Mapping of Degraded Lands from Multidate Remotely Sensed Data Using Decision Tree Based Classification (DTC)

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Abstract:

In the present study, efforts have been made to identify and map areas affected by various land degradation in Kheragarah *tehsil* of Agra, Uttar Pradesh, India. IRS-P6 LISS III satellite data of three dates *viz*., February, May and October, 2009 have been used in the study. Three remote sensing derived indices have been used such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Soil Brightness Index (SBI) for identifying vegetation, waterlogged area and salt affected land respectively. Decision Tree Classifier (DTC) has incorporated these derived indices for delineating and mapping different types of degradation. Results revealed that about 41.24% of area is non agricultural land in which four categories of degradation could be identified i.e. degraded hill (4.05%), degraded forest (3.46%), wetland (6.26%) and ravinous land (3.26%). The remaining (58.76%) is agricultural land out of which 75.08% is normal land and (24.92%) suffers from two types of degradation *viz*., chemical (salinity) and physical deterioration (waterlogged). An attempt was done to ensure the efficiency of DTC by comparing it with supervised classification approach .The values of the Kappa statistics were used to compare the performance of the classifiers and it was found to be higher (0.95) for the DTC than supervised classification (0.75). The *Z* statistics was computed for comparing Kappa coefficients obtained from the error matrices of two above mentioned classifications. Z value was found to be 21.08 which implied that there was a significant difference between Kappa coefficients in both approaches.

Introduction:

Soil degradation is a global phenomenon. The soil degradation occurs due to the interactive effects of anthropogenic and biophysical factors on soil properties and leads to adverse alter in soil properties, environmental quality, agricultural productivity and sustainability. Soil degradation has been defined in many ways where the prime attention has been given to declining productivity of the soils for example United Nations Environment Programme (UNEP, 1997) defined soil degradation as the rate of adverse change in soil quality resulting in decline in productive capacity of the land induced mainly by human interventions. Also Singer and Munns (2002) defined soil degradation as the loss of soil production by either chemical or physical processes.

India with geographical area of 329 M ha, has to support about 17 % human population and 15 % livestock population on world's only 2.3 % of land, 4.2 % of water resources, 1% of forests and 0.5 % of pastures. The net cultivated area of about 140 M ha has remained static for the last 39 years. Many prime farm lands are being diverted to non agricultural purpose such as industries, mining and urbanization, etc. (Yadav and Sarkar, 2009). Although, the data on the nature and extent of degraded lands of the country projected by various agencies vary widely, but it created enough awareness of the problem amongst the scientist and planners (Dhir, 1990). However, the accurate and reliable assessment of degraded lands, their spatial distribution and extent remains to be a major issue particularly in the context of optimal utilization of land.

More recently, remote sensing has opened new vistas in inventory, characterization and monitoring of degraded lands. The value of remote sensing along with GIS for mapping any landscape attribute such as soil degradation is clear enough. No other techniques offer the promise of spatially exhaustive, objective and repeated measurements at a cost comparable to satellite remote sensing. For mapping salt affected soils in Punjab, Pakistan, Khan *et al*. (2001) used IRS-LISS II digital data and different remote sensing derived indices such as salinity index (SI), Normalized Difference Salinity Index (NDSI), Brightness Index (BI), Normalized Difference Vegetation Index (NDVI). Mutlaq (2002) assessed degradation in Mathura district, Uttar Pradesh, India through visual interpretation and digital image processing. He could identify different types, extent and degree of degradation. Bai and Dent (2006) reported on a pilot study done in Kenya during the global assessment of land degradation in drylands. The study applied the Global Assessment of Land Degradation (GLADA) approach that involves a sequence of analyses to indentify *hot spots* of land degradation (referred to by LADA program of FAO) using remote sensing and existing data sets. Bai and Dent (2006) describe how the study was carried out using simple normalized difference vegetation index (NDVI) indicators such as mean annual sum NDVI and the trend of biomass productivity; integration of biomass and climatic data (rain-use efficiency); linking NDVI to net primary productivity and calculating the changes of biomass production for dominant land use types; and then, stratification of the landscape using land cover and soil and terrain data to enable a more localised analysis of the NDVI data. Jafari *et al.* (2008) investigated the use of the moving standard deviation index (MSDI) applied to Landsat TM band 3 data for detection and assessment of the zones in the arid grazing lands of south Australia. The study compared the NDVI and the perpendicular distance vegetation index (PD54) and showed that it was more appropriate than the NDVI in this perennially dominated arid environment. The piospheres (a zone of extreme degradation around the water points in grazed landscapes) were found to be more heterogenous in vegetative cover, with higher MSDI values, compared with non-degraded areas, and spatial heterogeneity in cover decreased with increasing distance from water points. The study indicated that MSDI could be used as an appropriate method for land degradation assessment in the naturally heterogeneous arid lands of south Australia. This result was found to be similar to that of Tanser and Palmer (1999). Ajai *et al*. (2009) successfully identified different types of degradation in India through remote sensing techniques.

In Mexico, Ferandez *et al*. (2009) described a synergistic approach that combined field and remote sensing data (Landsat ETM and color photographs) for mapping saline areas, whereby a spectral response index using NDVI was used for image enhancement. He further combined these data with spectral responses of bare soil and vegetation. Del Valle *et al.* (2009) evaluated the usefulness of radar derived parameters for detecting and mapping salt affected soils under irrigation in Chubut, Argentina. Four factors were significant when analysing the variations of the backscattering coefficients, namely soil texture, soil aspect, soil moisture and the presence of salts. They found that the average backscattering values for all salt affected soil classes were higher in the L-band than in the C-band of the spaceborne imaging radar (SIR-C) at the same polarization mode. Goldshleger *et al*. (2010) proved that a hyperspectral (narrow band) approach combined with active remote sensing such as frequency domain electromagnetic induction (FDEM) and ground penetrating radar (GPR) could be used to provide three dimensional maps of soil salinity status in croplands. Such a map could improve our understanding of salinization mechanism and salt sources and also could lead to improve drainage system planning and management.

Wetness Index (WI), Soil Brightness Index (SBI) and Soil Adjusted Vegetation Index (SAVI) were utilized by Koshal (2010) for degraded land characterization and delineation with emphasis on salinity and sodicity problems. Many approaches used for mapping land degradation such as visual interpretation, unsupervised, supervised classification and remote sensing derived indices (Gupta *et al*. 1998 ; Saini et al. 1999 ; Porarinsdottir, 2008 ; Jafari *et* *al.* 2008 and Koshal, 2010). Decision tree classifier (DTC) offers many advantages over other classification approaches. Mahesh and Mather (2003) demonstrated the advantages of the decision tree for land cover classification in comparison with other classifiers such as the maximum likelihood method and artificial neural networks. Tooke *et al*., (2009) used decision tree to extract urban vegetation characteristics, including species and condition. Eric *et al*. (2003) had examined the feasibility of using a decision tree to instrument to map 11 land cover types. The DTC works to reduce both intra-class and inter-class variability through recursive binary splitting of training data values (Venables and Ripley, 1994).

According to AIS & LUS (2000), Kheragarah *tehsil* of Agra suffers from many types of degradation such as salinity, watelogging, ravines, degraded hills and rock quarries. In this study, an attempt has been made for identification, categorization and mapping of degraded lands of Kheragarah *tehsil* of Agra from remotely sensed data using decision tree classification.

Materials and Methods

Study area

The study area forms part of Agra district, Uttar Pradesh, India (Fig. 1) and it covers an area of about 80,000 ha. It extents between geo-coordinates 26° 44′ 31.43″ to 27° 4′ 7.80″ North latitude and 77° 27′ 21.27″ to 78° 7′ 22.42″ East longitude. The area under study is characterized by hot dry sub-humid to semi-arid transition with intense hot summer, cold winter and general dryness through the year except during July and September. The mean annual air temperature varies from 34° to 46° C. The winter (December- February) average temperature ranges from 6.5° to 13° C dropping to minimum of 4°C during January. The area receives mean annual rainfall ranging between 600 to 1000 mm which is mostly received during southwest monsoon period followed by the post monsoon period from October to November. Unfortunately, the mean rainfall in winter is considered as insufficient for growing up *rabi* crops. Neem (*Azadirachta indica*), Babul (*Acacia arabica*), Dhak (*Butea monosperma*) and Faras (*Tamarix sp.*) are the predominant tree species among the natural vegetation. According to All India Soil and Land Use Survey AIS & LUS (2000), Kharagarah *tehsil* suffers from various types of degradation which preclude the use of its land.

Satellite data

IRS-P6 LISS3 satellite data of three dates namely, 1st February, 8th May and 23rd October 2009 (path: 097, row: 052) were used for the study (Fig. 2). Different time periods were chosen for visual analysis and digital image processing because of considerable variations in soil salinity, waterlogging and vegetation cover as well. In February image, potential agricultural land can be identified by observing the vegetation whereas in May image (dry season) salinity and / or sodicidy can be identified. Seasonal waterlogged area can be identified by studing the October image (post monsoon). The digital satellite data products were procured from National Remote Sensing Center (NRSC) (www.nrsc.gov.in), Hyderabad.

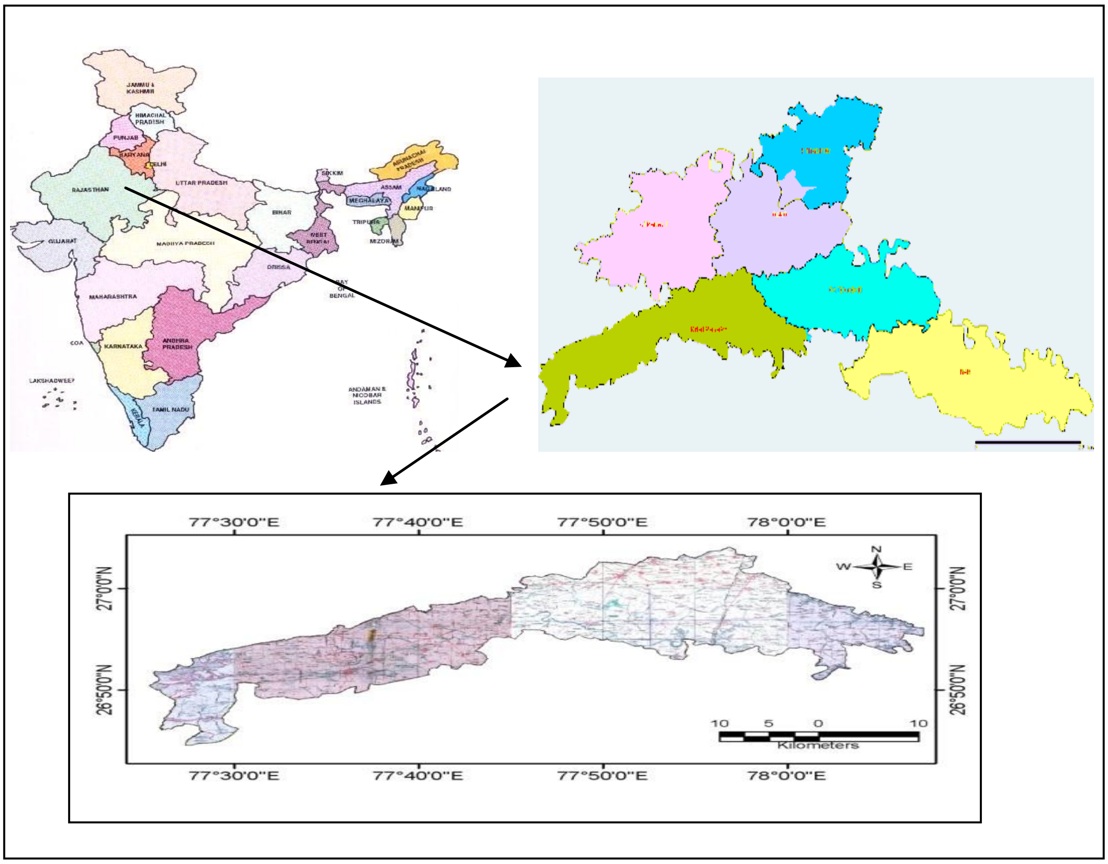

Fig. 1 Location of study area , Kharagarah *tehsil,*Agra, Uttar Pradesh, India.

Ancillary data:

The ancillary data used includes information and maps of the study area. Available reports (AIS & LUS , 2000 and 2009) pertaining to the area published by the All India Soil & Land Use Survey (AIS & LUS), Department of Agriculture & Cooperation, Ministry of Agriculture, Government of India, were very informative for the present study as these describe about different types of degradation and soil resources in Agra district. The survey of India (SOI) toposheets No. 54E/16, 54F/5, 54F/6, 54F/9, 54F/13, 54I/4 and 54J/1 of

1:50,000 scale were used to extract information for preparation of base maps and navigation during ground truthing.

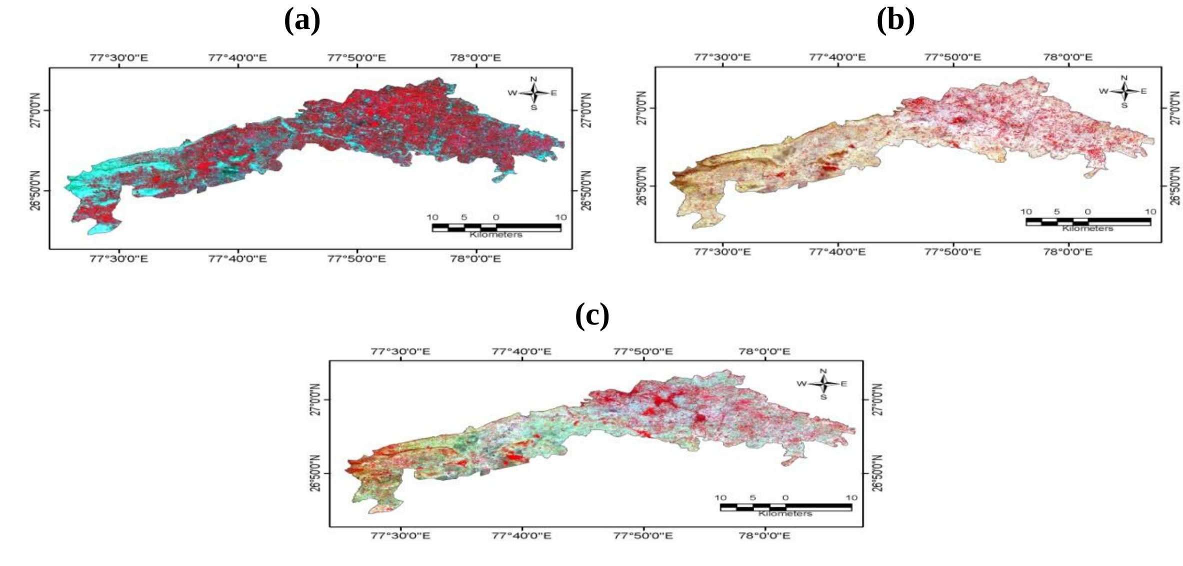

Fig. 2 False Colour Composite of the study area during (a) February, (b) May, (c) October, 2009.

Methodology

The methodology adopted in the study is shown in presented in the form of a flow chart (Fig. 3).

Digital image processing

Often the raw data image is not directly suitable for specific purpose and should be processed in some way or other. Essential steps known as pre-processing must be done before digital image processing. The main steps are as described here under.

(i) Geometric correction

In geometric correction, a standard geographic coordinate system is selected for all images of interest. The selection of ground control points (GCPs) is very important for geometric correction. Using SOI toposheets, the digital data of May 8, 2009 was registered (map to image registration) using about 10 GCPs that were easily recognizable on the satellite images. The first polynomial order and nearest neighborhood sampling method provided with ENVI (Environment for Visualizing Images, Research System, Inc.) software (ver.4.7) were used for image registration. The remaining images were rectified using the corrected image of May 8, 2009 as reference following the same re-sampling method.

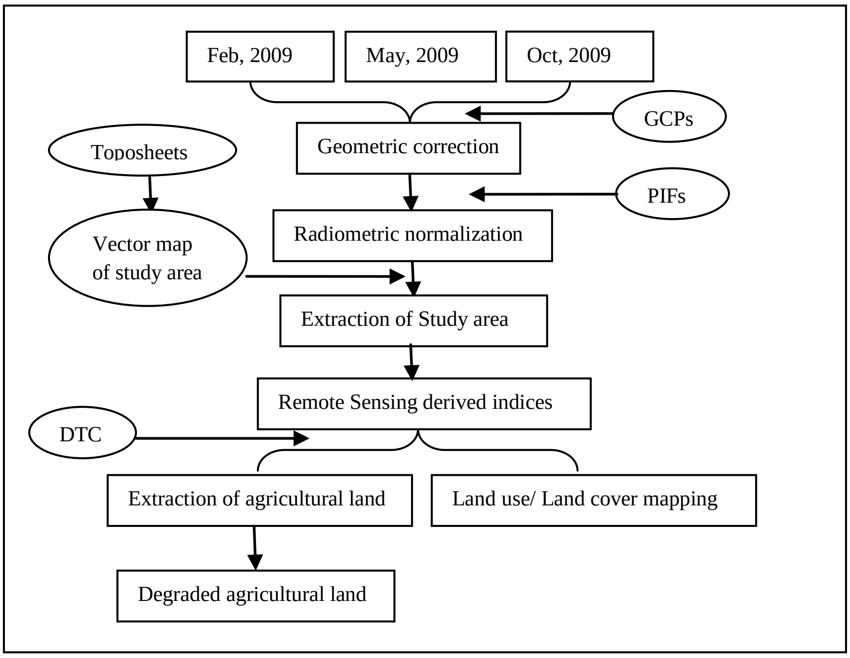

Fig. 3 Methodology followed in the study

(ii)Radiometric normalization

The temporal images need to be radiometrically corrected for further use in the study to normalize the change in brightness value (DN) due to varying atmospheric conditions and sun's positions. Radiometric normalization was done based on Pseudo-invariant features (PIFs) in the images, which are objects spatially well defined and spectrally and radiometrically stable. Schott *et al*., (1988) and sahoo et al (2006) mentioned the details criteria of (PIFs). The image having highest dynamic DN range, i.e. February 01, 2009 was selected as the reference or base image for radiometric normalization of other two images belonging to May 08, 2009 and October 23, 2009. The formula (1) elaborated by Schott *et al*. (1988) was used in radiometric normalization.

$$DN_{1i} = \frac{\sigma_{1i}}{\sigma_{2i}} DN_{2i} + \left(\mu_{1i} - \frac{\sigma_{1i}}{\sigma_{2i}} \mu_{2i} \right) \quad \text{..................(1)}$$

Where

DN_{1i} = Pixel value of day 1*
DN_{2i} = Pixel value of day 2**
σ_{1i} = Standard deviation (SD) of PIF of day 1*
σ_{2i} = Standard deviation (SD) of PIF of day 2**
μ_{1i} = Mean of PIF of day 1*
μ_{21} = Mean of PIF of day 2**
i = Band number (i= 2, 3, 4, 5)
1* = February (reference image)
2** = Either May or October image

The mean and standard deviation of PIFs of each band of images of three dates were retrieved and given in Table 2. The normalized bands of images of respective dates were stacked to get the FCC and for further analysis.

Table. 2 Mean and standard deviation of PIFs of three dates before and after normalization

Date-Band	Before normalization		After normalization	
	Mean	SD	Mean	SD
Feb- 2	80.66	18.92	80.66	18.92
Feb- 3	51.90	17.60	51.90	17.60
Feb- 4	65.05	12.42	65.05	12.42
Feb- 5	74.44	17.48	74.44	17.48
May- 2	91.45	12.53	82.17	18.92
May- 3	81.78	15.76	51.89	22.14
May- 4	83.84	7.29	65.05	12.43
May- 5	67.34	8.51	74.45	17.49
Oct- 2	68.95	10.40	80.65	18.91
Oct- 3	50.83	13.40	51.90	17.60
Oct- 4	72.95	6.65	65.05	12.43
Oct- 5	41.86	8.44	74.43	17.49

Extraction of study area

The boundary of study area was defined and vector layer of area of interest (AOI) was created using SOI toposheets of the study region. The images of three dates were masked out using the area of interest (AOI) vector.

Spectral indices

To differentiate between different types of degradation, appropriate spectral indices were calculated. Spectral index is a mathematical expression of number of bands to enhance the variation and to recognize vegetation and/or soil conditions. The main indices used in the present study are given hereunder:

1. Normalized Difference Vegetation Index (NDVI)

The (NDVI), being a potential indicator for crop growth and vigor, was used in the study, which is expressed by Rouse *et al.* (1974) as formula (2)

$$NDVI = \frac{(NIR - R)}{(NIR + R)} = \frac{(B4 - B3)}{(B4 + B3)} \qquad \text{..........(2)}$$

Where: NIR: Near infrared band (B4), R:Red band (B3)

2. Normalized Difference Water Index (NDWI)

The seasonal and permanent waterlogging affected soils were identified using normalized difference water index (NDWI) given by Mcfeeters (1996). It is expressed as formula (3)

$$NDWI = \frac{(Green - NIR)}{(Green + NIR)} = \frac{(B2 - B4)}{(B2 + B4)} \text{…………}(3)$$

Where: Green (B2), NIR: Near infrared band (B4)

3. Soil brightness Index (SBI)

This index enhances the bare soil reflectance and makes better visual contrast between soils and vegetation boundaries (Kauth and Thomas, 1976). Also, it is found useful for identifying mainly salt affected lands. SBI for the study region is defined by the formula (4):

SBI = 0.4328 (Green) + 0.6490 (Red) + 0.4607 (NIR) ……….(4)

Classification approach

The decision tree classifier (DTC) is a type of multistage classifier that can be applied to a single image or a stack of images. It is made up of a series of binary decisions (Fig.4) that are used to determine the correct category for each pixel with certain classes being separated during each step in the simplest manner possible. Many studies recommended the use of this technique as it has substantial advantages for remote sensing classification problems because of its flexibility, intuitive simplicity, and computational efficiency (Friedl and Brodley, 1997 ; Friedl *et al*., 1999 ; Simard *et al*., 2000 ; Mahesh and Mather, 2001; Sencan , 2004 ; Fisette *et al*., 2006 ; Wei *et al*., 2008 ; Hui *et al*., 2009 and Elnaggar and Noller , 2010).

To ensure the efficiency of DTC, an attempt was done to compare DTC with supervised classification. The maximum likelihood classifier (MLC) algorithm which is the most widely used supervised classification was applied for the classification of image pixels. 20 training areas (Fig. 5) identified in both toposheets and satellite images were used for supervised classification. On the analysis, ten different land cover classes were considered: water body, degraded hill, degraded forest, preserved forest and scattered vegetation, built up area, ravinous land, wetland and agricultural land which subdivided into three categories *viz*., seasonal water high saline (SWHA), seasonal water moderate saline (SWMS) and normal land.

Accuracy Assessment of Classification

Assessment of classification accuracy is controlled with the help of error matrix and Kappa Analysis technique, and, reference test pixel data (Mather 1987; Jensen1996; Richards and Jia 1999).

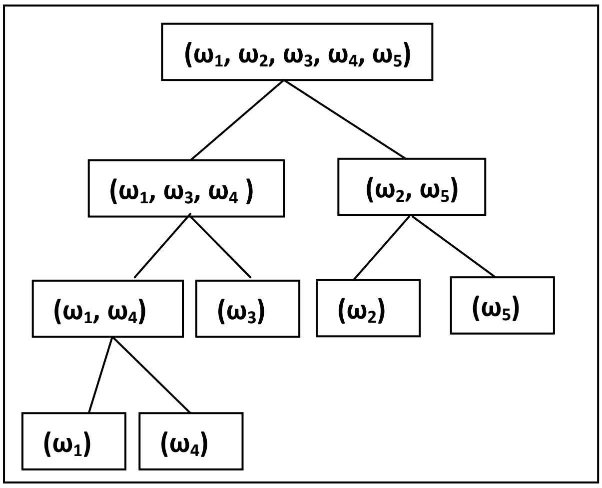

Fig. 4 An example of binary tree (**ω**: specific class)

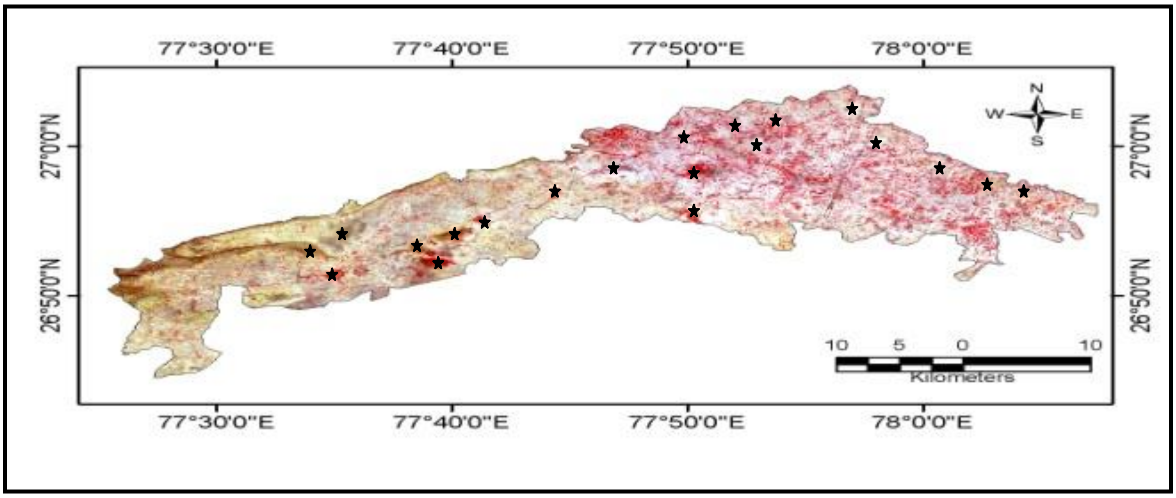

Fig. 5 Training sites overlaid on FCC of May image of the study area

Kappa analysis technique is used to measure the agreement between two observers on the same data; for remote sensing, it is used to measure the agreement between the classification approaches. Since, it takes into account the whole error matrix instead of only the diagonal elements, as the overall accuracy does, it has been recommended (Fung and Ledrew, 1988) as suitable measures of accuracy of classification. The Kappa analysis was applied by means of the formula given below (formula. 4):

$$K = \frac{\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} * x_{+i})}{N^2 - \sum_{i-1}^{r} (x_{i+} * x_{+i})} \quad ......(4)$$

r = number of rows in the error matrix

x_{ii} = number of observations in row *i* and column *i* (on the major diagonal)

x_{i+} = total number of observations for row *i*

x_{+i} = total number of observations for column *i*

N = total number of observations in error matrix

Kappa is a dimensionless real number between -1 and 1, the value close to 1 includes the maximum agreement while value of -1 can be interpreted as a total disagreement. Ladis and Koch (1977) proposed a classification of agreement based on the value of Kappa (Table. 3).

Table. 3 Interpretation of Kappa

K value	Rating	Agreement
≥ 0.81	Excellent	Almost perfect agreement
0.80 - 0.61	Good	Substantial agreement
0.60 – 0.41	Moderate	Moderate agreement
0.40 – 0.21	Poor	Fair agreement
0.20 – 0	Bad	Slight agreement
< 0.00	Very bad	Less than chance agreement

Once Kappa coefficients are calculated, the comparison between a pair of Kappa statistics obtained from the error matrices of two classifications was done to determine if they are significantly different. The determination of the normal distributed Z was obtained by the ratio among the difference value of two Kappa coefficients and the difference of the respective variance of them (Skidmore, 1999). The test statistics *Z* is obtained by using the formula (4) derived by Fleiss *et al*. (1969).

$$Z = \frac{K_1 - K_2}{\sqrt{Var_1 + Var_2}} \quad ....(5)$$

Where

K_1, K2 are kappa coefficients for DTC and Supervised classification respectively and Var_1, Var_2 are the variances of respective Kappa statistics. The Z statistics follows a normal distribution. For instance, assuming for Z test, the null hypothesis $H_0 : K_1 = K_2$ and the alternative $H_1 : K_1 \neq K_2$, the H_0 hypothesis is rejected if Z value obtained is greater than 1.96, the classification results (error matrices) are significantly different at a 95% confidence level. Whereas if Z value obtained is lesser than 1.96, the H_0 is accepted i.e. the classification results (error matrices) are not significantly different at a 95% confidence level. Z test was carried out for remote sensing data by Dwivedi *et al*. (2003) and Goncalves *et al.* (2007).

Result and Discussion:

Type and extent of soil degradation:

Land degradation study requires an accurate assessment of how wide spread it is, how sever the damage is and whether or not it is practically controllable or reversible (Barrow, 1991). By using DTC incorporated with remote sensing derived indices and by studying the information collected during ground truth verification and the reflectance of different objectives in the satellite images also by the consultant of toposheets of the study area, various classes could be delineated as described below:

(1) Preserved forest & scattered vegetation: As some scattered vegetations and also forest were observed during dry season (i.e May) and all having NDVI greater than 0.1, the decision was made for Pixels having NDVI of May image greater than 0.1 were classified as preserved forest and scattered vegetation. Table 4 reveals that about 3639.475 ha (4.51%) is under this class (Fig. 7).

Table. 4 land use/land cover in the study area

Categories	Area	
	ha	%
Degraded hill &Rock quarried	3270.004	4.05
Degraded forest	2791.287	3.46
Wetland	5055.986	6.26
River& water bodies	4808.035	5.96
Ravinous land	2921.400	3.62
Preserved forest Scattered vegetation	3639.475	4.51
Built up area	10796.900	13.38
Sub total	**33283.087**	**41.24**
Agricultural land	**47426.62**	**58.76**
Total	**80709.71**	**100**

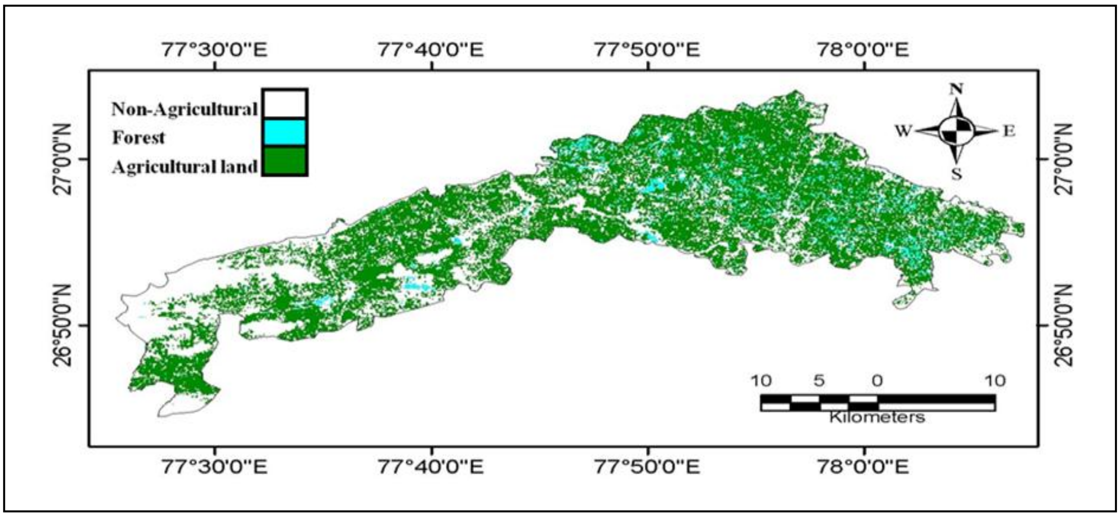

Fig. 7 Agricultural land, preserved forest and scattered vegetation in the study area.

(2) Potential agricultural land: Pixels that represent the potential agriculture area were delineated by using NDVI of February image due to almost of area is cultivated during this date. These areas (Table 4 & Fig. 8) occupy about 47426.62 ha (58.76%). These pixels were sub divided into three categories using NDWI of October image and SBI of May Image as here under:

(i) Normal land: Pixels having NWDI less than 0.3 and SBI less than 200, were neither waterlogged nor saline area i.e. normal soil which represents 75.08% (Table 5 & Fig. 9) of agricultural land and 44.12% of total geographical area (TGA).

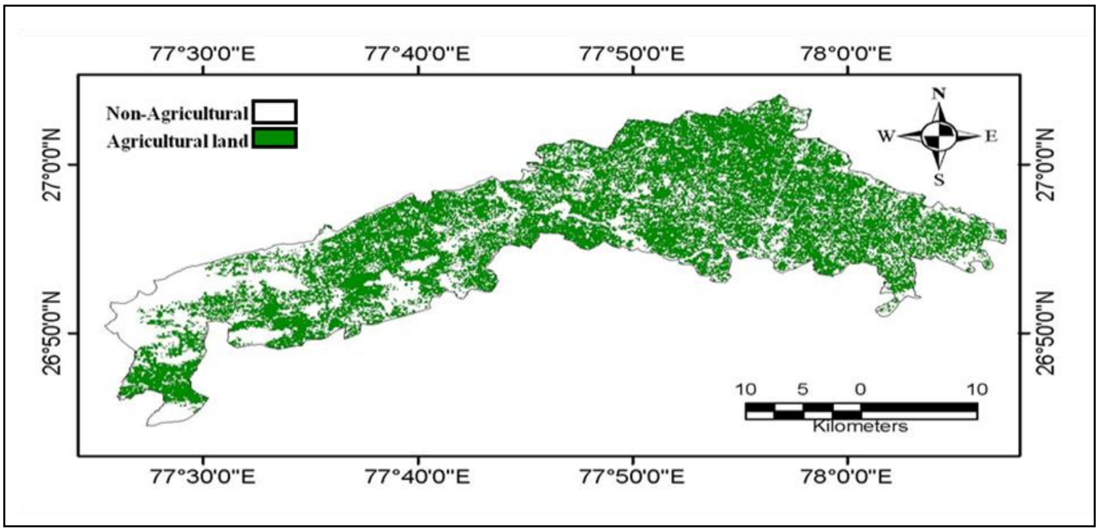

Fig. 8 Agricultural land in the study area.

Table. 5 Area under different categories in agricultural land

Categories	Area		
	ha	%	%TGA
Seasonal water and high saline (SWHS)	6064.44	12.79	7.51
Seasonal water and moderately saline (SWMS)	5753.852	12.13	7.13
Normal land	35608.33	75.08	44.12
Total	**47426.62**	**100**	**58.76**

(ii) Seasonal waterlogged and high saline (SWHS): Pixels having NDWI of October image greater than 0.3 were classified as seasonal waterlogged soil and the SBI of these pixels was found to be greater than 250 in May image hence the seasonal waterlogged high saline class was assigned to these pixels. The area under this class is about 12.79% of the area under agriculture use and 7.51% of TGA.

(iii) Seasonal waterlogged moderately saline: The remaining pixels, that having NDWI greater than 0.3 also the SBI of these pixels is varied from 200 to 250, were classified as seasonal waterlogged moderately saline. About 12.13% of agricultural land and 7.13% of TGA is under this class.

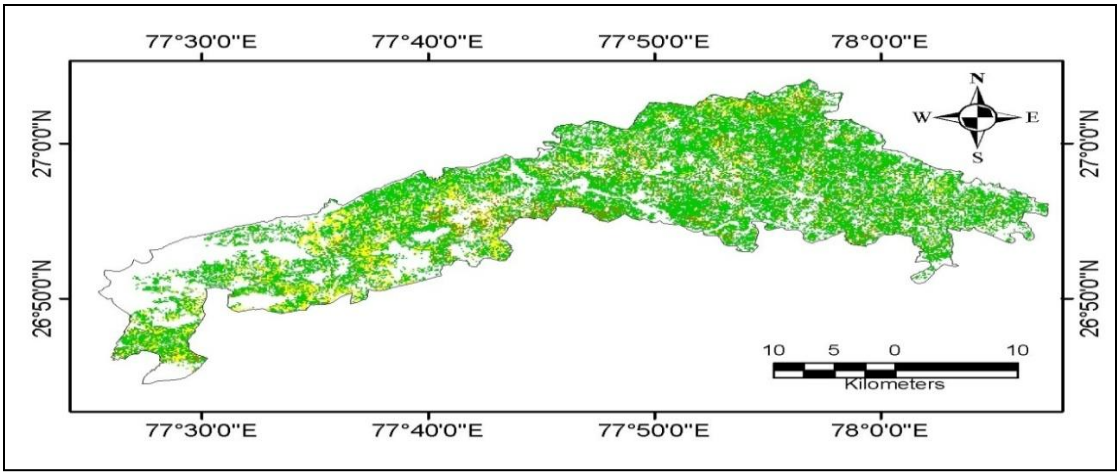

Fig. 9 Degradation in agricultural land in the study area

(3) Non agricultural land:

The remaining area (41.24%) is non agricultural land (Table 4 & Fig. 10) and could be successfully classified into six classes as following:

(i) Degraded hill& Rock quarried: Pixels having SBI greater than 190 were classified as degraded hill and rocks quarried. The area under this class is about 4.05% of TGA.

(ii) Degrade forest: These pixels have high reflectance in May (SBI greater than 200) whereas the NDWI of February image of these pixels is greater than 0.06. About 3.46% of the area is under this class.

(iii) Wetland: The NDWI of February, May and October images is greater than 0.06, 0.1 and0.06 respectively and the SBI of May image less than 200. This indicates that these areas are wet throughout the year and during dry season some salts mixing with water and hence the SBI is less than 200. Wetland occupies about 6.26% of TGA.

(v) Ravinous land: Pixels having NDWI of February and October images less than 0.11 and SBI of may image greater than 245 were classified as ravenous land which represents 3.62% of the area.

(iv) Built up area: The built up area (13.38%) having SBI of May image is greater than 255 whereas the NDWI of February and October image is greater than 0.11.

(vi)River (water bodies): The SBI of May image is greater than 285 whereas the NDWI of February and October image is greater than 0.12. About 5.96% of TGA is classified as river and water bodies.

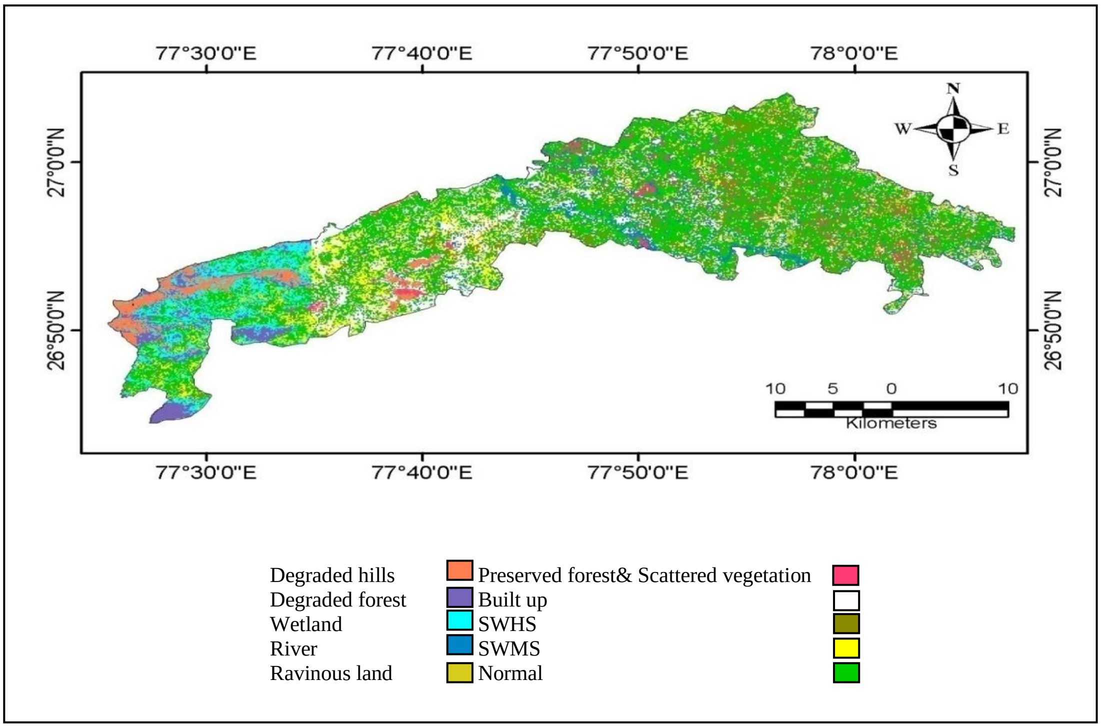

Fig. 10 Land use/ Land cover in the study area

Accuracy assessment:

The assessment is based on stratified random sampling approach. The classification outputs were subjected to post classification accuracy assessment. Accuracy assessment matrix of DTC and supervise classification were generated (Tables 6&7).

A close look at Tables 6&7 revealed that the using of DTC along with remote sensing derived indices were improved the overall accuracy by about 18% as compared with supervised classification (MLC). This indicates the efficiency of DTC and the efficiency was confirmed by the Z test (Table. 8) which shows that there is a significant difference between kappa coefficients computed for both DTC and MLC at (95 %) significant level.

Table. 6 The Error Matrix of decision tree classifier.

Classification data	Training site data (pixels)										
	DH	**DF**	**WL**	**W**	**RL**	**PF&SV**	**B**	**SWHS**	**SWMS**	**NL**	**Row total**
DH	1907	0	1	0	0	0	0	0	0	0	1908
DF	0	329	0	0	0	3	0	0	0	1	333
WL	0	6	130	0	0	16	0	0	3	3	158
W	0	0	0	98	0	10	14	0	1	0	123
RL	0	0	0	0	128	0	0	0	0	0	128
PF& SV	0	0	0	0	0	203	0	0	28	0	231
B	0	0	0	38	3	0	214	1	0	0	256
SWHS	0	0	0	0	0	0	0	132	1	0	133
SWMS	13	0	1	0	0	0	0	0	199	0	213
NL	0	1	2	0	0	0	0	0	3	331	337
Column total	1920	336	134	136	131	232	228	133	235	335	3820
Overall accuracy = 97.00%											**Kappa coefficient** = 0.95

DH: Degraded hill, **DF:** Degraded forest, **WL:** Wetland, **W:** Water body, **RL:** Revanious land, **PF&SV:** Preserved forest&Scattered vegetation, **B:** Built up, **SWHS:** Seasonal water and high saline, **SWMS:** Seasonal water and moderately saline, **NL:** normal land.

Table. 7 The Error Matrix of supervise classification MLC

Classification data	Training site data (pixels)										
	DH	**DF**	**WL**	**W**	**RL**	**PF&SV**	**B**	**SWHS**	**SWMS**	**NL**	**Row total**
DH	1490	10	2	6	2	3	8	1	1	0	1523
DF	6	184	5	1	1	0	9	0	5	7	218
WL	10	9	123	9	3	10	15	0	8	5	192
W	6	4	1	88	13	1	17	6	12	9	157
RL	2	0	0	10	140	3	29	5	13	6	208
PF& SV	9	1	0	3	5	230	7	0	7	10	272
B	7	10	3	4	7	2	200	2	9	10	254
SWHS	1	4	3	31	23	8	8	210	15	8	311
SWMS	8	18	5	11	10	2	5	4	170	4	237
NL	0	1	0	8	3	2	3	5	10	416	448
Column total	1539	241	142	171	207	261	301	233	250	475	3820
Overall accuracy =79.95%											**Kappa coefficient** = 0.75

DH: Degraded hill, **DF:** Degraded forest, **WL:** Wetland, **W:** Water body, **RL:** Revanious land, **PF&SV:** Preserved forest&Scattered vegetation, **B:** Built up, **SWHS:** Seasonal water and high saline, **SWMS:** Seasonal water and moderately saline, **NL:** normal land.

Table. 8 Comparison of the performance of various classifiers

	DTC	MLC	Z value
Kappa	0.95	0.75	21.08
Kappa varianc	0.00002	0.00007	

Conclusion:

The decision tree classifier incorporated with remote sensing derived indices successfully distinguishes between different types of degradation. Moreover, it was found to be an efficient and useful approach for mapping land use / land cover. The study has demonstrated the superiority of the DTC over supervised classification.

Although RS has already contributed a great amount to collective understanding of degradation patterns and processes, there is clearly much room for improvement. To refine the estimation of soil degradation using remote sensing approach, the following is recommended:

(1) Field data should be taken across as much of the region as possible.

(2) Field data should be as quantitative as possible.

(3) Combinations of different multi-sensor approach such as ground-base, airborne and satellite sensors (so-called data fusion).

(4) Also incorporated DTC with any other classification techniques such as supervised classification also with different types of algorithm such as maximum likelihood (MLC), minimum distance to mean and so on, may be improved the classification accuracy.

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