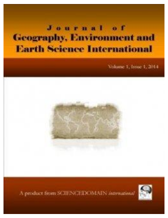

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Application of Digital Image Classification in the Identification of Culturable Wastelands Using Contrast in Vegetation Activity in Vadodara District, India

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Author's contribution

The sole author designed, analyzed, interpreted and prepared the manuscript.

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ABSTRACT

Increasing population worldwide has put tremendous pressure on the land. Recent studies reported that many areas covered by wastelands are decreasing because parts of wastelands are being converted into arable land. It is important to identify and monitor these changes in spatial planning and management. This paper adopts a remote sensing-based identification of culturable wastelands based on seasonal vegetation changes in Vadodara district, India. Supervised classification was applied on three MODIS images of 2016-17 of 3 different seasons. Separability analysis was applied to get the best data combination for image classification. Validation was done by ground referencing and Google earth images. The composite of winter season image with NDVI and EVI performed best with an overall accuracy of 78.2% with the kappa co-efficient of 0.7580. This method opens a possibility of using digital classification for identification of culturable wastelands in the study area which are so far mapped with visual interpretations only.

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Keywords: Culturable wastelands; vegetation activity; remote sensing; digital classification; separability analysis.

1. INTRODUCTION

Wastelands are degraded lands which can be brought under vegetative cover with reasonable effort. They are currently underutilised and are deteriorating due to lack of appropriate soil and water management or due to natural causes [1]. Wastelands develop naturally or due to the influence of the environment, chemical and physical properties of the soil or management constraints. Culturable wastelands are the categories of wastelands that have a potential for the development of vegetative cover but not being used due to several constraints such as erosion, water logging, salinity, etc. Location and spatial distribution of culturable wastelands are crucial for planning and management and optimum utilisation of these land resources.

Identification of wastelands in general and culturable wastelands in particular through digital image classification technique is a challenging task. The soil - vegetation interaction and its change throughout the season/year makes their identification difficult. Often, the spectral signatures of culturable wastelands are coinciding with other vegetation classes such as agriculture and forest. Direct extraction of culturable wastelands through any digital technique may not be feasible as it may lead to under or over classification of wastelands that too without any error estimate. Hence, it is advisable to perform digital classification using all delineable land use/land cover (LU/LC) classes and then extract the culturable wastelands from the output classified layer.

The use of satellite images to identify wastelands varies from classification of wastelands through visual interpretation [2,3,4,5,6,7,8,9,10] to more sophisticated digital analysis [11,12,13,14,15, 16,17].

Various researchers used a variety of approaches such as [11], incorporated supervised classification algorithm for delineation of different categories of wastelands at micro level in Matar taluka of the Kheda district, Gujarat, India; [12] incorporated Landsat with JERS-1 SAR (L-band); [13] used multi-nomial logistic regression to classify badlands (a category of wastelands) in the Spanish Pyrenees; [14] used the receiver operating curves to define the threshold for badland areas; [15] mapped badlands effectively by combining spectral information with the slope and aspect from a Digital Elevation Model (DEM), while [16] used Normalized Difference Vegetation Index (NDVI) to assess the dynamics of badlands [17]. Proposed a remote sensing-based detection method for mapping of badlands dynamics based on seasonal vegetation changes in the lower Chambal valley, India using supervised image classification, different band selection methods were applied to get the best classification.

Ideally, different combinations of these techniques should give the most accurate identification of wastelands because of the complex spectral behaviour and combined response from soil and vegetation classes. Until recent years, only visual interpretation of remote sensing image was applied in the Vadodara district, India [9], and no attempt has been made of using digital classification of satellite images for this area.

Vegetation indices provide a possibility to estimate vegetation cover based on significant differences of reflectance between the near-infrared (NIR) and the red (R) bands [18]. These indices include the NDVI, Enhanced Vegetation Index (EVI) and many others. NDVI is more sensitive to chlorophyll activity, whereas EVI is linked with vegetation structural variation and hence useful in the mapping of tropical forests [19] or land with dense scrub, a category of culturable wasteland used in this study.

The use of NDVI and other indices for vegetation studies is well known. Here an attempt has been made to use MODIS reflectance data along with two indices namely NDVI and EVI to achieve an improvement in wasteland classification through digital technique.

MODIS is a key instrument onboard the Terra and Aqua satellites. The sensor is viewing the entire Earth's surface every 1 to 2 days, acquiring data in 36 spectral bands. Terra MODIS spatial resolution varies from 250 m, 500m to 1000 m for various surface reflectance bands and derived products. Several data products have been generated from MODIS data including NDVI and EVI. In comparison to coarse resolution MODIS data, several moderate resolution satellite sensors exist such as LANDSAT, IRS and SPOT. For these sensors, the spatial resolution ranges from 15 to 30 m; this may have wider applicability. However, free data availability, higher data frequency and range of ready-to-use products make MODIS a good choice for many applications.

The present study aims at identifying spatial extent and distribution of culturable wastelands in the Vadodara district, India during the year 2016-17 using digital image classification technique. Also, the study tries to suggest the best season and data combination for delineation of culturable wasteland categories. As per the National Wastelands Atlas of India [9], the culturable wastelands occupy a significant share (99.92 %) among total wastelands in the study area (Vadodara district, India). Out of various categories of culturable wastelands, three important categories with larger extent (87 % of the total culturable wastelands) namely land with open scrub, land with dense scrub and gullied and/or ravinous land (medium) are considered for the present study.

2. STUDY AREA

Vadodara district, India is located between 21°49' to 22°48' N latitude and 72°51' to 74°17' E longitude and extends over an area of 7720 km^2, accounts for about 4 % of the total geographical area of the Gujarat state, India. The average annual rainfall in the district is 832 mm (1981-2002) [20]. The period from January to May is comparatively dry. The wastelands are mainly confined to south-west, south-east and south-central parts of the study area. Three culturable wastelands categories such as land with open scrub, land with dense scrub and gullied and/or ravinous land (medium) are the major vegetative wasteland classes found in the study area [9] and therefore, these three categories are considered in the present study. The gullied/ravinous lands have mainly developed along the courses of two major rivers namely the Orsang and the Narmada. Land with dense scrub is found mainly on undulating terrain with some soil development and moisture. Land with open scrub is mainly located in areas with poor soil, low rainfall and moisture.

Vadodara district forms a part of the great Gujarat plain. Geologically, the major part in east, west and south of Vadodara district fall under alluvium formation whereas some of the northern part comprises of a rocky formation. Sand, silt, clay and gravels form the alluvium. In general, the soils of Vadodara district are medium black to black having good prospects for agriculture. The climate of the study area has three main seasons, summer, monsoon and winter. The summer season extends from February to June, the monsoon from July to October and the winter from November to February. The climate of the study area can be classified as arid (B), Steppe (S) with hot arid (h), i.e. BSh according to the updated Köppen–Geiger classification [21]. The location map of the study area is presented in Fig. 1.

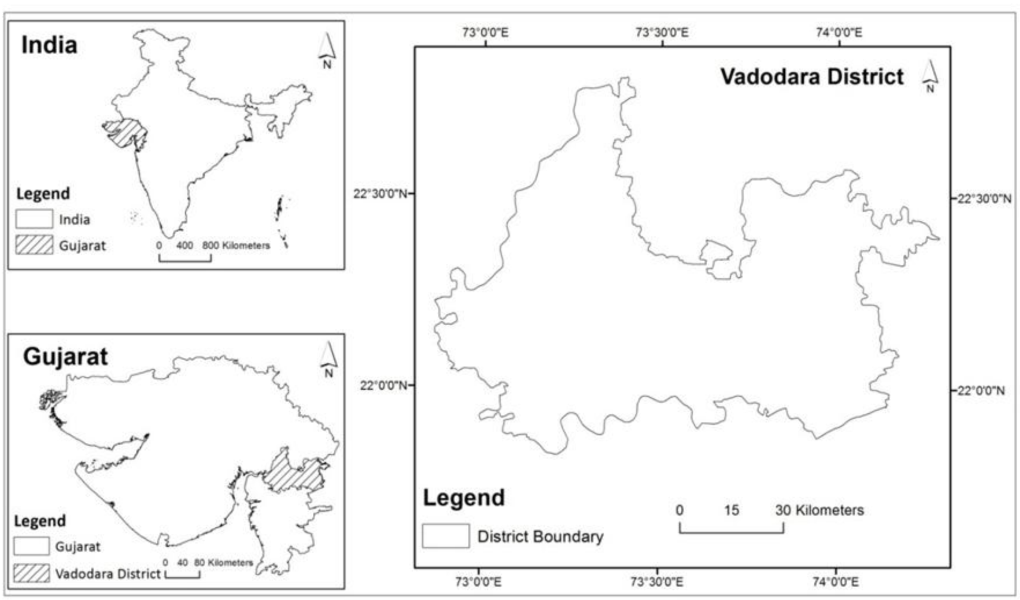

Fig. 1. Location map of study area

3. DATA SETS

Images from the *Moderate Resolution Imaging Spectroradiometer* (MODIS) sensor which is on board the Earth Observing System Terra as well as the Aqua satellites (http://modis.gsfc.nasa.gov/about/) were used in this study for identification of categories of culturable wastelands. The MODIS MYD13Q1 were retrieved from the online tool https://earthexplorer.usgs.gov/, courtesy of the NASA EOSDIS Land Processes Distributed Active Archive Center (LP DAAC), USGS/Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota (https://lpdaac.usgs.gov/). MODIS reflective bands namely Blue, Red and NIR and also the MODIS derived products i.e. NDVI and EVI have been incorporated as ancillary layers to achieve expected improvement in classification accuracy (Table 1). Three season data viz. 23rd October, 2016 (post-monsoon), 9th January, 2017 (winter) and 15th April, 2017 (summer) are considered for making comparative analysis and suggesting the best season and data combination for delineation of selected culturable wasteland categories. Three season images were so selected as to study differences in spectral signatures due to different vegetation activity. The dates of the image acquisitions were decided on the basis of data availability and percentage of cloud cover.

The MODIS reflective bands are an estimate of the surface spectral reflectance corrected for the effect of atmospheric gases, aerosols, and thin cirrus clouds [22]. This helps in achieving a spectrally unbiased image classification. Apart from spectral reflectance, MODIS provides a range of products with different spatial resolutions. This study used MYD13Q1 Vegetation indices data due to its better spatial resolution, i.e. 250 m than other MODIS products. Additionally, it always provides a well-timed NDVI value for each pixel even in persistent cloud cover or bad quality during the 16-day period [23].

The NDVI is calculated by taking the ratio of the difference in red and NIR portions of the electromagnetic spectrum. NDVI provides measures of the amount or condition of vegetation in a given area. NDVI ranges from −1 to +1 where negative values are generated from water; around zero values generated from non-vegetated surfaces, i.e. bare rocks and bare soil [24], while the increasing values towards positive one represent healthy vegetation activity. NDVI is one of the most used vegetation indices because it is successful as a vegetation measure and is sufficiently stable to allow meaningful comparisons of seasonal and inter-annual changes in vegetation growth and activity [25].

Another vegetation index from MODIS, the EVI is designed with improved sensitivity to differences in vegetation from sparse to dense vegetation conditions. The two VIs complement each other in global vegetation studies and improve upon the extraction of the canopy biophysical parameters [25].

4. METHODOLOGY

This section discusses the methodology used in analysing seasonal variation in wasteland categories, spectral separability of LU/LC classes from MODIS reflective bands and their derived products viz. NDVI and EVI, digital classification and accuracy assessment. These all are discussed under relevant subsections.

Table 1. MODIS data layer characteristics

Dataset name	Data layers	Description	Date of acquisitions	Spatial resolution (m)
MYD13Q1	Red band NIR band Blue band NDVI EVI	Surface reflectance - 16 days composite 16 days average	• 23rd October, 2016 (post-monsoon) • 9th January, 2017 (winter) • 15th April, 2017(summer)	250

Source: *adapted from https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/myd13q1_v006*

4.1 Wasteland Classification Schemes and Training Sites

The culturable wastelands were identified using 7 LU/LC classes, i.e. water body, cropland, fallow land, settlement and three classes of culturable wastelands viz. Gullied and/or ravinous land (medium), land with open scrub and land with dense scrub (Fig. 2). Land with scrub is the land with little soil cover, at times chemically degraded, extremes of slopes, severely eroded and lands subjected to excessive aridity with scrubs dominating the landscape. It can be further classified into two classes, land with open scrub and land with dense scrub based on the presence of vegetation cover on such lands. Gullied/ravine land results from localized surface run-off affecting the unconsolidated material converting into perceptible channels causing undulating terrain. Ravines are in fact an extensive system of gullies developed along the river courses. Gullied and/or ravinous land (medium) has an average depth of 2.5 to 5 metres [9].

The training sites were selected based on ground truth survey, Google Earth images and visual interpretation of MODIS images. From the ground survey, 75% of the sites were used for identifying training sites and remaining 25% of the sites were used for accuracy assessment which is discussed in the subsequent subsection of digital classification and accuracy assessment. It is often recommended that a training sample size for each class should not be fewer than 10-30 times the number of bands [26,27,28]. Hence, the minimum number of training pixels for each LU/LC class was decided based on the number of bands and proportion of the extent of each class within the study area image.

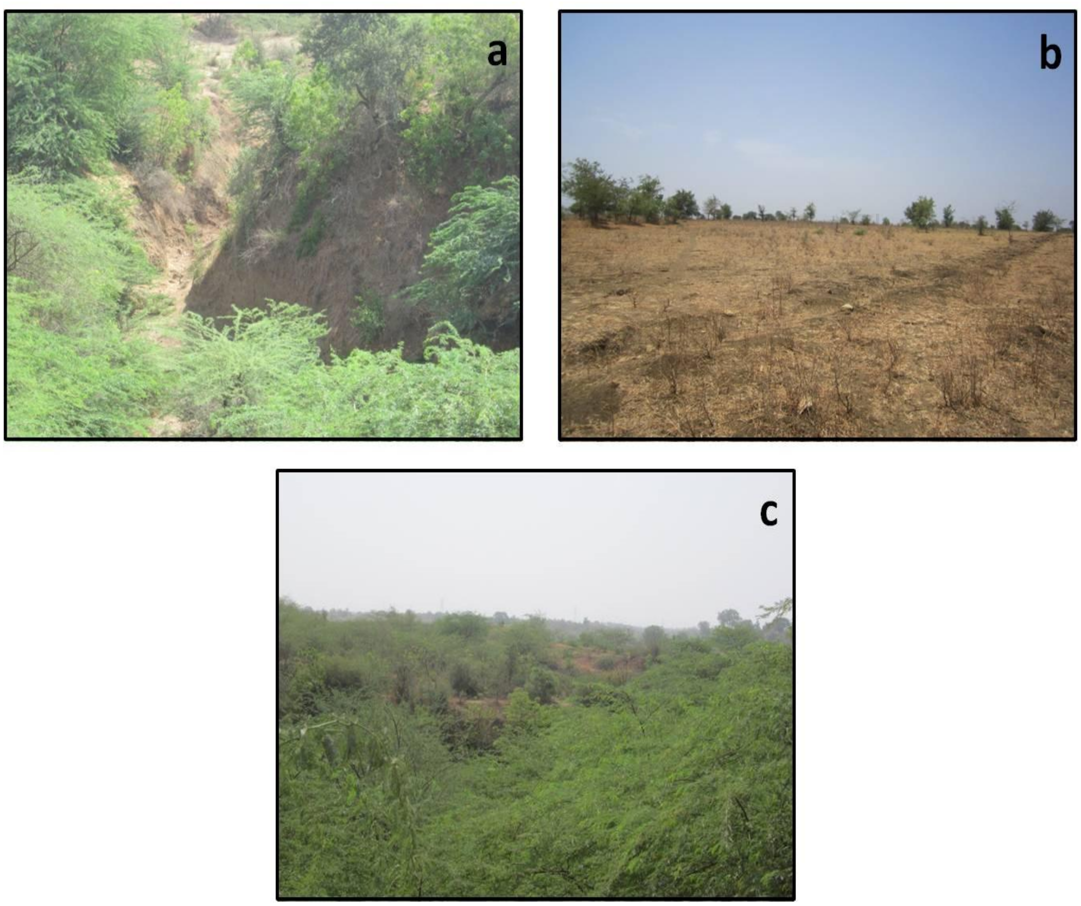

Fig. 2. Field photographs of types of wastelands (a) Gullied and/or ravinous land (medium) (b) land with open scrub (c) land with dense scrub

4.2 Spectral Separability Analysis

Spectral separability analysis is performed to determine the bands that are most effective to discriminate each class from others [29]. It involves statistical and graphical analysis to determine the degree of between-class separability in the training data. The present study has used transformed divergence (TD) to evaluate class separability for various combinations of bands and ancillary layers. TD value ranges between 0 and 2000, 0 being least separability between two classes and value 2000 represents highest separability between two classes considered. As a general rule, if the result is greater than 1,900, then the classes can be separated; between 1,700 and 1,900, the separation is fairly good and below 1,700, the separation is poor [29]. TD values have been calculated for various combinations of data viz. 3 season images individually, composite of 3 season images and their respective NDVI images, composite of 3 season images and their respective EVI images and composite of 3 season images and their respective NDVI and EVI images. Out of all these combinations, the combination with best separability for all LU/LC classes was used for digital classification. For all composites, TD values for water body class could not be produced as inverse covariance matrix could not be generated due to lower within class variability.

4.3 Digital Classification and Accuracy Assessment

As mentioned in the earlier section, the composite with highest separability for all considered LU/LC classes was then classified with the parametric rule based maximum likelihood classifier. As within class variability was less in case of water body class, inverse covariance matrix could not be produced. Hence, maximum likelihood classifier could not be applied on water body class. An additional non-parametric rule i.e. parallelepiped classifier was used for classifying water body class. Parallelepiped is a non-parametric supervised classifier which takes into consideration the mean and standard deviation of training pixels. The lower and higher threshold for the DN values for each class in each band is decided based on standard deviation. Pixels falling within the given threshold are classified under that class. Supervised classification module in Erdas Imagine software was used for applying these classification rules. A 3x3 majority filter was applied to reduce noise in the classification.

Ground truth survey was carried out in the month of April 2017 so that LU/LC class verification could be done for all three seasons considered. A stratified random sampling scheme was applied to generate accuracy check points. Total of 238 points including 25% of the field survey sites (ground truth) were considered within entire study area for accuracy assessment of all LU/LC classes. Classification accuracy was assessed by estimating producer's accuracy (PA), user's accuracy (UA), overall accuracy (OA) and kappa statistics (K) calculated from the error matrix.

An error matrix was created by making a cross-tabulation where columns represented reference data, while rows represented classified data of all LU/LC classes. Diagonal values are truly classified pixels which are used to calculate overall accuracy, i.e. ratio of summation of diagonal values to the total pixels in the error matrix, while the non-diagonal values represented errors. If the errors are estimated through columns, i.e. proportion of diagonal value divided by total summed value of a given column, it gives producer's accuracy or error due to omission. On the other hand, if errors are estimated through a row, it is termed as user's accuracy or error due to commission. Error due to commission occurs when pixels of a category wrongly assigned to another category by classification, thus adding erroneous pixels to a LU/LC class. On the contrary, Producer's Accuracy can be opposite of addition, i.e. omission. Additionally, kappa incorporates these errors with Overall Accuracy and gives a figure which can be interpreted as per cent to that classification is better than the random coincidence of the two data sets. Since it is hard to specify one single measure to assess the Overall Accuracy of the classification [30], all the aforementioned parameters were considered to evaluate the best possible accuracy.

5. RESULTS AND DISCUSSION

5.1 Spectral Separabilities of LU/LC Classes

Spectral separability analysis showed some peculiar patterns. Starting with post monsoon data of 23rd October, 2016 three spectral bands namely blue, red and NIR were used for calculating TD using selected training sites for each LU/LC class. Lowest TD value of 361 was observed for crop land and land with dense scrub (Table 2). This may be because of high vegetation activity from both LU/LC classes in post monsoon season. For other pairs of LU/LC classes, the TD ranged from 550 to 2000 suggesting moderately low to high separability (Table 1). In case of winter season (9th January, 2017) three bands image, lowest separability (998) was found between land with open scrub and land with dense scrub. This is expected because by winter season, dense and open scrub might give similar spectral response due to decreasing vegetation activity in both the classes. However, compare to post monsoon image, the lowest separability value is higher in case of winter image suggesting overall good separability. The third data i.e. summer season image (15th April, 2017) represented even lower separability compare to post monsoon season image. The lowest TD was found to be 251 for between land with open scrub and land with dense scrub. This is due to further decrease of vegetation activity in dense scrub resulting into similar spectral response from open and dense scrub. Even for gullied and/or ravinous land (medium) and dense scrub, the TD value was 1096 and for gullied/ravinous land (medium) and open scrub it was 1177 suggesting overall low to moderate separability.

After considering the separability statistics particularly for three wasteland categories in three different seasons, it was thought that inclusion of vegetation indices might give better separability as all wasteland classes are affected by seasonal variation in vegetation activity and varied soil - vegetation interaction resulting into variable spectral response. Hence, NDVI, EVI and NDVI and EVI together were included as ancillary layers along with three season image bands respectively. These composites were then used for performing separability analysis as it was done for individual three season images. In case of a composite of post monsoon image and its NDVI, lowest TD improved from 361 to

Table 2. Separability analysis - TD values for three bands image

Serial no.	23rd October, 2016 (Post monsoon)		9th January, 2017 (winter)		15th April, 2017 (summer)	
	Class pairs	**TD**	**Class pairs**	**TD**	**Class pairs**	**TD**
1	1:2	2000	1:2	1997	1:2	2000
2	1:3	1593	1:3	1981	1:3	1766
3	1:4	361	1:4	1543	1:4	1630
4	1:5	894	1:5	1995	1:5	1914
5	1:6	2000	1:6	2000	1:6	2000
6	1:7	2000	1:7	2000	1:7	2000
7	2:3	2000	2:3	1753	2:3	1980
8	2:4	2000	2:4	1339	2:4	1797
9	2:5	2000	2:5	1270	2:5	1734
10	2:6	1998	2:6	2000	2:6	2000
11	2:7	1996	2:7	2000	2:7	2000
12	3:4	1338	3:4	1204	3:4	1096
13	3:5	1971	3:5	1267	3:5	1177
14	3:6	2000	3:6	2000	3:6	2000
15	3:7	2000	3:7	2000	3:7	2000
16	4:5	550	4:5	998	4:5	251
17	4:6	2000	4:6	2000	4:6	1999
18	4:7	2000	4:7	2000	4:7	2000
19	5:6	1976	5:6	1995	5:6	1997
20	5:7	1994	5:7	2000	5:7	2000
21	6:7	2000	6:7	2000	6:7	2000
Class no.	**Class name**					
1	Crop land					
2	Fallow land					
3	Gullied and/or ravinous land					
4	Land with dense scrub					
5	Land with open scrub					
6	Settlement					
7	Water body					

Source: Author's calculation

619 for crop land and land with dense scrub (Table 3). For land with open scrub and land with dense scrub also, the TD improved from 550 to 888. This is mainly due to the fact that inclusion of the NDVI layer led to greater spectral distance between various culturable wasteland categories resulting into better separability. The composite of winter season image and its NDVI and summer season image and its NDVI showed the similar trend. The TD values were higher for composite than for winter season and summer season image alone for all culturable wasteland classes suggesting again an improvement.

Mean NDVI values for types of culturable wastelands show almost similar trend with slight differences in values over three seasons (Fig. 3). Mean NDVI values for crop land are quite high suggesting good separability except in post monsoon season. Also Fallow land mean NDVI values are low compare to all other vegetation classes in all three seasons.

The inclusion of EVI is based on the fact that it is designed to enhance the differences in vegetation from sparse to dense vegetation conditions. This idea was applied to achieve higher spectral separability between land with open scrub and land with dense scrub. However, results of separability analysis revealed that though inclusion of respective EVI with three season images led to improvement of TD values (Table 4) compare to three season images alone but, it was not higher than composite of three season images and their respective NDVI. For example, if we consider the class separability between land with open scrub and land with dense scrub then in case of winter season image, composite with EVI gave TD value of 1168 which is lower than TD value of 1650 for composite with NDVI and higher than TD value of 998 which is for winter season image alone.

Table 3. Separability analysis - TD values for composite of 3 bands image and NDVI

Serial no.	23rd October, 2016 (post monsoon)		9th January, 2017 (winter)		15th April, 2017 (summer)	
	Class pairs	**TD**	**Class pairs**	**TD**	**Class pairs**	**TD**
1	1:2	2000	1:2	2000	1:2	2000
2	1:3	1989	1:3	2000	1:3	1999
3	1:4	619	1:4	1993	1:4	1970
4	1:5	1296	1:5	2000	1:5	1997
5	1:6	2000	1:6	2000	1:6	2000
6	1:7	-	1:7	-	1:7	2000
7	2:3	2000	2:3	1978	2:3	2000
8	2:4	2000	2:4	1880	2:4	1947
9	2:5	2000	2:5	1328	2:5	1964
10	2:6	2000	2:6	2000	2:6	2000
11	2:7	-	2:7	-	2:7	2000
12	3:4	1684	3:4	1750	3:4	1713
13	3:5	1999	3:5	1833	3:5	1460
14	3:6	2000	3:6	2000	3:6	2000
15	3:7	-	3:7	-	3:7	2000
16	4:5	888	4:5	1650	4:5	793
17	4:6	2000	4:6	2000	4:6	2000
18	4:7	-	4:7	-	4:7	2000
19	5:6	2000	5:6	2000	5:6	2000
20	5:7	-	5:7	-	5:7	2000
21	6:7	-	6:7	-	6:7	2000

Class no.	**Class name**
1	Crop land
2	Fallow land
3	Gullied and/or ravinous land
4	Land with dense scrub
5	Land with open scrub
6	Settlement
7	Water body

Source: Author's calculation

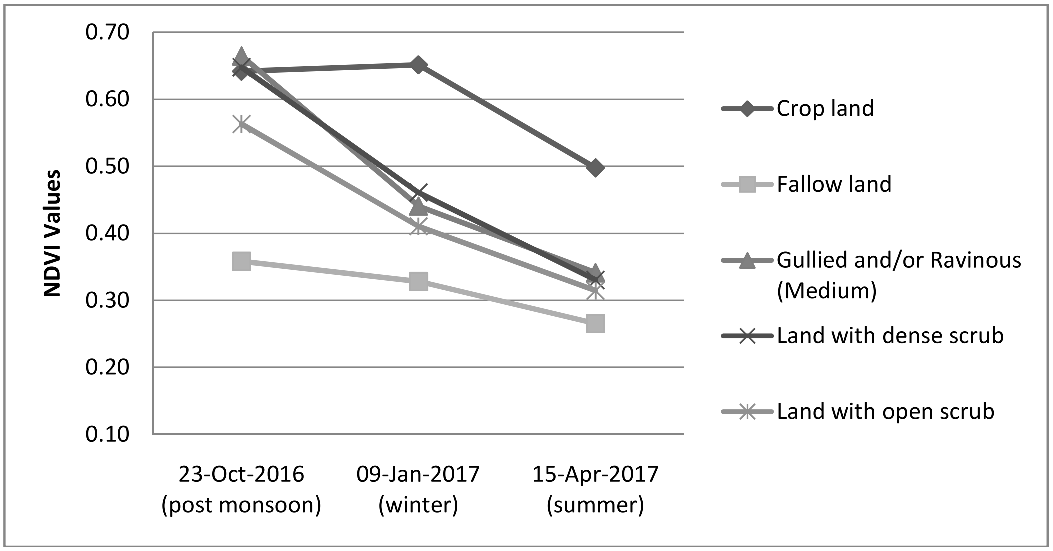

Fig. 3. Mean NDVI values for selected three seasons/dates

Table 4. Separability analysis - TD values for composite of 3 bands image and EVI

Serial no.	23rd October, 2016 (post monsoon)		9th January, 2017 (winter)		15th April, 2017 (summer)	
	Class pairs	TD	Class pairs	TD	Class pairs	TD
1	1:2	2000	1:2	2000	1:2	2000
2	1:3	1733	1:3	1991	1:3	1962
3	1:4	536	1:4	1769	1:4	1959
4	1:5	1147	1:5	2000	1:5	1999
5	1:6	2000	1:6	2000	1:6	2000
6	1:7	-	1:7	-	1:7	2000
7	2:3	2000	2:3	1948	2:3	1989
8	2:4	2000	2:4	1863	2:4	1913
9	2:5	2000	2:5	1574	2:5	1886
10	2:6	1999	2:6	2000	2:6	2000
11	2:7	-	2:7	-	2:7	2000
12	3:4	1452	3:4	1290	3:4	1173
13	3:5	1994	3:5	1431	3:5	1296
14	3:6	2000	3:6	2000	3:6	2000
15	3:7	-	3:7	-	3:7	2000
16	4:5	894	4:5	1168	4:5	511
17	4:6	2000	4:6	2000	4:6	2000
18	4:7	-	4:7	-	4:7	2000
19	5:6	1997	5:6	1999	5:6	1999
20	5:7	-	5:7	-	5:7	2000
21	6:7	-	6:7	-	6:7	2000
Class no.	**Class name**					
1	Crop land					
2	Fallow land					
3	Gullied and/or ravinous land					
4	Land with dense scrub					
5	Land with open scrub					
6	Settlement					
7	Water body					

Source: Author's calculation

Mean EVI values suggest the similar trend for types of culturable wastelands, crop land and fallow land as in the case with mean NDVI values (Fig. 4). The only difference is the mean values for EVI are low in comparison to NDVI.

Finally, both NDVI and EVI were included as two ancillary layers with respective three season images and TD values were calculated (Table 5). In general, all three season composites with NDVI and EVI performed better than three season images alone and their composites separately with NDVI and EVI. Out of the three season composites with NDVI and EVI, winter season image (9th January, 2017) composite with NDVI and EVI gave highest TD values for all wasteland classes. For example, for land with open scrub and land with dense scrub, the TD value calculated was 1786 which is highest among all considered combinations and composites. Similarly, for between gullied/ ravinous land (medium) and open scrub, the TD value achieved was 1965 which is again highest among all considered combinations and composites.

The composite with highest TD values for all LU/LC classes i.e. composite of winter season image with NDVI and EVI was finalized and further used for performing maximum likelihood digital image classification.

5.2 Digital Classification and Accuracy Assessment

Maximum likelihood classifier was used to classify various data composites. The classification output from the composite (MODIS reflectance bands, NDVI and EVI) of winter season possessing highest accuracy has been presented in Fig. 5.

The accuracy assessment results represented the similar trend as seen in separability analysis. In case of only MODIS reflectance bands data, culturable wastelands classes in particular and all LU/LC classes in general did not achieve high accuracy (overall accuracy of 60.9%) (Table 6). MODIS reflectance bands and EVI composite too achieved similar accuracy of around 61.3%. The inclusion of NDVI layer to MODIS reflectance bands has increased the accuracy up to 70.2%. However, the composite of MODIS reflectance bands with both NDVI and EVI performed best among all considered composites for three different season datasets; the results of which are discussed in length in following paragraph.

Accuracy assessment (Table 6) results show that fallow land has lowest producer's accuracy (55.6%) and land with dense scrub has lowest user's accuracy (64.7%). Low UA indicates high error due to commission, i.e. other categories are falsely classified as land with dense scrub. Land with dense scrub has similar reflectance pattern

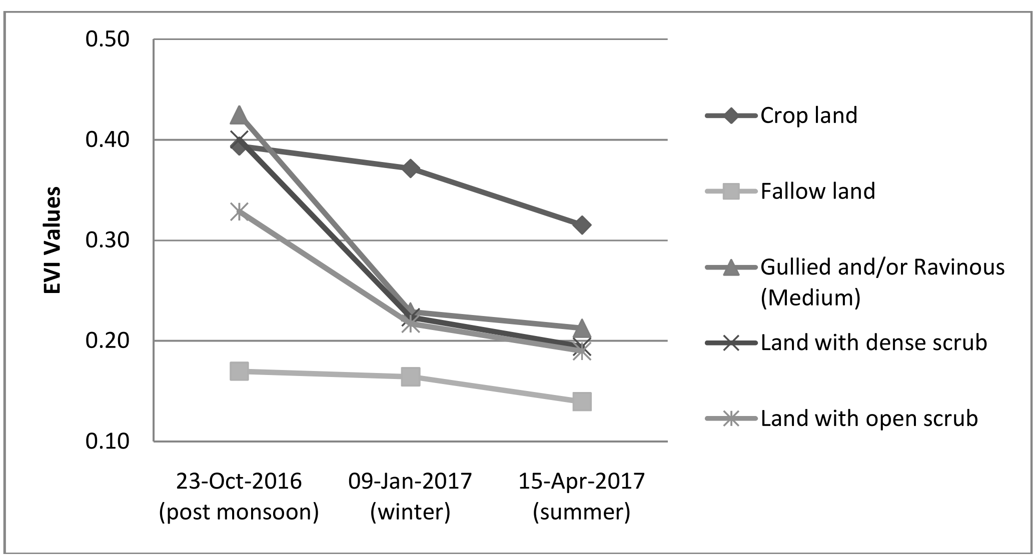

Fig. 4. Mean EVI values for selected three seasons/dates

Table 5. Separability analysis - TD values for composite of 3 bands image, NDVI and EVI

Serial no.	23rd October, 2016 (post monsoon)		9th January, 2017 (winter)		15th April, 2017 (summer)	
	Class pairs	**TD**	**Class pairs**	**TD**	**Class pairs**	**TD**
1	1:2	2000	1:2	2000	1:2	2000
2	1:3	1997	1:3	2000	1:3	2000
3	1:4	773	1:4	1999	1:4	1999
4	1:5	1415	1:5	2000	1:5	2000
5	1:6	2000	1:6	2000	1:6	2000
6	1:7	-	1:7	-	1:7	2000
7	2:3	2000	2:3	1999	2:3	2000
8	2:4	2000	2:4	1982	2:4	2000
9	2:5	2000	2:5	1752	2:5	1998
10	2:6	2000	2:6	2000	2:6	2000
11	2:7	-	2:7	-	2:7	2000
12	3:4	1821	3:4	1992	3:4	1851
13	3:5	2000	3:5	1965	3:5	1591
14	3:6	2000	3:6	2000	3:6	2000
15	3:7	-	3:7	-	3:7	2000
16	4:5	1155	4:5	1786	4:5	934
17	4:6	2000	4:6	2000	4:6	2000
18	4:7	-	4:7	-	4:7	2000
19	5:6	2000	5:6	2000	5:6	2000
20	5:7	-	5:7	-	5:7	2000
21	6:7	-	6:7	-	6:7	2000
Class no.	**Class name**					
1	Crop land					
2	Fallow land					
3	Gullied and/or ravinous land					
4	Land with dense scrub					
5	Land with open scrub					
6	Settlement					
7	Water body					

Source: Author's calculation

Table 6. Accuracies of winter season image (9th January, 2017) for different composites (in %)

Datasets		MODIS - 3 bands		MODIS - 3 bands and NDVI		MODIS - 3 bands and EVI		MODIS - 3 bands, NDVI and EVI	
Sr. no.	**Class**	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**	**PA**	**UA**
1	Crop land	60.5	76.5	69.8	88.2	58.1	73.5	74.4	94.1
2	Fallow land	51.1	67.6	53.3	70.6	42.2	55.9	55.6	73.5
3	Gullied/ravinous land (medium)	65.5	55.9	79.3	67.6	72.4	61.8	86.2	73.5
4	Land with open scrub	50.0	61.8	61.9	76.5	47.6	58.8	69.0	85.3
5	Land with dense scrub	62.5	44.1	83.3	58.8	75.0	52.9	91.7	64.7
6	Settlement	52.0	38.2	64.0	47.1	56.0	41.2	92.0	67.6
7	Waterbody	90.0	79.4	93.3	82.4	90.0	79.4	100.0	88.2
Overall accuracy		60.9		70.2		61.3		78.2	

Source: Author's calculation

as crop land and hence low UA. Also, there may be spectral confusion between land with dense scrub and plantation crops due to their similar vegetation activity. Open scrub on undulating terrain has also given similar reflectance pattern as dense scrub which was observed during accuracy assessment. Also, fallow land with trees on field boundaries might have spectrally confused with open or dense scrub. Interestingly, settlement has shown

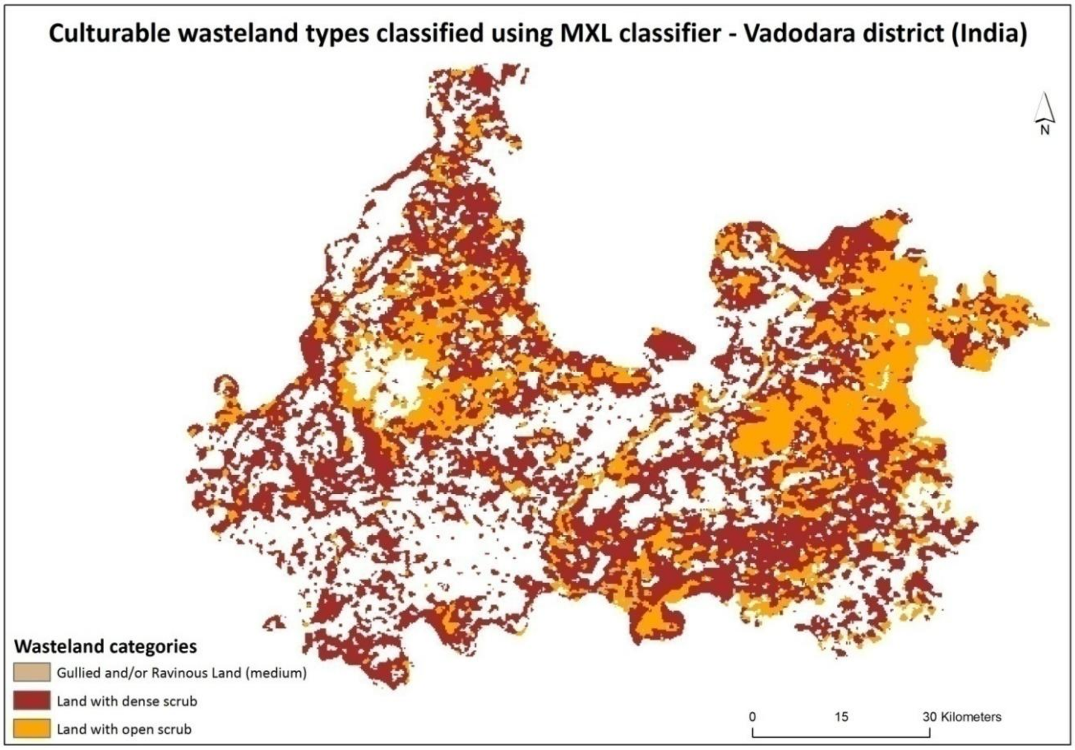

Fig. 5. Culturable wasteland types classified using MXL classifier - Vadodara district (India)

higher producer's accuracy of 92.0% meaning thereby less omission error and user's accuracy of 67.6% suggesting low commission error comparatively. Generally settlement is spectrally confused with land with open scrub, but this was avoided by use of NDVI and EVI layers; hence, good UA and PA of settlement class. Gullied/ravinous land (medium) also showed good producer's (86.2%) and user's accuracy (73.5%). User's accuracy was lower than producer's accuracy mainly because of spectral confusion with land with open scrub. Land with open scrub has been wrongly classified as gullied/ravinous land (medium) resulting into lower UA than PA. In case of land with open scrub, it is opposite i.e. PA is lower than UA meaning error of omission was higher than error of commission. This suggests that pixels of land with open scrub are wrongly classified as other categories leading to lower PA. The overall accuracy of the classification calculated to be 78.2 % with overall kappa statistic of 0.7580.

6. CONCLUSION

The inclusion of both NDVI and EVI with winter season MODIS reflectance bands (blue, red and NIR) data has improved the spectral separability between various classes for identification of culturable wastelands. The overall digital classification accuracy has improved to 78.2% from only NDVI (70.2%) and only EVI (61.3%) inclusion. Also, the class-wise user's and producer's accuracy has improved particularly for culturable wasteland categories gullied and/or ravinous land (medium), land with open scrub and land with dense scrub. The contrast of vegetation activity has helped the separation of wastelands from cropland and fallow land in the winter season when cropland is either fallow or at the peak of cultivation (*rabi* crop) and wastelands have least vegetation activity. Here, the exception is the NDVI values of land with dense scrub which follow the similar trend to those of cropland mainly of plantations. The study signifies the use of contrast of vegetation activity in digitally classifying the culturable wastelands from remote sensing data. Future work may be directed towards the use of moderate to high-resolution remote sensing data for better accuracy. Also, the inclusion of ancillary data related to climates such as temperature and rainfall may help in improving digital classification of culturable wastelands.

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COMPETING INTERESTS

Author has declared that no competing interests exist.

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