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Assessment of Agricultural Drought Using MODIS Derived Normalized Difference Water Index

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ABSTRACT

Remote sensing index NDVI or its derivatives are used for agricultural drought monitoring and early warning at regional scale worldwide. Studies have shown that NDVI has lagged response to rainfall deficit. Moreover the red band used in NDVI is highly absorbed by crop canopy in comparison to short infrared which has high penetration so thus there remains a discrepancy between the levels of penetration in crop canopy. In contrast, Normalized Difference Water Index (NDWI) uses both the bands in near infrared region and is very sensitive to liquid water content of vegetation canopy and so rainfall. So this study was conducted to evaluate the sensitivity of NDWI in detecting and monitoring the agricultural drought in comparison with NDVI. In the study three indices of NDVI, NDWI5 and NDWI6 were computed using MODIS 09A1 surface reflectance product from June to October of 2002 (drought year) and 2003 (normal year) for the state of Rajasthan. NOAA Climate Prediction Centre (CPC) rainfall product was used and averaged at district level. The NDWI5 showed very strong relation with current rainfall than NDWI6 and weakest was shown by NDVI. The relation of NDVI with lagged rainfall was much better than with current rainfall. The spatial comparison of changes in NDVI and NDWI5 between the drought year (2002) and normal year (2003) for each 8 days composite showed that NDWI5 very well picks up the intensity and extent of drought. Study also showed that NDWI5 is more sensitive to agricultural drought than NDWI6. The study recommends use of NDWI5 for better early detection and monitoring of agricultural drought in operational drought management programmes.

Key words: Drought, NDVI, NDWI, Rainfall, Monitoring, MODIS

Introduction

Monsoon rain is regarded as India's economic lifeline. Over 70 percent of the country's one billion plus population depends on agriculture for their living. Onset of monsoon and its progress dictates the sowing of crop till its harvesting. Due to failure of monsoon India used to face wide spread drought. When the actual rainfall in an area is significantly less (25% or more) than the climatological mean of that area we call it a meteorological drought. It leads to the hydrological drought with marked depletion of surface water causing very low stream flow and drying of lakes, rivers and reservoirs. This ultimately ends up with agricultural drought with inadequate soil moisture resulting in acute crop stress and fall in agricultural productivity. The total rainfall of the country may be normal but its uneven spatial and temporal variations often cause drought in some parts of India. Monitoring and delineation of drought affected area from space borne platform will be very useful for early warning of drought disaster and better preparedness by developing contingency plans by policy makers.

Water stress in vegetation leads to changes in different physiological and biochemical characters of crop plants. Remote sensing exploits this change in vegetation body to pick the water

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stress. It has been found that fairly accurate estimates of leaf pigments, nitrogen, dry matter, water content, and leaf area index (LAI) from remote sensing can assist in determining physiological status (Carter, 1994; Peñuelas *et al.*, 1994), the study of species and its seasonal dependence (Belanger *et al.*, 1995), and may serve as bioindicators of vegetation stress (Luther *et al.*, 1999; Zarco-Tejada *et al.*, 2001). The remote determination of one of these biochemical constituents, vegetation water content, has important implications in agriculture and forestry (Gao *et al.*, 1995), it is essential for drought assessment in natural vegetation (Peñuelas *et al.*, 1993). Several studies demonstrated the existing link between leaf-level reflectance in the 400–2500 nm spectral region and the amount of water in the leaf through optical indices, regression analysis and radiative transfer modeling (Aldakheel *et al.*, 1997; Allen *et al.*, 1971; Ceccato *et al.*, 2001; Danson *et al.*, 1992; Gausman *et al.*, 1970; Hunt *et al.*, 1987; Jacquemoud and Baret, 1990). The primary and secondary effects of water content on leaf reflectance were studied by Carter *et al.* (1991) showing that sensitivity of leaf reflectance to water content was greatest in spectral bands centered at 1450, 1940, and 2500 nm. Indirect effects of water content on reflectance were also found at 400 nm and 700 nm (Filella and Pen˜uelas, 1994) and on vegetation indices such as NDVI (Roberts *et al.*, 1997). The NDVI is the most widely used index for remote sensing of vegeta-tion in the past two decades. It is equal to $(\rho_{nir} - \rho_{red})/(\rho_{nir} + \rho_{red})$, where ρ_{red} is the radiance (in reflectance units) of a red channel near 660 nm, and ρ_{nir}, the radiance (in reflectance units) of a near-IR channel around 860 nm. This index has been used in many applications, including estimation of crop yields and end-of-season above-ground dry biomass (Tucker *et al.*, 1986). The two channels used in NDVI sense through different depths of vegetation canopies. The near-IR channel can see through roughly eight layers of leaves, while the red channel sees only one leaf layer or less (Lillesaeter, 1982) because of the strong chlorophyll absorption near 670 nm. In spite of its usefulness, NDVI is known to be saturated when applied to images over areas having leaf area index (LAI) of three or greater.

The normalized difference water index (NDWI) suggested by Gao (1996) demonstrated its potential applicability for canopy-level water content estimation based on the liquid water absorption band centered at 1240 nm enhanced by canopy scattering. The NDWI uses two near-IR channels can be written as

$$\text{NDWI} = \{\rho\ (860\ \text{nm}) - \rho\ (1240\ \text{nm})\} \,/\, \{\rho\ (860\ \text{nm}) + \rho\ (1240\ \text{nm})\} \quad \ldots(1)$$

where ρ_{860} is the radiance (in reflectance units) of channel centered around 860 nm, and ρ_{1240}, the radiance (in reflectance units) of channel centered 1240 nm. Because both the 860 nm and 1240 nm channels are located in the high reflectance plateau, the vegetation scattering properties for the two channels are expected to be about the same. The reflectance of the dry vegetation in the 800-1300 nm region generally increases with wavelength, except near 1200 nm, where a weak cellulose absorption band is present. The cellulose absorption effect at 1240 nm is much smaller than that at 1200 nm. Therefore, the use of a narrow channel at 1240 nm in the formation of NDWI largely avoids the cellulose absorption effects on NDWI. The value of NDWI for the dry vegetation spectrum is negative but for green vegetation is positive due to the weak liquid water absorption near 1240 nm. Liquid water absorption in the 1500-2500 nm region for a green vegetation spectrum is significantly stronger than that in the 900-1300 nm region. Still the region 1500-2500 nm is not used very popularly because the reflectance spectra of this region saturate when LAI reaches four or greater. On the other hand, because liquid water absorption in the 900-1300 nm is weak, the vegetation spectrum in this region is sensitive to changes in leaf water content until LAI reaches value eight.

NDWI can not remove the background soil effect completely. Typical soil reflectance increase with wavelength in the 800-1300 nm region. The reflectance of soils, including very wet soils, do not show liquid water ab-sorption bands centered near 980 nm and 1200 nm. As reflectances at 1240 nm for most wet and dry soils are greater than those at 860 nm, NDWI values are expected to be negative for most bare soils.

The center wavelength positions of water vapor and liquid water bands in the 900-2500 nm region are relatively shifted by approximately 50 nm. The shifts are due to O-H bonding strength differences for water in liquid phase and in gas phase. It is found that the largest errors introduced by atmospheric water vapor to NDWIs for liquid water thicknesses of 0.05 cm, 0.1 cm, 0.2 cm, and 0.4 cm are 1.50%, 0.74%, 0.37%, and 0.22%, respectively. Therefore, atmospheric water vapor effects on NDWIs are very small.

So, a study was undertaken to compare the effectiveness of NDWI in early detection of agricultural drought in comparison to NDVI for Rajasthan State which experienced drought in year 2002. Besides, comparison was also made between NDWI computed by Band 5 and Band 6 of MODIS sensor in detection of drought.

Material and Methods

Study Area

The study was conducted for the Rajasthan State, situated in the north-western part of India exhibiting arid to semi-arid climate in different parts. The mean annual rainfall in the west varies from 100 to 400 mm while it ranges between 557 mm to 1000 mm in the east with annual average of 574.3 mm for whole state. The total cultivated area of the state encompasses about 20 million hectares and out of this only 20% of the land is irrigated. Rajasthan was chosen as the area of study in the present investigation because Rajasthan was the worst affected states during 2002 drought. Drought occurred in all the 32 districts with a deficit monsoon rainfall of 53.4% in year 2002. Approximately 40 million people and 50 million cattle were affected that year alone.

Data Used

MODIS Satellite Data

To monitor the progress of drought and for its relative estimation 8 days composite image of surface reflectance product of MODIS, called MOD09A1 were downloaded from website *http://edcimswww.cr.usgs.gov./pub/imswelcome/* from June to October both for 2002 (drought year) and 2003 (normal year). MODIS surface reflectance product is generated from MODIS Level 1B land bands centered at 648 nm (band 1), 858 nm (band 2), 470 nm (band 3), 555 nm (band 4), 1240 nm (band 5), 1640 nm (band 6) and 2130 nm (band 7). The product MOD09 is an estimate of surface spectral reflectance for each band as it would have been measured at ground level. The correction scheme includes correction for the effect of atmospheric gases, aerosol and thin cirrus cloud; it is applied to all non-cloudy MOD 35 Level 1B pixels that pass the Level 1B quality control. The correction uses band 26 to detect cirrus cloud, water vapour from MOD05, aerosol from MOD 04 and ozone from MOD07; best available climatology is used if the MODIS water vapour, aerosol or ozone products are unavailable. Also, the correction use MOD 43, BRDF without topography, from the previous 16 day time period for the atmosphere-BRDF coupling term.

NOAA CPC Rainfall Product

For rainfall data NOAA CPC RFE2.0 rainfall product from June to October both for the year 2002 (drought year) and 2003 (normal year) was used. It gives daily estimated rainfall product at $0.1^0 \times 0.1^0$ grid size. This is an ensemble product of four rainfall estimates. Among the four estimates, one is ground based observations and other three are satellite based observations. It uses WMO GTS network for ground based observations. There are 2534 ground observations available daily; these are quality controlled and grided at 0.1^0 spatial resolution using Shepard technique for interpolation. Among the satellite based observation first is METEOSAT derived GOES Precipitation Index (GPI). It utilizes half hourly 0.05° infrared temperature data of cloud top and the resultant field is cold count duration (CCD) @ 0.1°. CCD (if T < 235 ° K) is used for calculating GPI. The second one is SSM/I Derived Precipitation. Two instruments take data twice daily (6 hourly interval) using passive microwave 85 GHz vertical polarized channel. It measures increase in brightness temperature due to the presence of liquid precipitation. Third one is NOAA AMSU-B derived precipitation. It measures humidity profiles data which is available 4 times daily and staggered temporally. The rainfall product is computed in two steps. At first it combines three satellite data sets linearly as given below:

$$S = \sum_{i=1}^{3} W_i S_i \quad \ldots(2)$$

where, W_i = weighting coefficients, S_i = precipitation estimate, and ói = random error and W_i for each estimate is computed using variance of that technique estimate as given below:

$$W_i = \frac{\sigma_i^{-2}}{\sum_{i-1}^{3} \sigma_i^{-2}} \quad \ldots(3)$$

The final precipitation estimate is generated by removing the bias of the satellite estimate using GTS observations.

Drought Assessment

All the surface reflectance products of MODIS were downloaded, geo-rectified and then projected in its native integerized sinusoidal projection. Then NDVI, NDWI5 and NDWI6 indices images were generated using band reflectances as given below:

$$NDVI = \frac{band2 - band1}{band2 + band1} \quad \ldots(4)$$

$$NDWI5 = \frac{band2 - band5}{band2 + band5} \quad \ldots(5)$$

$$NDWI6 = \frac{band2 - band6}{band2 + band6} \quad \ldots(6)$$

NOAA CPC daily rainfall product were accumulated pixelwise for 8 days corresponding to each period of MODIS data. The rainfall product was georeferenced in geographic coordinates. In order to match the MODIS derived vegetation indices images with corresponding period rainfall images, the VI images were reprojected and aggregated to match rainfall images. So, the images of different vegetation indices (NDVI, NDWI5, and NDWI6) and the corresponding rainfall products were brought to same projection (lat-long) and pixel size (10km). In order to study the relation between different VIs and rainfall for a time period, their 2-D scatter plot was studied. The average rainfall and VIs were aggregated at district level and their regression analysis was carried out for normal crop year 2003. In order to analyze the efficacy in detecting agricultural drought, the NDVI image of the same eight day period of 2003 was subtracted from 2002. The resultant image is named ΔNDVI. Likewise ΔNDWI5 and ΔNDWI6 were also computed. As the monsoon of 2003 was normal and 2002 was a drought year, the vegetation vigor and moisture must be higher in case of 2003 and it should have high NDVI, NDWI5 and NDWI6. These vegetation indices will be less in case 2002 due to drought. So higher the pixel value of ΔNDVI or ΔNDWI5 or ΔNDWI6 means higher the intensity of drought in that area. In this way an attempt has been made to estimate drought on a relative scale of +2 to -2. The value of +2 depicted highest level of drought in 2002 while value of -2 depicted best crop conditions in 2002. The ΔVI images were overlaid with agricultural crop mask to infer only about agricultural drought. By using multi-temporal images the progress and extent of drought were also studied.

Results and Discussion

The table 1 shows the coefficient of regression (R^2) between district average rainfall and VIs for corresponding eight day period in normal year 2003. In case of NDVI, table 1 also shows R^2 between current NDVI and eight day lagged rainfall. The NDWI5 showed highest values of R^2 for each period as compared to

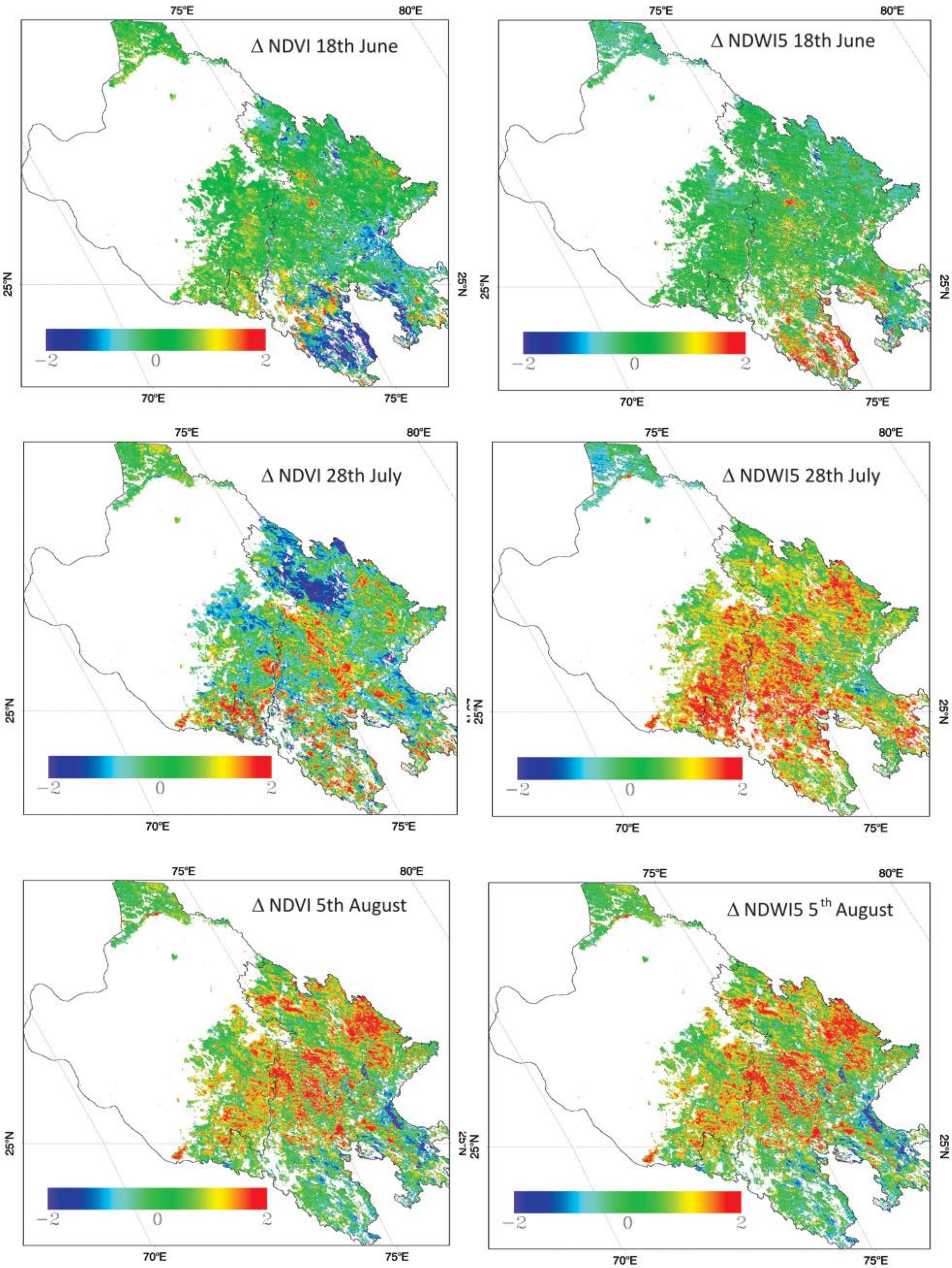
Table 1. Coefficient of determination (R^2) values between current rainfall (CR) and different vegetation indices averaged for different districts at different dates during crop season.

Date	CR* &NDVI	CR** and NDVI	CR* and NDWI5	CR* and NDWI6
12th July	0.36	-	0.62	0.18
20th July	0.33	0.47	0.65	0.44
28th July	0.25	0.43	0.66	0.40
5th August	0.38	0.45	0.60	0.49
13th August	0.26	0.35	0.74	0.53
21st August	0.23	0.43	0.62	0.23
29th August	0.11	0.32	0.63	0.48
6th September	0.33	0.41	0.68	0.29
14th September	0.14	0.41	0.73	0.53
22nd September	0.38	0.43	0.70	0.51
30th September	0.58	-	0.65	0.55

* means current CR
** means eight days lagged CR
Number of observations (i.e. Districts) = 24

NDVI and NDWI6. The R^2 value varied from 0.60 to 0.74 which is consistently higher than the performance of the other indices. It indicates the sensitivity of NDWI5 in picking up moisture status in crops. The NDWI6 did not show as good R^2 values with current rainfall as that of NDWI5 and varied between as low as 0.18 to as high as 0.55. But the NDWI6 R^2 values were generally higher than for NDVI again indicating that NDWI6 is more sensitive to moisture status in crops than NDVI. The reason for the poor performance of NDWI6 as compared to NDWI5 may be due to its earlier saturation at the higher LAI. Current NDVI also showed low R^2 value with the current rainfall. It varied from 0.11 to 0.55. Overall the average R^2 value is low with current NDVI and current rainfall (Table1). But the strength of relation improved when the eight day lagged rainfall data was regressed with NDVI (Table 1). It indicates that NDVI has a lag relation with moisture status in crops. So from statistical analysis it is very much evident that NDWI5 is a best index among the three VIs for drought monitoring as it is having highest R^2 value with current rainfall and strength of relation remain consistent even with the progress of crop season. NDVI did not prove to be as good an index as NDWI5 for the drought monitoring in crops. It was also found that NDVI has lagged relationship with current rainfall.

For comparative study of the sensitivity of the NDWI5 and NDVI for monitoring of drought, the ΔNDWI5 and ΔNDVI images of corresponding period during the crop season are presented in the figure 1. The blue to cyan colour means no water stress and yellow to red means moderate to high water stress in the images. As early as June 18 the south east part of Rajasthan started facing drought which is well picked up by ΔNDWI5 image as shown in the red colour but the ΔNDVI did not pick it. Similarly by 28th July, ΔNDWI5 started showing a large agricultural areas under high water stress but ΔNDVI showed only a small part of agricultural area under high water stress. Rather it showed better crop condition in north-central region as depicted by blue color. The images of 5th August shows a similar pattern of drought in ΔNDWI5 and ΔNDVI images. In other dates *viz.* 13 August and 6 September, ΔNDWI5 images efficiently picked up the water stress and large scale drought in the state as it is very much evidenced by the red colour and yellowness of the images. ΔNDVI showed a static nature and did not pick up the drought in its intensity and extent as the yellow and reddish colour is much less as compare to ΔNDWI5 images. These images clearly indicate that NDWI5 is very efficient in picking up the agricultural drought due to its higher sensitivity than NDVI.


Δ NDVI 18th June
Δ NDWI5 18th June
Δ NDVI 28th July
Δ NDWI5 28th July
Δ NDVI 5th August
Δ NDWI5 5th August
75°E
80°E
70°E
25°N
−2
0
2

Contd...

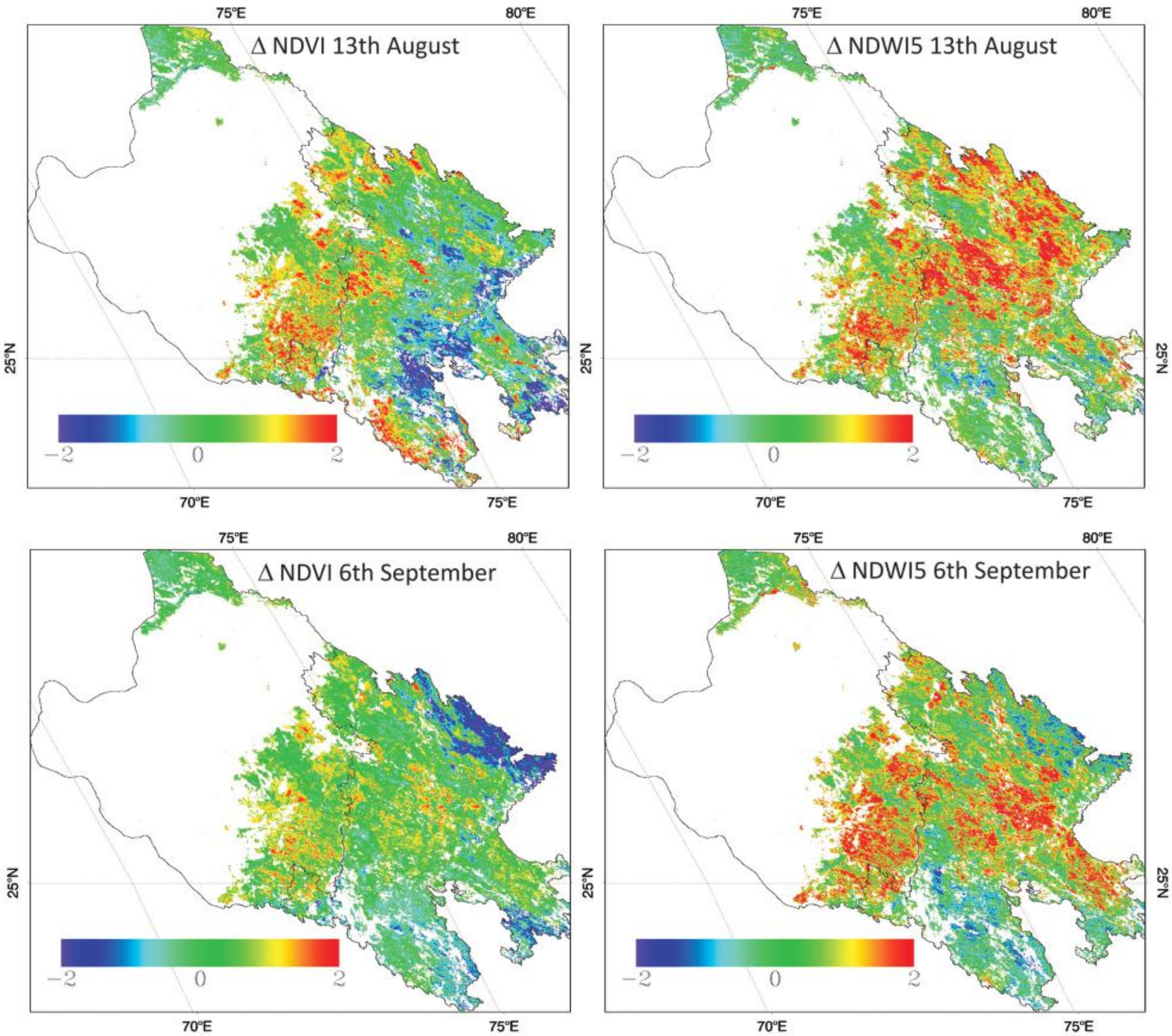


Fig. 1. Comparison of ΔNDVI and ΔNDWI5 for different periods during the crop season. A value of +2 (red) show highest level of agricultural drought in 2002 while a value of -2 (violet) shows better crop condition in 2002 than in 2003. The value 0 (green) shows that crop condition was nearly same in 2002 and 2003.

The comparison of ΔNDWI5 with ΔNDWI6 for detecting agricultural drought by 28th July is shown in figure 2. The ΔNDWI5 image show large agricultural area under red to yellow color as compared to ΔNDWI6 image. It clearly indicates that NDWI5 is more sensitive to agricultural drought than NDWI6 though both are based on bands which are sensitive to water content present in vegetation. So, NDWI5 is a better indicator of early detection of drought and its intensity than both NDWI6 and NDVI.

Conclusions

From the above study it can be concluded that NDWI5 is a very good index for early detection of agricultural drought and hence should be a better candidate for remote sensing based drought monitoring methodology. The NDWI5 also showed a very good and consistent relation with current rainfall at regional scale. Though NDWI6 was also sensitive to plant moisture content but its sensitivity was poorer than that of NDWI5. The NDVI could not able to pick up plant

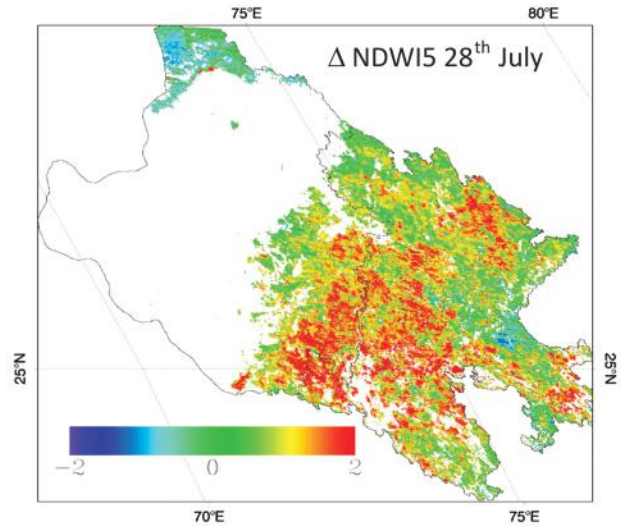


Fig. 2. Comparison of ΔNDWI5 and ΔNDWI6 for 28th July. A value of +2 (red) show highest level of agricultural drought in 2002 while a value of -2 (violet) shows better crop condition in 2002 than in 2003. The value 0 (green) shows that crop condition was nearly same in 2002 and 2003.

moisture status till mid of August (i.e. early crop season). Rather NDVI showed a lagged relationship with rainfall. This study concludes that real time MODIS data can be well utilized for regional level agricultural drought detection and monitoring for early warning by comparing NDWI5 index rather than basing the methodology on NDVI comparison as is the case worldwide.

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