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EFFICIENT SCHEMES OF CLASSIFIERS FOR REMOTE SENSING SATELLITE IMAGERIES OF LAND USE PATTERN CLASSIFICATIONS

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Udupi, S. [a]* - Hemamalini, H.C. [b] - Chittora, V. [c] - Prabhuraj, D. K. [d] - Patil, S.S. [e]

(a) Master in Agricultural Statistics.
ORCID: https://orcid.org/0009-0001-4272-212X.. **LATTES:** -.
(b) PhD in Education.
ORCID: https://orcid.org/0009-0004-4510-8725.. **LATTES:** -.
(c) Master in Agricultural Statistics.
ORCID: https://orcid.org/0000-0002-6503-731X.. **LATTES:** -.
(d) PhD in Agriculture.
ORCID: https://orcid.org/0009-0000-1808-0369.. **LATTES:** -.
(e) PhD. in Computer Science
ORCID: https://orcid.org/0000-0002-7939-0106.. **LATTES:** -.

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(*) CORRESPONDING AUTHOR
Address: University of Agricultural Sciences, GKVK Bangalore 560065. Phone:
E-mail: spatilsuasb@gmail.com

Abstract

Land use pattern classification of remote sensing imagery data is imperative to research that is used in remote sensing applications. Remote sensing (RS) technologies were exploited to mine some of the significant spatially variable factors, such as land cover and land use (LCLU), from satellite images of remote arid areas in Karnataka, India. Four diverse classification techniques unsupervised, and supervised (Maximum likelihood, Mahalnobis Distance, and Minimum Distance) are applied in Bellary district in Karnataka, India for the classification of the raw satellite images. The developed maps are then visually compared with each other and accuracy evaluations make using of ground-truths are carried out. It was initiated that the Maximum likelihood technique gave the finest results and both Minimum distance and Mahalnobis distance methods overvalued agricultural land areas. In spite of missing a few insignificant features due to the low resolution of the satellite images, a high-quality accord between parameters extracted automatically from the developed maps and field observations was found.

Keywords: Remote sensing (RS), land cover and land use (LCLU).

Resumo / Resumen

ESQUEMAS EFICIENTES DE CLASSIFICADORES PARA IMAGENS DE SATÉLITE DE SENSORIAMENTO REMOTO DE CLASSIFICAÇÕES DE PADRÕES DE USO DO SOLO

A classificação do padrão de uso da terra de dados de imagens de sensoriamento remoto é fundamental para pesquisas usadas em aplicações de sensoriamento remoto. As tecnologias de detecção remota (RS) foram exploradas para explorar alguns dos factores espacialmente variáveis significativos, tais como a cobertura e utilização do solo (LCLU), a partir de imagens de satélite de áreas áridas remotas em Karnataka, na Índia. Quatro diversas técnicas de classificação não supervisionadas e supervisionadas (máxima probabilidade, distância Mahalnobis e distância mínima) são aplicadas no distrito de Bellary em Karnataka, Índia, para a classificação das imagens brutas de satélite. Os mapas desenvolvidos são então comparados visualmente entre si e são realizadas avaliações de precisão com base em verdades básicas. Foi iniciado que a técnica de Máxima Verossimilhança deu os melhores resultados e ambos os métodos de Distância Mínima e Distância de Mahalnobis supervalorizaram as áreas de terras agrícolas. Apesar de faltarem algumas características insignificantes devido à baixa resolução das imagens de satélite, foi encontrado um acordo de alta qualidade entre os parâmetros extraídos automaticamente dos mapas desenvolvidos e das observações de campo.

Palavras-chave: Sensoriamento Remoto, Cobertura e Uso do Solo.

ESQUEMAS EFICIENTES DE CLASIFICADORES PARA SATELITES DE IMÁGENES SATÉLITES DE CLASIFICACIONES DE PATRONES DE USO DEL SUELO

La clasificación de los patrones de uso de la tierra de los datos de imágenes de teledetección es imperativa para la investigación que se utiliza en aplicaciones de teledetección. Se aprovecharon las tecnologías de teledetección (RS) para extraer algunos de los importantes factores espacialmente variables, como la cobertura y el uso de la tierra (LCLU), a partir de imágenes satelitales de áreas áridas remotas en Karnataka, India. En el distrito de Bellary en Karnataka, India, se aplican cuatro técnicas de clasificación diversas, supervisadas y no supervisadas (máxima verosimilitud, distancia de Mahalnobis y distancia mínima) para la clasificación de las imágenes satelitales sin procesar. Luego, los mapas desarrollados se comparan visualmente entre sí y se llevan a cabo evaluaciones de precisión utilizando datos reales sobre el terreno. Se inició que la técnica de Máxima verosimilitud daba los mejores resultados y que tanto el método de distancia mínima como el de distancia de Mahalnobis sobrevaloraban las áreas de tierras agrícolas. A pesar de que se omitieron algunas características insignificantes debido a la baja resolución de las imágenes de satélite, se encontró una concordancia de alta calidad entre los parámetros extraídos automáticamente de los mapas desarrollados y las observaciones de campo.

Palabras-clave: Teledetección, Cobertura y Uso del Suelo.

INTRODUCTION

local, provincial, and universal scales in current years. It has become a vital element of information knowledge and provides the capability for sustainable progress of natural resources and environmental fortification. Image data classification and accuracy complexity estimation of the classified images are imperative aspects of remote sensing image analysis. Numerous investigative mechanisms conceded using some algorithms with their complexity of accuracy are reviewed in this study. This is the science and art of obtaining information about an object, geographic area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or observable fact under investigation. This study deals with remote sensing data acquired through earth observation satellites. Remote sensing image analysis is done to extract useful information about the earth's surfaces. An important step in the analysis of such data is the process of land cover classification. In this, the image pixels are assigned to different land cover classes based on the spectral measurements of each pixel. Pattern recognition technique such as Mahalnobis distance classification is followed in this process. Machine learning techniques can be applied in a supervised and unsupervised approach. Supervised Classification is a procedure for identifying spectrally similar areas on an image by identifying 'training' sites of known targets and then extrapolating those spectral signatures to other areas of unknown targets.

DESCRIPTION OF STUDY AREA

The area selected to study in this work is Koluru Hobli of Bellary Taluk and District located in the Karnataka state central southern part of India covering which lies between 150 9´ to 150 15´N latitude and 760 55´ to 760 92´E longitudes.

RELATED WORK

Rao and Vaidyanadhan,(1981) in agricultural domain land use pattern in spatial data over occupied rising regions but across the world because of its association with dissimilar human marvels. It has been pragmatic that, remote sensing practice is the most competent systematic tool in amalgamation with ground truth and toposheet for assemblage of spatial evidence and actual use in empathy, classification, and mapping of the land use units. Bruzzone et al., (2002) The rising accessibility of remote sensing images, acquired sporadically by satellite sensors on the identical geographical area, makes it exceptionally motivating to extend the monitoring systems competent without human intervention producing and recurrently updating LULC maps of the measured site.

Lu and Weng, (2007) remote sensing satellite image data classification based on environmental and socioeconomic have long concerned the significance of the remote sensing community research since most applications are based on the classification results. Satio et al. (2003) Mangroves reach their optimal development in the wet tropics although some little-known mangrove stands are reported in subtropical arid coastlines especially from the Red Sea to Pakistan where they form one of the driest mangrove habitats in the world. Because they constitute the only available evergreen forest in hyper-arid warm coastal areas, the main wetlands for migratory birds, and essential nursery ground for many species of fish, it is imperative to produce a sufficiently accurate map for monitoring their changes and for their protection. The main objective of the present work is to test and select the best methodological approach to discriminate and map the mangroves and related coastal ecosystems in the United Arab Emirates (UAE), between Abu Dhabi and Dubai, a coastal stretch about 750 km long. It was found that the best practical results were produced by the Maximum Likelihood and Mahalnobis classifications although some limitations remain unsolved, especially in open ecosystems, which are common in arid areas. Goel et al. (2003) have evaluated the potential of hyperspectral aerial imagery for the detection of weed infestation and nitrogen fertilization levels in a corn (Zea mays L) crop.

A Compact Airborne Spectrographic Imager (CASI) was used to acquire hyperspectral data over a field experiment laid out at the Lods Agronomy Research Centre of Macdonald Campus, McGill University, Canada. Corn was grown under four weed management strategies (no weed control, control of grasses, control of broadleaf weeds, and full weed control) factually combined with nitrogen fertilization rates of 60, 120, and 250 N kg./ha. The aerial image was acquired at the tussle stage, which was 66 days after planting. The classification algorithms (maximum likelihood, minimum distance, Mahalanobis distance parallelepiped, and binary coding) and more sophisticated classification approaches (spectral angle mapped and linear spectral no mixing) were investigated. It was difficult to distinguish the combined effect of both weed and nitrogen treatments when only one factor, either wee or nitrogen treatment, was considered. With different classifiers, depending on the factors considered for the classifier, accuracies ranged from 65.84 percent to 99.46 percent. No single classifier was found useful for all the conditions. Shanmugam et al. (2003) have studied bare sand and semi-fixed dunes to represent ideal conditions for succession ally young slack habitats that support rare species of coastal dune flora such as fen orchid (Liparis loeselii) and liverworts (e.g., Petallophyllum ralfsii).

To map this habitat, mapping algorithms are applied to Compact Airborne Spectrographic Imager (CASI) data. Per-pixel mapping was performed using the Minimum distance, Maximum likelihood, and Mahalnobis distance classification algorithms with training data extracted for habitats at various levels of the National Vegetation Classification (NVC) scheme. Sub-pixel mapping was performed using a linear mixture model, fuzzy membership functions, and neural networks, and the sub-pixel proportions of the spectral end members viz. sand, vegetation, and shade/moisture were defined. Results indicate that per-pixel mapping can only be achieved for broad habitat categories that correspond to the level I of the NVC. of the algorithms used, the minimum distance, with an overall mapping accuracy of 92 percent, outperforms both maximum likelihood and Mahalnobis distance. Perumal and Bhaskaran (2010) have studied remote sensing imagery for a wide range of applications from military applications to farm development. The images may be panchromatic, multispectral, hyperspectral, or even ultra spectral of terra bytes.

A few image classification algorithms have proved good precision in classifying remote sensing data. But, of late, due to the increasing spatiotemporal dimensions of the remote sensing data, traditional classification algorithms have exposed weaknesses necessitating further research in the field of remote sensing image classification. So an efficient classifier is needed to classify the remote sensing imageries to extract information. The experiment included both supervised and unsupervised classification. Here, different classification methods and their performances are compared. It is found that the Mahalnobis classifier performed the best among the classification. Kun Wang and Youchuan Wan (2009) have studied fuzzy methods that have been widely applied in image classification, which is believed to be more appropriate for handling uncertainty in remote sensing. This research presents an algorithm integrating fuzzy multi-classifiers in classification. Traditional Mahalnobis distance and maximum likelihood classification are fuzzified by using fuzzy means and fuzzy covariance matrices, resulting in two fuzzy partitioned matrices. Experimental results indicate that this new method can increase classification accuracy. Hiremath and Kodge (2010) studied the visualization techniques for data mining in the Latur district of Maharashtra using the ENVI tools framework (ITTVIS, 2006).

In the maximum likelihood classification algorithms for checking training data sets in the normal distribution, pixels are classified according to the closest mean point in feature space. Patil et al, (2014) Machine learning techniques have delivered improvements in the accuracy of classification of patterns of features. Remote sensing color-based imageries have hard clustering color pixels with variability in the intensity of colors. It helps the estimation of the crop yield predictions through satellite imageries. Achieved converge accuracy of estimation of vegetation crop yield of fields. Kappa coefficient to achieve high degree accuracy estimation of crop-wise with suitable thresh hold to ground truth data. Validation of schemes of classifiers of the imageries data using various distance measures.

MATERIAL AND METHODS

The study area consists of Koluru Hobli of Bellary Taluk and District of Karnataka, which lies between 150 9´ to 150 15´N latitude and 760 55´ to 760 92´E longitudes.

Figure 1 - Karnataka State: Koluru Hobli of Bellary Taluk and District

IRS (Indian Remote Sensing Satellite)-P6 LISS-III(Linear Imaging Self Scanner) imageries of 21st November 2010 are used for the study. The geometrically corrected imageries are obtained from the National Remote Sensing Agency, Department of Space, Government of India, Hyderabad. The topographical map of the study area is overlaid on this image to extract the digital image of the study area (fig.2.). The spatial resolution of the images is 23.5mt. The images were recorded in three spectral bands. Among these only the first two namely Green and Red are in the small range of the electromagnetic spectrum and the third one namely the blue band is useful in the identification of green vegetation-like crops. Ground truth data is collected during field visits in the study area and the toposheet is used to accomplish the task of selecting training sites for each category for training the classifier in supervised classification. A part of the data was used as test sites for assessing classification accuracy.

DETAILS OF LAND COVER CLASSES CONSIDERED

The categories of interest were carefully selected and defined to successfully perform digital image classification. In the present study, a broad land use/land cover classification system is adopted with six categories for each study area as follows. Land use/Land cover categories of Koluru Hobli, Bellary Taluk.

METHODS OF IMAGE CLASSIFICATION

In the present study, both supervised and unsupervised methods are used for image classification. All classifications are done using ERDAS imagine 9.1 software at the Karnataka State Remote Sensing Applications Centre (KSRSAC), Department of IT and BT, Government of Karnataka, Major Sandeep Unnikrishnan Road, Doddabettahalli, Vidyaranyapura Post, Bengaluru, Karnataka 560097

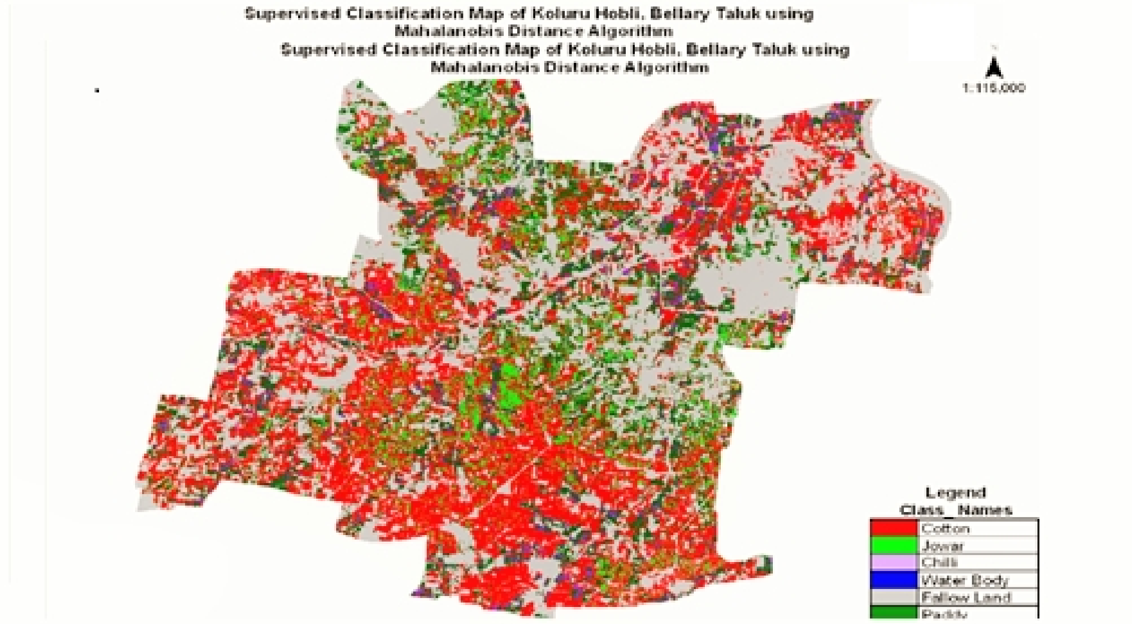

Figure 2 - study area satellite imageries (IRS P6 LISS-III from NRSA Hyderabad dated: 21st November, 2010)

UNSUPERVISED CLASSIFICATION ALGORITHM

Unsupervised classification algorithms are commonly used in remote sensing. The ISODATA algorithm has some further refinements by splitting and merging clusters. Clusters are merged if either the number of members (pixel) in a cluster is less than a certain threshold or if the centers of two clusters are closer than a certain threshold. Clusters are split into two different clusters if the cluster standard deviation exceeds a predefined value and the number of members (pixels) is twice the threshold for the minimum number of members. The number of classes (clusters), in the classification processes (was set to 6 classes), the maximum number of iterations (was set to 30), and the convergence threshold, which is the maximum percentage of pixels whose class values are allowed to be unchanged between iterations (was set to 0.95). These values were the same for all the areas. After the execution of the algorithm, the assigned classes (6 classes) were grouped into a number of categories according to their spectral appearance on screen.

THE MAXIMUM LIKELIHOOD CLASSIFICATION ALGORITHM

Maximum likelihood is one of the most popular supervised classification methods used with remote sensing image data. This method is based on the probability that a pixel belongs to a particular class. The basic theory assumes that these probabilities are equal for all classes and that the input bands have normal distributions. From a statistical viewpoint, the clusters obtained by k-mean can be interpreted as the Maximum Likelihood Estimates (MLE) for the cluster means if we assume that each cluster comes from a spherical Normal distribution with different means but identical variance (and zero covariance). However, this method needs a long time of computation, relies heavily on a normal distribution of the data in each input band, and tends to over-classify signatures with relatively large values in the covariance matrix.

The distance (spectral distance) method calculates the spectral distance between the measurement vector for the candidate pixel and the mean vector for each signature, and the equation for classifying by spectral distance is based on the equation for Euclidean distance. It requires the least computational time among other supervised methods, however, the pixels that should not be unclassified become classified, and it does not consider class variability.

MAHALNOBIS DISTANCE CLASSIFICATION ALGORITHM

Mahalnobis distance is similar to the minimum distance, except that the covariance matrix is used instead. Unlike minimum distance, this method takes the variability of classes into account. It could be more useful than the minimum distance in cases where statistical criteria must be taken into account, but the weighting factors that are available with the maximum likelihood option are not needed. However, this method tends to over classify signatures with relatively large values in the covariance matrix. Also, it is slower to compute than the minimum distance; and it relies heavily on a normal distribution of the data in each input band. In this algorithm, each pixel follows a multivariate normal distribution. Let μ1, μ2, . . . , μm and Σ1, Σ2,. . . , Σm denote the population mean vectors and population variance-covariance matrices for m classes respectively. The observation vector Xr at the pixel or when it belongs to class c is a multivariate normal distribution with mean μc and covariance matrix Σc. Then,

$$D^2_{rc} = \sqrt{(X_r - \mu_c)' \Sigma_c^{-1} (X_r - \mu_c)}$$

Give the Mahalnobis distance of pixel r belonging to class c. Since the class mean vectors μc and covariance matrix Σc are unknown, the sample estimates are obtained from the training set.

Let *x1, x2, x3, ..., xm* be the sample mean vectors and V1, V2 ,…., Vm be the sample variance-covariance matrices estimated from the training data for m classes respectively. The classification is performed for the whole data set on a pixel-by-pixel basis. The pixel assignment is made based on the value of drc

$$D^2_{rc} = \sqrt{(X_r - \bar{X}_c)^T (V_c)^{-1} (X_r - \bar{X}_c)}$$

where, xr is the observation vector for unclassified pixel r.

CLASSIFICATION ACCURACY

The extent to which a manual or automatic processing system correctly identifies selected classes. Overall accuracy (O's ac) is obtained as the ratio of total correct classifications for all the classes to the total test sample units. The individual class accuracies can be expressed in two ways: by calculating the producer's accuracy and the user's accuracy. Producer's accuracy (P's ac) is the ratio of correct classifications to the actual data. User's accuracy (U's ac) is the ratio of the correct classifications to the total number of pixels classified in specific classes.

$$\text{Overall accuracy} = \frac{\sum_{i=1} n_{ii}}{N}, \text{User's accuracy} = \frac{n_{ii}}{n_{i.}},$$

$$\text{Producer's accuracy} = \frac{n_{ii}}{n_{.i}}$$

where, n_{ii}= correctly classified pixels,

$n_{i.}$ = Marginal totals of classification categories, $n_{.i}$= Marginal totals of reference categories

KAPPA COEFFICIENT

Kappa statistic gives the proportion of agreement after the chance agreement is removed and it may be calculated as, Kappa statistic gives the proportion of agreement after the chance agreement is removed and it may be calculated as,

$\widehat{K} = \frac{P_o - P_c}{1 - P_c}$ where,

$P_o = \frac{\sum_{i=1}^{m} n_{ii}}{N}$, $P_c = \frac{\sum_{i=j=1}^{m} n_{i.} n_{.j}}{N}$

An approximation of variance of Kappa statistic is given by $\hat{\sigma}_K^2 = \frac{P_o(1-P_c)}{N(1-P_c)}$

Test of significance can be performed to determine if the Kappa coefficient is significantly different from zero using Z test. $H_o : K = 0$, $H_1 : K \neq 0$

Test statistics, $Z = \frac{\widehat{K}}{\sqrt{\hat{\sigma}_K^2}}$

follows Normal distribution with zero mean and unit variance. Decision: if observed value of $|Z| > 1.96$, the null hypothesis is rejected, at 0.05 level of significance, indicating that the confusion matrix is significantly different from a random result. The classified images were used to estimate the area under different land cover classes. This is done by aggregation. Area underclass c = (No. of pixels in class c) x (area of a pixel)

RESULTS AND DISCUSSION

Classification results obtained with Mahalnobis distance classification: Using Mahalnobis distance classification 86.15 percent of overall accuracy was achieved. The user's accuracy and producer's accuracy for individual classes ranged between 74.28 to 92.50 percent and 82.00 to 92.50 percent for different categories using the maximum likelihood algorithm. And producer's and user's accuracy is obtained and presented in the below table for all the classes under study.

Table glossary: F_ll= Fallow land, W_b= Water bodies; Pr's A=Producer's Accuracy, Ur's A= User's accuracy, f_m= f_measure; CA=Classification Accuracy, OCA= Overall Classification Accuracy, OKS= Overall Kappa Statistics

Classes	Jowar	Cotton	Chilly	F_l	Paddy	W_b	Total	f_m	Pr's A	Ur's A
Jowar	26	2	1	5	1	0	35	0.80	86.66	74.28
Cotton	1	41	2	3	1	0	48	0.84	82.00	85.41
Chilly	1	1	37	1	0	0	40	0.93	92.50	92.50
F_l	2	4	0	51	0	0	57	0.87	85.00	89.47
Paddy	0	2	0	0	43	4	49	0.87	86.00	87.75
W_b	0	0	0	0	5	26	31	0.85	86.66	83.87
Total	30	50	40	60	50	30	260		OCA	86.15
									OKS	0.83

Table 1 - Mahalnobis Classification confusion matrix

Classes	Jowar	Cotton	Chilly	F_l	Paddy	W_b	Total	f_m	Pr's A	Ur's A
Jowar	28	1	1	3	1	0	34	0.88	93.33	82.35
Cotton	1	44	0	2	1	0	48	0.90	88.00	91.68
Chilly	0	3	38	1	0	0	42	0.93	95.00	90.47
F_l	1	2	1	54	0	0	58	0.92	90.00	93.10
Paddy	0	0	0	0	45	2	47	0.93	90.00	95.47
W_b	0	0	0	0	3	28	31	0.92	93.33	90.32
Total	30	50	40	60	50	30	260		OCA	91.15
									OKS	0.89

Table 2 - Maximum Likelihood Classification confusion matrix

Classes	Jowar	Cotton	Chilly	F_l	Paddy	W_b	Total	f_m	Pr's A	Ur's A
Jowar	24	3	1	3	1	0	32	0.77	80.00	75.00
Cotton	0	39	1	4	1	0	45	0.82	78.00	86.66
Chilly	1	1	38	2	2	2	46	0.88	95.00	82.60
F_l	4	5	0	47	0	0	56	0.81	78.33	83.92
Paddy	1	1	0	3	41	3	49	0.83	82.00	83.67
W_b	0	1	0	1	5	25	32	0.81	83.33	78.12
Total	30	50	40	60	50	30	260		OCA	82.30
									OKS	0.79

Table 3 - Minimum Distance Classification confusion matrix

Classes	Jowar	Cotton	Chilly	F_l	Paddy	W_b	Total	f_m	Pr's A	Ur's A
Jowar	22	4	1	5	1	0	33	0.70	73.33	66.66
Cotton	3	37	2	4	2	0	48	0.76	74.00	77.08
Chilly	0	1	32	2	3	3	41	0.79	80.00	78.04
F_l	4	8	0	45	0	0	57	0.77	75.00	78.94
Paddy	1	0	5	4	39	4	53	0.76	78.00	73.58
W_b	0	0	0	0	5	23	28	0.79	76.66	82.14
Total	30	50	40	60	50	30	260		OCA	76.15
									OKS	0.71

Table 4 - Unsupervised Maximum Likelihood Classification confusion matrix

Classification	Supervised						Unsupervised	
	Maximum Likelihood		Mahalanobis		Minimum Distance		Maximum Likelihood	
Class Name	CA	f_m	CA	f_m	CA	f_m	CA	f_m
Jowar	82.35	0.88	74.28	0.80	75.00	0.77	66.66	0.70
Cotton	91.66	0.90	85.41	0.84	86.66	0.82	77.08	0.76
Chilly	90.47	0.93	92.50	0.93	82.60	0.88	78.04	0.79
Fallow land	93.10	0.92	89.47	0.87	83.92	0.81	78.94	0.77
Paddy	95.74	0.93	87.75	0.87	83.67	0.83	73.58	0.78
Water bodies	90.32	0.92	83.87	0.85	78.12	0.81	82.14	0.79
OCA's	91.15	0.91	86.15	0.86	82.30	0.82	76.15	0.76
OKS's	0.897		0.83		0.79		0.71	

Table 5 - Comparison of Classification Accuracy and f-measures

Test of significance of Kappa coefficients for Koluru Hobli, Bellary Taluk:The kappa coefficient is found to be 0.8321 and the variance of kappa is found to be 0.000675. The Kappa coefficient for Mahalnobis distance classification was highly significant, implying that the classifier produced classification significantly different from a random assignment.

Classification		Kappa (K)	Variance (K)	P Values	Significance
Supervised	Maximum Likelihood	0.8927	0.000456	<0.01	**
	Mahalnobis	0.8321	0.000675	<0.01	**
	Minimum Distance	0.7855	0.000823	<0.01	**
Unsupervised	Maximum Likelihood	0.7103	0.010300	<0.01	**
** : Significant @ 1% level					

Table 6 - Test of significance of Kappa coefficients for Koluru Hobli, Bellary Taluk.

In this study, classifiers were predicted by utilizing remote sensing in the arid region located in northeast Karnataka state. Classification of raw remote sensing satellite imageries data was applied to these with four methods of classification; these are the Unsupervised classification method and three different supervised classification methods. After classified features, accuracy was tested by different methods of accuracy assessment, and the post-classification process was implemented. By using the unsupervised technique it was found that features can be divided into main classes: Paddy, Cotton, Jowar, Chilly, and Fallow land, Water bodies constitute one land cover class achieving a good amount of time complexity and optimal level of classification accuracy.

Three supervised classification methods were utilized in this work; these are maximum likelihood, minimum distance, and Mahalnobis distance. It was noticed that applying the supervised classification methods in the study area enhances the extraction of production accuracy of outcrops. It can be shown also that both maximum likelihood and Mahalnobis distance methods agree with land truths in terms of production and user accuracy. Their predictions of the distribution of Paddy, Cotton, Jowar, Chilly, Fallow land, Water bodies' outcrops areas were very reasonable, but the minimum distance method overestimated the Paddy, Cotton, Jowar, Chilly, Fallow land, Water bodies' area in the study area. Error matrices produced to evaluate the classification methods show that the best overall classification accuracy method was the maximum likelihood for all the study areas; with an average accuracy of about 91.15%. The second best overall classification accuracy method was Mahalnobis distance; with an average accuracy of 86.15% and the least overall classification accuracy method was minimum distance with an average accuracy of 82%, and unsupervised maximum likelihood with an average accuracy of 76.15%.

CONCLUSION

The pairwise comparison between Kappa coefficients has shown a highly significant difference in maximum likelihood classification. Supervised classification using maximum likelihood, Mahalanobis distance, and minimum distance classifications, performing respective order. Unsupervised classification using maximum likelihood classification outperforms optimum. User's accuracy classified in specific classes achieved significant improvement in Cotton, Paddy, Chilly, and Fallow land, Jowar and Water body classes are more common variations in Producer's accuracy. Mahalnobis distance classification is estimated significantly converges to actual results.

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Author's Affiliation

Udupi, S. - University of Agricultural Sciences, Bangalore, India.
Hemamalini, H.C. - Bangalore Regional Centre, Bangalore, India.
Chittora, V. - University of Agricultural Sciences, Bangalore, India.
Prabhuraj, D. K. - Karnataka State Remote Sensing Applications Centre, Bangalore, India.
Patil, S.S. - Professor at University of Agricultural Sciences, Bangalore, India.

Authors' Contribution

Udupi, S. - The author contributed to the elaboration, realization and manipulation of the data and writing.
Hemamalini, H.C. - The author contributed to the elaboration, realization and manipulation of the data and writing.
Chittora, V. - The author contributed to the elaboration, realization and manipulation of the data and writing.
Prabhuraj, D. K. - The author contributed to the elaboration, realization and manipulation of the data and writing.
Patil, S.S. - The author contributed to the elaboration, realization and manipulation of the data and writing.

Editors in Charge