

**Accuracy Assessment of Different Supervised Classification Techniques for Land
Use Land Cover Mapping Using RS and GIS**Shivpuje Prakash R.¹¹School of Computational Sciences, SRTMU Nanded

Abstract — Remote Sensing research focusing on image classification has attracted the attention of many researchers and a number of researches have been conducted using different classification algorithms. It should be noted that valuable surface information extraction and analysis is also well performed using image classification. Image classification is a multi-step process followed by the preprocessing of the acquired data. The pre-processing and accuracy analysis of the LISS 3 data have been done in QGIS. There after the land cover and land use classification has been done followed by the proper mapping in QGIS. The analyses represented in this paper are based on the confusion matrix. The kappa statistics for each class and overall classification accuracy has been discovered. In order to improve the classification accuracy, thus, selection of appropriate classification method is required.

Keywords-confusion matrix, supervised classification, LU, LC, Accuracy assessment

I. Introduction

Here we have classified LISS 3 image of Naded taluka with six different classes such as agricultural land, water body, settlement, follow land, barren land, vegetation and asses their accuracy using 256 GCP(Ground Control Points). accuracy plays important role because whatever output shown by map is cross validated using GCP so the confusion matrix gives clear idea of overall accuracy as well as particular class wise accuracy, whereas kappa coefficient will guide us about choosing proper classifier.

II. Supervised Classification

Supervised Classification can be defined normally as the process of samples of known identity to classify pixels of unknown identity. Samples of known identity are those pixels located within training areas. Pixels located within these areas term the training samples used to guide the classification algorithm to assigning specific spectral values to appropriate informational class. The training stage feature selection of appropriate classification algorithm post classification smoothing accuracy assessment.[4] [6]

- 1 Maximum likelihood classifier
- 2 Mahalanobis classifier
- 3 Minimum distance classifier
- 4 Parallelepiped classifier

III. Study Material

The data required for the study is obtained from NRSC Balanagar, Hyderabad. The Survey of India. The geometrically corrected IRS-Resourcesat-1 LISS-III satellite single date multispectral imagery was used for the preparation of Land use Land cover map. This data is received from Linear Imaging and Self Scanning Sensor (LISS) which operates in three spectral bands in VNIR and one band in SWIR with 23.5 meter spatial resolution and a swath of 141 km. The IRSResourcesat-1 LISS-III satellite imagery has four bands i.e. Band 2 - Green, band 3 - Red, band 4 - NIR and band 5 – SWIR. Image date 23 oct 2009

3.1. Maximum Likelihood Classifier

It is based on statistical decision criteria for classification of overlapping signatures and pixels are assigned to the class of highest probability. Gaussian maximum likelihood classifier uses variance and co-variance to classify an unknown pixel of spectral response pattern. [3]

3.2. Mahalanobis classifier

This classifier based on the correlations between variables by which different patterns can be identified and analyzed [2]

3.3. Minimum distance classifier

It uses mean vector in each class signature, while standard deviation and covariance matrix are ignored.

3.4. Parallelepiped classifier

It is based on geometrical shape whose opposite sides are straight and parallel. It uses the class limits and stores of each class signature to determine if a weather pixel falls within the class or not. [7]

3.5. Accuracy assessment

One of the most common means of expressing classification accuracy is the preparation of classification error matrix sometime called confusion or contingency table. Error matrices compare on a category by category basis, the relationship between known reference data (ground truth) and the corresponding results of an automated classification. Such matrices are square, with the number of rows and columns equal to the number of categories whose classification accuracy is being accessed.

3.5.1 Overall Accuracy

OA of classification can be computed from the error matrix.

It is determined by dividing the total number correctly classified pixels (sum of elements along the major diagonal) by the total number of reference pixels

3.5.2 Producer Accuracy

Producer accuracy which indicates how well the training sets pixels of a given cover type are classified can be determined by dividing the number of correctly classified pixels in each category by number of training sets used for that category (column total)

3.5.3 User accuracy

User accuracy is computed by dividing the number of correctly classified pixels in each category by total number of pixels that were classified in that category (row total)

3.5.4 Kappa Coefficient

Kappa analysis is a discrete multivariate technique for accuracy assessment. [3] [2] [1]

IV. Result and Discussion

The result shows that classification of remotely sensed data into six different classes these classes are agricultural land, water body, vegetation, follow land, settlement, and barren land.

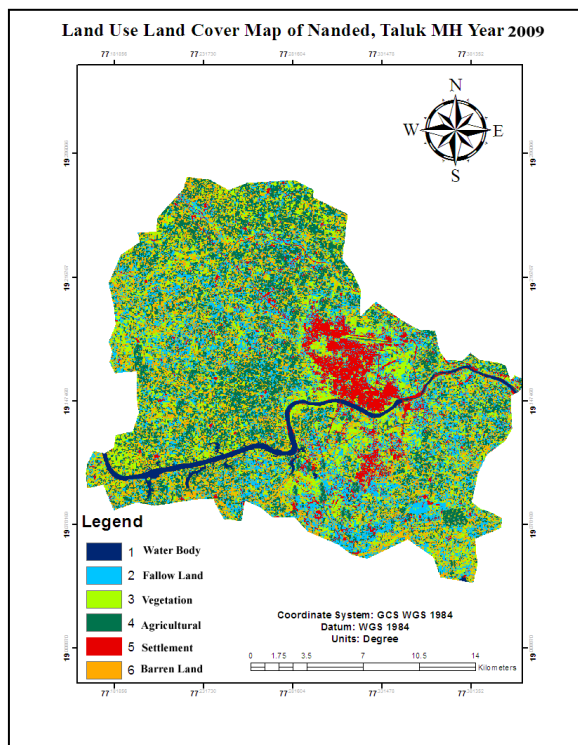


Fig.1 LU/LC map of MLC 2009

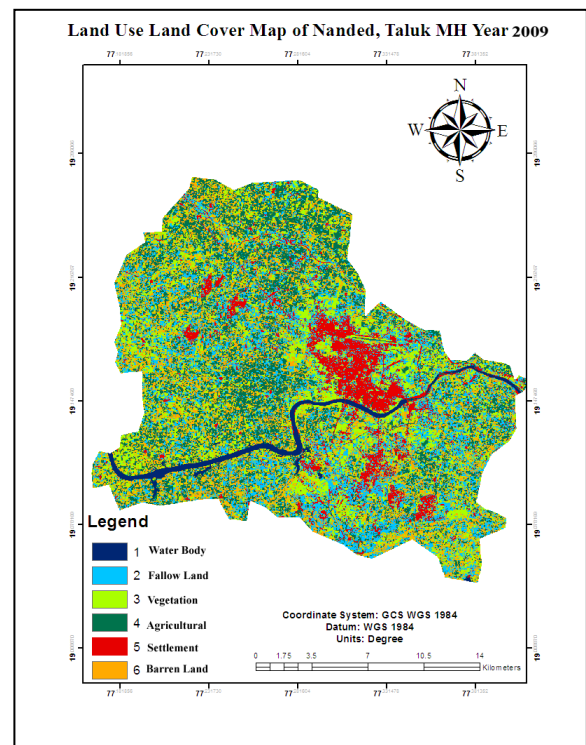


Fig.2 LU/LC map MBC 2009

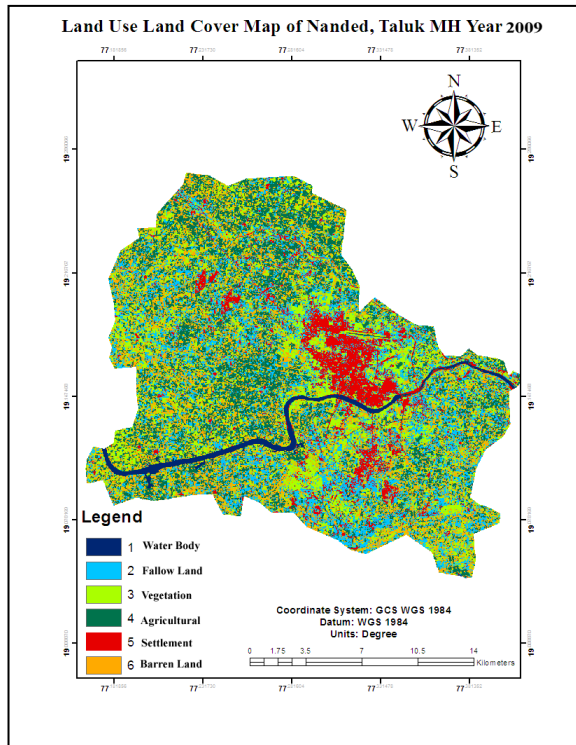


Fig.3 LU/LC map of MDC 2009

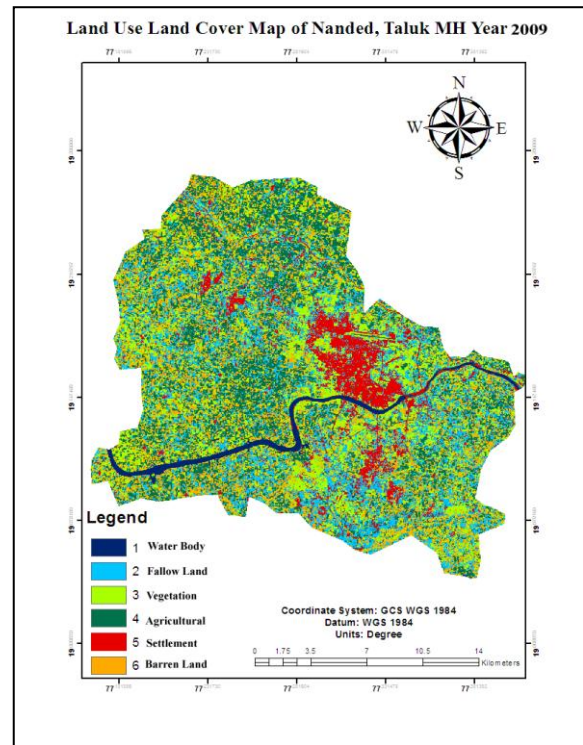


Fig.4 LU/LC map of PPC 2009

Table 1. Error Matrix for MLC algorithm

	AGL	WB	VG	FL	S	BL	TS	PA
AGL	33	3	2	2	1	1	42	78.57%
WB	1	40	1	1	1	2	46	86.95%
VG	2	2	32	1	0	3	40	80%
FL	2	1	2	37	1	4	47	78.72%
S	0	2	4	4	39	2	51	76.47%
BL	2	1	2	1	0	24	30	80%
TS	40	49	43	46	42	36	256	
UA	82.5%	81.63%	74.41%	80.43%	92.85%	66.66%		
OE	17.5%	18.36%	25.58%	19.56%	7.14%	33.33%		
CE	21.42%	13.04%	20%	27.02%	23.52%	20%		

OA=80.07%

Kappa 0.76

Table 2. Error Matrix for MBC algorithm

	AL	WB	VG	FL	S	BL	TS	PA
AL	27	3	2	2	2	2	38	71.05%
WB	1	40	1	2	1	2	47	85.10%
VG	2	2	25	1	2	3	35	71.42%
FL	2	1	2	37	1	2	45	82.22%
S	0	2	4	4	46	2	58	79.31%
BL	2	1	2	2	2	24	33	72.72%
TS	34	49	36	48	54	35	256	
UA	79.41%	81.63%	69.44%	77.08%	85.18%	68.57%		
OE	20.58%	18.36%	30.55%	22.91%	14.81%	31.42%		
CE	28.94%	14.89%	28.57%	21.62%	26.08%	27.27%		

OA=77.73%

Kappa 0.731

Table 3. Error Matrix for MDC algorithm

	AL	WB	VG	FL	S	BL	TS	PA
AL	33	5	2	2	2	0	44	75%
WB	0	38	2	2	2	4	48	79.16%
VG	2	0	24	2	1	3	32	75%
FL	4	2	2	35	3	7	53	60.03%
S	0	1	8	4	38	2	53	71.69%
BL	2	2	2	1	2	17	26	65.38%
TS	41	48	40	46	48	33	256	
UA	80.48%	79.16%	60%	76.08%	79.16%	51.51%		
OE	19.51%	20.83%	40%	23.91%	20.83%	48.48%		
CE	25%	20.83%	25%	33.96%	28.30%	34.61%		

OA=72.26%

Kappa 0.665

Table 4. Error Matrix for PPC algorithm

	AL	WB	VG	FL	S	BL	TS	PA
AL	31	5	2	2	2	2	44	70.45%
WB	1	35	2	3	3	4	48	72.91%
VG	2	0	24	2	1	3	32	75%
FL	4	2	2	35	3	7	53	60.03%
S	0	1	8	4	38	2	53	71.69%
BL	2	2	2	1	2	17	26	65.38%
TS	40	45	40	47	49	35	256	
UA	77.5%	77.77%	60%	74.46%	77.55%	48.57%		
OE	22.5%	22.22%	40%	25.53%	22.44%	51.42%		
CE	29.54%	27.08%	25%	33.96%	28.30%	34.61%		

OA=70.313%

Kappa 0.642

The below table shows that comparison analysis of LU/LC classes

Table 5. Area covered by LU/LC classes Year 2009

LULC Class	Area Covered (km ²) MLC	% M L C	Area (km ²) MBC	% M B C	Area Covered (km ²) MDC	% M D C	Area Covered (km ²) PPC	% P P C
AL	79.1932937	21.56	75.26301	20.49	80.5156307	21.92	75.63033	20.59
WB	7.56670617	2.06	7.383048	2.01	7.199390337	1.96	6.611685	1.8
VG	85.80497871	23.36	80.25851	21.85	84.2622522	22.94	84.26225	22.94
FL	70.30425053	19.14	77.09959	20.99	74.63857737	20.32	74.63858	20.32
S	78.3117357	21.32	84.11533	22.9	80.40543595	21.89	80.40544	21.89
BL	46.13486869	12.56	43.19634	11.76	40.29454693	10.97	40.29455	10.97
UC	0	0	0	0	0	0	5.473006	1.49
T	367.3158335	100	367.3158335	100	367.3158335	100	367.3158335	100

AL :Agricultural land **WB** : Water Body **VG** : Vegetation **S** : Settlement
TS : Total Samples **UA** : User Accuracy **OE** : Omission Error
CE : Comission Error **OA** : Overall Accuracy **MLC** : Maximum Likelihood Classifier
MDC : Minimum Distance Classifier **MBC** : Mahalanobis Classifier
PPC : Parallelepiped Classifier **T:-** Total
UC : Unclassified

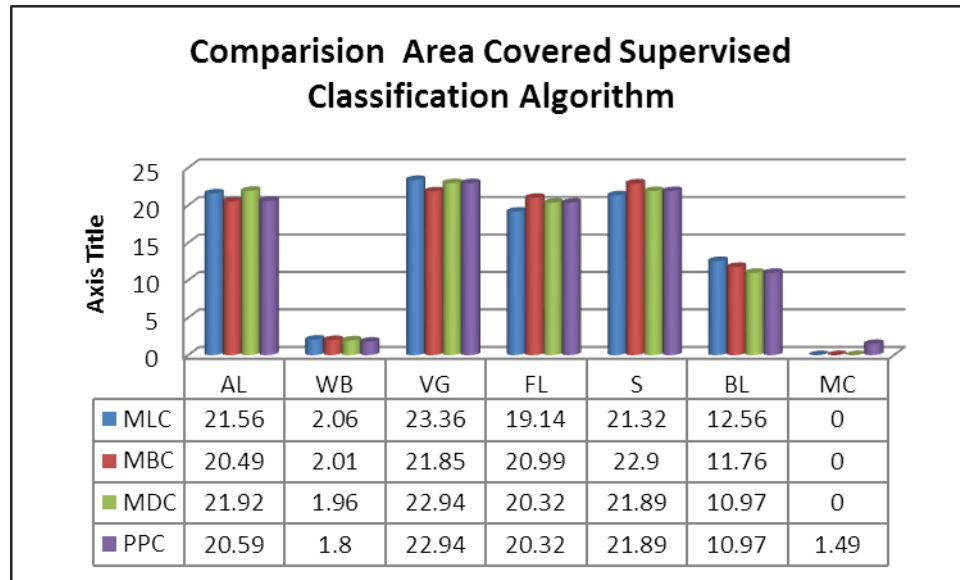


Fig 5 Map of Area covered by LU/LC classes Year 2009

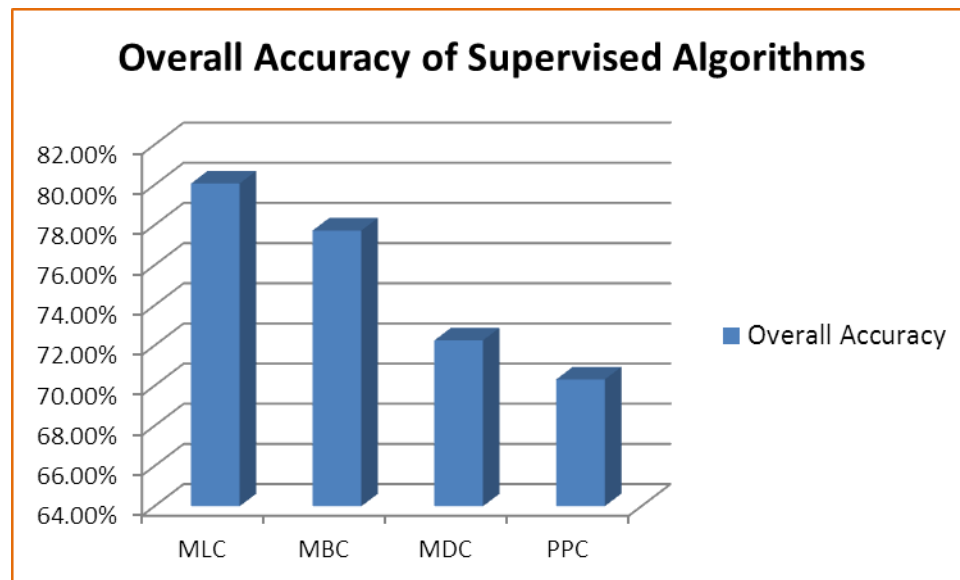


Fig 6 Overall Accuracy of Supervised Algorithms

V. Conclusion

From the results we have obtained that maximum likelihood classifier is best as compared with rest of the algorithms in overall accuracy as well as kappa coefficient. The Maximum likelihood classifier classify all the data properly and give output more better and more accurate than other classifier and we come to know that for water body the best classifier is Minimum distance and for agricultural land maximum like hood is best suited. For Settlement we can say that parallelepiped is best.

VI. References

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