Comparison Among Selected Landsat-5 TM Data For Forest Surveys

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ABSTRACT: The objective of this study was to evaluate different methods of numerically classifying forest cover using Landsat-5 TM data. The selected Landsat-5 TM data, i.e., 6-band TM data, 5 ratio images, 3 principal components and 3-band combinations selected by the Optimum Index Factor, were digitally analyzed for a 180 sq km mountainous area in central Taiwan. All image processing was performed on an Interactive Digital Image Manipulation System (IDIMS). Both supervised and unsupervised maximum likelihood classifier were used to classify the selected TM scene. The forest land cover classification system followed the procedures developed by Anderson et al. (1976). Results indicate that: (1) compared with an earlier study, the overall accuracy of forest land cover classification was improved 25% when compared Landsat-5 TM data with Landsat-3 MSS data. (2) the classification accuracy of the unsupervised approach is 17% higher than that of supervised approach. (3) the enhanced data (5 ratio images, 3 principal components and 3-band combination data) produced classifications 17% superior compared to those produced using 6-band TM data. (4) if shadow pixels were neglected in data processing, the land cover classification accuracy was increased by 6%.

1. INTRODUCTIONS

The Landsat Thematic Mapper (TM) is a modern natural resources imaging system. compared to the Landsat Multispectral Scanner (MSS), the TM offers higher spatial resolution, more spectral bands and increased grayscale levels, and should thus provide greater detail in inventorying land use and cover. Furthermore, numerous studies have reported that enhanced satellite digital data improves the accuracy of land cover classification. The objectives of this study is to investigate the effects of TM data and improved TM data, i.e., five ratio images, three principal components, and 3-band combination selected by Optimum Index Factor, with different approaches on land cover classification in a rugged froested area.

2. MATERIALS AND METHODS

2.1 The Study site

The study area is a 180 sq km section of national forest land in central Taiwan with elevations ranging from 1600m to 3450m. The study area, 24° 19'N latitude and 121° 17'E longitude, is approximately 100 km east of Taichung, the biggest city in Taiwan province, Republic of China. It is the site of the last forest land cover classification study using Landsat MSS data (Chaio et al., 1987). In this area, the forest is primarily composes of chinese hemlock (Tsuga chenensis), Taiwan red pine (Pinus taiwannesis), and Morrison Spruce (Picea morrisonicola). At the higher elevations (about 3000m), Taiwan fir (Abies kawakamii) and Yushan Cane (Yushania niitakayamensis) are mixed with hemlock and spruce species, while at the lower elevations (below 2,000m), Taiwan red pines, mixed harwood-conifer forest, hardwood forest, coniferous plantations and cultural lands are intermixed.

2.2 Data Utilized

The TM data were acquired by Landsat-5 on 16 January 1986 with path/row annotation of 117/43 (ID 8J50686-014810). This scene was obtained at a sun-elevation angle of 33°. A disadvantage of this low sun elevation is that it produces extened shadows that partly obscure the land use patterns in the image. Six nonthermal MT bands were utilized in this study. The thermal infrared data which have 120-m spatial resolution were not used. Black and white panchromatic 1:17,000-scale aerial photographs taken in December 1986 were also avaiable for use.

2.3 Data Preprocessing

The main phases of digital data processing are shown as Figure 1. All digital processing was conducted on the Interactive Digital Image Manipulation System (IDIMS) at National Central University, Chungli, Taiwan, ROC. Eighty ground-control points were used to compute the equations that transformed the Landsat TM image into the Transverse Mercater Coordinate System of the base map. The TM pixels were resampled to 30-m grid cells by nearest neighbour algorithm. The final results of the preprocssing phase became the data base from which a 512x392 pixels subsection about 180 sq km was drawn as a study area in this study.

2.4 Primary Classification

A multicluster blocks approach (Fleming and Hoffer 1977) was used to develop training statistics in fourteen carefully selected heterogeneous block within the study site. A clustering algorithm named ISOCLS was employed to define groups of clusters on the basis of their reflectance in the six nonthermal TM bands. The parameters in the ISOCLS function were (1) DLMIN: 4.5, STDMAX: 6.8, ISTOP: 20, NMIN:30, MAXCLS: 40, and (2) DLMIN: 4.5, STDMAX: 6.8, ISTOP: 16, NMIN: 30, MAXCLS: 25. The first ISOCLS function was used in the seventh and tenth blocks, while the second ISOCLS function was used in the other blocks. The algorithm calculates the mean and standard deviation of naturally occurring clusters for all the input pixels. The computer function assigns pixels to the nearest cluster center. If the standard deviation of a cluster is greater than STDMAX, the cluster is splited by adjusting the standard deviation and mean to form two new cluster centers. Once again, all pixels are reassinged to the nearest cluster center until an appropriate cluster is obtained. The pixels in the 14 blocks were clustered individually into a number of spectral classes. The number of spectral classes in 14 blocks varied from one another. For example, there was 8 spectral classes in block 3, but 33 in block 7. Spectral classes were compared to the corresponding land use patterns indentified from manually interpreted aerial photographs, and then assigned to appropriate land cover classes.

2.5 Land use mapping

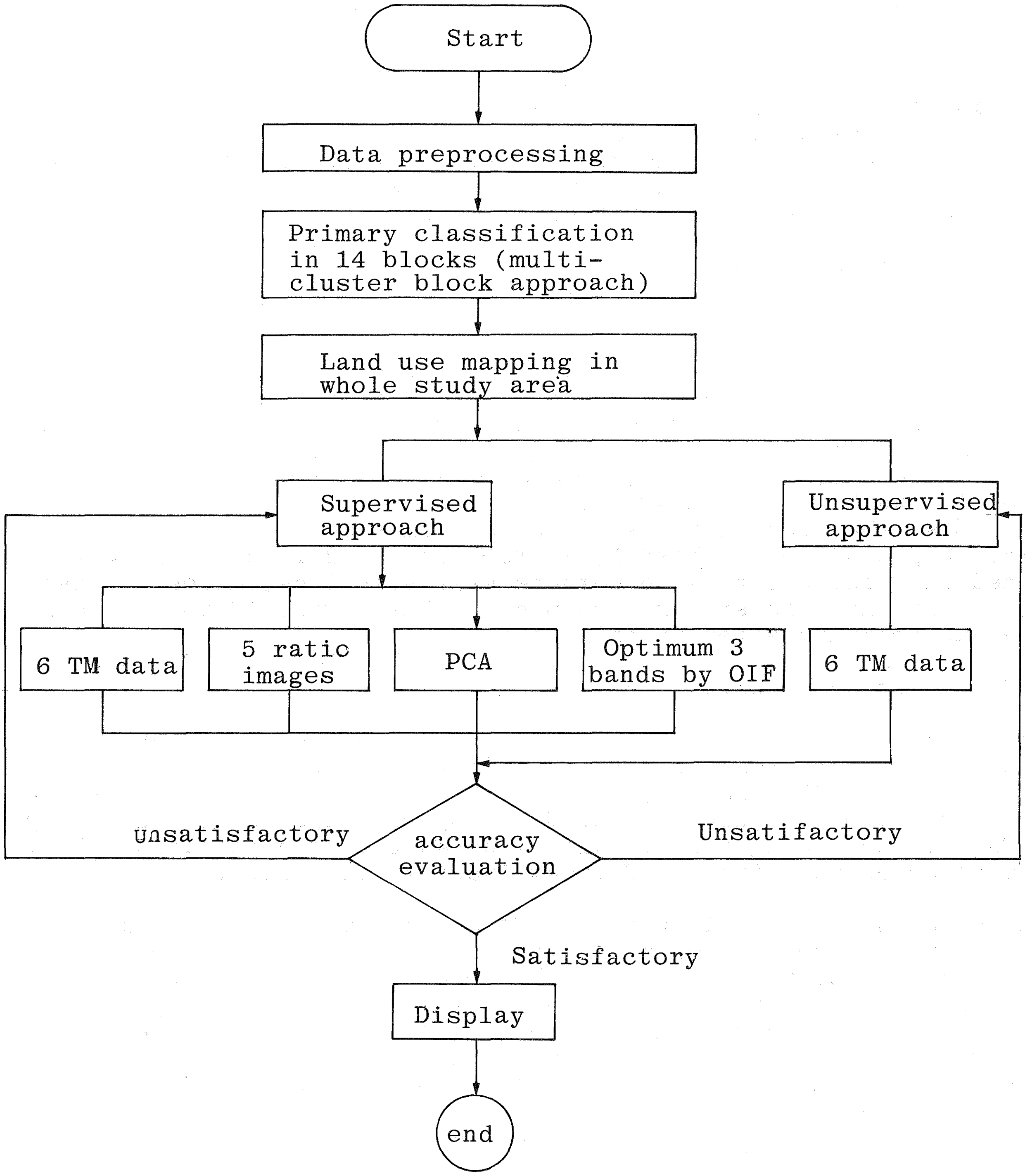

Figure 1. Schematic diagram of data processing.

The training class statistical parameters (mean vector and covariance matrix) developed within blocks were applied outside the blocks to the entire study area using a maximum-likelihood classification algorithm. The algorithm compared the reflectance value of each pixel to the mean and convariance matrix values obtained for each spectral class and assigned it to the class for which its probability of membership was highest. Thus, every pixel in the study area was assigned to one of the appropriate classes. Following Anderson's system (Anderson et al., 1976), different land cover images at Level I, II and III were obtained. (Table 1). Shadows were separated as their own special category.

2.6 Supervised approach

2.6.1 Traning plot selection

The supervised training plots were selected and delineated from the classified digital image of each block. Informationally homogeneous areas were selected from aerial photography, then transferred to the digital images. Owing to the rugged terrain, the training plot size was varied from 20x20 pixels to 50x50 pixels depending upon block. The plot number in blocks varied from 3 to 7 (Table 2). Among the 67 plots, the plot that was selected from same land-use pattern, e.g., 3 plots from orchard 1; 2 from orchard 2 in block 1, were combined into one category to compute statistical estimates because they bear the same spectral response. There were 47 total plots used as training sites in this study.

2.6.2 Selected TM data

The TM data used in the supervised classification approach were (1) 6 original nonthermal spectral bands, (2) 5 ratio images (TM1/TM3, TM2/TM3, TM4/TM3, TM5/TM3, and TM7/TM3), (3) 3 principal components (PC_1, PC_2, and PC_3) produced by principal component analysis (PCA) of the 6 original TM bands and (4) 3-band combination (TM1, 4 and 5) selected using the Optimum Index Factor (OIF).

The effects of ratio images and PCA on improving classification accuracy have been reported in many studies. Ratio images bear two important properties (1) strong differences in the intensities of the spectral response of different features, (2) removing differences in refelctance from surfaces composed of the same features brought about by topographical variations. Differences in spectral response makes it easy to differentiation the vegetation, soil and man-made structures. Ratio images also reduce the influence of shadows on land cover classification.

Principal component analysis is another digital enhancement technique. There are two advantages of using PCA in land cover classification: (1) PCA is effective in pinpointing subtle variations in the composition of soils, (2) PCA eliminates the redundancy in data without losing information necessary for land cover classification. For example, PC_1, PC_2, and PC_3 in this study explained 99.42% of the total variance in the 6-band TM data.

The best one of 20 possible 3-band combinations was selected by OIF. OIF is based on the amount of total variance and corelation within and between various band combinations (Jensen, 1986). It ranked TM_1, TM_4, and TM_5 combination with a value of 44.39 at

Table 1. Land use classification categories at Level I, II and III for block 3.

Level I	Level II	Level III	Spectral class
2 Farm land	21, Orchard 1		
	22, Orchard 2		
3 Grass land	31, Grass land 1		
	32, Grass land 2		5
4 Forest land	41, Deciduous forest		2, 6, 7
	42, Evergreen forest	421 Chinese hemlock	
		422 Morrison spruce	
		423 Taiwan fir	
		424 Other conifers	
	43, Mixed forest		
	44, Coniferous plantations	441 Coniferous plantation 1	
		442 Coniferous plantation 2	1
		443 Pine plantation	3, 8
7 Barren land			
8 Shadow			
9 Snow field			

Table 2. Training plots in 14 blocks.

Land use class			plots in 14 block														
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	Total
Farm land	Orchard 1		3												1		4
	Orchard 2		2	1											1		4
Grass land	Grass land 1						1		1	2		1		1		1	7
	Grass land 2				1				2			1	1	1		1	7
Forest land	Deciduous forest			2	2												4
	Evergreen forest	Hemlock					3		2	2		1				1	9
		Pine & spruce									1		1	1			3
		Pines									2						2
		Others										1	1	1	1		4
	Mixed forest			2													2
	Plantations	Conifer		2				3	1				1				7
		Pine			2				1								3
Barren land						3	2					1					6
Shadow					1		1					1		1		1	5
Total			5	7	6	3	7	3	7	4	3	6	4	5	3	4	67

the top of the 20 3-band combinations. Earlier work (Nelson et al., 1984) indicated that 3-band combination using one of the visible bands (TM_1), one of the near-infrared bands (TM_4), and one of the mid-infrared bands (TM_5) would contain the most information.

2.7 Unsupervised approach

The unsupervised classification approach was implemented using ISOCLS algorithm in the IDIMS. The ISOCLS function, as mentioned previously, uses a combination of distance measuremetns plus statistical parameters to help distinguish between cover classes. This type of procedure is used to train the maximum likelihood classifier that is applied to determing the statistical parameters which characterize the class. Six original bands of TM data were used in this operation. According to the statistical and spatial relatedness of the TM data, 25 spectral classes were obtained. Comparing these classes with panchromatic 1:17,000-scale aerial photographs and ground observations, the resultant image of land cover classification was obtained.

2.8 Accuracy evaluation

The classification accuracy of images derived from TM data was expressed using an error matrix. In an error matrix, the classified data was represented by the rows, while the reference data (aerial photography information or ground observations) was represented by the columns. The major diagonal indicates the agreement between these two data sets. Overall accuracy for classified images are then calculated by dividing the sum of the entries that from the major diagonal by the total number of pixels in the error matrix. Commission error and omission error which represent the individual category accuracies are also computed in order to reveal the effects of type I and type II errors on classification accuracy.

3 Results

3.1 Supervised approach

Digital images which were analysed using supervised clustering and maximum likelihood classification techniques were the 6-band original TM data, 5 ratio images, 3 principal components, and optimum 3-band combination selected by OIF. These data were extracted from 47 training sites. For each site, the means and covariances were calculated and the histograms were obtained. Histograms were checked to determine if each class was unimodel and all misidentified data points were deleted. From the statistical estimates, a bi-spectral plot was made and the transformed divergence (Dt) values calculated for each pair of classes. According to Dt values, a pooling diagram was developed. Appropriate classes were pooled or deleted, a land cover classification image which followed Anderson's system was formulated. In Level II, the land cover was grouped into six categories, i. e., orchard, barren land, coniferous forests, chinese hemlock, grassland, and shadows (Table 3). In Level III, the coniferous forest were subdivided into coniferous plantations and pines (Table 4). The entries in Table 3 and 4 are different than those of Table 2 because the sparse spruce, Taiwan fir and small snowfield were merged into pine stands and grasslands respectively.

Table 3. Contingency table produced by classifying the original 6-band TM data at the level II framework

		Aerial photography						Commission error (%)
		1	2	3	4	5	total	
TM data		329	13		3			
				1	23			
	1			47	89	8		
				1	48			
						5		
					8		575	57.21
		3				1		
			227	54	3			
			1	13	24	5		
	2			9	129			
					6	60		
							536	42.54
		324	12	5	360	4		
			20	138	614	7		
	3		2	261	189	15		
			5	7	383	4		
				487	81	35		
					263	27	3,243	27.70
		67	6	64	1522	17		
			10	99	1043			
	4		17	134	505	10		
			7	8	1479	20		
				99	544	70		
					782	13	6,516	90.16
		32		1	9	1		
			7	6	9			
				189	30	18		
	5			1	56	45		
				38	3	51		
						12	508	25.00
					481	14		
				123	378	2		
	6				207	1		
					33			
					163		1,402	
	Total	755	327	1786	9467	445	12,780	
Omission error (%)		43.58	69.72	50.27	62.06	28.54		

Overall accuracy: 7457/12780=58.35%

Code: 1. Orchard 2. Barren land 3. Coniferous forest 4. Chinese hemlock 5. Grassland 6. Shadow area

Table 4. Contingency table produced by classifying the original 6-band TM data at the level III framework

		Aerial photography							Commission error (%)
		1	2	3	4	5	6	Total	
TM data		329	13			3			
				1		23			
				47	16	89	8		
	1			1		32			
					8		5		
								575	57.22
		3					1		
			227	54	2	1			
			1	13	48	24	5		
	2			9	6	81			
				1			60		
								536	42.54
		324	12	5		360	4		
			20	138		614	7		
			2	261	206	189	15		
	3		5	7	81	177	4		
				487	85	178	35		
							27	3,243	27.70
				54	16	853	14		
			2	79	39	321			
	4		5	24	495	224	5		
			1	3	194	113	18		
					99	290	8		
							7	2,864	29.43
		67	6	10		653	3		
			8	20		683			
			12	110	528	281	5		
	5		6	5	350	343	2		
				99	139	254	62		
							6	3,652	60.62
		32		1		9	1		
			7	160	1	38			
				35	43	1	18		
	6			1	3	12	45		
				38			51		
							12	508	25.00
					19	462	14		
				123		378	2		
	7				33	207	1		
					40				
						123			
								1,402	
	Total	755	327	1786	2451	7016	445	12,780	
	Omission error (%)	43.58	69.72	50.85	34.39	31.57	28.54		

Overall accuracy: 4639/12780=36.29%

Code: 1. Orchard
2. Barren land
3. Coniferous plantation
4. Chinese hemlock
5. Pines
6. Grassland
7. Shadow area

The forest land cover classification accuracy was evaluated by contingency table analysis with the aerial photographs. A commission/omission frequency matrix was constructed for each classified image. The pixels used in the error matrix were drawn from six sample plots on the classified image. Because of the rugged terrain, the plot size varied one plot to another. Four of them were 50x50 pixels; one, 32x40 pixels; another one 30x50 pixels, for a total of 12,780 pixels, which represented approximately 115 hectares.

The overall accuracy of each classified image was calculated from contingency table. For example, the overall accuracy of the original 6-band TM data at Level II was 58.4% (Table 3). It was 36.39% at Level III (Table 4). As noted previously, the enhanced data, i.e., ratio images and PCA, are very useful in improving vegetation classification accuracy. In this study, the overall accuracy of 5 ratio images at Level II was 74.98%, while at Level III it was 44.62%. As for the PCA, the overall accuracy at Level II was 73.97%, while it was 49.23% at Level III. Compared with the original 6-band TM data, both ratio images and PCA made about 10-17% improvements is classification accuracy at the Level II and III framework. Three-band (TM1, 4, and 5) combination selected by OIF has the same effect on land cover classification as the ratio images and PCA. The overall accuracies were 74.00% and 56.51% at Level II and III, respectively.

The influence of shadows on land cover classification accuracy was serious in this rugged study area. If shadow traning plots were neglected in data processing, the classification accuracy was increased. For example, the overall classification accuracies of both 5 ratio images and optimum 3-band combinations were approximately 6% higher at both Level II and III when shadows were excluded (Table 5).

3.2 Unsupervised approach

A clustering algorithm (ISOCLS) was used to define clusters on the basis of their reflectance using six nonthermal TM bands. Using contingency table analysis, the overall accuracy of the original 6-band TM data was 75.30% at Level II, and 57.59% at Level III. The unsupervised approach was about 20% more accurate than the supervised approach.

3.3 Comparison between classifications

The accuracy of seven different methods of land cover classification ranged from 58-81% at Level II and 34-63% at Level III (Table 6), Table 7 compares the least significant differences (LSD) among means of land cover classifications at the Level II framework. In this table, a single asterisk indicates that means are different at the 95 percent confidence level, while a double asterisk indicates that means are different at the 99 percent level. Images without shadows (methods 3 and 6) yield similar results that are superior to other methods. The classification performance of ratio images, PCA, and 3-band combinations selected by OIF (Methods 2, 4, and 5) are not significantly different from the unsupervised approach (Method 7). All methods are superior to the 6-band TM

Table 5. Contingency table derived by classifying 5 ratio images without shadow plots at the level II framework.

		Aerial photogrphy						Commission error (%)
		1	2	3	4	5	Total	
TM data	1	544	1					
					2			
			8	182	35	11		
			4		6			
				29	1	51		
					4		878	61.96
	2		216	4	21			
				2	102			
							345	62.61
	3	87	1		12			
				96	63	2		
			4	209	92	12		
			7	15	97	1		
			1	331	26	125		
					8	17	1,206	53.98
	4	48	16	70	2363	37		
				316	2000	7		
			17	136	772	18		
			9	1	1866	30		
			11	265	607	31		
					1204	35	9,859	89.38
	5	76		9				
			32	113	5	14		
				80	124	14		
					57	40		
							492	13.82
	6							
	Total	755	327	1786	9467	445	12,780	
omission error (%)		72.05	66.06	36.45	93.08	15.28		

Overall accuracy: 10291/12780=80.52%

Code: 1. Orchard
2. Barren land
3. Coniferous forest
4. Chinese hemlock
5. Grassland
6. Shadow area

Table 6. Overall accuracy of different methods of land cover classification.

Methods	Overall accuracy (%)	
	Level II	Level III
Supervised approach		
1. 6-band original TM data	58.35	36.29
2. 5 ratio images	74.98	44.62
3. 5 ratio images without shadows	80.52	49.98
4. principal component analysis	73.97	49.23
5. Three-band (TM1,4,5) combination selected by OIF	74.00	56.51
6. Three-band (TM1,4,5) combination without shadows	80.37	62.52
Unsupervised approach		
7. 6-band original TM data	75.30	57.59

Table 7. Comparison between different methods of land cover classification.

Method	Mean	differences					
6	80.7867	-					
3	80.4883	0.2984	-				
7	76.2300	4.5567**	4.2583*	-			
2	76.1067	5.6800**	5.3816**	1.1233	-		
5	74.7150	6.0717**	5.7733**	1.5150	0.3917	-	
4	74.6283	6.1584**	5.8600**	1.6017	0.4784	0.0867	-
1	59.5717	21.2150**	20.9166**	16.6583**	15.5350**	15.1433**	15.0566**

$$LSD = t_{0.05(30)}\sqrt{2\times MS/N} = 2.36\times\sqrt{2\times 41.8128/42} = 3.3301$$

$$LSD = t_{0.01(30)}\sqrt{2\times MS/N} = 3.03\times\sqrt{2\times 41.8128/42} = 4.2755$$

data using a supervised approach (Method 1). To sumarize: (1) shadows yield low classification accuracy, (2) the effect of enhanced data, i.e., ratio images, PCA, and optimum 3-band combinations, are superior to that of original 6-band TM data, (3) the performance on land cover classification using an unsupervised approach is better than that of the supervised approach.

4. Conclusions

Image analysis of TM data, resulted in the following four conclusions: (1) compared to the results of previous study using Landsat-3 MSS data, Landsat-5 TM data resulted in about 25 percent more accurute land cover classification. (2) The performance of an unsupervised land cover classification was 17 percent better than that of a supervised approach. (3) The enhanced data i.e., 5 ratio images, 3 principal components, and optimum 3-bnad combinations (TM 1, 4, and 5), classified land cover similarly and all three were about 17 percent superior to the original 6-band TM data. (4) Shadows result in land cover classification errors in this mountainous area. If shadow pixels were neglected in data processing, classification accuracy increased by approxiamtely 6 percent.

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