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R. Kumar* and M.Niero**

Instituto de Pesquisas Espaciais (INPE)
Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq)
12.200 - S. J. dos Campos, S.P., Brasil

Abstract

The purpose of this study was to compare the classification accuracy of land use classes of S.J. dos Campos, S.P., Brasil, using the different options of classification available in the Image-100 of General Electric Co. and the sample classifier. In addition, the statistical separability of land use classes in the subsets of one to four spectral channels was investigated. With the help of ground observations and aerial photography, the multispectral scanner (MSS) data of LANDSAT were analysed using the Image-100. In the subsets of one to three spectral channels (ch. 4 = 0.5 to 0.6 μm, ch. 5 = 0.6 to 0.7 μm, ch. 6 = 0.7 to 0.8 μm, ch. 7 = 0.8 to 1.1 μm); channel 4, channels 4 & 7, channels 4, 5 & 7 were found to be the best choices. For the single-cell option of the Image-100, the errors of omission varied from 5% for the class industrial to 46% for the class institutional. The errors of commission varied from 11% for the class commercial to 39% for the class industrial. As expected, the multi-cell option increased the errors of omission and decreased the errors of commission. However, considering both the errors of omission and commission, this option considerably decreased the percentage of correct classification as compared to the single-cell option. On the whole, the sample classifier gave considerably more accurate results as compared to the single-cell or multi-cell option.

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The purpose of this study was to compare the classification accuracy of land use classes using the different options of classification available in the Image-100 (Image-100 is a data processing system marketed by General Electric Co., that extracts thematic information from multispectral imagery, enhances the image, etc.). In addition, the statistical separability of land use classes in the subsets of one to four spectral channels was investigated.

Cloud free multispectral scanner data from LANDSAT, of reasonable quality, over São José dos Campos (23° 10' S, 45° 50' W), São Paulo, Brasil, acquired on September 8, 1972, were available. In addition, aerial photography and ground observations were available to assist the analysis of the data. São José dos Campos was selected because it is one of the most industrialized and fastest growing small-size towns of Brasil and the authors are well familiar with it. Many of the problems of this town are similar to the problems of much larger urban centers.

With the help of ground observations and aerial photography, a map of São José dos Campos showing the following land use classes was obtained: residential areas, multi-family residential areas, commercial areas, industrial areas, institutional areas, agricultural areas and unoccupied areas.

The specific objectives of the study are stated as follows:

1. To determine what combinations of one through three spectral channels out of four available channels give the greatest overall statistical separability of the above seven land use classes.

2. To compare the classification accuracy of land use classes using 'single-cell signature acquisition' and 'multi-cell signature acquisition' options of classification available in the Image-100 and a sample classifier on-line-mode in the Image-100.

Literature Review

Many investigators have analysed the multispectral scanner (MSS) data of LANDSAT satellite for applications to land use classification. For example, Todd and Baumgardner[1] (1973) analysed LANDSAT MSS data, obtained over Marion County (Indianapolis), Indiana, by computer-implemented techniques, to

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Economy et al.[6] (1974) have given the classification accuracy of the Image-100 using single cell option (described later in the report). They reported an accuracy of 70 ± 12%. Factors which limited the classification accuracy were spatial resolution of the ERTS-1 (now called LANDSAT) scanner, the land-use classification system, and inaccuracies in the ground truth. Goldberg et. al.[7] (1975) have described methods and procedures which outside investigators may use with the automated processing equipment of the Canada Centre for Remote Sensing (CCRS) for the purpose of natural resource exploration and mapping. They have compared the accuracies of unsupervised and supervised methods on the basis of the confusion matrices generated by classifying exactly the same area.

Method of Analysis

Multispectral scanner data of computer compatible tapes of LANDSAT were analysed using Image-100. With the aid of land use map of São José dos Campos mentioned above, rectangular areas of each of the above seven land use classes were selected, avoiding the boundaries of classes on the display of the Image-100. The areas of each of these classes were selected carefully so that they could be considered to be representative of the respective land use classes. Assuming that each of these classes has a multivariate gaussian distribution, the B-distance, based on Bhattacharyya coefficient, was calculated between all possible pairs of these classes in all possible combinations of one, two, three and four spectral channels using the feature selection algorithm of the Brazilian Institute of Space Research (INPE) on-line-mode with the Image-100[8,9]. For each value of B-distance, the probability of correct classification was reasonably estimated from the curve of Swain evaluate the utility of satellite data for urban land use classification. Several land use classes, such as commerce/industry, single-family (Newer) residential, trees, and water exhibited spectrally separable characteristics and were identified with greater than 90 percent accuracy. Ellefsen et al[2].(1973) did computer-aided analysis of LANDSAT MSS data of the San Francisco Bay area. Smith et al.[3] (1974) have given the application of spatial features to satellite land-use analysis. Ellefson et al.[4](1974) have given new techniques in mapping urban land use and monitoring change for selected U.S. metropolitan areas. They analysed LANDSAT MSS data using automatic pattern recognition techniques for classification. Kumar and Silva[5](1977) have analysed the statistical separability of agricultural cover types in much detail, data quantity and depth in the subsets of one to twelve spectral channels.

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$$B = \int_x \left[\sqrt{p_1(x)} - \sqrt{p_2(x)} \right]^2 dx \tag{1}$$

If $p_1(x)$ and $p_2(x)$ are multivariate gaussian distributions as above, then

$$B = 2(1 - e^{-\alpha}), \tag{2}$$

where

$$\alpha = \frac{1}{8}(U_1 - U_2)^T \Sigma^{-1}(U_1 - U_2) + \frac{1}{2}\log_e\left[\frac{\det \Sigma}{\sqrt{\det\Sigma_1 \cdot \det\Sigma_2}}\right] \tag{3}$$

where U_1 and U_2 are mean vectors of classes one and two respectively; whereas Σ_1 and Σ_2 are the covariance matrices of classes one and two respectively.

$$\Sigma = \frac{1}{2}\left[\Sigma_1 + \Sigma_2\right] \quad \text{and } T \text{ denotes transpose} \tag{4}$$

B-distance is defined for two distributions. Remote sensing usually involves more than two classes. One strategy is to compute the average B-distance over all pairs of classes and select the subset of features for which the average B-distance is maximum, i.e., maximize, with respect to all n-tuples

$$B_{AVE}(C_1, C_2, \ldots C_n) = \frac{2}{m(m-1)} \sum_{i=1}^{m-1} \sum_{j=i+1}^{m} B(i, j | C_1, C_2, \ldots C_n) \tag{5}$$

where

m = number of classes

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B_{AVE} was computed for all possible subsets of one, two, three and four spectral channels, out of available four channels.

Each of these land use classes was divided into two independent sets: training fields and test fields. Using training fields of residential areas, test fields of each of the above seven classes and training fields of each of the classes except residential areas were classified, using the single-cell signature acquisition option of Image-100. This option creates a four-dimensional rectangular parallelepiped, each of the sides of which correspond to the signature limits of the training areas in each channel. The number of pixels classified as residential areas by the computer inside the test fields of each of these seven classes were determined. An identical analysis was repeated for each of the other six land use classes. Thus, a confusion matrix showing the total number of pixels (picture elements) of each class classified correctly as well as classified incorrectly into each of the other classes was obtained.

This whole procedure was repeated for the multicell signature acquisition option of the Image-100. In the multicell signature acquisition, the parallelepiped of spectral signature is subdivided into cells each of unit volume and the number of pixels in each of these unit cells is counted. These cell counts are thus measures of the probability distribution of the spectral cluster. By raising or lowering the threshold on the cell counts, one can vary the size and four dimensional probability distribution of the spectral cluster, by deleting or adding cells with counts greater than a variable threshold. In the interactive signature modification option, the user performs training on the misclassified area adding the errors of omission and subtracting the errors of commission until satisfied with the results. The preliminary results showed that this option did not seem to improve much the classification accuracy of the 'single cell" option, because the basic problem was the overlap between the classes in the four-dimensional spectral space.

The same training fields of each class were used to classify the test fields using the sample classifier based on B-distance. B-distance was computed between a test field and each of the seven training classes and was classified into the class for which the B-distance was minimum.

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Results and Conclusions

Table 1 shows the distribution of pixels of the training and the test fields of each class. Tables 2 to 5 give the values of B_{AVE} in all possible combinations of one, two, three and four channels respectively out of four available channels. As one would expect, the probability of correct classification increases with an increase in the number of channels. In the subsets of one to three spectral channels: channel 4, channels 4 & 7 (one in the visible and one in the near infrared), channels 4, 5 & 7 (two in the visible and one in the near infrared) are found to be the best choices. Table 2 shows that in the subset of two channels, channels 4 and 5 (visible wavelength region) give higher probability of correct classification than channels 6 & 7 (near infrared wavelength region). The authors believe that each wavelength region -- visible, near infrared, middle infrared and thermal infrared has valuable spectral information. Thus, in the subset of two spectral channels, one channel in the visible and one channel in the near infrared wavelength region are found to be the best choice. Kumar (1977)[11] has analysed the aircraft MSS data in much detail, data quantity and depth in the subsets of one to twelve spectral channels, to evaluate each spectral channel as well as possible combinations of wavelength regions, for statistical separability of agricultural cover types.

Using the training fields of a class, the number of pixels classified by the Image-100 into each of the seven classes (training + test fields, except the class being used to train the computer in which case only test fields) are given in Table 6. From Table 6, the errors of omission (while using training fields of residential, number of pixels of test fields of residential not classified as residential constitute the errors of omission, etc.) and the errors of commission (while using training fields of residential, number of pixels of classes other than residential but which are actually classified as residential) were calculated and are shown in Table 7. Similarly, the errors of omission and commission using the multi-cell signature acquisition ($m = 1$, $m = 2$ and $m = 3$) for the same training and test fields of each class were calculated and are given in Table 7. The option $m = 1$ means that all the unit cells in the four dimensional spectral space which had less than one pixel were deleted from the spectral signature of the training fields for doing classification. Similarly, the option $m = 2$ means that all the unit cells in the four dimensional spectral space which had less than two pixels were deleted from the spectral signature of the training fields for doing classification etc. Table 7 shows that for the single-cell option, the errors of omission vary from 5 % for the class

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Table 1 Distribution of pixels of each class

Class	No. of pixels of training areas	No. of pixels in test areas	No. of pixels in the training and test areas	Total number of pixels of the training and test areas of all the classes except this class
Residential	384	1196	1580	6412
Multi-family residential	48	192	240	7752
Commercial	108	344	452	7540
Industrial	360	1296	1656	6336
Institutional	272	944	1216	6776
Agricultural	276	1074	1350	6642
Unoccupied	300	1198	1498	6494
Summation of Columns	$\Sigma = 1748$	$\Sigma = 6244$	$\Sigma = 7992$	

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Table 2. Values of B_{AVE} in subset of one channel

Channel	B_{AVE}	Estimated percentage probability of correct classification (Swain and King, 1973)
4	0.7787	82.4
5	0.7250	81.6
6	0.4267	72.8
7	0.3510	69.6

Table 3. Values of B_{AVE} in subset of two channels

Channels	B_{AVE}	Estimated.. . . . (Swain and King, 1973)
4-5	0.8877	84.8
4-6	0.8959	85.6
4-7	0.9599	86.4
5-6	0.8436	83.2
5-7	0.8775	84.8
6-7	0.6075	77.6

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4-5-6	0.9920	87.2
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4-6-7	1.0186	87.2
5-6-7	0.9504	85.7

Table 5. Values of B_{AVE} in the available four channels

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Table 6 Number of pixels classified into each class using 'single cell' option

Using training areas of	Considering training and test fields of all classes except training fields of the class being used to train the computer for classification, number of pixels classified by Image-100 into the class							
	Res.	Mult.Res.	Comm.	Ind.	Ins.	Ag.	Uno.	Summation of row minus diagonal element Σ
Res.	876	48	270	430	408	17	114	2163
Mult. Res.	1206	128	137	872	497	0	51	2763
Comm.	160	46	288	230	203	0	190	829
Ind.	1364	180	219	1231	615	6	87	3471
Ins.	1219	88	240	589	507	49	390	2575
Ag.	8	13	31	93	258	866	1019	1422
Uno.	78	28	76	175	361	970	995	1688
Summation of column minus diagonal element	4911	403	973	2389	2342	1042	1851	
Previous row ÷ (test and training areas of all the classes except the class of diagonal element)	0.63	0.05	0.13	0.38	0.35	0.16	0.29	

Res. = Residential
Ins. = Institutional
Multi.Res. = Multifamily residential
Ag. = Agricultural
Comm. = Commercial
Uno. = Unoccupied
Ind. = Industrial

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Table 7. Percentage errors of omission and commission in 'single cell' and 'multicell' signature acquisition

(A) Percentage errors of omission

Class	Single-Cell	Multi-cell m = 1	Multi-cell m = 2	Multi-cell m = 3
Residential	26.8	63.21	73.91	83.61
Multi-family Residential	33.3	80.21	88.54	94.27
Commercial	16.3	74.71	78.49	83.43
Industrial	5.0	68.44	86.00	90.00
Institutional	46.3	59.32	82.56	87.50
Agricultural	19.4	73.46	80.26	86.69
Unoccupied	16.9	77.46	82.30	88.40

(B) Percentage errors of commission

Class	Single cell	Multi-cell m = 1	Multi-cell m = 2	Multi-cell m = 3
Residential	25.28	5.32	3.38	2.43
Multi-family Residential	35.64	0.92	0.27	0.01
Commercial	10.99	1.75	0.81	0.41
Industrial	39.00	11.08	1.88	1.59
Institutional	38.00	26.65	4.48	2.57
Agricultural	21.41	5.20	4.02	3.20
Unoccupied	25.99	2.97	1.58	1.23

Note: The option m = 1 means that all the unit cells in the four dimensional spectral space which had less than one pixel were deleted from the spectral signature of the training fields for doing classification.

Table 7. Percentage errors of omission and commission in 'single cell' and 'multicell' signature acquisition

(A) Percentage errors of omission

Class	Single-Cell	Multi-cell m = 1	Multi-cell m = 2	Multi-cell m = 3
Residential	26.8	63.21	73.91	83.61
Multi-family Residential	33.3	80.21	88.54	94.27
Commercial	16.3	74.71	78.49	83.43
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(B) Percentage errors of commission

Class	Single cell	Multi-cell m = 1	Multi-cell m = 2	Multi-cell m = 3
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industrial to 46% for the class institutional. The errors of commission vary from 11% for the class commercial to 39% for the class industrial. It shows that classification accuracy for all the classes is rather poor except the class commercial where the percentage of errors are reasonably small (errors of omission = 16.3%, commission = 11%). This is because of small values of standard deviation (and hence less overlap) of this class in each of the spectral channels especially in the channels one (0.5 to 0.6 μm) and four (0.8 to 1.1 μm). In general, an increase in the standard deviations of a class in the spectral channels tends to reduce the errors of omission and increase the errors of commission. It was found that taking into account both the errors of omission as well as the errors of commission, the classification accuracy generally reduces with an increase in the standard deviations. The sum of standard deviations for the class industrial in the four spectral channels were much higher as compared to the sum of standard deviations for any of the other classes. The intervals of its spectral response in each of the four spectral channels were very large and that is why it has low errors of omission. The errors of omission as well as commission for the class institutional are very large. An institution can have office buildings, parking areas, recreation areas, housing for employees, workshops, trees, etc. Thus, it would require a large number of training areas for them to be truly representative of the class institutional. The authors believe that the training areas of the class institutional were perhaps not truly representative of the class institutional and hence, the errors of omission as well as commission were found to be rather large.

The first element of the last row of Table 6 shows the total number of pixels that have been incorrectly classified as class residential divided by the total number of training and test fields of all the classes except the class residential. In this calculation, it should be noted that many pixels may have been classified incorrectly more than once as a class residential. Similarly, the other elements of the last row are self explanatory.

Table 7 shows as expected, that the multicell option increases the errors of omission and decreases the errors of commission. Considering the errors of omission as well as errors of commission, multicell option for m = 1 considerably decreases the percentage of correct classification for each of the classes. This is because the number of pixels used for training of each class were relatively small for statistical purpose. Thus, the unit cells in the four dimensional spectral space were sparsely populated. Thus, there may be many cells industrial to 46% for the class institutional. The errors of commission vary from 11% for the class commercial to 39% for the class industrial. It shows that classification accuracy for all the classes is rather poor except the class commercial where the percentage of errors are reasonably small (errors of omission = 16.3%, commission = 11%). This is because of small values of standard deviation (and hence less overlap) of this class in each of the spectral channels especially in the channels one (0.5 to 0.6 μm) and four (0.8 to 1.1 μm). In general, an increase in the standard deviations of a class in the spectral channels tends to reduce the errors of omission and increase the errors of commission. It was found that taking into account both the errors of omission as well as the errors of commission, the classification accuracy generally reduces with an increase in the standard deviations. The sum of standard deviations for the class industrial in the four spectral channels were much higher as compared to the sum of standard deviations for any of the other classes. The intervals of its spectral response in each of the four spectral channels were very large and that is why it has low errors of omission. The errors of omission as well as commission for the class institutional are very large. An institution can have office buildings, parking areas, recreation areas, housing for employees, workshops, trees, etc. Thus, it would require a large number of training areas for them to be truly representative of the class institutional. The authors believe that the training areas of the class institutional were perhaps not truly representative of the class institutional and hence, the errors of omission as well as commission were found to be rather large.

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Table 8 shows the results of classification using a sample classifier. As pointed out earlier, the same training and test fields were used in this case as in the "single cell" or "multicell" option of the Image-100. Unfortunately, one field of the class institutional could not be classified using sample classifier due to temporary malfunctioning of the Image-100 at that time. Comparing these results to the single-cell option, we find that the errors of commission are reduced significantly, whereas the errors of omission are increased for some classes and decreased for the others. The errors of omission for the class industrial are very large because the standard deviation of the class industrial was extremely large in each of the four spectral channels. For most classes, the larger were the standard deviations, the lower was the percentage of correct classification using sample classifier. Comparing sample classifier to the 'multicell option', we find that it gives much smaller errors of omission, whereas it gives greater errors of commission for some classes and smaller for the others. On the whole, the sample classifier gives percentage of correct classification much better than the single-cell or multi-cell options of the Image-100. Similar analysis will be done using the 'pixel by pixel maximum likelihood gaussian classifier'. In addition, computer compatible tapes of S.J. dos Campos of other times will be analysed to investigate the effect of time on these results.

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Table 8. Results of classification using sample classifier

Using training areas of	Considering the test fields of all classes, the number of pixels classified by Image-100 into the class								
	Res.	Multi.Res.	Comm.	Ind.	Ins.	Ag.	Uno.	Errors of omission	Errors of commission
Res.	1144		52					0.04	0.10
Mult.Res.		108	84					0.44	0.65
Comm.			344					0	0.06
Ind.	264	320	204	420	28		60	0.68	0
Ins.	220				576		128	0.39	0.04
Ag.						786	288	0.27	0.07
Uno.					198	340	660	0.45	0.09

overall percentage of correct classification = 65

Res. = residential Mult.Res. = multifamily residential Comm. = commercial

Ind. = industrial Ins. = Institutional Uno. = unoccupied

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