Separability of Vegetation and Non-vegetation Using MOMS-1 Visible and Infra-red Data

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Abstract: Moms-1 (Modular Optoelectronic Multispectral Scanner) is the world first scanner by push-bloom method using CCD(Charge Coupled Devices) technology. Although this method was adopted for the French SPOT/HRV and also the Japanese MOS-1/MESSR, another distinct characteristics of MOMS-1 is the two channel method using visible and infra-red spectral zone. The farmland south-west from Riyadh, Saudi Arabia, was chosen as a test site. This area is very typical where the vegetation and non-vegetation area are clearly separated because of the center pivot irrigation system. Taking the training area at vegetation and nonvegetation area, one dimensional spectral reflectance signature were compared. Next, two dimensional spectral reflectance signature was also investigated. We have a result, one dimensional signature is not enough to discriminate the vegetation from non-vegetation, but two dimensional signature is almost enough for it. Some results in the intermediate area with vegetation and non-vegetation are also obtained.

 Measure of Separability (Historical Background) Divergence is known as a measure of separability between classes. The pairwise divergence measure, which is defined by Jeffreys 1948 and discussed by many authors as Beers 1972, Swain et al 1978, and Moik 1980, is considered as one of the best measure to determine the statistical separability among the pair of classes. For the multivariate normal distribution, the pairwise divergence between class pairs i and j is given by -1 -1

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where C is the class covariance matrix, C is the inverse of the covariance matrix, M is the mean vector, T refers to the transpose of matrices and tr is the trace of the matrices. The range of Dij is O to infinity, higher values implying greater separation.

Singh 1984 gives a very clarified explanation of this pairwise divergence measure as;

..... so the pairwise divergence measure is expressible as the sum of two components, one due to the differences in variance and covariances and the other due to the differences in means. These may be interpreted, respectively, as differences in shape and size..... Furthermore, the next is also suggestive; If Ci = Cj = C, i.e. covariance matrices are equal, then equation (1) reduces to

Dij = tr [C (Mi - Mj) (Mi - Mj)]T -1 (2)

Let M = Mi - Mj, then Dij = M C M, which is Maharanobis' generalized distance.

(3)

Swain et al 1971 define a transformed divergence as;

$$TDij = 2000[1 - exp(-Dij/8)]$$

This measure has a saturating behavior, that is, the probability of correct classification saturates at 1 when transformed value reaches 2000. A value for TDij of zero means no separability. Although, there is no critical value of TDij which defines a boundary between those pairs which have clear separation and those which do not, a value of TDij of 1700 is often taken as an indicator in practice (Harris 1987).

Divergence in one dimensional distribution

In this case, Dij means a generalized square of the mean difference of class pairs i and j by the variance Vi.

Test data
 1 Moms-01 spectral bands

Two spectral bands of MOMS are chosen to have optimal performance for geological applications and vegetation discrimination (ref. 1). Fig. 1 (Kaufmann et al 1984) shows the two spectral bands with the spectral signature of vegetation (curve #1) and rock surface (curve #2).

Band 1 : 600 (+-)25 nm

Band 2 : 900 (+-)75 nm

Band 1 corresponds to the orange part of the visible spectrum and band 2 to the near infra-red region. As expressed in Fig.1, spectral reflectance of vegetation defers from that of rocks in these bands. There is an intense chlorophyll absorption between 0.5 and 0.65 um and a high reflectance beyond 0.7 um. By means of these two bands, it is possible to detect limonitic alternation zones and or the presence of vegetation.

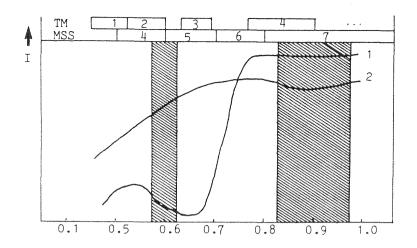


Fig. 1 MOMS-01 spectral bands with Landsat-MSS and -TM bands. Curve 1: average reflectance of vegetation Curve 2: average refrectance of rock surface (after Kaufmann et al)

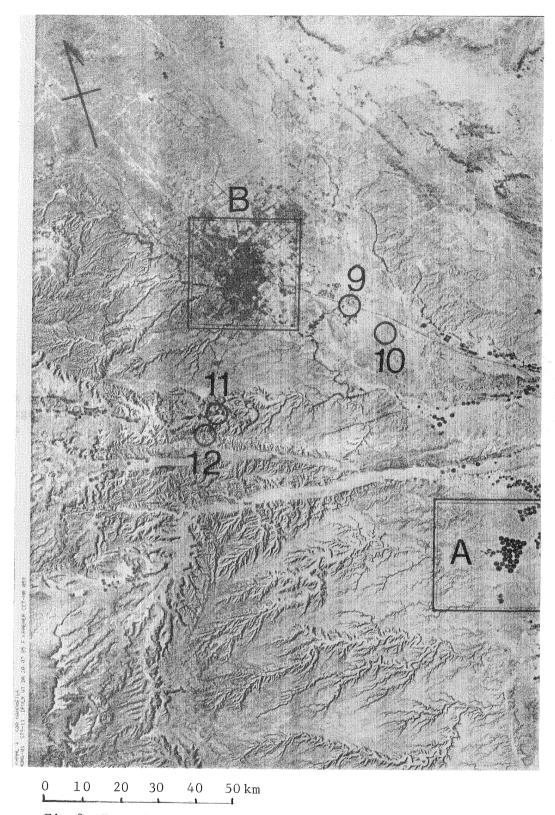
2.2 Classes and the training area

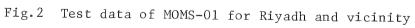
Riyadh and vicinity are chosen as the test site. This region includes deserts, vegetation, urbanized area, and agricultural vegetation by the center pivot irrigation system. Fig. 2 shows the whole area from where the training areas i.e. the sections for obtaining the class training samples, are designated.

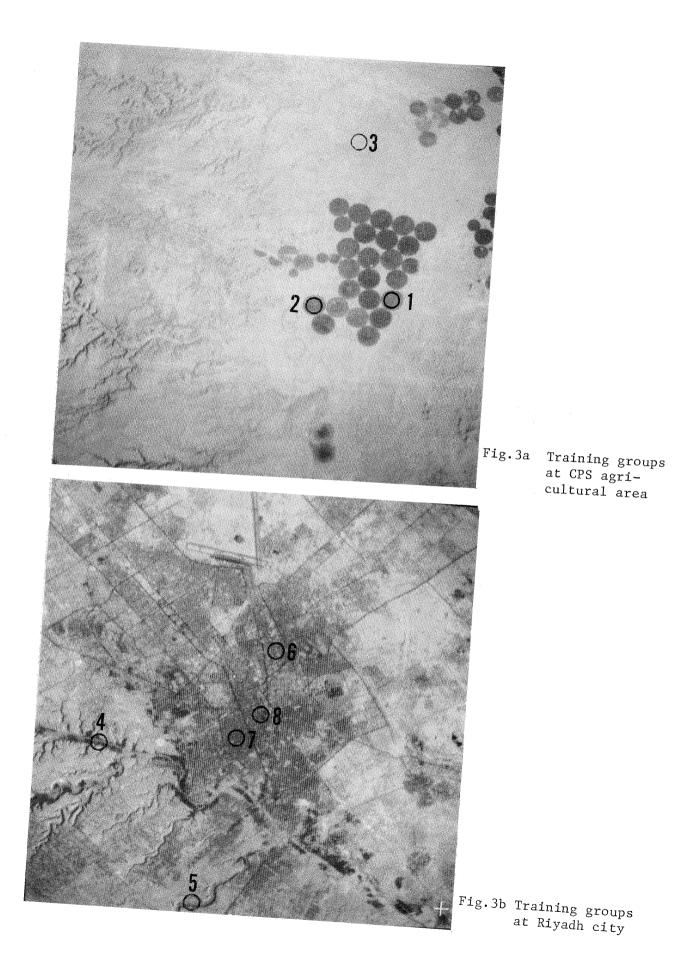
Especially from the urbanized area of Riyadh and also from the agricultural area south-east from Riyadh, typical vegetation and non-vegetation areas are selected as shown in Fig. 3a and 3b. Number of training areas is 12. Among those training areas, area No. 1 to 8 are investigated by a digital analysis. The other areas are examined by an on-site study.

List of classes (corresponding to training areas)

Vegetation with high vitality
 Vegetation with low vitality
 Desert
 Vegetation along valley
 Non-vegetation along valley
 Residential area with vegetation
 Down-town with non-vegetation
 Vegetation in the city central
 Highway through non-vegetation desert
 Desert beside the highway
 Agricultural vegetation along the river bottom
 Mountain slope with non-vegetation







3. One dimensional separability analysis

Two dimensional distributions of each training samples are in Fig.4a to 4b. When all training samples shown are superimposed on a same sheet, Fig. 4i can be obtained. Means and standard deviation of each training samples are recorded on the figures. Using Eq.(4) with these data set, one dimensional separability analysis was done. Table 1 and 2 are the results. Among training samples, vegetation groups are #1,#2,#4,#6,#8, and no vegetation groups are #3, #5, and #7. Training samples #1, i.e. vegetation with high vitality has good separability from the other samples. Namely, the TD value of sample #1 are 2000 to the other samples except to sample #8 in channel 1 and also channel 2 data. These results are guessed by looking the distribution patterns of groups in Fig. 4. The cluster with good separability is isolated from the other clusters. the other hand, training sample #5, i.e. On non-vegetation

on the other hand, training sample #5, 1.e. hon-vegetation along valley, has low separability to #2, #6, #7 by channel 1 data, though this data has good separability #2 by channel 2 data.

4. Two dimensional separability analysis

Two dimensional separability analysis was done likely as the case of one dimensional separability analysis. Table 3 is the result. Class pairs which have relatively small TD values are 5-6, 5-7, and 6-7. The following values can be extracted from Table 1 and 2.

Class pairs	Ch. 1	Ch. 2
5-6	266	1267
5-7	414	357
6-7	43	1081

Whereas, the TD values of the same class pairs improve greatly in the two dimensional separability as follows.

Class pairs Two dimensional result 5-6 1265 5-7 1254 6-7 1203

The TD value of class pair 5-6 improves from 266(Ch.1) or 1267(Ch.2) to 1265. In this case, the improvement effect is said to be little, because the values between Ch.1 and two dimensional cases are almost same. In same discussion, the TD values of class pair 5-7 improves three times. The effect by two dimensional analysis can be said to be great. The TD values of class pair 6-7 indicate a little improvement.

The reason of the TD value improvement in class pair 5-7 improved is that the centers of the classes are positioned on a 45 degree line. In this positioning, one dimensional distribution has a tendency to be overlapped with each other. However, if these distribution was seen from the top of the plotted plain, the two clusters can be identified as two separated distributions. These discussion can be imagined with Fig. 4.

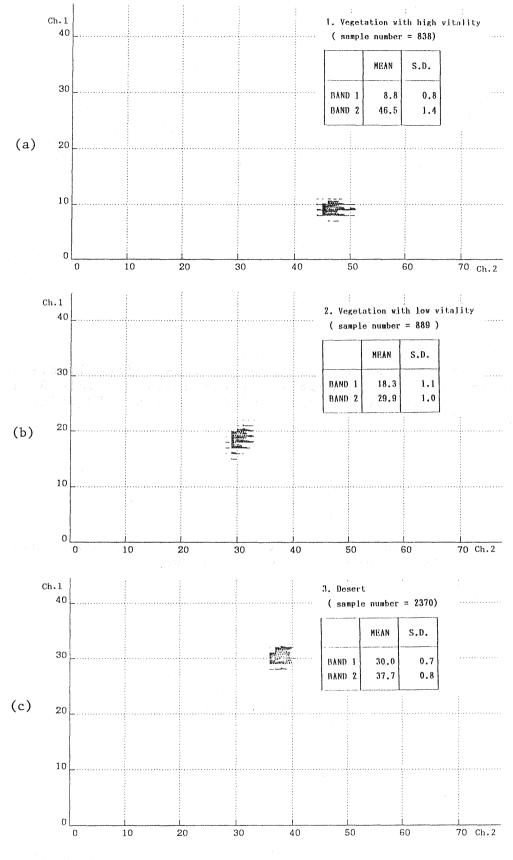
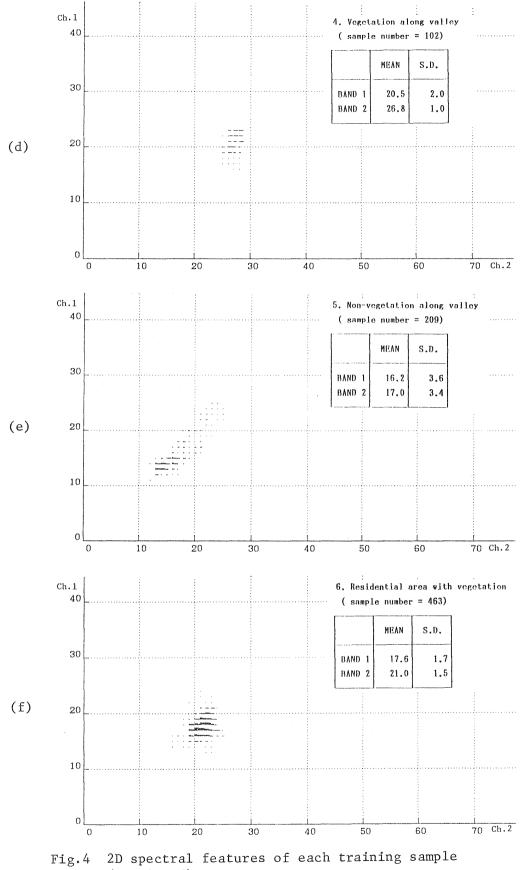
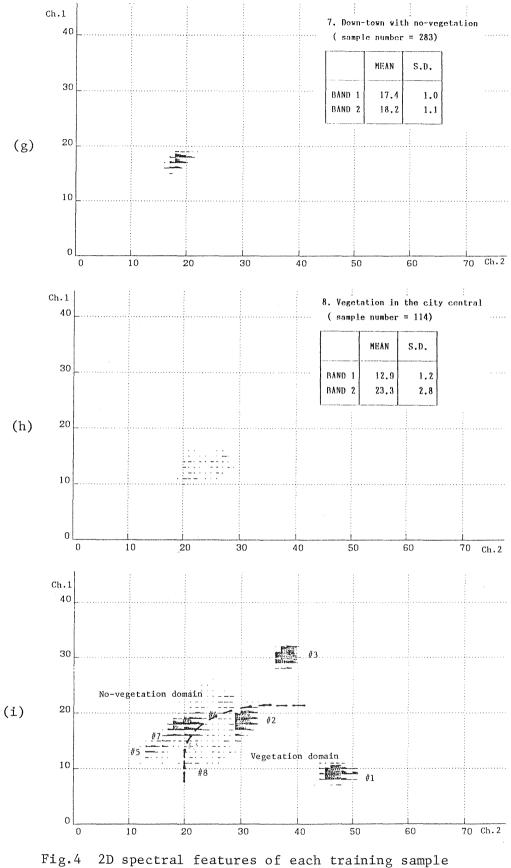


Fig.4 2D spectral features of each training sample



(continued)



(continued)

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Traning SET	1	2	3	4	5	6	7	8
1	0	2,000	2,000	2,000	2,000	2,000	2,000	1,778
2		0	2,000	723	693	112	185	1,916
3			0	2,000	2,000	2,000	2,000	2,000
4				0	1,203	873	1,212	1,984
5					0	266	414	1,136
6						0	43	1,721
7			-				0	1,803
8								0

Table 1 One D. Transformed Divergence of Ch.1 Data (by Eq(4))

Table 2 One D. Transformed Divergence of Ch.2 Data (by Eq(4))

Traning SET	1	2	3	4	5	6	7	8
1	0	2,000	2,000	2,000	2,000	2,000	2,000	2,000
2		0	2,000	1,398	2,000	1,998	2,000	1,953
3			0	2,000	2,000	2,000	2,000	2,000
4				0	1,999	1,940	2,000	1,341
5					0	1,267	357	1,603
6						0	1,081	609
7							O %	1,759
8				-1				0

Traning SET	1	2	3	4	5	6	7	8
1	0	2,000	2,000	2,000	2,000	2,000	2,000	2,000
2		0	2,000	1,810	2,000	1,999	2,000	1,975
3			0	2,000	2,000	2,000	2,000	2,000
4				0	1,999	1,923	2,000	1,930
5					0	1,265	1,254	1,950
6						0	1,203	1,720
7							0	1,999
8								0

5. Ground verification and categorical performance

order to verify the separability analysis, ground In verification was done on May 10, 1988. All training areas from #1 to #12 were inspected and photographed. There is many change between the satellite image of 1984 and the ground scene. But. tried to get the same vegetation on 1984. The ground we views the training areas can be found in Fig. 5. of The ground verification was started from the time when the sun elevation was coming up above 19 degrees to maintain the quality. All photos are taken to include a reference white board to be compared with each other in an optically equal condition. The sun elevation at the place on May 10, 1988 are as shown below.

 Time
 The Sun Elevation

 6:45
 15 DEG 13 MIN

 7:15
 26 DEG 17 MIN

 7:45
 33 DEG 4 MIN

 8:15
 39 DEG 52 MIN

 8:45
 46 DEG 41 MIN

Training areas can be expressed as below. Verification point number (Training area number), verification time, and descriptions of the state are described.

(8:15a.m.): Strong vegetation. Pt. No. 1 Green leaves of vegetables cover entirely the soil surface. Pt. No. 2 (8:30a.m.): Weak vegetation. Leaves of vegetables cover sparsely the soil surface. Pt. No. 3 (8:35a.m.): Desert. Cracked soil surface appears light brown, but the flat fixed ground surface turns whitish. Pt. No. 4 (3:10 p.m.): Vegetables with wide leaves are grown along the valley. Pt. No. 5 (3:20p.m.): The most part of the ground is dried au except for the sparsely distributed vegetation area. Pt. No. 6-1 (6:45a.m.) and Pt. No. 6-2 (6:55a.m.): Residential mixed with non-vegetation area by pavement (No. 6-1) area and vegetation area at the garden (No. 6-2). Pt.No.7 (7:20a.m.): Down town with non-vegetation. The photo shows an open area of the West of Makkah Road. Pt. No. 8 (7:10a.m.): Lawn at Tower park. This is a typical vegetation of the city central. Pt.No.9 : Highway pavement. Pt.No.10 : Desert beside the highway. Pt. No. 11 (8:45a.m.): Young vegetation to produce a kind grain along the valley. Pt.No.12 (7:55a.m.): Non-vegetation area along the valley, but the bottom of the valley is covered with the Pt. No. 12 vegetation.

As discussed at section 4, the separability among classes 5,6,7 are poor. Ground views of these classes are resemble as shown in Fig. 5-#5 to #7. Any scene includes broad area of nonvegetation and small area of sparse vegetation. Low performance of separability among these classes is due to the similar ground signature. Difference among these classes must be found in the quantity of vegetation included in the area. To define the class more precisely, a domain definition method may be applicable. For example, a dotted line on Fig. 4i separate the vegetation domain and non-vegetation domain on the two dimensional signature space. Furthermore, when the value of Ch.2 data increase, the degree of vegetation as of strongness or healthiness increase.

Table 4 shows a categorization performance prediction using the same training samples for Table 2 and 3. Samples of #1 training area (strong vegetation) and samples of #3 area (desert) are categorized as the designated class itself respectively. Contrary, as for the samples of training set #5,6,7, 80 % of them go to the designated class but the residuals go to the other classes. This means the mixture of each class or the similarity. This fulfillment of computer analysis is confirmed by our ground verification study on May 10, 1988.

		· · · · · · · · · · · · · · · · · · ·								
TNG.	Un-	Percent categorized as group								
SET	Cla.	1	2	3	4	5	6	7	8	
1	0	100.0	0	0	0	0	0	0		
2	0	0	98.8	0	0	0	0	0	1.1	
3	0	0	.0	100.0	0	0	0	0	0	
4	0	0	3.9	0	95.1	0	0	0	1.0	
5	0	0	0	0	1.4	76.6	11.0	10.5	0.5	
6	0	0	0	0	0.2	6.0	80.1	10.6	3.0	
7	0	0	0	0	0	6.4	10.6	83.0	0	
8	0	0	0	0	2.6	0	3.5	0	93.9	
[]	10.11 at 12.12 at 12.12 at 12.12 at 12.12					erinkanisti oʻngeriktiristing kasa atasa sasariying	an i al al adaménter na againta again gan a san ara		a contraction of the second second second second second	

Table 4 Categorization Performance Prediction

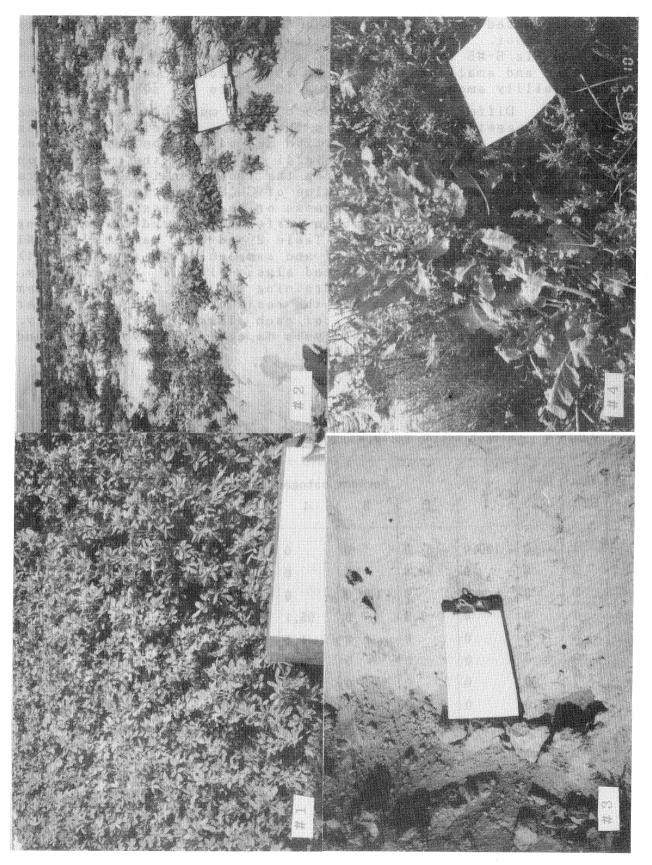


Fig.5 Ground views of training areas

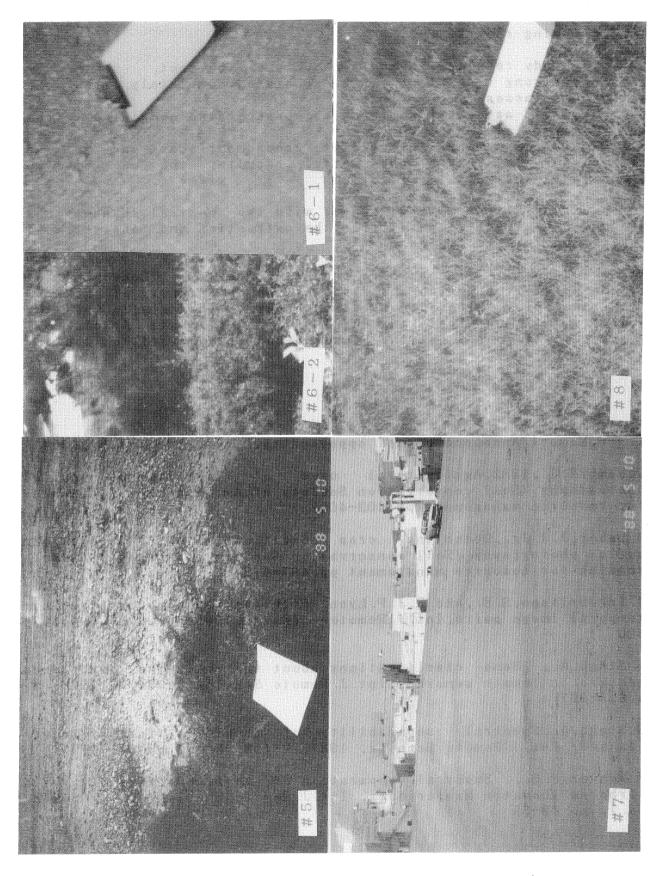


Fig.5 Ground views of training areas (continued)

6. Concluding remarks

This study resulted in the discovery of the fact. Pure strong vegetation can be separated completely from the 1. all other classes. 2. Pure soil as desert surface can be separated completely from the all other classes. 3. Separation among intermediate ground surfaces be can not completed. obtain the better results, the Τо use of two dimensional analysis is effective.

As a result, the MOMS-01 sensor with two spectral channel can produce an effective result for the extraction and analysis of vegetation in arid region.

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