Mapping Agricultural Vulnerability for India Employing Time-series Satellite Data Products

Kaushalya Ramachandran*, CA Rama Rao, BMK Raju, M. Gayatri,

V. Praveen Kumar and J. Satish

CRIDA (ICAR), Santoshnagar, Hyderabad – 500059

**E-mail:kausalya@crida.in*

Keywords: *MODIS, AVHRR, NDVI, AESR, SPI, Rainfed Agriculture,Vulnerability, Climate Change*

Abstract: Advanced Very High Resolution Radiometer (AVHRR) 8-km Normalized Differential Vegetation Index (NDVI) data and Moderate Resolution Imaging Spectroradiometer (MODIS) 16-day 250m NDVI data product were taken to analyse vulnerability of Indian agriculture to climate change impacts. Predicted higher temperature and altered rainfall patterns accompanied by extreme weather events would impact vegetation growth in natural forest, open scrub, agricultural land and plantations. NDVI derived from 2-band information (Red & Near-infra Red) of multi-spectral imagery of NOAA-AVHRR (1982 to 2006) and from MODIS (2000-2010) were analyzed. CV of Max NDVI from 15-day composites for the total length of study period was used to assess agricultural vulnerability and results were corroborated with Standard Precipitation Index (SPI). AVHRR time-series data helped to identify vulnerable areas at regional scale i.e., agro-ecological sub-regions (AESR) while MODIS data products helped to identify vulnerability at sub-district level. It is estimated that over 263.74 M ha area in the country may be vulnerable to climate change of which over 81.3 M ha are located in arid, semi-arid and dry sub-humid regions. Study indicated that over 12.1 and 1.81 M ha of Kharif cropland would be mildly and severally vulnerable respectively, while 6.86 and 0.5 M ha of Rabi cropland may be adversely affected in a similar manner. Of the remaining agricultural lands, 29.93 and 5.24 M ha would also be vulnerable similarly.

Introduction

Tools and techniques of remote sensing and GIS can help in examining impacts of weather aberrations on bio-physical cover of earth like vegetation, land use, water resource and soils. Weather variables like precipitation and temperature result in change in LULC and they also impact vegetation growth and vigour for which Normalized Difference Vegetation Index (NDVI) are used. Due to perceived increasing variability in climatic conditions in India as a result of frequent drought and flood occurrences in resent past, Govt of India adviced the ICAR to study the impact of climate change on agriculture. With this end in view, ICAR launched a large network research program titled National Initiative on Climate Resilient Agriculture (NICRA) in February 2011 to study trends in climate variability in the country in order to develop strategy and adaptation methods to manage climatic disasters. Study was initiated to identify agriculturally vulnerable regions in the rainfed regions which forms a major chunk of net sown area in the country. NDVI derived from time-series satellite data like NOAA-AVHRR and TERRA-MODIS were downloaded and an assessment was attempted.

GIMMS dataset of NOAA- AVHRR with 8km resolution was used to analyse agricultural vulnerability at a region level namely, State- and AESR- level for 1982-2006 period, while MODIS - TERRA NDVI data product with 250m resolution was used to assess agricultural vulnerability at district–level from 2001 onwards. Standard Precipitation Index (SPI) instead of actual rainfall data was used to corroborate extreme weather events to explain resultant variations in NDVI.

Material and methods

Time-series NDVI data products of AVHRR space-borne sensor of NOAA polar-orbiting satellites were used for a 27-yr period starting from 1982 onwards. The first two spectral bands of satellite data out of five, i.e., Red (0.58 to 0.68 μm) and Near-Infrared (0.75 to 1.1μm) essentially useful for mapping clouds and land surface and for delineating surface water bodies respectively, when combined was found useful for monitoring vegetation cover on earth surface (Tucker *et al.*, 2004, 2005). This data product was used for assessing agricultural vulnerability in the country. AVHRR NDVI product which is available for whole of Indian sub-continent was sub-set from the global coverage as one tile for each year starting from 1982. Bi-monthly NDVI images were stacked and pre-processed, followed by identification of pixel-wise Max NDVI for arriving at Maximum Greenness during corresponding year (1982 – 2006). This was followed by estimation of Mean and Standard Deviation of Max NDVI. To assess vulnerability, CV of Max NDVI was calculated which formed the basis for vulnerability analysis at AESR-level. This task helped in estimating spatial extent of agriculturally vulnerable region in India (Kaushalya *et al.*, 2013a). MODIS (16-day 250m) NDVI data product was used to downscale vulnerability analysis to district-level so that it can help in implementing mitigation and adaptation strategies at the local administrative-level. Geo-statistical analysis was used to estimate the extent of vulnerable regions in the country (Kaushalya et al., 2013b).

The source of AVHRR NDVI is the Global Inventory Modeling and Mapping Studies (GIMMS) data set obtained from AVHRR instrument onboard NOAA satellite series 7, 9, 11, 14, 16 and 17 for the period 1981 till 2006. The data has been corrected for calibration, view geometry, volcanic aerosols and other effects not related to vegetation change and hence was found useful for the present study. NDVI values range from – 1.0 to +1.0. The data was downloaded from the Global Land Cover Facility (GLCF) website at www.landcover.org*(http://www.glcf.umd.edu/data/gimms/ at 15-day Maximum-Value Composite)*. MODIS data set was obtained from NASA experiment with Moderate Resolution Imaging Spectroradiometer (MODIS) on board TERRA and AQUA earth observation research satellites. It has a sweeping swath of 2330 km width and covers all parts of the earth in 1-2 days in 36 discreet spectral bands and is thus a great improvement on earth sensing capability over AVHRR (http://terra.nasa.gov/). MODIS was found ideal for monitoring large-scale changes in biosphere and hence used for the the study. MODIS - 250m NDVI composite data products are freely available from *Land Processes - Distributed Active Archive Centre (LPDAAC)* website of USGS <*http://mrtweb.cr.usgs.gov/*>. The Indian sub-continent is covered in 13 tiles, i.e., h25v08, h25v07, h24v07, h26v07, h25v06, h24v06, h26v06, h23v05, h24v05, h26v06, h21v07, h27v08 and h25v08 and the NDVI data product is available from February 2000 till date.

Standardized Precipitation Index (SPI) which represents total difference of precipitation for a given period of time from its Climatological Mean and then normalized by Standard Deviation (SD) of precipitation for the same period, provides an improved tool to assess variations in precipitation and its associated impacts (Saikia and Kumar, 2011). IMD provides daily rainfall data of more than 100 years for many stations from its archives. Daily gridded rainfall dataset for 1901–2007 was developed by Rajeevan et al (2008). The authors used rainfall data of 1384 stations to generate rainfall data set on regular grids of 1°latitude x 1°longitude. Using this value we estimated SPI using the following formulae:

$$\mathrm{SPI} = \frac{a - A}{sd}$$

where,

a= current precipitation for a given period

A = long- term normal of precipitation for the same period

sd = Standard Deviation of precipitation for the given period

Thus, long-term precipitation record was fitted to a probability distribution which was then transformed into a normal distribution so that Mean SPI for a location and desired period is equal to zero. Positive SPI values indicated greater than Median precipitation, while negative values indicated less than Median precipitation. As SPI is normalized, both wetter and drier climates can be presented in a similar manner, and both wet and dry periods denoting flood and drought respectively, could be monitored using SPI, thus making it time and space- independent (McKee et al 1993). Accordingly, SPI of ≤ 1.00 for any given period was considered as start of reduced rainfall period which could lead to drought, if prolonged. On the other hand, drought is said to end if SPI is positive. This data was used to corroborate the NDVI variations in the country.

Normalized difference vegetation index (NDVI) which is a contrast –stretch ratio calculated from Red band and Near –Infrared band (NIR) of sensors like LANDSAT – TM; AVHRR; IRS-1B, 1C, 1D, P6 : LISS-3 / LISS-4; and MODIS besides several others was used to take the advantage of typical low reflectance values of vegetation in the Red wavelength range which corresponds with chlorophyll absorption and high reflectance values in NIR range which signifies leaf structure, thereby enhancing contrast between vegetated, un-vegetated and sparsely vegetated areas. Land use and/or Land Cover (LULC) analysis helped in identifying NDVI variations in agriculture, forest and open scrubland. The methodology used for the present study has been indicated in Figure 1.

At the outset, NDVI data sets were ordered from the respective websites in Geo-tiff format and re-projected in Geographic Projection. MODIS - NDVI data required pre-processing involving several steps like stacking of 16 - day composite consisting of 23 images annually, followed by cloud screening to clean NDVI data. Later the data was multiplied with a scale-factor (0.0001) in order to convert the16-bit signed integer value (ranging from -3000 to 10,000) to derive pixel- wise Float Point or NDVI value. Cloud screening involved using 8-bit data layer which provides information on quality of pixel-wise NDVI value for pixel reliability ranging from 0-1; similar values meant reliable data. *Savtizky-Golay* filter was used to reconstruct a high- quality NDVI time-series data through smoothening of data using Polynomial - Least-Square Fit method on a 4*4 pixels moving window (Chen, 2004). To analyse NDVI variations, CV of Max NDVI value was calculated as in case of Central, West Asia & North Africa region carried out by ICARDA

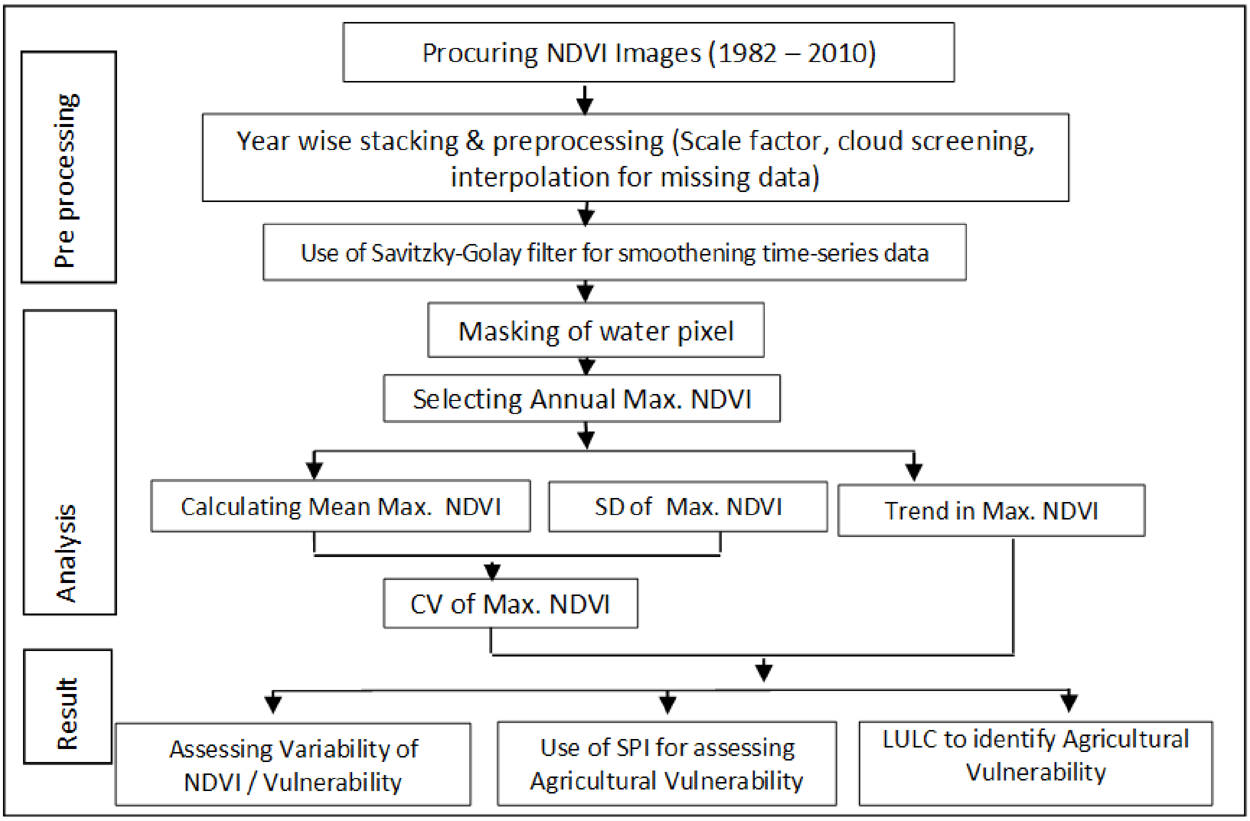


Fig. 1 Methodology

(Celis *et al.,* 2007) and suitably modifications for Indian conditions

Results and discussion

Climate change is an insidious process and hence long-term studies become essential for understanding trends and magnitude of this problem. In India where agriculture is largely rain-dependant, the need to understand slow and scarcely perceptible change in vegetation growth and its dynamics is critical for planning agricultural strategies and adaptation mechanisms, in order to, mitigate or reduce vulnerability to extreme weather events and / or to slow progress of climate change owing to natural and anthropogenic factors.

Climate change leading to aberrant weather conditions can result in reduction in length of crop growing period (LGP) due to early onset or withdrawal of monsoon, increase in intense rainfall events and reduction in number of rainy days, monsoon failure or floods and a general shift in spatial pattern of rainfall. For instance, analysis of rainfall pattern in last 107 years (Rajeevan et al., 2008) has shown an increase in rainfall in drought-prone Anantapur district in Rayalseema region in Andhra Pradesh but a fall in NE region (Ravindranath *et al.*, 2011) which could be disastrous for thr country. Even irrigated agriculture may not be immune to climate change as snow cover and glaciers shrink and perennial rivers receive lesser waterflow on one hand, while lower rainfall would cause lesser groundwater recharge.

Large variations were seen in vegetation dynamics in the country owing to climatic variability. While arid regions in W Rajasthan and Gujarat and south-central India in Bellary and Anantapur have sparse vegetation and large livestock population, their dependency on this sparse vegetative cover makes it critical for vulnerability monitoring and evaluation on one hand while implementing adaptation mechanisms on the other. In the semi-arid and sub-humid zones which account for a large proportion of rainfed agriculture region, vulnerability to climate change owing to poor natural resource base and large number of marginal and small farm holdings and over dependence on SW monsoon rainfall, makes the region critical. Humid regions with two or three cropping seasons may be also be devastated due to floods or drought while per-humid regions like the NE region in India, may suffer due to decline in rainfall.

Study revealed that rainfall was highest during the months of July-Aug. and Max NDVI occurred during the months of Sept. – Oct. annually. Only SW monsoon rainfall data was used for the present study and 1982 was taken as the base year. Mean NDVI ranged from 0.0 to 0.79 while Max NDVI ranged from 0.014 to 0.995. Although the country saw normal rainfall across various ecozones, SPI indicated a moderate drying condition in West Bengal, eastern Bihar and Jharkhand, in a small part in Vidharba and southern Madhya Pradesh and around National Capital Region, south eastern Punjab, southern Himachal Pradesh and south-west Uttarakhand, which is an important agriculture belt in northern India.

To understand the dynamics of weather abberations, a temporal analysis was carried out for each year during the study period. CV of Max. NDVI from AVHRR (8-km) data was calculated for a period of 25 years (1982-2006) and one CV of Max NDVI value was arrived at which was used to plot Vulnerability Map at pixel-level for each State and AESR in the country (Figure 2). As is revealed in the figure, there is a clear north - south axis to the spatial distribution of agricultural vulnerability to climate change based on AVHRR NDVI data. The vulnerable zones indicated therein correspond with the arid and semi-arid regions which also include the transition belt between semi-arid and dry sub-humid zones.

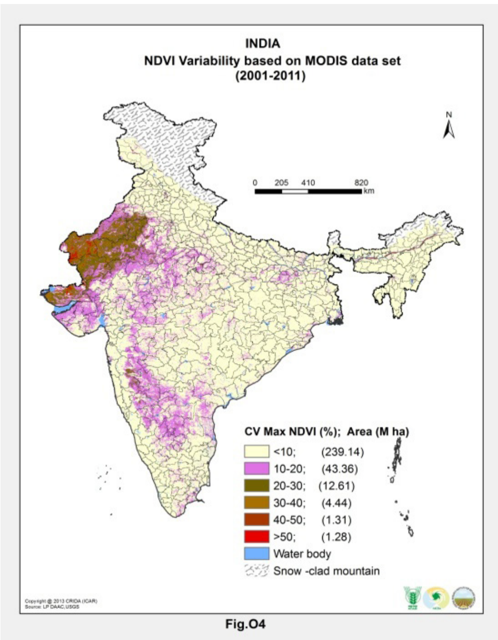
Vulnerability was analysed with reference to land use / land cover based on LULC Atlas of NRSC (2011). Table 1 indicates that over 1.81 and 12.1 M ha of *Kharif* cropland may be severely and moderately vulnerable respectively, to climate change. Additionally over 0.5 and 6.86 M ha of *Rabi* cropland may be severely and moderately vulnerable. Rest of the agricultural land including double, triple cropped area, current fallow, plantation and orchards in 5.24 M ha would be adversely affected while 29.93 M ha may be only marginally vulnerable to climate change in India.

Analysis of vulnerability at AESR -level indicated that Thar desert and the Kachchh Peninsula besides Malwa plateau, Vindhyan scrubland and Narmada river valley may be

*Table 1***:** *Extent of agricultural vulnerability to climate change in India*

AESR No.	Geographical region in India	Climate type	Geog. area (M ha)	Soil type	Vulnerability (CV Max NDVI) Extent (Area in M ha) <10	10 - 20	20 - 30	30 - 40
2.1 & 2.2	Thar & Kacchh region	Hot hyper arid	14.3	Shallow - deep sandy desertic; deep loam; saline & alkali	0.82	3.61	5.52	4.02
2.3	Plains of Rajasthan, N Gujarat & SW Punjab	Hot Typic arid	11.5	Deep loamy desertic	3.7	4.3	2.99	0.42
2.4 & 3.0	S Kacchh, N Kathiawar & Karnataka Plateau	Hot arid	7.0	Deep loamy; saline & alkali; mixed red & black	2.72	6.77	1.07	0.30
4.1	N Punjab Plain; Ganga-Yamuna Doab; Rajasthan Upland	Hot semi-arid	11.8	Deep loamy alluvium-derived	9.45	2.17	0.16	0.01
4.2, 5.1, 7.1 & 6.1	N Gujarat Plain (incl. Aravalli Uplands); Kathiawar; S Telangana & N Karnataka Plateau; SW Maharastra	Hot dry semi-arid	21.8	Deep loamy grey brown & alluvium-derived; Shallow loam; clayey; mixed red & black; shallow - medium loam	11.78	9.2	0.66	0.09
5.2 & 5.3	Plateaus & ranges of Central India, Malwa, E Maharashtra, N Karnataka & NW Telangana & E Gujarat plain	Hot moist semi-arid	42.1	Medium - deep clayey black; Deep loamy coastal alluvium; Shallow - medium loam; Deep loamy clay; mixed red & black	29.93	11.59	0.18	0.31
10.1	Malwa plateau; Vindhyan hills & Narmada valley	Hot dry sub-humid	8.1	Medium and deep clayey black; shallow loamy black	0.48	2.09	3.29	2.22

severely vulnerable to climate change followed by central India and northern Gujarat. According to the MODIS data sets used to refine the study further, over 239.14 M ha may be marginally affected by climate change. Over 55 M ha may be moderately vulnerable while over 8 M ha may be severely affected in the country.



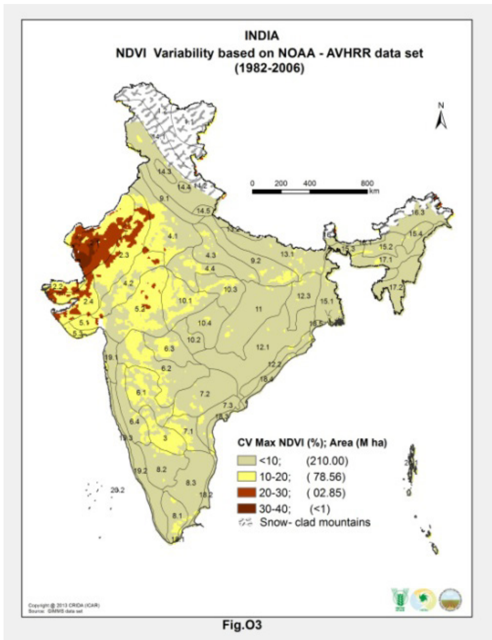


Fig. 2.

In most parts of the country, vulnerability based on CV of Max. NDVI ranged from 10-20% only. However, western Rajasthan was seen to be the most vulnerable with an estimated CV of 30-40%. The snow- clad Himalayan regions were excluded from the study for the present owing to shortfalls in data availability.

Conclusion

Study revealed that AVHRR and MODIS NDVI time-series data are useful for investigating the slow process of climate change as they provide an authentic spatial reference to analysis of agricultural vulnerability. As these datasets are readily available, their inclusion in planning for adaptation and mitigation strategies is recommended. AVHRR 8km dataset was used to acquire a synoptic view of agricultural vulnerability at a regional level due to restrictions of resolution. MODIS 250m NDVI products was used to down-scale the study at sub-district level which would help in actual implementation of mitigation strategies at the local-level. Study indicated that nearly 241 M ha of India may remain unaffected from climate change while over 81.3 M ha may be vulnerable in Rajasthan, Gujarat, Marathwada and Vidharbha regions in addition to semi-arid tracts in Karnataka and Andhra Pradesh where rainfed agriculture is widely practiced. Availability of similar products from IRS data may be very useful for the country.

References

Celis D, Pauw E D, and Geerken R (2007) Assessment of Land Cover and Land Use in Central and West Asia and North Africa – Part 1: LULC – Base Year 1993. ICARDA

Chen (2004) Simple Method for reconstructing a high – quality NDVI time-series dataset based on Savtizky -Golay Filter. *Remote Sensing of Environment* 91: 332-344

GIMMS (2004) Global Inventory Modeling and Mapping Studies <http://www.glcf.umd.edu>

Kaushalya Ramachandran, Venkateshwarlu, B., Ramarao, C.A., Rao,V.U.M., Raju, B.M.K., Rao, A.V.M.S., Saikia, U.S., Thilagavathi, N., Gayatri, M. and J. Satish (2013): Assessment of Vulnerability of Indian Agriculture to rainfall variability - Use of NOAA-AVHRR (8km) & MODIS (250m) Time-Series NDVI Product. Climate Change & Environmental Sustainability 1(1):37-52.

Kaushalya Ramachandran, Venkateshwarlu, B., Ramarao, C.A., Rao, V.U.M., Rao, K.V., Raju, B.M.K., Rao, A.V.M.S., Ramana, D.B.V., Manoranjan Kumar, Nagasree, K., Ravi Shankar, K., Gayatri, M., Satish, J. and Praveen, V. (2013): Assessing Agricultural Vulnerability to Climate Change using NDVI data products. (In): Geospatial Technologies for Natural Resources Management (Eds. Soam, S.K., Sreekanth, P.D. and Rao, N.H.). New India Publishing Agency, ISBN: 978-93-81450-80-2, 345-362.

McKee T B, Doesken N J and Kleist J (1993) The relationship of drought frequency and duration to time scales. Preprints, 8th Conference on Applied Climatology, 17-22 January, Anaheim, CA, 179-184

Rajeevan M, Jyoti Bhate and Jaswal A K (2008) Analysis of variability and trends of extreme rainfall evants over India using 104 years of gridded daily rainfall data, Geophysical Research Letters (35) LI8707 doi: 10.1029/2008GL035143

Ravindranath N H, Rao S, Sharma N, Nair M, Gopalakrishnan R, Rao A S, Malaviya S, Tiwari R, Sagadevan A, Munsi M, Krishna N and Bala G (2011) Climate Change Vulnerability profiles for North East India. *Current Science* 101 (3): 384-394

Saikia U S, Manoranjan Kumar, (2011) Standardized Precipitation Index (SPI): An effective drought monitoring tool. 5th SERC school on Agricultural Drought: Climate Change and Rainfed Agriculture. 1-10

Tucker C J, Pinzon J E and Brown M E (2004) Global Inventory Modeling and Mapping Studies, Global Land Cover Facility, University of Maryland, College Park, Maryland, 1982-2006

Tucker C J, Pinzon J E, Brown M E, Slayback D, Pak E W, Mahoney R, Vermote E and Saleous N El (2005) An extended AVHRR 8-km NDVI Data set Compatible with MODIS and SPOT vegetation NDVI Data. *International Journal of Remote Sensing* 26(20): 4485-4498z