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

Subhasis Ghosh^{1*}, Subhajit Bandopadhyay² and Dany A. Cotrina Sánchez³

¹Department of Geography; Visva-Bharati University, Santiniketan, West Bengal, India; ²Department of Ecology and Environmental Protection; Poznan University of Life Sciences; Piatkowska 94; 60-649 Poznan; Poland;

³ Instituto de Investigación para el Desarrollo Sustentable de Ceja de Selva (INDES-CES) de la Universidad Nacional Toribio Rodríguez de Mendoza de Amazonas; Perú;

*Presented by: Subhasis Ghosh

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What is drought?

- 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.
- Hence, vegetative condition is an ideal indicator of the level of atmospheric droughtiness.



Drought Condition

Regular Condition

vegetation condition



What is PDSI?

- The Palmer Drought Severity Index (PDSI) 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.
- The index was developed by Wayne 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.
- This standardized drought index that generally spans -10 (extremely dry) to +10 (extremely wet), however maps of operational agencies like NOAA typically show a range of -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.
- PDSI does not consider human impacts on the water balance, such as irrigation.



What is the need for this study?

- Several studies were already conducted on the application of PDSI, however, the sensitivity of PDSI has not been explored yet over a humid-subtropical forest ecosystem based on-
 - 1. Productivity (i.e. Gross Primary Productivity or GPP)

2. Biophysical parameters (i.e. biomass- Leaf Area Index or LAI, Enhanced Vegetation Index or EVI; greenness content- Normalized Difference Vegetation Index or NDVI),

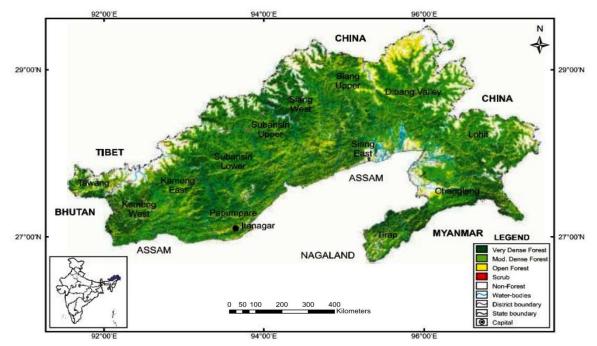
3. Absorbed solar radiation by the plants (i.e. fraction of Absorbed Solar Radiation or fAPAR)

- It was also observed that most of the existing literatures on drought severity preferred to use productivity, net photosynthesis (GPP, NPP) [1-6] or NDVI or Near-Infrared (NIR) based vegetation indices [7-12] for long-term drought condition assessments without testing the other vegetation parameters.
- 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.



Study Area

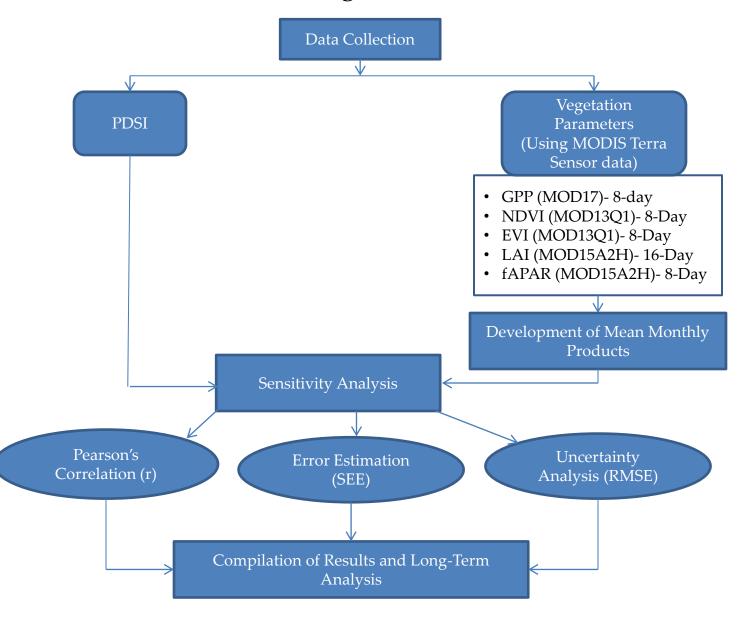
- The study was carried out over the humid-subtropical forest region of Arunachal Pradesh, India.
- The study area is enriched with the second largest forest cover spreading over 79.63% of the total geographical area of the state.
- This north-eastern state lies at the eastern Himalayan region of the 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.



Source: India State of Forest Report 2019, Forest Survey of India, Ministry of Environment, Forest & Climate Change, Govt. of India



Methodological Framework

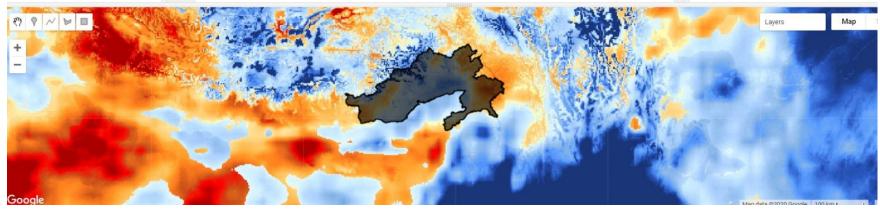




Extraction of PDSI Information

The monthly PDSI data for the year 2015-2019 has been obtained from the TerraClimate products developed by the University of Idaho, USA using Google Earth Engine that provide monthly climate and climatic water balance for global terrestrial surfaces.







Development of Vegetation Parameters

- Gross Primary Productivity or 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.
- LAI (LAI = leaf area / ground area, m^2 / m^2) typically characterizes plant canopies.
- EVI is highly responsive to plant physiognomy. EVI also indicates the water balance and atmospheric doughtiness of leaves that are the major eco-physiological parts of a plant that interact with the atmosphere. The formula used for computing EVI is-

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

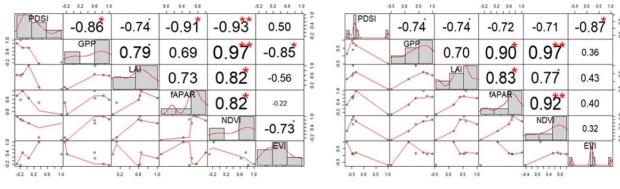
Where, NIR/red/blue are atmospherically-corrected or partially atmosphere corrected (Rayleigh and Ozone absorption) surface reflectance, L is the canopy background adjustment that addresses non-linear, differential NIR and red radiant transfer through a canopy, and C1, C2 are the coefficients of the 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.
- 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.

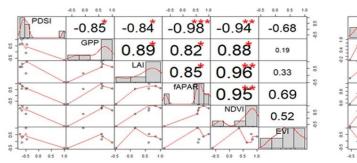


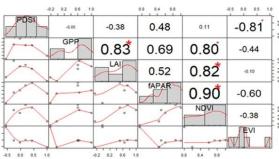
Results

Pearson Correlation



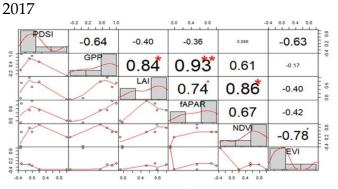
2015





2016

2018



EVI shows the most promising long-term agreement with PDSI

2019



Error Estimation Analysis

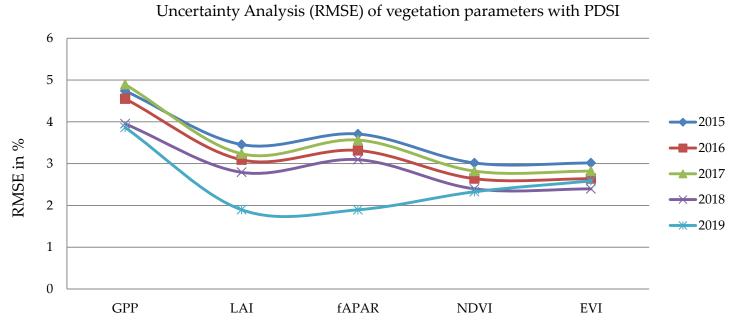
(Standard Error of the Estimates)

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

- EVI continuously managed to show least estimated standard error values for all five years, clearly indicating the highest level of long-term sensitivity with PDSI.
- Though, NDVI also gave values very near to EVI.



Uncertainty Analysis (RMSE)



- Both EVI and NDVI showed the least uncertainties compared to the other vegetation parameters in respect to PDSI for all five years.
- 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 less RMSE values than EVI, but in that year, it was fAPAR that actually showed the optimum 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.



Compilation of the outcomes of correlation, error estimation, and uncertainty analysis

Parame ters		2015			2016			2017			2018			2019	
			RMSE			RMSE			RMSE			RMSE			RMSE
	r	SEE	(%)	r	SEE	(%)	r	SEE	(%)	r	SEE	(%)	r	SEE	(%)
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

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

• EVI overall showed the best result in all of the statistical testing measurements, and NDVI took the next place for showing second best result in both Error Estimation and Uncertainty Analysis.



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
- We found 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.
- 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.
- The authors assumed that this study will support sustainable forest management practices and drought monitoring under climate change scenarios for tropical ecosystems.



Acknowledgement

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If you have any question, please feel free to contact the corresponding authors at:

Subhajit Bandopadhyay : subhajit.bandopadhyay@up.poznan.pl Subhasis Ghosh: mail.subhasis@yahoo.com