Supervised classification of Nal Sarovar wetland area and Trend Analysis using LISS-III data

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Abstract— This paper classifies wetland of Nal Sarovar by using LISS-III remote sensing data. Taking the Nal Sarovar as study area, LISS-III data of 2013 is used as data source and various classification processes like k-means, ISODATA, Min-Max classifier etc. are utilized. Two types of supervised classification techniques are more efficient and frequently used. These methods are 1) maximum likelihood classification and 2) parallelopiped classification. The paper describes the utilization of accuracy assessment using kappa coefficients.

I. Introduction

Wetlands are valuable ecosystems that play important roles in our environment. It is human settlement and natural resources, and also one of the ecological landscapes full of biodiversity in the nature. Wetlands are defined as areas that are transitional between terrestrial and aquatic systems, where the water table is usually at or near the surface or the land is covered by shallow water (Using remote sensing data to study wetland dynamics in IOWA, 2004). Wetlands are more economically and ecologically valuable than many other natural land cover types and provide numerous and unique ecosystem functions, including storing flood (Bauer, 2002) (Chaen, 2005) (Pietroniro, 2005) , minimizing sediment loss and controlling runoff volume, improving water quality (Bauer, 2002) (Chaen, 2005), (Baker, 2006) and recharging groundwater aquifers (Bauer, 2002) (Pietroniro, 2005) (Baker, 2006). Wetlands also provide unique and critical habitat to rare and endangered flora and fauna, support biodiversity (Chaen, 2005), protect shore and coastlines (Bauer, 2002), and play an important role in global carbon and methane cycles (Chaen, 2005). In addition, the local economies of many countries depend on wetlands for fisheries, reed harvesting, grazing, and recreation (Bauer, 2002).

The classification of remotely sensed image is the one of the most important links in the research of land use change and also the basis of the extraction of the land use change information (x, 1997) (B, 2002) (S, 2002) How to improve the classification accuracy of remotely sensed image has been and now still is one of hotspots on remotely sensed researches. A lot of scholars home and abroad have carried out much positive and useful exploration (S., 1999) (C, 1999) (X, 1995). At present, various methods have been developed and practiced for land-use/land-cover. There are several major approaches to these methods: multi-source, multi-date remotely sensed data merge classification method; remotely sensed image classification supported by GIS method; non-parametric remotely sensed image classification method.

Recently, The non-parametric classification methods different from conventional models such as (ANN), intellectual technology, vague mathematics, expert system and so on have matured step by step, available for application continually. Some achievements have been got on the aspect of wetland research, such as Carpenter use the remotely sensed imagery of Landsat for modeling to monitor inland water quality of the wetland (D.J., 1983) (S.M., 1983). Wani execute remotely sensed quantitative study of suspended sediment concentration for India Dal Lake by the use of IRS LISS-II remotely sensed data (S.K., 1986)

II. Study area and data collection

A. *STUDY AREA*

Nal sarovar is located in Gujarat state between 71^{0}92' E & 72^{0}08' E and 22^{0}40' N& 22^{0}55' N. It falls in two districts of Gujarat state Ahmedabad and Surendranagar. Area of 120.82 sq. Km of this wetland is being protected as bird sanctuary by the State Forest Department of Gujarat State since 1982. The natural and seasonal spread of this wetland is of irregular shape. It is shallow and in most parts muddy. Formerly an eustary, this depressed portion had come into existence by tectonic uplift, increased sedimentation.

Climatically, Nal Sarovar is located in the semi-arid saline tract, where temperature is highest during months of April and May. The basin of nal sarovar is of elongated type and the overall shape is very gentle running from east to northwest and northwest to south. The depth of water seldom exceeds 3 metres. The entire land of Nal Sarovar and its environs is salt affected with saline and alkaline salts concentrated in the upper layer of clayey, medium black soil. Soon after the rains water in the shallow parts of Nal Sarovar also becomes brackish, which, by the end of March becomes saline. There are several elevated plateaus in basin. They are locally called as “Bet” meaning islets as they may remain above the water surface.

In this study the wetlands are categorised under various classes and mapped using satellite remote sensing data from Indian Remote Sensing Satellite: IRS-P6 LISS-III sensor. The results are organised at 1:50,000 scales at district, state and topographic map.

Fig. 1: Satelite image of Nal Sarovar. (Source: Google Map)

B. DATA COLLECTION

Increasing concern about how our wetlands are being influenced has led to formulation of a project entitled "National Wetland Inventory and Assessment (NWIA)" (National Wetland Atlas) to create an updated database of the wetlands of India.

In present study we used pre monsoon and post monsoon data of Nal Sarovar to carry out our study. We have used LISS-III sensor data for our study. Pre- monsoon data: April 2013 LISS-III image of Nal Sarovar Post-monsoon data: January 2013 LISS-III image of Nal Sarovar

Fig. 2: FCC(False colour composite) of pre-monsoon image (Source : BISAG)

Fig. 3: FCC(False colour composite) of post-monsoon image (Source: BISAG)

III. STUDY METHODS

A. SOFTWARE USED

Two software are effectively used for performing supervised classification and to identify wetland vegetation in our study area.

- ENVI 4.5
- QUANTAM GIS 1.7.0

B. INPUT PARAMETERS AND OUTPUT FOR SUPERVISED CLASSIFICATION

(1) For different supervised classification we have to assign training signatures in terms of Region of Interest (ROIs) and the satellite image as source data.

(2) The output of supervised classification is rendered in raster format having clusters of various classes.

(3) By using QUANTAM GIS software we get vector format of our supervised classification.

(4) We can give final layout and legend to the supervised classification image in QUANTAM GIS software.

C. Defining ROIs (Region Of Interest)

Regions of interest (ROIs) are portions of images, either selected graphically or selected by other means such as thresholding. The regions can be irregularly-shaped and are typically used to extract statistics for classification, masking, and other operations. To perform ROI definition, I use the ROI Tool dialog. Defining Regions of Interest describes how to open the ROI Tool dialog, and how to turn off ROI definition. The sections that follow describe how to define ROIs**.** Authors have used same ROIs of pre-monsoon and post-monsoon image for both supervised classification methods**.**

Authors have used polygon type ROI in this study.

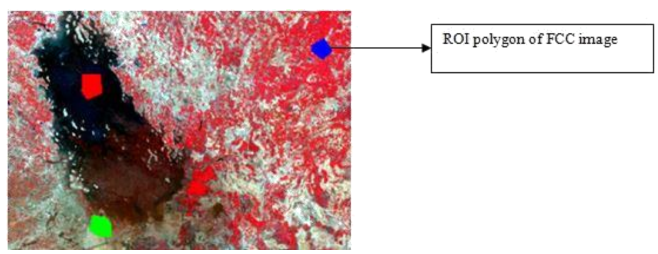

Fig. 4: ROI of FCC image

D. SUPERVISED CLASSIFICATION

1) PARALLELOPIPED CLASSIFICATION

In this classifier mean and standard deviations for each band and each class is calculated. The range for each class may be defined as mean 1 standard deviation for each spectral band. It forms a rectangular box in two dimensional. The number of box will equal to number of features. All the pixels covered in a box will classify to that class. And when there is overlap, that region will be labeled as unclassified. The boundary is modified to the stepped boundary.

2) MAXIMUM LIKELIHOOD CLASSIFICATION

The previous classification is non parametric, while MXL assumes that the DN values for each class has a Guassian distribution. Each pixel from the lass mean is also linked with probability that pixel to be in that class. Pixel is classified to that class for which its probability will be maximum and above the threshold. If probability falls bellow the threshold than the pixel may be lebelled as unclassified. For any pixel if probability is equal for two features than additional conditions are applied. If the pixel value is closest to mean value of any class then it will have highest probability to belong that class. This probability decreases as pixel value moves away from the mean. So we may have equiprobability contour around the mean. In two dimesion contour will take the shape of ellipse. The shape and the orientation of ellipse is based on the scatter. Thus MXL classification takes into account the shape and distribution, it is more accurate than the previous two classifiers.

ROI NAME	OLOR	XEL	LYGO
aterbody 1	d	65	03965
aterbody 2	een	30	03230
etland vegetation	ue	68	02068
etland vegetation	llow	9	0769
etland vegetation	an	5	0935
ating vegetation	agenta	3	0393
nd vegetation	aroon	1	0261
ear-land vegetation	a gree	84	01184
ear-land vegetation	rple	14	01914
llow land	ral	74	03574

Table. 1: ROI TABLE OF PRE-MONSOON IMAGE

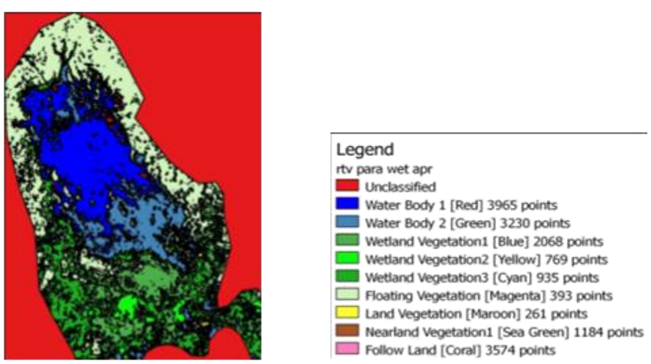

Fig. 5: Parallelopiped classification of pre-monsoon image

Fig. 6: Maximumlikelihood classification of pre-monsoon image

ROI NAME	OLOR	XEL	LYGO
waterbody	red	813	/03813
aterbody vegetation	green	289	/03289
aterbody vegetation	blue	416	/04416
aterbody vegetation	ellow	478	/02478
wetland vegetation	cyan	632	/02632
floating vegetation	agent	190	/0190
land vegetation	aroo	962	/0196
earlang vegetation1	a gree	426	/0426
earland vegetation2	urple	359	/01359
follow land	coral	631	/0463

Table. 2: ROI TABLE FOR POST-MONSOON IMAGE

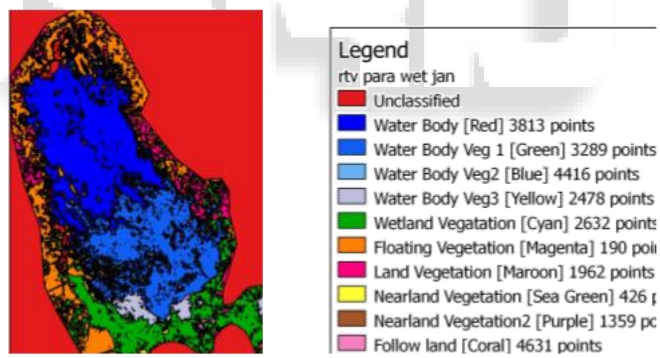

Fig. 6: Parallelopiped classification of post-monsoon image

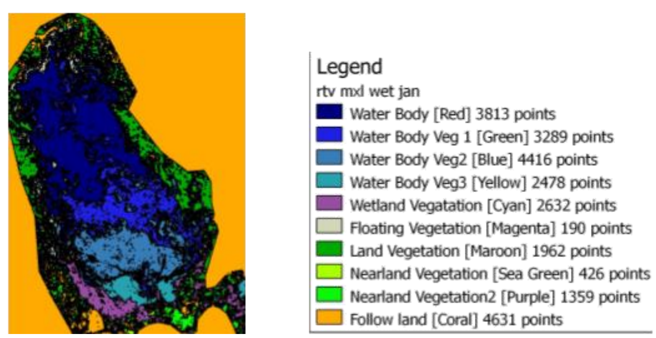

Fig. 8: Maximumlikelihood classification of post-monsoon image

3) KAPPA COEFFICIENT

Items such as physical exam findings, radiographic interpretations, or other diagnostic tests often rely on some degree of subjective interpretation by observers. Studies that measure the agreement between two or more observers should include a statistic that takes into account the fact that observers will sometimes agree or disagree simply by chance. The kappa statistic (or kappa coefficient) is the most commonly used statistic for this purpose. A kappa of 1 indicates perfect agreement, whereas a kappa of 0 indicates agreement equivalent to chance.

IV. CALCULATING CONFUSION MATRICES

Use Confusion Matrix to show the accuracy of a classification result by comparing a classification result with ground truth information. ENVI can calculate a confusion matrix (contingency matrix) using either a ground truth image or using ground truth ROIs. In each case, an overall accuracy, producer and user accuracies, kappa coefficient, confusion matrix, and errors of commission and omission are reported.

V. USING GROUND TRUTH IMAGE

When using a ground truth image, we can also calculate error mask images for each class showing which pixels were incorrectly classified. To Kappa coefficient the ground truth image and ROIs are to be used and from that we can find out kappa coefficient.

Generally, the kappa coefficient can be given by following equation:

$$\text{Kappa coefficient} = \frac{\text{Total pixels which are classified in that particular class}}{\text{Grand total of pixel classified by supervied classification}}$$

From above equation we can find out the accuracy of each and every class which is classified by supervised classification.

Note: Unclassified Area is considered while calculating kappa coefficient.

VI. CALCULATION OF KAPPA COEFFICIENT OF PARRELLELOPIPED CLASSIFICATION

A. KAPPA COEFFICIENT OF PRE-MONSOON IMAGE

Overall Accuracy = (11041/18293) = 60.3564%

Kappa Coefficient = 0.5518

CLASS	ater bod 1	ater bod 2	Wetland Vegetation 1	Wetland Vegetation 2	Wetland Vegetation 3	Floating Vegetation	Land Vegetation	Near land Vegetation 1	Near land vegetation 2	Fallow land
Water body 1	3952	493	0	0	0	0	0	1	0	0
Water body 2	3	2702	0	0	0	0	0	641	0	0
Wetland vegetation 1	0	0	2061	27	57	1	33	0	0	17
Wetland vegetation 2	0	0	3	739	19	0	1	35	426	11
Wetland vegetation 3	0	0	1	3	829	17	32	26	864	96
Floating vegetation	0	0	3	0	30	375	107	0	624	3405
Land vegetation	0	0	0	0	0	0	87	200	0	0
Near land vegetation 1	0	0	0	0	0	0	0	281	0	0
Near land vegetation 2	0	0	0	0	0	0	0	0	0	0
Follow land	0	0	0	0	0	0	0	0	0	15
TOTAL	3965	3230	2068	769	935	393	261	1184	1914	3574

Table. 3: KAPPA COEFFICIENT TABLE FOR PRE-MONSOON IMAGE

B. KAPPA COEFFICIENT OF POST-MONSOON IMAGE

Overall Accuracy = (14083/25196) = 55.8938%

Kappa Coefficient = 0.5080

CLASS	Water body	Water body vegetation 1	Water body vegetation 2	Water body vegetation 3	Wetland vegetation	Floating vegetation	Land vegetation	Near land vegetation 1	Near land vegetation 2	Fallow land
Water body	3704	336	12	0	0	0	0	0	0	0

Water body vegetation 1	0	2894	3524	863	4	0	0	3	0	0
Water body vegetation 2	0	2	861	3	0	0	0	0	0	0
Water body vegetation 3	0	4	1	1604	37	0	0	90	0	26
Wetland vegetation	2	29	0	5	2550	2	117	75	1196	655
Floating vegetation	13	0	0	0	20	181	169	2	117	3535
Land vegetation	0	0	0	0	2	3	1668	0	31	0
Near land vegetation 1	9	23	0	3	14	2	0	256	11	3
Near land vegetation 2	0	0	0	0	0	0	0	0	4	5
Follow land	3	0	0	0	5	0	0	0	0	361
TOTAL	3813	3289	4416	2478	2632	190	1962	426	1359	4631

Table 4: Kappa Coefficient Table For Post-Monsoon Image

Kappa Coefficient = 0.9004

VII. CALCULATION OF KAPPA COEFFICIENT OF MAXIMUMLIKELIHOOD CLASSIFICATION

A. KAPPA COEFFICIENT OF PRE-MONSOON IMAGE

Overall Accuracy = (16731/18293) = 91.4612%

CLASS	ater bod 1	ater bod 2	Wetland vegetation 1	Wetland vegetation 2	Wetland vegetation 3	Floating vegetation	Land vegetation	Near land vegetation 1	Near land vegetation 2	Fallow land
Water body 1	3872	179	0	0	0	0	0	0	0	0
Water body 2	93	3051	0	0	0	0	0	1	0	0
Wetland vegetation 1	0	0	2020	2	0	0	11	0	1	0
Wetland vegetation 2	0	0	8	745	0	0	0	0	54	0
Wetland vegetation 3	0	0	0	3	825	0	7	3	131	30
Floating vegetation	0	0	0	0	3	314	14	0	0	643
Land vegetation	0	0	24	0	12	10	225	0	5	91
Near land vegetation 1	0	0	0	0	0	0	0	1178	3	8
Near land vegetation 2	0	0	10	19	65	0	0	2	1718	19
follow land	0	0	6	0	30	69	4	0	2	2783
TOTAL	3965	3230	2068	769	935	393	261	1184	1914	3574

Table. 5: KAPPA COEFFICIENT TABLE FOR PRE-MONSOON IMAGE

Kappa Coefficient = 0.8621

B. KAPPA COEFFICIENT OF POST-MONSOON IMAGE

Overall Accuracy = (22150/25196)= 87.9108%

CLASS	Water body	Water body vegetation 1	Water body vegetation 2	Water body vegetation 3	Wetland vegetation	Floating vegetation	Land vegetation	Near land vegetation 1	Near land vegetation 2	Fallow land

Water body	3768	34	0	0	0	0	0	0	0	0
Water body vegetation 1	10	3024	136	221	5	0	0	0	0	0
Water body vegetation 2	0	127	4257	44	0	2	0	0	0	0
Water body vegetation 3	0	64	23	2189	10	0	0	0	0	3
Wetland vegetation	0	27	0	13	2423	0	19	6	59	520
Floating vegetation	13	0	0	0	8	171	3	3	0	1299
Land vegetation	2	0	0	0	6	0	1931	0	0	19
Near land vegetation 1	1	3	0	1	25	0	0	402	49	14
Near land vegetation 2	1	10	0	0	99	0	3	15	1238	29
Follow land	18	0	0	10	56	17	6	0	13	2747
TOTAL	3813	3289	4416	2478	2632	190	1962	426	1359	4631

Table. 6: KAPPA COEFFICIENT TABLE FOR POST-MONSOON IMAGE

	XL CLASSIFICATIO		RALLELOPIPE	
	APR	JAN	APR	JAN
ppa coefficie	91.46%	87.91%	60.35%	55.89%

Table. 7: TREND ANALYSIS

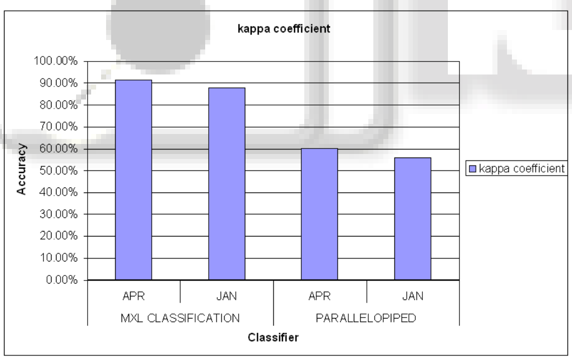

Fig. 9: trend analysis of kappa coefficient

Thus, by trend analysis of kappa coefficient we can say that maximum likelihood classification is more accurate than parallelepiped classification for both pre monsoon and post monsoon images.

From the calculation of kappa coefficient we can say that the overall accuracy of maximum likelihood classifier is (91.46%) and kappa coefficient is (0.9004) for pre-monsoon image, (87.91%) overall accuracy and (0.8621) kappa coefficient for post-monsoon image. The overall accuracy of parallelopiped classification is (60.35%) and kappa coefficient is (0.5518) for pre-monsoon image and overall accuracy is (55.89%) and kappa coefficient is (0.5080) for post-monsoon image. Thus, from this study we can say that maximum likelihood classification is more accurate than parallelopiped classification.

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References

[1] Baker. (2006). Satelite remote sensing of wetlands. *Wetlands ecology and management* .
[2] Bauer, O. a. (2002). Satelite remote sensing of wetlands. *Wetlands ecology and management* .
[3] Chaen, L. a. (2005). A rule based method for mapping Canada's wetlands using optical, radar and DEM data. *International Journal of Remote Sensing.*
[4] *National Wetland Atlas.* ISRO and BISAG.
[5] Pietroniro, T. a. (2005). Satelite remote sensing of wetlands. *Wetlands ecology and management* .
[6] S, L. (2002). *Remote sensing digital image analysis.*
[7] S.K., M. (1986). The use of Normalised Differance Water Index (NDWI) in the delineation of open water features. *International Journal Of Remote Sensing* .

[8] S.M., C. (1983). Modelling inland water quality using landsat data. *Remote sensing of environment* .
[9] Sugumaran. (2004). Using remote sensing data to study wetland dynamics in IOWA.
[10] X, L. (1995). Study on layered methods and its application for landcover thematic information . *Remote sensing technology and application*.