Analysis of Multi-Frequency Polarimetric SAR Data using Different Classification Techniques

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ABSTRACT
Classification of polarimetric SAR images has become a very important topic after the availability of Polarimetric SAR images through different sensors like SIR-C, ALOS-PALSAR etc. The data over wet regions of India has been processed for classification of various land features like mangrove, ocean water, and clear water. In this study the utility of NASA's Shuttle Imaging Radar-C (SIR-C) data is evaluated for wet regions of India. Supervised and unsupervised classification techniques are used to classify the data. The SIR-C data is acquired over Kolkata region of West Bengal, India. The results show that multipolarization and multi-frequency SAR data helps to classify wetlands effectively. The combinations of different polarizations from L- and C- band helps to improve the classification accuracy. It was found that the combinations of channels (L-HV, C-HH, C-HV) and (L-HH, C-HH, C-HV) gave the best overall accuracies. These two 3 channel combination can differentiate well the six classes. The five band combination L-HH, L-HV, L-VV, CHH, C-HV gives the highest classification accuracy. It is greater than the three band combinations as given above. By applying enhanced Lee filter the accuracy can be further increased. The enhanced Lee filter removes the speckle effectively. Among all the classifiers Maximum Likelihood classifier gives the best accuracy.

Categories and Subject Descriptors
I.4.6 Image Processing and Computer Vision

General Terms
Algorithms, Measurements, Performance.

Keywords
Radar polarimetry, polarization, synthetic aperture radar, wetland, speckle, classification.

1. INTRODUCTION
Wetlands are under pressure due to high demand for land development for housing and agriculture. Most of mangrove forests were cleared for settlements, agriculture and fire wood. It is important to manage the wetlands and conserve them for the benefit of the society, flora and fauna. Remote sensing is very useful tool to map the wetlands and classify them.
Synthetic aperture radar technology is an advantage over optical remote sensing due to microwave penetration through vegetation and interaction with water under vegetation. Classifying remotely sensed data into a thematic map is very challenging because of many factors such as the complexity of the landscape in a study area, selected remotely sensed data, image-processing and classification approaches may affect the success of a classification. The major steps of image classification may include determination of a suitable classification system, selection of training samples, image preprocessing and feature extraction, and selection of suitable classification approaches, post-classification processing and accuracy assessment.
In this paper different both supervised and unsupervised classification techniques are used to process the multi-frequency multipolarized SIR-C C- and L- band data. In supervised classification technique Minimum Distance (MDC), Maximum Likelihood (MLC) and Decision Tree (DTC) are used and in unsupervised technique K-mean clustering is used. The results of different classifiers are compared and the classification accuracy with and without applying speckle filter is also compared.

2. LITERATURE REVIEW
Landsat and aircraft MSS data was processed by Butera (1983) [1] to classify the wetlands. Neural network classifier was used for wetland classification with a multi-temporal dataset of RADARSAT images [2] along with the textural information to improve the classification accuracy. SIR-C polarimetric SAR data have been used by Bourgeau-Chavez et al. (2001) [3] to map the wetlands and to find out the efficiency of various bands (polarization and frequency). In this study the utility of NASA's Shuttle Imaging Radar-C (SIR-C) data are evaluated for wetland mapping and monitoring. The fully polarimetric L- and C-band data are used in hierarchical analysis and maximum likelihood classification techniques. Results show that both L- and C- band are necessary for detection of flooding beneath vegetated canopies. HH- polarization is found in this study and others to be better than VV for wetland discrimination. The cross-polarizations (HV or VH) are needed for discrimination of woody versus herbaceous vegetation. RADARSAT multitemporal data with different incident angle were used to assess flooding and vegetation structure in forested wetlands by Townsend (2002) ([4], [5]). Touzi (2006) [6] had shown that the polarimetric information provided by RADARSAT-2 permits compensating for RADARSAT-1 weakness in vegetation specie discrimination and leads to an effective unsupervised classification of wetlands. The results from optical and SAR were combined by Ruan (2007) ([7], [8]) to improve the classification accuracy to identify inland fresh water wetland from crop. Hong (2007) [9] measured the backscattering coefficients and phase difference

for various bands for different polarization throughout a growth period of wetland rice field. Touzi et al. (2007) [10] introduced the new phase information of the complex symmetric scattering type which provides the information for an enhanced vegetation discrimination and wetland classification. ALOS PALSAR data have been used by Sato et al. (2008) [11] for water area classification in wetlands. The seasonal changes of wetland areas using high resolution POLSAR data is shown by Boerner et al. (2008) [12]. Multisensor, multitemporal SAR and multispectral data is used by Bourgeau-Chavez et al. (2008) [13] for wetland monitoring. The best method for mapping wetland type and adjacent land use was a fusion of data from multiple SAR sensors (JERS, ERS, Radarsat-I) and Landsat. This data fusion allows for the unique SAR and optical/IR information to be integrated for improved mapping capabilities. By merging optical with microwave SAR data, the number of land cover classes can be increased. A modified four component scattering power decomposition scheme for various bands fully polarimetric data was proposed by Yajima et al. (2008) [14] for retrieving scattering characteristics of POLSAR images. Polarimetric behavior of the backscattering temporal signatures is analyzed by Marti-Cardona et al. (2009) [15] with the aid of extensive site data, such as a precise digital elevation model and continuous record of water level and meteorological parameters. Conclusions on the feasibility to discriminate emerged versus flooded land are derived for the different incidence angles, land cover types and phenological stage. Whitecomb et al. (2009) [16] developed a thematic map of wetlands changes in Alaska based on 1997-1998 JERS data and 2007 PALSAR data. They compared the results of the PALSAR classification to those of the JERS classification for the state of Alaska which covers around nine wetlands classes and two uplands classes in order to detect changes in wetlands type during the decade long interval between the two sets of SAR imagery. Sato et al. (2009) [17] proposed an accuracy improvement of the vegetation area classification based on the POLSAR image analysis, when vegetation and man made areas are both included in the radar target region. They introduced a simple compensate polarimetric marker, T13 or T31. The proposed marker works well not only for Pi-SAR data but also for ALOS/PALSAR data. A simple water area classification technique using the scattering power decomposition based on POLSAR image analysis has been proposed by Sato et al. (2009) [18].

Decision tree algorithms can be used to solve the problems of feature selection. Decision trees are commonly used for variable selection to reduce data dimensionality in image analysis [19]. Classification accuracies from decision tree classifiers are often greater compared to using maximum likelihood or linear discriminant function classifiers [20]. Some studies have indicates that decision trees can provide an accurate and efficient methodology for classification of remote sensing data ([21], [22], [23]). Z. Qi a et al. (2010) [24] proposed a new method that integrates polarimetric decomposition, object-oriented image analysis, and decision tree algorithms. The comparison between the proposed method and the Wishart supervised classification method indicates that the proposed method outperforms the Wishart supervised classification method.

3. TEST SITES AND DATA SOURCES

SIR-C fully polarimetric data acquired at L- and C-bands on Oct. 5, 1994 have been used to map the wetlands in Kolkata region of India.

Kolkata is located in the eastern part of India at 22°82'N latitude and 88°20'E longitude. It has stretched linearly along the banks of the river Hooghly and has an elevation ranging between 1.5 to 9 metres. The city originally, was a vast wetland and now one of the most populated cities of the world. The city has a total geographical area of 1480 sq. kms. The city has been divided into different topographical regions. There are mainly five geographical units including east, west, north, south and central Kolkata. The adjoining regions include Howrah, Hooghly, North 24 Parganas, South 24 Parganas and Nadia. The city's soil type is mainly alluvial similar to the soil of Indo-Gangetic plains. Quaternary sediments consisting of clay, silt, various grades of sand and gravel underlie the city. These sediments are sandwiched between two clay beds, the lower one at depths between 250 and 650 m and the upper one ranging between 10 and 40 m in thickness. However, the city comes under the "Cyclonic Zone" creating very high damage risk from a Cyclone. Around Kolkata city also many wetlands and lakes are present. Fish cultivation is more in this area.

4. DATA PROCESSING AND CLASSIFICATION TECHNIQUE

In the supervised classification the selection of classes i.e. training areas play an important role. Divergence is a measure of separability between classes and may therefore be used to assess the quality of the statistics prior to image classification. Training set separability is a statistical measure of distance between two signatures and can be calculated for any combination of bands that is used in the classification, enabling you to rule out any bands that are not useful in the results of the classification. For the distance (Euclidean) evaluation, the spectral distance between the mean vectors of each pair of signatures is computed. If the spectral distance between two samples is not significant for any pair of bands, then they may not be distinct enough to produce a successful classification. The spectral distance is also the basis of the minimum distance classification. Therefore, computing the distances between signatures helps you predict the results of a minimum distance classification.

The formulas used to calculate divergence are related to the maximum likelihood decision rule. Therefore, evaluating signature divergence helps predict the results of a maximum likelihood classification. There are three options for calculating the separability. All of these formulas take into account the covariances of the signatures in the bands being compared, as well as the mean vectors of the signatures.

Both the Jeffries-Matusita and Transformed Divergence separability measures are used. These values range from 0 to 2.0 and indicate how well the selected training sites are statistically separate. Values greater than 1.9 indicate that the classes have good separability. For classes with lower separability values, the separability can be improved by editing the training sites or by selecting new training sites. If the separability value between two training sites is very low then those training sites can be combined into a single training site or region of interest (ROI).

Table 1: ROI (Class) separability for ALOS-PALSAR Sunderban data

ROI (Class) Pair		Jeffries-Matusita Distance
Marshy	land	0.71144136
Marshy	Vegetation	1.45088341
Urban	Vegetation	1.81676363
Urban	land	1.93542323
sea	land	1.94428483
Urban	Marshy	1.98040038
Sea	Marshy	1.99609833
lake	land	1.99824815
lake	Marshy	1.99893685
Sea	Vegetation	1.99999277
Sea	lake	1.99999826
Sea	Urban	1.9999998
lake	Vegetation	2
lake	Urban	2

Table 1 gives the ROI separability for SIR-C Kolkata. From table 1 it is seen that the marshy and land class are not well separated. On the other hand lake-vegetation and lake-urban are well separated.

For SIR-C C-band and L-band the data is first converted to its backscattering values by using special software developed by CSRE, IIT Bombay. Four db files are obtained by this software one for each polarization, HH, HV, VH and VV. The three files HH, HV and VV are merged for C-band and L-band using following command on command prompt.

Copy /b hh_L_db + hv_L_db + vv_L_db hh_hv_vv.img

After getting hh_hv_vv file, for C- and L- band the image is classified using minimum distance classifier for each band and the accuracy is computed using confusion matrix. The classes are sea, lake, urban, marshy, vegetation and land. For both C- and L-band the same training areas are used. The three bands from C-band and three bands from L-band are merged and then the results are classified. Similarly different combinations of bands from C- and L-bands are merged and classified with the same training areas.

Decision tree classifier is applied on C-band with hh_hv_vv bands together using ENVI. The backscattering values are used to set the expression for each class.

5. RESULTS AND DISCUSSION

5.1 Minimum Distance Classifier (MDC)

The results of each band combinations using a MDC are presented in table 2 and 5. Among the two frequency and three polarization combinations for Kolkata (West Bengal) region, combinations of L-HV, C-HH, C-HV and L-HH, C-HH, C-HV had the best overall accuracies (around 87.5%) (Bourgeau-Chavez et al., 2001). These two 3 band combination can differentiate well the six classes. The five band combination L-HH, L-HV, L-VV, C-HH, C-HV gives the highest classification accuracy (around 91%). It is greater than the three band combinations which are mentioned above.

By applying enhanced Lee filter the accuracy can further increased to 93.9%. Table 3 shows the results for classification of single polarized data. From the table it is seen that for all the land covers L-band is more effective than C-band except “Land” class. The C-band has less penetration power than L-band. For L-band, L-HV gives better classification accuracy for sea. L-HH and L-VV gives good accuracy for Lake. L-HH compare to L-HV and L-VV gives good results for urban class. For Vegetation class L-HH gives good results and L-VV gives good results for Marshy.

Overall results for L-VV are better than remaining polarizations. For C-band, C-HH gives better classification accuracy for Sea, Lake, Urban and Vegetation classes compared to other polarizations. C-HV gives good results for Marshy and C-VV gives better results for Vegetation. Overall results for C-HH are better than remaining polarizations.

Table 2 shows the effective band for a particular land cover.

Table 2: Effective bands for land covers

Land Cover	Effective Band
Sea	LHV
Lake	LHH and LVV
Urban	LHH
Marshy	LVV
Vegetation	LHH
Land	CHH

Figure 1 shows the accuracy for various land covers. From table 2 it is clear that the combination of all the bands from L-band and HH from C-band is used then the classification accuracy is much higher than the individual band as well as entire C- or L-band.

Table 5(a) shows the result for MDC. Table gives the image accuracies for different land covers as well as overall accuracy. The table also gives the respective value of Kappa. The classification accuracy is good when the value of Kappa is near to one.

Figure 2(a) shows the classified image for C-HH, C-HV, C-VV combination, figure 2(b) shows classified image for L-HH, L-HV, L-VV combination and figure 2(c) shows a classified image for L-HH, L-HV, L-VV, C-HH, C-HV for Kolkata (West Bengal) area. The data is classified for six classes namely sea, lake, urban, marshy, vegetation and land.

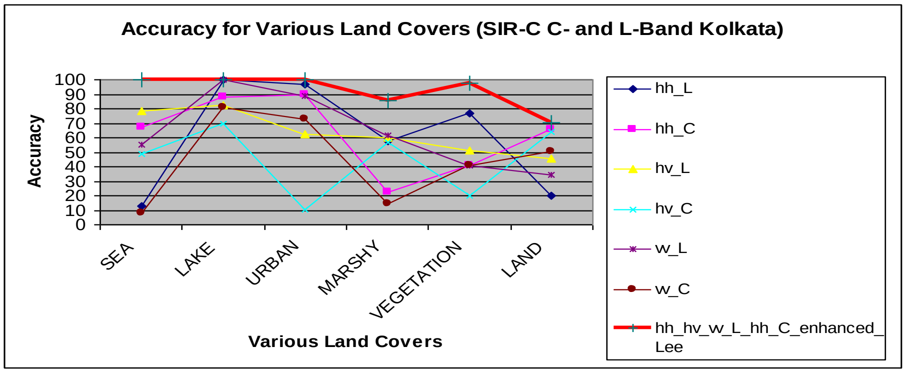
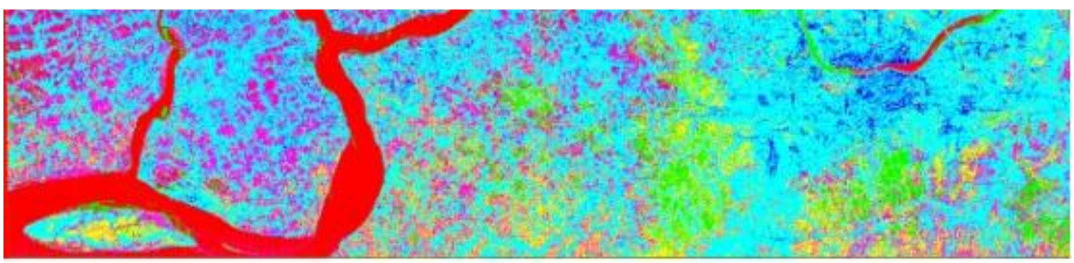


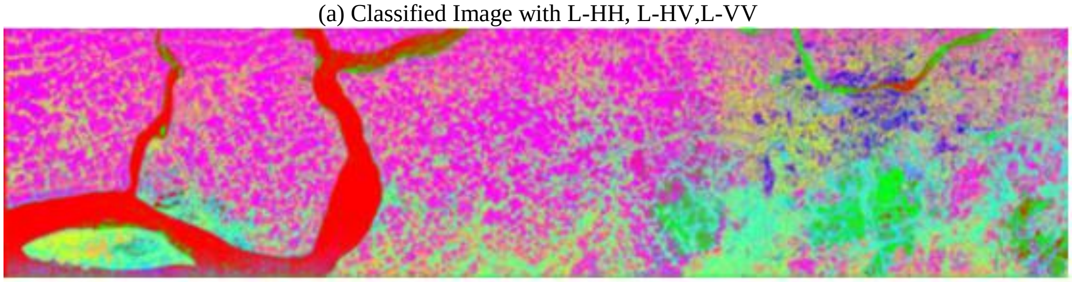
Figure 1: Accuracies for various land covers for different band combinations for SIR-C C- and L-band Kolkata data

Table 3: Classification accuracies for single band SIR-C C-and L- band Kolkata data after applying MDC

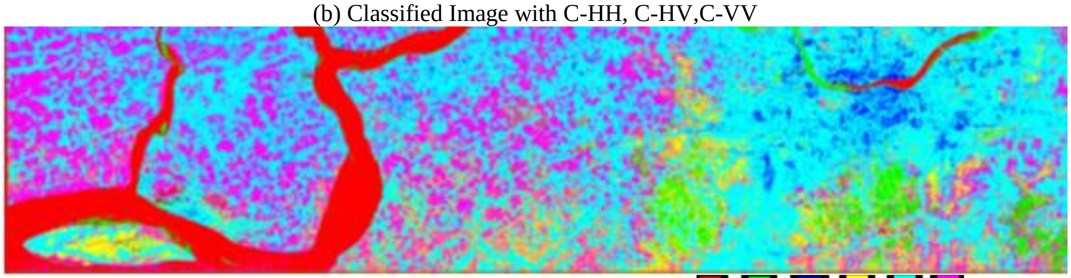
Classes	Sea	Lake	Urban	Marshy	Vegetation	Land	Accuracy
CVV	7.91	80.9	72.92	14.48	40.7	50.68	42.65%
CHV	48.97	69.52	10.79	56.48	20.13	64.27	45.30%
CHH	67.28	88.2	89.86	22.45	41.02	65.9	59.88%
LHH	12.78	100	96.66	57.85	76.61	19.97	62.03%
LHV	78.01	82.25	62.35	59.85	51.47	45.24	63.68%
LVV	55.04	100	88.67	61.61	40.48	34.78	64.49%



(a) Classified Image with L-HH, L-HV,L-VV



(b) Classified Image with C-HH, C-HV,C-VV



(c) Classified Image with L-HH, L-HV,L-VV, C-HH, C-HV 1 2 3 4 5 6
1: Sea, 2: Lake, 3: Urban, 4: Marshy, 5: Vegetation, 6: Land
Figure 2: SIR-C C- and L-band Kolkata (W.Bengal) Data Classified by Minimum Distance Classifier

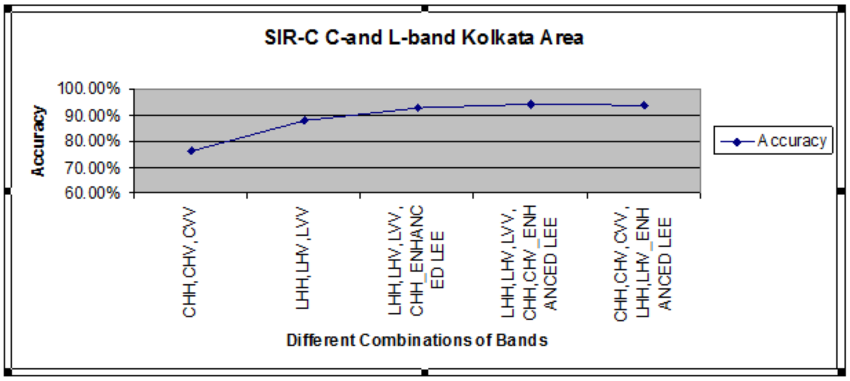


Figure 3: Classification accuracies for different band combinations for SIR-C L- and C-band Kolkata

Classification accuracy is computed using confusion matrix. Accuracy is computed for the training areas. Figure 3 shows the plot of accuracy versus 3 band and 5 band combinations of SIR-C L- and C- band for Kolkata area.

5.2 Maximum Likelihood Classifier (MLC)

The Maximum Likelihood classifier is applied on the five band combination L-HH, L-HV, L-VV, C-HH, C-HV after applying Lee speckle filter. From table 5 (b), it is observed that MLC gives better classification accuracy (around 95%) than MDC.

5.3 Decision Tree Classifier (DTC)

The Decision Tree is a simple and effective hierarchical classifier. The Decision Tree classifier performs multistage classifications by using a series of binary decisions to place pixels into classes. Each decision divides the pixels in a set of images into two classes based on an expression. Each new class can be divided into two more classes based on another expression.

Each new class can be divided into two more classes based on another expression. There is no limitation on number of decision nodes. The results of the decisions are classes. Ruan, et. al. (2007) [8] has explored the potential of knowledge rules in inferring information classes of wetland on historical imagery using decision tree classifier. They have used Landsat MSS and Landsat TM/ETM+ images for classification.

The backscattering values of 3 bands are used to form an expression. Figure 6 shows the decision tree used for classifying SIR-C L-band (LHH, LVV, LHV) data for Kolkata area. It is classified for 4 classes namely Sea, Vegetation, Lake and Urban. In the expression variables b1, b2 and b3 are used for bands LHH, LVV and LHV respectively.

The expression for node 1 is shown in the figure 6; similarly expression can be set for each node. Figure 4 shows the result of decision tree classifier which is shown in figure 6. Figure 5 shows the result of minimum distance classifier. It is classified with the same training areas as DTC. The data is processed using ENVI software. The classification accuracy for test sites is given in table no. 4 for DTC and table no. 6 for MDC. An example of a classification decision tree is presented in Bourgeau-Chavez et al. (2001) [3] to illustrate the hierarchical classification procedure. Only two channel SAR data (LHV and CHH) were used. More channels can be used to get better classification accuracy. In this paper the algorithm is applied for LHH-LHV-LVV and LHH-LHV-LVV-CHH-CVH five band combinations. The hierarchical classification theoretically would seem to be a better method for image classification provided the expressions are selected properly.

The confusion matrix for test areas using DTC and MDC is shown in table no. 4, and 6.

Table 4: Confusion matrix for test areas (DTC) (Overall Accuracy 95.80%)

Class	Sea	Vegetation	Lake	Urban
Sea	99.95	0	0	0
Vegetation	0	99.43	0	21.39
Lake	0.05	0.17	100	0.24
Settlement	0	0.4	0	78.37

From table 4 and 6 it is clearly seen that DTC gives equally good results as MDC. The accuracy for "Urban" class is better in MDC than DTC. The accuracy of DTC can be further improved by selecting proper expression at the respective nodes to divide the data into appropriate classes. The figure 7 shows the decision tree used for classifying 5 band combination (LHH, LHV,LVV,CHH,CHV) data into 5 classes. Table 7 gives the confusion matrix and figure 8 shows the classified image.

Table 5(a): Classification accuracies of each band combinations using a MDC for SIR-C L- and C- band Kolkata area

Classes	Sea	Lake	Urban	Marshy	Vegetation	Land	Accuracy	Kappa
LHH, CHH, CVV	69.99	99.48	98.81	49.04	79.65	55.43	74.46%	0.6931
CHH, CHV, CVV	94.37	85.39	92.13	56.55	63.22	71.88	76.13%	0.7125
LHH, LVV,CHH, CVV	74.11	100	99.24	68.89	80.52	48.78	79.06%	0.7473
LVV, CHV, CVV	99.57	100	91.69	67.2	82.15	61.55	83.43%	0.8007
LHH, LHV	99.67	100	96.98	70.34	92.82	44.02	84.47%	0.8128
LVV, LHV	100	100	91.26	68.12	92.82	58.97	85.00%	0.8196
LHV, CHH, CHV	98.81	89.14	96.76	73.33	96.3	74.18	87.57%	0.8504
LHH,LHV,LVV	100	100	97.41	76.02	94.12	56.52	87.67%	0.8513
LHV,LVV,CHV,CVV	100	100	91.91	71.11	93.8	73.78	87.83%	0.8537
LHH,CHH,CHV,	99.13	100	99.24	76.86	87.27	67.26	88.30%	0.8589
LHH,LHV,CHV,CVV	100	100	96.44	76.78	93.69	71.06	89.48%	0.8732
LHH,LHV,CHH,CHV	100	100	99.03	81.23	96.3	73.91	91.68%	0.8996
LHH,LHV,LVV,CHH,CVH	100	100	99.57	81.61	96.19	74.32	91.89%	0.9021
LHH,LHV,LVV,CHH,ENHANCED_LEE	100	100	100	85.67	97.71	70.52	92.63%	0.911
CHH,CHV,CVV,LHH,LVH_ENHANCED LEE	100	99.90	99.68	86.59	98.26	75.68	93.52%	0.9217
LHH, LHV, LVV, CHH, CVH ENHANCED LEE	100	100	100	86.97	98.26	77.72	93.93%	0.9268

Table 5(b): Classification accuracy using a MLC for SIR-C L- and C- band Kolkata area

Classes	Sea	Lake	Urban	Marshy	Vegetation	Land	Accuracy	Kappa
LHH, LHV, LVV, CHH, CVH ENHANCED LEE	100	100	100	91.57	96.08	79.89	94.9%	0.9384

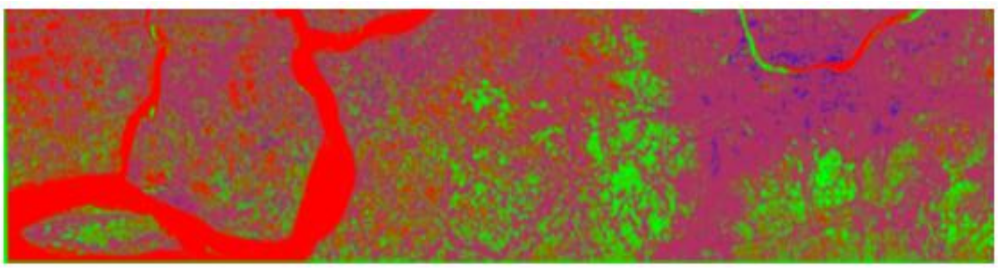


Figure 4: SIR-C L-band (LHH, LHV, LVV) Clas sified Image using Decision Tree Classifier

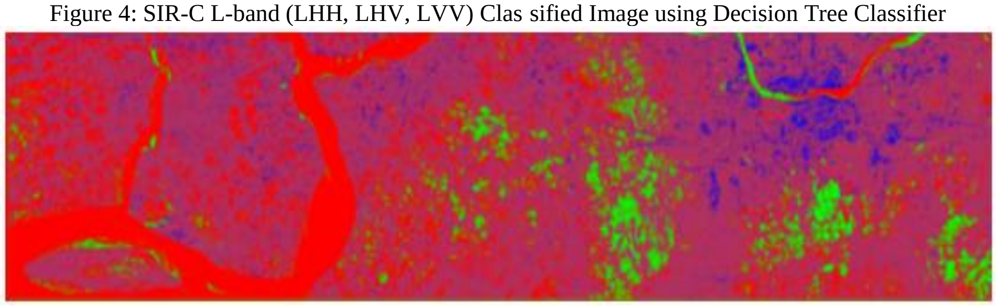


Figure 5: SIR-C L-band (LHH, LHV, LVV) Classified Image using Minimum Distance Classifier

Table 6: Confusion matrix for test areas (MDC) (Overall Accuracy 98.5270 %)

Class	Sea	Vegetation	Lake	Urban
Sea	99.48	0.06	0	0
Vegetation	0	98.8	0	5.45
Lake	0.52	0	100	0
Settlement	0	1.14	0	94.55

(b1 GT -17.504097) AND (b1 LE 2.147944) AND
(b2 GT -17.041639) AND (b2 LE 2.831671) AND
(b3 GT -37.171310) AND (b3 LE -22.308220)

Figure 6: Decision Tree for SIR-C L-band data (four classes)

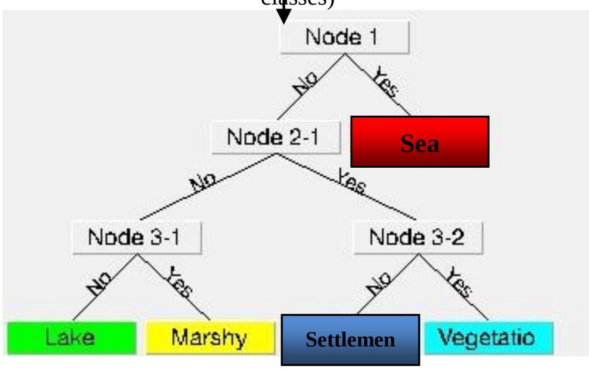


Figure 7: Decision Tree for Five Band Combination (LHH, LHV, LVV, CHH, CHV) data (five classes)

Table 7: Confusion matrix for training areas (DTC) (Overall Accuracy 87.18 %) for five band combination (LHH, LHV, LVV, CHH, CHV) data

Class	Marshy	Sea	Vegetation	Lake	Urban
Marshy	51.65	0	0	0	0
Sea	0	99.46	0	0	0
Vegetation	11.72	0	99.35	0	0
Lake	0.38	0.54	0	100.00	0.32
Urban	36.25	0	0.65	0	99.68

5.4 K-means

K-Means unsupervised classification calculates initial class means evenly distributed in the data space then iteratively clusters the pixels into the nearest class using a minimum distance technique. Each iteration recalculates class means and reclassifies pixels with respect to the new means. All pixels are classified to the nearest class unless a standard deviation or distance threshold is specified, in which case some pixels may be unclassified if they do not meet the selected criteria. This process continues until the number of pixels in each class changes by less than the selected pixel change threshold or the maximum number of iterations is reached. Figure 9 shows the result of applying k-means clustering for 6 classes after applying Lee speckle filter. After comparing it with the MDC and MLC results it is found that some classes like Marshy, Land and Vegetation are classified as a single class and in few places the land class is misclassified as water.

6. CONCLUSION

The multi-band SAR data can be used to map wetlands with reasonable accuracy. The advantage of using SAR over visible data is the detection of wetlands. It is very difficult to detect flooding beneath a forested canopy without SAR.

For SIR-C L- and C-band Kolkata polarimetry data the results show that multi-polarization SAR data helps to classify wetlands effectively. The combinations of different polarizations from L- and C- band helps to improve the classification accuracy. The combinations of L-HV, C-HH, C-HV and L-HH, C-HH, C-HV had the best overall accuracies (around 87.5%). These two 3 band combination can differentiate well the six classes. The five band combination L-HH, L-HV, L-VV, C-HH, C-HV gives the highest classification accuracy (around 91% for MDC). It is greater than the three band combinations which are mentioned above. By applying enhanced Lee filter the accuracy can further increased to 93.9% for MDC and 94.9% for MLC. The enhanced Lee filter removes the speckle effectively. It is observed that the unsupervised classification technique does not perform well compared to supervised techniques for this type of data. It is also observed that the Decision tree algorithms are efficient tools for the PolSAR data classification.

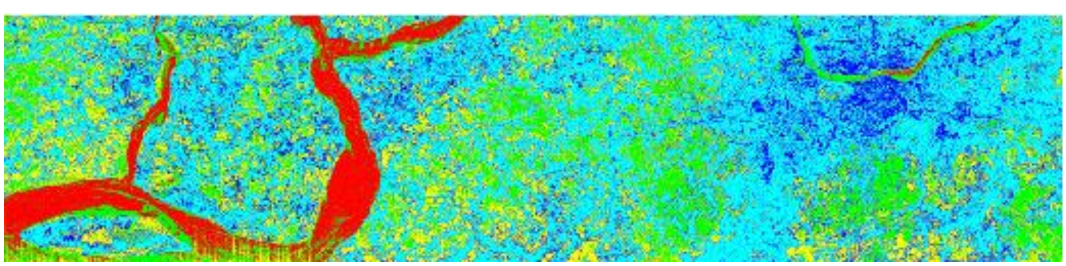


Figure 8: SIR-C C- and L-band Kolkata (W.Bengal) Five Band Combination (LHH, LHV, LVV, CHH, CVH) Data Classified by DTC for 5 classes

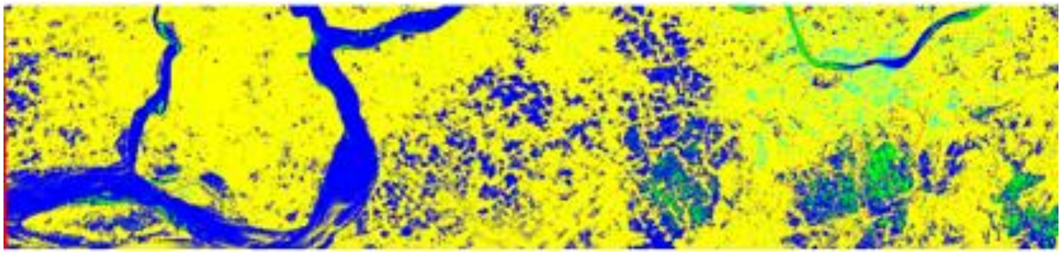


Figure 9: SIR-C C- and L-band Kolkata (W.Bengal) five Band Combination (LHH, LHV, LVV, CHH, CVH) Data Classified by K-means for 6 classes

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