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Classification and Mapping of Land Use Land Cover change in Kanyakumari district with Remote Sensing and GIS techniques

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Abstract

The LULC features in Kanyakumari district are particularly associated with agriculture expansion, ground water depletion and urbanization. Monitoring LULC is necessary in order to understand the overall dynamics of population and quality of life. The primary objective of this study is to analyze the LULC of kanyakumari district, where the increase of population and climatic variability causes the greatest environmental impact on vegetation, forest, ground water pollution and also deterioration of bare land with more built-up and dumping of garbage. This study mainly focuses on the comparison of three different classifiers namely Mahalanobis Distance Classifier, Neural Net Classifier (NN) and Adaptive Coherence Estimator in ENVI 5.1 for LULC classification from Landsat images, to select the best suitable method of classifier for the different features. The classified LULC features are categorized as built-up areas, waterbodies, agriculture land, hilly areas, forest and bare land.

The accuracy was analyzed by finding the error matrix using google earth and photo interpretation, which had helped to get the accurate accuracy. The overall analysis shows that the Adaptive Coherence Estimator overperformed to other classifiers studied in this work. The change analysis map of the Landsat images generated using QGIS2.14.4 indicates the overall changes.

Keywords: Land use/Land cover, Remote Sensing, Envi 5.1, QGIS, Kanyakumari.

INTRODUCTION

Global environmental changes can be well understood by Land Use/Land Cover (LULC) analysis and change detection (Dickinson, 1995; Gupta and Srivastava, 2010; Mukherjee et al., 2007; Patel et al., 2012; Srivastava et al., 2011). The prime causes and factors for global and regional LULC changes are many such as tropical deforestation, rangeland modification, agricultural escalation, urbanization and globalization (Agarwal et al., 2001; Geist, 2005; Lambin, 1997; Veldkamp and Lambin, 2001; Zeng et al., 2008). Biophysical features and social and economic factors are also playing a part in this remarkable change in land cover (Aspinall, 2004; Zeng et al., 2008). The term "land cover" and "land use" play different roles. Land cover can be taken as what covers the surface of the earth naturally and land use is how the land is used by human beings. Examples of land cover classes that are used in this work include: water, forest, bare soil and hilly areas. Land use examples include built-up and agricultural land. LULC classification and analysis plays the main role in the development of the environment (Iqbal and Khan, 2014; Kantakumar and Neelamsetti, 2015; Lin et al., 2015). This can be achieved with the use of different classification algorithms (Richards and Jia, 2006; Amin and Fazal, 2012; Mohammad et al., 2015). Accurate output can be achieved with the use of spectral properties of the classification of Landsat images (USGS, 2004; Muttitanon and Tripathi, 2005; Kawakubo et al.,2011). Better understanding of the changes in the environment can be achieved with the use of satellite images (Misra et al., 2013). The mapping of LULC features which is performed using available records, field survey data and old maps (conventional method) is often time consuming, exhaustive and expensive and cannot be updated to meet up with the rapidly changing environment (Anderson et al., 1976; Wickware and Howarth, 1981; Singh, 1989; Nemani and Running, 1997; Nayak, 2002; Wang et al., 2004, 2008; Rawat et al., 2013). GIS and developments in the field of remote sensing deals with better accuracy and decision making in the scientific field. The main objective of this study focuses on the comparison of three different classification algorithms for Landsat images of KanyaKumari district, which are Mahalanobis Distance, Neural Net (NN) and Adaptive Coherence Estimation in order to select the best method.

Study area and data

Satellite images provide accurate geospatial information describing the transformation in LULC (Foody, 2003; Herold et al., 2002; Yuan et al.,2005). The study area chosen for analysis is Kanyakumari district, which is the southernmost district in the state of Tamil Nadu and is also the southernmost tip of Indian peninsula. Established on 1 November 1956, it has the headquarters in Nagercoil, and it has four talukas Agastheeswaram, Kalkulam, Thovalai, and Vilavancode bearing a total area of 1,684km^2. The sensex rate of 2011 has shown the population as 1,863,174, having a sex ratio of 1000/F-1014/M. The literacy rate is 97.6%. Kanyakumari is the popular tourist place where three seas meet, namely Bay of Bengal, Indian ocean and Arabian sea making a better place to reach between November and March. The image selected for analysis was recorded on 22-01-2015. The landsat image with datum WGS-84 of 2015-Landsat_8 was taken for analysis. According to the survey done by the Government of India, Ministry of Water, Central Ground Water Board, South East Coastal Region, Chennai, September 2008, the land use of Kanyakumari district is 167200 hectares. Forest cover is 50486ha, Non agricultural land is 28409ha and the cultivable barren land is 4000ha.

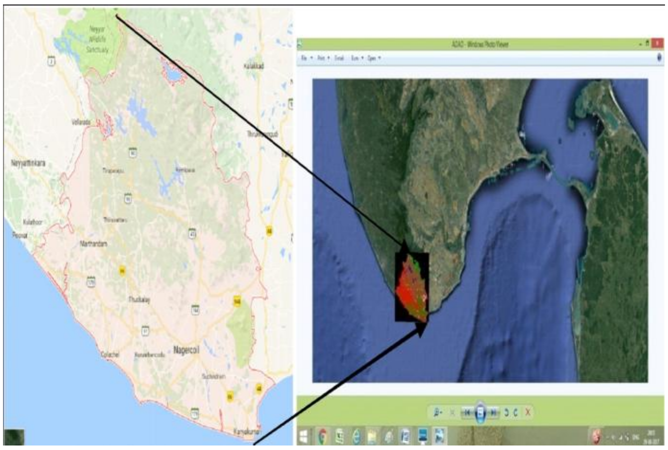

Figure 1 : Base map of Kanyakumari and the position of the chosen area in google earth

The present study is carried out for the analysis of the changes in LULC features in the Kanyakumari district using remote sensing and GIS technology. The Landsat -8 image for the year 2015, covering the study area was obtained from the http://bhuvan.nrsc.gov.in online portal.

Methodology

The methodology used for LULC change analysis is shown in Figure 2. The methodology is divided into three main parts. They are Pre-processing, Classification and Post-processing.

Satellite image pre-processing

Satellite image pre-processing prior to the detection of change is immensely needed and has a primary unique objective of establishing a more direct affiliation between the acquired data and biophysical phenomena (Coppin et al., 2004). The spectral properties of the multispectral images were enhanced using different filtering algorithms to obtain accurate attributes from the image (Wood, 1996; Wright et al., 2006; Mujabar and Chandrasekar, 2011).

Conversion of raster bands from DN to Reflectance

The first part of the analysis was started with the conversion of Landsat DN to the Atmospheric reflectance using the equation

$$L_{\lambda} = N * g + b$$

Where:

Lλ- radiance-cell value
N - digital number-cell value
g- gain for a specific band
b- bias for a specific band

The Band set RGB = 432 was chosen for the interpretation of the image, and with this combination the healthy vegetation reflects the maximum part of the incident light making the vegetation pixels appear red in colour.

Dark Object Subtraction

The radiometric Correction for the image was carried out using QGIS. This technique was applied to the satellite imagery to bring out the pixels that are hidden in complete shadow. This is known as Dark Object Subtraction. Within the satellite image some pixels are in complete shadow and the radiances received at the satellite are due to atmospheric scattering. Working with atmospherically corrected data produces the most accurate results for satellite image processing applications.

Land use and Land cover feature extraction

The base map which is the vital part required for classification was created by using a Google Earth image. Google Earth and photo interpretation were used to recognize and confirm the different features in the study area. In this study, training samples were generated by creating signature files and the samples were generated using polygon vectors for each feature. The polygons were drawn manually around the selected features to create the region of interest(ROI). Confusion among the features can be avoided by having a satisfactory spectral signature (Gao and Liu, 2010). The created signature file was finally used for supervised classification to classify the pixels to the correct class without error. For the classification of LULC, the created polygon ROI's were used and six classes were determined from the Landsat satellite imagery of 2015.

Satellite image Annotation

The Landsat metadata image was imported into the ENVI(v5.1)(Environment for Visualizing Images) image processing software by importing the directory containing landsat bands and the MTL file and the atmospheric correction was done for the Landsat-8 imagery of 2015 for the LULC classification. The image georeferencing can be done before or after classification depending on the need. This was done using a digitized and cropped base map, shown in Figure 1 to get the exact study area coverage. This helps to reduce the size of the image file and removes the inapplicable data in the file, and the processing time will be less which makes the analysis easier and simpler.

Segmentation of satellite images into multiple predefined land cover classes was done by drawing polygons. Following segmentation is the preview mode that was used to check and correct whether the sample is correctly chosen or not. Repeated segmentation and testing of previews helped to improve the accuracy. The same band set (4,3,2) was used for the classification of all the classes, in order to minimize the bias caused by using different band combinations.

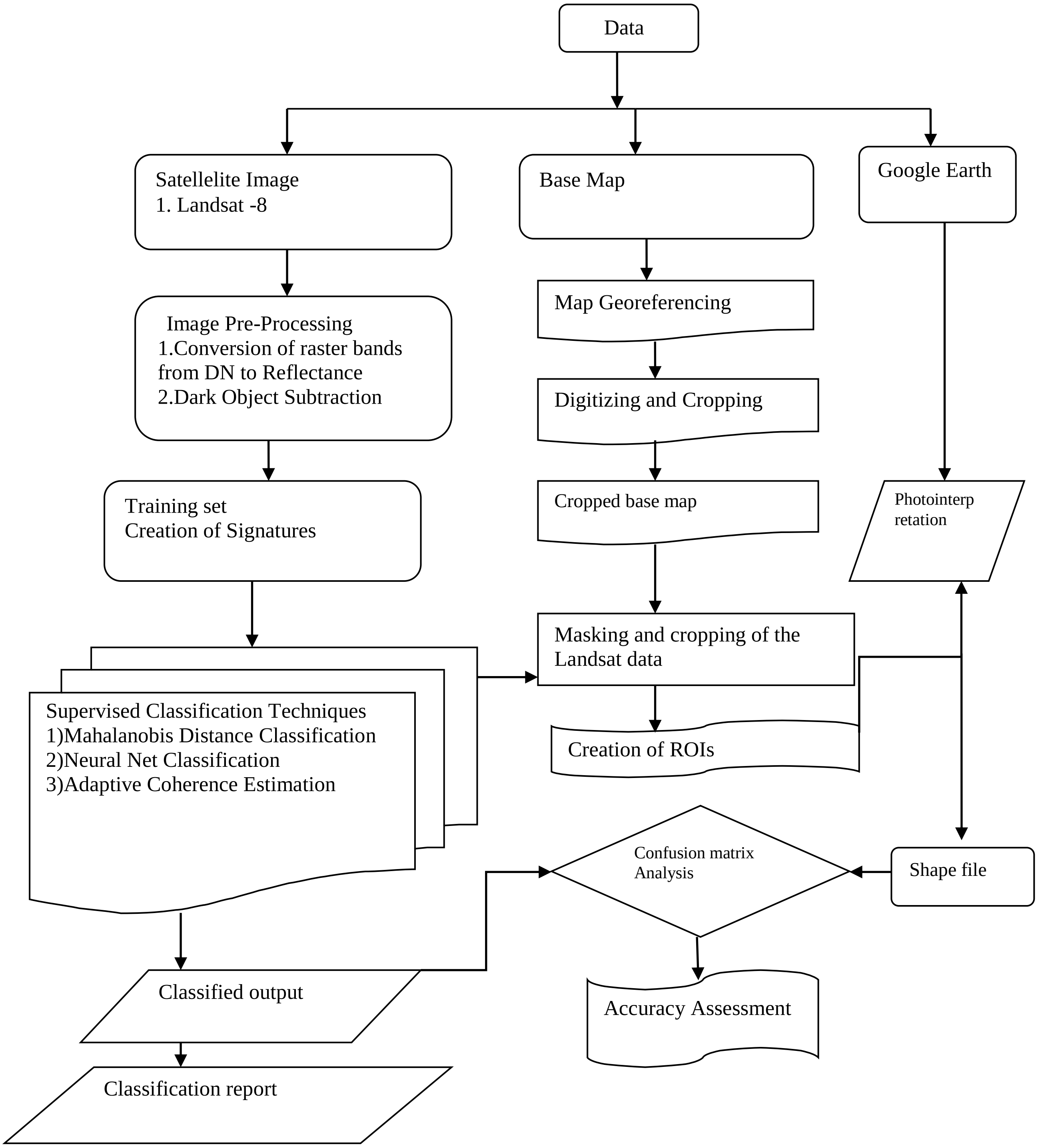

Figure 2: Methodology

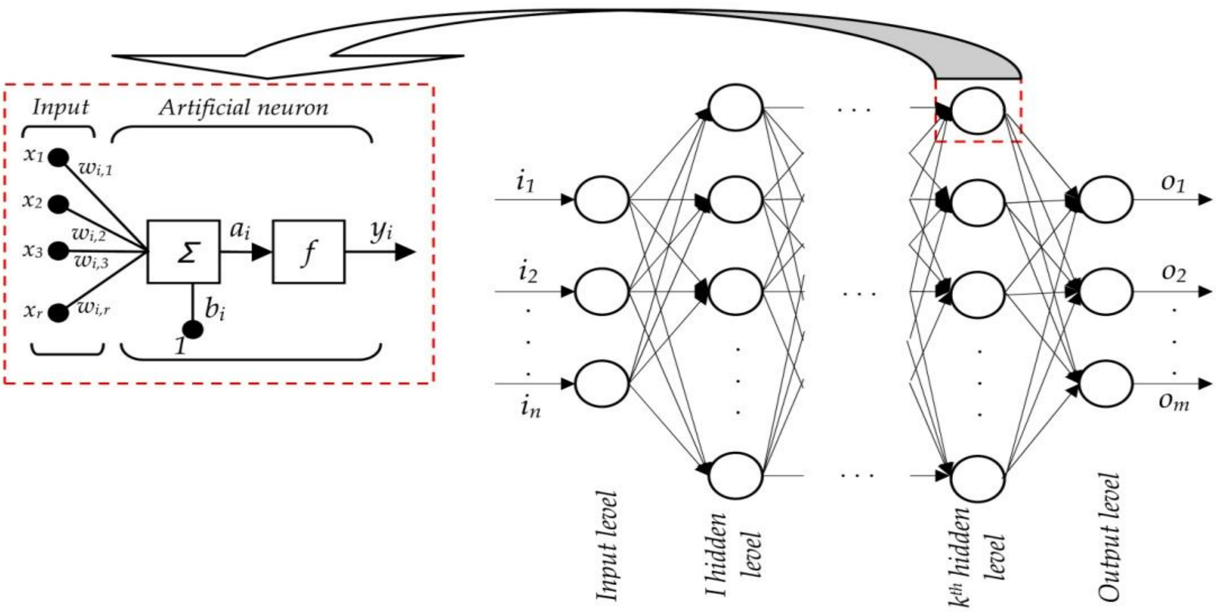

Figure 3: Neural Network

Mahalanobis Distance classification

The Mahalanobis distance is a measure of the distance between two points. It has the ability to capture the statistical differences between two distributions of colour components. Given a set of pixels x and another set of pixels y, we can estimate the mean and covariance, and then we compute the distance between two pixels as the minimum of their relative mahalanobis distance. The equation given below is equivalent to the Mahalanobis distance for a two dimensional vector with no covariance. The general equation for the Mahalanobis distance uses the full covariance matrix, which includes the covariances between the vector components. Mahalanobis distance can also be defined as a dissimilarity measure between two random vectors and of the same distribution with the covariance matrix S:

$$d_M(x,y) = \sqrt{(x-y)^T S^{-1}(x-y)}$$

The Mahalanobis distance reduces to the Euclidean distance, only if the covariance matrix is the identity matrix. If the covariance matrix is diagonal, then the resulting distance measure is called a normalized Euclidean distance:

$$d(\vec{x}.\vec{y}) = \sqrt{\sum_{i=1}^{n} \frac{(x_i - y_i)^2}{s_i^2}}$$

Neural Net Classification

Neural net classification can be carried out in n number of steps. The output error from the first layer is fed back as input into the network and the weight can be modified to get the required output, by modifying the network algorithm for further iterations. The three different layers used in this process are input, hidden and output. There is one input layer and one output layer, but there can be 'n' number of hidden layers. The output layer of the classifier is the final layer, where there is one node for each class. Complex urban environment classification can be effective using deep Belief networks (Qi Lv,Yong Dou ,2015). Supervised training, preview and classification, are helpful in assigning the correct class for each pixel, and the output nodes can be assigned with the correct value 1 for the node corresponding to the correct class, and 0 for other nodes. (In analysis, better results have been found using values of 0.9 and 0.1, respectively). It is thus possible to calculate the error associated with each node by comparing the network's output values to these exact values, (the Delta rule). The error terms in each node are then used to assign the weights in the hidden layers so that the next classified output values will be closer to the correct values.

Adaptive Coherence Estimator

For nonhomogeneous environments, the Adaptive Coherence Estimate detector satisfies the constant false alarm rate (CFAR) property. A particular pixel level is fixed and if the pixel level crosses the threshold it is considered that it belongs to that particular class. The threshold can be raised and lowered to maintain a constant probability of false alarm. A particular threshold level was fixed, as the background against which the targets are to be detected is constant with time and space. Unwanted clutter and interference cause changes in disturbance level. The standard binary hypothesis test for the detection problem is formulated as.

$$H_0: \begin{cases} k = n \\ k_l = n_l \end{cases}, l = 1, \dots \dots L$$

$$H_1: \begin{cases} k = \alpha v + n \\ k_l = n_{l,} \end{cases}, \text{l=1,......L}$$

Where n and n_l are independent of each other.

Accuracy Analysis

The Neural net, Adaptive coherence and Mahalanobis distance parameters need to be optimized for better results and thus require a preliminary analysis using a validation tool. In this study, six features were chosen for analysis. Ten polygon training samples were selected for each feature for training and classification. After classification, for accurate estimated results, another set of forty ROI's as shown in Figure 6 were taken into account. The class separability of all six classes were assessed for all ROI's and assigned based on the six spectrally separable groups generated for the training. The performance of all classifiers were measured in terms of overall accuracy and kappa coefficient.

To evaluate the performance of the classifiers, the accuracy assessment was carried out with the use of validation tools and datasets. That specific observations were assigned to each category on the classified image. The kappa coefficient was computed, using the formula

$$x = \frac{\text{Observed accuracy} - \text{Chance agreement}}{\text{Sum of product of row and column totals for each class}}$$

A kappa value of 1 shows, the agreement is perfect and the values less than 1 implies that the agreement is not perfect. Rarely, does kappa give a negative value. But, the interpretation about a good level of kappa agreement varies, as there are different opinions about the kappa interpretation. According to Altman (1991) the interpretation of kappa accuracy is considered as

Poor accuracy = Less than 0.20

Fair accuracy =0.20 to 0.40

Moderate accuracy = 0.40 to 0.60

Good accuracy = 0.60 to 0.80

Very good accuracy =0.80 to 1.00

Classification errors occur when a pixel belonging to one class is assigned to another class. Accuracy is calculated in terms of percentage. Figure 5 clearly shows the accuracy analysis and kappa coefficient of the three classifiers. User Accuracy (Errors of commission) occurs when a pixel belonging to some other class is included in the class being evaluated. In the present analysis the classified image is evaluated using a pixel-by-pixel comparison. The consumer's accuracy (CA) or User accuracy (UA) is computed by finding the ratio of correctly classified pixels to the total number of pixels assigned to a particular class. Table 3 and 4 clearly shows the producer accuracy and user accuracy of our analysis. Producer Accuracy (Errors of omission) occur when a pixel belonging to a particular class is left out of the class or assigned to some other class. This evaluation is done in reference with the sample or reference image. The PA is the correctly classified pixels of a particular category in the image.

Assessment of LULC of Kanyakumari district is extracted from the Landsat-8 image of 2015 using the three algorithms of supervised classification, Mahalanobis, Neural net and Adaptive coherence.

Table 1: Class Vs Percentage

	Percentage Classification %		
Class	**Neural Net**	**Mehalanobis**	**Adaptive Coherence**
Builtup	17	5.85	1.3
Waterbodies	0.8	1.7	1.77
Agriculture	10.3	14.2	19.8
Hilly Area	22.2	26.4	17.1
Forest	3.18	6.16	12.1
Bare land	1.05	0.2	0.5

Experimental results and Discussions

The experimental results have given a crystal clear map of different Classifications. The six different types of land form are shown in different colours. Yellow colour shows the built-up area, blue indicates the waterbodies, light green shows the vegetation, dark green indicates forest, pink shows the bare land and finally brown indicates the hilly areas. When analyzed all three results with the google earth using photo interpretation, and the hands on experience in the image analysis, we came to a conclusion that Adaptive coherence classification has given the most accurate result compared to Mahalanobis and Neural Net. Thus the result gives the overall accuracies of 72.78% for neural net, 73% for Mahalanobis distance and 96.32% for Adaptive Coherence Estimation. The overall kappa co-efficient values are 0.34, 0.34 and 0.49 respectively.

Post-processing analysis is used for the analysis of producer accuracy and user accuracy which helped in saving time and acquiring the best results. Figure 7 clearly shows the spatial distribution of the major LULC classes in the study area for the year 2015. The classification is done in the aerial extent of LULC features and the percentage of the pixel count and the corresponding values for all classifiers are shown in Table 1 and its corresponding graphical representation is shown in Figure 4. Hilly area is one of the natural features of Kanyakumari district. The hilly area which is the land cover at Kanyakumari district are at different elevation with unique climate and vegetation. Mahendragiri marks the highest peak in Kanyakumari District. Other important hills are Kattadimalai, Vellimalai, Thadamalai, and Maruthamalai.The hilly area is given as 22% in Neural net and 26.4% in mahalanobis, and 17.1% in Adaptive Coherence Estimation. The analysis shows that all three algorithms have given almost the same output. Builtup refers to the land used for human habitation for the buildings which is the main need of humanbeings. This is directly proportional to the population.

As Kanyakumari is a tourist spot we could see a rapid increase in builtup areas in the shore areas. As shown in Figure 4 most of the coastal plains and sand dune complexes are coveted to resorts and hotels and the barren land and agricultural lands are encroached for settlements too. Built-up which is less in Adaptive coherence(1.3%) and 17.0% for neural net and 5.85% for mahalanobis is almost equal to the classification made by Minimum likelihood distance which is 5.32% (S.L.Senthil lekha, S.S.Kumar.2015) and (S. Kaliraj,2017) by maximum likelihood classification for settlements and builtup as (6.01%).

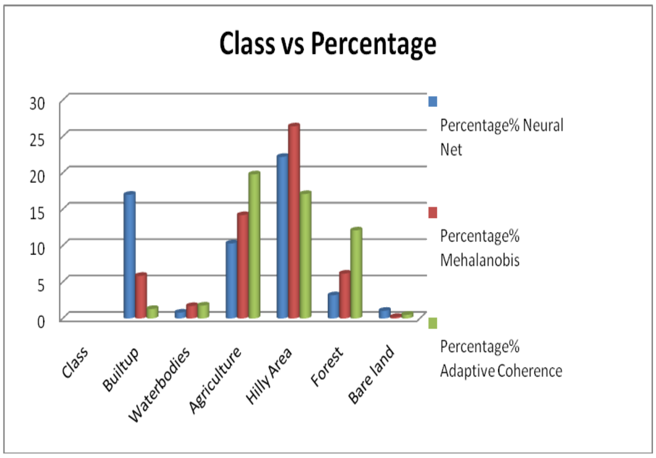

Figure 4: Change analysis- Class v_s Percentage

According to the analysis and results it is considered that mahalanobis is the best classifier for classification of builtup areas. Kanyakumari district is enriched with immaculate and manifold forests with different varieties of flora and fauna. Though small in area, it has as many as 14 forest types which mostly comprise of teak and thorn forest. It occupies an area of 50486 hectares which is about 30.2% of the total district geographic area. In our analysis the Forest area is shown as 12.1% in Adaptive coherence estimation and 3.18% in neural net and 6.16% in Mahalanobis Distance Estimation.The waterbodies of Kanyakumari district include rivers, dams, lakes, ponds, waterfalls and also beaches. There are three major rivers in kanyakumari district, namely Thamirabarani, Valliyar and Pazhayar. The main dams include Pechiparai and Perunchani. Neural net classification gives an estimate of 0.8% of waterbodies while Mahalanobis distance of 1.7% and Adaptive Coherence Estimation with 1.77%. Mahalanobis and Adaptive coherence have given the same percentage and these two algorithms can be considered as the best for the analysis of waterbodies. This is almost equal to the percentage of water bodies using Minimum likelihood distance (S.L.Senthil lekha, S.S.Kumar.2015). When considering waterbodies almost all algorithms have given the same percentage. Bare land in Adaptive Coherence is 0.5%, 0.2% in Mahalanobis Distance and 1.2% in Neural net classification. Economically, people mainly depend on agriculture. Agriculture of Kanyakumari District mainly depends on monsoon rains. Many irrigation projects have been constructed to utilize the rainwater in a useful manner. According to the map Agriculture is 19.8 in Adaptive Coherence, 14.2% in Mahalanobis and 10.3% in Neural Net Classification.

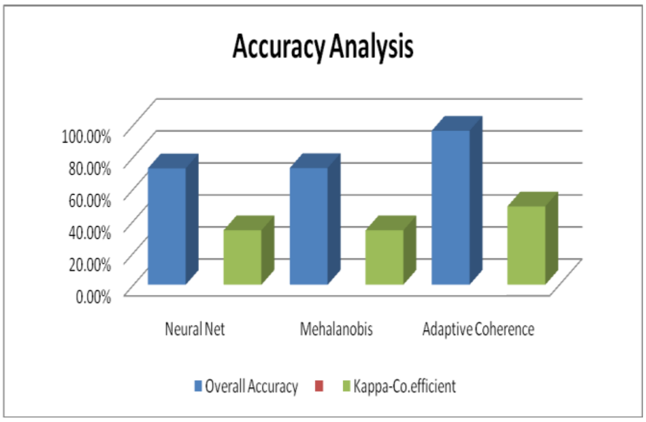

Figure 5: Accuracy analysis

Overall accuracy and Kappa statistics analysis of classified images (post processing)

The accuracy analysis for the three classified images were done by using photo interpretation using the extra ROI's created for the analysis. Google earth was used for the confirmation of the created ROI's. The overall accuracy shown in Figure 5, has specified that the ACE has acquired the highest accuracy as compared to other two classiifers. For the built-up class the classifiers Neural Net and Mahalanobis returned the user's accuracy of nearly 79.6% and 79.8%, except Adaptive Coherence Estimation giving 89.6% accuracy and giving a producer's accuracy of 79.45 for Neural Net, 78.6% for Mahalanobis and 89.2% for Adaptive Coherence Estimation, meaning that all of the pixels classified as builtup class has almost the same percentage for user's and producer's accuracy.

Table 2: Error matrix Result, Kappa statistics and Overall classification accuracy.

Classification	**Neural Net**	**Mehalanobis**	**Adaptive Coherence**
Overall Accuracy	72.78	73%	96.32%
Kappa-Co.efficient	0.34	0.34	0.49

The classification of the waterbodies by the Neural net and Mahalanobis showed an user's accuracy and producer's accuracy of 89% and 82.8% and 88.79% and 83.99% and the Adaptive Coherence gives an accuracy of 99.9% in both which is higher than the other two. Neural net and mahalanobis with user's and producer's accuracy of nearly 54% and 13-15% but Adaptive Coherence with 5.7% user's accuracy for the class agriculture and 2.07% producer's accuracy respectively which shows a very less accuracy when compared to other two. In general, both the User's and producer's accuracy for the hilly area class using Neural Net and Mahalanobis are in the range of 0.5% and less when compared to Adaptive Coherence which has 25% user's accuracy and 3.8% producer's accuracy. Other classes implemented herein are forest which has an user's accuracy of 100% for both Neural Net and Mahalanobis and 0.15% for Adaptive Coherence which shows a very low accuracy. On the other hand bareland class for Neural Net and Mahalanobis have an user's accuracy of 30% and 100% and 0.00 for Adaptive Coherence and producer accuracy of 11.15% and0.39% and 0.0% which is a relatively poor accuracy. The other two classifiers have almost same kappa coefficient.

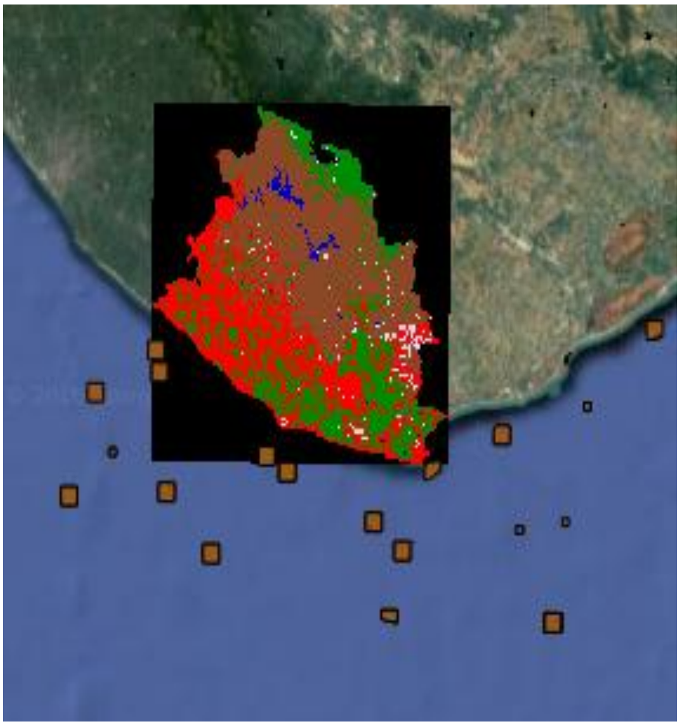

Figure 6 : Randomly created ROI's for Photointerpretation

Land use Land cover Distribution

The classification maps formed from the execution of the Mahalanobis, Neural net and Adaptive Coherence are shown in Figure 7 a,b,c. The LULC distribution and their change values for different algorithms are given in Figure 4,5. The land cover land use is given in percentage for all three algorithms. In this analysis the Landsat-8 satellite image for the year 2015 has been classified for six classes such as (1) Builtup, (2) waterbodies, (3) Agriculture, (4) Hilly area, (5) Forest, and (6) Bare Land. From the analysis the Adaptive Coherence classification was found to be the best by analyzing the overall accuracy and the kappa coefficient. The results indicate that in all the three algorithms the Adaptive Coherence Estimator has shown the best performance and it is considered as the best algorithm for the classification of Landsat-8 images.

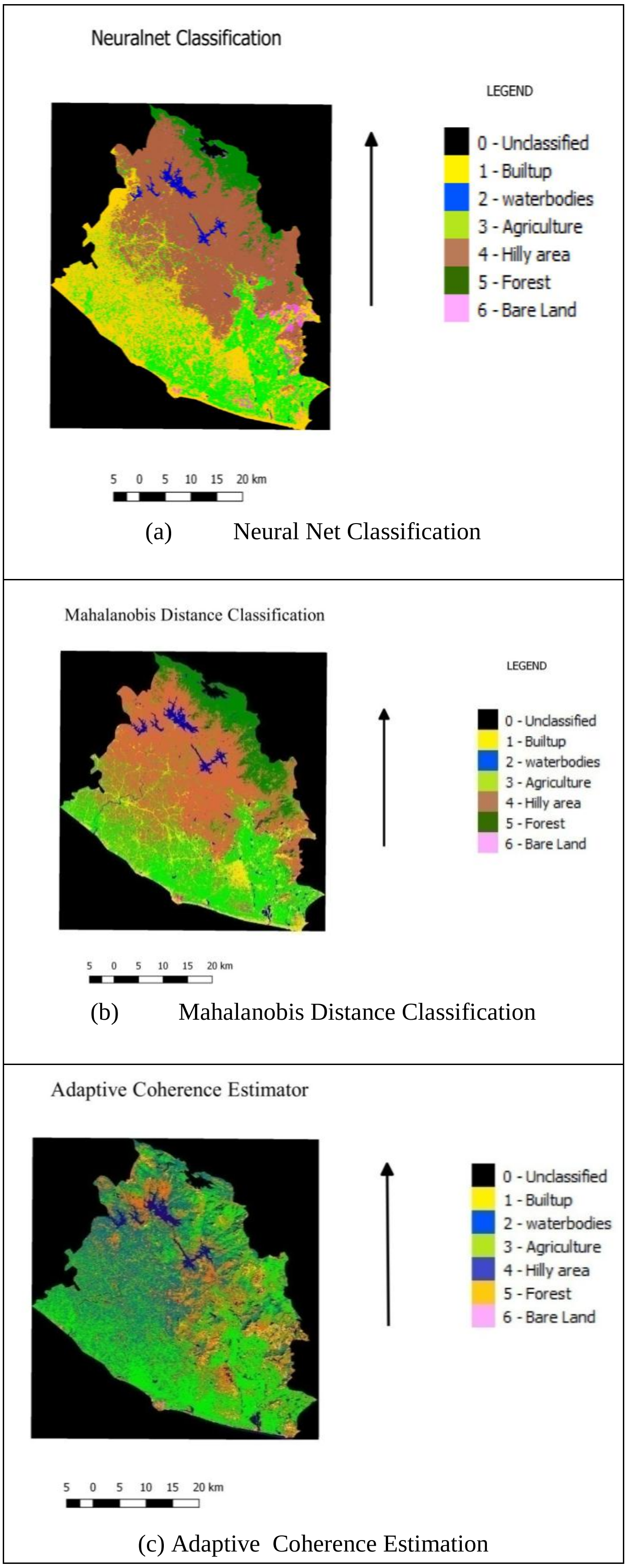

Figure 7 : Experimental Results, (a) Neural net classification, (b)Mahalanobis Distance Classification, (c) Adaptive coherence Estimation

Table 3: Producer Accuracy

	Classifier		
	Neural Net	**Mehalanobis**	**Adaptive Coherence**
Class			
Builtup	79.4	78.6	89.2
Waterbodies	82.8	83.99	99.9
Agriculture	13.14	15.35	2.07
Hilly Area	0.05	0.05	3.80
Forest	10.416	8.33	0.51
Bare land	11.15	0.39	0.0

Table 4: User Accuracy

	Classifier		
	Neural Net	**Mehalanobis**	**Adaptive Coherence**
Class			
Built-up	79.6	79.8	89.6
Waterbodies	89.0	88.79	99.9
Agriculture	54.8	59.04	5.70
Hilly Area	0.1669	0.09	25.5
Forest	100	100	0.155
Bare land	79.6	79.8	0.0

CONCLUSION

The error matrix is used to calculate the overall classification accuracy, Kappa Coefficient, User accuracy and Producer accuracy. The analyzed output is clearly shown in Table 1,2,3 and 4 and Figures 4,5 and 7 respectively.

Accuracy assessment was performed by comparing the maps of the three algorithms created by pixel analysis to a reference map of information sources. The main purpose of accuracy and error matrix analysis is to have quantitative and qualitative comparisons of different algorithms. In this analysis the results are examined to direct the "most suitable" and "most applicable" algorithm for a particular image and class.

The accuracy analysis using photo interpretation and error matrix was evaluated to identify the best classifier and the best suited algorithm for each class. The performance was also evaluated by validating the kappa coefficient, overall accuracy, user accuracy and producer accuracy. The classified images, the Adaptive Coherence Estimator, Neural Net Classification and Mahalanobis Distance Classification have proved that each algorithm is effective for a specific LULC. Adaptive Coherence has an overall accuracy of 96.3 % and kappa Coefficient 0.49 which is the best among all three classifiers in the overall accuracy and proved that it is more applicable for satellite image classification compared with Mahalanobis Distance which has an overall accuracy of 72.78% and kappa coefficient of 0.34. Neural Net has an overall accuracy of 73% and kappa coefficient of 0.34 which is the same as Mahalanobis Distance classification.

Study also shows that even though Adaptive Coherence outperformed the other two algorithms in the overall accuracy, each algorithm has its best analyzing power for the particular class of LULC.

Further analysis to improve the classification accuracy has to be conducted to enhance the accuracy of the algorithms for all classes and to test the capability of more classification algorithms in mapping Kanyakumari district. More analysis will also be carried out to find the most optimal algorithm for each class by other ensemble learning techniques.

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