

Proceeding Paper

# Long-Term Sensitivity Analysis of Palmer Drought Severity Index (PDSI) through Uncertainty and Error Estimation from Plant Productivity and Biophysical Parameters <sup>†</sup>

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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., Gross Primary Productivity (GPP)), biophysical parameters (i.e., biomass—Leaf Area Index (LAI) and Enhanced Vegetation Index (EVI) and greenness content—Normalized Difference Vegetation Index (NDVI)), and absorbed solar radiation by plants (i.e., fraction of Absorbed Solar Radiation (fAPAR)) over a humid-subtropical forest ecosystem. In this study, the sensitivity of the 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 the PDSI in long-run observation based on a 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 the Pearson's *r* ranged from –0.87 to –0.63, except 2015. Hence, it is stated that EVI is the simple, effective, and most complementary indicator for assessing the 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

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## 1. Introduction

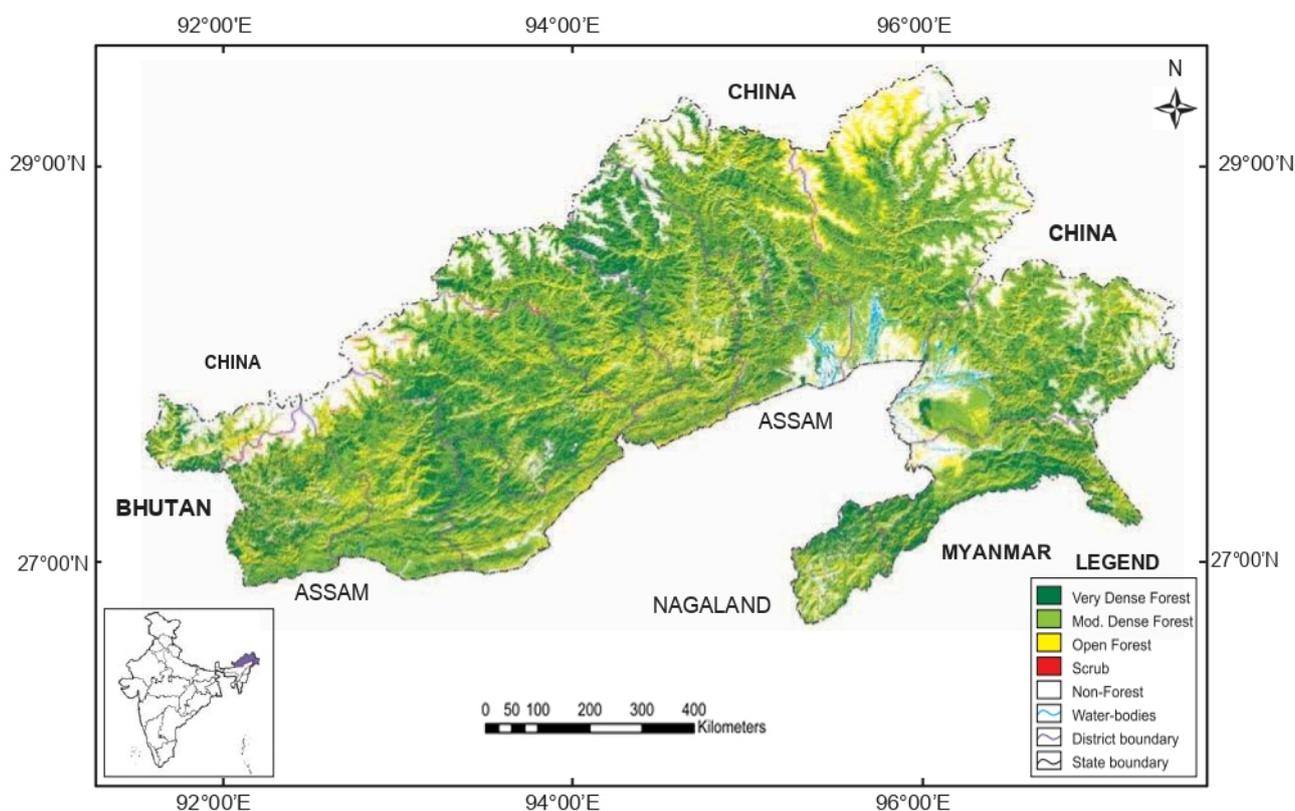
Drought is the dryness condition of the environment that creates ecological stress due to lack of precipitation and shortages in water supply for plant growth. The Palmer Drought Severity Index (PDSI) [1] is one of the most effective, well-acknowledged, and widely used drought severity index that particularly 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 the PDSI; however, the sensitivity of the 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 and Enhanced Vegetation Index or EVI and 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 (Gross Primary Productivity and Net Primary Productivity) [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, and 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 subtropical 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, and LAI) and fAPAR using the 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 northeast, 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 annual temperatures from <0 °C to 31 °C [20].



**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 was obtained from Terra-Climat products that provide monthly climate and climatic water balances for global terrestrial surfaces developed by the University of Idaho, USA [21]. Similarly, long-term (2015–2019) GPP products (MOD17) were obtained from a Moderate Resolution Imaging Spectroradiometer (MODIS) Terra sensor with the temporal resolution of 8 days. Other required vegetation parameters such as NDVI (MOD13Q1), EVI (MOD13Q1), LAI (MOD15A2H), and fAPAR (MOD15A2H) were also collected from the MODIS Terra sensor with the temporal resolutions of 16 days and 8 days respectively. The mean monthly products of GPP, NDVI, EVI, LAI, and fAPAR were developed through cloud computing using the GEE platform.

#### 3.2. Methodology

##### 3.2.1. Development of PDSI

PDSI was developed by Palmer in 1965 and uses readily available temperature and precipitation data, as well as the locally available water content of the soil, to estimate the relative dryness. The step-wise retrieval of PDSI was 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 the five most commonly used vegetation parameters (i.e., GPP, NDVI, EVI, LAI, and fAPAR) was tested with PDSI to understand the most sensitive parameter in reference to PDSI for the long term under tropical or humid-subtropical climatic contexts. 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 droughts 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 nonlinear, differential NIR and red radiant transfer through a canopy, and C1 and 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 in 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 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 varied in terms of their temporal resolutions, data standardization was very much necessary for any kind of further analysis. “Naive” method of conversion [22] 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 the PDSI and the other vegetation parameters, as this statistic allows to construct a confidence interval within which the true population correlation will fall [23]. 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 indicated the low uncertainty between variables and vice versa. Open-source computing (R studio, version: 3.6.1) was used for statistical calculations.

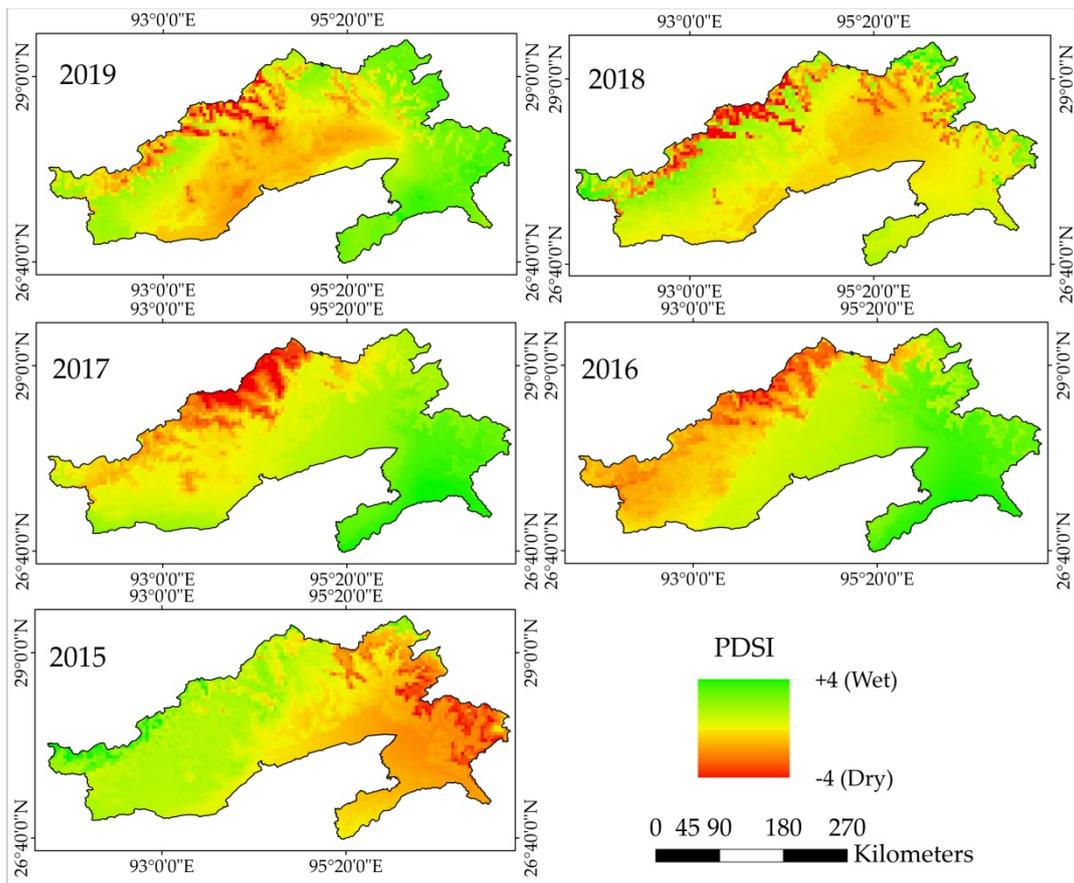
## 4. Result and Discussion

### 4.1. Interpretation of Pearson’s Correlation Analysis

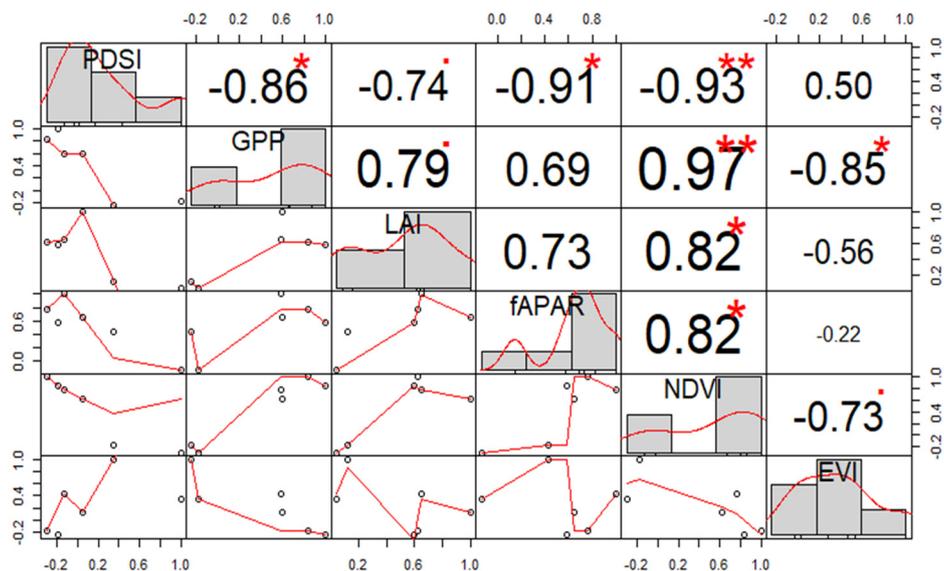
Figure 2 shows the spatiotemporal distribution of PDSI on the study region over time (2015–2019).

In Pearson’s correlation analysis (Figure 3), EVI showed as the most promising indicator in the long-term agreement between vegetation parameters and PDSI. Pearson  $r$  values for EVI was the highest negatively correlated parameter, with the 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 [24]. Such a huge amount of rainfall effectively recharged the soil layers, which helped the forest region to overcome the water deficit conditions.

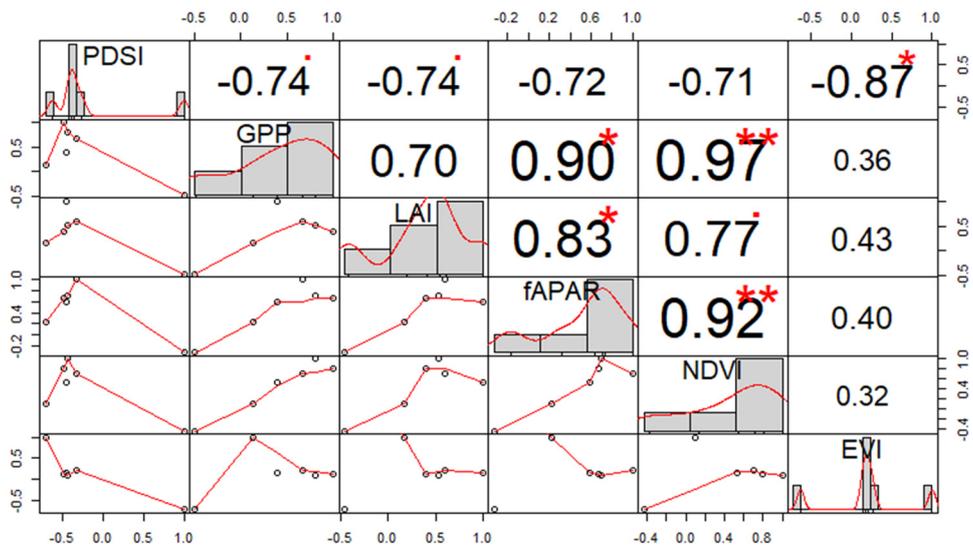
After EVI, the other vegetation parameters, i.e., LAI, NDVI, GPP, and fAPAR, respectively, were found to have high negative agreement with the PDSI.



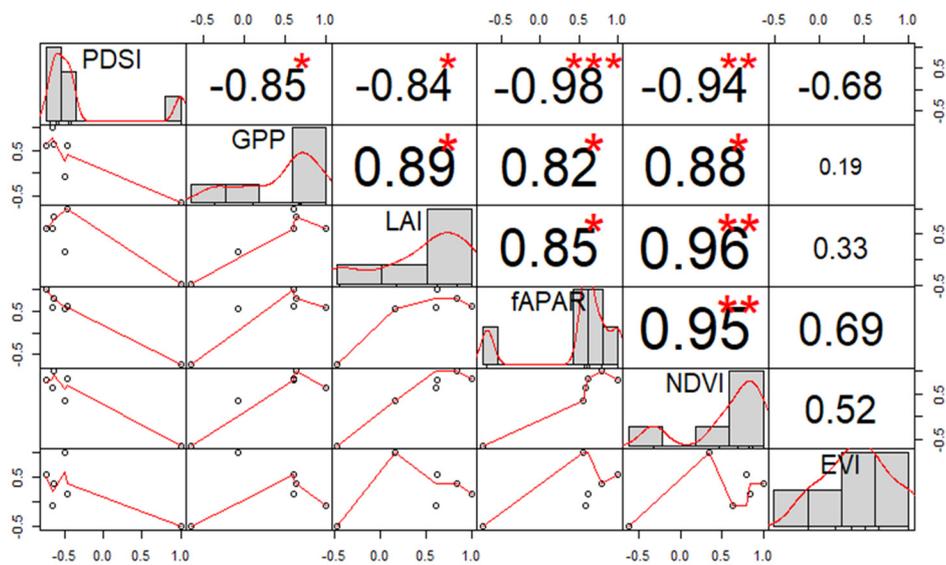
**Figure 2.** Temporal distribution (2015–2019) of the Palmer Drought Severity Index (PDSI) over Arunachal Pradesh, India. PDSI value  $-4$  represents the dry conditions, and  $+4$  represents the wet conditions.



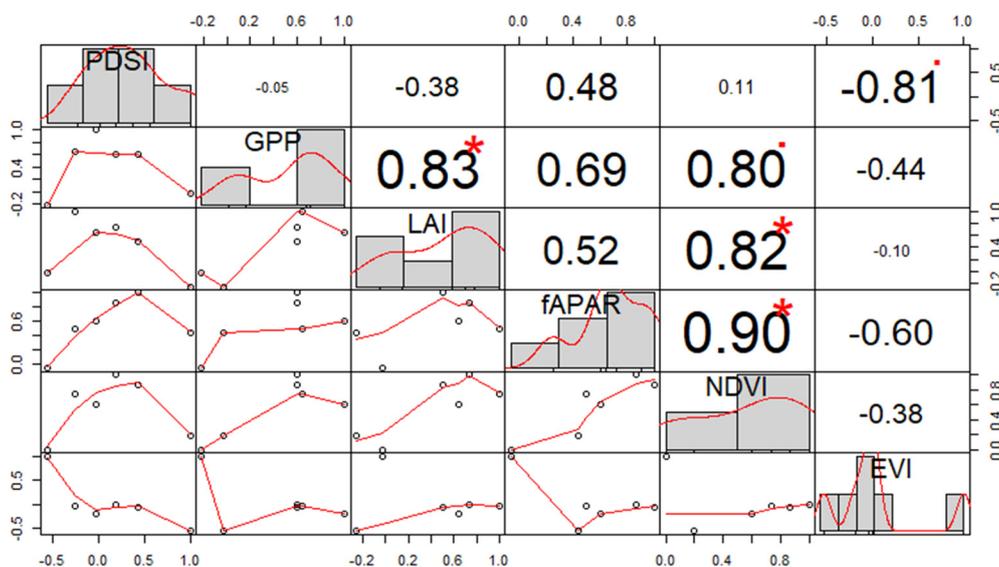
(a)



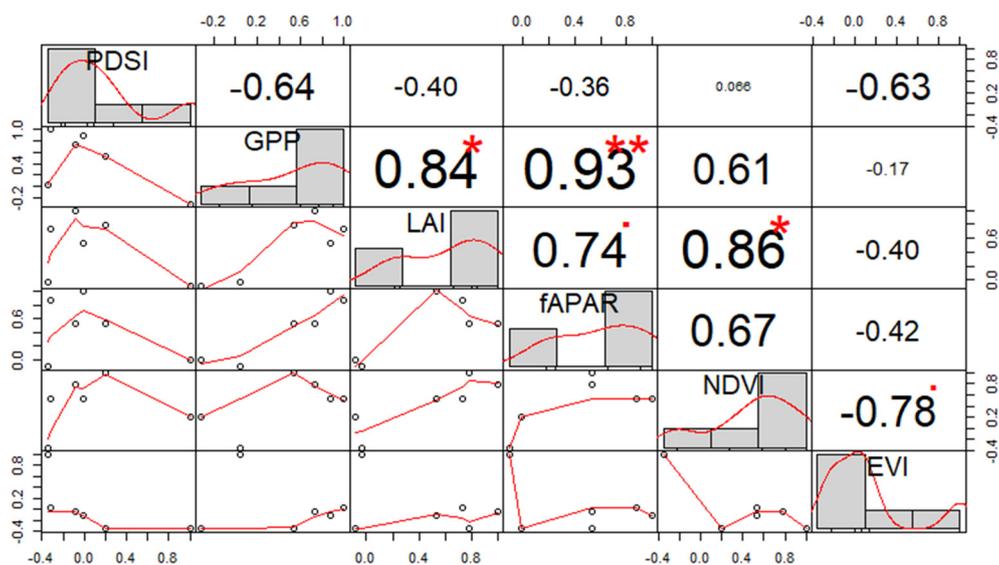
(b)



(c)



(d)



(e)

**Figure 3.** Correlation of the vegetation parameters with the PDSI in the years 2015 (a), 2016 (b), 2017 (c), 2018 (d), and 2019 (e). Significance codes 0 '\*\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 '' 1.

#### 4.2. Interpretation of Error Estimation Analysis

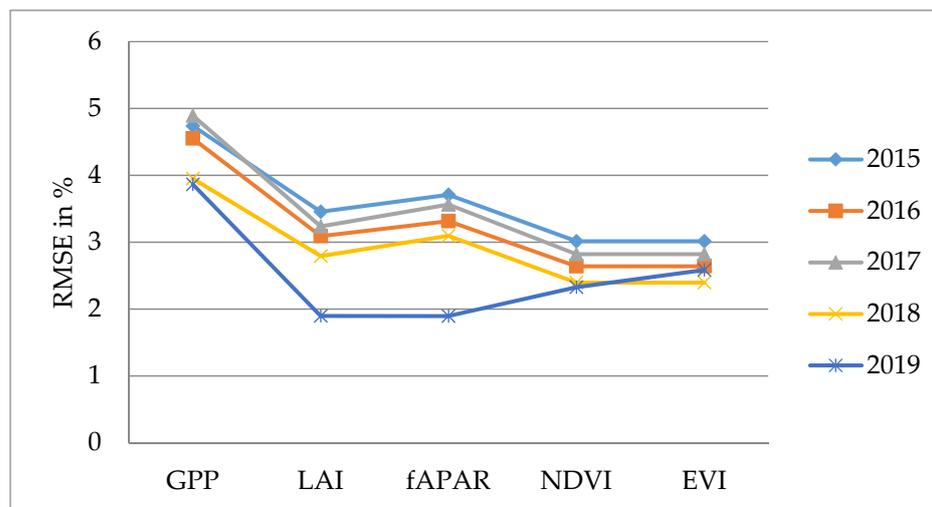
The following table (Table 1) shows the calculated standard error values between the PDSI and vegetation parameters during 2015–2019 that were under consideration. The results showed that the estimated errors ranged from 70.10 to 105.98 between GPP and PDSI, 11.23 to 18.01 between LAI and PDSI, 9.07 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 the 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 showed the most accurate negative agreement in all five years and, also, better represented the sensitivity compared to the NDVI, LAI, GPP, and fAPAR.

**Table 1.** Calculated Standard Error of the Estimate between the Palmer Drought Severity Index (PDSI) and other vegetation parameters. GPP: Gross Primary Productivity, LAI: Leaf Area Index, fAPAR: fraction of absorbed Solar Radiation, NDVI Normalized Difference Vegetation Index, and EVI: Enhanced Vegetation Index.

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



**Figure 4.** Uncertainty analysis (Root Mean Squared Error (RMSE)) of the vegetation parameters with the PDSI. GPP: Gross Primary Productivity, LAI: Leaf Area Index, fAPAR: fraction of absorbed Solar Radiation, NDVI Normalized Difference Vegetation Index, and EVI: Enhanced Vegetation Index.

#### 4.4. Sensitivity Ranking for the PDSI

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

tistical analyses. Detailed results of the three statistical analyses are provided in the Appendix (See Table A1 of Appendix A).

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

Analysis	Overall Most Sensitive Parameters
Pearson’s Correlation	EVI
Error Estimation	EVI
Uncertainty	NDVI, EVI

### 5. Conclusions

Based on the long-term analysis from this experimental study over the subtropical forest region of the Arunachal Pradesh state of India, it was observed that the EVI was the most sensitive parameter to the 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 the EVI is the simple, effective, and most complementary indicator (among the vegetation parameters) for assessing the PDSI over forest regions of a tropical ecosystem. Besides, the EVI can also be used as a promising tool for the effective evaluation of long-term drought impacts on a forest ecosystem that indicates actual water deficit-induced stress conditions. In other words, the EVI can also act as a direct proxy of the actual drought conditions of the region. Similarly, after the EVI, the NDVI can be considered as the next promising sensitive indicator that is highly responsive to the PDSI. In future studies, more advanced vegetation parameters like Sun-induced fluorescence or SIF [25] 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.A.C.S.; validation, S.B., S.G., and D.A.C.S.; formal analysis, S.B. and S.G.; investigation, S.B., S.G., and D.A.C.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.A.C.S.; visualization, S.B. and S.G.; and project administration, S.B. All authors have read and agreed to the published version of the manuscript.

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**Data Availability Statement:** Derived data supporting the findings of this study are available from the corresponding author [SG/SB] on request.

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**Conflicts of Interest:** The authors declare no conflicts of interest.

### Appendix A

**Table A1.** Statistical outcomes of 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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