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Original Paper

Comparing Maximum Likelihood and Minimum Distance Classifiers for Land Cover Mapping using LISS-III Imagery

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ABSTRACT

Remote sensing is an important tool for producing land use and land cover maps through a process known as image classification. With the respect to this study compared the accuracy of two classification techniques as Maximum Likelihood classification (MLC) and Minimum Distance classification using multispectral images acquired from remotely sensed Linear-Imaging-Self-Scanning-Sensor-III(LISS-III) image of 05 Apr 2019.Here used study area of (upper Godavari basin) Chhatrapati Sambhajinagar and Ahmednagar region of upper Jaykwadi dam, Maharashtra. India. The area has been classified in five LULC classes as Water body, Vegetation, Fallow land, Bulit up area, Barren land. The overall accuracy with the classifier was found the Maximum Likelihood classifier has provided satisfactory results. The overall accuracy of Maximum Likelihood was found to be 92.29% with Kapp coefficient 0.86% and Minimum distance has over all accuracy is 78.81% with Kapp coefficient 0.71%. So Maximum Likelihood classification gives better accuracy than minimum distance classification techniques with Resoursat-2 LISS-III image. If the two classes are well-separated, then MLC and MDC will likely give the same result. However, if the two classes overlap, then MLC is more likely to give the correct result. This is because MLC takes into account the probability distribution of the data, while MDC does not.

KEYWORDS

Remote sensing, Supervised classification, Resorcesat-2 LISS-III, Maximum Likelihood Classifier (MLC), Minimum distance, Upper Jaykwadi Dam.

1. INTRODUCTION

Remote sensing is a valued device for gaining information about the Ground's surface using sensors mounted on satellites, aircraft, or other platforms. Image classification in remote sensing involves categorizing the pixels of an image into specific land cover or land use classes, such as water bodies, forests, agricultural lands, urban areas, etc. Improved image classification in remote sensing can be achieved through various techniques. Remotely sensed images provide quantitative and qualitative information that reduces the complexity and period mandatory for ground work and can be used to create LULC maps the procedure as image classification [1]. Image sorting is an important step in image analysis process. Image organization procedures aim to automatically classify picture elements in an image into themes. Classically, data of multi-band are used to perform image cataloguing, and the spectral forms represented by each pixel serves as the numerical basis for categorization [2]. Image classification is a step-by-step process that begins with the creation of a classification scheme for desired images. The images are then pre-processed, which includes image clustering, image enhancement, scaling, and so on. The desired areas of those images are selected and initial clusters are generated. The algorithm is to useful for the images get to the desired classification, and corrective actions are taken in the algorithm phase, which is also known as postprocessing and then evaluate the classification's accuracy [3]. Sat image is sorting related with a number of approaches and methods. However, most sat images are organized into two main categories: pixel-based and object-based. Pixel-based techniques are further classified as unsupervised and supervised.

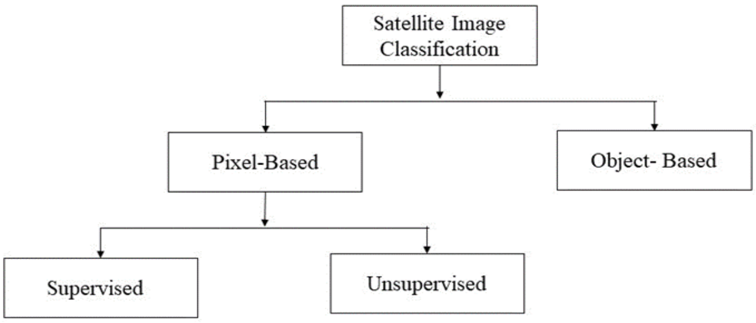

Fig.1: Types of classification

Pixel-based classifications are according to the results grey value of pixels, and only spectral information is used for classification. These are the smallest units that represent an image. This method makes use of reflectance statistics for specific pixels. It assembles pixels to represent land cover characteristics [4]. Supervised classification is a popular method for analysing sat images to identify and categorize land cover or land use classes Unsupervised organization is a technique used in sat image analysis and remote sensing to automatically categorize pixels into distinct classes without the need for pre-defined training data or class labels.

2. Study Area and Data Used

The Godavari River is the country's second largest basin, accounting for nearly 9.5% of its total geographical area. The Godavari basin is split into eight sub-basins. The upper Godavari sub-basin the Ahmednagar and Aurnagabad region has been selected for study. The Godavari basin has a tropical climate. From mid-October to mid-February, the weather in the basin is cold, with the western and north-eastern parts being colder than the rest of the basin [5].

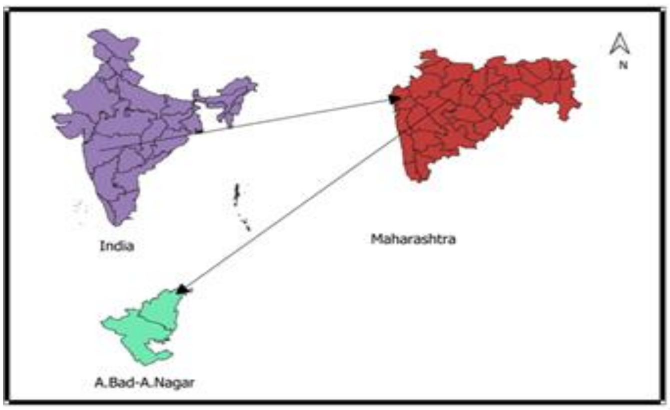

Fig.2: Study Area.

In the upper Godavari basin, the mean monthly Tmax ranges from 29.64 to 38.60, with a mean annual Tmax of 32.45[6]. The Godavari River basin receives an average annual rainfall of about 1132 mm, with the monsoon season accounting for nearly 84% of total rainfall [7].

Satellite Resourcesat-2 LISS-III imagery used in the study and acquired from free sphere of Bhuvan Indian Geo-Platform of ISRO. The image is ortho rectified [8].

2.1. LISS-III Data Set

ResourceSat-2 is an ISRO (Indian Space Research Organization) data continuity mission with improved spectral bands over IRS-P6/ResourceSat-1The ResourceSat data are used in a variety of applications, including farm production supervision and judgement, crop area, precision agricultural, water properties, forestry mapping, country organization development, tragedy management, and so on. Along with ResourceSat-2 provides continuity and increases observation timeliness (receptivity) [9]. The LISS-III sensor is a multispectral camera that is used to acquire images of the Earth's surface. The four spectral bands of the LISS-III sensor and familiar with the variety of features on the Earth's surface, such as undergrowth, bodies of water, types of soil, and built-up areas. The Resourcesat-2 satellites collect data in four wavebands extending from Visible and Near-Infrared (VNIR) to Shortwave Infrared (SWIR). At elevation of 817 kilometers, the satellite is in a sun-synchronous orbit. one rotation around the earth the satellites complete in 101.35 minutes and approximately 14 orbits per day. During a 24-hour cycle, 341 orbits circle the Earth. With a 24-day repeat cycle, the LISS-3 sensor covers a 140-kilometer orbital swath and space resolution of 24 meters [10]. The following Table.1 is shows the major specification of Resorcesat LISS-III image.

Table:1 The Major specification of Resorcesat-2 LISS-III image

IGFOV	23.5 m
Spectral Bands	B2 0.52 – 0.59 (GREEN) B3 0.62 - 0.68(RED) B4 0.77 - 0.86((NIR) B5 1.55 - 1.70(SWIR)
Swath	141 Km
Average Saturation	B2 53 radiance B3 47 (mw/cm2/sr/micron) B4 31.5 B5 7.5
Integration time	3.32 msec
Quantization	10 bits
No. of gains	Single

3 Methodology

The methodology as described in Fig.3 shows the steps of image classification for land use and land cover classification. The data accumulation can be done by acquiring sat image. The image's layers must be stacked. This entails combining the image's various spectral bands into merged image. This makes it likely to determine the various surface features of the Earth. Create a shape file of the area of concern (AOI). The digital representation of the zone that is being classified. After the training data select for extract the signature of spectral each class. The signature of spectral is a curve that shows the reflectance of the class in each waveband. After the extract signature is categorised the image, such as supervised classification or unsupervised classification. After image classification assess the accuracy of the classification. This can be done by comparing the classified image to a reference image or by ground truthing and analysis the result This can be done by looking at the space distribution of the different classes or by likening the results to other sources of information and write conclusions from the analysis. This can be done by identifying patterns or trends in the data or by making recommendations for future research.

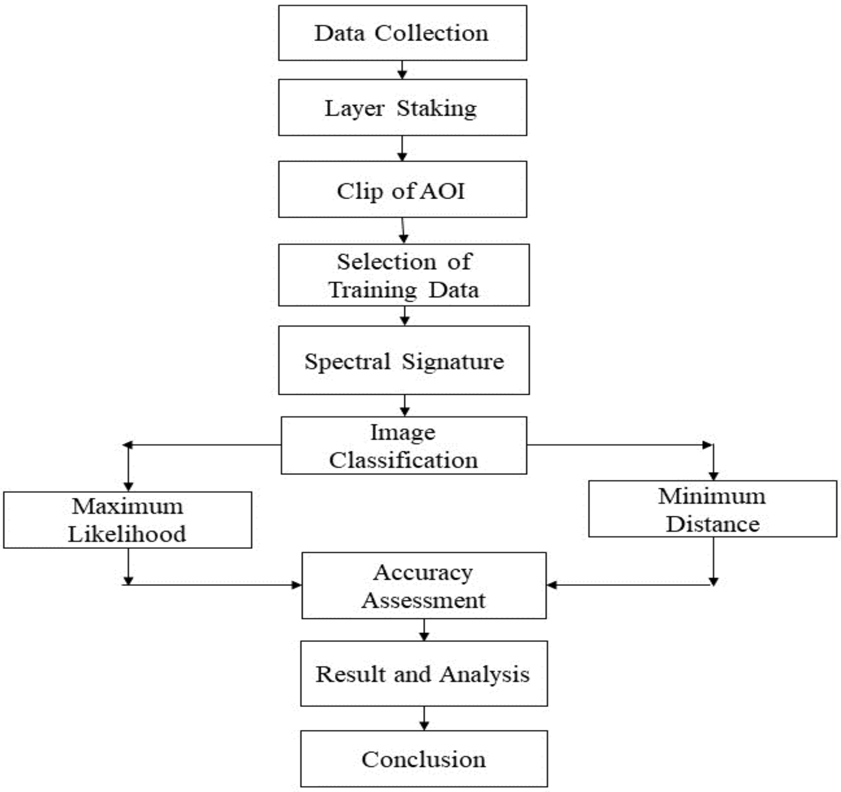

Fig.3: Methodology

In this study Resourcesat -2 LISS-III images of 5 Apr 2019 was used. LISS-III images remote sensing data having 4 bands and each band has separate file along with tiff extension. The layer stacking is the method of combining multiple distinct bands to generate a new multiband image. For imagining the multiband images are beneficial and identifying the various Land Use Land Cover classes. Multiple image bands must have the same extent (number of rows and columns) [11]. The following Fig.4 shows layer stack image. The layer staking was performed and it give single tiff file having four bands. A Resourcesat-2 LISS -III image covers an area of upper Jaykwadi dam (region of Ahmadnagar and Aurngabad) so there is need of perform a subset of image and it is performed by using shape file of upper area of Jaykwadi dam.

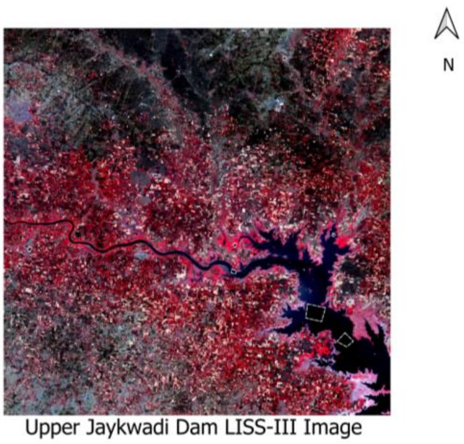

Fig.4: Layer Stack image of LISS-III image

3.1 Spectral Signature

The LISS-III image obtained different signatures from sat images. The set of pixel that represents the equivalent class of that signature. To train the classifiers got different signatures form images [12]. The following are class-wise signature of spectral for a water body, vegetation, fallow land, built-up area, and barren area.

3.1.1 Water Body

Water has a high absorption in the near-infrared (NIR) regions of the electromagnetic spectrum, and a low reflectance in these regions. This is because water molecules can absorb the energy of photons in these regions of the spectrum. Water has a high reflectance in the shortwave infrared (SWIR) region of the spectrum as demonstrated in following fig.5.

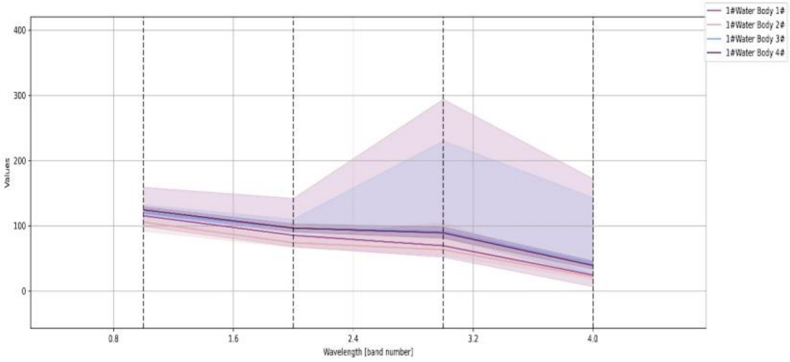

Fig.5 Water body signature

3.1.2 Vegetation

The following fig.6 shows the vegetation has a high reflectivity in the observable and NIR regions of the spectrum. This is because chlorophyll, the green pigment in plants, absorbs red and blue light and reflects green and NIR light. The SWIR region of the band vegetation has a low reflectance. This is because water molecules in plant cells absorb the energy of photons in the spectrum of this region .

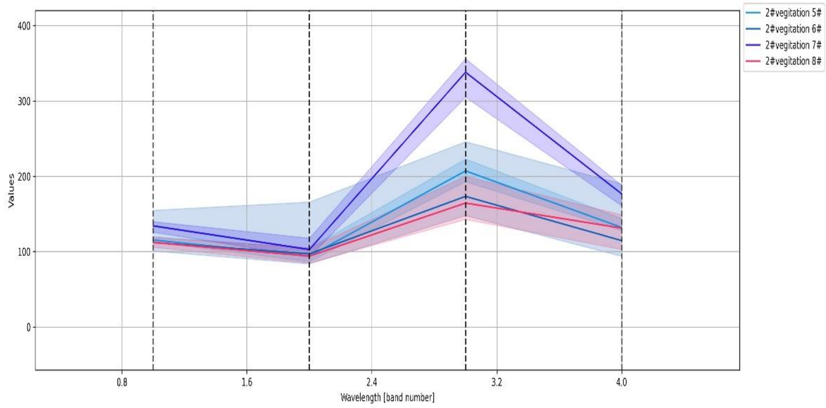

Fig.6 Vegetation signature

3.1.3 Fallow Land

Fallow land has a moderate reflectance in the visible, NIR, and SWIR regions of the spectrum. This is because fallow land typically consists of a mix of bare soil, vegetation, and other materials. The following fig.7 shows the signature of fallow land.

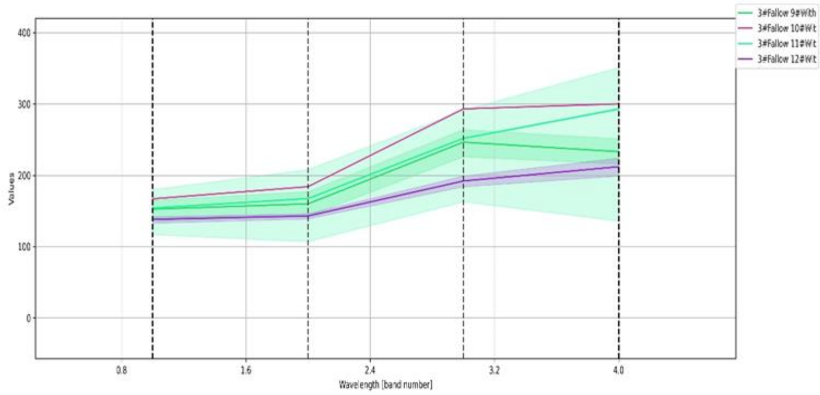

Fig.7 Fallow land signature

3.1.4 Built-up Area(Rural)

Built-up areas, such as roads and buildings, have a high the reflectance in NIR regions of the spectrum. This is because the materials used to construct built-up areas, such as asphalt and concrete, have a high reflectance in these regions of the spectrum. The following fig.8 shows built up area signature.

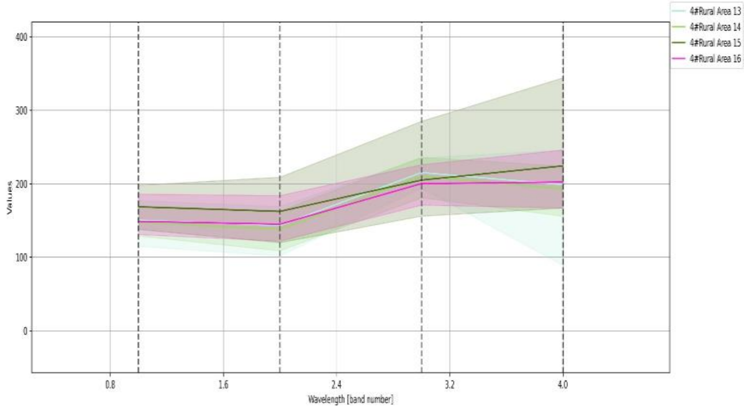

Fig.8 built up area signature(Rural)

3.1.5Barren Area

Barren areas, such as deserts and rocky outcrops, have a moderate to high reflectance in the visible, NIR, and SWIR regions of the spectrum as shown in fig.9. This is because barren areas typically consist of a mix of bare rock, sand, and other materials that have a high reflectance in these regions of the spectrum.

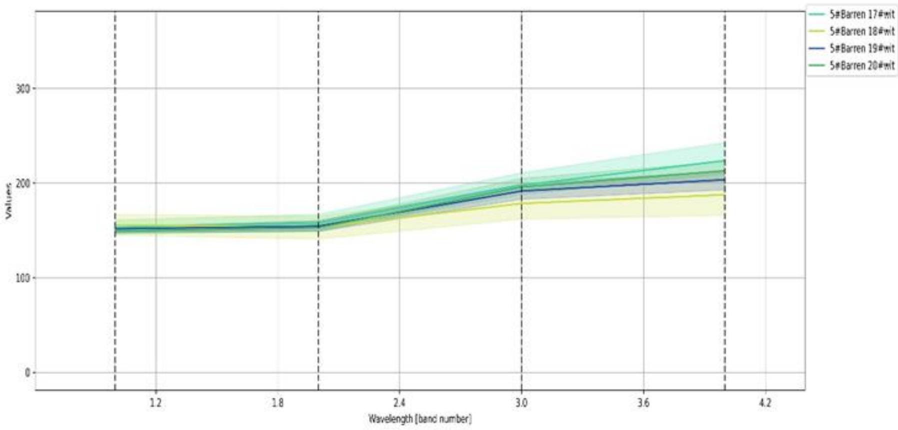

Fig.9 Barren area signature

Table.2 shows summarizes the key characteristics of the spectral signatures

Class	Visible	NIR	SWIR
Water body	Low	Low	High
Vegetation	High	High	Low
Fallow land	Moderate	Moderate	Moderate
Built-up area(Rural)	High	High	Moderate
Barren area	Moderate-high	Moderate-high	Moderate-high

3.2 Image Classification

The comparison of two supervised classification to determine best classification techniques for satellite image classified with two different classification Maximum likelihood and Minimum distance. The statistical technique of maximum likelihood classification that gives each pixel in an image to the class that is most probably to have produced that pixel's spectral signature. The signature of spectral a pixel is a vector that contains the reflectance of that pixel at different wavelengths of light. The maximum-likelihood classifier is predicated on the assumption that apiece class in each band can be described by a normal distribution. Under the supervised classification maximum-likelihood is method derived from the Bayes theorem, which states the a posteriori distribution P(i|), i.e., the probability that a pixel with feature exists. In the eq(1) vector belonging to class i is given by[13]

$$P(Ci|x) = P(x|Ci)*P(Ci)/P(x) \qquad \text{eq .(1)}$$

Where,

$P(Ci|x)$ – testing most probability;
$P(x|Ci)$ – conditional probability;
$P(Ci)$ - prior probability, the probability that i is observed;
$P(x)$ – probability of pixel for any class;
Ci – that class;
x – pixel

The class can be estimated from mean and covariance matrix for each training dataset of pixels that are known to belong to each class. The training dataset should be representative of the entire image that is being classified. Minimum distance algorithm is a distance-driven technique that assigns individual pixel in an image to the class that is closest to its spectral signature. The distance among two signatures of spectral is measured using a distance metric, such as the Euclidean distance or the Mahalanobis distance. The minimum distance method (MDM) computes the Euclidean distance d(x,y) among the signatures of spectral in the training data set and the image pixels' spectral signatures. The following formula calculated the spectral space:

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \qquad \text{eq. (2)}$$

where x is the image's spectral signature vector, y is the training area's spectral signature vector, and n is the image's band count[14]. After computing the spectral distance for each pixel, the class with the closest spectral signature to the training set is assigned using the discrimination function shown eq(3)[15].

$$x \in c_k \Leftrightarrow \mathrm{d}(x, y_k) < d(x, y_j) \qquad \text{eq.(3)}$$

Where,
c_k is the land cover macro-class or class
y_k, is the signature of spectral class k
y_j is the signature of spectral class j.
This equation is valid when k ≠j.

The Fig.6 shows the five different land cover classes: water bodies, vegetation, fallow land, rural areas, and barren land. The maximum likelihood classification technique would classify pixels that have signatures of spectral that are closest to the water body signature as water bodies. The minimum distance classification technique would classify pixels that are closest to the water body signature as water bodies. The Fig.6 also shows the classification boundaries for the two techniques. The classification boundary for the maximum likelihood classification technique is a smooth curve that separates the water body pixels from the other pixels. The classification boundary for the minimum distance classification technique is a jagged line that separates the water body pixels from the other pixels.

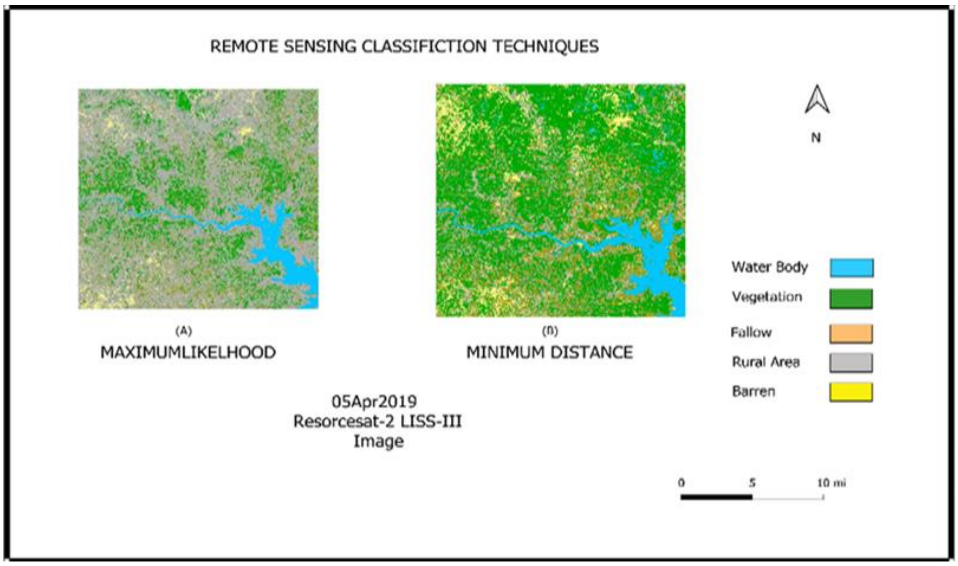

Fig.10: Liss-III classified image

3.3 Accuracy Assessment

An accuracy assessment compares a classification to field data to regulate how accurately the classification represents the ground data. When the classified results are to be compared with actual ground ground truth data, an appropriate number of ground truth (samples) for each Class must be gathered [16]. Maximum likelihood classifier gives a highest overall accuracy which is 92.29% whereas Kapp statistic is 0.86%. The minimum distance classifier gives lowest overall accuracy is 78.81 and Kapp statistic is 0.71. The following Table.3 shows overall accuracy and Kapp coefficient.

Table.3: overall accuracy & kappa-coefficient of all classifiers

Classifiers Name	**Kappa Coefficient**	
Maximum likelihood	92.29 %	0.86
Minimum distance	78.81%	0.71

3.4 Result and Analysis

In this study Comparing the results of two classifiers, it is observed that there is no significant difference using two types of classifiers [17]. In this study the LISS-III image classified by using two techniques Maximum likelihood and minimum distance classification techniques. The overall accuracy result of maximum likelihood got 92.29% and Kapp coefficient is 0.86 and minimum distance classification techniques got over all accuracy 78.81 and Kapp coefficient 0.71. The maximum likelihood classification is a popular technique for land cover organization because it is relatively simple to implement and it is relatively accurate. However, it can be sensitive to noise and shadows, and it can be difficult to choose the right number of land cover classes.

Table.4: Maximum Likelihood classification result

Class	**Pixel Sum**	**Percentage**	**Area SQ. Km**
Water Body	71109	5.37%	39.27
Vegetation	243156	18.35%	134.28
Fallow	125126	9.44%	69.1
Built up area	847826	63.10%	468.21
Barren land	37584	2.837%	20.75

The maximum likelihood classification results shows the percentage of each land cover class in the image. The land cover classes are Water body, Vegetation, Fallow, Bulit up area, Barren. The table.4 shows that water bodies make up 5.3675% of the image, vegetation makes up 18.3542%, fallow makes up 9.4449%, rural area makes up 63.9965%, and barren landmakes up 2.8369%. In above table.4 to each land cover class in square kilometre’s. The water bodies are 39.2699 square kilometre’s. The vegetation is 134.282 square kilometre’s. The zone of fallow is 69.1 square kilometre’s. The zone of rural zone is 468.211 square kilometres. The zone of barren is 20.755 square kilometre’s.The minimum distance algorithm is a supervised classification technique that allocates every pixel in an image to the class that is nearby in feature space. The multidimensional space where each measurement represents a different wave band . The minimum distance classification is a simple and efficient method that is relatively insensitive to noise and shadows. The number of classes and the definition of the feature space it can be delicate.

Table.5: Minimum Distance Classification Result

Class	**Pixel Sum**	**Percentage**	**Area SQ.Km**
Water Body	84126	6.35%	46.45
Vegetation	628927	47.47%	347.32
Fallow	208864	15.76%	115.35

Built up area	248450	18.75%	137.21
Barren	154434	11.65%	85.29

The minimum distance algorithm result gives the percentage of each land cover class in the image, as well as the overall number of pixels in each class and the area of all class in square meters and square kilometres. The land cover classes are Water body, Vegetation, Fallow, Bulit up area, Barren land. The table.5 shows that water bodies make up 6.35% of the image, vegetation makes up 47.47%, fallow makes up 15.77%, built up area makes up 18.75%, and barren makes up 11.66%. The zone of water body class is 46.4586 square kilometres, vegetation zone is 347.3249 square kilometres, fallow land is 115.345 square kilometres. The rural area is 137.206 square kilometres, barren land is 85.2862 square kilometres.

3.5 Conclusion

This study compared two supervised classification techniques as Maximum likelihood algorithm and Minimum distance algorithm with Resorcesat-2 LISS-III image.MDC simply calculates the distance of each pixel to the mean signature of spectral each class and assigns the pixel to the class with the shortest distance. MLC, on the other hand, uses Bayes' theorem to calculate the probability of each pixel belonging to each class. This allows MLC to account for the variability within each class, which can lead to more accurate classifications. MLC can handle more complex data. MDC is a relatively simple classifier that is not well-suited for handling complex data, such as data with multiple bands or data with overlapping class distributions. More complex data can handle by the MLC. This study Indicate that found the maximum likelihood algorithm gives able accuracy other than minimum distance classification. The minimum distance gives low accuracy. Among supervised technique the Maximum Likelihood algorithm has given total accuracy of 92.29% with Kappa value 0.86%. total maximum likelihood gives most accurate result for remotely sensed image. Maximum Likelihood algorithm gives a higher total accuracy and Kappa value than the Minimum Distance algorithm. This advises that the Maximum Likelihood algorithm is a better for land cover organization using. It is important to note that the performance of the algorithm can vary depending on several factors, including the quality of the training data, the complexity of the land cover classes, and the presence of noise in the imagery. The two classes are well-separated, then MLC and MDC will likely give the same result. if the two classes overlap, then MLC is more likely to give the correct result. This is because MLC considers the probability distribution of the data, while MDC does not.

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