

## The Use of TM Thermal Band for Land Cover/Land Use Mapping in Two Different Environmental Conditions of Iran

S. K. Alavi Panah<sup>1</sup>, M. De Dapper<sup>2</sup>, R. Goossens<sup>2</sup> and M. Massoudi<sup>1</sup>

### ABSTRACT

Many investigations have demonstrated that arid regions display ideal conditions for remote sensing applications such as, land cover/land use detection. The aim of this study was to evaluate the capability of Thematic Mapper (TM) thermal band in land cover/land use mapping in the Ardakan region of Yazd province, an area of desert with severe salinity conditions, and the Mook region in the Farse province, an area of mountains, forests, dry farming and orchards. Landsat TM imagery recorded on September and October, 1990 were used for land cover/land use classifications of Ardakan and Mook areas respectively. Maximum likelihood classifications were used by including TM thermal band (TM6) in band combinations. The results of image classifications showed that TM6 has improved the accuracy of classification in Ardakan, while no meaningful role was found in Mook region. Based on the results obtained it may be concluded that the effectiveness of TM bands for classification is highly dependant on land cover type, climatic, and geographic conditions. Based on the results obtained it was also concluded that TM6 plays a key role in separating urban and dark colour salt crust classes as in Ardakan area. In other words, in climatic and geographic conditions represented by dry surface and sparse vegetation, thermal band data may prove more useful.

**Keywords:** Classification, Desert, Land cover, Land use, Mountain, Thermal band.

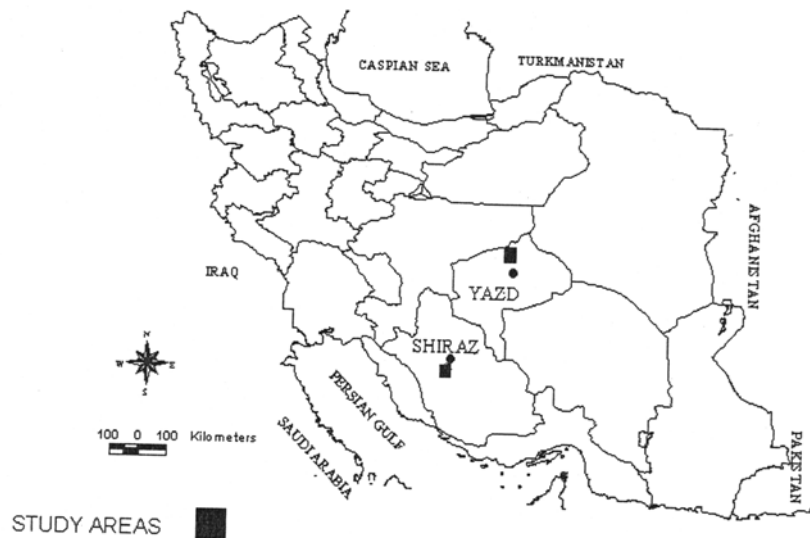
### INTRODUCTION

The increasing pressure of population leading to intensive use of soil for various purposes has resulted in constant shrinking of our finite natural resources. To meet these demands we have to use soil resources in a most sustainable manner. For sustainable development of any region, a sustainable land use plan is essential. Remote sensing data help in mapping land resources, especially in desert and mountainous areas where accessibility is limited. In such areas, degradation is also a main concern. Land cover and land use mapping are thus very important for evaluating the natural resources. Classification of remote sensing data in mountainous terrain faces the problem of

variations in the sun illumination angle. The results of image classification and information content of TM bands in arid regions, more specifically in the Ardakan and Abarkooh areas have revealed that some valuable information on soil and land cover could be found in TM thermal band while these may not be detected in TM reflective bands (Alavi Panah, 1997; Alavi Panah *et al.*, 1999). The great diversity of environmental conditions in the desert can cause a complex pattern of landforms. The variability of climate over time and space has led not only to a wide range of landform-producing processes, but also a complementary diversity of soils and vegetations (Cooke *et al.*, 1993). The salt affected and sandy soils of Indo-Gangetic alluvial plain in India, have posed problem in their dis-

<sup>1</sup> Iran Desert Research Center, University of Tehran, Islamic Republic of Iran.

<sup>2</sup> Department of Regional Geography and Landscape Study, University of Gent, Belgium.



**Figure 1.** Geographic locations of the study areas.

crimination on TM False Colour Composite (FCC), however the problem of spectral similarity was solved through integration of interpretation of thermal data (10.4 -12.5  $\mu\text{m}$ ) with TM FCC (bands 2, 3 and 4) interpretation (Verma, 1994). This range of electromagnetic spectrum registers features caused by energy absorption of sulphates, phosphates, and chlorides (Siegal *et al.* 1980; Mulders, 1987). The thermal infrared is commonly used to estimate moisture and salinity. Metternicht and Zink (1995) have shown that incorporation of the TM thermal band was decisive for salt and sodium detection. The proportion of the energy reflected, absorbed and transmitted will vary for different features, depending on their material types and conditions (Lillesand and Kiefer, 1994). These factors are complex, variable and interrelated. Lee and Tyler (1988) concluded that the TM thermal band is a useful one for discriminating between mineral and organic soils, in spite of its low spatial resolution. Goossens and Van Ranst (1996) have shown the possibility of detecting different soil types, especially gypsiferous soils, by the choice of thermal band. In this study, both areas, Mook and Ardakan, with almost different climatic, pedologic, geomorphologic, and geographic conditions were selected to study the capability of TM reflec-

tive and thermal bands for land cover/land use mapping based on digital image classification.

### Study Areas

In order to study the role of TM reflective and thermal bands in digital image classification, two areas with different geographic, topographic, climatic and pedologic conditions were selected (Fig. 1).

*Mook Area:* The study area is located between latitudes,  $29^{\circ}$  -  $29^{\circ} 15'$  N and longitudes,  $52^{\circ} 30'$  -  $52^{\circ} 45'$  E in the south of Shiraz city. The study area is of an elevation varying from 1450 m a.s.l. to 2939 m a.s.l. in the mountain areas. Mountains with dense and scattered vegetations, weathered and solid rocks, complex slopes with exposures, south and north looking faces, and various soil types (alluvial, colluvial and/or residuals) with varying depth normally show a great variability. Diversity in land forms of Mook mountains has resulted in a variety of forest and agricultural systems in the region.

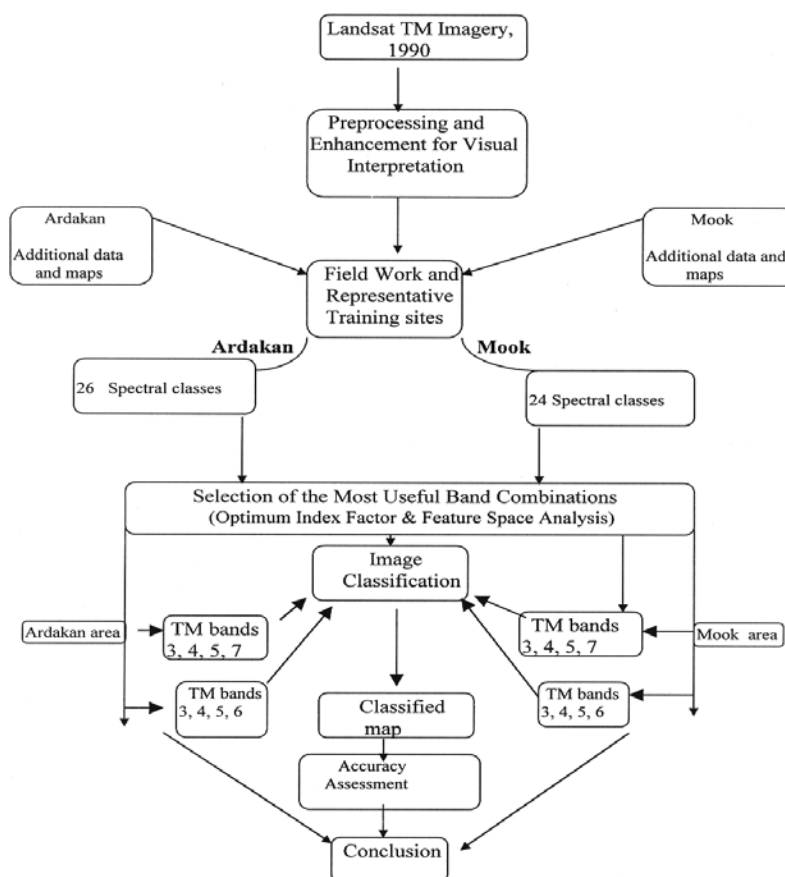
*Ardakan Area:* The Ardakan-Yazd watershed with an area of about 15,951  $\text{km}^2$  is one of the greatest watersheds in the central part of Iran. This watershed is located between the latitudes  $31^{\circ} 13'$  -  $32^{\circ} 48'$  N and longi-

tudes 52° 57' - 54° 59' E. The selected area is located in the Central Iran Deserts (Fig. 1). The Yazd watershed comprises the Ardakan area which is located in the Ardakan playa margin in the north of the city of Yazd and south of the Ardakan playa.

**MATERIALS AND METHODS**

The main steps in this study comprised of:

and data were collected and then the field data collection as one of the most important steps was carried out. In order to choose representative training sites, different sources of information were used and it was also attempted to have the field data confirmed by the local farmers and experts. Figure. 2 shows the sketch of the field investigation and supervised classification of the study areas respectively. Geometric and atmos-



**Figure 2.** Flowchart of the supervised classification of the study areas.

- 1) Acquisition of 7 bands of Landsat TM (1200 \* 1200 pixels) dated Sep. 11 and Oct. 13, 1990 for Ardakan and Mook areas respectively. Other information sources such as topographic maps, Digital Elevation Model (DEM), soil, soil salinity maps and data as well as computer software including ILWIS, IDRISI were used.
- 2) In the preparatory step, different maps

pheric corrections, contrast stretching, creation of false color composites were performed. The TM images were geometrically corrected using the Universal Transverse Mercator (UTM) co-ordinates. The nearest neighbor resampling approach which offers the advantage of computational simplicity and does not alter the original pixel values was used (Lillesand and Kiefer, 1994).



3) Processing and classification of Landsat satellite images to define homogenous areas with reference to prevailing land use cover and spectral characteristics: In this step, the training classes in the cultivated area were described and defined based on the type, density and their associated soil salinity. In the bare soil, the classes were mainly based on the soil salinity. Due to the large heterogeneity of some land cover /land use types, 26 and 24 classes were used for training in the Ardakan and Mook areas respectively in order to improve the classification results (Table 1). Spectral heterogeneity is related to high frequency features which are due to both effects of complexity of ground features and data of high spatial resolution sensors. The non-saline and very severe saline soils exhibit a great spectral heterogeneity in the field and therefore training classes such as non saline soil 1 (class no. 8), non saline

soil 2 (class no. 23), and eroded non-saline soil (class no. 9), were necessary to be trained (Table 1). The validity of the training data was evaluated both from two dimensional feature space, while quantitative evaluation involved by statistical separability analysis (mean and standard deviation), and classification accuracy assessment.

4) The standard deviation and correlation coefficient values of the TM data were used for computing a statistical parameter called the Optimum Index Factor (OIF) which is indicative of the information content of the data (Chavez *et al.*, 1984; Rao *et al.*, 1991). The algorithm used to compute the OIF for any subset of three bands is:

$$OIF = \frac{\sum sk}{\sum Abs(rj)}$$

where  $sk$  is the standard deviation from band  $k$  and  $rj$  is the absolute value of the correlation coefficients between any two of the

**Table 1.** The training classes based on field observations, maps and reports used in the field work.

Ardakan				Mook			
Class no.		Class no.	Class symbols	Class no.	Class symbols	Class no.	
1	Salt affected vegetation	14	Healthy vegetation	1	Irrigated farming 1	14	Orchard
2	alluvial fan 1	15	Pistachio 1	2	Irrigated farming 2	15	Grape Yard 1
3	Sparse vegetation	16	Whitish salt crust	3	Irrigated farming 3	16	Grape Yard 2
4	Urban	17	Soil with gypsum 2	4	Irrigated farming 4	17	Dry Farming 1
5	Alluvial fan 2	18	Affected pistachio 2	5	Irrigated farming 5	18	Dry Farming 2
6	Very severe saline soil low gravely surface	19	Highly eroded non saline soil	6	Irrigated farming 6	19	Dry Farming 3
7	Neogene	20	Dark colour salt crust	7	Rangeland 1	20	Harvested Land
8	Non saline soil 1	21	Slightly saline soil 1	8	Rangeland 2	21	Forest 1
9	Erroded non saline soil	22	Severe saline soil	9	Plouing 1	22	Forest 2
10	Very severe saline soil 1	23	Non saline soil 2	10	Plouing 2	23	Forest 3
11	Desert pavement	24	Very severe saline soil	11	Plouing 3	24	Forest Shadow
12	Non saline soil covered by desert crust	25	Mountain	12	Paddy land1	25	-
13	Soil with gypsum 1	26	Slightly saline soil 2		Paddy land 2	26	-

three bands being evaluated. Among all the 35 three band combinations, the two highest rank band combinations (rank 1 and 2) were found to be the best in terms of information content. It should be noted that two dimensional Feature Space (FS) analysis was performed on the monitor, the obtained results validating the conclusion of OIF. Based on the obtained result from the OIF approach, two different band combinations of TM bands 3, 4, 5, 7 and TM bands 3, 4, 5, 6 were used as the most informative bands to classify the whole TM scene by the maximum likelihood classifier in both study areas. In the first attempt the thermal band was excluded in the image classification and in

the second step the thermal band was included and then the accuracy of classified images were compared (Fig. 2).

RESULTS AND DISCUSSIONS

Based on the obtained results from the multiband statistics, OIF and FS analysis the band combinations of TM 3, 4, 5, 7 and TM 3, 4, 5, 6 were used to classify the whole TM scene of both areas by the maximum likelihood classifier based on the 26 and 24 training classes in the Ardakan and Mook areas respectively. The results of the image classification of the selected TM bands 3, 4, 5 and

Table 2. Error matrix resulting from maximum likelihood classification using band combinations, TM 3, 4, 5, and 7.

No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	Tot	accu	
1	331					4						1			2						3	5	1				347	95.4	
2		600			13																				1			614	97.7
3			502	3														2		2								509	98.6
4			2	172																29								203	84.7
5					1022						41														1			106	96.0
6						464		9				65	15				31				1	2					4	587	79.0
7							719																					719	100
8								116																				116	100
9									824							2	10					1		21				858	96.0
10										421																		421	100
11											911		1															912	99.9
12						9		14				94	7					20			17		4					165	57.0
13							22					7	429					38										496	86.5
14				1										218	2													221	98.6
15															386													386	100
16									3	10						345								1				359	96.1
17							17	5				11	84					601			2		7					727	82.7
18			1																			117						118	99.2
19																2				279				3				284	98.2
20			6	37																	184	1						228	80.7
21															1							103						104	99.0
22						2		2	2	2		2											124	3				135	91.9
23	17		1			18		2	2	1		17	1					40			3	46	87	1				236	36.9
24									31	29						2				12					420			494	85.0
25					94							1														974		106	91.1
26																										223	223	100	100
Tot	348	600	512	213	1129	536	719	146	862	463	953	197	537	218	391	351	740	119	291	215	130	178	102	446	976	223		11595	
Accu	95.1	100.0	98.0	80.8	90.5	86.6	100.0	79.5	95.6	90.9	95.6	47.7	79.9	100.0	98.7	98.3	81.2	98.3	95.9	85.6	79.2	69.7	85.3	94.2	99.8	100		92.0*	

\* = Overall accuracy, Accu = Accuracy, Tot = Total pixels , No. = Class number (see table1)



7 in the Ardakan area have shown that many pixels are wrongly classified in some regions. For example, based on our prior knowledge of the study area, some parts of the urban areas are wrongly classified as dark crusts in the Ardakan area. In this study the method of the error matrix was used to represent the classification accuracy. Although the overall accuracy of this classified image is relatively high (92%), a careful look at the accuracy per classes shows that the accuracy of some classes are too low to be accepted (Table 2). Based on the results of image classifications, the accuracy of both classified images were compared (Fig.

conditions.

The accuracy percentages of the classifications for the informational classes of both areas are plotted in figures 3 and 4. These figures clearly show that some training classes in the Ardakan area possess a low accuracy (separability) in the non TM thermal based classified image, while they have a higher accuracy in the thermal based classified image. The lower accuracy in some non TM thermal based classified images is due to confusion with classes that are mainly covered by desert pavement and crusted surfaces. From the above results, the effect of TM thermal band in improving the classifi-

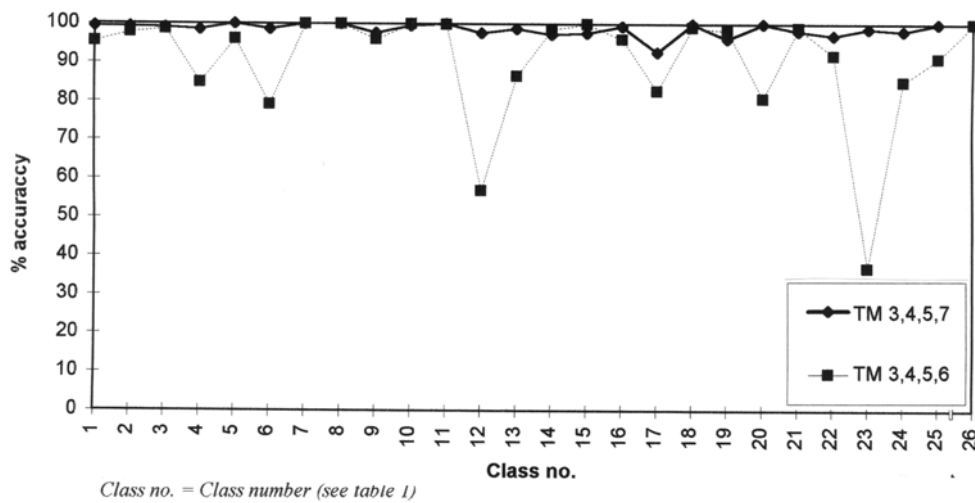


Figure 3. Comparison between the classification accuracy using 3, 4, 5, 6 and 3, 4, 5, 7 band combinations in the Ardakan area.

3). The obtained results of both image classifications showed that thermal band possesses a more meaningful role in improving classification accuracy in the Ardakan area. The reason may be attributed to the dry condition of Ardakan area with mean annual pan evaporation (potential evaporation) of about 2660 mm while low annual rainfall of about 70 mm. Therefore appreciable soil moisture is not available at soil surface and it seems that the high radiation results in heating of different soil types. The accuracy per classes of both band combinations indicates almost the same result in the Mook area with mountainous lands and semi-arid

classification accuracy is demonstrated. The effect of thermal band on separating some surface phenomena can be due to their different temperatures. For example, the TM thermal band indicates a key role in separating urban and dark color salt crust classes in the Ardakan area. The temperature rise of the dark crust class may be due to location in a depression which leads to the capturing of more radiation and retaining more temperature.

Table 2, shows the error matrix resulting from classifying the sampled training set pixels and listing the 26 classes used for training versus the pixels actually classified

**Table 3.** Error matrix resulting from maximum likelihood classification using TM bands 3, 4, 5, and 6.

No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	Tot	Accu
1	337											1											1				339	99.4
2		607			3																					1	611	99.3
3			500	3											2												505	99.0
4			3	199																							202	98.5
5		9			105 4																						1063	100.0
6						591		1					7														599	98.7
7							718						1														719	100.0
8								116																			116	100.0
9									910						4	18											932	97.6
10									1	417																1	419	99.5
11											907																907	100.0
12												161				3								1		165	97.6	
13		4				2							489														495	98.8
14														213	6												219	97.3
15			5											2	378		1				1						387	97.7
16										1						356		1									358	99.4
17	3							5				40	5				671									724	92.7	
18																		117								117	100.0	
19																9	2		275							286	96.2	
20																				225						225	100.0	
21					1										1						103					105	98.1	
22													2										131	2		135	97.0	
23			1													1					1		237			240	98.8	
24									6	3														485		494	98.2	
25																									104 9	1049	100.0	
26																										222	222	100.0
Tot	340	620	509	202	105 8	593	718	122	918	420	907	202	504	215	387	370	695	118	275	225	105	131	241	485	105 0	223	11633	
Accu	99.1	97.9	98.2	98.5	99.6	99.7	100	95.1	99.1	99.3	100	79.7	97.0	99.1	97.7	96.2	96.5	99.2	100	100	98.1	100	98.3	100	99.9	99.6	99.2	*

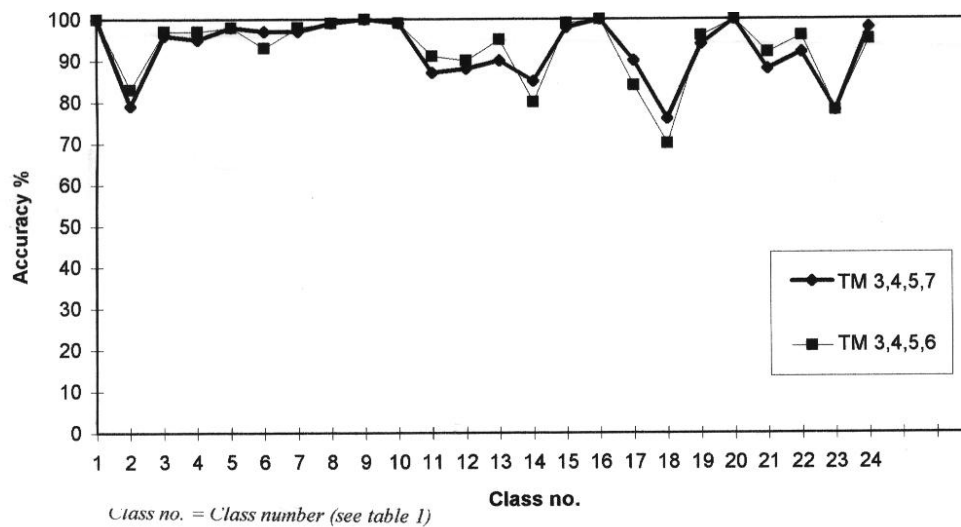
\* = Overall accuracy, Accu = Accuracy, Tot = Total pixels , No. = Class number (see table 1)

into each land cover category by the classification. Table 2, shows training set pixels that are properly classified located along the major diagonal of the error matrix. The accuracy per category for the training data were computed by the number of correctly classified pixels by the total number of pixels that were classified in each category (row total ). The error matrix resulting from classifying the sampled training set pixels and listing of the 26 classes using TM bands 3, 4, 5, 6 are shown in table 3. The results of %accuracy per category from class no. 1 to class 26 shows that the accuracy of all 26 classes, except class no.12 is higher than 90

%. Desert crust class (no. 12) shows that the percentage of the correctly classified pixels as desert crust is high 97.6%, but only 79.7% of the areas called desert crust are actually desert crust.

### CONCLUSION

It could finally be concluded that selection of TM thermal band in the image classification in the desert area can be a crucial step in supervised classification. It is essential to evaluate the information content of the TM thermal band for computer aided digital



**Figure 4.** Comparison between the classification accuracy using 3, 4, 5, 6 and 3, 4, 5, 7 band combinations in the Mook area. Class no. = Class number (see table 1).

classification. Based on the obtained results from TM image classifications, we may realize that TM reflective bands are not sufficient to classify the land cover/ soil salinity conditions in arid regions with a high accuracy. This problem can be mainly overcome by including TM thermal band for supervised classification. It should be noted that the results of this research may have been affected by the use of TM thermal and TM reflective bands with two different spatial resolution and specially different atmospheric conditions of the study areas at the time of Landsat overpass. To achieve a high classification accuracy a well organised and extensive field work is necessary. Obtained results show that TM thermal band may have an important role in land cover discrimination in desert areas. The TM thermal band contains information complementary to the TM reflective bands and a combination of the TM thermal and the TM reflective bands may provide a strong tool for land cover and soil salinity classifications. The reason why TM thermal band is most often excluded from soil analysis is usually due to low spatial resolution. But the obtained results indicate that in determining the nature of an extensive material, spatial resolution might not be so important, while more detailed spectral information relevant to the

physical and chemical composition can be quite helpful.

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## استفاده از باند حرارتی TM برای تهیه نقشه های پوشش و کاربری اراضی در دو شرایط متفاوت محیطی در ایران

### چکیده

تحقیقات زیادی نشان می دهد که مناطق خشک شرایط ایده آلی برای کاربرد سنجش از دور و تهیه نقشه های پوشش و کاربری اراضی دارند. هدف اصلی این مطالعه ارزیابی و مقایسه باند حرارتی TM در تهیه نقشه پوشش و کاربری اراضی در دو منطقه زیر بوده است: ۱- منطقه اردکان واقع در استان یزد با شرایط شدیداً کویری و تقریباً عاری از پوشش گیاهی و شوری زیاد خاک، ۲- منطقه موک استان فارس که دارای اراضی کوهستانی، جنگلی، دیم و باغات می باشد. تصاویر ماهواره لندست TM منطقه اردکان و موک به تاریخهای به ترتیب سپتامبر و اکتبر ۱۹۹۰ برای طبقه بندی پوشش و کاربری اراضی انتخاب گردیدند. طبقه بندی حداکثر احتمال با استفاده از TM6 در ترکیب باندی انجام گردید. نتیجه طبقه بندی نشان داد که باند حرارتی نقش مهمی در افزایش دقت طبقه بندی در منطقه کویری اردکان دارد ولی اثر معنی داری برای منطقه کوهستانی و نیمه خشک موک فارس ملاحظه نگردید. براساس نتایج حاصله، ممکن است نتیجه بگیریم که رفتار باندهای TM نه تنها بستگی به وضعیت پوشش و کاربری اراضی بلکه به شرایط جغرافیایی و اقلیمی دارد. به عبارتی دیگر نتایج حاصل از کاربرد باند حرارتی در طبقه بندی به شرایط اقلیمی و جغرافیایی، نظیر شرایط خشک سطح الارض با پوشش گیاهی فقیر، داده های ترمال مفیدتر می باشد.