Drought Monitoring & Changes in the Vegetation Cover of Aurangabad Region, Maharashtra Over Last Two Decades: A Comparative Study of Remote Sensing Indices VCI and SVI Using Time Series MODIS Data Product MOD13Q6

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Abstract. Aurangabad district is part of Marathwada region of Maharashtra, India. The region suffers with frequent drought occurrences resulting in substantial crop yield losses. The times series analysis of the satellite imagery is helpful in monitoring the short term and long-term changes and understand the reasons for recurrent drought occurrences. In this study we analyze time series multispectral data products obtained from MODIS the spectroradiometer on board Terra. The dataset of MOD13Q6 (2001–2020) 250 m for the Aurangabad region is investigated using remote sensing indices VCI and SVI. The statistical tools and techniques were implemented to understand if there is any drought recurrence pattern over the years and then time series regression analysis of both the VCI and SVI indices were done to find out which remote sensing index gives better results. After comparing the results of two indices it is confirmed that though both indices gave same results for some statistical tests. The Generalized Linear Regression analysis performance of SVI is better and can be used for predicting the vegetation condition to some extent. Although the accuracy of such prediction is low because of the unpredictability of the climatic variables and the changing dynamics of the land use due to urbanization and human induced factors. This study was also useful in understanding the limitations of Satellite imagery and vegetation indices.

Keywords: multispectral · vegetation condition index · standard vegetation index

1 Introduction

Drought monitoring and Assessment has become the need of an hour as droughts impact the socio-economic condition of the country adversely. Droughts is one of the worst natural calamities because it spreads slowly and impact the food security of the region.

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Though atmospheric and naturally occurring phenomena are very unpredictable but Space technology has given us opportunities to observe and analyze this data and find patterns to predict or forecast the occurrence of the event. Satellite based vegetation indices has become an important method for examining agricultural droughts as no field measurements, interpolation or large-scale modelling is required [16].

In recent years India has evolved from food deficient and import dependent nation to a global agricultural powerhouse [1] still drought monitoring at regional scale in India suffers a setback as Indian agriculture is characterized by agro-ecological diversities in soil, rainfall, temperature, and cropping system [2]. Drought monitoring and development of new methods for the regional level agricultural drought assessment can be done through proper analysis of data products obtained from the satellites [3]. In the current study we have taken Moderate Resolution Imaging Spectrometer (MODIS) time series vegetation product and surface reflectance product to understand the changes in vegetation dynamics of the region. MODIS is a key instrument aboard Terra and Aqua Satellites. The MODIS instrument provides high radiometric sensitivity in 36 spectral bands ranging in the wavelength from 0.4μm to 14.4 μm.[4].

The second section of this study elaborates the MODIS data products in general. The version 006 product used in this study is planned for retirement soon, the reasons are further elaborated in Sect. 2. The third section describes the study area, fourth section summarizes the vegetation indices and material and methods used and, fifth section gives the results and conclusions.

2 Moderate Resolution Imaging Spectrometer (MODIS)

MODIS Terra & Aqua are the key instruments on Earth Observation Satellite (EOS). Both the instruments view the earth surface in 36 spectral bands and three spatial resolutions. MODIS data products are useful for our understanding of the earth processes. The data product used in this study is MODIS Terra product for vegetation cover. Out of 36 spectral bands Two bands are imaged at a nominal resolution of 250 m at nadir, with five bands at 500 m, and the remaining 29 bands at 1 km. A ± 55-degree scanning pattern at the EOS orbit of 705 km achieves a 2,330-km swath and provides global coverage every one to two days. Bands 1–19 are in nm whereas Bands 20–36 are in μm [4]. Table 1 gives the general specifications of the Terra satellite [5].

Terra is now scheduled to exit the morning constellations of Earth science satellites by October 2022 because of onboard fuel shortage [6]. Terra has five instruments on board ASTER, CERES, MISR, MODIS and MOPITT and the terra's orbital drift has affected all the sensors of Terra though Impacts will be minimal, but will be noticeable in data and imagery. Longer shadows will be visible in images of mountain landscapes. The sensors views will become narrower leading to smaller swath widths as Terra drifts to an earlier crossing time [7].

2.1 MODIS Data Products

Both MOD13Q1.006 is Land data product of MODIS. MOD13Q1 version 6 data are generated every 16 days at 250 m(m) spatial resolution as a level 3 product. MOD13Q1.006

Table 1. MODIS Terra Specification

TERRA Specification	
1. Orbit	705 km 10:30 AM Descending mode
2. Scan rate	20.3 rpm, cross track
3. Swath Dimension	2330 km (cross track) by 10 km along track at Nadir
4. Telescope	17.78 cm diameter, off axis, afocal with intermediate field stop
5. Size	1.0 × 1.6 × 1.0 m
6. Weight	228.7 kg
7. Power	162.5 W (single orbit average)
8. Data Rate	10.6 Mbps(peak day time) 6.1 Mbps (orbital avg)
9. Quantization	12 its
10. Spatial Resolution	250 m (bands 1–2), 500 m (bands 3–7) 1000 m (bands 8–36)
11. Design Life	6 years

provides two vegetation layers first is Normalized Difference Vegetation Index (NDVI) also referred as continuity index and the other one is Enhanced Vegetation Index (EVI) which has improved sensitivity over high biomass regions. The algorithm chooses the best available pixel values from the 16-day period [8]. In the current study we have utilized the MOD13Q1.006 data set from period DOY 001_2001- DOY 001_2020.

It should be further noted that the collection 6 forward processing is planned to be discontinued soon since there are issues detected in this product. The list of issues for each product is summarized in Table 2.

The incorrect representations of the aerosol quantities in collection 6 MOD09 surface reflectance products have impacted MOD13 vegetation index data products particularly over arid bright surfaces [9].

3 Study Area

Aurangabad district is one of the 36 districts located in the state of Maharashtra, India. It is located mainly in Godavari Basin and some of its part lays North West of Tapi river basin. Total area of Aurangabad district is approx. 10.08 lakh hectares out of which area under cultivation is 8.52 lakh hectares, 141.1 sq·km is urban and 99,587 sq·km is rural area. The district occupies 1362 villages and is divided in 8 divisions which are sub grouped into five subdivisions. The region is arid and the year is divided in three seasons i.e., summer, Rainy (Monsoon) and winter. In Aurangabad rainy season starts from month of June–September, winter season starts from October–February and summer season starts from March- May. The average rainfall received is 734 mm and

Table 2. MODIS Data Product issues

MOD13Q1.006 Vegetation Product Issues detected	
1.	Unexpected missing data in the last cycles of the year
2	Incorrect instances of "No Data" and spikes in NDVI values
3.	VI Usefulness Bits are not correctly assigned
MOD09A1 v006 Surface reflectance issue detected	
4.	The incorrect representations of the aerosol quantities in collection 6 MOD09 surface reflectance products have impacted MOD13 vegetation index data products particularly over arid bright surfaces

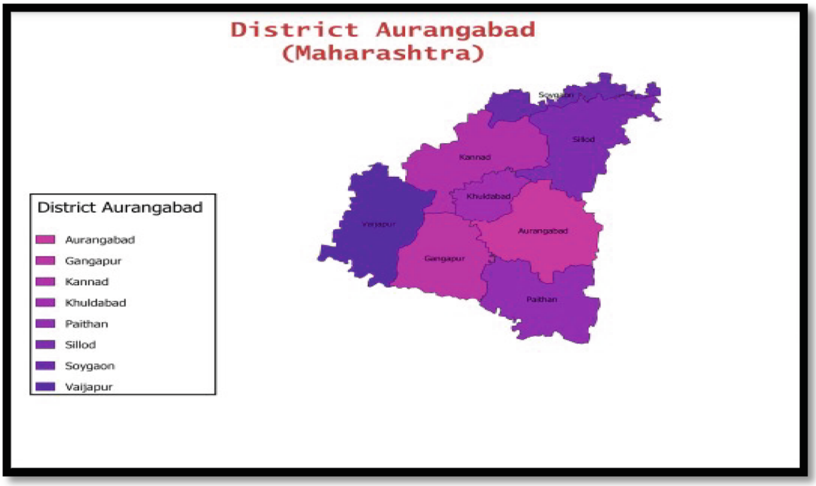


Fig. 1. Map of Aurangabad, Maharashtra, India

min temp is as low as 5.6 °C and max temperature is 45.9 °C. There are two main crop cycles followed Monsoon season crops are called Kharif crops and winter seasonal crops are called Rabi. Major food grains grown in this region are Jowar, pearl millet, wheat and gram, oilseeds soyabean is major crop and cotton is major cash crop of the region [10]. Figure 1 shows the map of the study region.

4 Vegetation Indices (VCI and SVI)

Remote sensing of vegetation is mainly performed by obtaining the electromagnetic wave reflectance information from canopies using passive sensors [11]. MODIS Vegetation Indices product NDVI and EVI produced on 16-day intervals and at multiple spatial resolutions provide consistent spatial and temporal comparisons of vegetation canopy greenness, chlorophyll and canopy structure [12]. In this study MOD13Q1.006 250 m

EVI vegetation product for the time period of 20 years is utilized The Enhanced Vegetation Index (EVI) minimizes the canopy soil variations and improves sensitivity over dense vegetation conditions moreover EVI can be associated with stress and changes related to drought [14].

Vegetation condition Index (VCI) focusses on the impact of drought stress on vegetation and can provide information on the onset, duration and severity of drought by noting vegetation changes and comparing them with historical values [13]. The Eq. (1) shows the calculation of VCI

$$VCI_{ijk} = \frac{EVI_{ijk} - EVI_i, min}{EVI_i max - EVI_i min} * 100 \tag{1}$$

where,

EVIijk = The EVI value for the pixel i, during j time period for year k.

EVIi,min = The minimum value of the pixel i

EVIi,max = The maximum value of the pixel i

The other vegetation Index used in the current study is Standard Vegetation Index (SVI). It is an estimate of the probability of occurrence of the present vegetation condition. SVI is based on the calculations of z-score of each pixel. The z-score is a deviation from mean in units of standard deviation calculated from the EVI values for each pixel location [15]. The Eq. (2) describes SVI equation.

$$Z\_ijk = (EVI\_ijk - EVImean\_ij)/(\sigma\_ij) \tag{2}$$

where,

EVIijk = The EVI value for the pixel i, during j time period for year k

EVImean ij = Mean EVI value for the pixel i during the j time period

σ_ij = Standard deviation of pixel i during j time period

In this study both VCI and SVI are used in conjunction with the EVI times series data product of MOD13Q1.006 from 2001–2020 for the assessment of vegetation condition in Aurangabad region of Maharashtra. The aim of this study is to compare and identify the strengths and weakness of both in the assessment of agricultural drought on a regional scale.

4.1 Material and Methods

Input Data

The present study utilizes 250 m resolution Terra MODIS Enhanced Vegetation Index (EVI) time series starting from year DOY 001_2001 to DOY001_2020. Sixteen-day composites of EVI and the corresponding pixel reliability layers were extracted from the MODIS product MOD13Q1, version6 resulting in 23 Days of the year (DOY) per year. In total 460 images were analyzed to assess the agricultural drought conditions using VCI and SVI.

Data Processing and Analysis

The MODIS data shows data gaps towards the later part of the year therefore the analysis of vegetation condition over the Aurangabad region is based on the assessment of the deviations of MODIS 16-day EVI measurements therefore EVI mean, median and standard deviation was calculated for the period of 19 years i.e., 2001–2020. The Skewness in the data set was observed using the Karl Pearson method. Similarly, mean, median and standard deviation of Standard Vegetation Index (SVI) and Vegetation Condition Index (VCI) were calculated and compared. We conducted non parametric statistical tests on the mean values of VCI and SVI to detect the trend in the data. The list of statistical tests is shown in Table 4. A brief description of the statistical functions is given in Table 5; the results are discussed in Sect. 5.

To develop a prediction model on VCI and SVI firstly pixel wise point wise values of the study area was extracted of the time period 2001–2020, then splitting the data frame in to train and test set we then calculated two sets of row quantiles with probabilities 0.50 and 0.75 was calculated on both the VCI and SVI train data frames. The flowchart of the methodology is shown below.

Non-parametric Tests

Non parametric trend test is more suitable for natural time series data set because assumptions required for parametric testing are not usually present in this type of data set [17]. To identify whether or not there is a trend in the dataset Cox and Stuart trend test is implemented. The idea of the Cox-Stuart test is based on the comparison of the first and the second half of the sample [18]. The statistical hypotheses in testing for the trend in the series of random variables are

H0 = No monotonic trend exists in the series

Ha = Monotonic trend exist in the series

Mann Kendall trend test is considered to be appropriate to identify climate change and trend identification [19]. The correlation can significantly influence the results in positive correlation there is a possibility of rejecting the null hypothesis whereas in negative correlation acts to accept the null hypothesis [20]. The other rank based non parametric test called as Pettit's test for detection of abrupt change in the time series [21]. This test gives the point of change in the time series dataset. Additionally, Wallis and Moore phase frequency test was conducted to verify the significance of the trend and the Sen's slope test was conducted to determine the magnitude of the trend.

Regression Analysis

Regression analysis is most commonly used statistical tool to analyze the time series data set. The three distinguished processes in regression analysis are (i) model selection (ii) Parameter estimation and (iii) prediction of future values [22]. Regression analysis helps us to understand the relationship between the variables as well as it can be used for the purpose of prediction. Till date only Ordinary Linear square regression (OLS) method is implemented in spatial time series data [24]. Therefore, out of various regression techniques we have used the Generalized linear regression to determine whether prediction modeling of the Remote Sensing Indices Standard Vegetation Index (SVI) and Vegetation Condition Index (VCI) is possible or not. The idea is to use a general exponential family for the response distribution. In addition to real and binary responses, GLMs can

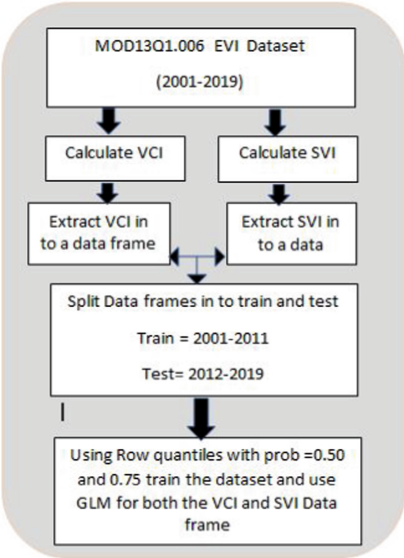


Fig. 2. Flowchart for regression modelling

handle categorical, positive real, positive integer, and ordinal responses. GLM help us build probabilistic predictors of many kinds of responses. GLM [23]. The flowchart in Fig. 2. Explains the steps followed for modelling Generalized Linear regression model. And Table 5 shows the results of generalized linear regression analysis on the extracted point wise values of the time series data set. The Data processing and statistical analysis is done using R studio.

5 Results and Discussion

5.1 Observed Changes in MODIS Vegetation Product MOD13Q1.006 EVI Data Set

To observe the spatial skewness in the vegetation product of MODIS the EVI mean, EVI Median is calculated for the time period 2001–2020. It is observed that though the impact is minimal but it is observable at regional scale and can be considered as one of the indicators of vegetation shift. The EVI Skewness for the region over the time period 2001- 2020 was equal to 0.5 which implicates that vegetation paradigm shift is occurring slowly in the region. Comparing Differences in standard deviation and skewness of remote sensing indices SVI and VCI (Fig. 3).

5.2 To Conduct Performance Analysis of the Two Remote Sensing Indices

We extracted mean, median of both the indices for the period of two decades [2001–2020]. It is observed that there is very little difference in standard deviation of SVI values

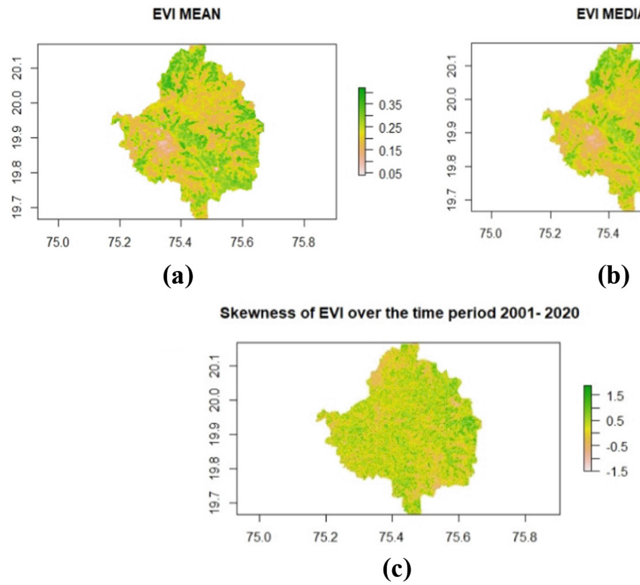


Fig. 3. (a) Mean EVI from 2001–2020. (b) EVI Median from 2001–2020. (c) Skewness of EVI from 2001–2020

over the years but VCI Standard deviation has visible fluctuations over the years. After finding the skewness over the years for both the indices the results yield that though both indicated that years 2011 and 2014 are negatively skewed and is an indication of deviation from normal and of severe drought stress. SVI was also able to detect negative skewness for the years 2010, 2017 and 2018 clearly. Table 3 shows the Mean, Median Standard Deviation and skewness of both SVI and VCI and the comparison chart is displayed in Fig. 4 (a) and Fig. 4 (b).

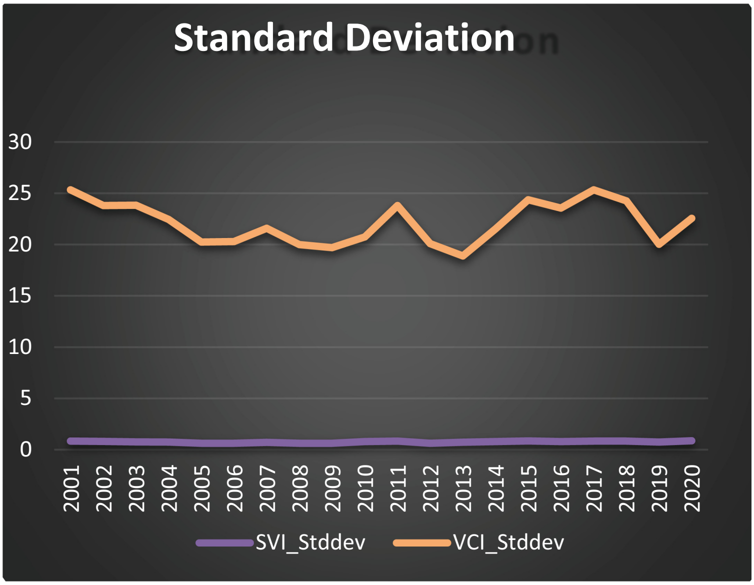
5.3 Statistical Results of VCI_Mean and SVI_Mean

The statistical tests performed on VCI and SVI mean values gave us following interpretations

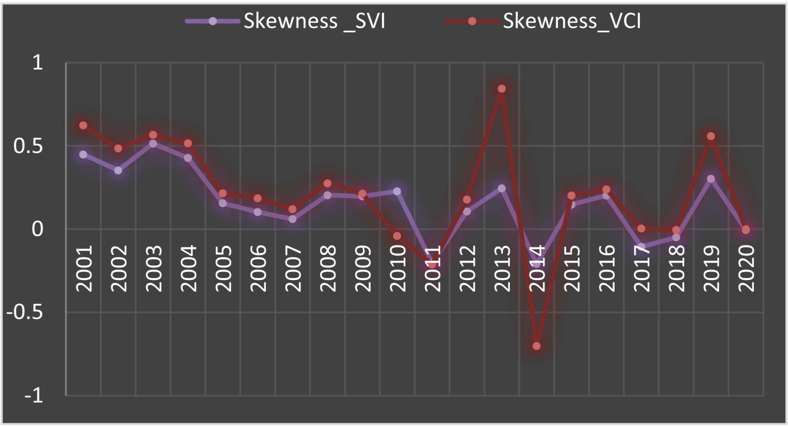
1. There is Monotonic trend in the data set (observed by MK test and Cox & Stuart test)
2. Probable change point at time k is of period 9 (Pettit's test)
3. The series is significantly different from randomness (Wallis and Moore test)
4. The positive value of Tau means there is increasing trend. The tau values vary from $+1$ to -1 in this case tau is 0.33 for both the VCI mean and SVI mean which signifies slightly increasing trend
5. Sen slope which estimates overall slope of the time series and is considered to be test of magnitude of the time series shows higher magnitude of the change for VCI (1.44) than SVI (0.0519)

Table 3. Mean, Median, Deviation and Skewness of SVI & VCI

Year	SVI_Mean	SVI_Median	SVI_Stddev	Skewness _SVI	VCI_Mean	VCI_Median	VCI_Stddev	Skewness_VCI
2001	−0.557842	−0.682234	0.831614	0.448738	29.285310	24.016640	25.325420	0.624117
2002	−0.441379	−0.536129	0.803442	0.353792	32.345350	28.495140	23.792990	0.485464
2003	−0.564494	−0.693425	0.752195	0.514220	29.118640	24.618200	23.825380	0.566678
2004	−0.458086	−0.562361	0.730806	0.428053	31.904130	28.042640	22.431370	0.516440
2005	−0.222535	−0.254647	0.617362	0.156043	38.353720	36.899770	20.237160	0.215535
2006	−0.047574	−0.069237	0.627305	0.103597	43.134730	41.873500	20.280120	0.186572
2007	−0.068700	−0.082897	0.697900	0.061026	42.651160	41.779350	21.574870	0.121225
2008	−0.175545	−0.218438	0.628758	0.204654	39.718270	37.879860	19.992060	0.275872
2009	−0.459463	−0.500380	0.621450	0.197525	31.941560	30.538240	19.689110	0.213821
2010	1.031398	0.972434	0.777391	0.227544	72.483090	72.756060	20.729730	−0.039504
2011	0.806118	0.861679	0.826416	−0.201693	66.586340	68.258770	23.801980	−0.210793
2012	−0.107332	−0.129613	0.629794	0.106134	41.665240	40.468910	20.078560	0.178747
2013	−1.013263	−1.072020	0.716493	0.246022	17.136140	11.828040	18.878440	0.843517
2014	1.268227	1.322712	0.785615	−0.208061	79.004970	84.034170	21.508850	−0.701460
2015	−0.037956	−0.079485	0.842884	0.147811	43.575820	41.933500	24.348760	0.202350
2016	−0.099889	−0.152975	0.784704	0.202955	41.997060	40.121950	23.548290	0.238885
2017	0.530887	0.560125	0.831134	−0.105538	59.185200	59.145430	25.327350	0.004711
2018	0.566413	0.579991	0.836356	−0.048705	60.185170	60.217240	24.246890	−0.003968
2019	−0.807389	−0.881798	0.735128	0.303656	22.556210	18.827050	20.008870	0.559127
2020	0.858476	0.859771	0.863333	−0.004502	68.018250	68.010870	22.538380	0.000983



(a)



(b)

Fig. 4. (a) Comparison of VCI and SVI by Standard Deviation. (b) Skewness of VCI vs SVI

6. Low p values signify that the test reject the null hypothesis and is statistically significant.

Table 4. Statistical Results [17, 18]

Sr. No.	Name of the test	Result VCI	Result SVI
1.	Cox and Stuart Trend test	data: vci_mean z = 1.6783, n = 20, p-value = 0.09329 alternative hypothesis: monotonic trend	data: svi_mean z = 1.6783, n = 20, p-value = 0.09329 alternative hypothesis: monotonic trend
2.	Mann-Kendall trend test	data: vci_mean z = 2.1089, n = 20, p-value = 0.03496 alternative hypothesis: true S is not equal to 0 sample estimates: S varS tau 66.0000000 950.0000000 0.3473684	data: svi_mean z = 2.044, n = 20, p-value = 0.04095 alternative hypothesis: true S is not equal to 0 sample estimates: S varS tau 64.0000000 950.0000000 0.3368421
3.	Pettitt's test for single change-point detection	data: vci_mean U* = 55, p-value = 0.2305 alternative hypothesis: two.sided sample estimates: probable change point at time K = 9	data: svi_mean U* = 55, p-value = 0.2305 alternative hypothesis: two.sided sample estimates: probable change point at time K = 9
4.	Wallis and Moore Phase-Frequency test	data: vci_mean z = 0.83419, p-value = 0.4042 alternative hypothesis: The series is significantly different from randomness	data: svi_mean z = 0.83419, p-value = 0.4042 alternative hypothesis: The series is significantly different from randomness
5.	Sen's slope	data: vci_mean z = 2.1089, n = 20, p-value = 0.03496 alternative hypothesis: true z is not equal to 0 95 percent confidence interval: 0.08295624 2.26710065 sample estimates: Sen's slope 1.447817	data: svi_mean z = 2.044, n = 20, p-value = 0.04095 alternative hypothesis: true z is not equal to 0 95 percent confidence interval: 0.001860815 0.083704114 sample estimates: Sen's slope 0.05197757

5.4 Regression Analysis Result of SVI and VCI

Regression analysis after extraction of year wise per pixel SVI and VCI values from the raster stack it is observed that Generalized Linear Model (GLM) performs better in case of SVI. The results are summarized in Table 5.

Table 5. Regression Model Summary for SVI &VCI [23, 24]

<table>
<tr><th>Regression Models</th><th>Summary of Results</th></tr>
<tr><td rowspan="2">Generative Linear Model</td><td>Call:SVI
glm(formula = formula1 ~ formula2, data = traindf, method = "glm.fit")
Deviance Residuals:
Min 1Q Median 3Q Max
-1.03362 -0.14694 0.01296 0.15875 0.74595
Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.397181 0.001836 -216.3 <2e-16 ***
formula2 0.619747 0.003866 160.3 <2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for gaussian family taken to be 0.05167335)
Null deviance: 2966.5 on 31715 degrees of freedom
Residual deviance: 1638.8 on 31714 degrees of freedom
AIC: -3958.5
Number of Fisher Scoring iterations: 2</td></tr>
<tr><td>Call:VCI
glm(formula = formula1 ~ formula2, data = traindf, method = "glm.fit")
Deviance Residuals:
Min 1Q Median 3Q Max
-45.107 -4.194 0.835 5.099 18.296
Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept) -5.151033 0.151186 -34.07 <2e-16 ***
formula2 0.827144 0.002709 305.31 <2e-16 ***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
(Dispersion parameter for gaussian family taken to be 51.28153)
Null deviance: 6406598 on 31715 degrees of freedom
Residual deviance: 1626342 on 31714 degrees of freedom
AIC: 214886
Number of Fisher Scoring iterations: 2</td></tr>
</table>

6 Conclusion

The objective of this research was to understand the scope and challenges in the development of prediction system of remote sensing indices. In the process of our study we found that due to changing land use land forms either occurring due to natural causes or by human induced changes there is impact on these remote sensing indices. Some of the key points of this study are listed below.

- MOD13Q1.006 EVI data set contained unexpected missing data values after Julian Day of the Year (DOY) 177 for all years.
- The Remote sensing vegetation indices SVI and VCI extracts the vegetation information successfully though both performs statistically equivalent the magnitude analysis (Sen's slope) shows that there is higher change in VCI than SVI.
- There is less skewness observed in SVI than in VCI
- The strength of these indices is that they give real time information about the vegetation condition at regional scale and real time monitoring is possible but use of these indices for prediction purpose with greater accuracy needs more robust models and systems. The major challenges observed in using Remote sensing indices for prediction includes missing values in the raw data and spatial skewness (Tables 6 and 7).

Table 6. Result Summary GLM for SVI

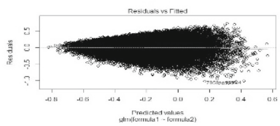
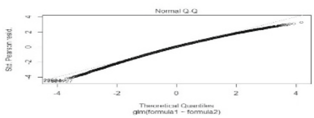
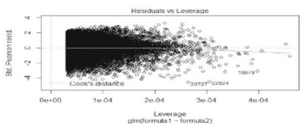
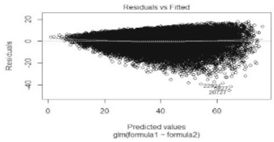
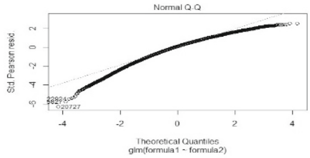
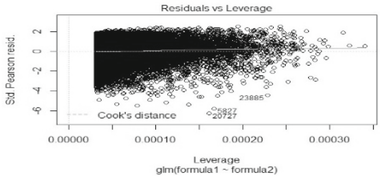
Result Summary	
Generalized Linear Model	SVI 2001-2020 Output
1. Predicted values	
2. Theoretical Quantiles	
3. Residuals vs Leverage	

Table 7. Result Summary GLM for VCI

Result Summary	
Generalized Linear Model	VCI 2001-2020 Output
1. Predicted values	
2. Theoretical Quantiles	
3. Residuals vs Leverage	

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