Comparison of Landsat TM and MOMS-2P using Principal Componets Analysis (PCA) and Classification of Land-Use and Land-Cover-South African Journal of Geoinformation - vol. 17(6), p...

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EVALUATION OF THE MEDIUM-RESOLUTION SATELLITE DATA (LANDSAT TM AND MOMS-2P) FOR LAND USE ANALYSIS IN AN URBAN/SUBURBAN ENVIRONMENT

By

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ABSTRACT

A challenge encountered with remote sensed (RS) data today is the determination of which RS data source gives the most informative data for a three-image set for colour compositing or digital analysis. In this paper, in order to compare the spectral contrast from Landsat TM and MOMS-2P (MODE B), for urban-suburban mapping, different procedures for spectral contrast optimisation: colour composite display and principal component transformation (PCT) were tested. The scene features/objects were classified using a hybrid maximum-likelihood classification approach.

For these two steps of image processing, the best results were obtained by respectively using selective PCT and colour compositing for the Landsat TM and MOMS-2P data optimisation. Classification results analysed using the statistical KAPPA and TAU coefficients of agreement indicate a slight improvement in the object/feature classification from the lower medium-scale (MOMS-2P-18mx18m) in comparison to the upper medium-scale (Landsat TM-30mx3om) data for the scene. These results are illustrated using divergence and scatterplots for class separability analysis.

INTRODUCTION

Faced with the increasing availability of RS data, the user has to choose the appropriate data source for mapping as much information as possible into a reduced sub-set of images for digital analysis and/or colour compositing. A user is often interested in the information that is unique in each data source and spectral band as compared to information that is common to all the data sources and their bands. That is, what new information does each sensor and its bands contribute that is not contained in others? Mapping this spectral difference or contrast and understanding what causes the contrast can be important in different applications. The urban-suburban area presents a case study of heterogeneous spectral responses. These areas require detailed and concise spectral contrast analysis for any meaningful feature/object analysis to be done.

The objective of this paper is to illustrate the utility of the medium-scale data sources for urban-suburban mapping. The following execution steps were taken: (1) multispectral data optimisation, (2) training class evaluation, (3) supervised maximum-likelihood classification and (4) classification results validation.

In this paper, (1) "information" is used in an informal rather than formal sense. The definition for information is taken as "new information indicates the apparent presence of previously unavailable clues or insights into the characteristics of the scene being viewed". (2) Medium-scale, in terms of spatial resolution, is considered to range between 6-30m. Lower medium-scale is 6-18m spatial resolution and upper medium-scale is 20-30m spatial resolution. Micro scale would be considered between 1-5m, while macro-scale is considered above 30m. (3) Features/objects are also referred to as land uses where relevant.

TEST SITE AND DATA

The six reflective bands of the Landsat TM and the four reflective bands of MOMS-2P (MODE-B) (Table 1) were examined to assess their utility for part of Cape Town City. Figure 1 shows the location of the study area. The area under consideration lies between latitudes 33°45′-33°56′S and longitudes 18°26′-18°34′E. Ancillary data included aerial photos, base maps and ground reconnaissance.

Table 1: Landsat and MOMS-2P images characteristics

	Landsat TM	MOMS-2P
Sensor	TM	MS/P
Date	1993-07-20	1996-10-13
Season	Winter	Spring
Resolution	30m	18m
Bands	6	4
Projection	UTM-USGS	-

URBAN-SUBURBAN SPECTRAL RESPONSE

The fundamental premise of remote sensing is that object/feature information is transmitted through space via force fields, and in particular via spatial, spectral and temporal variations of these fields. Then to capture the sensed data, one must measure those variations and relate them to classes of material of interest.

The sensor material must measure the variations, and then the analysis system must provide for relating the measurements to the classes of materials of interest in any particular case and with acceptable accuracy. All sensors focus on spectral variations for pragmatic reasons, although spatial and temporal variations have not been ignored.

The concept of how these variations are represented mathematically and conceptually is an important step in defining how the analysis process should proceed. There have been three principal ways in which multispectral data are represented quantitatively and visually. These are: (1) in image form, i.e. pixels displayed in geometric relationship with one another, (2) as spectra, i.e. variations within pixels as a function of wavelength, and (3) in feature space, i.e. pixels displayed as points (clusters) in a N-dimensional space.

In this paper the spectral-space representation is used to illustrate the spectral variability or response within the urban-suburban space. Figure 2 shows land cover (water, soils and vegetation) spectral response within the visible (VIS), near-infrared (NIR) and mid-infrared (MIR) parts of the spectrum. Figure 3 shows the urban surface spectral plots in comparison to the land cover.

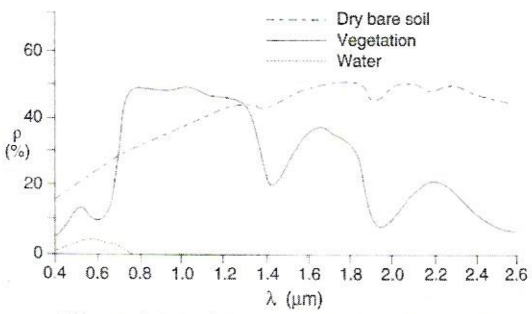

Figure 2:Land cover spectral reflectance *(after Bird, 1991)*

From Figure 2 it is observed that all the land cover features can be mapped in the VIS. Water absorbs all the energy in the NIR and MIR. Dry soil shows progressive increase in reflectance from the VIS and peaks at MIR with only slight dips in between. Vegetation spectral reflectance peaks at the reflective infrared.

Figure 3 gives discrete spectral reflectance values in digital numbers (DN) for the urban land use, water and soil surfaces.

The soil and water curves are comparable to those in Figure 2. The urban surface has much variance in the blue part of the VIS and the MIR parts of the spectrum. From the above spectral illustrations, is it is possible to judge which spectral bands are suitable for mapping specific land use/land cover. However, for a scene with both land use and land cover features/objects coexisting, one may not easily determine the most contrasting spectral bands from the signatures alone.

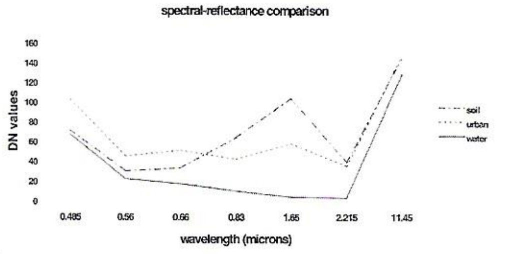

Figure 3: Land use-and cover spectral response *(modified from ERDAS Imagine, 1994)*

DATA OPTIMISATION: SPECTRAL CONTENT EXTRACTION

Table 2 shows the spectral resolutions of the Landsat TM and MOMS-2P in terms of the wavelengths.

Table 2: Test Data Spectral Wavelengths (μm)

	Landsat TM	MOMS-2P
VIS	TM1: 0.450-0.560	M-2P1: 0.440-0.505
	TM2: 0.520-0.600	M-2P2: 0.530-0.575
	TM3: 0.630-0.760	M-2P3: 0.645-0.680
NIR	TM4: 0.760-0.900	M-2P4: 0.770-0.810
MIR	TM5: 1.550-1.740	-
	TM7: 2.080-2.350	

From Table 2, it is observed that these two sensors possess different spectral resolutions with respect to their spectral positioning. The subsequent sections report on the techniques applied to map the urban-suburban information from the two data sets.

COLOUR COMPOSITE DISPLAY-FCC

The six Landsat TM bands and the four MOMS-2P bands provide 20 and 4 possible band

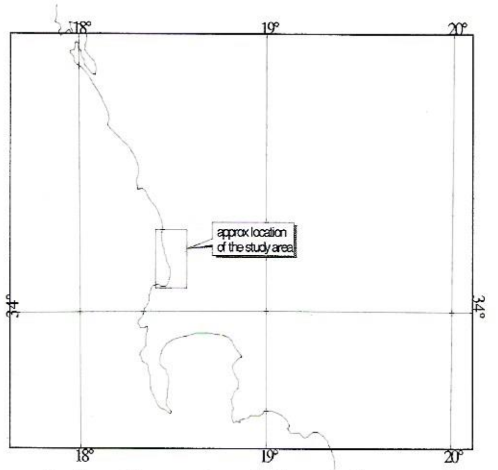

Figure 1: Location map of the study area-Cape Town sub-scene.

combinations for colour display respectively. To get an optimal colour composite, the three bands used must be individually informative and also have to show minimal redundancy. Two ways to determine the optimum band combination in this study are the empirical and statistical approaches.

Tables 3 and 4 shows the statistical details of the Landsat TM and MOMS-2P for the test area.

From Table 3, standard deviations show that in the VIS of the Landsat TM, TM1 has the highest amount of variance. In the MIR, band seven has less than half the variance of band 5. The correlation coefficients (*r*) show that the VIS bands and the MIR bands are highly correlated.

Table 4 (MOMS-2P) statistics show that band 4 (M-2P4) has most variance, followed by M-2P1, M-2P2 and finally, M-2P3. The NIR band (M-2P4) shows very low correlation with the VIS bands. The MOMS-2P inter-band correlations are lower compared to the TM bands. This indicates lower information content redundancy in the MOMS-2P compared to TM.

Empirical procedure for FCC

The three channels are selected from an *a priori* knowledge of the spectral properties. Figures 2 and 3 illustrate the spectral response. This approach reduces the number of possible band combinations. A visual examination based on spectral parameters and luminosity contrast of the different colour composites allows for the determination of the most informative bands.

Table 5 and Table 6 show results of the visual ranking (Vi Rank), of some of the informative band combinations for the Landsat TM and MOMS-2P data respectively.

For the Landsat TM, 13 combinations are presented. In decreasing order, the most discriminative sets are 5-4-1, 7-4-1, 7-4-3, then 5-4-3 followed by 7-4-2. Combination 5-4-1 gave the most contrasted colour composite according to the empirical approach. This observation is supported by the signatures (Figures 2 and 3), the standard deviation and correlation coefficient statistics (Tables 3 and 4). Combinations not tested (e.g. 4-2-1, 5-2-1, 5-3-1, 7-3-1, 5-3-2, 5-2-1 and 7-3-2) are from the signature and statistical logic, considered unsuitable since they are highly correlated.

For the MOMS-2P, Table 6 shows the empirical analysis results. In decreasing order, 4-3-1, 4-3-2, 4-2-1 and 3-2-1 combinations are obtained. According to the variance statistics (σ), band 4-2-1 would have been the most informative, yet Vi Ranks it third. This may not be directly justified, but the correlation between M-2P1, M-2P2 and M-2P3 overrules the variance reasoning. According to the correlation coefficients, bands 4-3-1 are the most informative. This implies that band M-2P2 contains the most redundant information in the VIS and that is why 4-2-1 ranks third.

Statistical procedures for FCC

In order to save time in processing and analysing multiband data, some authors propose to use statistical procedures (Chavez *et al.*, 1982; Sheffield, 1985; Crippen, 1989).

Table 3: Standard deviation and correlation coefficients computed for the six Landsat TM bands

Bands and σ	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	0.44	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 4: Standard deviation and correlation coefficients computed for the four MOMS-2P bands

Bands and σ	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

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 band and the bands' correlation coefficients are redundancy indicators.

The Optimum Index Factor, 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 the inter-band correlation coefficients.

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

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

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

where σ_i is the standard deviation for channel *i*, and $r_{i,j}$ the correlation coefficient between the channels *i* and *j*. The higher the OIF or the INDEX, the more uncorrelated spectral information is transformed into a contrast-rich colour composite.

These two statistical procedures were performed on the Landsat TM and MOMS-2P data. Results are presented in Table 5 and 6 respectively.

From Table 5, results obtained by Chavez (OIF) indicate that TM5-4-1 is the most informative and that TM7-4-1 and TM4-3-1 etc in order, are also informative. Using Crippen's INDEX, TM7-4-1 is the most contrasting combination followed by TM7-4-2 and TM5-4-1 etc. The two statistical methods give coinciding results only for a few of the combinations (3-2-1, 5-4-2, 7-5-3). OIF and Vi Rank give similar results supporting TM5-4-1 to be the most informative set. This is supported by the correlation coefficients.

Table 6 gives the statistical approach (INDEX and OIF) results for the MOMS-2P. OIF show 4-3-2 to be the most informative, while the INDEX gives 4-3-1 to be the most informative combination. However from the correlation coefficients analysis the INDEX and Vi Rank results are correct, with 4-3-1 FCC being the most informative triplet.

In conclusion, no one of the methods described for colour composite display can be considered adequate in reaching conclusive decisions for choosing band combinations. Combinations of the tests do give results that may be used to tie up the theoretical logistics and experimental observations. In this case, from colour composite display, it is concluded that, bands 5-4-1 of Landsat TM are the most spectrally contrasting combination as derived from the Vi Rank and OIF results. For the MOMS-2P the INDEX and Vi Rank indicated that 4-3-1 combinations is the most informative. In summary, colour composite display analysis, the use of both the empirical and statistical techniques is found to be useful in deciding upon the best FCC.

Table 5:OIF, INDEX and Vi Rank computed for Landsat TM data

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 6: OIF and INDEX computed for MOMS-2P data

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

PRINCIPAL COMPONENTS PRANSFORMATION (PCT)

PCT is a statistical method that transforms a 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). The sum of the variance of the generated PCs is equal to the total variance of the initial variables. Each successive PC depicts decreasing variance levels. This capability to compress multiple spectral bands is a useful data reduction technique that can be used directly in feature/object extraction. This is because differences between similar or different materials may be more apparent in the PCs than in the individual channels (Jensen, 1996; Yésou *et al.*, 1993; Jensen 1986; Faust, 1989).

In addition, the method allows for the determination of the number of linearly independent sources of variation within the data set that can effectively summarise the data without significant loss of information. A good description of PCT can be found in Mather, 1986. PCT has been used for data enhancement (Soha and Schwartz, 1978; Gillespie *et al.*, 1986), as a data compression technique (Chavez and Kwarteng, 1989), to detect changes in land cover (Byrne *et al.*, 1980; Richards, 1984) and as a technique of merging multisensor data, e.g. radar and/or multispectral images (Yésou *et al.*, 1993).

Two PCT procedures were tested: (1) standard PCT and (2) selective PCT.

STANDARD PCT

The 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 of the MOMS-2P are the PCT input.

The band linear correlations are given in Tables 3 and 4. Tables 7 and 8 give the eigen-values and eigen-vectors of the Landsat TM and MOMS-2P bands respectively.

Landsat TM Standard PCT

The standard PCT is performed using all the six TM bands as input. The results presented in Table 7 shows the eigen-values expressed as % of variance and eigen-vectors [-1, +1]. It is observed that the first three PCs explain more than 98% of the total variance. PC1 receives positive contributions from all the input channels, contributing about 80% of the transformed variance. PC2 has positive contributions from the VIS and negative from the MIR and the NIR. PC3 contains mostly information from the VIS (TM1 and TM2) and TM4 (NIR). This constitutes less than 5% of the transformed data. PC4, PC5 and PC6 in total contribute less than 2% of the transformed information. The spectral information contents (PCs) are as illustrated in Figures 4-9.

Figure 4, PC1, contains detailed information of the scene. No specific object/features are outstandingly mapped in PC1 except for the land water interface (coastal land).

Table 7: Standard PCT applied to Landsat TM data

	PC1	PC2	PC3	PC4	PC5	PC6
% of variance	80.7	12.7	4.9	0.8	0.5	0.4
input band						
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


Fig 4: TM Standard PC1


Fig 5: TM Standard PC2


Fig 6: TM Standard PC3

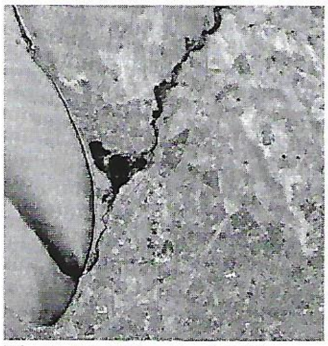
Fig 7: TM Standard PC4


Fig 8: TM Standard PC5


Fig 9: TM Standard PC6

PC2 (Figure 5) shows features that are well enhanced, especially roads and river courses. It also gives more structural information and defines land use/land cover extents. PC3 (Figure 6) maps more clearly the recreational facilities (e.g. golf course) compared to PC1 and PC2. It does not show any clear discrimination between other land use/land cover. The lower PCs (Figures 7-9) hardly contain any spectral information except for PC4 that maps the river course and swampy (wet) land cover.

In conclusion, the six TM data are transformed effectively into three PCs.

MOMS-2P (MODE-B) Standard PCT

Standard PCT gave the following results (Table 8). From the results, the first three PCs explain more than 99% of the total variance, with the last PC, (PC4), representing less than 1% of the total variance. Figures 10-13 shows the PCs.

PC1 (Figure 10) contains detailed information of the scene accounting for about 80% of the total variance. Most of the PC1 information is from band 1 (VIS) and least from band 4 (NIR). PC2 (Figure 11) contains about 15% of the transformed data mostly from the VIS (band 1). PC2 maps out regions of specific dense vegetation type (deep green). PC3 (Figure 12), with information content of about 1% outstandingly maps out areas of concentrated commercial and industrial land use leaving out, for example, the residential land use! PC4 (Figure 13) with less than 1% of the total data contains no specific information. However with a lot of information from the NIR band, PC4 reflects good demarcation between land covers.

In conclusion, comparing the MOMS and TM standard PCT analysis, despite spectral differences, both of them map above 90% of the total spectral variance in the first three PCs. For specific applications using PCT only, MOMS may be more useful for vegetation and industrial/commercial mapping.

Table 8: Standard PCT applied to MOMS-2P (MODE-B)

	PC1	PC2	PC3	PC4
% variance	82.60	15.41	1.14	0.85
input band				
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

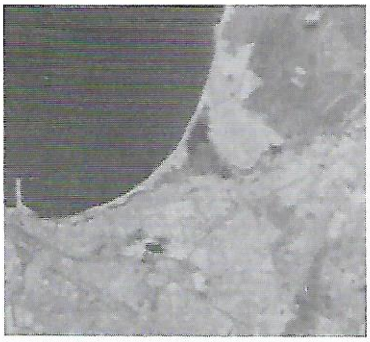
Fig 10: MOMS Standard PC1


Fig 11: MOMS Standard PC2

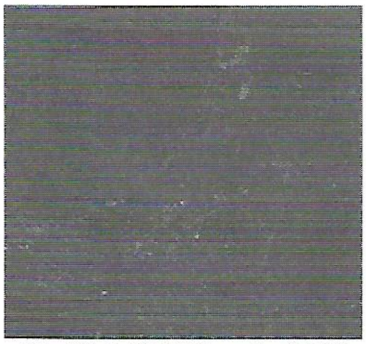
Fig 12: MOMS Standard PC3


Fig 13: MOMS Standard PC4

SELECTIVE PCT

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

Landsat TM Selective PCT

Selective PCT is applied to the TM-VIS and TM-MIR bands. The eigen-values and eigen-vectors for the VIS and MIR PCTs are presented in Tables 9 and 10 respectively.

Landsat TM-VIS Selective PCT

The VIS-PC1 (Fig 14) contains about 90% of the transformed data. The spectral content contains detailed scene data. The PC2 (Fig 15) contains about 8% of the data and roughly maps inland water body (marsh/swamp), land water interface and industrial/commercial land use. PC2 has most of the input data from band 3 of the VIS. PC3 (Fig 16) with less than 0.5% of the transformed of the data only has noise contents from the VIS.

Table 9: TM-VIS Standard PCT statistics

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

Landsat TM-MIR SelectivePCT

Table 10 gives the statistical output for the Landsat TM-MIR PCTs.

Table 10: TM-MIR Standard PCT statistics

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

Figures 17 and 18 shows the PCs. The TM-MIR PC1 maps the general content within the scene with good delineation of large structures, especially industrial/commercial land use. The second PCT (containing less than 1.5% of the transformed variance) roughly maps industrial, commercial and residential land uses.

From the selective PCT, TM seems to be able to map specific land use and in this it is comparable to the MOMS standard PCT. For example the TM-MIR seems suitable for mapping built land use similarly to TM-VIS PC2.

MOMS-2P Selective PCT

In the case of the MOMS, only the VIS is suitable for selective PCT. Table 11 shows that PC1 (Fig 19) contains about 94% of the variance as compared to PC2 (Fig 20) and PC3 (Fig 21) which contain approximately 3% and 2.5% of the total transformed data respectively.
Figure 20 roughly shows land use/cover demarcation, but no specific mapped features/objects. This is because of the low contributions from the input bands (Table 11).

The same applies to PC3 (Fig 21), which only shows more noise components of the VIS.

Table 11: MOMS-2P VIS selective PCT

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


Fig 14: TM-Selective VIS PC1


Fig 15: TM-Selective VIS-PC2


Fig 16: TM-Selective VIS-PC3

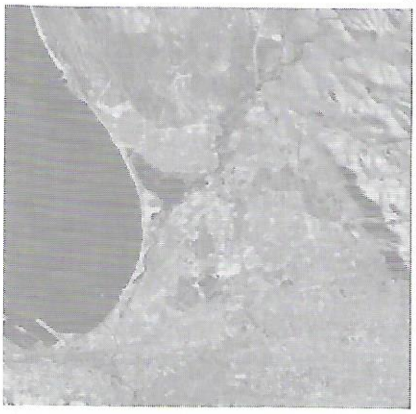
Fig 17: TM-Selective MIR PC1

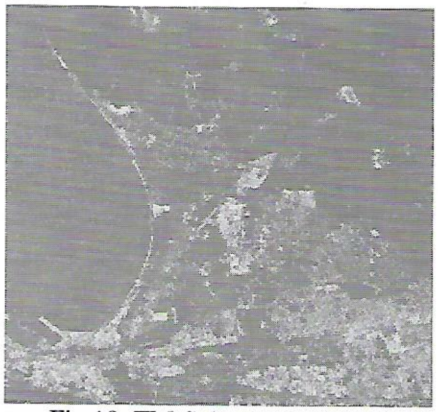
Fig 18: TM-Selective MIR PC2


Fig 19: -2P-SelectiveVIS PC1

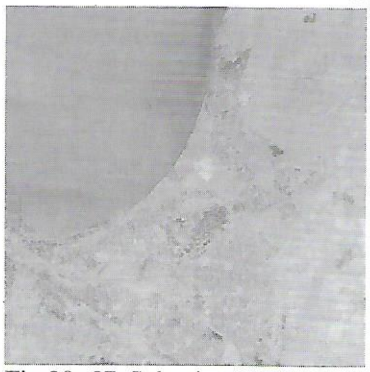
Fig 20:-2P-Selective VIS PC2

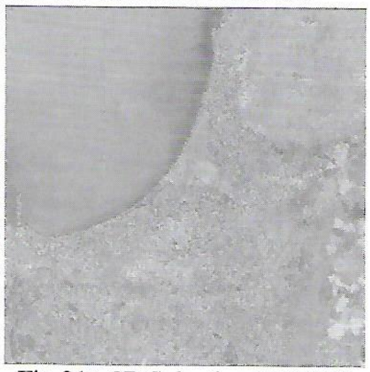
Fig 21: -2P-Selective VIS PC3

MULTISPECTRAL DATA OPTIMISATION ANALYSIS

The next step is to determine which of the methods (colour composite display and PCT) gives the most informative three-band combination for digital analysis. In this study the consideration is for land use/land cover analysis. Thus apart from appreciating the significance of PCT for direct feature/object detection and possibly extraction thereof, a colour composite of the informative PCs from the selective and standard PCTs is derived based on spectral contrast. The decision is based on empirical and histogram comparison and analysis of the bands making up the composite. All the possible informative composites were considered for the analysis.

Based on this approach, the TM standard PCT composite (PC1, PC2 and PC3) was compared with the TM selective PCT composite (VIS-PC1, TM4 and MIR-PC1), and the colour composite display TM5-4-1. The TM selective PCT composite (Fig 22) gave the most contrasted colour composite and is the original raw image.

The same procedure was applied to the MOMS-2P FCC 4-3-1, MOMS-2P standard PCT composite (PC1, PC2 and PC3) and selective PCT composite of (VIS-PC1, VIS-PC3 and M-2P4). The false colour composite 4-3-1 (Fig 23) gave the most informative three-set combination for the scene and is the original raw image.

In conclusion, the TM selective PCT and the MOMS-2P false colour composite 4-3-1 were compared for the scene landuse analysis.

CLASSIFICATION METHOD

TRAINING SAMPLE (DATA) ANALYSIS

A supervised training technique based on areal extraction of spectral values, with spatial and spectral constraints determined by the user (ERDAS Imagine, 1994), was used to generate the spectral signatures of the information classes. Transformed divergence and scatter plot analyses were implemented to statistically evaluate class signature separability.

Transformed divergence (TD_{ij}) is a modification of the divergence measure (D_{ij}), which provides prior probability of correct classification. It can be computed from the following formula (Swain and Davies, 1978):

$$D_{ij} = \frac{1}{2} tr[(C_i - C_j)(C^{-1}{}_i - C^{-1}{}_j)] +$$

$$\frac{1}{2} tr[(C^{-1}{}_i - C^{-1}{}_j)(\mu_i - \mu_j)(\mu_i - \mu_j)^T]$$

where i and j are the two classes being compared, C_i is the covariance matrix of class i, μ_i is the mean vector of class i, tr is the trace function of the matrix, ^{T} is the transposition function, and $TD_{ij} = 2(1 - e^{D_{ij}/8})$. According to Richards (1986), the probability of a correct classification (P_c) is bounded by:

$$P_c < 1 - \frac{1}{8}(1 - \frac{1}{2} TD_{IJ})^4$$

TD varies between 0 and 2000. A TD of zero indicates that the classes are totally inseparable. For TD greater than or equal to 1600, good separability is expected (Richards 1986). A separability listing containing the average and minimum divergence for every class pair and band combination is generated from Erdas Imagine software.

TD for class separability measure results

Table 12 gives a summary of the TD analysis of the training sample evaluation for the Landsat TM and MOMS-2P.

Table 12: TD analysis summary

	Landsat TM	MOMS-2P
Training sample	14	15
TD average	1961	1986
TD minimum	1030	1526

It is observed that fewer classes were determined from the TM data compared to the MOMS-2P. Despite more classes in MOMS-2P, the TD values were higher in MOMS than in the Landsat TM. This is an indication of higher spectral separability in the MOMS-2P compared to the TM with respect to multispectral analysis for the urban-suburban scene. In both cases the minimum TD is observed between the industrial/commercial classes and the residential (high/medium density) land use.

Scatterplot class separability results

Figures 24-26 illustrate the separability of the 14 training classes from TM (TM VIS-PC1, TM 4 and TM MIR-PC1 composite-Fig 22).

These plots show that for this scene, there is low spectral separability of the classes from TM. This is also supported by TD results. Only TM VIS-PC1 and TM MIR-PC1 (Fig 25) show fair spectral separability compared to the other two.

Figures 27-29 illustrates the 15-classes separability ellipse plots from the MOMS-2P 4-3-1-colour composite. The result show that in the VIS (Fig 27, band1-band3) not much urban-suburban land use/land cover information can be extracted. However, Figures 28 and 29 illustrate positive contributions from the VIS and NIR of the MOMS-2P data.

SPECTRAL INFORMATION CONTENT

In terms of spectral (band) information content, it is evident that high spectral separability measures are observed from land cover (vegetation, soil and water types), as opposed to land use (roads, residential, commercial, industrial, recreational facilities) with high spectral overlaps, characterised by low TD values and ellipsoid plots with greater overlaps. From the above inter-class, inter-band analysis, it can be concluded that MOMS-2P is seen to be more informative for the urban-suburban object/feature extraction than the TM data.

MULTISPECTRAL LAND USE/LAND COVER EXTRACTION

The land use/land cover was mapped based on the above training classes. Mapping consisted of several stages, cluster analysis and supervised classification. Class labelling was performed using maximum-likelihood classifier based on equal class *a priori* probabilities

The post-classification processing comprised class merging and application of a 3x3-majority filter to improve (smooth) the thematic map readability by deleting small patches. Finally accuracy assessment by matching ground reference data with the labels of the classified image were statistically analysed using the KAPPA and TAU coefficients of agreement (Cohen, 1960; Ma and Redmond, 1995).

CLASSIFICATION RESULTS

Figures 30 and 31 present the spatial distributions of land use/land cover in the Landsat TM and MOMS-2P data respectively. The results show the 14 classes that were mapped from the Landsat TM and the 15 classes generated from MOMS-2P. Table 13 shows the land use/land cover checklist for the classes that were present and could be derived from the scene. Important classes that were visually observable but could not be spectrally extracted e.g. roads, are also shown.

Remarkably, more types of vegetation were detected in MOMS-2P than in Landsat TM. This was largely due to the temporal differences. This difference was verified by analysing the normalised difference vegetation index (NDVI's) and the NIR bands for vegetation mapping. These ratio results identified and confirmed more vegetation cover types in MOMS-2P than in TM and were attributed to seasonal difference i.e. spring growth between July (TM) and October (for the MOMS data) as well as the narrow spectral range of the MOMS-2P band 4 that is sensitive for vegetation mapping.

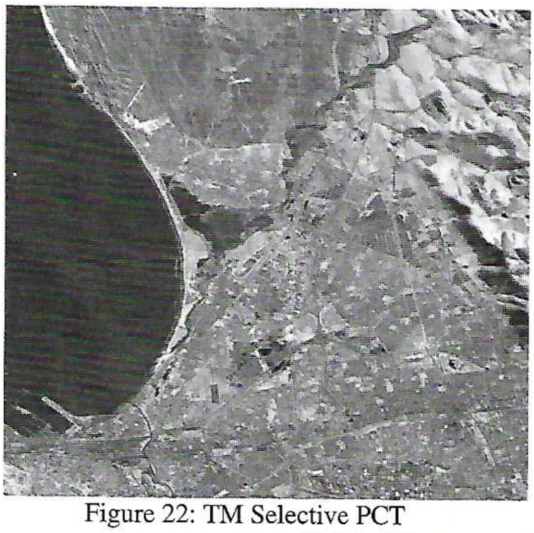

Figure 22: TM Selective PCT

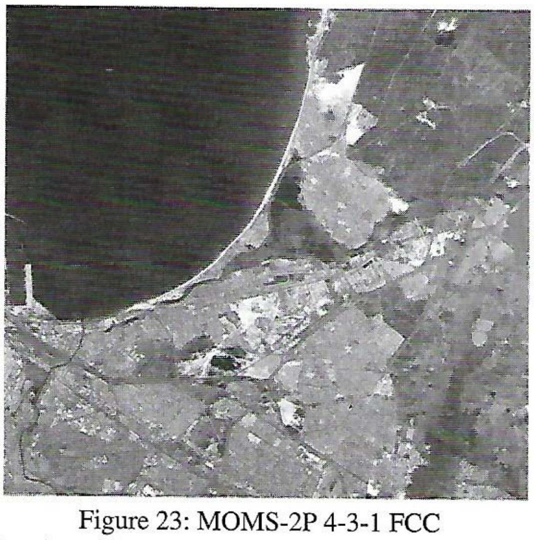

Figure 23: MOMS-2P 4-3-1 FCC

(Original images are in RGB colour composite)

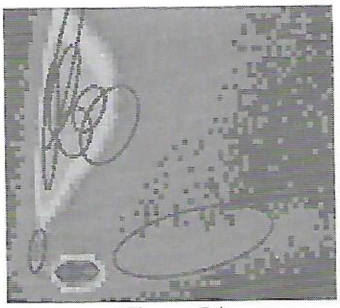

Figure 24:
TM VIS-PC1 versus TM 4

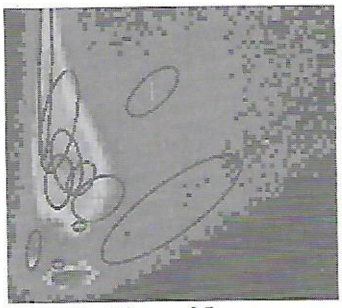

Figure 25:
TM VIS-PC1 versus MIR-PC1

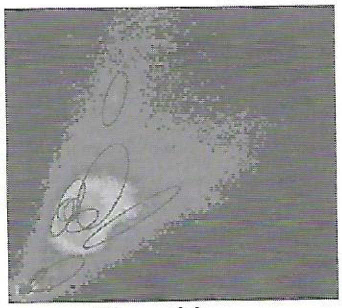

Figure 26:
TM TM4 versus MIR-PC1

Figure 27:
MOMS band1 versus band3

Figure 28:
MOMS band1 versus band4

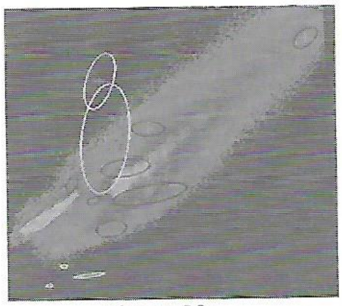

Figure 29:
MOMS band3 versus band4

Table 13: Land Use/Land Cover Classes from Landsat TM and MOMS-2P

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

From Table 13 it is evident that from both the lower and upper medium-scale spatial resolutions, it is not possible to separate commercial, industrial, and roads via multispectral classification. It is further observed that, in consideration of the entire scene, beaches (coastal land) are extractable from TM and not MOMS-2P. With respect to vegetation, more types were extractable from the MOMS-2P than TM, as already explained above.

Table 14 gives a summary of the KAPPA (K) and TAU (T) coefficients of agreement as computed for the classification results. Common areas, from the scenes, were considered for the assessment of the classification performance. The reference data were obtained from aerial photographs and true colour composites (bands 3-2-1) of the Landsat TM and MOMS-2P.

CONCLUSIONS

A comparison of Landsat TM and MOMS-2P data sets was conducted to evaluate the capabilities and limitations of these two sensors for the purpose of identifying and mapping urban-suburban land use classes. Multiband optimisation for selection of the most informative band combination was performed using colour composite and PCT approach. Statistical, empirical and histogram techniques were combined to evaluate the most informative set. Transformed divergence and scatterplot analysis were used to choose and consequently determine the degree of training class separability before classification. Classified mixed pixels (mixels) smoothing was achieved by using a 3x3-majority neighbourhood filter, and finally accuracy report of the classified data sets was produced using KAPPA and TAU coefficients of agreement in order to quantify the differences in mapping urban-suburban land use classes from the MOMS-2P and Landsat TM. The results can be summerised as follows:

(1) Selection of the most informative RS data is indeed a difficult task especially in mapping areas that are particularly heterogeneous. In these areas it is observed that a simple use of sensor statistics alone may not adequately or necessarily (spectrally) represent a specific scene.

(2) Irrespective of the problem at hand, the study recommends PCT analysis to RS users, as a powerful approach for the unique mapping of land use directly. This may lead to the advantage of using PCT for change detection and mapping of specific features. However, for multispectral based classification, PCT method alone may not be the appropriate and therefore other methods like colour composite display become equally useful. This means that a single optimisation approach may not be adequate.

(3) Eigenvector loadings in the PCT analysis are useful in understanding the spectral-object response, as depicted in the principal component image.

(4) TD and scatterplot analysis for evaluating the strength of training data also proved to be a good illustration for spectral overlap determination within the considered optimal data sets. Both data sets proved to be better in identification of natural land cover than the built-up (land use). In particular MOMS-2P showed greater achievement in mapping of vegetation classes.

(5) Finally it is observed that more spectral classes were extracted from the MOMS-2P with about 2% (KAPPA/TAU results) higher accuracy than from the Landsat TM for the same scene. This implies that the lower-medium scale data may be more informative compared to upper-scale satellite data, irrespective of spectral resolution. However, the study suggests that the spectral resolution of MOMS may be inadequate for the accuracy and specificity required for urban applications especially if computer-assisted processing is adopted. Visual interpretation may give better accuracy for the urban land use than machine based digital image processing. This study serves as a pilot application of the MOMS system. It shows positive contributions in the development of higher spatial resolution satellite data. Further research is being conducted to assess the feasibility of merging the two data sets to improve the mapping accuracy in urban-suburban land use and land cover studies.

Table 14: Summary of accuracy assessment results

Data	No. of classes	Sample size	Sample size correctly classified	*KAPPA (K)*	*TAU (T)*
Landsat TM	14	4044	3425	0.833	0.835
MOMS-2P	15	3394	2950	0.8594	0.860

Urban-suburban land use/land cover raster data

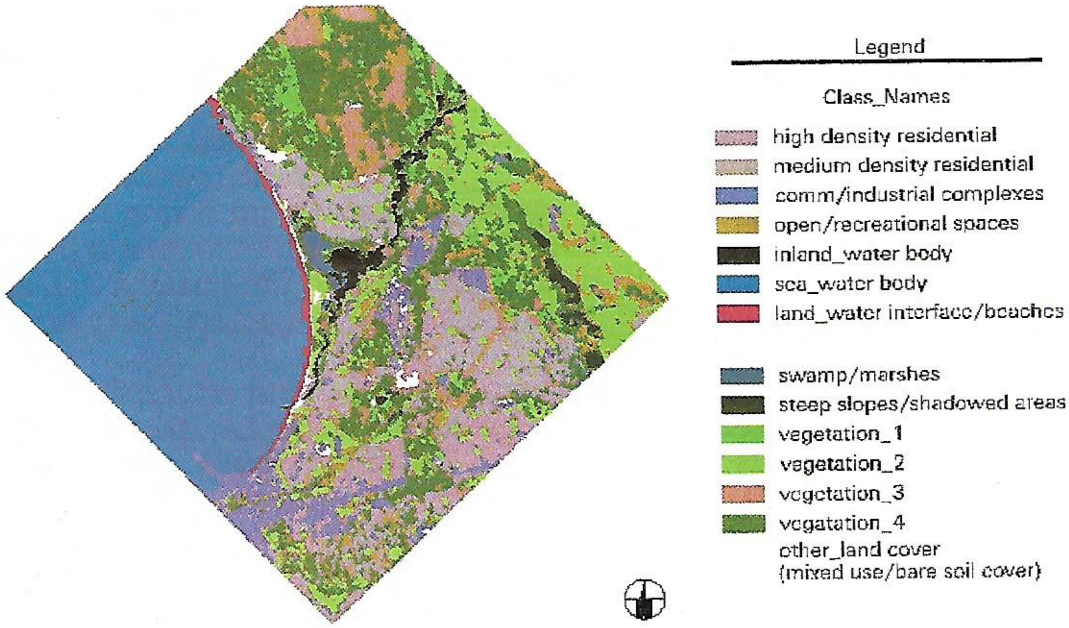

Figure 30: Classified Land Use/Land Cover Data of Cape Town sub-scene
Data Source: Landsat TM-Selective PCT

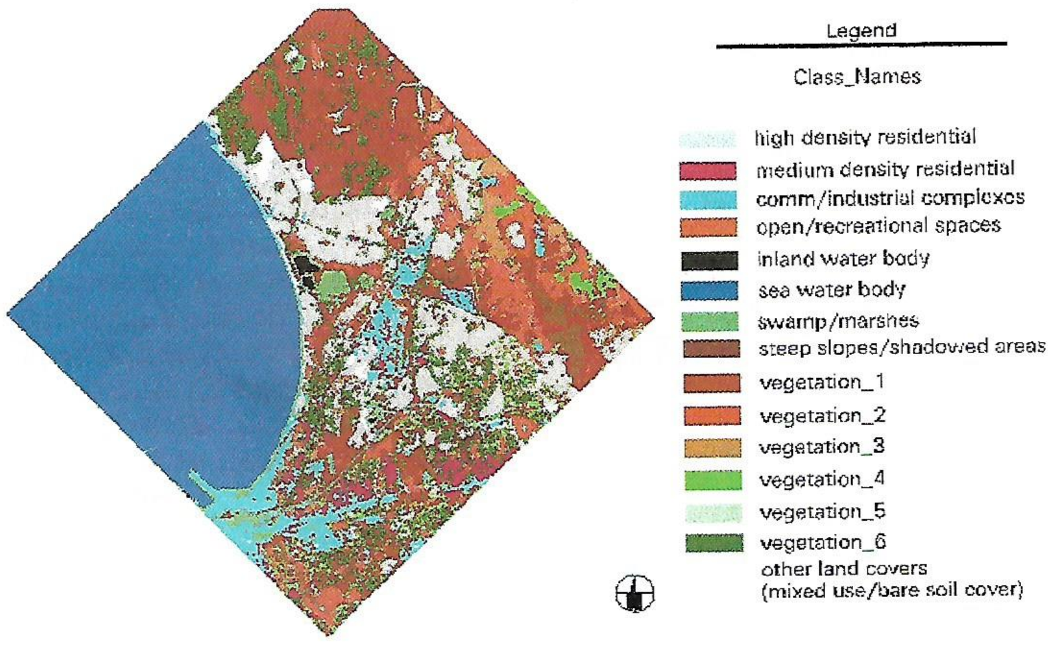

Figure 31: Classified Land Use/Land Cover Data of Cape Town sub-scene
Data Source: MOMS-2P (MODE-B) FCC 431

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