IMAGE VISUALISATION AND CLASSIFICATION OF MODIS/ASTER AIRBORNE SIMULATOR (MASTER) REMOTELY SENSED DATA FOR AGRICULTURAL AREA

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ABSTRACT

A Best Band Selection Index (BBSI) algorithm to select the best band combination for image visualization and classification of high spectral resolution remotely sensed dataset was introduced in this paper. The BBSI is calculated by two components, one based on class mean (or cluster mean) difference and the other based on correlation coefficients. Using MODIS/ASTER Airborne Simulator (MASTER) images taken over Jertih, Terengganu in 2000 as the test dataset, the BBSI correctly predicted the best three-band combination that provided useful information for visualization of the image to collect training samples in supervised classification. The BBSI also accurately selected the best four-band combination that produced high overall accuracy classification map with value of 89.7%.

Keywords : *Best Bands Selection, Image Classification, Image Visualisation, MASTER Remotely Sensed Data*

1. INTRODUCTION

Remote sensing technology has been widely used to observe earth surface and made it possible to take detailed measurements over the entire surface of earth relatively cheaply and efficiently. Nowadays, advances in sensor technology are being operated for earth observation make it possible to collect multispectral remotely sensed data in more spectral bands with a large dynamic range and fine spatial resolution for instance, MODIS/ASTER Airborne Simulator (MASTER) dataset. The MASTER dataset is simultaneously recorded in 50 spectral bands from visible through thermal infrared at variety of spatial resolutions 5 – 30 m and 50 m. The details of spectral characteristics of the 50 bands, which are referred to the [18] are shown in Tables 1 and 2.

Analysis of multispectral remotely sensed data is usually performed by pattern recognition techniques. One of the most widely used pattern recognition techniques for land cover determination is supervised classification. The first step in supervised classification is to obtain training samples that are representative of each class of land-cover interest. The collected training samples must be enough and adequately represent the spectral characteristics of each class in the image to be classified. The quantity and quality of the training samples has a significant effect on the classification process and accuracy [3]. Hughes phenomenon [9] has proven that the number of training samples limits the accuracy of classification using optimum bands. Jensen [12] suggested a general rule of estimating the number of training, where more than 10 time b pixels of training samples must be collected for each class, if b bands are used to perform classification. According to [16], the process of finding and verifying training samples is labour intensive, since the analyst must select accurate and sufficient pixels for each class of interest. Generally, the training samples collection is performed by direct visual interpretation of the image or by comparing the information extracted from image visualisation against the field data and existing maps. It can be seen that image visualisation is important in training samples collection because it incorporates association information of surrounding pixels, such as texture and context to assist data analyst identify more accurate training samples. In addition, many experienced users of remote sensing had argued that automated classification methods should only be accomplished

Table 1: Spectral characteristics of the visible-shortwave infrared MASTER channels referred to the [18]

Channel	Full width half maximum	Channel centre (µm)	Channel peak (µm)
1	0.0433	0.4574	0.458
2	0.0426	0.4981	0.496
3	0.0427	0.5400	0.538
4	0.0407	0.5807	0.58
5	0.0585	0.6599	0.652
6	0.0420	0.7110	0.710
7	0.0418	0.7499	0.750
8	0.0420	0.8000	0.800
9	0.0417	0.8658	0.866
10	0.0407	0.9057	0.906
11	0.0403	0.9452	0.946
12	0.0542	1.6092	1.608
13	0.0526	1.6645	1.666
14	0.0514	1.7196	1.718
15	0.0521	1.7748	1.774
16	0.0506	1.8281	1.826
17	0.0457	1.8751	1.874
18	0.0575	1.9244	1.924
19	0.0504	1.9807	1.980
20	0.0481	2.0806	2.080
21	0.0511	2.1599	2.160
22	0.0508	2.2106	2.212
23	0.0513	2.2581	2.258
24	0.0683	2.3284	2.320
25	0.0641	2.3939	2.388

after visual techniques have been fully assessed [7]. To produce the best quality of colour composite image for visual interpretation and training samples collection, it is essential to select the best three-band among the all bands in a dataset that could provide maximum information on natural resources.

Second step of supervised classification is selecting the best bands for classification. Once the training samples have been collected, a judgment must be made by the analyst to select those bands that are most effective in discriminating each class of information from all others based on the training samples statistics [11]. In this way, number of bands to be used for classifying the dataset can be reduced. The Hughes phenomenon [9] has been proven that for a fixed training sample size, as the number of bands increases, the separability is increase, therefore this give potentially improved classifier performance. Unfortunately, the reliability is when the number of bands increase more than optimum or certain limit for a fixed training sample, the accuracies of training statistics estimation and classification is decrease. As a result, it is important to select the best optimum bands for classification.

Table 2: Spectral characteristics of the mid- thermal infrared MASTER channels referred to the [18]

Channel	Full width half maximum	Channel centre (μm)	Channel peak (μm)
26	0.1559	3.1477	3.142
27	0.1459	3.2992	3.292
28	0.1478	3.4538	3.452
29	0.1544	3.6088	3.607
30	0.1345	3.7507	3.757
31	0.1524	3.9134	3.912
32	0.1548	4.0677	4.067
33	0.1530	4.2286	4.224
34	0.1530	4.3786	4.374
35	0.1446	4.5202	4.522
36	0.1608	4.6684	4.667
37	0.1521	4.8233	4.822
38	0.1487	4.9672	4.962
39	0.1495	5.1160	5.117
40	0.1578	5.2629	5.272
41	0.3645	7.7599	7.815
42	0.4333	8.1677	8.185
43	0.3543	8.6324	8.665
44	0.4235	9.0944	9.104
45	0.4083	9.7004	9.706
46	0.3963	10.1160	10.115
47	0.5903	10.6331	10.554
48	0.6518	11.3293	11.365
49	0.4929	12.1170	10.097
50	0.4618	12.8779	12.876

In remote sensing application, many statistical band selection methods have been developed to identify the best bands for image visualisation and classification. Optimum Index Factor (OIF) algorithm is one of the methods to select the best three-band for image visualisation. This algorithm was developed by [2] and used by [5]; [7]; [12]; to predict the best three bands of Landsat Thematic Mapper (TM) dataset for visual discrimination of land cover classes. The OIF method relies on an index devised to rank band subsets (e.g. three-band) according to their information content (i.e. variance and correlation) [1]. Chavez et al. [2] suggested that the three-band combination having the highest values of OIF should be selected for display because of this combination having the most information content. The OIF has been compared to the Best Three Bands Combination Index algorithm (BTBCI) in the best three-band combination selection for image visualisation of Landsat TM and MASTER datasets [19]. In the study, the BTBCI is calculated by two components, one based on cluster mean difference and the other based on correlation coefficients. The comparison results indicated that, both BTBCI and OIF algorithms correctly predicted the best three-band combination for image visualisation of Landsat TM dataset. However, the two algorithms tested on MASTER dataset produced different results. The image quality of band combination selected by BTBCI was smoother and better than OIF. Some algorithms also available to select the best band combination for classification. For instance, Transformed Divergence (TD), Divergence (D), Bhattacharyya Distance (B-distance) and Jeffreys-Matusita Distance (JM-distance) algorithms have been used and evaluated by [15] in the best four-band combination selection for classifying multispectral remotely sensed dataset of an agricultural area.

The best band combination selection for image visualization and classification is relatively complex, difficult, subjective, time consuming and often data dependent. Sometimes, the best band combination selected to classify the image is not necessarily the best for image visualisation [15]; [7]; [1]. According to [2] and [17], three-band having high variances (standard deviation) and low pair-wise correlation should be selected for image visualisation. In the study of [15] showed that the bands selection based on variances give poor classification results, but based on mean differences and covariance differences produced good classification accuracy results. Another study done by [1] showed that the correlation coefficient is rather more essential than covariance in bands selection for classification. It can be concluded that the mean differences and correlation coefficients are important in the best bands selection for image visualisation and classification. Objective of this study is to propose a Best Band Selection Index (BBSI) algorithm, which is based on the calculation of class mean (or cluster mean) differences and correlation coefficients to select the best three-band for image visualisation and the best four-band for image classification of MASTER dataset.

2. METHODOLOGY

2.1. DATA SOURCE AND STUDY AREA

The MASTER dataset was obtained on 19 September 2000 of Jertih area. Jertih is located in the south of Terengganu state, latitude 5° 44’ 47” and longitude 102° 28’ 43” and covers approximately 25 sq km. Figure 2 shows the colour composite image of MASTER bands 3, 7, and 20 for Jertih area. The main land cover types in the image were paddy, water, rubber, cleared land and urban. Even though the MASTER dataset has 50 bands, 23 bands were identified as noisy bands, which have very little energy reflectance from the earth surface. As a result, only 27 bands of the MASTER dataset were used for analysis. The 27 bands are bands 1 to 15, bands 20 to 24, and bands 42 to 48.

2.2. BBSI ALGORITHM

The BBSI (Equation 1) is an algorithm extended from the BTBCI algorithm that is introduced by [19] to select the best three-band combination for image visualisation of Landsat TM and MASTER datasets.

$$\text{BBSI} = \frac{\sum_{k=1}^{n}\sum_{i=1}^{m-1}\sum_{j=i+1}^{m}\left|\mu_{i,k} - \mu_{j,k}\right|}{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left|CC_{i,j}\right|} \quad (1)$$

where, m is total number of classes (or clusters), n is total number of bands, |mi,k - mj,k | is absolute value of the mean values difference between classes (or clusters) i and j, (i π j) in band k, and |CCi,j| is absolute value of the correlation coefficient values between any two bands i and j, (i π j). Advantage of BBSI compared to the BTBCI is the BBSI capable to select a best band combination more than three bands. The BBSI was calculated by dividing the sum of class mean (or cluster mean) differences by the sum of correlation coefficients. The class mean (or cluster mean) differences are essential in determining the effective bands in discriminating each class (or cluster) from all others. The greater sum of class mean (or cluster mean) differences between any two of the possible all pairs in a spectral band, the greater the degree of separability between any two classes (or clusters) for all possible pairs in that spectral band. The sum of correlation coefficients are important in selecting low correlated band-pairs in a band combination because high correlated bands will contain of tremendous amount of redundant spectral information content among the bands. The BBSI is favoured of selecting the band combination having high sum of class mean (or cluster mean) differences and low sum of correlation coefficients. The higher the value of the BBSI of a band combination, the more important the band combination is considered for image visualisation and classification.

2.3. BEST THREE BANDS SELECTION FOR IMAGE VISUALISATION

The 27 bands of MASTER dataset produced 2925 possible three-band combinations. Two main steps of the best three-band combination selection for image visualisation are cluster means generation and correlation coefficient extraction. The cluster means generation process was performed by Iterative Self-Organising Data Analysis (ISODATA) technique. Four highest standard deviation bands 5, 8, 9, and 10 of the dataset were chosen to generate 10 clusters means by the ISODATA technique. This is because of the selected bands having greater spread and inhomogeneous among the brightness values of the pixels. The generated cluster means of all bands and correlation coefficient of all possible band pairs for the dataset were extracted to calculate the BBSI values. The three-band with the highest BBSI value among the all 2925 band combinations was selected to produce a colour composite image for visual interpretation and collecting training samples.

2.4. BEST FOUR BANDS SELECTION FOR CLASSIFICATION

Four bands were used to classify the image because this number of bands produced optimal classification accuracy results for high dimensional dataset [4]; [15]. The number of four-band combinations for the 27 bands of MASTER dataset is 17550 combinations. The procedures for selecting the best four-band combination are shown in Figure 1. The training samples collection was performed after integrating all information extracted from the image visual interpretation and existing land- used maps. The training sample means and correlation coefficient values were extracted to calculate the BBSI values. The four-band combination that has the largest BBSI value was selected to produce a classification map using maximum-likelihood classifier. The generated classification map was evaluated for classification accuracy. A total of 750 pixels (150 pixels per class) were collected from land-used map as reference data to determine the accuracy of classification. These pixels are belonged to a different set of ground information from those used for training samples in the classification. User's, producer's, and overall classification accuracies were assessed by comparing the reference data with the classification map using an error matrix (Table 5). The user's accuracy provides the user information about the accuracy of the land-cover data. This accuracy calculated as the number of correctly classified samples divided by the row total. The producer's accuracy is calculated by dividing the number of correctly classified samples by the column total. This accuracy indicates the percentage of samples of a certain (reference) class that are correctly classified. The overall accuracy is a measure of the classification accuracy as a whole, which is calculated by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels [14] and [10].

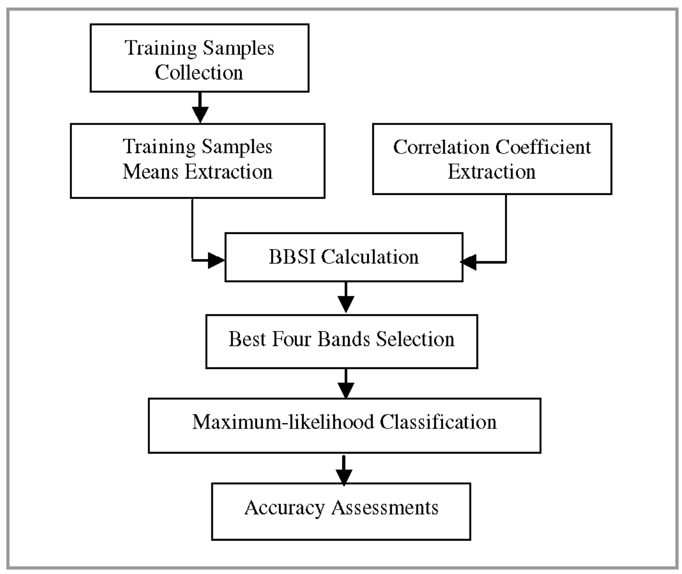

Figure 1: Procedures of best four-band selection for image classification

3. RESULTS AND DISCUSSIONS

The BBSI values calculated based on 10 generated cluster means and correlation coefficients for the top 3 and last 3 ranks of all 2925 three-band combinations are shown in Table 3. The ranking results showed that band combination 3, 7, and 20 ranked first with values of 8005.79, while, the band combination 21, 22, and 23 ranked last with value of 1585.97. False colour composite images for the bands 3, 7, and 20 and 21, 22, and 23 are shown in Figures 2 and 3, respectively. It can be seen that the image of band combination 21, 22, and 23 present extremely low information content and poor display quality compared to the band combination 3, 7, and 20. Generally, the band combination having higher sum of cluster means differences and lower sum of correlation coefficients is produced better display image quality. This is due to the greater sum of cluster means differences, the greater the degree of separability among the clusters in that combination and the lower sum of correlation coefficient suggests the lower redundancy in the information content among the bands in that combination. The BBSI calculation showed that the sum of cluster mean differences and correlation coefficient values in the bands 3, 7, and 20 were higher and lower, respectively than bands 21, 22, and 23. As a result, the display image quality of bands 3, 7, and 20 was much better than bands 21, 22, and 23.

Table 3: BBSI values of the top 3 and last 3 ranks of the 2925 three- band combinations

Rank of BBSI	Band Combination	Sum of cluster means	Sum of correlation coefficients	BBSI
1	3 7 20	6804.925	0.85	8005.79
2	3 7 22	6704.719	0.84	7981.81
3	3 7 24	6768.586	0.85	7963.04
2923	20 22 23	4689.219	2.89	1622.57
2924	20 21 22	4653.962	2.89	1610.37
2925	21 22 23	4615.178	2.91	1585.97

Figure 2: False colour image of band combination 3, 7, and 20

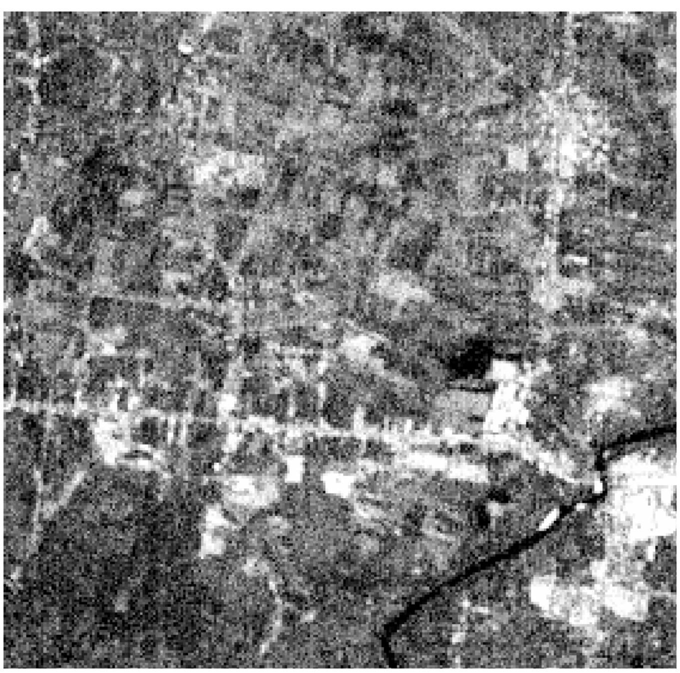

Figure 3: False colour image of band combination 21, 22, and 23

According to the studies of [17]; [13]; [6]; [8], the three bands corresponding to visible, near-infrared and mid-infrared produced better display image quality. In this case, the spectral wavelength range of the bands 3, 7, and 20 were visible, near-infrared, and mid-infrared, respectively therefore, this band combination provided maximum information for image visual interpretation.

Varied number of training samples for paddy (350 pixels), water (93 pixels), rubber (312 pixels), cleared land (141 pixels), and urban (84 pixels) classes have been obtained by integrating the information extracted from visual interpretation of the image of bands 3, 7, and 20 and existing land-used maps.The BBSI values calculated using the training sample means and correlation coefficients for the top 3 and last 3 ranks of all 17550 four-band combinations are shown in Table 4. The bands 7, 11, 20, and 24 ranked first with value of 1842.65, while, the bands 44, 45, 46, and 47 ranked last with value of 452.86. Maximum-likelihood classification maps of the bands 7, 11, 20, and 24 and 44, 45, 46, and 47 are shown in Figures 4a and 4b, respectively. These classification maps were evaluated for user's, producer's, and overall classification accuracies using error matrix. Tables 5 and 6 show the error matrices of the classification results for the bands 7, 11, 20, and 24 and 44, 45, 46, and 47, respectively. A simple comparison of both tables showed that, the band combination 7, 11, 20, and 24 producing overall accuracy with value of 89.7% much higher than the band combination 44, 45, 46, and 47 with value of 51.9%. The user's and producer's accuracies of each class for bands 44, 45, 46, and 47 also lower than bands 7, 11, 20, and 24, especially, paddy, water, and cleared land classes in user's accuracy with values of 44.5%, 47.3% and 21.5%, respectively and producer's accuracy with values of 59.3%, 34.7%, and 15.3%, respectively. An analysis of the sum of training sample means differences and sum of correlation coefficients of the two band combinations was carried out to determine why both combinations produced different classification accuracies. The analysis of sum of training sample means differences was done by using a class means multispectral plot (Figure 5). The plot clearly illustrated that the class mean differences between any two of the possible all pairs of bands 7, 11, 20, and 24 were greater than bands 44, 45, 46, and 47, especially for paddy and cleared land classes. As a result, the degree of separability among the classes in bands 7, 11, 20, and 24 was better than bands 44, 45, 46, and 47. Sum of correlation coefficients in a band combination has been analysed by [1], the study showed that a band combination with low sum of correlation coefficient between two bands of all pairs has produced high accuracy classification map. In this case, the sum of correlation coefficient of bands 7, 11, 20, and 24 with value of 1.88 was much lower than bands 44, 45, 46, and 47 with value of 5.56. The analysis results showed that, the bands 7, 11, 20, and 24 having higher sum of class mean differences and lower sum of correlation coefficients than the bands 44, 45, 46, and 47, therefore, the bands 7, 11, 20, and 24 yielded higher classification accuracies than bands 44, 45, 46, and 47.

Table 4: BBSI values for the top 3 and last 3 ranks of the 17550 four-band combinations

Rank of BBSI	Band Combination	Sum of means	Sum of correlation coefficients	BBSI
1	7 11 20 24	3464.186	1.88	1842.65
2	7 11 23 24	3479.318	1.90	1831.22
3	7 11 21 24	3473.488	1.91	1818.58
17548	42 43 44 45	2479.906	5.38	460.95
17549	42 43 44 46	2474.816	5.37	460.86
17550	44 45 46 47	2517.900	5.56	452.86

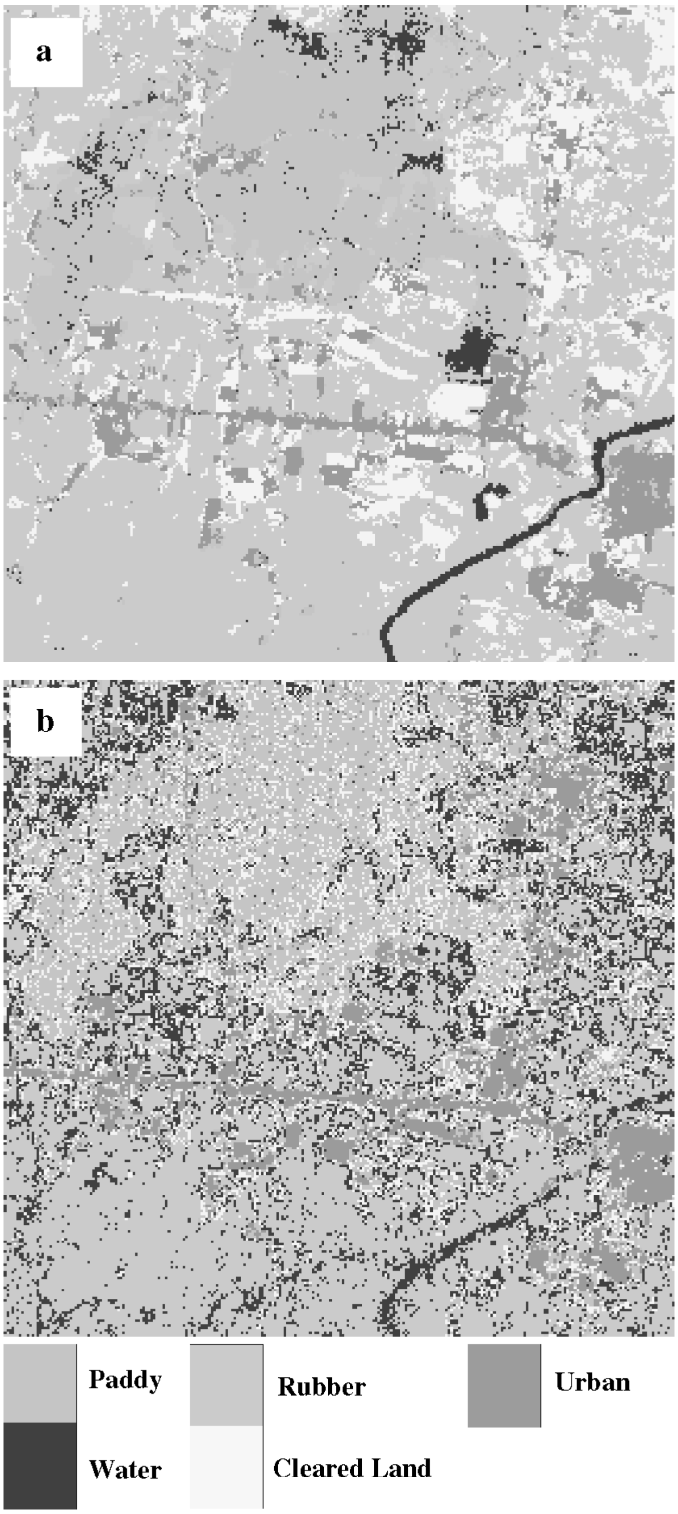

Figure 4: Classification maps of (a) bands 7, 11, 20, and 24 (b) 44, 45, 46, and 47

Table 5: Error matrix of the classification result of bands 7, 11, 20, and 24

Classified Data	Reference Data: Paddy	Water	Cleared Land	Rubber	Urban	Total	User's accuracy
Paddy	127	27	0	2	2	158	80.38
Water	15	121	8	0	0	144	84.03
Cleared Land	8	0	140	4	3	155	90.32
Rubber	0	2	2	142	2	148	95.95
Urban	0	0	0	2	143	145	98.62
Total	150	150	150	150	150	750	
Producer's accuracy	84.67	80.67	93.33	94.67	95.33		

$$\text{Overall accuracy} = \frac{(127+121+140+142+143)}{750} \times 100\% = 89.7\%$$

Table 6: Error matrix of the classification result of bands 44, 45, 46, and 47

Classified Data	Reference Data: Paddy	Water	Cleared Land	Rubber	Urban	Total	User's accuracy
Paddy	89	39	52	7	13	200	44.50
Water	11	52	17	27	3	110	47.27
Cleared Land	34	26	23	9	15	107	21.49
Rubber	1	29	11	107	1	149	71.81
Urban	15	4	47	0	118	184	64.13
Total	150	150	150	150	150	750	
Producer's accuracy	59.33	34.67	15.33	71.33	78.67		

$$\text{Overall accuracy} = \frac{(89+52+23+107+118)}{750} \times 100\% = 51.9\%$$

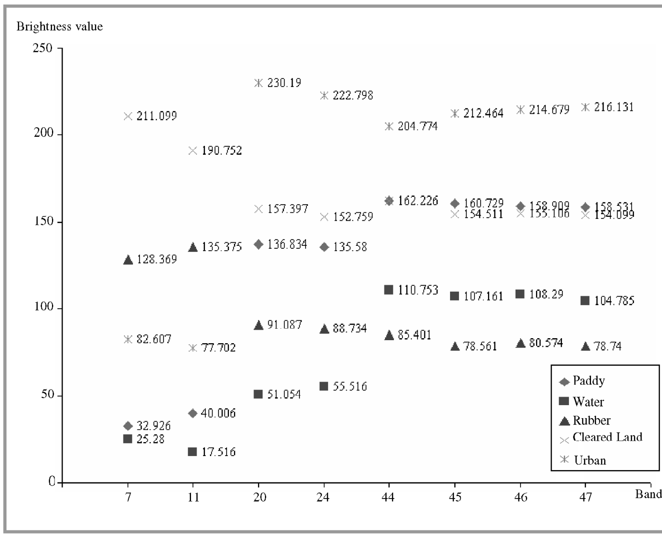

Figure 5: Class mean values versus spectral bands plot

4. CONCLUSIONS

The results of best three-band selection showed that, the bands 3, 7, and 20 and 21, 22, and 23 were ranked first and last in term of BBSI value, respectively. The band combination 21, 22, and 23 produced extremely low information content and poor display quality compared to the band combination 3, 7, and 20. The results of best four-band selection indicated that, the bands 7, 11, 20, and 24 with the highest BBSI value producing much greater user's, producer's, and overall classification accuracies than the bands 44, 45, 46, and 47 with lowest BBSI value. The user's and producer's accuracies of each class and overall accuracy for the classification map of bands 7, 11, 20, and 24 were more than 80%. The proposed BBSI algorithm based on the calculation of class mean (or cluster mean) differences and correlation coefficients capable to select the best band combination for image visualisation and classification of MASTER dataset. ■

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PROFILE

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