indicates the biomass of vegetation ignoring soil background and atmospheric effects, showed the most promising result in terms of long-term sensitivity to PDSI in all five years (Table 2). However, it was also observed that NDVI (greenness indicator) also showed an overall similar result to EVI in uncertainty analysis, and gave values very near to EVI in error estimation analysis. Though NDVI could not outperform EVI in the overall context, but it’s sensitivity remained pretty impressive throughout the analyses, making NDVI the second most sensitive vegetation parameter after EVI as per the study. Table 2 shows the best performances of vegetation parameters in all three statistical analyses. Detailed results of the three statistical analyses are provided in Appendix (See Table A1).

Table 2. Compilation of the outcomes of correlation, error estimation, and uncertainty analysis.

Analysis	Overall most sensitive parameters
Pearson’s Correlation	EVI
Error Estimation	EVI
Uncertainty	NDVI, EVI

6. Conclusion

Based on the long-term analysis from this experimental study over the sub-tropical forest region of the Arunachal Pradesh state of India, it was observed that EVI was the most sensitive parameter to PDSI in a long-term observation based on promising correlation, low uncertainty, and low error, where most of the existing studies on drought severity showed a high sensitivity of GPP and NDVI in determining drought conditions. It is therefore stated that EVI is the simple, effective, and most complementary indicator (among vegetation parameters) for assessing PDSI over forest regions of a tropical ecosystem. Besides, EVI can also be used as a promising tool for effective evaluation of the long-term drought impacts on forest ecosystem that indicates the actual water deficit induced stress conditions. In other words, EVI can also act as a direct proxy of the actual drought condition of the region. Similarly, after EVI, NDVI can be considered as the next promising sensitive indicator that is highly responsive to PDSI. In future studies, more advanced vegetation parameters like Sun-induced fluorescence or SIF [26] can be added for PDSI based drought monitoring. The authors assumed that this study will support sustainable forest management practices and drought monitoring under climate change scenarios for tropical ecosystems.

Author Contributions: conceptualization, S.B.; methodology, S.B. and S.G.; software, S.B., S.G. and D.S.; validation, S.B., S.G. and D.S.; formal analysis, S.B. and S.G.; investigation, S.B., S.G. and D.S.; resources, S.B. and S.G.; data curation, S.B. and S.G.; writing—original draft preparation, S.G.; writing—review and editing, S.B. and D.S.; visualization, S.B. and S.G.; project administration, S.B.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix

Table 1. Statistical Outcomes 2015-2019**.**

Parameters	*2015*			*2016*			*2017*			*2018*			*2019*		
	r	SEE	RMSE (%)	r	SEE	RMSE (%)	r	SEE	RMSE (%)	r	SEE	RMSE (%)	r	SEE	RMSE (%)
GPP	-0.86	97.12	4.73	-0.74	105.98	4.55	-0.85	84.3	4.89	-0.05	85	3.95	-0.64	70.1	3.86
LAI	-0.74	12.47	3.45	-0.74	18.01	3.09	-0.84	14.99	3.23	-0.38	14.7	2.79	-0.4	11.23	1.89
fAPAR	-0.91	16.85	3.7	-0.72	18.11	3.31	-0.98	9.07	3.56	0.48	14.64	3.09	-0.36	16.35	1.89
NDVI	-0.93	0.21	3.01	-0.71	0.21	2.63	-0.94	0.18	2.82	0.11	0.26	2.39	0.066	0.22	2.32
EVI	0.5	0.11	3.01	-0.87	0.07	2.63	-0.68	0.12	2.82	-0.81	0.07	2.39	-0.63	0.07	2.58

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