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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 from remotely sensed (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 Waterbody, Vegetation, Fallow land, Bulit up area, Barren land. The overall accuracy of the classifier was found, and the Maximum Likelihood classifier produced suitable results. The overall accuracy of Maximum Likelihood was 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. The quantitative and qualitative information provide by remotely sensed images that reduces the difficulty to land works and can be used to create LULC maps as image organization.[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]. The stepwise process of the image classification with the creating of classification system for desired images. The images are subsequently pre-processed, which includes image gathering, improvement, scaling, and other operations. The desired sections of those pictures are selected, and starting clusters are created. The algorithm is 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.

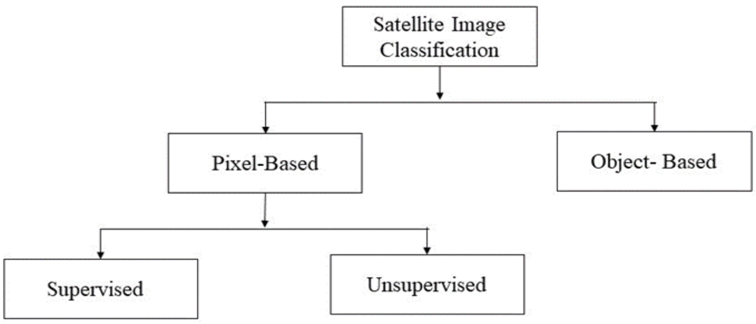

Fig. 1. Types of classification.

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. AREA OF STUDY & DATA SET

Godavari River is the second largest river basin in the country, its total geographical area is nearly 9.5%. The Godavari basin is split into eight sub-basins. The Ahmednagar and Aurnagabad region has been selected for study situated at greater Godavari sub basin. The Godavari basin has a steamy climate from October to February, the basin weather is cold, the western and north-eastern sections are colder than the remainder of the basin. [5].

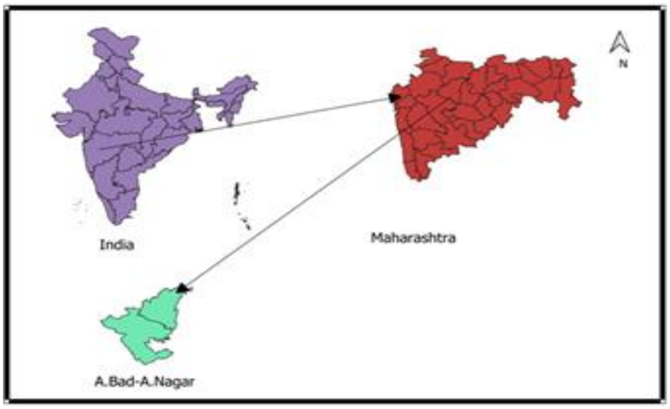

Fig. 2. Study Area.

In the greater Godavari basin, Tmax ranges from 29.64 to 38.60 the average monthly, and an average annual Tmax of 32.45 [6]. An average annual rainfall of 1132 mm in the Godavari River basin has obtains, 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

Resource sat 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]. To the acquire images of the earth's surface used liss-iii multispectral satellite camera. LISS-III sensor has four spectral bands and familiar with the different features on the earth's surface, such as undergrowth, bodies of water, types of soil, and built-up areas. Gather the data in four wavebands by the LISS-III image ranging from Visible and Near-Infrared (VNIR) to Shortwave Infrared (SWIR). At promotion of 817 kilometre's, the satellite is in a sun-synchronous orbit. One revolution round the earth the satellites completed in 101.35 minutes and per day 14 circles, 341 revolutions circle the earth throughout the 24-hour rotation. The sensor covers a 140-kilometer diversion by 24 days return cycle, swath and space resolution of 24 meters in LISS-III [10]. The following Table.1 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)
Strip	141 Km
Average Capacity	B2 53 vivacity B3 47 (mw/cm2/sr/micron) B4 31.5 B5 7.5
Combination period	3.32 msec
Quantization	10 bits
Number of gains	Single

3. METHODOLOGY

The methodology as described in Fig. 3 shows the steps of 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. Evaluate the classification accuracy. This can be done by comparing the classified image with a reference image or by ground truthing and analyzing the result. This can be done by looking at the spatial distribution of different classes or by comparing the results with other sources of information and drawing conclusions from the analysis. This can be done by identifying patterns or trends in the data or making recommendations for future research.

In this study, LISS-III images of April 5, 2019 were used. There are 4 bands in LISS-III image and has tiff extension of separate bands file. A new image is created by combining multiple different bands. Combine image is useful and classify various Land Use Land Cover classes [11]. The following Fig. 4 shows layer stack image. The layer staking was completed and produced stack image of four bands of greater Jaykwadi dam covers by LISS-III image of Resource sat 2 (region of Ahmednagar and Aurangabad).

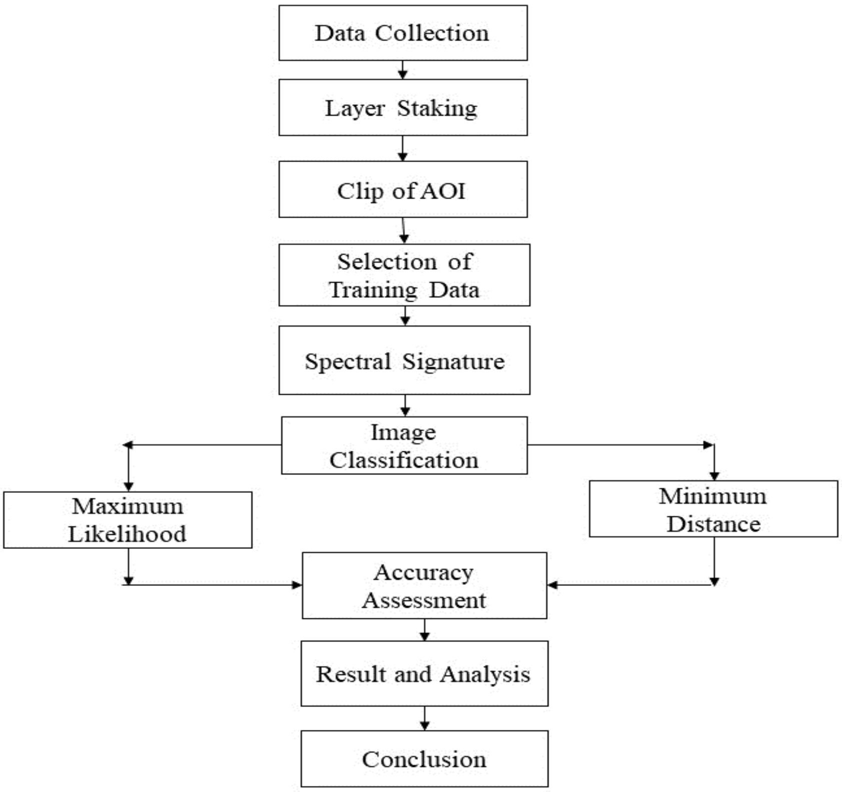

Fig.3. Methodology.

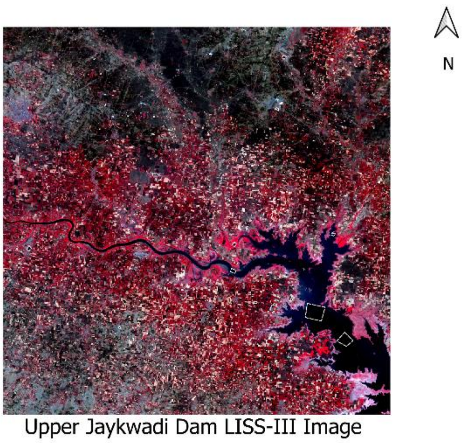

Fig. 4. Layer Stack image of LISS-III image.

3.1 Spectral Signature

The LISS-III image obtained different signatures from sat images. The set of pixels 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 waterbody, 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 low reflectance in these regions. This is because water molecules can absorb the energy of photons in these regions of the spectrum. Shortwave infrared (SWIR) region of the spectrum has high reflectivity of the water as demonstrated in Fig. 5.

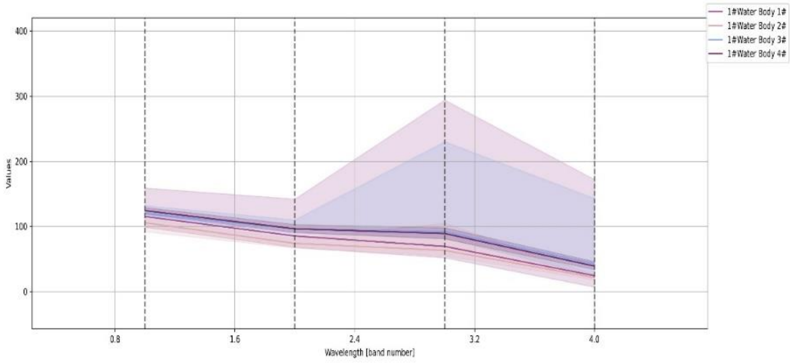

Fig. 5. Water body signature.

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 vegetation, grips red and blue radiant and reflects green and NIR radiant. 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.

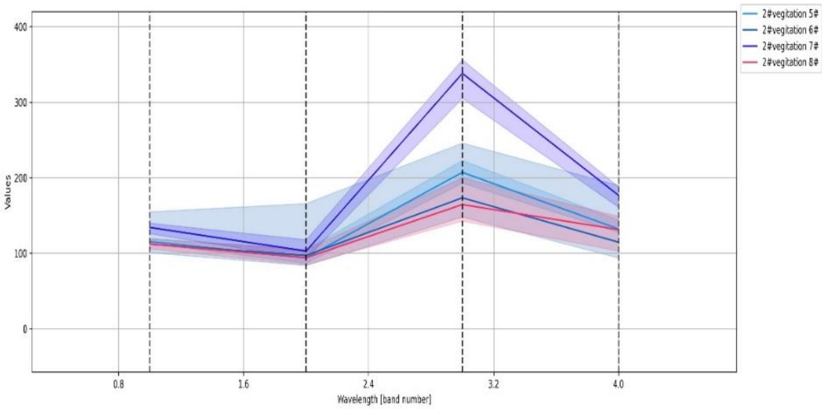

Fig. 6. Vegetation signature.

3.1.3 Fallow Land

Fallow land has a moderate reflectivity in the observable, 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.

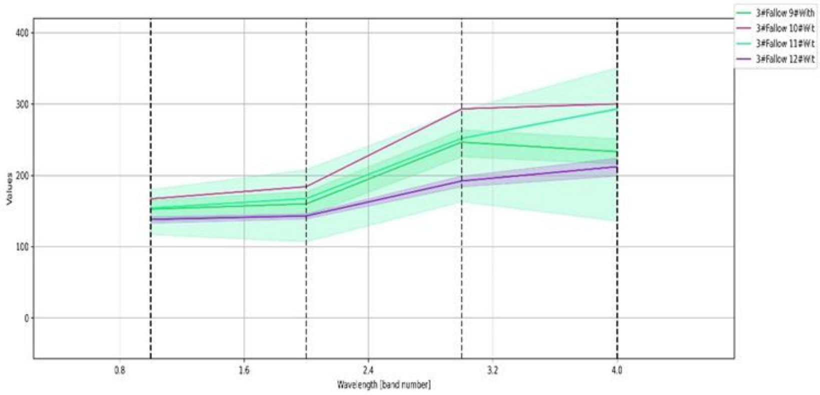

Fig. 7. Fallow land signature.

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. Some examples of how your references should be listed are given at the end of this template in the 'References' section, which will allow you to assemble your reference list according to the correct format and font size.

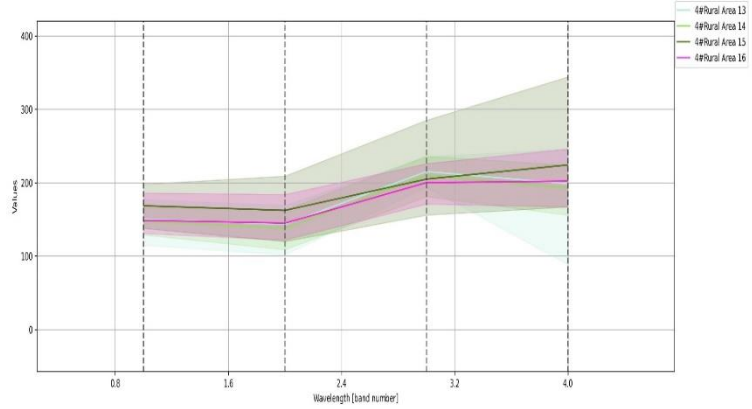

Fig. 8. built up area signature (Rural).

3.1.5 Barren Area

Barren areas, such as deserts and rocky outcrops, have a moderate to high reflection are observable, NIR, and SWIR areas of the band 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.

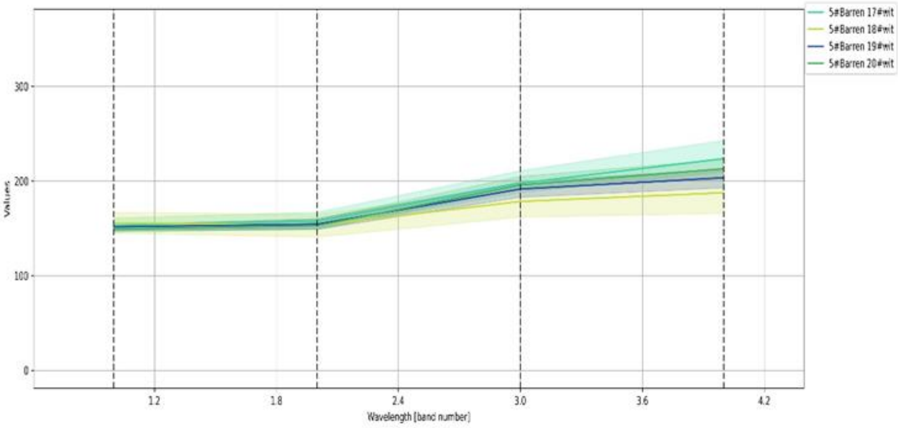

Fig. 9. Barren area signature.

Table. 2 shows summarize 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 algorithm assumes that the apiece class in each class can be described by a normal distribution. The Bayes theorem, which specifies the a posteriori distribution P(i|), or the likelihood that a pixel with an edge exists, is the source of the maximum likelihood criteria under supervised classification. The class I vector in equation (1) is provided by [13].

$$P(Ci|x) = P(x|Ci) * P(Ci) / P(x) \quad (1)$$

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) calculates the Euclidean distance d (x, y) between the spectral signatures and the spectral signatures of the image pixels in the training data set. The following formula calculated the spectral range:

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

where x and y are the spectral signature vectors of the image and training area respectively, and n is the number of bands in the image [14]. After calculating the spectral distance for each pixel in an image, the appropriate class is assigned with the closest spectral signature respective to the training set using the discrimination function shown eq (3) [15].

$$x \in c_k \Leftrightarrow \mathrm{d}(x, y_k) < d(x, y_j) \tag{3}$$

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.

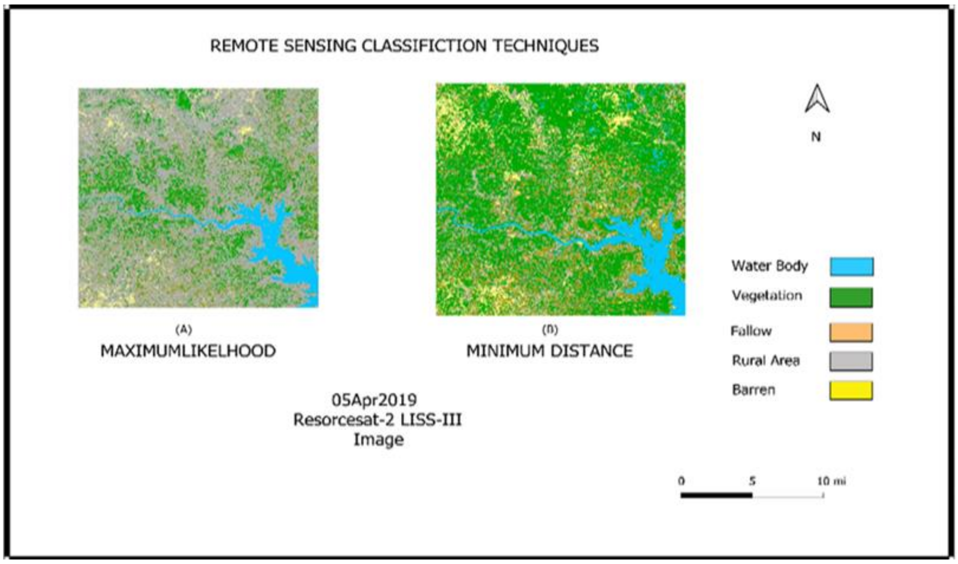

Fig. 10. Liss-III classified image.

3.3 Accuracy Assessment

Accuracy assessment compares the classification to field information to regulate how well the grouping matches with the field information. When comparing the classifier's findings with the actual ground truth data, it is necessary to obtain a suitable amount of field information (sample) for every group. [16]. The uppermost absolute accuracy which is 92.29% given the maximum likelihood algorithm while Kapp is 0.86%. The minimum distance classifier gives lowest overall accuracy is 78.81 and Kapp statistic is 0.71. The following Table.3 demonstrations overall accuracy and Kapp coefficient.

Table. 3 overall accuracies

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

4. RESULT AND ANALYSIS

In this study compare the result of two classifiers. Shows that there is significant difference in the use of the dual types of classifiers. [17]. In this study the LISS-III images 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 results

Class	Sum of Pixel	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 show the ratio to each land cover classes. 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 land makes up 2.8369%. In above table.4 to each land cover class in square kilometre's. The water bodies is 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 kilometre's. The zone of barren is 20.755 square kilometre's. The Minimum distance algorithm is a managed organization technique that allocates all pixel in an image for 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 Results

Class	Sum of pixel	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 results give the percentage of each terrain class in the image, as well as the whole number of pixels in all class and area of all classes in square meters and square kilometers. Land cover classes are water bodies, vegetation, fallow, built 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.

5. CONCLUSIONS

In this study two supervised classification techniques, Maximum Likelihood Algorithm and Minimum Distance Algorithm are compared with Resoursat-2 LISS-III images. MDC calculates the spectral mean signature distance of each class of pixels and assigns a level to the smallest class of pixels. 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. Performance of the algorithm can dependent on several factors, as well as the value of the training data. 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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All authors have equally contributed.

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