USE OF FREELY AVAILABLE MODIS DATA DERIVED NDVI TO STUDY CROP VEGETATION

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ABSTRACT

A study was taken up to make use of free and open sources of software and data to observe vegetation in Nalgonda district of Telangana. The study period considered water years from 2011-12 to 2015-16. NDVI derived from MODIS-Terra data product MOD09Q1, 8 day composite with 250 m resolution was utilised. Secondary data on crop area, rainfall and certain edaphic factors were used to understand NDVI, a crop stress indicator.

Bi-modal NDVI curves of monthly maximum value composites indicated two crop seasons i.e. *Kharif* and *Rabi* while there were temporal differences in maximum NDVI in 8 day composites. Peak NDVI was seen on 14th, 22nd, 30th, 30th September and 24th October in *Kharif* of 2011, 2012, 2013, 2014 and 2015, respectively with a range from 0.729 to 0.878. Similarly, maximum NDVI during *Rabi* was noticed on 26th February in 2011 and 2012, on 22nd and 14th March in 2013 and 2014 and on 25 January, 2015 with a range from 0.692 to 0.795.

Rice area and rainfall during June and July in deficit SW monsoon years, 2011 and 2014 had correlation ('r' values of 0.295* 0.323*, respectively) (n = 59). Number of pixels in 0.0-0.2, 0.2-0.4, 0.4-0.6, 0.6-0.8 and 0.8-1.0 NDVI classes varied among years. There were significant correlations between area under rice and 0.6-0.8 class pixels in 2011, 2012, 2014 and 2015 ('r'= 0.350**, 0.360**, 0.535* and 0.403**, respectively) and with 0.8-1.0 class pixels in 2012 and 2015 which received normal SW monsoon (r = 0.485** and 0.536**, respectively).

Further work to model dependence of NDVI on causative factors is needed while using other free high resolution imagery including Sentinel 2 and Cartosat DEM etc.

INTRODUCTION

Computer based information systems have been adopted as a way to improve the performance of government in serving and protecting the public interest by increasing government's efficiency, effectiveness, and accountability. Availability of user-friendly and affordable geospatial technologies, including geographic information systems (GIS), remote sensing, and global positioning systems has prompted their intensified adoption by both public and private organizations at all levels (Nedović-Budić and Budhathoki 2006). In addition to that, Geoinformatics have become the mainstay of Internet and Communication Technology (ICT) and GIS and ICT tools are interdependent. Prudent and effective use of Geoinformatics requires skills in developing, maintaining, customizing and localizing indigenous ICT solutions suited for diverse Indian conditions.

Agro-geoinformation is an aspect of applied geoinformatics to the cause of allied agricultural activities and is critical for the agricultural sustainability, natural resource conservation, land use management, agricultural industry, agricultural decision making and policy formulation all being connected to food security. These sets of data on the farmlands help agricultural scientists and farmers while working together to evolve more effective and efficient farming techniques that help increasing food production. Sridhar (2012) maintained that the National Agricultural Research System (NARS) of India having the responsibility for the agricultural research, education and extension is looking at the possible interventions for sustainable agriculture and food security. As agriculture being the principal occupation in India, timely communication of agricultural information assumes a greater priority as it would helping taking informed decisions. Therefore, use of Information and Communication Technologies (ICTs) in NARS, assumes an important role in all the efforts towards sustainable food production and food security.

Although use of ICTs would provide the right information at right time for the benefit of farming, the affordability to procure hardware and software had become the major constraint for the wide adoption of ICTs in the developing countries. There are instances where the student research in applied geoinformatics particularly in cash strapped Universities and Institutes was troubled owing to the costs involved in procuring hardware and commercial software. This situation could easily be overcome by the adoption of Free Open Source Software (FOSS) products/applications. The adoption of FOSS would increase the access to ICTs by overcoming the price barrier compared to the expensive commercial/proprietary software packages (Sridhar 2012). Over the last two decades, Free and Open Source Software Solutions for Geoinformatics (FOSS4G) has gained wide spread acceptance everywhere. Proliferation of GPS-enabled devices including most commonly used smartphones also facilitated value addition and updating of geospatial data. Under these situations, adoption of free and open sources of software and data would add more to building of a strong and vibrant geospatial workforce in universities and research institutions offering high-level training, sharing of knowledge and experiences.

Accurate and timely data that describes vegetation conditions is crucial to assess vegetation development and to best understanding and monitoring the land use practices. The field survey methods are generally associated to high costs, subjectivity and low spatial and temporal coverage, which limits the effectiveness of the process (Langley et al., 2001). The field collected data can be supplemented using EOS data. The capability to obtain regular observations at various scales, and information for areas with limited *in situ* accessibility, makes possible the use of remote sensing imagery and the study of vegetation from local to global scales.

Thus a study was planned and implemented considering the importance of applied geoinformatics to agriculture, as supported by a volume of literature, particularly with reference to vegetation studies. This study intended to grasp the area dynamics of irrigated and unirrigated crops and the crop stress caused by abiotic and biotic factors, as reflected by NDVI (normalised difference vegetation index). In this temporal study, NDVI derived from freely available MODIS-Terra data was used to observe the agricultural crops in general and rice in particular grown in a given geographical area. The idea was to link the spectral responses of vegetation to secondary data sets to identify a method to monitor the vegetation in conjunction with secondary datasets pertaining to atmospheric, edaphic and management factors. In this study, the secondary datasets were obtained from different government agencies and research institutes on procurement and sharing basis. The results were analysed, discussed and presented in the text to follow.

MATERIALS AND METHODS

The details of the study area, data and methods of analysis followed are detailed bellow under respective heads.

Study area

Nalgonda district (prior to re-organisation of districts) of Telangana (Figure 1) was selected for the study and the details are given in the text to follow. The details of the district were adopted from the report published by the Central Ground Water Board (CGWB, 2013). Nalgonda district has a total geographical area of 14240 Sq.km. The district lies between North latitudes 16° 25’ and 17° 50’ and between east longitudes 78° 40’ and 80° 05’ forms a part of major basin of Krishna river. Out of total geographical area of the district in 2011-2012, forest area was 83073 ha current follow land was 253851 ha and net area sown is 573291 ha. The average annual rainfall of the district is 751 mm, which ranges from 2.0 mm in February to 171 mm in July. July is the wettest months of the year contributing about 23% of annual rainfall. The mean seasonal rainfall is 562 mm in southwest monsoon (June-September), 139 mm in northeast monsoon (Oct-Dec), 7 mm rainfall in Winter (Jan-Feb) and 43 mm in summer (March – May). The percentage distribution of rainfall, season-wise, is 74.8% in southwest monsoon, 18.5 % in northeast monsoon, 0.93 % in winter and 5.73 % in summer.

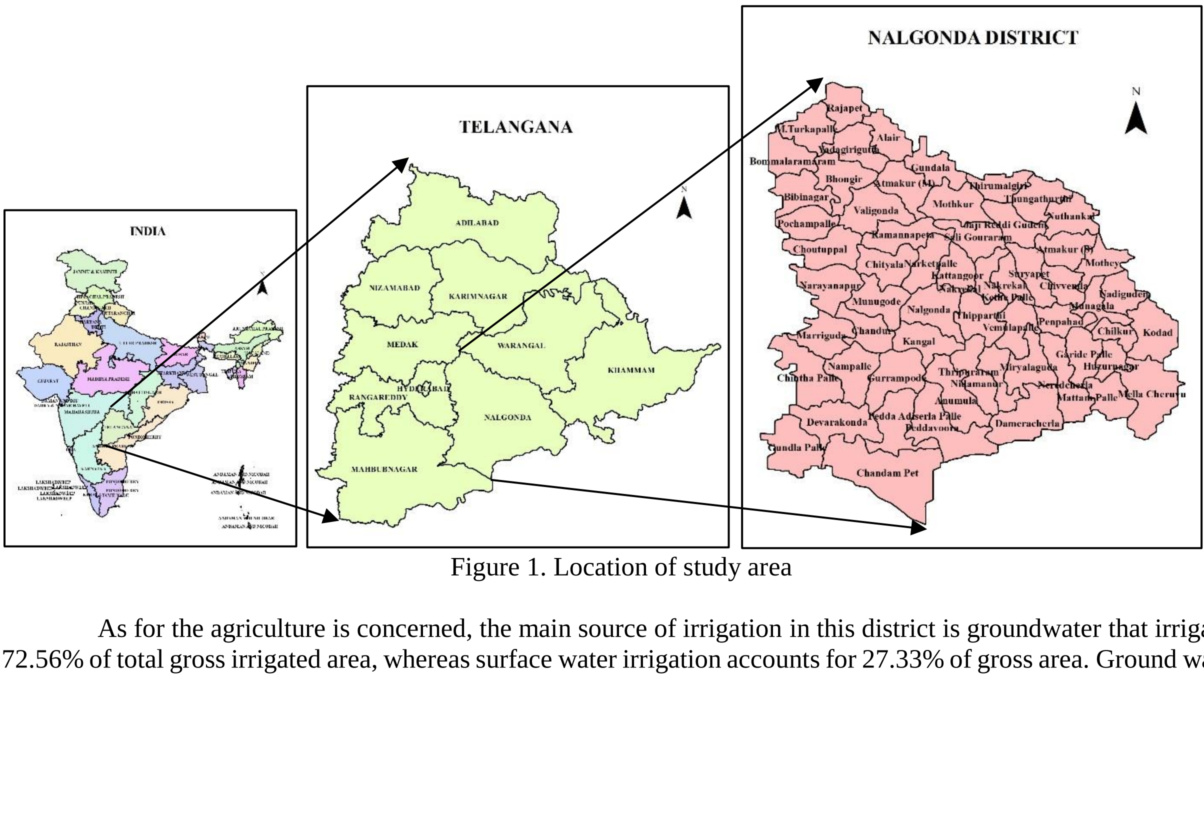


Figure 1. Location of study area

As for the agriculture is concerned, the main source of irrigation in this district is groundwater that irrigates 72.56% of total gross irrigated area, whereas surface water irrigation accounts for 27.33% of gross area. Ground water plays a predominant role in the net irrigated area 192350 ha, whereas surface water irrigation accounts for 92337 ha, out of the total net irrigated area of 297796 ha.

The cropping pattern is practiced based on climatic conditions and availability of irrigation sources. Paddy has been a staple crop since ages and cultivated in an area of 273430 ha (as in 2013) mostly under canals, tanks and wells. Other principal crops like jowar, bajra, grams, are mostly rainfed crops. The commercial crops like chilies, cotton and groundnut are grown under irrigation.

Data

Satellite data: Single tile of freely available 8 day composite data of MODIS-Terra data in 250 metre resolution (MOD09Q1) were downloaded (from https://mrtweb.cr.usgs.gov) for five water year period from June 2011 to May 2016. Processed and created the NDVI images and clipped to Nalgonda district and a total of 230 NDVI images were used in the analysis. Monthly MVC (maximum value composites) were created from the respective 8 day composites for the analysis. NDVI images acquired on 30 September (when there is cessation of southwest monsoon) every year were classified in to five groups of equal interval of NDVI i.e. 0.0-0.2, 0.2-0.4, 0.4-0.6, 0.6-0.8 and 0.8-1.0 and extracted the pixel statistics to understand the crop health through stress, its intensity and distribution.

Area statistics: Mandal wise (sub-district unit) statistics under all the crops grown in the district were obtained from the Directorate of Economics and Statistics, Government of Telangana for the corresponding period of 2011 to 2016. Similarly, mandal wise mean monthly rainfall data were also procured from same Agency.

Soil maps: Important soil theme maps like soil depth, texture, available water capacity, erosion, drainage and salinity pertaining to Nalgonda district were generated from the paper prints of soil maps of Andhra Pradesh developed by NBSS and LUP and as inputs for analysis.

Statistical analysis

Pearson correlation studies were carried out to establish the relationships among the variables selected and discussed.

RESULTS AND DISCUSSION

Temporal changes in cropping pattern

The data on net sown area in Nalgonda district during *Kharif* season in the water years from 2011 to 2016 were given in Table 1. The total net sown area in the district varied from 552245 ha (2012-13) to 644698 (2013-14). There was a jump in the cropped area by 92453 ha during *Kharif* of 2013-14 when compared to 2012-13. Similarly, there was a considerable reduction in the cropped area during 2014-15 in comparison with previous year (2013-14) while the changes were not much in 2012-13 and 2015-16. Rice cultivation occupied 21 to 39 per cent of the net sown area in *Kharif*, the lowest being in 2012 while the highest was seen in 2011. Among irrigated crops rice had a major chunk of area ranging from 69 (2012) to 80 percent (2014). According to the DES, rice is totally grown as irrigated crop during *Kharif* in Nalgonda district.

Table 1. Net sown and rice area in *Kharif* (ha)

Water year	Total	Irrigated crops	Unirrigated crops	Irrigated rice	% of rice in NSA	% of rice in irrigated crops
2011-12	555896	273026	282870	216547	39.0	79.3
2012-13	552245	170682	381563	117059	21.2	68.6
2013-14	644698	242708	401990	192185	29.8	79.2
2014-15	559062	221927	337135	177458	31.7	80.0
2015-16	556928	173221	383707	127904	23.0	73.8

NSA = Net sown area

(Source: Directorate of Economics and Statistics, Government of Telangana)

As far as the rainfall was concerned, 2011 and 2014 received 21 and 39% of less rainfall than normal while other years were normal in rainfall during SWM (Table 2). The monthly deviation from normal indicated quite different patterns, for instance, during June and September months in 2011, there was a deficit rainfall by 47 and 79%, respectively than their corresponding monthly normal. Similarly, in another deficit rainfall year 2014, all the months

(June to September) received deficit rainfall by 63, 47, 25 and 30 per cent from their corresponding monthly normal in June, July, August and September, respectively.

Although, the initial amount and distribution of rainfall would influence the cropping pattern and acreage, there was the highest area under rice in 2011 during *Kharif*, which actually received deficit rainfall (216510 ha). Similarly, during 2014 also substantial area was cultivated with rice (177542 ha). It was imperative from the analysis that the deficit rainfall in 2011 and 2014 did not affect the area under rice probably due to the assured irrigation with groundwater. According to the CGWB (2013), the main source of irrigation is groundwater for 72.56% of total gross irrigated area, whereas surface water irrigation accounts for 27.33% of gross area. It was also imperative that large part of irrigation was used for rice cultivation as it occupied the large part of area under irrigated crops to the extent of 69 to 80 percent.

Table 2. Rainfall (mm) and its deviation (%) from normal

Water year	Jun	% dev	Jul	% dev	Aug	% dev	Sep	% dev	SWM	% dev
2011-12	52.8	-46.7	184.8	29.2	149.8	11.0	32.4	-78.8	419.9	-20.8
2012-13	67.9	-31.4	125.8	-12.0	113.5	-15.9	143.7	-6.1	450.9	-14.9
2013-14	95.4	-3.6	176.5	23.4	184.1	36.4	142.9	-6.6	598.9	13.0
2014-15	36.5	-63.1	76.3	-46.6	101.9	-24.5	106.6	-30.3	321.4	-39.4
2015-16	182.6	84.4	58.0	-59.4	156.6	16.0	158.4	3.5	555.7	4.8

(Source: India Meteorological Department)

As far as unirrigated crops raised during *kharif*, the rainfall certainly affected the acreage in Nalgonda district. The total area under unirrigated crops was 282870 ha in 2011 and 337135 ha in 2014 when compared to other years where the area was more than these values (Table 1). Nevertheless, other reasons also would determine the cropping pattern including the Government schemes, incentives, availability of inputs and market driven preferences etc., besides rainfall pattern.

Pixel counts

The pixel distribution among five classes of NDVI (between 0.0 and 1.0) of the images acquired on 30 September, the date of cessation of SWM was shown in Figure 2. The pixel count in each class was the sum of the pixels in all mandals of the district. Larger concentration was seen mainly around two classes, 0.4-0.6 and 0.6-0.8 of NDVI in all five years.

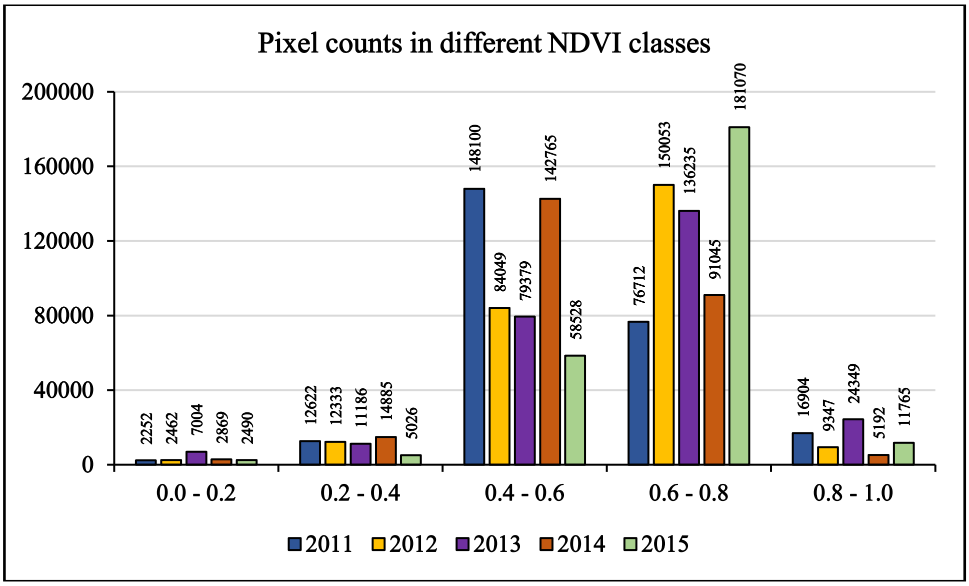


Figure 2. Pixel distribution in different NDVI classes (as on 30 September)

The pixel count in class 0.0-0.2 in general was less compared to other classes in all years with an exception in 2013 with 7004 pixels. The next higher number of pixels were found in class 0.2-0.4 with an exception in 2015 where the pixels were 5026 pixels while in other years it was more than 11000 pixels. In another class of NDVI, 0.4-0.6, the larger numbers were seen on 2011 and 2014 and the least number was observed in 2015. In 0.6-0.8 class, the lower number of pixels (less than 100000) were recorded in 2011 and 2014 and the highest number was noticed in 2015 with 181070 pixels. In the last class of NDVI, 0.8-1.0, the four digit number of pixels were seen in 2012 and 2014 while the largest number was in 2013 (24349 pixels). 2011 and 2015 registered 16904 and 11765 pixels, respectively in this class.

The results indicated clearly the response of vegetation to the rainfall in general. For instance, 2013, which received 13% excess of rainfall above SWM normal, had higher number of pixels in 0.0-0.2 class where there would have been proliferation of weed species resulting in some greenness in non-cropped areas. For similar reason, there were higher number of pixels on class 0.8-1.0 of NDVI. However, caution is needed in interpreting the reason for higher number in this class and probably sub-classification of this range to narrower widths might help understanding as a slight increase beyond 0.8 would classify a pixel to this class. Likewise, in 2015 there was an excess of rainfall, which resulted into the highest number of 181070 pixels in class of 0.6-0.8. Similarly, in the years of deficit rainfall like in 2011 and 2014, the pattern of pixel distribution was different. For instance, there were large number of pixels in the class 0.4-0.6 by the end of SWM (with 148100 and 142765 pixels, respectively) unlike more pixels in the next class as was seen in excess rainfall years. It was evident from this analysis that the impact of rainfall on the greenness was direct where the water, which is the fundamental requirement for plant growth and thus greenness. However, the greenness is also likely to be affected by other factors including pests and diseases (biotic factors), temperature, plant nutrient status etc.

Relationship between pixel count and cropped area

Year wise correlation studies with the number of pixels in three NDVI classes, extent of area under cultivation and rainfall received in 59 mandals revealed certain relationships (Table 3). In this analysis, the NDVI classes of 0.4-0.6, 0.6-0.8 and 0.8-1.0 only were included for one reason that these pixel counts were extracted from the image acquired on 30th September (at the end of SWM) of all years with the assumption that pixels with less NDVI values in beginning would become greener as the time moved from June to September and would represent the cropped area and growth, so that the relationships would be clear.

Table 3. Correlation coefficients

Year	NDVI class	Area (ha)			Total rainfall (mm)
		Irrigated crops	Unirrigated crops	Irrigated rice	
2011	0.4 - 0.6	-.429**	.498**	-.515**	-.538**
	0.6 - 0.8	.449**	NS	.433**	.437**
	0.8 - 1.0	.641**	-.469**	.700**	NS
2012	0.4 - 0.6	NS	.591**	-.436**	-.620**
	0.6 - 0.8	.301*	NS	.360**	.607**
	0.8 - 1.0	.384**	-.472**	.485**	.408**
2013	0.4 - 0.6	-.477**	.648**	-.478**	-.347**
	0.6 - 0.8	NS	.307*	NS	NS
	0.8 - 1.0	.826**	-.498**	.845**	.295*
2014	0.4 - 0.6	-.552**	.545**	-.559**	NS
	0.6 - 0.8	.602**	NS	.535**	.272*
	0.8 - 1.0	.754**	-.456**	.808**	NS
2015	0.4 - 0.6	-.457**	.620**	-.479**	-.438**
	0.6 - 0.8	.490**	NS	.403**	.279*
	0.8 - 1.0	.477**	-.393**	.536**	NS

* and ** indicate statistical significance at 5 and 1%, respectively
NS = non-significant

It appeared from the data and analysis that the relations among certain basic parameters were same in both rainfall deficit and normal years. The area under irrigated crops and the number of pixels in 0.6-0.8 and 0.8-1.0 NDVI classes were significantly and positively correlated in all years except 2013 where the relation was insignificant with pixels in 0.6-0.8 class. But, there was a significant and positive correlation with pixels in 0.8-1.0 class all the times.

Interestingly, the correlations were negative between area under irrigated crops and pixel count in 0.4-0.6 class, which indicated a lesser greenness in this class in all years except 2012. It was imperative from the data that irrigation increased greenness and resultant NDVI thus a direct and positive relation. The negative relation also inferred the same where stressed pixels did not reflect irrigated areas.

Contrarily, the area under unirrigated crops were positively and significantly correlated to the pixels in NDVI class, 0.4-0.6 in all the years, which underscored the limitation posed by rainfall on greenness. Similarly, in all the years, the relationship between the area under unirrigated crops and the pixels in 0.8-1.0 were significantly negative indicating the opposite relations between greenness and crop stress as expected in rainfed and irrigated crops.

Like irrigated crops, rice, (which is irrigated during *kharif*) also exhibited exactly similar relationship between area and pixels in different classes; significant negative relationship in 0.4-0.6 class and significant and positive relationship in 0.6-0.8 and 0.8-1.0 NDVI classes in all years with an exception in 2013 where the relationship was insignificant in 0.6-0.8 NDVI class. But there was a highly significant and positive correlation in class, 0.8-1.0 in 2012 and 2015. As mentioned earlier, sub-classification of this range of 0.8-1.0 into narrow width classes might add more to clarity as the pixels even slightly more than 0.8 would automatically be classified to this class. According to the DES, rice was cultivated always with irrigation during *kharif* season.

Rainfall and NDVI relationship

It is known that good rainfall and its distribution would alleviate the moisture related stress and in the present study also similar such inferences could be drawn. It is obvious that the correlations would be significant when the variables included in the correlation study posed limitation on the behaviour of other variable. For example, rainfall, was one such variable, which was deficient in certain times posing the limitation. Since the rainfall received in the initial periods of the season would determine the cropping pattern, a correlation analysis was done using rainfall and pixels in different classes. In 2011, when the rainfall was more, the number of pixels in 0.6-0.8 class increased consequently (0.437^{**}), indicating increased vigour of the vegetation due to crop growth while it also meant that crop stress area was reduced by reducing the number of pixels in lesser range of NDVI, 0.4-0.6 (-0.538^{**}). In 2012, where the rainfall was sub-normal during SWM, similar relations were maintained with an additional significant and positive relation with pixels in 0.8-1.0 NDVI class (0.408^{**}). In case of 2013 that received excess rainfall, the relation with the pixels in 0.4-0.6 class was similar (0.347^{**}) and a significant and positive relation with pixels in 0.8-1.0 NDVI class. In another deficit rainfall year, 2014, the increase in rainfall decreased the pixels in 0.2-0.4 class (-0.356^{**}) while it increased the pixels in 0.6-0.8 class ($r = 0.272^{*}$). In 2015 that received the above normal rainfall during southwest monsoon, the relations were similar like what were seen earlier where the 'r' values were $-0.392^{**,}$ -0.438^{**} and 0.279^{*} with the pixel counts in 0.2-0.4, 0.4-0.6 and 0.6-0.8 classes, respectively (Table 3).

In the earlier instance, Rao *et al*. (2012) reported more or less similar relationships when the MODIS data derived NDVI was used in understanding the moisture stress in Anantapur district of Andhra Pradesh in deficit, excess and normal rainfall conditions. Analysis by Rao *et al.* (2013) indicated that low groundnut yields in general could be related to NDVI based stress measurements and rainfall quantum and distribution in Anantapur district however, with some exceptions. Rao and Surekha (2015) reported a direct and positive relationship between rainfall and NDVI as evident through significant correlation with pixels in 0.6-0.8 class. This was further corroborated by positive and significant correlation of pixels in 0.6-0.8 class of NDVI with rice area when pooled data (of three years) was analysed.

The results of this analysis unequivocally described the response of vegetation to the rainfall, as indicated by the vegetation index, which directly determines the agricultural crops and area in any geographical area. However, finer weather analysis would add more to the understanding of the vegetation and its response to one of the most important abiotic stressor.

Response of rice vegetation in terms of NDVI

A temporal analysis of NDVI was attempted to understand the rice vegetation response. Point vector files were created representing rice growing fields using Google Earth imagery and coordinates. The monthly MVC (maximum value composite) for the water years from 2011-12 to 2015-16 were used and the NDVI values were extracted to those points. A plot of NDVI of one such point vector representing a rice field in Pehpahad mandal was shown in Figure 3. Bi-modal NDVI curves of monthly MVC indicated two crop seasons i.e. *Kharif* and *Rabi* though there were temporal differences in maximum NDVI in 8 day composites. Analysis of 8 day composites indicated that the peak NDVI was seen on 14th, 22nd, 30th, 30th September and 24th October in *Kharif* of 2011, 2012, 2013, 2014 and 2015, respectively with a range from 0.729 to 0.878 (Table 4) . Similarly, maximum NDVI during *Rabi* was noticed on 26th February in 2011 and 2012, on 22nd and 14th March in 2013 and 2014 and on 25 January, 2015 with a range from 0.692 to 0.795. There variations were directly ascribable to all the factors that influenced the NDVI including abiotic and biotic factors plus management practices. Besides, the onset of monsoon and the distribution of rainfall must have caused the variations in the dates of peak NDVI.

Table 4. Dates of observed peak NDVI values

Year	Date	NDVI
2011-12	14-Sep	0.773
	26-Feb	0.747
2012-13	22-Sep	0.729
	26-Feb	0.795
2013-14	30-Sep	0.878
	22-Mar	0.766
2014-15	30-Sep	0.808
	14-Mar	0.776
2015-16	24-Oct	0.761
	25-Jan	0.692

Spatial variability in soil resources

The maps of available important physical edaphic factors (Figure 4) indicated the spatial variability, which in combination with other factors would ultimately influence the NDVI. The extent of different depth categories followed the order; moderately deep (44.6%) > deep (31.0%) > moderately shallow (9.5%) > rock outcrops in hills and ridges (5.3%) > very deep (4.6%)> shallow = rock outcrops in undulating areas. Among textural classes, the order was; Gravelly loam (calcareous) (29.9%) > clay calcareous (25%) > gravelly clay calcareous (12.8%) > clayey (9.2%) > cracking clay (4.4%) > loams (3.4%) followed by other minor classes. Moderately eroded soils dominate in 35.9% of area followed by slightly eroded soils (29.1%) and severely eroded (20.6%).

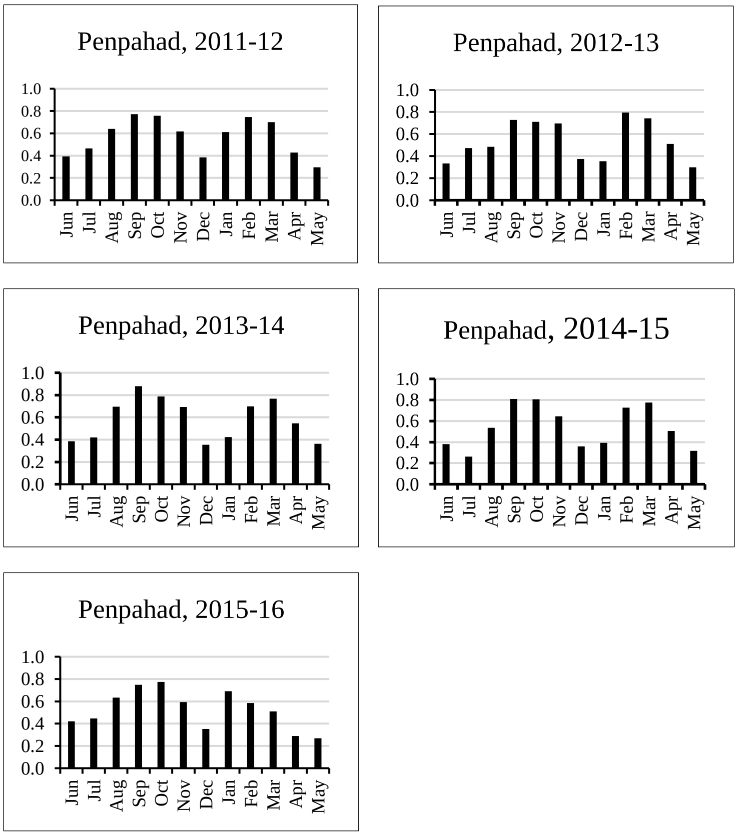
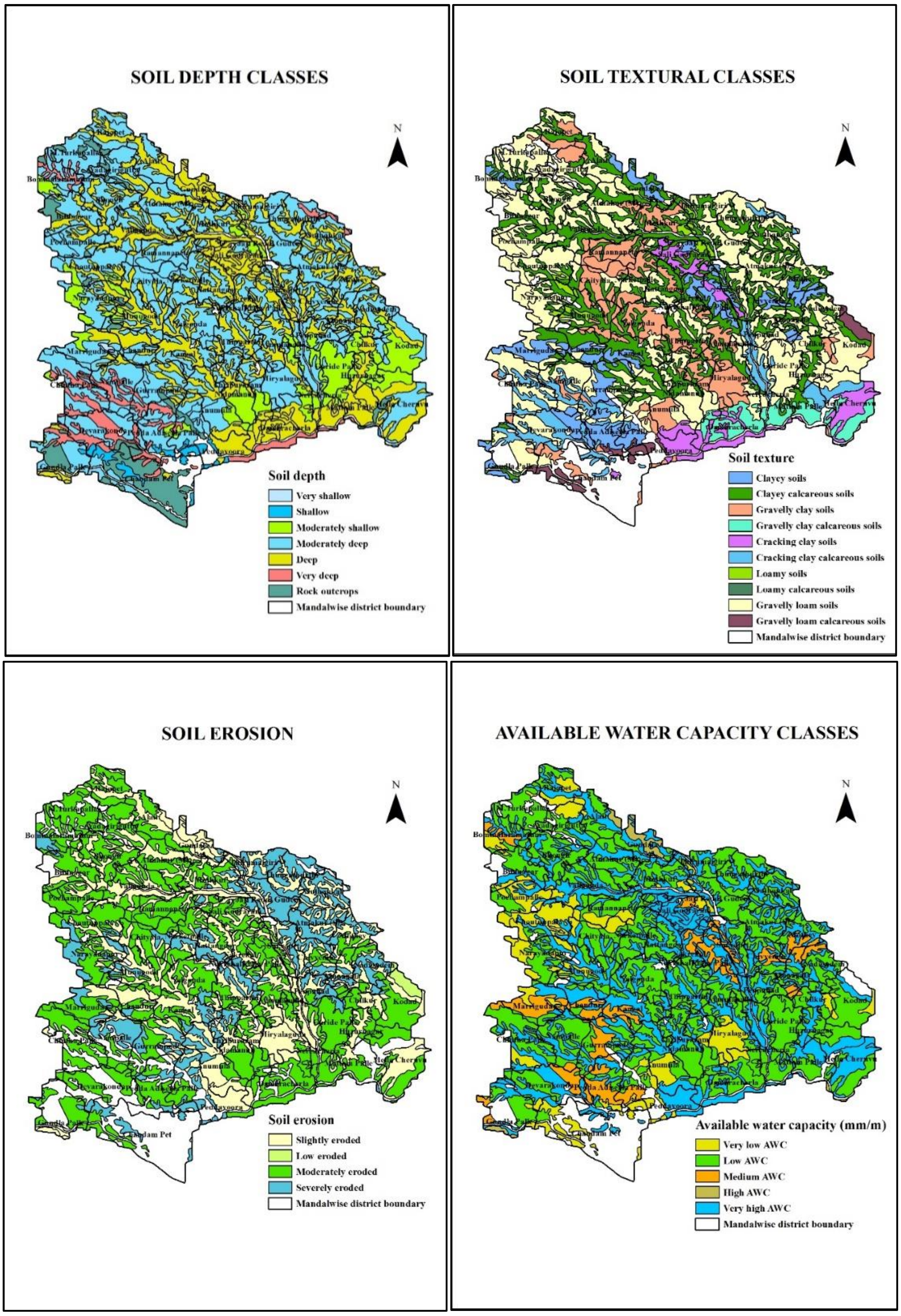


Figure 3. Temporal changes in spectral response of rice vegetation

The most important soil physical property, the available water capacity (AWC), which is determined by soil texture, depth and coarse fragment content and organic matter showed wide variability. Interestingly, the classes of very high and low AWC occupied equal proportion of 35% each while 12.9% area was characterised by very low AWC and medium AWC was present in 8.3% area. 7.8% area of water bodies was unclassified while 0.7 % area possessed high AWC. Although the map of drainage was not shown, about 53% area was well drained followed by imperfectly drained area of about 26% while 9.2% area was moderately well drained. Somewhat excessively drained soils occupied 4% of area.



(Source: NBSS & LUP, Nagpur)

Figure 4. Spatial variability in selected edaphic factors

Although not shown, the chemical edaphic factors like soil reaction, electrical conductivity and nutrient status etc. are of paramount significance, which affect the crop performance at every stage. As for some earlier work on some edaphic factors and NDVI was concerned, Rao *et al.* (2013) showed the negative impact of soil salinity on the NDVI and thus groundnut yield in Anantapur district.

Anyway, it is beyond the scope of this article to describe the role of soils and their management in deciding the spatial variability in the agricultural crop distribution. Nevertheless, soil being the fundamental growth medium and resultant of five forming soils factors acting in permutations and combinations led to enormous spatial variability that could reflect in the plant growth.

CONCLUSIONS

This analysis of temporal 250 meter resolution data coupled with available secondary data gave some information to understand the behaviour of vegetation of agricultural crops in different situations of varied rainfall and soil resources. The study period of water years between 2011-12 and 2015-16 characterised by deficit and normal rainfall had different crops and acreage as well. The impact of rainfall was probably prominent on unirrigated crops as reflected through the acreage when compared to that of irrigated crops, which was unaffected because of the assured irrigation. Besides rainfall pattern, other reasons also would determine the cropping pattern including the Government schemes, incentives, availability of inputs and market driven forces.

The results of image analysis clearly indicated the response of vegetation to the rainfall in general with specific patterns in both deficit and normal rainfall situations, through the number of pixels in different classes of NDVI. The rainfall situation referred to both quantum and distribution of rainfall during the southwest monsoon.

However, the greenness also could have been affected by other factors including pests and diseases (biotic factors), temperature, plant nutrient status and other abiotic factors. However, certain basic relationships between rainfall and NDVI were same both in deficit and normal rainfall situations. It was felt that further sub-classification of 0.8-1.0 NDVI into narrow width would yield better results as even a slightest increase beyond 0.8 NDVI would classify it to 0.8-1.0 NDVI class, probably leading to inappropriate inferences.

A huge volume of literature highlighted the role of different edaphic factors in determining the adoption of agricultural crops and their growth. Nevertheless, soil being the fundamental growth medium and resultant of five forming soils factors acting in permutations and combinations led to enormous spatial variability that gets reflected in the plant growth as reflected through NDVI derived from the remotely sensed data.

This attempt to use freely available data and resources certainly yielded certain results to understand the dynamics in the agricultural activity in a given area, although there could be some missing information owing to the coarse resolution. Nevertheless, the information was useful in studying the temporal and spatial variability in the NDVI, the index of crop health, which was affected by abiotic, biotic and management factors. Although some of the factors were analysed in this study, there is a requirement to go further to analyse dependence of NDVI on its causative factors at finer resolution. This process includes further study with freely available fairly good resolution imagery acquired by Resourcesat, Sentinel 2 and Landsat 8 etc. Similarly, topographical studies using digital elevation models (DEM) would help in understanding the terrain in relation to soils. In this regard, DEM developed from Cartosat 1 (2.5 meter) data, which is also available for free from Bhuvan portal of ISRO (bhuvan.nrsc.gov.in) could be of significant purpose. Besides, Bhuvan portal also offers several thematic services, which are of great use. Similarly, there are sources of several free software for image processing and GIS works including QGIS, GRASS etc., a few to mention.

This exercise also aimed at popularising Agro-geoinformatics using free and open sources of software and data particularly among the students and other users in the cash strapped universities and research institutes because of the cost factor involved in procuring hardware and software. With the advent of technology the cost of computers had also came down heavily so that one can choose the field of Agro-geoinformatics using freely resources. This certainly helps in the development of work force to contribute to this field of agricultural application effectively.

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