Drought severity identification and classification of land pattern using Landsat 8 data based on spectral indices and Maximum Likelihood Algorithm

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Abstract The manual survey of drought severity is very hectic and time consuming task. This paper reports the study to assess the adeptness of satellite based drought indices for observing the spatio-temporal extent of agricultural drought events. The Land Use Land Cover (LULC) has been categorized into six classes such as Vegetation, Settlement, Barren land, Harvested land, Hill with rocks and Water bodies and computed using Maximum Likelihood (ML) supervised algorithm. Moreover, an attempt has been made to analyze the drought condition using multi-date Landsat 8 images of Vaijapur taluka which falls in drought prone zones. The severity of drought was determined and defined based on the Normalized Difference Vegetation Index (NDVI) with good outcome. The drought severity was classified into three groups viz severe, moderate, and normal. The present study shows that, the entire area was affected by a severe drought condition during the period of 2013 and 2014. The experimental results examines that, the overall accuracy of ML classifier was 81.31% with kappa coefficient 0.81 for the year 2013 and it was 78.02 % with kappa value of 0.73 for the year 2014. The present study is essential for assessment of drought condition with advance technology before the drought get severe.

Keywords Drought assessment, Maximum Likelihood classifier, NDVI, Land use land cover, Landsat data.

1. Introduction

Drought is complex and damaging natural disaster known to the world. This has significant impact on various sector like economy, ecology, social life, industry, and agriculture [1], [2], [3], [4], [5], [6], [7]. Drought is classified into four categories viz meteorological, hydrological, agricultural and socioeconomic drought. The meteorological drought is occurring due to a lack of precipitation over a region for a long period of time [8]. The lower precipitation leads to the hydrological and agricultural drought. The hydrological drought is having an impact on water resources like declining flow of water in the river, lake, reservoir, and streams [9], [10]. The agricultural drought is related to reduce soil moisture which is not enough to sustain the health of the crop. The economy of the various countries is depending upon the agribusiness. The Socioeconomic drought is defined on the basis of gap between demand and supply of economic goods which is responsible to the societal imbalance [6], [11].

Traditionally, the drought monitoring has been carried out by rainfall data collected by local weather stations. The rainfall measurement was considered for cluster of village. The cluster can includes 10 or more villages. The government of India has installed the weather station at tehsil and district level but it has a limitation of spatial coverage [11]. The satellite remote sensing is having world-wide coverage which provides data in a frequent manner. The drought monitoring and forecasting model utilizes satellite data along with ground observation detail to forecast the drought warning and risk assessment. The satellite based drought indicators like NDVI, VCI, SAVI, and TCI were used to assess the health of vegetation, soil moisture condition and temperature profile of the geographic location [12], [13], [14], [16], [17], [18], [19].

In the present work, the analysis of agricultural drought has been analyzed using the relevant satellite data. The section 2 of the paper gives the details of the study region and the dataset. The methodology used in the work is described in section 4. The section 5 describes the result and discussion. The paper is concluded in section 6.

2. Study area

For this research study, we have chosen Vaijapur tehsil of Aurangabad district, Maharashtra, India. Vaijapur is a known as gateway of Marathwada region, which is located at latitude of 19°40’ to 20°15’ north and longitude of 74°35’ to 75°00’ E. The average rainfall is reported to be 500.20mm. The study area has average temperature 34 ° C to 42° C. The total area of Taluka is 1, 54, 378 Hectors out of which 1, 21, 830 Hectors area falls in agricultural sector. The Onion, Sugarcane, Jawar, Bajra, Corn, is the main crop whereas cotton is major cash crop. The economy of study area is depend upon agriculture and associated business.

3. Satellite dataset

The Landsat 8 satellite images of the month June, July, August, and September of Kharif season of year 2013-2014 has used for experimental analysis. The Landsat 8 dataset were obtained from USGS on November 2014. The image is Orthorectified, and geometrically corrected by USGS. The Landsat scenes are processed to standard level-1 precision terrain corrected (L1T) product. It is packaged as Geographic tagged image file format (GeoTIFF). The package includes 13 files, in which 11 band images, Quality Assurance file, and metadata file. A Quality Assurance (QA) file includes the cloud, terrain shadow and data artifact. The band 1-9 is designated to OLI and 10-11 bands to the TIRS sensor. The spatial resolution of image is 15m panchromatic, 30m multispectral, and 100m Thermal data which is registered to the OLI sensor data in order to create level 1 T product. The Geomaticasoftware with Atmospheric CORrection (ATCOR) plug-in has used for preprocessing of Landsat 8 image data. The Erdas Imagine 2014 software is used for data processing, spatial feature extraction, vegetation indices computation and classification. The ESRI ArcGIS 10.2.3 software was used to generate spatial map of study area.

4. Methodology

4.1. Preprocessing of Landsat 8

The atmospheric correction is essential procedure before apply the classification algorithm. The value of the actual ground reflectance can be varies due to dust, smoke, cloud, and fog in the atmosphere. The atmospheric algorithm like ATCOR is used to removes the effect of atmospheric layer and converts the radiance image into reflectance image. The band no 2-7 has used for computation of Vegetation Indices (VI) like Normalized Difference Vegetation Index (NDVI). The band 8 is having 15m spatial resolution which is utilized for visual interpretation of study area.

4.2 Normalized Difference Vegetation Index (NDVI)

The vegetation absorbs the photo synthetically active radiation (PAR) spectral region such as visible spectrum region of electromagnetic spectrum. The absorbed energy is used for process of photosynthesis. The pigment of the green leaf such as chlorophyll absorbed the solar radiation of wavelength 0.4 to 0.7 µm, and re-emit in NIR region from 0.7 to 1.1 µm which is nearly half of total absorbed solar energy [20]. The damaged or dry leaves cannot absorb the solar radiation due to absence or less chlorophyll, so that it cannot re-emit the solar energy. The high intensity of re-emitted solar energy shows the healthy condition of the leaf. The NDVI (Eq. 1) is a very world-wide popular index for vegetation health analysis. The NDVI classified the image into -1 to +1 value, where as negative values shows non-vegetation, and positive value shows vegetation [20].

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

4.3 Maximum Likelihood classification

The Land use, land cover analysis was done by Maximum Likelihood (ML) supervised classification approaches. The ML classifier is based on Bayes theorem which is used for decision making process. The other approach is the cells in an each cluster sample in the multidimensional space being normally distributed. The classifier considers variance and covariance of the class signatures during assignment each cell to the likelihood classes. The maximum probability pixel would be assigned to the most probable class after calculating the probability in each class or tagged as an "unknown" if the probability values are all below a threshold [21]. The analysis of maximum likelihood classifier can be implemented using Eq. 2 for the satellite imagery.

$$p(X / C_j = \frac{1}{(2\pi)^{\frac{n}{2}} |\sum j|^{0.5}} \text{X} \exp\left[-\frac{1}{2}(DN - \mu_j)^T \textstyle\sum_j^{-1} (DN - \mu_j)\right] \tag{2}$$

where, $p(X / C_j)$ is the conditional probability of observing X from class C_j(probability density function, $\mu_j = (DN_1, DN_2, DN_3, \dots \dots \dots \dots DN_n)^T$ is the vector of pixel with n number of bands $\mu_j = (\mu_{j1}, \mu_{j2}, \mu_{j3}, \dots \dots \dots \dots \mu_{jn})^T$ is the mean vector of the class C_j and $\sum_j$is the covariance matrix of classC_j which can be written as (Eq. 3):

$$\sum_j = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \dots \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & \dots \ \sigma_{2n} \\ \dots & \dots & \dots \ \dots \\ \sigma_{n1} & \sigma_{n2} & \dots \ \ \sigma_{nn} \end{bmatrix} \tag{3}$$

5. Result and Discussion

Total 8 image of Kharif season of 2013 and 2014 were preprocessed using ATCOR atmospheric correction module, then subset were generated using Region Of Interest (ROI) as administrative boundary. The False Color Composite (FCC) image has generated using band (Red-5, Green-4, Blue-3) for visual analysis of spatial features. The image of September month of the year 2013 and 2014 were used for Land use and Land cover classification using ML classifier. The ML classifier has trained with pure pixel of respective classes like Vegetation, Settlement, Barren land, Harvested land, Hill with rocks and Water bodies. The Fig. 1 shows the classified land use, land cover map which clearly depicts that green vegetation in 2013 is nearly half of 2014. The green vegetation area is lower down in 2013 due to unavailability of soil moisture. The result indicates that harvested land has increased in year 2013 because the most of crops were damaged or water stressed due absence of surface and ground water. The Fig. 2 and 3 illustrates the vegetation health in year 2013 and 2014 respectively. The vegetation health is categories into three groups, such as severe, normal, and healthy on the basis of NDVI values.

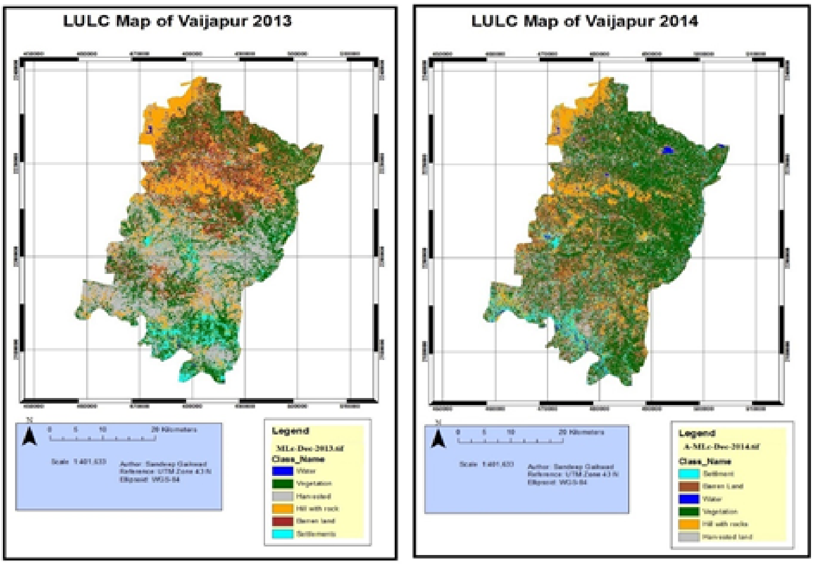

Fig. 1. Land Use Land Cover (LULC) of year 2013 and 2014 of study area.

In the month of June, the rainfall was much below average monthly rainfall. The entire tehsil was suffering from a drought condition in the month of June and July. Due to further lack of precipitation in the month of July, the available crop has been badly affected by lack of water. The entire Kharif season of 2013 has received less rainfall than the year 2014.The health of the vegetation has degraded from June to September. In the month of August 2013, the total 7639.47 Hectors area was affected by a severe drought condition.

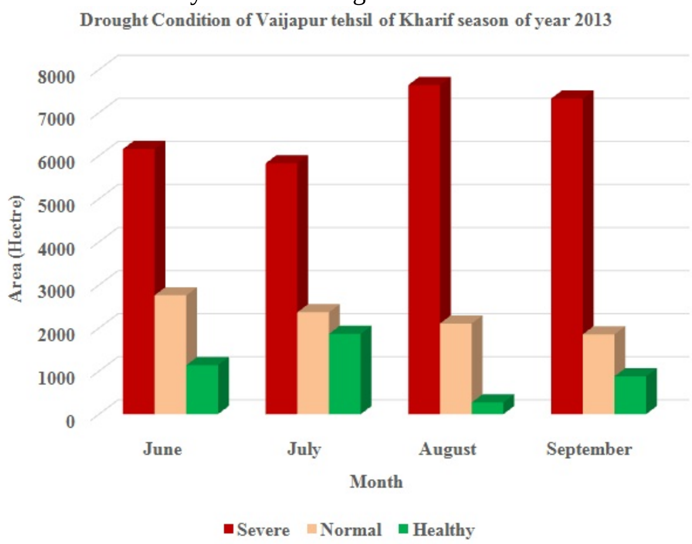

Fig. 2. Land Use Land Cover (LULC) image of Vaijapur of year 2013 and 2014

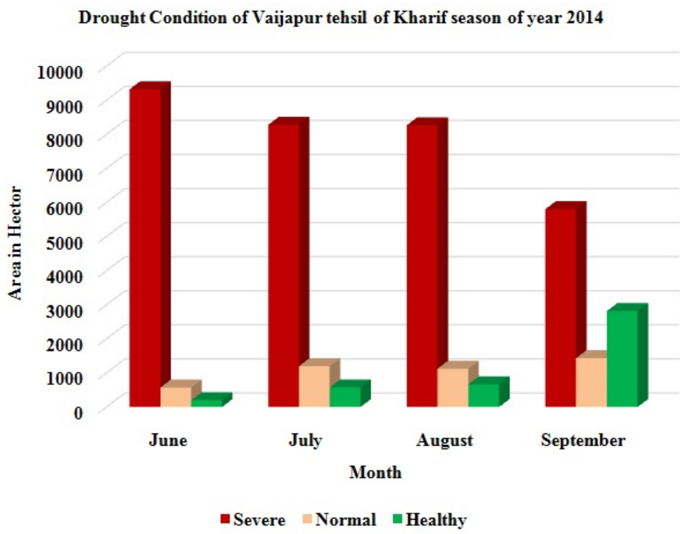

Fig. 3. Drought condition of Kharif season of year 2013.

In the Kharif season of 2014, month of June, and July month did not receive sufficient rainfall for sowing activity. The 9321.21H area was affected by severe drought conditions in June. Kharif season of 2014 has faced high severe condition due scanty rainfall. The severe condition has decreased from June to September month.

5.1 Accuracy Assessment

The total numbers of 91 ground truth points were collected into study area region. The accuracy of the classified data was assessed with error matrices, producers, user's accuracies, and Kappa statistics are shown in Table 1. The results of this study show that, classification of remotely sensed imagery gives valuable information on land use, land cover activities in the form of different objects on the earth's surface. The overall accuracy of error matrix for Maximum Likelihood classifier accuracy is 81.31% and Kappa coefficient was 0.811 of year 2013. The accuracy of year 2014 was 78.02% and Kappa Coefficient was 0.773. Accuracy estimation in terms of producer's accuracy, user's accuracy, overall accuracy and kappa coefficient was calculated after generating confusion matrix for ML classifier.

Table 1. Error matrix resulting from classifying Training sets pixels (ML Classifier)

Classes	**Ground Truth (Pixels)**													
	Vegetation		**Harvested Land**		**Settlement**		**Barren Land**		**Hill with Rocks**		**Water Body**		**Total**	
	2013	2014	2013	2014	2013	2014	2013	2014	2013	2014	2013	2014	2013	2014
Vegetation	**22**	**21**	2	3	0	0	2	2	0	0	0	0	26	26
Harvested Land	1	2	**9**	**8**	0	0	1	1	0	0	0	0	11	11
Settlement	0	0	0	0	**23**	**24**	4	2	3	4	0	0	30	30
Barren Land	1	1	2	2	0	0	**5**	**4**	0	1	0	0	8	8
Hill with Rocks	0	0	0	1	1	1	0	0	**8**	**7**	0	0	9	9
Water body	0	0	0	0	0	0	0	0	0	0	**7**	**7**	7	7
Total	24	24	13	14	24	25	12	9	11	12	7	7	**91**	**91**
PA (%)	91.67	87.05	69.23	57.14	95.83	96	41.67	44.44	72.73	58.33	100	100		
UA (%)	84.62	80.77	81.82	72.73	76.67	80	62.50	50	88.89	77.78	100	100		
Overall accuracy-2013 =81.31, 2014= 78.02, **Kappa Value**-2013=0.811, 2014=0.73														

PA-Producers Accuracy, UA-Users Accuracy.

6. Conclusion

The agriculture sector is highly dependent on rainfall. The late arrival of monsoon rainfall in June month was responsible for getting smaller area available for crops in Vaijapur tehsil. If there is no enough soil moisture present in the soil for sowing activity, then the farmer have to wait for retrieval of sufficient rainfall for sowing operation.

The Landsat8 images were used for analysis of agricultural drought severity based upon drought indices. The LULC mapping was analyzed by supervised maximum likelihood algorithm through Landsat 8 satellite data. It is observed that Maximum Likelihood classifier has successfully classified Vegetation, Harvested land, Hill with rocks, Settlement, Barren land, and Water bodies. The maximum likelihood method estimates the optimum parameters using unified approach and works well for well defined distribution.

The NDVI has indicated that, the study area has affected by high severity of drought in the year 2013 as compare to the year 2014. The research study has investigated high drought severity condition in the study area.

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