Assessment of drought extent using vegetation indices and rainfall data: A case study of Rajasthan, India

¹Neha Sharma, ²Sarvesh Palria

¹Ph.D. Scholar, ²Professor ¹Dept. of Remote Sensing and Geoinformatics, ¹MDS University, Ajmer, India

Abstract: Drought is an insidious hazard of nature. Unlike rapid onset disasters, it tightens its grip over time, gradually destroying an area. As the Indian economy is primarily driven by agriculture, the effects of meteorological droughts are direct and can be large. Timely assessment of drought can alleviate its severe consequences.

This study emphasis upon the use of space technology and geographic information system in drought risk assessment. In the present work, an effort has been made to assess, monitor and delineate risk areas facing agricultural as well as meteorological drought by using vegetation indices (NDVI and VHI) and rainfall data. Resultant risk map obtained by integrating agriculture and meteorological drought risk map indicates the areas facing a combined hazard. NDVI trend analysis has also been done to assess the long-term changes occurred as a result of irrigation, deforestation, and urbanization. It absolutely was evident from the study that western and central parts of Rajasthan are more prone to drought either agricultural or meteorological. The analysis shows that increasing irrigation facility within the area causes a major positive change in the vegetation. The results obtained provide objective information on incidence, severity level and persistence of drought conditions, which can be useful to the resource managers in optimally allocating limited resources.

IndexTerms: Drought assessment, Normalized Difference Vegetation Index (NDVI), Vegetation Health Index (VHI), Agriculture Stress Index (ASI), Yield Anomaly, Rainfall Anomaly.

I. INTRODUCTION

Anomalous dry weather conditions and scarce rainfall leads to the drought event. It causes reduced water flow in rivers and decreased water level in lakes, ponds, wells and other reservoirs. Drought deteriorates the sustainable development of the society. Agriculture is the most vulnerable and risk-prone sector that is extremely affected by the climate change and its variability. Satellite-based drought indices can detect spatial and temporal variation of agriculture drought pattern and severity. Using advanced techniques of remote sensing and GIS we can assess the past and the present agriculture drought scenario and can prepare baseline information to monitor real-time condition (Legesse and Suryabhagavan, 2014).

The Normalized Difference Vegetation Index (NDVI) is calculated using reflectance in NIR and Red channel i.e. NIR-RED/NIR+RED. It is the most widely used vegetation indices applied in avariety of applications related to agriculture and forestry (Kogan 1987; Marj&Meijerink, 2011). It is commonly used in drought monitoring and assessment due to its capability to eliminate the effects of atmosphere, illumination angle, geometry etc. It is a good tool to monitor prevailing vegetation conditions and its variability.

Unlike NDVI, Vegetation Health Index (VHI) takes into account both vegetation health and temperature condition to identify thespatial-temporal extent of agriculture drought. VHI has proved its capability in detecting agriculture drought and its severity level (Rizqi et al. 2016). According to Bhuiyan et al. (2004), VHI represents the collective impact of moisture-stress and thermal-stress on vegetation vigor and is proved to be an effective drought-monitoring index. VHI estimates can detect inception of agricultural drought. It can be used as a tool for drought monitoring and early warning system.

Another useful index that can be used for drought monitoring is Agricultural Stress Index System (ASIS). It represents, per administrative unit, the percentage of cropland area affected by drought over the growing season (Hoolst et al. 2016). It works on per regions basis, not per pixel, it also allows the comparison between drought conditions of two different regions. ASIS can be served as an effective tool to keep an eye on drought conditions prevailing over any region.

To identify the spatial-temporal extent and intensity of drought, crop yield, rainfall and NDVI anomaly were computed. Rainfall and vegetation indices are the main data sources for vegetation and crop monitoring. Anomaly data detects location and extent to which vegetation and rainfall conditions are different from long-term normal. Negative anomaly conditions relate to water stress (drought) and positive conditions could indicate good vegetation condition. Anomaly map basically gives an idea of how good or bad the present situation is when compared with the long-term average condition. Anomaly map can identify the intensity and frequency of the drought events.

This study is focused to identify the increasing or decreasing trends in vegetation using long-term NDVI data and to delineate the agricultural and meteorological drought risk areas using long-term rainfall and vegetation indices data. In order to prepare combined hazard map by integrating agriculture and meteorological drought risk maps. Rajasthan is the most drought-prone state and due to the severe negative impacts of drought, it is essential to monitor drought conditions in atimely manner for food security and disaster mitigation.

II. STUDY AREA

The study area consists of Rajasthan state. Rajasthan has a tropical desert climate, it is one of the most drought-pronestates of India, its climate varies mostly from arid to sub-humid. Aravalli's mountain chain divides the state into two parts. The western part of the state is characterized by low rainfall, extreme diurnal and annual temperature, low humidity and high-velocity winds. While, in the eastern part, the climate is semi-arid to sub-humid marked by lower wind velocity and higher humidity and agood amount of rainfall. The average annual rainfall ranges from less than 10 cm in thenorth-west part of Jaisalmer region to the 163.8 cm (Highest rainfall) in Mount Abu (Sirohi district) in the southwest part of Rajasthan (Rajasthan tourism). Agriculture in the state is mostly rain-fed, only 34.5 percent of total agriculture land is irrigated. (Mrutyunjay et al. 2012)

III. MATERIAL AND METHODS

3.1 Data used

3.1.1 Satellite data

Terra MODIS 16-day L3 global 500m (MOD13A1) NDVI data of tile h24v06 from theyear 2000-2016 have been used in this study to identify agriculture drought-prone areas. For long-term trend analysis, NDVI data for the period 1982 to 2016 of advanced very high-resolution radiometer (AVHRR) vegetation health product from NOAA NESDIS Center for Satellite Applications and Research (STAR) data have been used. Data is noise reduced (smoothed) weekly maximum NDVI at 4 km spatial resolution.

To assess the impact of drought on cropland and other land use classes, AWiFS data at 56 m spatial resolution onboard Resources-2 of date 14-Sep-2015 and 29-Feb-2015 was used to prepare land use/cover map of the study area to identify different land use classes.

To compute ASI for drought monitoring and delineation, Vegetation Health Index (VHI) weekly data from 1982-2016 at 4km spatial resolution from NOAA NESDIS Center for Satellite Applications and Research (STAR) data is used. It considers both vegetation condition (termed VCI) and thermal condition of vegetation (TCI) within a period of observation. Therefore, VHI subsequently evaluates vegetation drought stressed by temperature (Bhuyian et al. 2006; Kogan 1995). Both parameters can be derived from Normalized Difference Vegetation Index (NDVI) and land surface temperature (LST).

The Vegetation Condition Index (VCI), the Temperature Condition Index (TCI), and the Vegetation Health Index (VHI) have been developed further using the following equations as:

$$\label{eq:VCI} \begin{split} VCI &= 100*(NDVI-NDVI_{min}) \; / \; (NDVI_{max}-NDVI_{min}) \\ TCI &= 100*(BT_{max}-BT) \; / \; (BT_{max}-BT_{min}) \\ VHI &= 0.5*VCI + 0.5*TCI \end{split}$$

where NDVI, NDVI_{min}, and NDVI_{max} are the seasonal average of smoothed weekly NDVI, its multiyear absolute minimum and its maximum respectively; BT, BT_{min} , and BT_{max} are similar values for brightness temperature.

3.1.2 Crop yield data

The data about area and production of crops in Rajasthan state were collected from Centre for Monitoring Indian Economy(CMIE) and Directorate of Economics and Statistics(DES), India.

3.1.3 Rainfall data

Monthly rainfall data of each rain gauge stations of Rajasthan state for the period 1962-2016 was downloaded from the website of water resource department. Their location is shown in Fig. 1.





Fig. 1 (a) Location of rain gauge stations and IGNP canal in Rajasthan (b) Annual average rainfall of Rajasthan state

3.2. Methods

3.2.1 Land use/coverpreparation

Land use/covermap was prepared by using K-means clustering algorithm. Rabi and Kharif season classification was done, which was then, later on, merged to form acombined map. Total 9 classes were made i.e. forest, water body, built-up, Kharif crop, rabi crop, double crop, fallow land, scrubland, and wasteland. To compute the accuracy of the classified image confusion matrix was prepared. The strength of a confusion matrix is that it identifies the nature of the classification errors, as well as their quantities (Fitzgerald et al. 1994). The confusion matrix, derived from animage map and high-resolution Google map was generated for the accuracy assessment. Additionally, a coefficient of agreement between classified image data and reference data were calculated using Kappa and its variance (Ismail et al. 2008; Janssen et al. 1994; Rosenfield et al. 1986). Overall Accuracy of the classified map is 84%. It is calculated as the total number of correctly classified pixels (diagonal elements) divided by the total number of test pixels. The Kappa statistic was calculated from the result of the land cover classification and it is 0.80.

3.2.2 NDVI trend analysis

The non-parametric Mann-Kendall test is commonly performed to detect monotonic trends in the long-term data. To estimate NDVI trend over the period of 1982-2016 nonparametric Mann-Kendall trend test was performed (Mann, 1945; Kendall, 1975). To calculate the slope of a trend Sen's nonparametric method is used (Sen, 1968). Trends were estimated at 5% significance level. To estimate the change in NDVI over the entire time period, trend slope was multiplied by total no. of years.

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sign(X_j - X_k)$$

where X_i are the values of the data; *n* is the length of the time series and

 $sign(X_i - X_k) = 1$, if $X_i - X_k > 0$ = 0 if X₁ - X₁ = 0

$$= -1$$
, if $X_j - X_k < 0$

3.2.3 Agriculture drought assessment

3.2.3.1 Data screening and smoothing through HANTS (Harmonic ANalysis of Time Series)

HANTS algorithm was applied over MODIS 16 day's maximum value composites data for the screening and removal of cloud contaminated observation. It calculates a Fourier series of the data, identify and remove outliers and replace them with the value calculated by the Fourier series (Sharma et al., 2014; Verhoef et al., 2005; Roerink et al., 2000). During this process, we have to set five parameters who control the whole process, as shown in Table 1.

Table 1. UANTO memory stand and the in such as

Table 1: HANTS parameters and their values				
Parameters	Value	Usage		
Number Of Frequency (NOF)	5	Total five frequencies are considered during curve fitting		
		process.		
HiLo Flag	Low	As cloudy pixels leads to low NDVI value.		
Invalid Data Rejection Threshold	0-255	Scaled NDVI values more than 255 are excluded.		
(IRTD)				

JETIR1807123	Journal of Emerging	Technologies and Innovative Research	(JETIR) V	www.jetir.org	763
			· · · ·		

Fitting Error Tolerance (FET)	12	Observations deviating more than 12 during curve fitting are discarded.
Degree Of Over-Determinedness	12	Minimum observations required are calculated as NOF*2-1.
(DOD)		Thus, Each curve fitting process is based upon minimum 21
		(12+9) observations

3.2.3.2 Agriculture Stress Index System (ASIS)

ASIS classifies administrative areas according to the percentage of their crop area affected by droughts. ASIS classifies as drought-affected areas those pixels for which a Vegetation Health Index (VHI) value is below 35. ASIS shows the percentage of arable land within an administrative area which has been affected by drought conditions over the entire cropping period. Weekly VHI data was aggregated monthly, the seasonal maximum value composite of VHI data was calculated. Pixels having VHI value less than 35 were marked as drought pixels. LULC map was used to extract drought pixels over agriculture land. Finally, district wise percentage of agriculture land affected by drought was calculated for last 35 years.

3.2.3.3 Anomalies calculation

The anomalies were calculated to identify the change in drought severity on atemporal scale. NDVI, crop yield, and rainfall data were used to discern the anomalies. Negative anomalies support the drought condition.

Crop yield anomalies

The crop yield trend was calculated using time series data and then crop yield anomaly was computed. The crop yield anomaly was adeviation from the yield trend.

Y = a + b(X) $Y_a = ((Y_i - Y_t) / Y_t)) * 100$ Where,

Y_a is yield anomaly;

Y_i is yield in particular year and

Y_t is yield trend

Following the guidelines of Indian Meteorological Department (IMD), 0 to -25% deviation is categorized as slight drought, -25% to -50% as moderate drought, while below -50% as severe drought. Slight, moderate and severe drought risk maps were prepared and given weights of 0.2, 0.3, 0.5 respectively. These maps were then weighted sum to get final resultant risk map. The final risk map was categorized into no risk, slight, moderate, severe and very severe class respectively.

NDVI anomalies

NDVI anomalies were calculated pixel-wise. Year wise seasonal NDVI max images were generated after that **long-term** NDVI mean was calculated. To derive the seasonal pattern of NDVI firstly, maximum NDVI for each year was computed by using the following expression:

$NDVI_y = max (NDVI_1, NDVI_2 + \dots + NDVI_{10})/10$

Where, NDVI_v is max NDVI for y year and NDVI₁, NDVI₂..... NDVI₁₀ stands for NDVI of the 16-day interval in that year.

Mean NDVI was then calculated by using thefollowing expression

Mean NDVI = (Max NDVI_{y1}+ Max NDVI_{y2}+.....+ Max NDVI_{yN})/ Total Year

Where, MaxNDVI_{y1}...... MaxNDVI_{yN} stands for seasonal max NDVI value.

NDVI anomaly has been computed as: **NDVI**_i = ((**NDVI**_{maxi}-**Mean NDVI**)/ **Mean NDVI**) *100 Where,

 $NDVI_i$ is NDVI anomaly for particular year $NDVI_{maxi}$ is maximum NDVI of particular year

LULC map was used for generating crop mask to differentiate between crop and non-crop pixels. The anomaly of only crop pixels was taken into consideration for generating agriculture drought risk map. Similar to the crop yield drought risk, total 5 categories are made.

3.2.4 Meteorological drought

3.2.4.1 Rainfall anomalies

Rainfall data from rain gauge stations were interpolated using kriging method to prepare year wise seasonal rainfall maps. To identify the meteorological drought-prone areas for the growing season of Kharif; rainfall anomalies were computed as:

$\mathbf{RFA}_i = \left[\left(\mathbf{RF}_i \cdot \mathbf{RF}_a \right) / \left(\mathbf{RF}_a \right) \right] * 100$

Where,

RFA_iis rainfall anomaly for given year;

RF_i is seasonal rainfall for given year and

RF_a is mean seasonal rainfall

Similar to the crop yield anomaly, drought severity categorization was done and total five classes are made.

IV. RESULTS AND DISCUSSION

NDVI trend analysis using Mann-Kendal trend test shows increasing trend of NDVI in the western part of Rajasthan. Trend test clearly shows the impact of Indira Gandhi Nahar Project (IGNP) canal, Districts in the IGNP command area i.e. Ganganagar, Hanumangarh, Bikaner, Jodhpur and Jaisalmer shows apositive change of 0.2 to 0.3 NDVI value. Built-up area in Jaipur district show negative trend, which clearly shows the negative impact of urbanization on vegetation. Forest area near Udaipur district also shows a negative trend over the years, showing the signs of deforestation. Land use/cover map and trend test results are depicted in Fig. 2.



Fig. 2 (a) LULC map of Rajasthan state of theyear 2015 (b) Changes in NDVI using Mann-Kendal and Sens's method of trend analysis

As expected, the long-term analysis reveals the similar trend between NDVI and rainfall data. There is huge climatic variability exists within Rajasthan state. Western Rajasthan receives scant rainfall while eastern part receives ample amount of rainfall. Thus, Eastern Rajasthan is green while western Rajasthan is covered by desert. Long-term average of rainfall and NDVI data is shown in Fig. 3. District wise crop yield anomaly data was used for identifying most drought-prone administrative units. Districts like Barmer, Churu, Jaisalmer, Bikaner, Jhunjhunu, Jodhpur, shows highest fluctuation in the drought years (up to -70%) as well as in the wet years (up to 60%) that shows their dependency over climatic variability. The resultant risk map is shown in Fig. 4.

ASIS which represents the percentage of crop area affected by drought in an administrative unit, captured drought conditions very well in the study area as illustrated in Fig. 5. Rajasthan state witnessed widespread and severe drought in the year 1987 and 2002, mild drought in theyear 2000 and 2009, while theyear 2006, 2011 received thevery good amount of rainfall. ASIS shows that in theyear 1987, 80% cropland of all districts of Rajasthan were affected by drought. A similar situation was raised in theyear 2002 also. In theyear 2009 only western districts were affected by drought, while in anormal year (2011) ASI considered all districts under no drought category.



Fig. 3 (a) Long-term mean rainfall (b) Long-term mean NDVI, amap of Rajasthan



Fig. 4 Resultant crop yield risk map

NDVI based agriculture drought risk map (Fig. 6a) reveals that districts in the western part of the Rajasthan like Jaisalmer, Bikaner, Jodhpur, Barmer, Ganganagar, Churu come under severe drought risk category. Districts like Nagaur, Ajmer, Tonk, Sawai Madhopur, Jalore and some part of Baran and Kota district comes under moderate risk category. While remaining districts in the northern and eastern part of state come either in slight or no risk category. Few agriculture patches near IGNP canal shows consistent greenness in drought years also. This shows the positive impact of IGNP canal in the Thar desert region.



Fig. 5 Agriculture Stress Index (ASI) for drought (1987, 2002 and 2009) and normal (2011) years.



Fig. 6 (a) NDVI based agriculture drought risk map (b) Rainfall based meteorological drought risk map

Meteorological drought risk map (Fig. 6b) shows that Jalore, Barmer, Jaisalmer, Bikaner, some part of Jodhpur, Ganganagar and Churu comes under severe drought category. Districts like Nagaur, Pali, Sikar, some parts of Jodhpur and Churu comes under moderate drought category. Ajmer, Jaipur, Jhunjhunu, Alwar Jaipur, Dausa faces slight drought. While other remaining districts in the eastern and south-eastern part of state come either under slight risk or no risk category.

The weighted sum of meteorological and agricultural drought risk map was done to prepare combined drought risk map (Fig. 7). Both maps were given the equal weight of 0.5 to make resultant risk map. Combined drought risk map shows that 30% area is at severe risk, 33% area under moderate risk, 29% under slight risk and 8% under no risk.



Fig. 7 Combined drought hazard map

V. CONCLUSION

This study concludes that the drought risk areas can appropriately be delineated by using satellite, meteorological and ancillary data. This study reveals that south-western and western part of Rajasthan state is more vulnerable to drought. However, agriculture land within the IGNP command area is increasing incessantly because of the availability of irrigation facility. Trend test results also indicate the increasing trend of NDVI in the agriculture land which is a sensible indication for drought-prone areas. Most districts in the eastern part of the state stay unaffected even in the drought year due to the heavy rain in the monsoon season and accessibility of irrigation facility. Whereas most of the areas in the central and western part of the state are rain fed and thus crop yield reduced drastically in the drought years. The present study illustrates that space technology plays a significant role in drought assessment and monitoring that is otherwise not feasible through conventional mapping techniques. ASI system proves to be a useful tool for monitoring and early warning of drought disaster. It is capable of capturing agriculture drought condition prevailing in theadministrative unit. Thus, can be utilized by government authorities to manage the available resources.

REFERENCES

 Bhuiyan, C., Singh, R.P., Kogan F.N. 2006. Monitoring drought dynamics in the Aravalli region (India) using different indices based on ground and remote sensing data. International Journal of Applied Earth Observation and Geoinformation; 8:289-302.

- [2] Bhuiyan, C. 2004. Various drought indices for monitoring drought condition in Aravalli terrain of India, In: Proceedings of the XXth ISPRS Conference, Int. Soc. Photogrammetry and Remote Sensing, Istanbul.
- [3] Fitzgerald, R.W.,Lees, B.G. 1994. Assessing the classification accuracy of multi-sources remote sensing data. Remote Sensing of Environment, 47: 362-368.
- [4] Hoolst, R.V., Eerens, H., Haesen, D., Royer, A., Bydekerke, L., Rojas, O., Li, Y., Racionzer, P. 2016. FAO's AVHRR-based Agricultural Stress Index System (ASIS) for global drought monitoring, International Journal of Remote Sensing, 37:2, 418-439, DOI: 10.1080/01431161.2015.1126378
- [5] Ismail, M.H., Jusoff, K. 2008. Satellite Data Classification Accuracy Assessment Based from Reference Dataset, International Journal of Environmental, Chemical, Ecological, Geological and Geophysical Engineering Vol: 2, No: 3, 2008.
- [6] Janssen, L. F. J. Van Der Wel F. J. M., 1994. Accuracy assessment of satellite derived land cover data: A review. Photogrammetric Engineering and Remote Sensing 60:419–426.
- [7] Kendall, M. G. 1975. Rank Correlation Methods, 4th ed., 8 pp., Charles Griffin, San Francisco, Calif
- [8] Kogan, F.N. 1987. Vegetation index for areal analysis of crop conditions, In: Proceedings of18th conference on agricultural and forest meteorology. West Lafayette, IN: American Meteorological Society, 103–107.
- [9] Kogan, F.N. 1995. Application of vegetation index and brightness temperature for drought detection. Advances in Space Research. 1995;15(11):91-100.
- [10] Legesse, G. and Suryabhagavan, K.V. 2014. Remote sensing and GIS based agricultural drought assessment in East Shewa Zone, Ethiopia, Tropical Ecology 55(3): 349-363, ISSN 0564-3295
- [11] Mann, H. B. 1945. Nonparametric tests against trend, Econometrica, 13, 245–259
- [12] Marj, A.F., Meijerink A.M.J. 2011. Agricultural drought forecasting using satellite images, climate indices and artificial neural network, International Journal of Remote Sensing, 32:24, 9707-9719, [doi: 10.1080/01431161.2011.575896].
- [13] Mrutyunjay, S., Kalamkar, S.S., Ojha, M. 2012. State of Rajasthan Agriculture 2011-12, AERC Report 145. Agro-Economic Research Centre, Sardar Patel University, VallabhVidyanagar, Anand, Gujarat.
- [14] Rizqi,I., Sholihah. 2016. Identification of agricultural drought extent based on vegetation health indices of Landsat data: case of Subang and Karawang, Indonesia, Procedia Environmental Sciences 33,14 20.
- [15] Roerink, G. J., Menenti, M. and Verhoef, W. 2000. Reconstructing cloudfree NDVI composites using Fourier analysis of time series, Int. j. remote sensing, vol. 21, no. 9, 1911–1917.
- [16] Rosenfield, G.H., Fitzpatrick, L.K. 1986. A coefficient of agreement as a measure of thematic classification. Photogrammetry Engineering and Remote Sensing, 52, (2): 223-227.
- [17] Sen, P. K.1968. Estimates of the regression coefficient based on Kendall's tau, J. Am. Stat. Assoc., 63(324), 1379–1389
- [18] Sharma, N., Rajak, D.R., Jain, R.K., Palria, S., Parihar, J.S. 2014. Monitoring rabi crop area usingmulti-year MODIS data: A case study of Gujarat, India, Journal of geomatics, Vol. 8(2):211-215.
- [19] Verhoef W., Albert V.D.K. and Koelemeijer R. 2005. Climate Indicators from Time Series of NDVI images (CITISEN), Final report, National Aerospace Laboratory NLR, NLR-CR-2005-474.