MULTI-DATA FUSION FOR SUSTAINABLE FOREST MANAGEMENT: A CASE STUDY FROM NORTHERN PART OF SELANGOR, MALAYSIA

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Keywords: Forest, Fusion, Landsat TM and SAR

ABSTRACT

The developments in remote sensing technology have further enhanced the opportunity to integrate a varity of images from different sensors of different part of electromagnetic spectrum, to provide data sets with complimentary information content and improving the spatial resolution of the satellite imagery. The process of integrating optical and microwave data become a valuable approach to serves as tools for forest resources evaluation over time and present at regular interval. Monitoring the paradigm of forest resources by Landsat Thematic Mapper (TM) has been a problem due to the dependence on the atmospheric conditions. Thus, the exploration of merging optical and radar data must therefore be investigated. This paper shows that we can improve the spectral and spatial quality and enhance ability to accurately detect the forest resources by using some algorithms that bring together optical (TM) and Satellite Synthetic Aperture Radar SAR data (ERS-1, JERS-1 and Radarsat). The fusion techniques proposed allow us to distinguish more forest cover types and show a good indicator which corresponding in contribution additional information, in order to manage forest resources in effective and efficient manner.

1. INTRODUCTION

Forest management policy in Malaysia was formulated to ensure the continuity of product flow while conservation in complex ecosystem and minimizing the negative caution on the environment. Due to its objectives of sustainable productivity and increasing forest management practices, forest inventory has been undertaken to plan, manage and conserve the forest resources.

Attempts to improve the inventory situation are hindered by the expanses and difficulty of carrying out the task to assess stocking, brush competition or regeneration performances. The successful management of these resources will require more efficient methods of data collection and analysis.

The concept of using satellite remote sensing in Malaysian forest inventories is not new and was recognised as a powerful technique and sometimes become a valuable tools for data collection. However, up until now, the use of satellite remote sensing in Malaysian forest faced with difficulties such as broken terrain, multistoried forest canopies, perpetual cloud cover, high humidity, poor access, difficult logistics and a few maps or baseline data. This cause the data from the optical range of spectrum become rare and unable to support the information gathered from these images. The information provided by such images will be useless.

In Southeast Asia, including Malaysia, the cloud covers problem dominating the whole year. Thus, the acquisition of a cloud free image with optical satellite system is almost impossible. In order to be able to assess the forest area from optical sensor data, which can provide information on the vegetation condition, it is necessary to develop a technique, which can optimise and enhanced the information extracted from remotely sensed optical data.

The objective of this research is to assess the possibilities and potential use of multi-sensor fused images in strengthening and guidance the Malaysian forest resource management program. Since most of the planning involved surveying and needed to revise the current forest management maps recently, in order to continuously monitor the resources, it is important to find out the technique which will allow the map revision to be carried out contemporary, and increase resources monitoring efficiency.

2. MATERIAL AND METHODS

2.1 Study Area

The region chosen for this research lies on the western side of Peninsular Malaysia and covers an area of approximately 50km x 30km (1900 km^2) near the city of Kuala Lumpur. The main activities in this area are industrialisation. However, agriculture and forestry are still continue play a major role in social economic development. Topographically, the area is characterised by a reasonably flat relief except for one rugged mountains region in the east, which is rising to almost 1200 meter above sea level. The natural forests are situated in the eastern part of the study area, which is composed of variety of species and stand density. The dominant hardwood is dipterocarps with occasional emergent trees has a regular canopy at a height of around 40-meter. In the western part, on the gently undulating plain area the forest can divide in to two types, plantation forest and peat swamp forest. The land cover in this area is very varied and includes, besides forest areas, extensive zones of rubber and oil palm plantation, which distribute all over in the middle of the study area. Other type of land cover in this area is grassland area, which is often subjected to golf course.

2.2 Data used and Image Processing

This research was carried out using digital satellite data, obtained both from the optical and from the Synthetic Aperture Radar (SAR) imaging system. Landsat TM with the 30-meter resolution and 8 bits pixels value on the quadrilateral frame of 127/57, was acquiring on 1996. The SAR images of the study area were acquired in the same year, with the three types of processing level, PRI, CEOS and BSQ. Radarsat having C-band, (5.6 cm : wavelength and 30 ^{o} - 37 ^{o} incidence angle), meanwhile ERS-1 operates on C-band (5.7 cm: and 23 ° incidence angle). JERS-1 image is received in BSQ format. It is an L-band (23 cm: wavelength and incidence angel of 38.5 °). All the SARs imagery receives with 16 bit backscattering intensity values sampled with 12.5 meter ground resolution. After pre processing all the optical and SAR images were subset according to the study area boundary using sub map in ILWIS image processing software.

The general approach of the processing technique is illustrated in Figure 1. This included the pre-processing technique, field checks, the classification step and comparison of the results of different types of data. Stratified random sampling with the proportional allocation was used to obtain the samples to determine the accuracy of the classifications obtained in this research. From the additional information acquired in the field, a supervised classification was performed on the available fused and unfused data sets and a classification was run using maximum likelihood algorithm. Quantitative and qualitative evaluation of the classification results was evaluated to attempt the best result.

2.3 Procedure in Fusion Techniques

Image fusion is the combination of different digital images in order to create a new image by using a certain algorithm (Van Genderen and Pohl, 1994). Different technique can be used to fuse remotely sensed images, but the most commonly used technique is based on advanced image processing for pixel based image fusion. Since pixel-based image fusion presumes an accurate image registration, Landsat TM and SARs images were geocoded to cover the same geographical area and have the same pixel size.

In this research, other than single band or single image, statistical method also used to transform Landsat TM data set from intercorrelated variables into a data set consisting of new uncorrelated variable through linear combination. This was known as Principle Component Analysis (PCA). This option was taken in order to compare either using each of those bands independently, which is introducing redundancy and collinearity, which can affect the fusion accuracy. The first three principle components, which is explain the highest percent of the variance was selected as a new bands or images. This later tested using Intensity Hue Saturation (IHS) and Brovery Transformation.

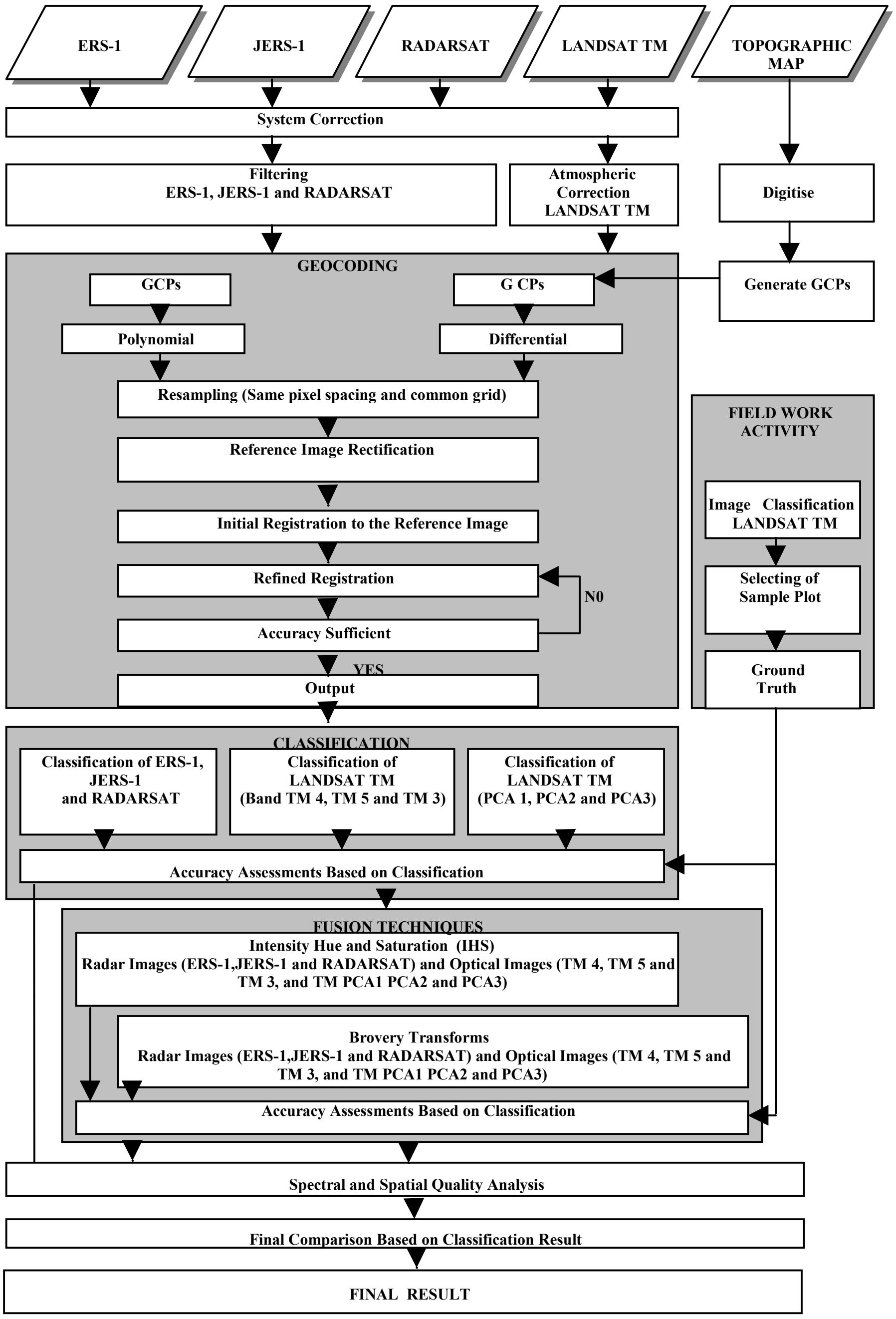


Figure1: Procedures of research method

The IHS transformation method (Photographic procedure) is a standard procedure in image merging analysis. It was successfully used for color enhancement of highly correlated data and for combining multispectral data and also multispectral data and SARs imagery (Chavez et al 1991). IHS image fusion was performed in ILWIS, which offered through map calculation module called MAPCALC. Here, the data sets are fused by means of a replacement of the combination intensity of the optical data bands, by the intensity of the SAR image. As suggested by Harrison and Jupp, (1990), the following formula were applied. This formula actually was developed by Hussin and Shaker, (1996) based on the IHS algorithm formulated by Harrison and Jupp, (1990). The Transformation was applied to two different groups of Landsat TM data, which is a combination of three PCA bands and three single bands, TM band 4, 5 and 3. In the formula Image 1, Image 2 and Images 3 were substituted by either TM bands 5, 4, 3 or PCA1, PCA2 and PCA3. Meanwhile, RADAR images were substituted by ERS-1or Radarsat or JERS-1 images.

Red Image =(Image 1* 2/3) – (Image 2*1/3)-(Image 3*1/3)+(RADAR Image*1/√3).
Green Image =(Image 2* 2/3) – (Image 1*1/3)-(Image 3*1/3)+(RADAR Image*1/√3).
Blue Image =(Image 3* 2/3) – (Image 1*1/3)-(Image 2*1/3)+(RADAR Image*1/√3).

The other procedure, Brovey Transformation or arithmetic procedure is based on the normalization of sun illumination in the optical images and subsequent multiplication with the SAR image. This method is a simple one to merge data from different sensor. As applied in this research, the formula used as shown below. This equation follows the same procedure as IHS.

Red band = Image 1/ (Image 3 + Image 2 + Image 1) * RADAR
Green band = Image 2/ (Image 3 + Image 2 + Image 1) * RADAR
Blue band = Image 3/ (Image 3 + Image 2 + Image 1) * RADAR

2.4 Assessments Criteria

Although there is quite a large amount of literature on the study of the appropriate assessments criteria for determining the accuracy of the classification obtained from remotely sensed data, most of the author depending on common ones, which is, Error matrices and Kappa or K statistics. In evaluating the results, two statistical method mentioned above were used.

2.5 Information Content

One of the aims in integration low spatial and high spatial resolution is to solve the problem in visual content. In 1997, Van Der Meer, made a revision about the measuring of the effect of data fusion on image spatial structure through image statistic and image spatial continuity. Inversely, the conclusion that image fusion aiming at improving visual content and interpretability will be more successful in the case of homogenous data than for heterogeneous data. Following the same procedure, image windows were extracted from several images characterizing the forest cover type. Histogram and accompanying image statistics were calculated for the fused and unfused images. Among the statistical parameter were used, number of pixels, minimum, maximum, mean, median and standard deviation. Through this statistics parameter, conclusion can be made to decide whether the spectral and spatial quality of the images had change or not. The spectral and spatial quality of the image will give the information content for interpretation. The rate of change defined by

$$\Delta\theta = [\theta_{\text{Fused image}} / \theta_{\text{Unfused image}} - 1] * 100$$

Where: θ = statistics parameter.

3. RESULTS AND DISCUSSION

3.1 Qualitative Evaluation

In total, there were 16 land cover classes in the research area. However, only 12 out of 16 classes of interest were detected through Maximum Likelihood Classification (MLC). This was due to the fact that most of the logged over forest already recover and the gap area already covered by the secondary forest. As such some of the logged over forest will give an overlap between the spectral signature in the feature space. Other than that, due to species composition of the study site, in which almost all of the deciduous stands in the area are mixes of more than one species, this creates difficulties in identifying some classes. However, among the classes were detected are primary forest (inland \ superior), primary forest (inland \ moderate), logged over forest (inland \ 1991-1992), logged over forest (inland \ 1986-1990), logged over forest (inland \ 1971-1980), peat swamp forest (logged in 1991-1992) and plantation forest, Rubber Plantation, Palm Oil Plantation, Grass field, Bush and Shrub, Urban area and Water. Close examination of the supervised classification result, indicated that most of the classes mentioned above were easily identified on the fused image than on the non-fused images. It also showed that using increasing number of bands increased the classification accuracy.

A comparison of the images show that fused image is better than non-fused images, not only in the number of classes identified on the images but the quality of the images. This is because more bands were used to create the image in data set will had higher spectral dimension, consequently will give more information. From the visual observation of the images produced from Brovey Transformation combinations with JERS-1, individual forest cover types appearing more prominent especially in peat swamp area. It can be seen that the improvement in the result obtained here with PCA123+JERS-1 data was because the use of JERS-1 image. In this case, using short wavelength (ERS-1 and Radarsat), it is expected that the radar signal are dominantly scattered by the canopy, hence, L– band (23.5 cm wavelength of JERS-1) are expected to penetrate deeper through the canopy and interact with secondary regrowth and the ground.

Table 1: Number of classes identified by Maximum Likelihood Classification and overall accuracy for different data sets.

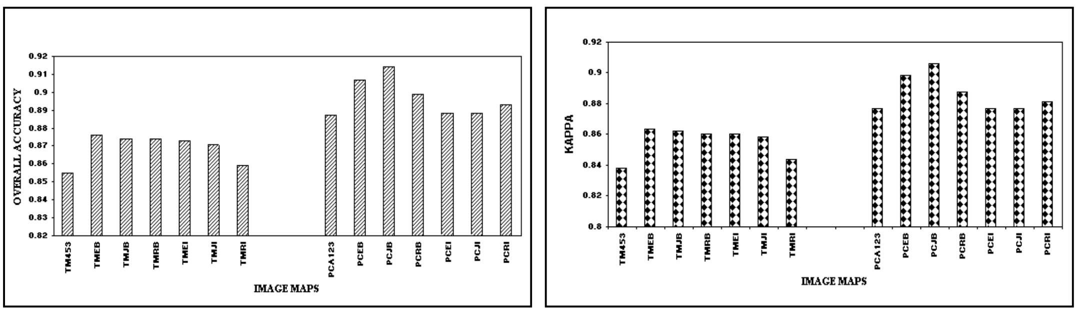
Number of bands	Bands used	Transformation method	Class identified	Overall Accuracy of the classification (%)
3	TM bands 4, 5, and 3	-	10	85.5
7	TM, bands 1 – 7	PCA	12	88.7
4	TM453+ERS-1	BT	12	87.6
4	TM453+JERS-1	BT	12	87.4
4	TM453+Radarsat	BT	11	87.4
8	PCA123+ERS-1	BT	12	90.7
8	PCA123+JERS-1	BT	12	91.4
8	PCA123+Radarsat	BT	11	89.9
4	TM453+ERS-1	HIS	12	87.3
4	TM453+JERS-1	HIS	12	87.1
4	TM453+Radarsat	HIS	11	85.9
8	PCA123+ERS-1	HIS	12	88.8
8	PCA123+JERS-1	HIS	12	88.8
8	PCA123+Radarsat	HIS	11	89.3

Transformation PCA: Principle Component Analysis, BT: Brovery Transformation, IHS: Intensity, Hue and Saturation

3.2 Quantitative Evaluation

A quantitative evaluation of the supervised classification results was necessary in order to facilitate allows a degree of confidence to indicate weather the study objective had been successfully achieved. Figure 2 indicated that fused images using Brovey transformation technique had significantly higher accuracies than the IHS technique. The highest classification accuracy (91.4 percent of pixels classified correctly) is obtained using PCJB. It can be observed that in image fusion, the accuracy is increased significantly when all bands of TM are used instead of three bands, thereby increasing the accuracy of the classification up to 4 percent (compering the fusion image in TMJB and PCJB). Moreover, the producer's and user's accuracy indicated the degree of homogeneity of each class also increase as compared to the performance of transformation using single TM bands. Using the IHS transformation method, it does not improve the classification accuracy, as TMJI and PCJI yield a classification accuracy of 87.1 and 88.8 percent respectively, indicating that Brovey transformation performs better than IHS transformation. Although the fused images with IHS method show less performance in overall accuracy, compared to Brovey transformation, the overall accuracy of the data sets with seven bands of TM in IHS transformation, still give the better result, although it was only 1.70 percent higher in accuracy than the fused of three bands (TM 453).

While the classification accuracy was changed as a function of fusion technique, the type of radar data used also had its own effect on the improvement of classification accuracy. Due to different orbit and hardware configuration for the JERS-1 and ERS-1, they also different in terms of polarisation, wavelength, and incidence angle. The backscatter response between SARs data can be considered in relative manner, showing a different backscatter response to cover type as the nominal case. The effect of this is evident when comparing fusion technique for each SARs data. Figure 2 shows more clear evidences that the result of this classification was varied when different SAR data was used. The overall classification accuracy changes slightly as shown by the varied of the overall accuracy and kappa of the same transformation technique.



(a) (b)

Figure 2. Performance of the classification of the image maps between unfused and fused images as estimate using a) Overall accuracy (b) Kappa.

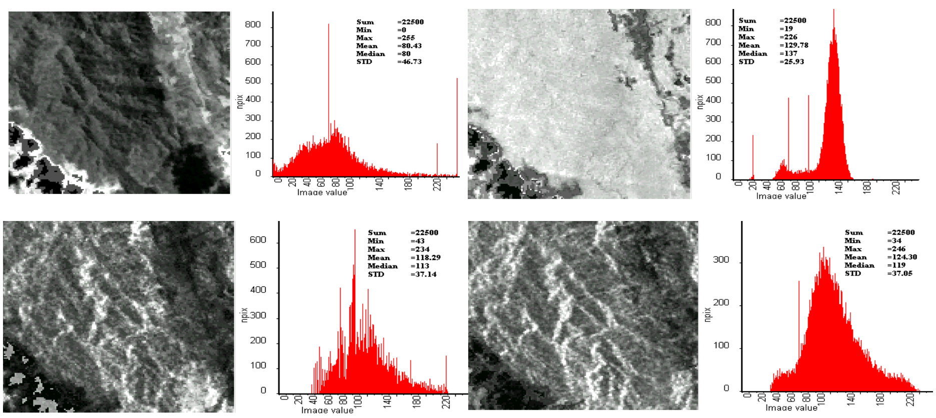
Classification of the fused images of Landsat TM data sets and Radarsat showed the lowest accuracy resulted in Brovey transformation. However using IHS transformation in the case of Radarsat with TM 453, it still the lowest comparing to ERS-1 and JERS-1, while PCRI is the highest. The classes obtained in fused image between optical data and SAR data as a Radarsat has one class less compare to fuse images using JERS-1 and ERS-1. Although the class detection was lower than other fused images, they are typical of classes accuracies achieved in identification of detailed vegetation classes. Some classes have been extracted with very height accuracy. For this reason PCRI, achieve the highest overall accuracy among other data sets classification in IHS transformation with the total classification accuracy achieved for the eleven classes was 89.3 percent.

As a control, two sets of unfused data for comparison and evaluation was provide by Landsat TM453 and PCA 123. The classification accuracy based on three bands TM 453 showed overall map accuracy 85.5 percent with 10 classes, meanwhile PCA123 improved map accuracy slightly to 88.7 with 12 classes. PCA123 also gave a good agreement between cover types statistic and field survey, compared with TM 453. The result of the natural forest classification for the PCA123 ranging from only 67 percent for the "logged over forest \ inland 1986-1990" to 98 percent for the "logged over forest \ inland 1991-1992". Three out of five classes of forest cover types achieved over 90 percent accuracy. In case of TM 453, the class which was least accurately classified was "primary forest \inland superior" (with only 58 percent) and the class which most accurately classified was again "logged over forest \ inland 1991-1992" (complete error matric in Musa, 1999). Once again, it can be seen from Figure 2 that the additional of the SARs data has yielded an overall improvement in the classification accuracy and association compared with the use of TM data set image alone.

Comparisons between two error matrices are readily accomplished using the conditional probabilities represented by the parameter derived from matrix table. Through this research, decision is made to compare images map with such fundamental structure different, presumably the same cover type categories are being used and the reference proportions (row and column marginal proportions) same for each image data set being compared. The comparison based on kappa statistic and Z tests were conducted to determine if the kappa values for different data set pairs are differed. Ones comparing differences between used of the SARs imagery in the fused technique the result shows that there was not an overall significant differences between both imagery for the same transformation approach, except when the different transformation approach and Landsat data sets was used. The results also indicated that, the classification of fused images through Brovey transformation performed significantly better than classification of fused image through IHS transformation and unfused images classification, with a 95 per cent confidence level. This concludes that supervised classification of fused images with Brovey transformation approach perform better when discriminating complex vegetation cover types.

3.3 Spectral and Spatial Quality of the Fused Images.

This discussion will focus on the improvement of the content of fused images in terms of spectral and spatial quality. Image histograms for both, original Landsat TM data sets and fused images, which previously were extracted through image window, were calculated. Histogram of the image windows as well as accompanying image statistics were calculated for the seven different forest types. These types of forest were used for comparison because it can be found in classification result of fused and original TM data sets. Example of the image windows accompanying with histogram as well as the basic statistics for each one of sub image is given in Figure 3.



a. TM bands 4,5,3 b. TM PCA 123
c. TM PCA bands 123 \ JERS-1 (Brovey Transformation) d. TM PCA bands 123\ JERS-1 (HIS Transformation)
Figure 3. Image windows and histogram of primary forest (inland \ superior), to illustrate the image statistics and spectral and spatial quality concept.

Table 2 (a) shows that, TMJB has the least spectral distortion compared with TMEB and TMRB in all individual forest cover types. However, for the IHS transformation TMRI gave the best fidelity compared to TMJI and TMEI. In case of PCA123 (Table 2 (b)) PCJB (fused image between PCA123 and JERS-1 through Brovey transformation) once again achieves the best result, but in certain forest cover type such as logged over forest

Table 2: (a) The rate of change (%) of the statistic parameters calculating from original TM 453 and fused images. (b)The rate of change (%) of the statistic parameters calculating from original PCA 123 and fused images

Forest Types	(a) The rate of change (%) of the statistic parameters calculating from original TM 453 and fused images.						(b) The rate of change (%) of the statistic parameters calculating from original PCA 123 and fused images.					
	Image maps	**□ Min**	**□Max**	**□Mean**	**□Median**	**□Std. Dev.**	**Image maps**	**□ Min**	**□Max**	**□Mean**	**□Median**	**□Std. Dev.**
Primary Forest (Inland) Superior	TMEB	0.00	-3.92	52.01	51.25	-35.39	PCEB	221.05	0.88	-4.91	-12.41	15.50
	TMJB	0.00	0.00	-0.63	-13.75	0.47	PCJB	126.32	3.54	-8.80	-17.52	43.23
	TMRB	0.00	-4.71	7.93	-6.25	20.07	PCRB	126.32	3.10	-7.01	-16.79	52.64
	TMEI	7600.00	0.00	105.57	106.25	-51.00	PCEI	142.11	2.65	12.05	9.49	20.52
	TMJI	2500.00	0.00	49.84	40.00	-16.82	PCJI	78.95	8.85	-4.16	-13.14	42.88
	TMRI	900.00	0.00	37.87	21.25	16.26	PCRI	-63.16	7.96	-27.88	-43.80	111.69
Primary Forest (Inland) Moderate	TMEB	0.00	-6.27	47.27	48.75	-24.65	PCEB	416.67	-10.59	-13.98	-17.76	-7.31
	TMJB	0.00	0.00	-1.22	-8.75	9.93	PCJB	275.00	-8.24	-16.02	-21.05	22.48
	TMRB	0.00	-4.31	16.94	10.00	25.64	PCRB	275.00	-8.63	-11.89	-17.11	33.53
	TMEI	7600.00	-1.18	104.04	106.25	-50.56	PCEI	266.67	-13.33	2.23	0.66	-0.21
	TMJI	2200.00	0.00	50.48	43.75	-5.76	PCJI	183.33	-0.39	-11.89	-17.11	26.23
	TMRI	200.00	0.00	48.28	40.00	24.10	PCRI	-50.00	-3.92	-29.34	-36.84	95.53
Logged Over Forest (Inland)1991-1992	TMEB	242.86	28.26	49.44	45.65	1.22	PCEB	27.42	9.44	-17.90	-19.33	-1.15
	TMJB	-80.95	36.96	8.16	1.09	93.12	PCJB	-3.23	28.89	-17.11	-19.33	71.79
	TMRB	-100.00	31.52	30.79	25.00	117.33	PCRB	9.68	28.33	-10.68	-14.00	102.56
	TMEI	566.67	36.41	91.90	89.13	-34.40	PCEI	43.55	21.11	3.67	2.00	11.49
	TMJI	152.38	38.59	49.56	44.57	58.97	PCJI	-8.06	38.33	-6.75	-10.00	114.15
	TMRI	-28.57	38.59	53.84	47.83	111.57	PCRI	-85.48	33.33	-19.11	-22.67	264.01
Logged Over Forest (Inland)1986-1990	TMEB	590.00	46.06	81.35	83.33	-15.70	PCEB	1.15	29.31	-11.84	-13.42	86.16
	TMJB	-80.00	53.94	18.44	12.12	60.08	PCJB	-16.09	33.33	-13.68	-18.12	228.22
	TMRB	-100.00	47.88	45.40	40.91	96.54	PCRB	-17.24	33.91	-7.97	-12.08	305.56
	TMEI	1230.00	54.55	140.45	146.97	-40.68	PCEI	19.54	33.91	7.06	6.04	88.20
	TMJI	380.00	54.55	75.09	74.24	33.46	PCJI	-21.84	40.80	-9.96	-13.42	250.47
	TMRI	20.00	54.55	75.70	72.73	94.81	PCRI	-93.10	36.78	-25.70	-30.87	538.81
Logged Over Forest (Inland)1971-1980	TMEB	1766.67	-5.88	44.13	40.91	-15.32	PCEB	49.02	10.27	-18.02	-18.92	-4.56
	TMJB	-100.00	0.00	-4.66	-14.77	69.24	PCJB	13.73	27.03	-19.53	-22.30	90.04
	TMRB	-100.00	-4.31	14.68	5.68	93.88	PCRB	25.49	25.95	-14.52	-18.24	121.39
	TMEI	4166.67	0.00	93.62	93.18	-40.61	PCEI	50.98	23.78	2.59	1.35	15.44
	TMJI	1500.00	0.00	39.97	34.09	36.88	PCJI	11.76	35.68	-11.84	-16.22	135.37
	TMRI	33.33	0.00	39.61	31.82	89.62	PCRI	-84.31	31.35	-29.10	-35.81	298.07
Peat Swamp Forest - Logged 1991-1992	TMEB	3600.00	50.00	87.16	87.50	23.61	PCEB	73.33	22.70	-14.40	-15.76	-12.22
	TMJB	2000.00	100.00	42.55	35.94	178.94	PCJB	28.89	23.24	-10.99	-15.76	28.87
	TMRB	1900.00	80.95	57.94	54.69	151.14	PCRB	48.89	22.70	-7.99	-9.09	44.85
	TMEI	13100.00	75.40	156.70	159.38	-22.24	PCEI	153.33	7.03	3.47	1.82	-42.05
	TMJI	6800.00	102.38	101.08	96.88	132.36	PCJI	97.78	30.81	-8.54	-11.52	29.15
	TMRI	4100.00	95.24	93.66	92.19	151.69	PCRI	-35.56	25.95	-24.30	-27.27	91.19
Plantation Forest	TMEB	318.18	4.94	44.36	58.67	-36.47	PCEB	19.67	-0.51	-17.74	-19.11	-21.79
	TMJB	-63.64	4.53	2.63	5.33	24.06	PCJB	-6.56	20.00	-17.85	-21.02	19.50
	TMRB	-100.00	-1.65	11.21	14.67	34.22	PCRB	-1.64	16.92	-16.93	-21.02	22.11
	TMEI	1072.73	4.94	98.30	121.33	-60.62	PCEI	13.11	25.13	0.49	-0.64	-10.23
	TMJI	354.55	4.94	49.14	60.00	3.96	PCJI	-21.31	30.77	-11.51	-15.92	36.87
	TMRI	-36.36	4.12	37.35	44.00	33.46	PCRI	-80.33	26.67	-33.76	-39.49	104.48

(inland \ 1986-1990) and plantation forest, PCEB and PCRB respectively have much better result. For the IHS transformation, both PCJI and PCRI gave best spectral fidelity except for the plantation forest, where PCEI gave more fidelity result. In general Table 2 also indicated that most of the classes in image fusion, fused with IHS Transformation preserved more constancy of pixel value as compared to Brovey technique, which have more spectral distortion. Among the fusion techniques and data sets, PCA123 fused with JERS-1 through IHS transformation was found to be the best with respect to retaining the spectral quality.

Table 2 clearly, indicated that changing in maximum and minimum value of pixels also affecting other statistical parameters of the images. This table also present the mean, median and standard deviation of fused TM data sets and SARs images, which corresponding to original TM data sets for different fusing techniques. In order to evaluate the spatial quality of fused images, measurement was do and based on spreading of the distribution of pixel value and short-range value.

With the Brovey and IHS transformations technique, it is evidence that TM bands 4 , 5 and 3 fused with ERS-1 have the best result in the reduction of the spread of the pixel values, which is indicated that the images data is only correlated over relatively short distance and is therefore more homogeneous. However, their spectral quality is the lowest. It is interesting to see that PCA123 fused with ERS-1 also have the same result followed by fused with JERS-1 and Radarsat for both transformation methods.

The short rang value, which indicated the homogeneity of the image data was showed by the TMJB and TMJI in the case of fusion with Landsat TM453 and SARs data for both transformation methods. But in case of fusing images with PCA123 and SARs data through Brovey Transformation, PCJB show more rapid symmetrization of the image histogram, in which that sample means tend toward a normal distributions regardless of the distribution of the sample. Meanwhile for the IHS transformation PCRI shows domination among other in almost all classes.

4. CONCLUSIONS

- This paper has demonstrated that combined TM and radar data images give more information than unfused images. The automated interpretation approach could serve to differentiate individual forest cover types and other classes with a mean overall accuracy of 91.4 % (through Brovery Transformation). However, a more detailed identification within individual forest type classes were not to be possible because an overlap between the spectral signature in the feature space.
- The classification results indicate that the possibility of extracting more and accurate information from fused images is high and that it proves to be of great benefit to forest management. It helps to reduce the effect of cloud cover and supply more information about multi-stories forest canopy and can therefore directly contribute to sustainable forest management.
- Both, Brovery and IHS Transformation methods presented produced images data that resulted in a statistically increase in classification accuracy when compare with unfused images. However, Brovery Transformation method has the added advantage because of its improved spatial and spectral quality and letter give better overall accuracy and association results.
- For tropical forest area having similar land cover types to those found in this area, the use of JERS-1 SAR data on fusion technique for discriminating individual forest types was found to be better than ERS-1 and Radarsat.

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