

Research Article

Monitoring of Agricultural Drought using Satellite based Drought Severity Index over Andhra Pradesh State of India

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Abstract Several indices both conventional and satellite based are used in drought monitoring and assessment. In this study, a satellite derived Drought Severity Index (DSI) was used to monitor and assess the agricultural drought over Andhra Pradesh state, India from 2002 to 2012. The components of DSI are the Normalize Difference Vegetation Index (NDVI) and Evapotranspiration. The NDVI and evapotranspiration products of MODIS were used in this study to derive the DSI. The DSI is expected to capture the drought event that has been reported in the state between 2002 and 2012 and provide a quantitative measure of severity. The analysis showed that the DSI was having a larger variance during June due to the large variation in the onset of monsoon. The DSI variance was low in the predominantly irrigated districts. The spatial cumulative seasonal DSI captured the drought affected districts during the reported drought years. When the seasonal cumulative DSI was correlated with seasonal rainfall, it showed a strong relation with the current month rainfall in the rainfed crop growing districts. The annual DSI showed strong positive correlation with the annual Net Primary Productivity. This study clearly shows that the DSI was able to discern the drought affected regions in the state of Andhra Pradesh, India during the study period.

Keywords Drought; Drought Severity Index; ET; NDVI; Standardized Vegetation Index

1. Introduction

Under the changing climate scenario, drought events may become more frequent and severe in nature (Dai et al., 2004). Drought is one of the major natural disasters which impair the food production leading to unemployment, malnutrition, migration, conflicts and environmental degradation. Though prediction of drought is neither accurate nor precise, it is critical to monitor and assess drought through timely and reliable weather information, including seasonal forecasts, to aid decision makers. This information, if properly applied, can reduce the impact of drought and other extreme climate events (Wilhite and Svoboda, 2000). Several indices are used to assess and monitor drought from local to global scale. However due to the multi-disciplinary character of drought, a single unique definition of drought does not exist; but is subject to the domain of interest of the observer (Wilhite and Glantz, 1985; Maracchi and Sivakumar, 2000; Tate and Gustard, 2000). Drought indices may use parameters which are meteorological, hydrological, spectral, agricultural and social in nature. Ideally, a drought index integrates large amounts of data, such as precipitation, snowpack, stream flow and other water supply indicators, to monitor drought severity in a comprehensive framework and to measure how much the climate in a given period has deviated from historically established normal condition

(Narasimhan and Srinivasan, 2005; Mu et al., 2013). The American Meteorological Society (1997) suggests that the time and space processes of supply and demand are the two basic processes that should be included in an objective definition of drought and thus, in the derivation of a drought index (Heim, 2002). Mu et al. (2013) reviewed various drought indices like Palmer Drought Severity Index (PDSI) (Palmer 1965; Alley, 1984), United States Drought Monitor (USDM) (Svoboda, 2002), and Evaporative Drought Index (EDI) among other indices. The relative strengths and weaknesses of these indices were discussed and concluded that most of them were designed to detect meteorological and/or hydrological drought without incorporating vegetation responses into drought. Except the USDM and the EDI which use both reanalysis meteorological data and remotely sensed data (Svoboda et al., 2002; Yao et al., 2010), most drought indices use reanalysis meteorological data that contain substantial uncertainties (Zhao et al., 2006; Chen and Bosilovich, 2007; Gao et al., 2010; Mu et al., 2013). To overcome these limitations, Mu et al. (2013) developed a remotely sensed global Drought Severity Index (DSI). DSI was derived using satellite derive Evapotranspiration (ET), Potential Evapotranspiration (PET) and Normalized Difference Vegetation Index (NDVI) to identify and monitor drought.

In India, organizations like the Central Research Institute for Dry Land Agriculture (CRIDA), Hyderabad, provide information on drought conditions and their mitigation measures during the season. The India Meteorological Department monitors the meteorological parameter while the Central Water Commission provides the latest storage status of the major water bodies of the country. A project called National Agricultural Drought Assessment and Monitoring System (NADAMS), operational since 1989 and presently being carried out by Mahalanobis National Crop Forecast Centre (www.ncfc.gov.in) has been using satellite derived indices like NDVI, Normalized Difference Water Index (NDWI), Vegetation Condition Index (VCI), meteorological, crop and field parameters to provide agricultural drought information in terms of prevalence, severity and persistence at state, district and sub-district level for India. However, development of a unified index for drought severity assessment by integrating data from different sources is an important challenge. Use of a process based indicator like the DSI which describes the actual process taking place on the ground will provide the realistic condition of the crops in the field. Towards this objective the DSI proposed by Mu et al. (2013) was used to monitor the drought condition in the state of Andhra Pradesh, India during the time period of 2002-2012. The DSI will be evaluated on how best it is able to identify the reported drought year between 2002-2012, quantify the severity of drought and address the drought in a near real time basis. It was also envisaged to find the relation between the DSI with the monthly rainfall and Net Primary Productivity over the study area.

1.1. Study Area and Data Used

Study Area

The region chosen for this study is the erstwhile state of Andhra Pradesh in India presently bifurcated into two states namely Andhra Pradesh and Telangana. For this study the two states Andhra Pradesh and Telangana will be called with its erstwhile name of Andhra Pradesh. The Andhra Pradesh state had a total geographical area of 27.44 million hectares. It has a vegetation types ranging from the forested districts in the north to the dry arid districts in the south offering diverse agro-climatic condition. The state gets its major share of rainfall (68.5%) during the four southwest monsoon months (June to September). The southern arid district received as low as 300 mm while the northern forested districts receive over 1000 mm of rainfall during the monsoon. The majority of the crops (65% of the 13.02 million hectare) that are grown during the monsoon season rely on the monsoon rainfall for its sustenance (Mishra, 2005). Almost 45% of the state is prone to drought according to Seth (1998).

This study uses the districts of this state as the study unit which is approximately 4000-5000 km². Some of the major crops grown in the state are paddy, groundnut, cotton, chilli, maize and millets among other crops. Figure 1 shows the study area of the erstwhile state of Andhra Pradesh, India.



Figure 1: Study area - the erstwhile state of Andhra Pradesh, India

1.2. The Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) is the most widely used vegetation index for its long legacy, simplicity and robustness. It has been extensively used for assessing and monitoring vegetation dynamics, biomass production, changes in vegetation conditions and many more (Tucker et al., 1985; Hielkema et al., 1986; Prince and Tucker, 1986; Kogan, 1990). The Moderate Resolution Imaging Spectroradiometer (MODIS) sensor onboard Terra and Aqua satellite has been providing spectral information in 36 spectral bands since 1999 and 2002 respectively. MODIS Vegetation Index 16 day's products at multiple spatial resolutions have been providing consistent spatial and temporal information on vegetation canopy greenness, canopy structure and other biophysical parameters. This study uses the Terra MODIS Vegetation Index (VI) 16 day (MOD13A2) products for its analysis. The theoretical basis, algorithm description, product specification and quality assurance of the MODIS VI product is provided in the MODIS Vegetation Index User Guide (Didan et al., 2015) The VI downloaded LADDS DAAC (http://vip.arizona.edu). products from (https://ladsweb.nascom.nasa.gov) web page were processed using the open source software (QGIS), to derive the NDVI. The cloud contaminated and erroneous pixels were eliminated by using the quality assurance flag of NDVI. The NDVI data from the first fortnight of June 2002 till the second fortnight of April 2013 were used in the analysis.

1.3. Evapotranspiration

The amount of water lost to the atmosphere from the soil surface as evaporation and through vegetation as transpiration combined together is called Evapotranspiration (ET). Evapotranspiration is an important component of the hydrological cycle which is responsible for the mass and heat transfer into the atmosphere. Since the amount of ET depends on the imbalance in the soil-water-atmospheric continuum, it helps in assessing the moisture deficit over a region which in turn will help us in assessing the drought condition. This study uses the MODIS Global Terrestrial ET (MOD 16) products which were derived using the Mu et al.'s improved ET algorithm (2011). The algorithm theoretical basis and the details of the ET product are provided in www.ntsg.umt.edu/project/mod16 web page and also in Mu et al. (2007). Mu et al. (2007, 2011) integrated the Penman-Monteith equation (Monteith, 1965) with the Priestley-Taylor (1972) method to estimate the Potential Evapotranspiration, while the global remotely sensed actual ET was derived using the Penman-Monteith equations. The main input parameter for the Penman-Monteith equations are the meteorological variables, remotely sensed vegetation parameter of Leaf Area Index (LAI) (Myneni et al., 2002), fraction of photo synthetically active radiation (FPAR) (Los et al., 2000). It provides the day and night cumulative ET estimates.

The limitations with the MOD16 products are i) it uses a static MODIS land cover map, ii) wind and precipitation are not used in the calculations of ET, iii) the relative humidity influence on saturated soil and standing water and canopy intercepted water are not considered and iv) the meteorological inputs to this product is coarse. Several studies have attempted the validation of global evapotranspiration product (MOD16) using flux tower and Large Aperture Scintillometer (LAS) measurements (Ramoelo et al., 2014; Tang et al., 2015). The results show that the 8-day MOD16 actual ET product tends to underestimate at higher ET levels and overestimate at low ET levels. Under irrigated condition MOD16 tends to underestimate significantly. Though there are limitations in using MOD16 ET data, it provides a spatial time series data which is readily available for the entire globe for over a decade. Tang et al. (2015) points out that the temporal pattern of ET estimate matches with the LAS and flux tower values. In this study the Moisture Adequacy Index (MAI) which is used in the derivation of Drought Severity Index (DSI) is the ratio of actual ET to Potential ET. This ratio helps in cancelling out the common error in actual ET and PET thus reducing the uncertainty in the MOD16 product for the use in DSI.

1.4. The Gross Primary Production and Net Primary Production

Primary productivity is defined as the rate at which the sun's energy is transformed into biomass through plants photosynthesis or chemosynthesis. The primary productivity can be Gross Primary Productivity (GPP) which is the total amount energy converted as biomass which includes the energy consumed by the plant for respiration while the Net Primary Productivity (NPP) is the net amount of energy consumed by the plant resulting in dry plant biomass. NPP gives an idea on the amount of energy that is consumed by the plant resulting in the carbon dioxide assimilation. It represents the availability of carbon in the form of plant material for consumption as food, fuel and feed (Abdi et al., 2014). In this study the MODIS Gross Primary Production (GPP) and Net Primary Production (NPP) product (MOD17) were used which provides estimates of vegetation GPP and NPP at consistent spatial and temporal resolutions for global vegetated land areas (Running et al., 1999). The algorithm theoretical basis and the details of the MOD17 GPP/NPP product can be had from 'User's Guide -Daily GPP and Annual NPP (MOD17A2/A3) Products, NASA Earth Observing System MODIS Land Algorithm (Running and Zhao, 2015) (http://www.ntsg.umt.edu/sites/ntsg.umt.edu/files/ modis/MOD17UsersGuide2015_v3.pdf). The MOD17 GPP/NPP product has been widely validated and applied to regional and global scales (Turner et al., 2005, 2006; Heinsch et al., 2006; Zhao and Running, 2010). It is a known fact that during drought year the NPP is expected to reduce due to

abiotic stresses. The MOD17 GPP/NPP product was used in this study for comparison against the DSI as a surrogate measure of vegetation activity and associated NPP response to different drought scenarios during various time periods.

1.5. Rainfall Data

Rainfall forms an important input for any vegetation and drought studies. In this study, the Climate Prediction Centre's (CPC) RFE2.0 daily accumulation rainfall estimates product was used, which was downloaded from its FTP site (ftp://ftp.cpc.ncep.noaa.gov/fews/S.Asia /data/). It provides the southern Asian region daily rainfall estimates in millimeters with a resolution of 0.1° x 0.1°. The inputs for the rainfall estimate include Global Telecommunication System (GTS) station data, as well as geostationary infrared cloud top temperature fields and polar orbiting satellite precipitation estimate data from SSM/I and AMSU-B microwave sensors. All satellite data are first combined using a maximum likelihood estimation method, and then GTS station data is used to remove bias. Warm cloud precipitation estimates are not included in RFE 2.0 estimates (www.cpc.ncep.noaa.gov/ products/fews/RFE2.0_desc.shtml). The data was provided in binary format which was imported using commercial image processing software and rainfall data was extracted for the Andhra Pradesh state and its districts which were used in the analysis.

1.6. The Drought Severity Index

The remotely sensed Drought Severity Index (DSI) has two components namely 1. The vegetation condition component which helps in detecting the vegetation health and vigour and 2. The evapotranspiration deficit component which helps in detecting the moisture stress in the crop. Since the causative and the manifestation indicators are combined in a single index called the DSI, it clearly helps in addressing the drought holistically.

For the vegetation health/vigour monitoring purpose, MODIS Vegetation Index has been used. The long term VI data (2002-2012) was used to drive the standardized NDVI (Z_{NDVI}) also called the Standardized Vegetation Index (SVI) for each composite period (monthly) during the classified growing season at each grid cell which is given in equation 1.

$$Z_{NDVI} = \frac{NDVII - \overline{NDVI}}{\sigma_{NDVI}} \dots (1)$$

The SVI allows visualization of relative vegetation greenness in terms of 'greenness probability' through the use of a probability estimate, which suggests comparison over time periods that are longer than the archival imagery. The value of the SVI ranges between zero and one (0 < SVI < 1). Zero is the baseline condition in which a pixel NDVI value is lower than all possible NDVI values for that week in other years and *vice versa* (Peters et al., 2002).

Evapotranspiration has a commanding roll in the transportation of energy and mass into the atmosphere. The rate of ET is actually controlled by the vapour pressure deficit in the atmosphere and the moisture availability in the soil water reservoir. When the supply component of soil water is unlimited the ET takes place at its potential rate which is known as the Potential Evapotranspiration (PET). Hence, the ratio of the ET versus the PET can indicate the amount of water stress that exists in the region. This ratio of actual ET to PET is also called the Moisture Adequacy Index (MAI) (Drought Manual, 2009) which is expressed in percentage. MAI is critical in ascertaining the agricultural drought condition. For each monthly period, the ratio of actual ET to PET is derived as given in equation 2.

$$MAI = \frac{ET}{PET} \dots (2)$$

The temporal standard deviation of MAI (σ_{MAI}) and MAI average (MAI) were then computed on a grid cell basis over the available satellite record (2002 - 2012). The standardized MAI (Z_{MAI}) was then calculated using equation 3.

$$Z_{MAI} = \frac{\text{MAII} - \overline{\text{MAI}}}{\sigma_{MAI}} \dots (3)$$

The standardized NDVI (Z_{NDVI}) and standardized MAI (Z_{MAI}) were summed as given in equation 4 to give a Z value.

$$Z = Z_{MAI} + Z_{NDVI} \dots (4)$$

The standardization of the Z value would provide the remotely sensed DSI as given in equation 5.

$$DSI = \frac{Z-\overline{Z}}{\sigma} \dots (5)$$

The DSI ranges from unlimited negative value to positive values. Negative DSI indicating drier conditions while positive DSI indicating wetter conditions. It is always suggested that to have sufficiently longer database so that the DSI derived represents the realistic ground conditions.

2. Results and Discussion

2.1. Variance of the DSI in the Irrigated and Rainfed Crop Growing Districts

Figure 2a and 2b shows the DSI values during the Kharif season (May to November) plotted for the years from 2002 to 2012 for few predominantly irrigated crop growing districts (viz East and West Godavari, Krishna and Guntur) and predominantly rainfed crop growing districts (viz. Ananthpur, Prakasam, Mahabubnagar and Kurnool) of Andhra Pradesh state respectively. The DSI usually ranges between -1.5 to +1.5 where -1.5 indicates extreme drought while +1.5 indicates extremely wet conditions. It can be observed from Figure 2a and 2b, that only during the month of June the DSI varied widely between -1.5 to +1.5 under both irrigated crop and rainfed crop growing districts. The variation of the DSI between maximum and minimum was much less in all the remaining months. The large variations of the DSI in the month of June can be attributed to the variation in the onset of monsoon and the variations in the amount of rainfall received during this month. Table 1 gives the monsoon onset date and rainfall deviation of the three meteorological sub-divisions of Andhra Pradesh along with the DSI values of the districts under study. The years 2003, 2009, 2011 and 2012 showed negative DSI deviation in all the districts. Though the rainfall received in June 2003 was normal, the negative deviation in 2003 was due to the carryover effect of the huge deficit in the previous year's (2002) seasonal rainfall which resulted in drought that year. The previous year's (2002) seasonal rainfall deviation in Coastal Andhra, Telangana and Rayalaseema were -25%, -22 and -33 respectively. In the years 2009, 2011 and 2012, the majority of the state experienced poor rainfall in June resulting in negative DSI. During other months of the season the dynamic range of the DSI was not as large as observed during June. It was ranging between -0.5 to +0.5. The variation was the least during the month of August followed by July and September. The variation demonstrates that the DSI is sensitive to the rainfall during these months.



Figure 2a: The DSI during Kharif season from 2001-2012 for predominantly irrigated crop growing districts



Figure 2b: The DSI during Kharif season from 2001-2012 for predominantly irrigated crop growing districts

Figure 3 shows the monthly variance of the DSI, for the typical irrigated and rainfed crop growing districts of Andhra Pradesh during 2002-2012. It can be observed that the variance of the DSI was the highest during the month of June in both the irrigated and rainfed crop districts. In the irrigated crop growing districts the variance of DSI was low in the month of July, August and September in the Kharif

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season. During Rabi cropping season the variance was low in December, January and February. The values of variance among districts were also very close during these periods. The variance of the DSI was high during the month of June due to the variation in the onset and amount of monsoon rainfall. During the months of October and November, which is the transition period between the Kharif and Rabi cropping seasons, the variance increased. The harvest of the Kharif crop takes place during these months. Any staggering during the sowing month will also reflect in the harvesting months and hence the higher variance in October and November. The variance of the DSI was also high during the summer months of March, April and May when there is a large uncertainty in rainfall and crops.



Figure 3: The variance of the DSI during 2002-2012 for (a) irrigated crop growing district and (b) rainfed crop growing districts

	Monsoon	Rainfall	deviation	n during								
	onset day	June	over Me	t-sub			Dist	rict average	e DSI during	June		
Year	over	divisions of AP										
	Andhra	Rayala	Telan	Coastal	East	West	Krishn	Cuptur	Mahabub	Kurnool	Prakasa	Ananth
	Pradesh	seema	gana	Andhra	Godavari	Godavari	а	Guntur	nagar	Kumoor	m	pur
2002	10th June	31	2	7	0.687	0.424	-0.002	-0.171	0.517	-0.312	0.017	-0.003
2003	15th June	20	-11	-5	-1.183	-1.393	-1.225	-0.983	-0.782	-0.645	-1.330	-1.255
2004	10th June	-53	-55	9	-0.437	0.436	0.894	1.102	0.499	1.196	1.045	1.222
2005	21st June	-1	-26	-22	0.438	0.609	-0.166	-0.452	-1.061	-0.329	-0.614	0.615
2006	24th June	57	-24	15	0.774	1.089	1.131	1.299	0.898	0.538	0.857	0.024
2007	14th June	285	26	159	0.762	0.902	0.940	1.156	1.176	0.459	1.118	0.757
2008	10th June	-35	-8	-16	0.440	-0.155	-0.368	-0.719	-0.315	-0.269	-0.662	-0.697
2009	26th June	5	-52	-46	-0.428	-0.514	-0.333	-0.289	-0.664	-0.437	-0.082	-0.086
2010	14th June	57	-24	39	0.469	0.405	-0.071	-0.061	0.036	-0.316	0.230	-0.237
2011	16th June	-24	-41	-27	-0.210	-0.447	-0.474	-0.372	-0.780	-0.742	-0.457	-0.572
2012	18th June	-48	-14	-22	-1.146	-1.327	-1.144	-1.199	-1.309	-1.347	-1.216	-1.369

Table 1: The monsoon onset dates, rainfall deviations and the DSI during June month for few typical districts

The rainfed crop growing districts also showed larger variance in the DSI during the months of June, October, and November and during summer months. The low variance was observed in July, August and September during Kharif, and in December and January during Rabi. It is clearly seen that the coherence of variance values among districts observed during low variance months in irrigated crop growing districts was not observed in the rainfed crop growing districts. There was larger variation of

variance among the district throughout the season. This analysis demonstrates that the DSI is sensitive to the variations in the onset of monsoon and the amount of rainfall received during each month, which results in variations in the NDVI and the evapotranspiration. It also clearly distinguishes between the irrigated crop growing districts which has lower DSI variance and rainfed crop growing districts by registering larger variance during the cropping season.

2.2. Response of the DSI to Rainfall

Since the DSI was found to be sensitive to the onset of monsoon rainfall and had a greater variance in the rainfed crop growing districts, it was appropriate to establish the strength of relationship between the rainfall and the DSI. A correlation analysis was carried out between the rainfall and the DSI from the year 2002 to 2012. Table 2 shows the district wise correlation of the DSI to the rainfall of the current month and the previous month. It was observed that the DSI had a higher correlation with the current month rainfall when compared with the previous month rainfall. The SVI which is one of the two components of the DSI is a function of the NDVI. It is proven that the NDVI as a standalone index has a lagged response to rainfall. In a study over Andhra Pradesh on a satellite based NDVI response to rainfall, the NDVI lags rainfall by two months in most of the districts (Chandrasekar et al., 2006).

S No	Districts	Correlation	Percent irrigated	
5. NU.	Districts	Current Rainfall	One month Lag	cropped area
1	Adilabad	0.711	0.167	17.94
2	Ananthpur	0.791	0.324	15.93
3	Chittoor	0.717	0.143	47.51
4	Cuddapah	0.757	0.000	41.80
5	East Godavari	0.528	0.127	60.35
6	Guntur	0.488	0.295	63.79
7	Karimnagar	0.744	0.153	83.20
8	Khammam	0.691	0.163	47.77
9	Krishna	0.600	0.392	51.05
10	Kurnool	0.777	0.041	29.79
11	Mahabubnagar	0.724	0.315	38.73
12	Medak	0.745	0.298	43.24
13	Nalgonda	0.643	0.292	61.13
14	Nellore	0.629	0.061	78.98
15	Nizamabad	0.757	0.138	88.04
16	Prakasam	0.623	0.144	36.85
17	Rangareddy	0.681	0.407	41.19
18	Srikakulam	0.646	-0.102	50.33
19	Vishakhapatnam	0.643	0.094	39.98
20	Vizianagaram	0.791	0.050	44.18
21	Warangal	0.745	0.160	72.03
22	West Godavari	0.550	0.338	85.94

Table 2: Correlation between DSI vs current and one month lagged rainfall

However, the SVI is an estimate of the 'probability of occurrence' of the present vegetation condition. Peters et al. (2002) in a study over the Great Plains states from North Dakota to Texas compared the SVI with the US Drought Monitor (DM) outputs and found that the SVI reflects short-term vegetative response to weather conditions while the DM maps show both short term and long-term drought conditions. The SVI map will show areas of relatively good or poor vegetation status and will show

changes more quickly than the DM maps. This could be the reason for the immediate response of the DSI to rainfall despite having the NDVI as a component. The highly irrigated delta districts of Guntur (r=0.488), Krishna (r=0.60), East Godavari (r=0.528) and West Godavari (r=0.55) were having low correlation coefficients. Since these delta districts are in the tail reach of the river basin, the reservoirs which supply irrigation water get filled up with a lag. Because of this the irrigated crop calendars in these districts have a lag with monsoon rainfall and hence the poor relation with rainfall.

Figure 4 shows the cumulative DSI (June to November) of the state of Andhra Pradesh from 2002 to 2012. It can be observed from the Figure 4 that the DSI was negative in most of the districts of the state in the years 2002, 2003, 2009, 2011 and 2012. Based on the analysis of historic rainfall it was found that the years 2002, 2003, 2009, 2011 and 2012 were meteorological drought years with deficient rainfall. In all the other years the DSI was positive if the districts had experienced normal to excess rainfall.



Figure 4: Cumulative DSI (Jun-Nov) of Kharif cropping season in the state of Andhra Pradesh

The district average cumulative DSI was extracted for each district for all the years under study and was plotted against the district cumulative rainfall of the corresponding period. It can be observed from Figure 5a & 5b that whenever there is deficient cumulative rainfall during the season there is a negative DSI and vice versa. The conformity between the positive or negative cumulative rainfall events to the positive or negative cumulative DSI respectively is more pronounced in the rainfed crop growing districts (Figure 5b) rather than in the irrigated crop growing districts (Figure 5a). This clearly brings out that the DSI is sensitive to the rainfall events.



Figure 5a: Cumulative rainfall plotted against cumulative DSI during Kharif cropping season (Jun-Nov) in irrigated crop growing districts



Figure 5b: Cumulative rainfall plotted against cumulative DSI during Kharif cropping season (Jun-Nov) in rainfed crop growing districts

2.3. Relation between the DSI and the NPP

The Net Primary Productivity (NPP) refers to the production of organic compounds from atmospheric or aquatic carbon dioxide (CO_2) by plants, principally through the process of photosynthesis (photosynthesis minus autotrophic respiration) (Pei et al., 2013). Studies by Zhao and Running (2010) showed that large-scale drought events have reduced the global NPP. Xiao et al. (2009) have found that most of the drought events which occurred in China had reduced the NPP and the Net Ecosystem Productivity (NEP) in large parts of the drought affected areas. Extreme droughts can impact the terrestrial productivity in a significant way and can reduce the sink strength at sub-continental scale

(Ciais et al., 2005; Reichstein et al., 2007; van der Molen et al., 2011). Since the NPP is directly related to drought, it was found appropriate to find the relation between the DSI and the NPP over the study area. This study used the MOD17 GPP/NPP product as a surrogate measure of vegetation activity/productivity and associated the NPP response to drought, for comparison against the DSI. The DSI and the NPP results should be correlated, especially for water supply-constrained regions (Nemani et al., 2003) through vegetation moisture constraints on canopy transpiration; net photosynthesis and CO_2 exchange (Mu et al. 2013).

Figure 6a and 6b shows the plot of the annual DSI along with the annual NPP of few typical districts of the study area. It can be observed that the DSI closely followed the annual NPP for all the years except 2011. The DSI was having low negative values during 2002, 2003, 2009 and 2012 and the annual NPP was also low during these years compared to its mean for each district. The annual NPP during a good monsoon year was above 0.7 PgC/year for the irrigated crop growing districts while it was around 0.5 PgC/yr for the rainfed crop growing districts. The higher annual DSI did not always result in higher NPP on the contrary lower negative annual DSI consistently resulted in lower annual NPP irrespective of whether it was an irrigated or rainfed crop growing district.



Figure 6a: Annual DSI and corresponding NPP in irrigated crop growing districts of Andhra Pradesh



Figure 6b: Annual DSI and corresponding NPP in rainfed crop growing districts of Andhra Pradesh

Table 3 shows the correlation coefficient of the annual DSI against the annual NPP. It can be observed that most of the districts were having strong relation between the DSI and the NPP. The correlation coefficient was the highest in the districts of Ananthpur (0.88), Khammam (0.78), Kurnool (0.77), Adilabad (0.75), Rangareddy (0.74), Vizianagaram (0.74), Medak (0.73) and Chittoor (0.72). Majority of the cropped area in these districts are rainfed crop as the percent irrigated cropped area was less than 50% of the total cropped area (Table 3). The low correlation coefficient was observed in the districts of Prakasam (0.39) and Nellore (0.46) as these two districts are predominantly northeast monsoon (October to December) dependent districts. The DSI has also captured all the reported drought years which are 2002, 2003, 2009 and 2012. The DSI recorded the negative values in all these years in all these districts. This clearly indicates that the DSI was able to discern the drought year very clearly in the state of Andhra Pradesh.

S. No.	Districts	NPP	% Irrigated cropped area
1	Adilabad	0.75	17.94
2	Ananthpur	0.88	15.93
3	Chittoor	0.72	47.51
4	Cuddapah	0.65	41.80
5	East Godavari	0.62	60.35
6	Guntur	0.62	63.79
7	Karimnagar	0.51	83.20
8	Khammam	0.78	47.77
9	Krishna	0.42	51.05
10	Kurnool	0.77	29.79
11	Mahabubnagar	0.65	38.73
12	Medak	0.73	43.24
13	Nalgonda	0.82	61.13

Table 3: Correlation coefficient of annual DSI versus annual NPP

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14	Nellore	0.46	78.98
15	Nizamabad	0.69	88.04
16	Prakasam	0.39	36.85
17	Rangareddy	0.74	41.19
18	Srikakulam	0.66	50.33
19	Vishakhapatnam	0.63	39.98
20	Vizianagaram	0.74	44.18
21	Warangal	0.69	72.03
22	West Godavari	0.62	85.94

3. Conclusions

The DSI is a function of standardized ratio of ET to PET and standardized NDVI. This enables the DSI to be sensitive to water availability and also the vegetation stress condition in the region. The negative DSI values represent drier than normal conditions and positive values represent relatively wet conditions. The spatial average monthly DSI for each year was plotted for each district. It was observed that the dynamic range was large in the month of June. The variance plot showed that in the month of June, the DSI was having larger variance. The variance was also high during the transition period between two cropping seasons and during summer. It was also observed that the variance was low in the predominantly irrigated crop growing districts compared to the rainfed crop growing districts. The spatial pattern of the cumulative seasonal DSI clearly captured the drought affected districts during the reported drought years. When the seasonal cumulative DSI was correlated with the seasonal rainfall, the DSI showed a very strong relation with the current month rainfall in all the districts. It was also observed that in delta districts with predominant irrigated crop, the DSI vs rainfall relation was poor as the delayed crop calendar in the irrigation command does not synchronize with the rainfall distribution during the cropping season. The Net Primary Productivity (NPP) of a region gets greatly reduced due to the incidents of drought. In this study the MOD17 GPP/NPP product was used as a surrogate measure of vegetation activity/productivity and associated the NPP response to drought, for comparison against the DSI. When the annual DSI was plotted along with the annual NPP, it was observed that the DSI co-varied with the NPP in all the years and study. It also captured all the reported drought years by recording negative values during those years. When correlated with the NPP, most of the district showed very strong relation with the DSI. This study over Andhra Pradesh state of India reveals that the DSI could discern the problem area within the time scale considered. The DSI was able to provide a quantitative degree of severity of the drought in a region and hence DSI can be one of the important drought indicators for early assessment of drought.

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