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EXTRACTION AND EVALUATION OF SPECTRAL CONTENT FROM MOMS-2P AND LANDSAT TM BY DATA COMPARISON FUSION

A CONTRIBUTION TO THE STUDY OF URBAN-SUBURBAN ENVIRONMENTS

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A digital analysis of the Landsat TM and MOMS-2P (MODE-B) data was implemented to detect and discriminate between urban-suburban land use/land cover in part of Cape Town City. Three objectives were pursued: (1) multispectral data optimisation and scene land use analysis; (2) fusion of the Landsat TM reflective bands with the MOMS-2P blue band using three different fusion methods; and (3) evaluation of the quality and significance of the fusion results. The synergy of the Landsat TM and MOMS-2P provided a unique combination that allowed enhancement of different urban-suburban features/objects, as compared to Landsat TM and MOMS-2P data sets.

'n Digitale analise van die Landsat TM en MOMS-2P (MODE-B) data *is* geïmplementeer om stedelik-voorstedelike grondgebruik/grondbedekking uit te ken en daartussen te onderskei in 'n gedeelte van die stad Kaapstad. Drie doelwitte *is* nagestreef: (1) multispektrale data optimisering en grondgebruik analise; (2) samesmelting van die Landsat TM weerkaatsende bande met die MOMS-2P blou band deur gebruik te maak van drie verskillende samesmeltingmetodes; en (3) evaluering van die kwaliteit en betekenisvolheid van die samesmelting uitslae. Die sinergie van die Landsat TM en MOMS-2P het 'n unieke kombinasie verskaf wat verhoogde waarde verskaf het aan veskillende stedelik-voorstedelike kenmerke/voorwerpe, wanner dit vergelyk is met Landsat TM en MOMS-2P datastelle.

INTRODUCTION

Information about the current land use/land cover in urban-suburban land is important for the monitoring, management and planning of these areas. Conventional methods such as aerial photography and ground surveys have been used to acquire such information. However, these methods are costly, time consuming and difficult to obtain with sufficient accuracy. Satellite remote sensing provides a means of acquiring temporal, up-to-date information for urban-suburban land. There are different satellite data available today. However, the choice of the remote sensing (RS) data suitable for a specific application is not always obvious. This paper reports on the utility of the upper medium-scale RS data for applications in the urban-suburban land use/ land cover detection and discrimination.

In this paper, medium-scale is defined in terms of spatial resolution and is considered to range between 6-30m. Lower medium-scale is categorised between 6-18m spatial resolution and upper medium-scale is 18-30m spatial resolution. Micro-scale would be considered between 1-5m, while macro-scale is considered above 30m (Schultz, 1994). For urban-suburban environmental analysis, it is theoretically considered that upper medium-scale is suitable. This is because of the high spectral confusion that would arise if lower medium or micro-scale RS data were used and the scene spectral over generalisation if macro-scale RS data is used especially in urban scenes. These categorisations are dependent on the scene contents spatial sizes.

In this study, results are presented on the comparison between techniques that may be used to: (1) determine optimal data sets in a multispectral domain: colour composite display and principal components transformation (PCT); (2) evaluate the accuracy and extent of feature separability; (3) fuse high spectral and spatial resolutions data sets; and finally (4) assess the quality of the resultant data sets. This study thus focuses on the performance of the fusion algorithms and their significance in mapping urban-suburban environments.

STUDY AREA

The study area is part of Cape Town City extending, approximately, between latitudes 33°45´-33°56´ E and longitudes 18°26´-18°34´ (Figure 1). The sub-scene consists of different land use/land cover and neighbours the Atlantic Ocean.

TEST DATA

Two image sets, six-band Landsat TM and four band MOMS-2P MODE-B were used to identify land use and land cover information of the scene. MOMS-2P MODE-B refers to the multispectral modes of the MOMS-2P imaging system. The MOMS-2P imaging system also contains panchromatic (P) mode. For this study, only the MODE B multispectral bands were available for investigation.

Table 1 shows the characteristics of the sensor systems used in this study. Ancillary data included aerial photographs, base maps and ground reconnaissance. The original Landsat TM data was georeferenced to the UTM projection system, while the MOMS-2P was not georeferenced. Both data sets were processed in the raw format in order to maintain the spectral quality, as the process of goereferencing often distorts the spectral quality of the original image (Haydin *et al.*, 1982).

METHODS OF MULTISPECTRAL DATA OPTIMISATION

The objective of multispectral optimisation was to determine the most informative or contrasting data set. This was carried out using PCT and colour composite display techniques. This study only reports on the conclusions of these analyses.

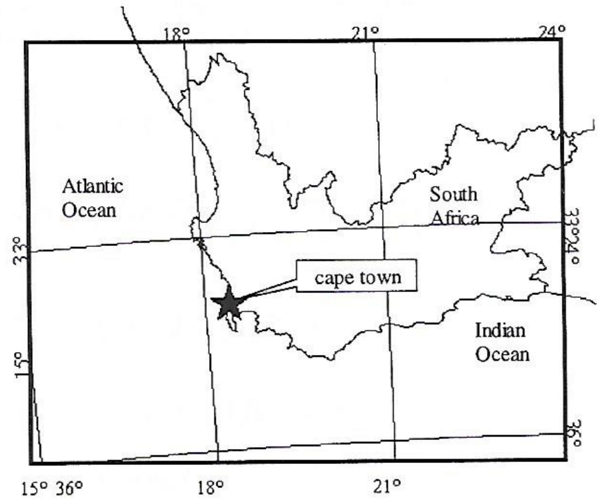

Figure 1: Location map of the study area Cape Town sub-scene

FALSE COLOUR COMPOSITE (FCC)

The following principal approaches to multispectral data analysis were employed: (1) empirical; and (2) statistical.

EMPIRICAL PROCEDURE FOR FCC

In this technique, the three bands are selected from an *a priori* knowledge of the spectral properties. Fig 2 shows "discrete" spectral response (signatures) for urban, water and soil surfaces, adopted from the Jet Propulsion Laboratory (JPL) results (ERDAS Imagine, 1994). DN refers to surface reflectance in digital numbers. From such plots it is possible to define which spectral domain is suitable for mapping specific earth surface features. Another approach is by comparing the band-band correlations.

Tables 2 and 3 show the standard deviation and correlation coefficients of the Landsat TM and MOMS-2P data respectively. Table 2 indicates that the visible (VIS) bands of Landsat TM are highly correlated. Least correlation is observed between TM1 with: TM4, TM5 and TM7. For

Sensor	Date	Band (μm)	Resolution (m)	Projection
Landsat TM	19930720	TM1:0.450-0.560 (visible-VIS)	30	UTM
		TM2:0.520-0.600 (VIS)	30	(USGS PROJ)
		TM3:0.630-0.760 (VIS)	30	
		TM4:0.760-0.900 (near-infrared-NIR)	30	
		TM5:1.550-1.740 (mid-infrared-MIR)	30	
		TM7:2.080-2.350 (MIR)	30	
MOMS-2P	19961013	M-2P1:0.440-0.505 (VIS)	18	
(M/S MODE-B)		M-2P2:0.530-0.575 (VIS)	18	
		M-2P3:0.645-0.680 (VIS)	18	
		M-2P4:0.770-0.810 (NIR)	18	

Table 1: Characteristics of the RS data used in this study

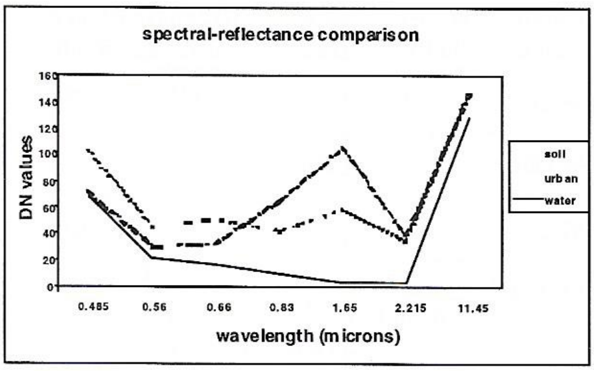

Figure 2: Urban-suburban spectral response

MOMS-2P, Table 3, the VIS bands are not as highly correlated as the TM bands. The VIS and the near infrared (NIR) bands of the MOMS-2P show a very low correlation implying that there is low redundancy in the information contents.

A visual (empirical) examination and comparison based on spectral parameters and luminosity contrast of different possible colour composites allows for the determination of the most informative bands. The results of empirical analysis are expressed in terms of visual ranking (Vi Rank-Tables 4 and 5).

STATISTICAL PROCEDURES FOR FCC

In order to save time in processing and analysing multiband RS data, some authors propose the use of statistical procedures (Chavez *et al.*, 1982; Sheffield, 1985; Crippen, 1989). These procedures are based on band variances and correlations. The variance of the bands, indicated by the standard deviation, is related to the information content of the bands and the bands' correlations are redundancy measures. Two procedures for statistical analysis are: (1) optimum index factor (OIF); and (2) INDEX.

The Optimum Index (OIF) developed by Chavez *et al.*, (1982), is computed for each possible set of three bands according to equation 1. OIF is based on the band standard deviation and correlation coefficients.

$$OIF = \frac{(\sigma_1 + \sigma_2 + \sigma_3)}{\left|r_{(1,2)}\right| + \left|r_{(1,3)}\right| + \left|r_{(2,3)}\right|} \quad (1)$$

The second statistical procedure, INDEX, proposed by Crippen (1989), corresponds to the square root of the determinant of the correlation matrix as shown by equation 2.

$$INDEX = \sqrt{1 + 2(r_{1,2} r_{1,3} r_{2,3}) - r_{1,2}^2 - r_{1,3}^2 - r_{2,3}^2} \quad (2)$$

where: σ is the standard deviation for channel *i*, and $r_{i.j}$ the correlation coefficient between channels *i* and *j*. The higher the OIF or the INDEX, the more uncorrelated the spectral channels.

Tables 4 and 5 give a summary of the empirical and statistical approach to colour composite display.

PRINCIPAL COMPONENT TRANSFORMATION (PCT)

PCT is a well known statistical method that transforms multivariate data of intercorrelated variables into a data set consisting of new mutually uncorrelated variables, obtained by linear combinations of the original ones called principal components (PCs) (definition adopted from Mather, 1976). It has been used for various applications (Jensen, 1996; Yésou *et al.*, 1993). In this study, two PCT procedures were tested: (1) standard PCT; and (2) selective PCT.

STANDARD PCT

Standard PCT is performed using all the spectral bands of the sensor. For this study, the six reflective bands of the TM and the four MODE B bands of the MOMS-2P are the PCT input.

Tables 6 and 7 show the statistical details (eigen-values and eigen-vectors) of the Landsat TM and MOMS-2P data respectively.

SELECTIVE PCT

Selective PCT implies that only subsets of the original data are used as input bands in the PCT. The selection of the input subset can be done in a number of ways (Chavez and Kwarteng, 1989). The method adopted in this study involves grouping the bands according to their spectral coverage, i.e. VIS or mid infrared (MIR). The objective of using selective PCT is to try to minimise: (1) the problems of mapping information of interest in one of the unused bands in standard PCT, and (2) difficulties that may be encountered in colour composite interpretation as might be experienced in standard PCT (Chavez and Kwarteng, 1989).

Figure 3: Landsat TM-Selective PCT

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Bands and s	TM1 13.762	TM2 6.166	TM3 9.533	TM4 17.674	TM5 19.380	TM7 8.081
TM1	1.00	0.90	0.84	.044	0.53	0.55
TM2		1.00	0.95	0.66	0.75	0.75
TM3			1.00	0.68	0.82	0.84
TM4				1.00	0.88	0.75
TM5					1.00	0.94
TM7						1.00

Table 2: Standard deviation and correlation coefficients computed for the six Landsat TM bands

Band Combination	OIF	Rank	INDEX	Rank	Vi Rank
321	10.952	13	0.135	13	13
431	20.903	3	0.376	4	10
432	14.573	10	0.229	9	12
541	27.468	1	0.401	3	1
542	18.873	6	0.314	6	6
543	19.570	5	0.269	8	4
741	22.711	2	0.552	1	2
742	14.778	9	0.426	2	5
743	15.545	8	0.355	5	3
751	20.407	4	0.285	7	7
752	13.782	12	0.221	10	9
753	14.228	11	0.183	11	8
754	17.662	7	0.142	12	11

Table 4:OIF, INDEX and Vi Rank computed for Landsat TM data

% of variance input band	PC1 80.7	PC2 12.7	PC3 4.9	PC4 0.8	PC5 0.5	PC6 0.4
TM1	+0.272	+0.577	+0.216	+0.654	+0.344	-0.034
TM2	+0.394	+0.411	+0.178	-0.177	-0.757	+0.200
TM3	+0.424	+0.316	-0.127	-0.667	-0.460	-0.220
TM4	+0.439	-0.508	+0.675	-0.042	+0.185	+0.241
TM5	+0.467	-0.330	-0.217	+0.217	-0.235	-0.711
TM7	+0.425	-0.180	-0.635	-0.635	+0.090	+0.588

Table 6 Standard PCT applied to Landsat TM data

% of variance input bands	PC1 98.60	PC2 1.40
TM5	+0.371	+0.928
TM7	-0.928	+0.371

Table 9: TM-MIR Standard PCT statistics

Bands and s	M-2P1 35.01	M-2P2 31.95	M-2P3 22.81	M-2P4 58.60
M-2P1	1.000	0.878	0.515	0.007
M-2P2		1.000	0.756	0.010
M-2P3			1.000	0.016
M-2P4				1.000

Table 3: Standard deviation and correlation coefficients computed for the six MOMS-2P bands

Colour Composite	OIF	Rank	INDEX	Rank	Vi Rank
321	41.78	4	0.275	4	4
431	216.43	2	0.857	1	1
432	233.38	1	0.654	2	2
421	126.68	4	0.479	3	3

Table 5: OIF and INDEX computed for MOMS-2P data

% variance input band	PC1 82.60	PC2 15.41	PC3 1.14	PC4 0.85
M-2P1	+0.769	+0.622	-0.002	+0.150
M-2P2	+0.448	-0.448	+0.644	-0.430
M-2P3	+0.394	-0.419	-0.763	-0.430
M-2P4	+0.231	-0.487	+0.061	+0.840

Table 7: Standard PCT applied to MOMS-2P (MODE-B)

% of variance input bands	PC1 90.94	PC2 8.65	PC3 0.41
TM1	+0.504	-0.787	+0.354
TM2	+0.353	-0.187	-0.917
TM3	+0.788	+0.587	+0.183

Table 8: TM-VIS Standard PCT statistics

% of variance input bands	PC1 94.19	PC2 3.29	PC3 2.52
M-2P1	+0.418	-0.904	+0.080
M-2P2	+0.604	+0.211	-0.768
M-2P3	+0.678	-0.768	+0.635

Table 10: MOMS-2P VIS PCT statistics

The results of the selective PCT on the Landsat TM VIS and MIR bands and for MOMS-2P VIS bands are presented in Tables 8, 9 and 10 respectively.

DATA OPTIMISATION-CONCLUSIONS

From the above statistics, the following results were obtained:

- From FCC methods: (a) 5-4-1 false colour composite (FCC) of Landsat TM was the most informative set; (b) MOMS-2P FCC 4-3-1 was the most informative combination (see Tables 4 and 5 respectively).
- PCT analysis showed that, selective PCT for the Landsat TM was the most informative, while for the MOMS-2P standard PCT was better contrasting than the selective PCT.
- Results from (2) and (3) were compared to determine which combination was the overall best for this analysis. The comparison was based on visual (empirical), band correlation and histogram analysis. Landsat TM Selective PCT (Figure 3) and the FCC 4-3-1 (not shown) for the MOMS-2P gave the most informative results.

SURFACE OBJECT EXTRACTION FROM THE OPTIMISED DATA SETS

A supervised training technique based on aerial extraction of spectral values, with spatial and spectral constraints determined by the user (ERDAS Imagine, 1997), was used to generate the spectral training signatures of the informational classes shown in Table 11 *(see page 222)*. Classes listed in Table 11 are those that could be spectrally differentiated through training as well as those that could be identified visually but could not be separated spectrally via training e.g. roads, commercial, industrial land uses. The differences in the number of vegetation classes were largely attributed to temporal differences. This was confirmed by comparing the individual band Normalised Difference Vegetation Index (NDVI's) and NIR bands for vegetation mapping. Transformed divergence (TD) and scatterplot signature evaluation techniques (Richards, 1986) were implemented to statistically and visually evaluate the class signature separability.

From the Landsat TM, 14 classes were determined, while from the MOMS-2P, 15 classes were derived (Table 11). Table 12 *(see page 223)* gives a summary the TD values observed from the two data sets. The results indicate that the classes from the MOMS-2P are much more accurately extractable than from the Landsat TM.

The scatterplot results (Figures 4-6 for Landsat TM and Figures 7-9 for MOMS-2P) further illustrate the differences in the class separabililties.

From the results in Tables 11 and 12, and Figures 4-9, it can, in a summary, be concluded that MOMS-2P appears to be more useful in the urban-suburban scene analysis than the Landsat TM. It is further observed that Landsat TM detected one more land cover (land_water interface) than

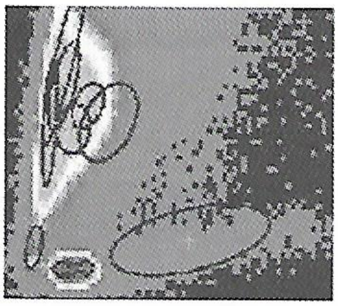

Figure 4:
TM VIS-PC1 versus TM 4

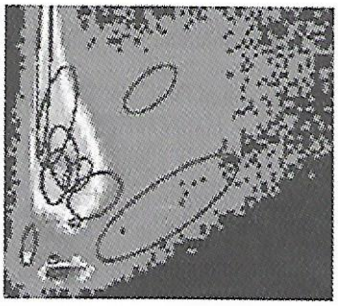

Figure 5:
TM VIS-PC1 versus MIR-PC1

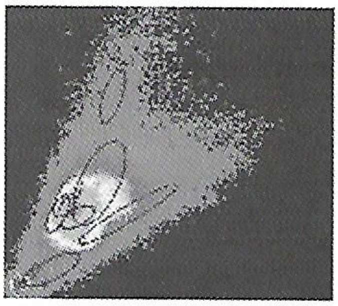

Figure 6:
TM TM4 versus MIR-PC1

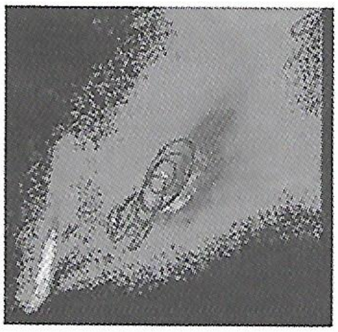

Figure 7:
MOMS band1 versus band3

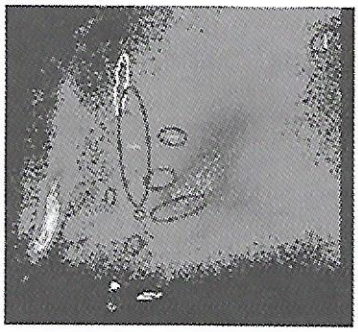

Figure 8:
MOMS band1 versus band4

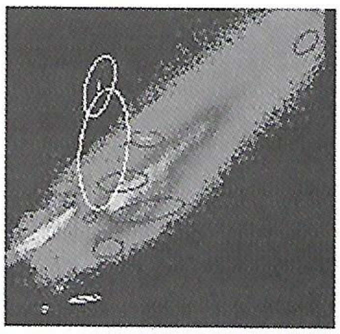

Figure 9:
MOMS band3 versus band4

the MOMS-2P. In terms of class separability, the MOMS-2P class-band scatterplot results (Figures 7-9) are, compared to the Landsat TM scatterplots, much more separable. From these observations, it is concluded that the inability to detect more features/objects from MOMS is because of its lower spectral resolution in comparison to the Landsat TM. And the capability to accurately detect more spectral classes from the MOMS-2P is due to its higher spatial resolution. An additional factor are the narrower bandwidths of the MOMS data, which also contributes to higher spectral separability. Referring to Table 1, the difference in bandwidth of TM1 (0.56-0.45=0.11) compared to M-2P1 (0.505-0.44=0.065).

Based on the above conclusions, the study was extended to investigate on the fusion of the two data sets in order to exploit the spectral and spatial advantages inherent in the two data sets.

MOMS-2P AND LANDSAT TM DATA FUSION: METHODS

A number of methods have been proposed for the fusion of the high spectral and high spatial resolution data. While some methods are specific, e.g. SPOT method (Pradines, 1986), others are more general (Blanc *et al.*, 1996; Chavez *et al.*, 1991; Li *et al.*, 1995; Munechika *et al.*, 1993). Few of the methods propose any assessments of the quality of the

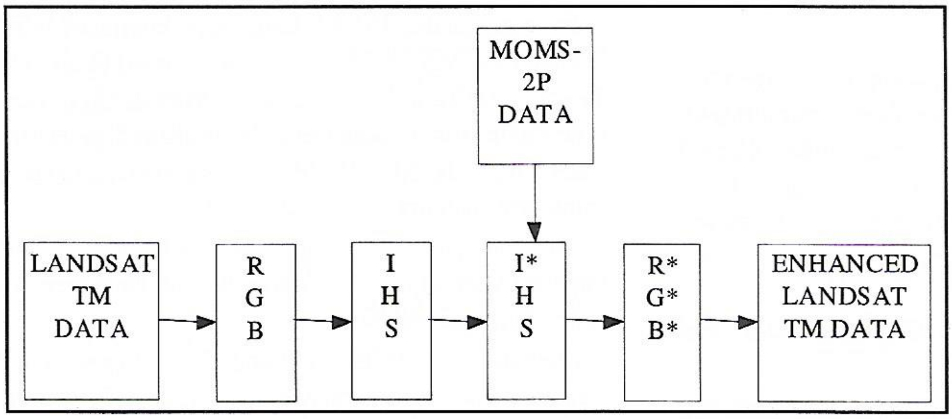

Figure 10: Concept of PCT technique for spatial enhancement

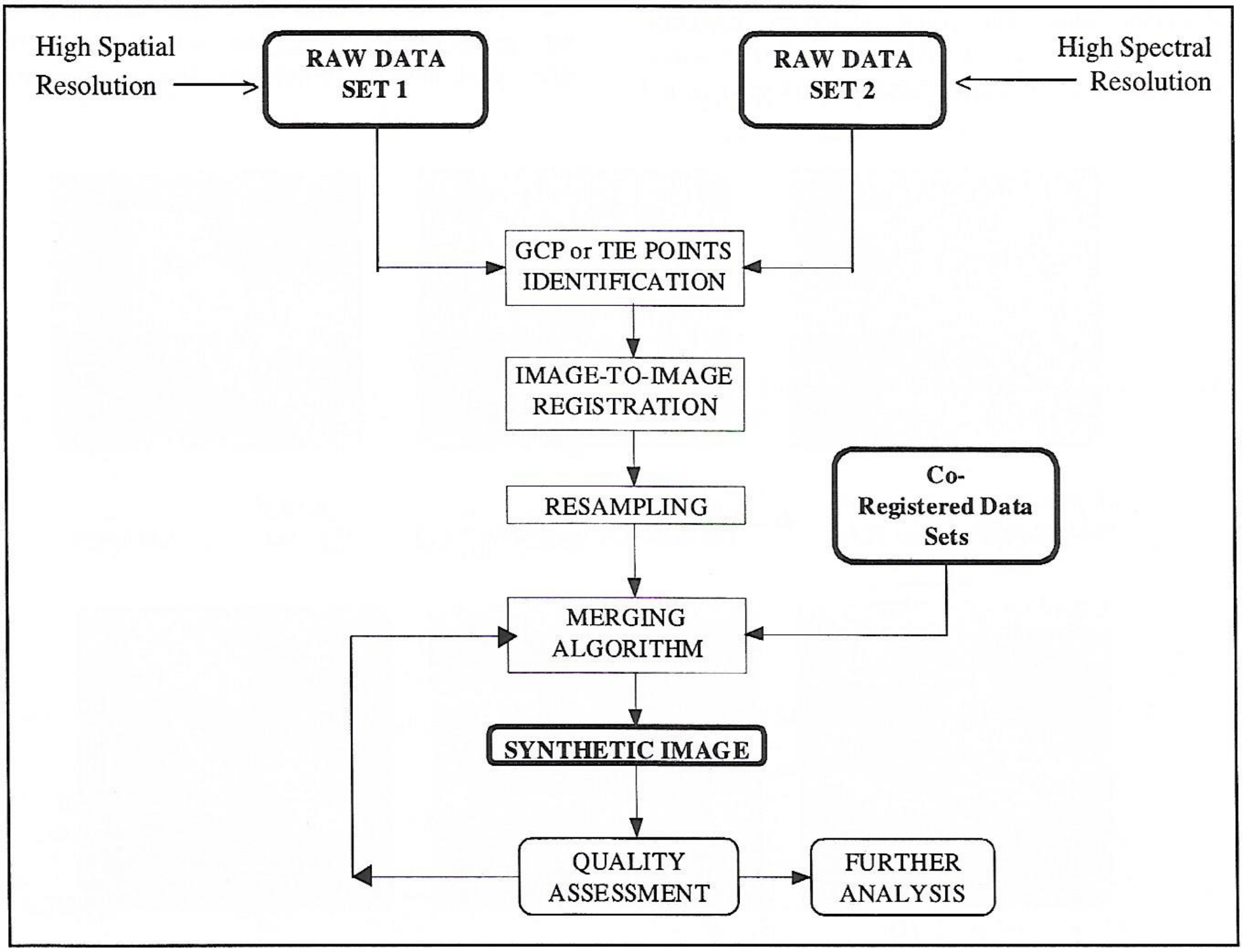

Figure 11: A proposed multisensor digital image simulation approach

resulting synthetic images except for Blanc *et al.*, Munechika *et al.*, and Li *et al.*

The following methods were tested for in this study: (1) Principal Components Transformation; (2) Linear (Multiplicative) Transform and (3) Brovey Transform.

PRINCIPAL COMPONENTS TRANSFORMATION (PCT)

Figure 10 illustrates the concept of PCT technique for data fusion. The methodology consists of calculating the Intensity, Hue and Saturation (IHS) parameters for a set of three bands, which means coding the RGB display of an image in co-ordinates of IHS colour space. Then a fourth band (high spatial-panchromatic) resolution is merged by substitution with one of the three computed parameters, usually intensity. Finally a reverse transform to RGB colour space is achieved. The resulting RGB composite shows the combined information.

The high spatial resolution (panchromatic) replaces the first principal component image before the data are transformed back into the original space. The justification used for replacing the first PC image with the panchromatic data is that the panchromatic data are approximately equal to the first PC image. This assumption is made because the

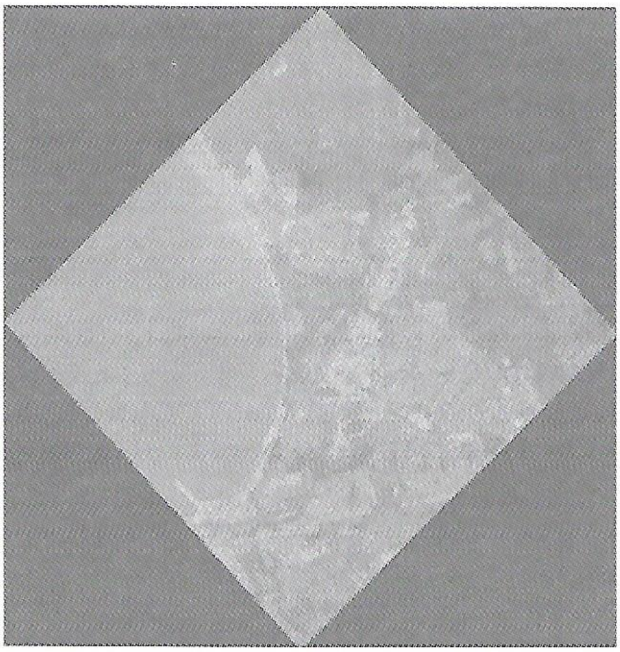

Figure 12: MOMS-2P blue band registered to the Landsat TM

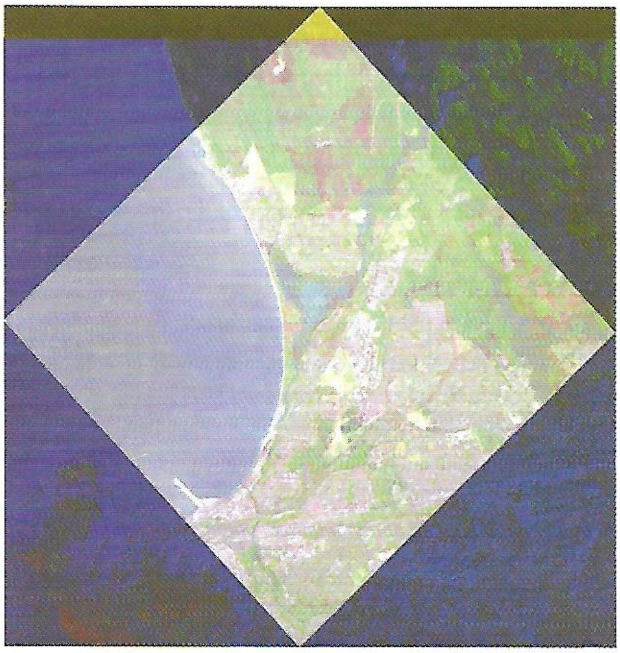

Figure 13: PCT fusion results

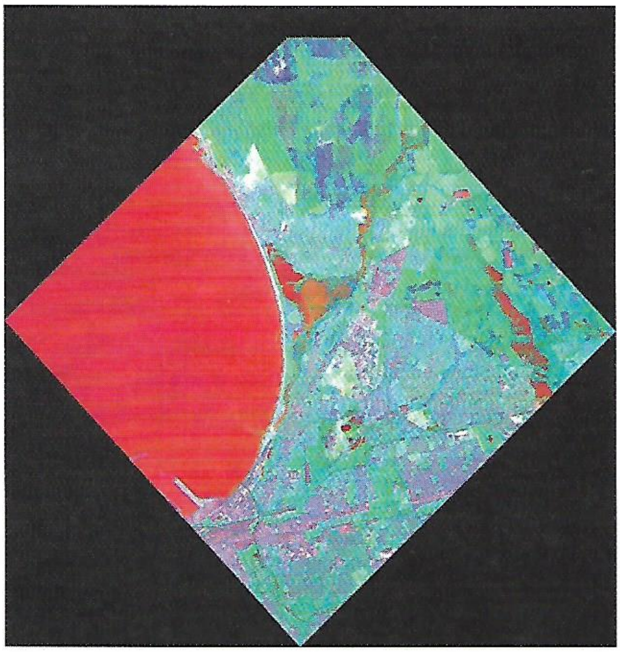

Figure 14: Brovey Transform fusion

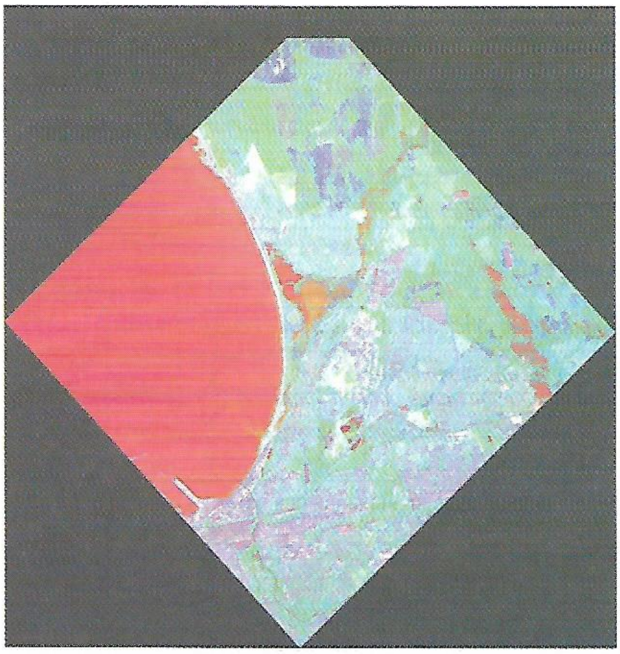

Figure 15: Linear (Multiplicative) fusion

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first PC image will have the information that is common to all the bands used as input to PCT, while spectral information unique to any of the bands is mapped to the other components (Chavez and Kwarteng, 1989).

LINEAR (MULTIPLICATIVE) TRANSFORM

To enhance contrast content, linear combinations and multiplication of images are often used as fusion procedures of RS data. Compared to the PCT method, these combinations allow for a better control of the disturbance of the spectral information (Chavez, 1986; Yésou *et al.*, 1993). The linear combination procedures and the multiplication processes can be summarised in the following equation:

$$DN_f = A(w_1 * DN_a + w_2 * DN_b) + B$$

where:

A and B are scaling factors, w_1 and w_2 are weighted parameters. DN_f, DN_a and DN_b refer to the digital values of the final mixed image, and of the first and second input images respectively (ERDAS Imagine, 1997).

BROVEY TRANSFORM

This transform uses a ratio algorithm to fuse the layers. The technique is simple and straightforward. The model is derived from a simple algorithm (ERDAS Imagine, 1997):

$$[DN_{B1} / (DN_{B1} + DN_{B2} + \ldots + DN_{Bn})] * [DN_{highres.image}] = DN_{B1\_new}$$

$$[DN_{B2} / (DN_{B1} + DN_{B2} + \ldots + DN_{Bn})] * [DN_{highres.image}] = DN_{B2\_new}$$

etc, where B=band.

This method is comparable to the linear transform since they are founded on the same mathematical concept.

FUSION STRATEGY

Figure 11 gives a summary of the strategy for the fusion in this study. The following steps were adopted:

(1) determination of high spectral and spatial resolution data from the Landsat TM and MOMS-2P (MODE B) data respectively.

(2) image-to-image registration of the data sets

(3) carrying out the fusion of the two images to produce a third synthetic (fused) image.

(4) assessment of the quality of the fusion results (geometric and spectral of the synthetic image).

In order to determine the most informative band from the MOMS-2P, histogram analysis and visual (empirical) assessments were carried out on the MODE-B four bands. The MOMS-2P bands were registered to the Landsat TM

Classes	Landsat TM (Selective PCT)	MOMS-2P (MODE-B 4-3-1)	Class Inference
High density residential	y	y	Mixed types of rooming, buildings, with closely spaced storey (3-5 flats)
Medium density residential	y	y	Medium plot mixed with small individual or common open spaces and little vegetation cover if any, 1-2 storeys, single row houses
Roads	n	n	Main roads-termaced
Recreational facilities	y	y	Play grounds, golf and race courses, drive in
Commercial activities	n	n	Commercial centers (ware houses and shopping centers)
Industrial activities	n	n	Large industrial sites or complexes
Commercial/Industrial	y	y	Areas characterized by mixed industrial and commercial features and activities
Seawater body	y	y	Ocean, sea waters
Inland_water body (rivers)	y	y	River courses, lakes, dams
Swamp/marshes	y	y	Shallow waters-vegetated wet lands
Land_water interface	y	n	Land that borders sea/ocean and the land
Steep slopes/shadowed areas	y	y	Steep landscapes, mostly wet due to angle of orientation from the sun
Vegetation types	y(4)	y(6)	Any vegetated (natural or artificial) land cover
Other land cover	y	y	Unclassified (undefined) pixels

Table 11: Land Use/Land Cover Classes from Landsat TM and MOMS-2P

	Landsat TM	MOMS-2P
Training classes	14	15
Average TD	1961	1986
Minimum TD	1030	1526

Table 12: TD analysis summary

(UTM projection) with a root mean square error (RMS) of 0.203 pixel. All the four bands were compared for information content. They all appeared shady. The blue band (band1) was the most informative with respect to information content and clarity. This observation is in agreement with spectral-reflectance curves (Fig 2) for urban-suburban surfaces.

Figure 12 shows the registered MOMS-2P blue band. The geometric correction process induces this shady effect. This, however, is a common observation (Haydn, 1982), resulting from the geometric correction and resampling procedures. Attempts to correct for the shady effect using histogram equalisation and filters (wallis adaptive filter, 3x3 low/high-pass filters) did not give any better quality results when compared to the original image (Figure 12).

FUSION RESULTS

The resulting imagery have pixel sizes of 18m (MOMS-2P) and are assumed to be the same in spectral quality and resolution as that of the Landsat TM selective PCT. The positional accuracy of the fusion results were compared by overlaying the output to the original MOMS-2P data and visually examining for any feature positional mismatch. The results showed correct fit or tie between the two images, meaning accurate positional registration.

PCT FUSION RESULTS

Figure 13 shows the PCT data fusion results. Comparing the original image (Figure 3) with the fused image (Figure 13), the following observations were made: (1) from visual inspection the spectral quality of the synthetic image is lower than that of the original image. This may be due to the fact that the PCT image did not eliminate the shady component of the MOMS-2P blue image, (2) the synthetic image has better spatial quality definition of the features than the original data; and finally (3), the synthetic image presents good spatial discrimination, but rather poor spectral quality, hence not good enough for multispectral based image analysis. However, the spatial quality can be useful in feature extraction based on spatial parameters.

BROVEY TRANSFORM (BT) FUSION RESULTS

Figure 14 shows the BT fusion imagery. Compared to the PCT results (above) and the original data, the following observations were made: (1) the BT imagery shows enhanced industrial/commercial areas; (2) there is low spectral difference between the residential classes and the neighbouring features especially vegetation; (3) sea water is spectrally mapped similar to some inland objects; (4) linear features (especially roads) are easily discernible; (5) tracks of vegetated land and soil are well enhanced compared to urban land; (6) built up structures are well enhanced spatially; and finally, (7) the luminance of the BT imagery is higher than that of the PCT. This implies that the BT technique minimised the shady effect of the MOMS-2P blue band.

These mixed observations may not be suitable for multispectral analysis, however for visual and spatial feature/object analysis, the results are considered sound.

LINEAR (MULTIPLICATIVE) TRANSFORM RESULTS (LT)

The LT results (Figure 15) show similar characteristics to the BT results, except for a slightly lower spectral luminance. Again this manifests the shady effect. The similarity between these two results confirms the fact they operate on the same mathematical concept.

In feature/object identification, LT has the same characteristics as the BT except they appear in the LT with lower luminance.

ANALYSIS AND COMPARISON OF THE FUSION RESULTS

The observations above may not be sufficient for suitability judgement. In this study, three simple techniques are used to assess the quality of the fusion results: (1) visual; (2) graphical and (3) statistical comparison techniques.

VISUAL COMPARISON

In a visual approach, a comparison is made on how the fusion technique distorts the brightness and the spectral characteristics of the original image. The concept used here is by image subtraction or difference, which can be expressed mathematically as follows:

$$C(i,j) = I_1(i,j) - I_2(i,j)$$

where: $C(i,j)$ = value of pixel (i,j) in the difference image; $I_1(i,j)$ = value of pixel (i,j) in the original image; and $I_2(i,j)$ = value of pixel (i,j) in the new output image. The hypothesis for judgement is that least difference means lower spectral distortion and vice versa.

Figures 16, 17 and 18 show differences between the original and the PCT, BT and LT fusion results respectively. A comparison of these differences indicates that PCT fusion gave the best (least distorted) results. The BT and LT results were the same and they both reflect spectral distortion across the entire image.

GRAPHICAL COMPARISON

In a graphical analysis for synthetic image quality assessment, DN values of land cover types from the synthetic and original imagery are plotted on the same scale. The rationale in this approach is that perfect fusion results should maintain the spectral resolution of the original high-resolution

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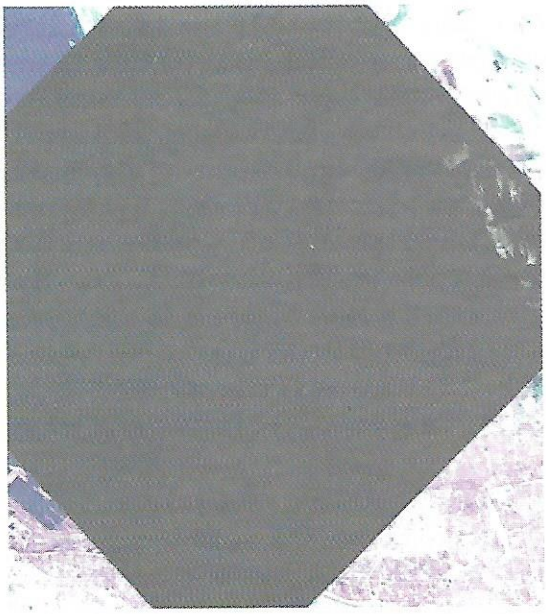

Figure 16: Original-PCT results

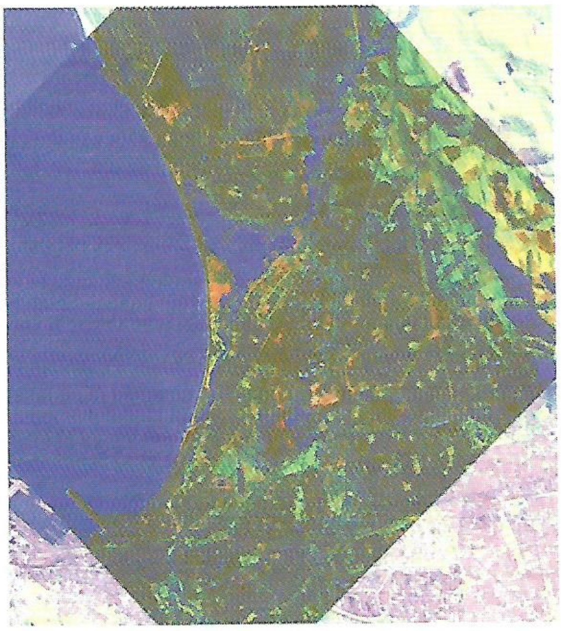

Figure 17: Original -Linear results - and Figure 18: Original-Brovey results. These two images are identical and are shown as one image in the text.

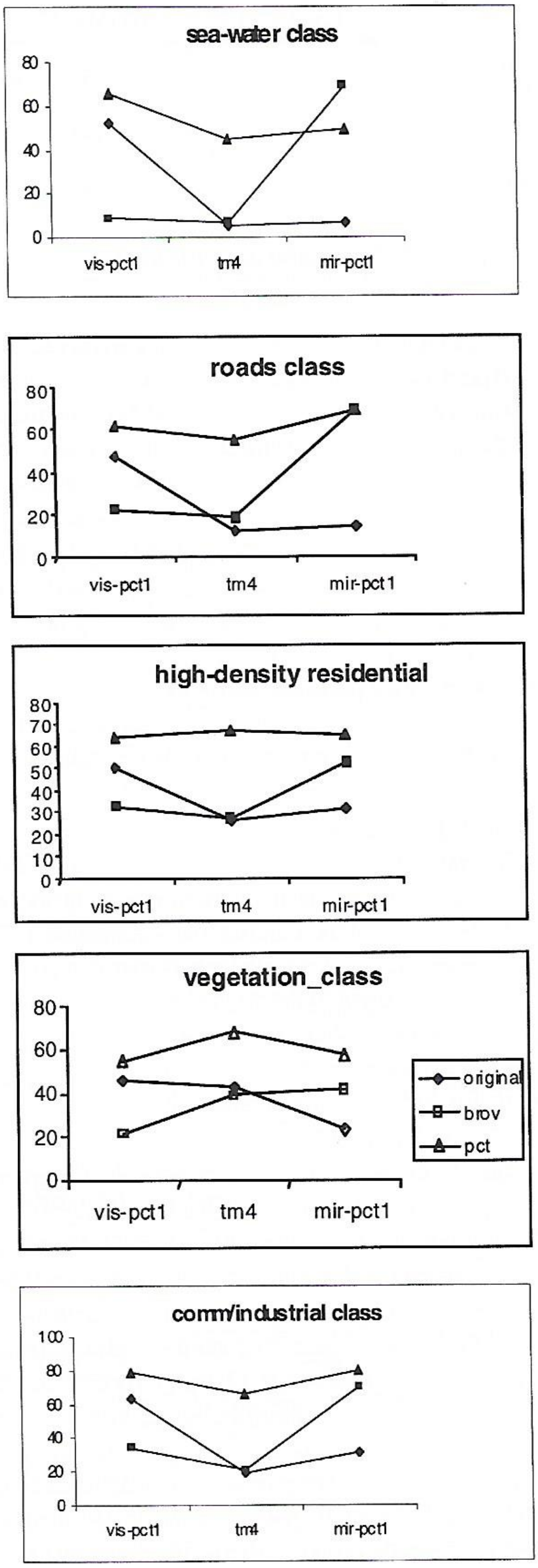

Figure 19: Plots generated from the average DNs of 5 classes for the three bands.

Figure 18: Original-Brovey results

imagery. Thus the DN plots should ideally be the same for the compared images. Figure 19 shows the results as obtained from 5 land cover classes (vegetation, high-density residential, seawater, road surface and commercial/industrial).

From the plots, it is observed that the BT and LT methods changed the original DN values in an irregular manner. The PCT results also changed the DN values but in a linear trend. The PCT and the original image curve depicts a linear (predictable) pattern, with PCT values higher than original values. Further, it is observed that in the VIS domain, PCT results are closer to the original values than the BT and LT. In the TM4 (NIR), the fusion results show consistent results in which the BT/LT results are closer to the original than the PCT values. In the MIR, the BT/LT results are closer but better than the PCT.

From these observations, it is concluded that the PCT gave closely consistent and more realistic results compared to the BT/LT. The large difference in the DN values between PCT and the original data are attributed to the shady effect of the MOMS-2P data.

STATISTICAL COMPARISONS

In statistical analysis, the correlation coefficients between the original data bands and the output data bands are computed and compared. Tables 13, 14 and 15 gives the correlation coefficients for the original, PCT and BT/LT fusion results.

Statistically comparing the original, PCT and the BT/LT fusion correlation coefficients its is observed that the PCT results are highly distorted compared to the BT/LT results. The resulting bands are more correlated in the synthetic imagery compared to the original. From the statistical standpoint, the PCT gave the poorest results. This is illustrated in the luminance of the PCT fusion results (Figure 13).

DISCUSSIONS AND CONCLUSIONS

RS data optimisation and evaluation is a very significant step for any realistic results to be obtained in a project. Various analysis tools are essential for simultaneous data processing and interpretations as illustrated in this study. From this study it is evident that not one method will be sufficient in judging the most informative data for scene analysis. This, for example, is illustrated in this study by the remarkable improvements in the correlation between the raw TM bands (Table 2) and the selective PCT bands (Table 13).

From the above RS data fusion results the negative influence of geometric corrections and resampling on digital data is observed. This, in effect, influences the output of any other digital analysis that follows and may lead to misleading results. This implies that for good quality results, data with similar geometric properties may be more desirable (e.g. MOMS-2P (MS/P)).

Fusion of digital data leads to outputs that can be very useful in digital or visual image analysis. No single method can be considered as appropriate. Thus depending on the nature of the input data and the task, alternative techniques are advisable. In this study, it is concluded that the PCT fusion is superior to BT/LT methods since it was least distorted. However the graphical and statistical analysis reflect the magnitude of the shady effect on the fusion results. The BT/LT is observed to be more suitable for data fusion in areas of land cover analysis (water, vegetation and soils) and not urban land.

The study emphasises that the visual interpretation of these fusion results could be more accurate and useful than digital analysis.

The study suggests that a fusion algorithm that can cater for radiometric and noise corrections in the input data in the fusion and can simultaneously take as many bands as possible (like PCT) is recommended. The Intensity, Hue and Saturation (IHS) fusion may be especially recommended for the urban scene data fusion.

Finally, urban-suburban environments are spectrally heterogeneous. This implies that spectral separation of features/objects in these environments is a complex task. The study suggests that for effective mapping/monitoring of

	Orig-1	Orig-2	Orig-3
Orig-1	1.00	0.29	0.42
Orig-2		1.00	0.72
Orig-3			1.00

where: Orig-1 is the PC1 of the TM-VIS, Orig-2 is the TM4 and Orig-3 is the PC1 of the TM-MIR

Table 13: Corr. coefficients for the original data

	PCT-1	PCT-2	PCT-3
PCT-1	1.00	0.97	0.98
PCT-2		1.00	0.93
PCT-3			1.00

where: PCT-i is the new PCT fusion band corresponding to the original data.

Table 14: Corr. coefficients for the PCT bands

	BT/LT-1	BT/LT-2	BT/LT-3
BT/LT-1	1.00	0.51	0.57
BT/LT-2		1.00	0.89
BT/LT-3			1.00

where: BT/LT-i is new band from the fusion results corresponding to the original data.

Table 15: Corr. coefficients for the BT/LT bands

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these environments, higher spectral resolution data may suffice. A need to investigate theutility of hyperspectral and radar imagery is recommended for the analysis of urban-suburban environments.

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