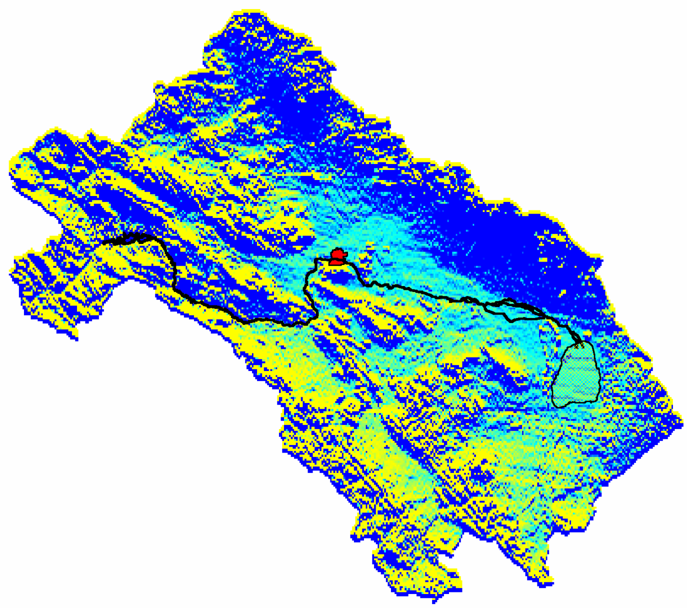
Sustainable Irrigation and Water Management in the Zayandeh Rud Basin, Iran

Crop and Land Cover Classification by Landsat 7

Zayandeh Rud Basin, Iran (July, 2000)

A. Gieske, A.R. Mamanpoush, M. Akbari, M. Miranzadeh, M. Torabi, H.R. Salemi



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The IAERI-EARC-IWMI collaborative project is a multi-year program of research, training and information dissemination fully funded by the Government of the Islamic Republic of Iran that commenced in 1998. The main purpose of the project is to foster integrated approaches to managing water resources at basin, irrigation system and farm levels, and thereby contribute to promoting and sustaining agriculture in the country. The project is currently using the Zayendeh Rud basin in Esfahan province as a pilot study site. This research report series is intended as a means of sharing the results and findings of the project with a view to obtaining critical feedback and suggestions that will lead to strengthening the project outputs. Comments should be addressed to:

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Crop and Land Cover Classification by Landsat 7 - Zayandeh Rud Basin, Iran (July, 2000) -

A.Gieske, A.R. Mamanpoush, M. Akbari, M. Miranzadeh, M. Torabi and H.R. Salemi

Abstract

In order to obtain more information with regard to crop patterns in the irrigated areas of the Mahyar, Nekouabad, Borkhar, and Abshar Districts along the Zayande Rud, a classification analysis was made of the Landsat 7 image of July 2nd, 2000. The target of the classification was to primarily focus on the agricultural land use. The date of the image fell in the transition period where the first crops were harvested and many fields were being prepared for the second crop. The image has therefore captured an instantaneous picture of a system generally in transition from the first to the second crop, but with significant differences from system to system, both with respect to crop types and agricultural cycles.

The seven-band Landsat 7 image was georectified with high accuracy positional data obtained with a number of GPS instruments (15 m error). These instruments do not only provide waypoints at crossroads and bridges, but are also able to track roads continuously. The overall accuracy of image registration was about 30 m (one pixel). The thermal band 6 with 60 m pixel size was resampled to 30 m pixel size, and then treated in the same way as the other 6 bands. Fieldwork was conducted on various occasions in September and October 200 and in October 2001. Farmers were interviewed to determine the situation on July 2, 2000. Fields were mapped in detail with the GPS instruments, and data were compiled for 112 fields.

Using a supervised classification system, training areas were selected and initial classifications were made to determine the validity of the classes. After merging several classes and testing several new classes a final classification system was made. All seven Landsat bands were used in the determination of the feature statistics. The final classification was made with the minimum distance algorithm.

The statistics with respect to areas and crop type for the districts was obtained by crossing the raster map with the irrigation district raster map. The results with respect to crop type and total irrigated area per district were compared with those of previous studies. This included both NOAA/AVHRR and conventional agricultural district statistics.

Introduction

A common way of describing irrigation system performance is by comparing water supply and demand. Estimation of water supply has been a straightforward exercise in the present case. The Ministry of Energy Esfahan Office has provided the project with data for water releases from Chadegan reservoir (see Fig. 1) and for the diversions into the major irrigation systems in the Zayandeh Rud Basin. Data are available from 1987/88 onwards.

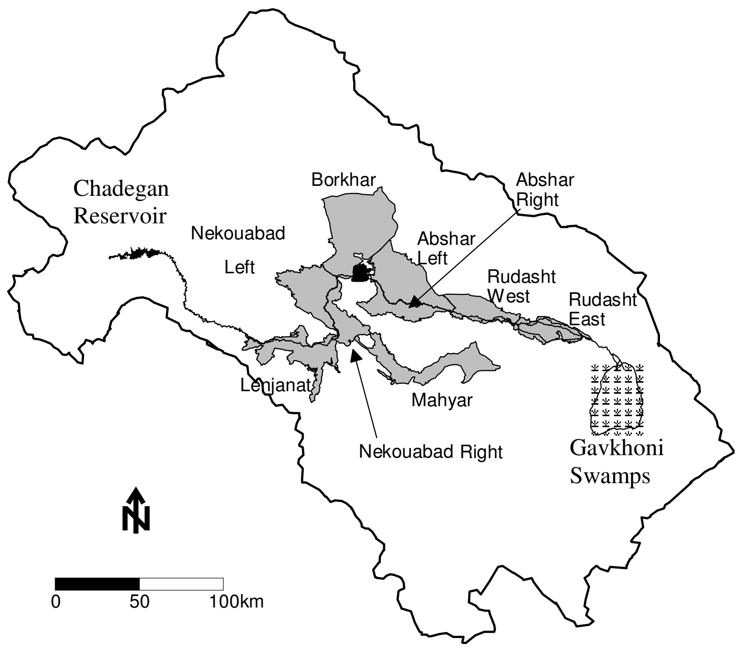

Figure 1. Major irrigation systems in the Zayandeh Rud Basin.

However, the estimation of the water demand has proved to be much more difficult. Data are required on irrigated areas, types of crops, cropping calendars and specific crop water demands. Given these data it becomes possible to calculate the total crop water requirement for each system and compare this with the total amount of water diverted into the system.

Data on cropping patterns, cropping calendars and estimated cropping intensities were available at the Provincial Offices of the Ministry of Agriculture. The data are typically organized by village, and then aggregated into administrative districts. Because these districts are not coinciding with the irrigation system command areas, problems arise in the compilation of crop data for each command area, as discussed in Research Report 9 (Sally et al., 2001).

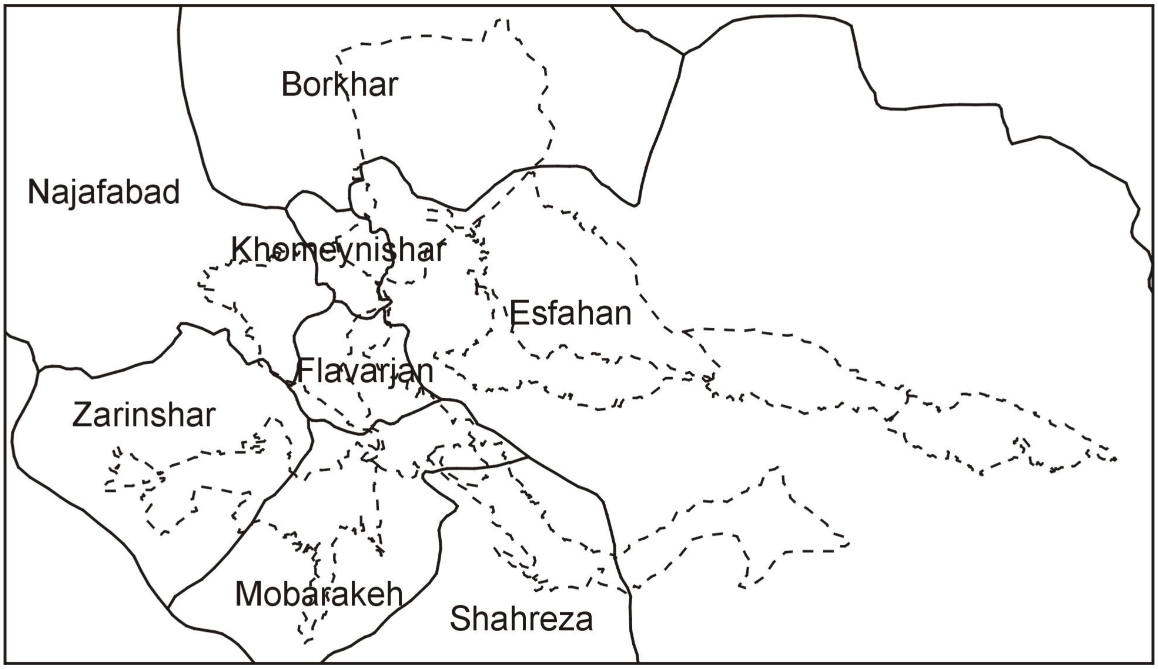

Figure 2. Map of the Agricultural Districts. Boundaries are shown as solid lines. Irrigation system boundaries are shown as dashed lines (compare with Fig. 1).

NOAA/AVHRR and Landsat satellite images can be used for the determination of instantaneous irrigated areas (Gieske et al., 2002) and assessment of irrigation performance (Droogers et al., 2001). These images can also be used in crop pattern analysis through image classification techniques, thus assisting in the study of irrigation supply and demand problems. The subject of this paper is to make a crop classification by means of the Landsat 7 ETM image of July 2nd 2000, and compare the results with those obtained earlier from district level statistics (Sally et al., 2001). The target of the classification was to primarily focus on agricultural land use in the Nekouabad, Abshar and Borkhar command areas (see Fig. 1). Although the classification techniques used here, are well-known to remote sensing experts, considerable care was taken to explain these techniques in detail in view of the training aspects of the project. Further information may be found in Lillesand and Kiefer (2000), Sabins (1996) and ILWIS3 (2001)

The date of the image fell in the transition period where the first crops were harvested and many fields were being prepared for the second crop (see Fig. 3). However, harvesting in the downstream Abshar District tends to be a little later than in the more upstream Lenjanat District. Furthermore, agricultural practices differ from district to district. In the Borkhar irrigation system plot sizes are generally larger than in the Nekouabad and Abshar systems. In the Borkhar system irrigation more strongly depends on groundwater than on surface water, and since there is in general less water available, many farms produce only one crop per year. Farmers in the Abshar and Nekouabad irrigation systems traditionally use the river water to produce two crops per year. The image has therefore captured an instantaneous picture of a system generally in transition from the first to the second crop, but with significant differences from system to system, both with respect to crop types and agricultural cycles.

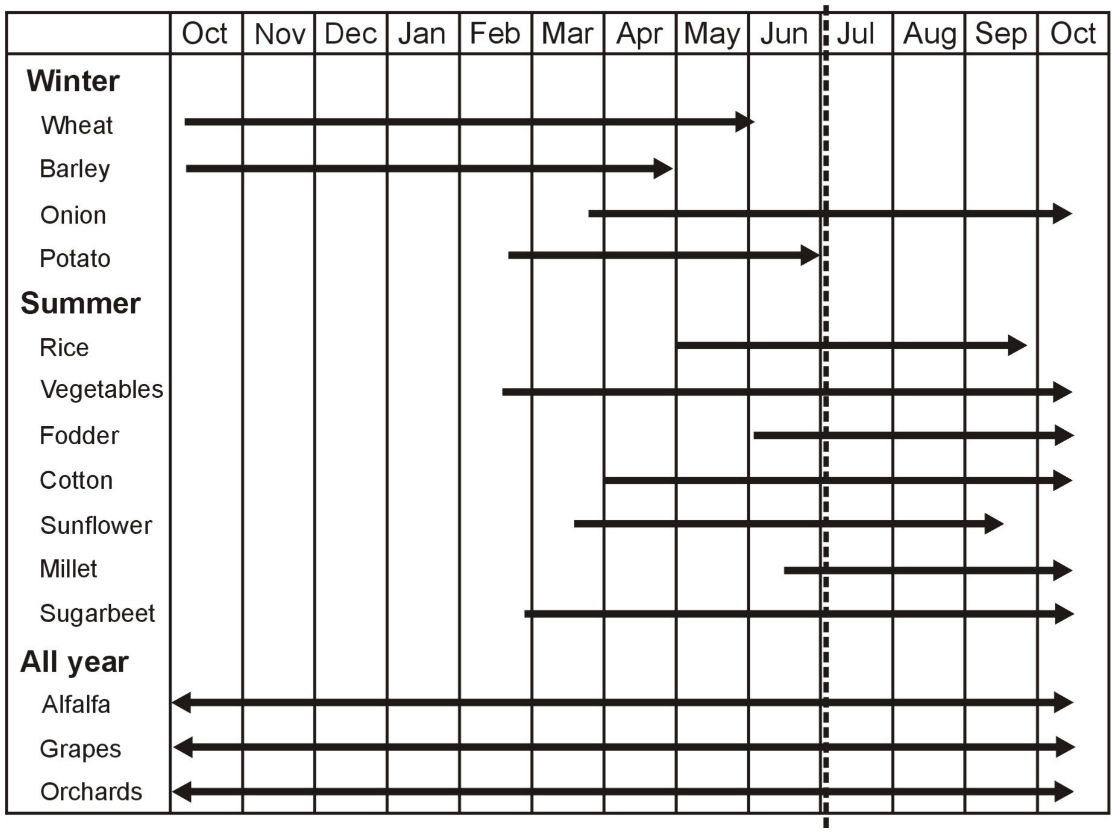

Figure 3: Typical crop calendar, Zayandeh Rud basin. The vertical dashed line indicates the overpass time of the Landsat satellite (2nd July 1990).

Methods

Georectification

The seven-band Landsat 7 ETM image was georectified with high accuracy positional data obtained with a number of GPS instruments (15 m error). These instruments do not only provide waypoints at crossroads and bridges, but are also able to track roads continuously. The overall accuracy of image registration was about 30 m (one pixel). The thermal band 6 with 60 m pixel size was resampled to 30 m pixel size, and then treated in the same way as the other bands. Fieldwork was conducted on various occasions in September and October 2000 and in October 2001. Farmers were interviewed to determine the situation on July 2, 2000. Fields were mapped in detail with the GPS instruments, and crop data were compiled for 112 fields.

Supervised Classification

Supervised classification is an interactive process where pixel values are identified with the crop types found in the pixels corresponding to the fieldwork areas. In general many layers of rasterized information may be used apart from the bands in the visual part of the spectrum, such as, for example, the infrared thermal band 6 of the Landsat image. Another possibility is a digital elevation map (DEM). In the present case a DEM was not available, and only the 7 bands of the image were used. If a pixel corresponds to a rice area, this means that rice is characterized by 7 values. Different rice pixels will obviously have different sets of values and all these rice pixels are collected in what is called a sample set. Each of the 7 sets of values has a mean and an average. This process is repeated for all (n) classes of crop types and cover classes as determined by the fieldwork or by previous experience. Thus a set of n 7-dimensional vectors is found in 7-dimensional feature space, one for the means and one for the standard deviations. The classification problem now consists in determining to which of the n classes each unknown pixel belongs. Several standard classification methods are briefly discussed below. In summary, the ground data is transformed into a sample set of all the classes that are identified on the ground, while the dimension of the feature space is determined by the available number of bands in the image or layers from other sources.

Feature Space Statistics

Table 1 below shows an example of a vector in feature space. In total 546 pixels were found to be rice areas during fieldwork and the statistical properties mean and standard deviation of the 7 bands are given in the 2nd and 3rd columns. Also the number of pixels with the predominant value (Nr) is given. The predominant pixel value (Pred) or the mode of the distribution is given in the 5th column, while the last column indicates the total number of pixels in this particular sample set selection for rice.

A feature space gives a visual overview of the separation of classes of training pixels. The spectral values of one map are put along a horizontal axis, and the spectral values of another map are put along the vertical axis. At the position of a sampled pixel, the color or symbol of the assigned class appears. Fig. 4 below indicates the clustering of pixels, which would arise from a subdivision of two classes: green and not-green.

For simplicity, only the diagram for bands 3 and 4 is shown. Classification of unknown pixels now proceeds from distance calculations to the known sample classes. In Fig. 4 unknown pixels are illustrated by black squares. It is obvious that pixel 1 must be classified as belonging to the green class, while pixel 2 should probably be classified as belonging to the not-green class. The situation is less clear for pixel 3, which lies about the same distance from the green and not-green classes. Different classification methods would probably yield different class properties for this pixel.

Finally, pixel 4 lies closer to the not-green class than to the green class. If the criterion is that membership only depends on distance, then pixel 4 would be not-green. However, often threshold values are used such that pixels further away than the threshold are considered undefined. In that case pixel 4 would in all likelihood be undefined. In the present case 7-dimensional space is considered, and therefore all distances and memberships have to be calculated in 7-dimensional space.

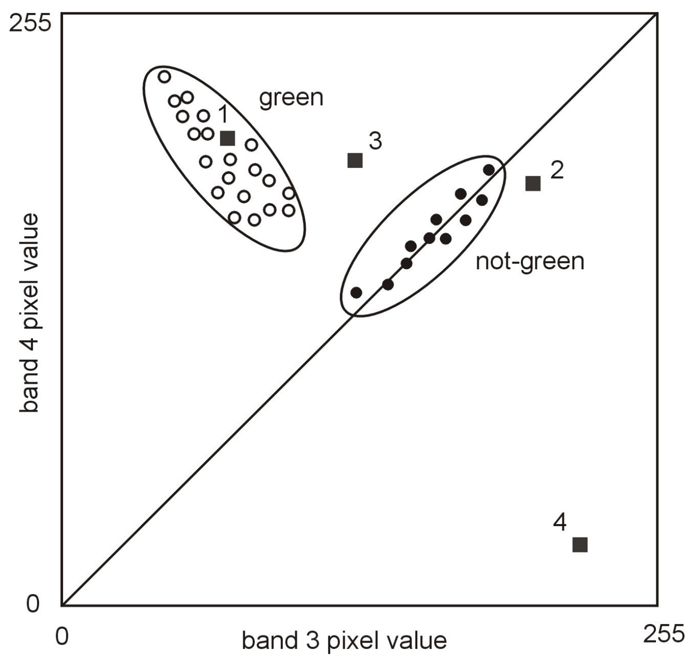

Figure 4. The figure shows an example visualization of feature classes. The number of classes is two (green and not-green). The training pixel values for bands 3 and 4 are plotted on the x- and y-axis respectively. Any combination of the 7 bands may be taken. For simplicity only the diagram for bands 3 and 4 is shown. Classification of unknown pixel 1 (black square) is obviously into the class of green pixels. Pixel 2 probably belongs to the "not-green" class. Pixel 3 poses a more complex problem and different methods may yield different results. Pixel 4 lies closer to the "not – green" class. However, it is probably better to classify this pixel is "undefined".

Table 1. Feature vector characteristics for a rice example.

Band	Mean	StDev	Nr	Pred	Total
1:	83.7	3.8	97	82	546
2:	75.7	4.7	79	73	546
3:	64.6	7.7	61	60	546
4:	112.3	13.5	26	123	546
5:	94.5	8.3	34	98	546
6:	141.7	1.9	160	142	546
7:	53.7	5.7	64	52	546

Classification methods

The decision-making algorithm tries to make a partition in feature space, using the information from the training samples. The method must decide for every possible feature vector in the image to which sample feature class it belongs. Sometimes the method has to decide whether the pixel feature vector is not identifiable with any class, and has to be assigned an undefined value. In general the classification problem has a highly statistical nature. The probabilities that a pixel belongs to class A or B may be identical or marginally different. The user often has to decide what is acceptable.

All classification methods calculate the means per band (class means) for each class of training pixels as defined in the sample set. Following ILWIS3 (2001) the following categories are commonly used:

- Box classifier method
- Minimum distance method
- Minimum Mahalanobis distance classifier
- Maximum likelihood classifier

The ***Box classifier*** method is based on the distances towards class means and the standard deviation per band of each class. Multi-dimensional boxes are drawn around class means based on the standard deviation of each class. The user can insert a multiplication factor (usually > 1) to make all boxes a bit wider. If the spectral values of a pixel to be classified fall inside a box, then that class name is assigned. If the spectral values of a pixel fall within two boxes, the class name of the box with the standard deviation is assigned. If the spectral values of a pixel do not fall within a box, the undefined value is assigned. The default multiplication factor is $\sqrt{3}$ for 3 bands. For the other classifiers a threshold distance has to be specified. The threshold value has to be specified in terms of the spectral values to be classified, i.e. when classifying a satellite image, the threshold value must be a value between 0 and 255. The larger you choose the threshold, the easier a pixel will be assigned to a class.

The ***Minimum Distance*** classifier is based on the Euclidean distances towards class means only. For the spectral values of a pixel to be classified, the distances towards the class means are calculated. If the shortest (Euclidean) distance to a class mean is smaller than the user-defined threshold, then this class name is assigned to the output pixel. Else the undefined value is assigned.

For the spectral values of a pixel to be classified with the ***Minimum Mahalanobis Distance*** classifier, the distances towards the class means are calculated as Mahalanobis distance, which depends on the distances towards class means and the variance-covariance matrix of each class. The class name with the shortest Mahalanobis distance is assigned, if this distance is smaller than the user-defined threshold value. Else, the undefined value is assigned.

The ***Maximum Likelihood classification*** assumes that spectral values of training pixels are statistically distributed according to a multi-variate normal probability density function. For each set of spectral input values, the distance is calculated towards each of the classes is calculated using Mahalanobis distance. Another factor is added to compensate for within class variability. The class name with the shortest distance is assigned, if this distance is smaller than the user-defined threshold value. Else, the undefined value is assigned.

Some more mathematical information is given in Appendix A. Classification relies on the spectral separability of classes. Heterogeneous classes that contain elements of many other classes, for example towns (mixture of roofs, roads, forest, grass, water etc.), are in general difficult to classify. If all town pixels are to be classified as town, then elsewhere the forest, grass and water pixels are likely to be misclassified.

At the border of two distinct classes both classes usually influence pixel values. In a feature space, these pixels are usually positioned between the two classes. During classification such pixels may obtain the value “undefined” when they are not similar enough to either class.

The spectral values of elongated terrain objects, such as roads, having a width smaller than the image's pixel size, are usually influenced by the spectral values of surrounding pixels. Elongated features may therefore be difficult to classify. Classification is mainly suitable for classes that form areas in the terrain.

Confusion matrix

To get an idea of the overall accuracy of the classification, use has to be made of a test set which contains additional ground truth data, which have not been used to train the classifier. Crossing the test set with the classified image and creation of a so-called confusion matrix is an established method to assess the accuracy of a classification. It is not recommended to use the sample map for both the classification and the accuracy assessment, because this will produce figures that are too optimistic. Details on the interpretation of a confusion matrix are given in Appendix B.

Post classification operations

The final classification may not meet the expected results. This can be due to spectral overlap in the sample set, or because the classifier has not been trained properly. If this is the case the classification process should be repeated, incorporating for example more spectral classes, or splitting existing classes. After the classification process some classes may be merged if they are not important for the study at hand. Sometimes there are many isolated pixels within homogeneous areas that show deviating classes, in which case standard filter techniques may be applied.

Results

Training classes and legend

The collection of ground GPS data serves a dual purpose:

- A number of clearly identifiable points (bridges, crossroads, etc) with accurate coordinates are required to accurately position the image with respect to a coordinate system.

- To be able to identify ground control points with known crops on the image, fields have to be mapped with a GPS.

It is recommended not to take a single point in the middle of the fields, but to try to take coordinates of all corners. An example is shown in Fig. 5, where a farm is shown in the Borkhar District on a false colour composite of bands 5, 4 and 3. The red dots indicate the GPS points taken at the corners of the individual fields. This procedure avoids errors because fields can be recognized on the image much better by their shapes and sizes than by a single point. The importance of this type of fieldwork cannot be overemphasized. The quality of the image classification very much depends on the quality and amount of data collected in the field. Because it is impossible to collect field crop data all at once during the time of the satellite overpass, regular fieldwork has to be carried out in all parts of the study area, especially when image classifications have to be made several times per year.

Figure 6 shows the same fields as in Fig. 5 after the classification and all fields have been assigned to a class. The legend shows the classes used for the irrigated areas covered by the satellite image. Two aspects must be noted straightaway:

- Not all fields are always assigned the correct crop. The training samples of various crops may have spectral characteristics (feature vectors) that are very close together. Therefore small deviations in spectral values may cause the pixels to be classified in a different category.

- Within the same field small differences may cause the classification procedure to assign deviating classes to isolated pixels in a field.

Both effects are visible in figure 6. The classification is never 100 % correct and assignment into a number of classes has a certain accuracy and reliability. Checks can be made through the use of a so-called confusion matrix, if an independent sample set is available. After initial tries and checks a decision has to be made as to whether to reduce or increase the number of classes. In the present case the initial classification was made with 20 classes, which turned out to be slightly over ambitious. Nevertheless it is instructive to start the analysis with 20 classes.

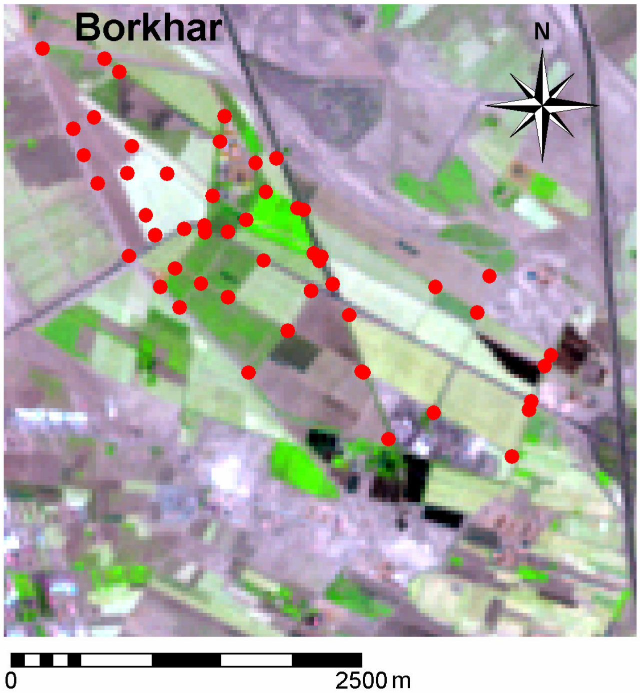

Figure 5. False Colour Composite part of the Landsat image (2/7/00) showing a farm in the Borkhar District. Red dots indicate the GPS ground control points used to correctly position the image. Information with regard to crop patterns was also collected here.

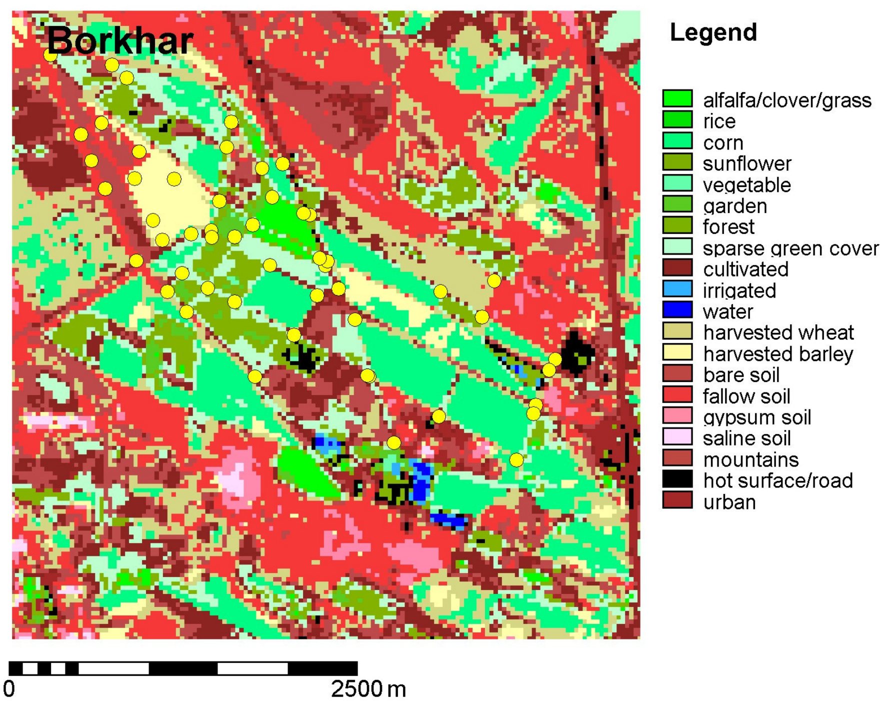

Figure 6. Example of crop classification of the same area as in Fig. 5.

Map classes and Feature statistics

The legend as shown in Fig. 6 was adopted for the image classification. It should be interpreted as follows:

1. Alfalfa/Clover/Grass/Millet

Alfalfa is normally observed in the field as dark green. On the False Color Composite (fcc742) image, it has a bright green appearance. However, when the alfalfa is cut then the ground cover is reduced significantly and classification becomes difficult because on the image it then looks like sparse vegetation with a large amount of bare soil. Grass is also observed on the fcc742 image as bright green when it is well watered. Typical locations are for example the soccer field of Esfahan Technical University or along the Zayande Rud in Esfahan. There are a few fields of clover, which are difficult to distinguish from alfalfa. The same holds for the few millet areas.

2. Rice

Because the date of the satellite overpass (July 2, 2000) was between harvesting the first and preparing for the second crop in large parts of the irrigated areas, rice was mainly found in the Lenjanat irrigation system and to a lesser extent in the Nekouabad and Abshar systems. In many places irrigated land is found where farmers are preparing the rice fields.

3. Corn

Corn was mostly in the first growing stage on the date of the satellite overpass. It was found to have a distinct light green appearance in the fcc742 image and was easy to classify with the 7 band spectral analysis.

4. Sunflower

This crop type has distinct dark green appearance on the fcc742 image and was easy to classify. An added advantage in the classification is the presence of large plots of this crop type in the Mahyar and Borkhar irrigation systems.

5. Vegetable

The pixels of this class represent a variety of different kinds of vegetables such as potato, onion, squash, cabbage, carrot, cucumber, melon and watermelon. An added complication to this class is the normally small plot size, which leads to a large number of mixed pixels. Furthermore, many of these small plots are surrounded by rows of trees, and therefore this class consists of a mixture of many different vegetation types.

6. Garden

This class (garden or orchard) consists of fruit trees such as apple, pomegranate, chary, fig, apricot, quince, peach, almond and pistachio.

7. Forest

This class consists mostly of pine, cypress, and ash tree with some mulberry forest. Typical areas are found around Esfahan Technical University and around the oil refinery.

8. Sparse green cover

In many places crops were water stressed covering the fields unevenly, hence the pixels have green and bare soil characteristics. In addition there are many young forests or widely spaced forest with poor canopy cover. Finally, many pixels are of a mixed nature, where gardens (orchards) and other crops are bordered by, for example, bare soil, roads and houses. Rather then trying to assign specific crop types to these pixels, a general class of sparse vegetation cover was introduced.

9. Cultivated

On the date of the satellite overpass many farmers were preparing the fields for the second crop. The plowing and irrigation reduce the reflectance and soil temperature and cause the pixels to have a dark appearance. This class should be included in the agricultural land use area.

10. Irrigated land

The main characteristic of many pixels is the water content, as shown by the low temperatures, low reflection and the absence of significant green cover of these pixels. It is therefore difficult to attach a crop type to these pixels. They are not only showing rice fields in preparation but also other irrigated crop.

11. Water

Typical areas representing open water surfaces are found in wide river areas, dams and in ponds with industrial or urban wastewater.

12. Harvested wheat

The harvested wheat fields are easy to classify because of the reflection characteristics of dry plant material left behind.

13. Harvested barley

These fields also have a distinct spectral signature, which is different from that of the harvested wheat fields.

14. Bare soil

The pixels belonging to this class lie outside the agricultural land and consist, for example, of colluvial and alluvial fans at the foot of the steep mountain slopes, around the rivers and on the mountain plateaus.

15. Fallow

These fields did not show any sign of recent cultivation, but were clearly part of the agricultural land use area.

16. Gypsum soils

Gypsiferous soils are mainly found in the northern part of the Borkhar district and are easy to classify. There is a partial overlap with the saline soil class.

17. Saline soils

The pixels of this class strongly reflect light in all bands and have a white to light blue appearance in the fcc742 image. The high surface reflectance is presumably caused by the precipitates halite, trona and gypsum.

18. Mountains

The mountain areas appear as heterogeneous areas on the image as a result of steep slopes and gullies with alternating sunlit slopes and shadow areas. Elevation differences cause further temperature differences. Finally, differences in geology lead to additional variations in spectral signature. Because the variations in this class are so large, a large overlap occurs with the bare soil and fallow ground classes. As a result some of the agricultural land (fallow and bare soil) is mapped erroneously as mountainous.

19. Hot Surface/roads

This class was necessary to properly classify a few dark mountain areas. In the agricultural area this class is found to represent tar roads, parking lots and some waste areas.

20. Urban

This class is also rather variable since it comprises are many different elements, such as houses, roads, large buildings and factories. The response of many pixels in this class is mixed with that of green vegetation. The different temperature and reflectance properties of these elements lead to a large variance in this feature's statistical properties. There is a large overlap with the properties of the pixels in the mountainous areas.

The feature vector statistics of these 20 classes is compiled in Appendix C. Table 2 shows the means of the 20 sample feature vectors. These vectors are 7-dimensional because 7 layers of information have been used in the training set. The classification procedure now calculates the distances from an unknown pixel to each of these 20 vectors and finds the minimum.

Table 2 Means of the 20 sample feature vectors (see Appendix C for standard deviations)

	alf	rice	corn	sunf	veg	gard	for	sgc	cult	irr	wat	hw	hb	bs	fa	gyp	sal	mo	sil	urb
Band	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1:	98	84	137	119	105	98	99	125	133	100	92	142	162	138	148	168	213	134	118	140
2:	92	76	152	124	101	93	89	129	139	95	76	155	185	143	163	190	235	135	112	137
3:	96	65	216	168	106	99	97	166	181	102	67	208	242	185	223	253	255	171	129	163
4:	140	112	130	106	87	105	81	108	95	76	34	122	148	93	113	131	155	87	62	87
5:	128	95	207	150	92	115	104	170	174	86	38	204	233	177	203	240	247	173	110	148
6:	153	142	175	165	151	156	164	173	182	150	142	176	176	184	184	181	184	174	191	175
7:	73	54	139	96	63	75	73	127	151	61	30	154	168	157	182	215	154	150	95	132

Distances can also be calculated between the sample vectors, as shown in Table 3. The smaller the distance between classes the more similar they are, and the more difficult it will be to decide in which class the unknown pixel will fall. This depends not only on the mean but also on the range of the sample values. The table below shows immediately that it will be difficult to decide between classes 9 (cultivated) and 14 (bare soil), because the distance is only 10. Classes 17 (saline soil) and 11 (water) on the other hand will be very easy to distinguish because they are so far apart. In general, the matrix given in Table 3 can be analyzed with cluster or factor analysis techniques, to decide which are the main components that can be distinguished on the satellite image. However, these techniques are beyond the scope of this report.

Table 3. Distances between the 20 mean sample vectors

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0	62	175	95	66	37	65	115	148	78	149	178	234	157	207	270	284	141	101	124
2	62	0	230	140	60	52	58	164	194	60	100	231	290	204	259	324	339	185	116	165
3	175	230	0	96	193	180	193	72	62	205	284	20	65	61	51	103	129	73	161	91
4	95	140	96	0	98	89	100	39	68	110	189	99	158	77	127	193	210	65	77	48
5	66	60	193	98	0	34	27	126	153	16	96	193	253	162	218	285	299	144	66	119
6	37	52	180	89	34	0	28	113	143	44	120	181	241	152	208	274	291	134	72	114
7	65	58	193	100	27	28	0	123	150	28	100	193	254	159	217	285	304	140	60	119
8	115	164	72	39	126	113	123	0	35	137	217	70	133	45	96	163	190	33	94	35
9	148	194	62	68	153	143	150	35	0	163	239	51	115	10	68	137	172	16	110	39
10	78	60	205	110	16	44	28	137	163	0	82	205	265	172	229	297	312	154	70	129
11	149	100	284	189	96	120	100	217	239	82	0	283	344	247	306	373	388	229	136	204
12	178	231	20	99	193	181	193	70	51	205	283	0	65	48	35	95	129	63	158	84
13	234	290	65	158	253	241	254	133	115	265	344	65	0	109	58	53	76	126	219	146
14	157	204	61	77	162	152	159	45	10	172	247	48	109	0	61	129	166	21	117	45
15	207	259	51	127	218	208	217	96	68	229	306	35	58	61	0	69	122	80	177	103
16	270	324	103	193	285	274	285	163	137	297	373	95	53	129	69	0	92	147	246	170
17	284	339	129	210	299	291	304	190	172	312	388	129	76	166	122	92	0	183	266	196
18	141	185	73	65	144	134	140	33	16	154	229	63	126	21	80	147	183	0	102	32
19	101	116	161	77	66	72	60	94	110	70	136	158	219	117	177	246	266	102	0	77
20	124	165	91	48	119	114	119	35	39	129	204	84	146	45	103	170	196	32	77	0

Classification

After some tries it was found that the Minimum Distance method (see Appendix A) without threshold performed best.

The classification results with the 20 sample classes, is shown in Figures 7 to 10. Figure 7 shows an overview of the Borkhar, Lenjanat, Abshar and Nekouabad Districts. The green colors show active vegetation, while the lightblue color should be interpreted as irrigated land with vegetation (mainly rice) in the early growing stage. The light blue areas clearly show that irrigation took place in these areas in the last weeks of June 2000, when water from the Zayandeh was already getting on low supply. The Borkhar irrigation district clearly shows much less green vegetation on a background of bare, gypsiferous soils.

Figure 8 shows a detailed view of a northern Borkhar farm area. Irrigated farm land only is a fraction of the total. Water shortage and poor soil conditions are clearly limiting factors in this district.

In Figure 9 a detailed view is given of the situation in the Abshar Left and Right irrigation districts. Abshar right bank shows freshly irrigated land near the Zayandeh and in the south near the main diversion channel. It is also clear that there more patches of bare/uncultivated land in Abshar Right than in Abshar Left. It appears that there is not much irrigation for the summer season in Abshar Left at this stage.

Finally, Figure 10 shows Nekouabad Right Bank, where normal irrigation was taking place. All the suitable land is utilized and the few brownish areas are rocks outcrops and hills. Misclassification occurs on the hill slopes in the northeastern part of the area, where a few blue spots indicate the presence of irrigation. The reason for this is that hill slopes are highly heterogeneous, because of shade. Slopes exposed to the sun become very hot, while those in the shade remain very cool. The properties cool and dark are generally those of watered surfaces, because these tend to be cooler than their environment and because they have low reflective characteristics (they absorb the incident light).

Confusion matrix

A second data set of lower quality than the one used for the classification, was employed to generate a confusion matrix (see Appendix B for definitions of terms). Table 4 shows the results. Because the second set was not as reliable as the first, conclusions have to be drawn with care. However, some obvious points can be noted.

- The classes 9 (cultivated), 14 (bare soil), 15 (fallow soil) have a low reliability because they are very similar and cannot be distinguished well enough. It would be better to combine them into a single class.

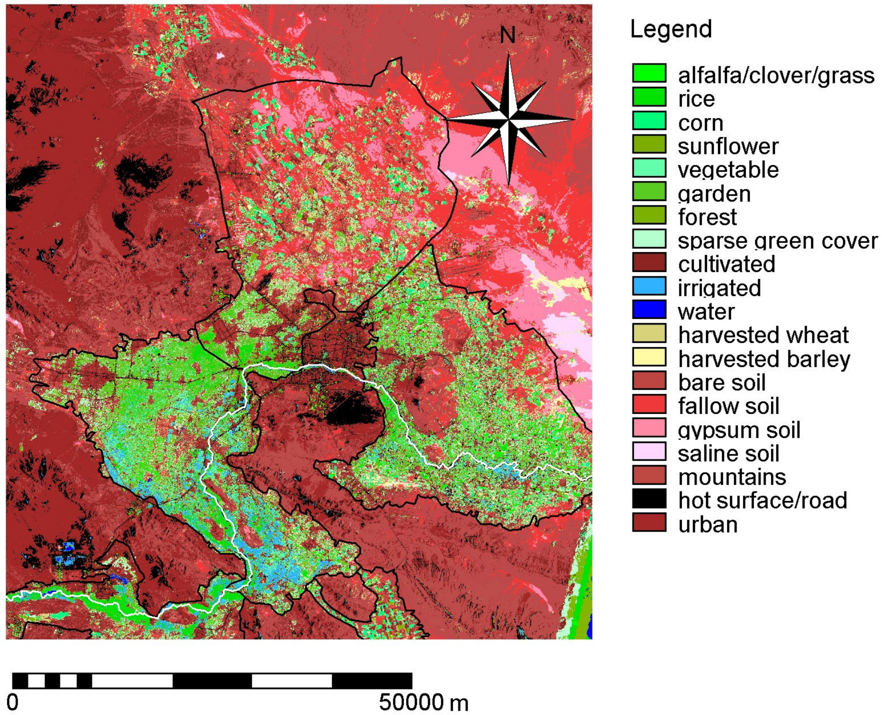

Figure 7. Land cover classification with different soil and vegetation types (see also Figure 1 for the names.

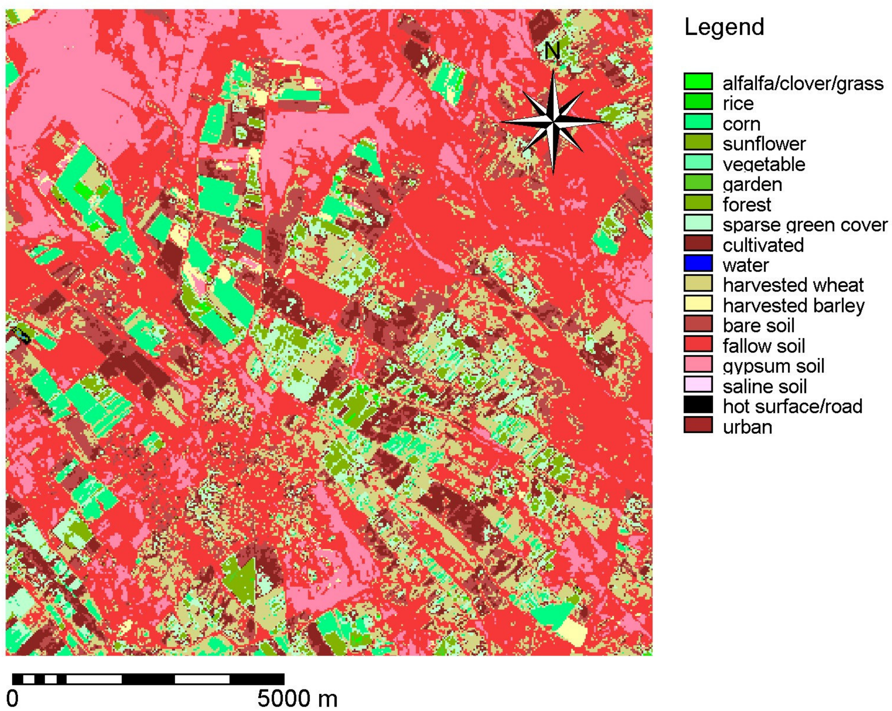

Figure 8. Land cover and crop types of the Borkhar District.

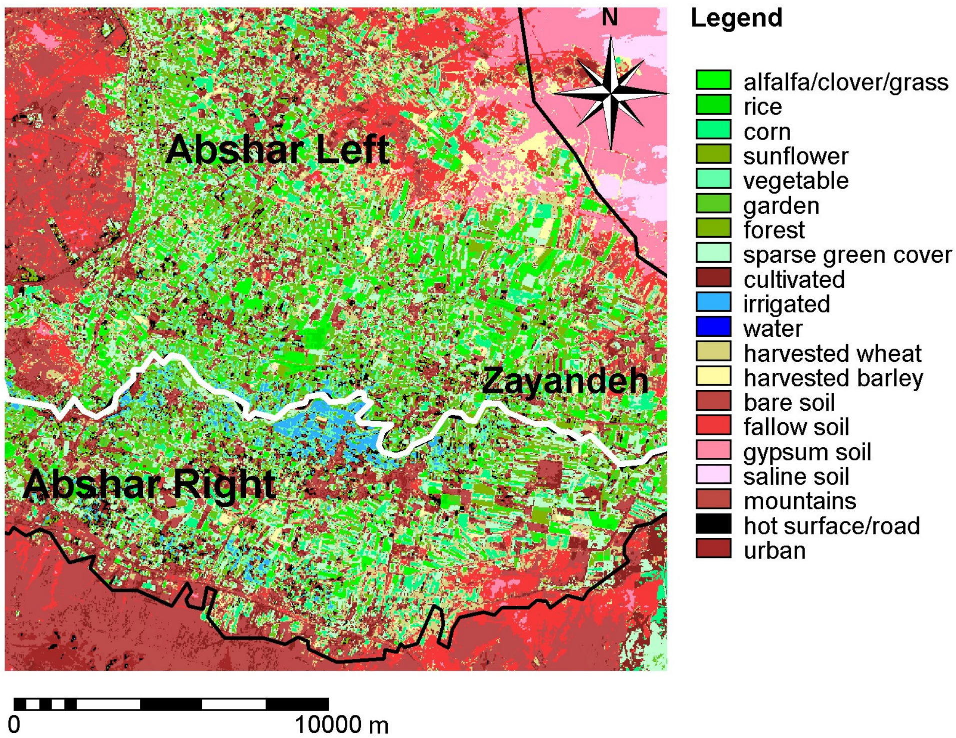

Figure 9. Detailed view of the Abshar crop classification.

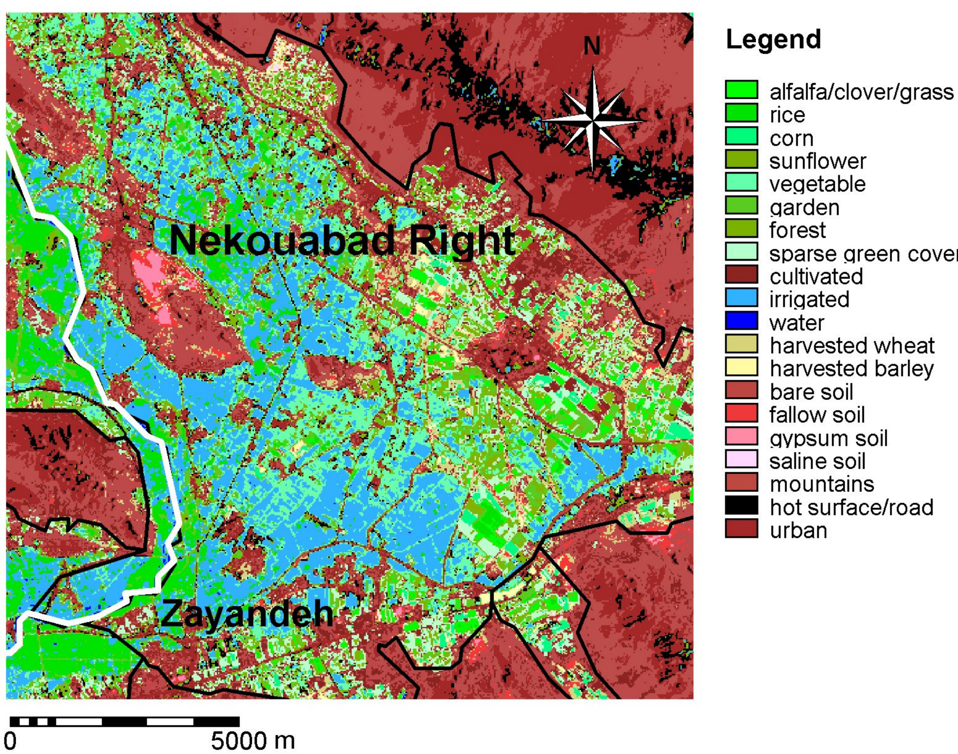

Figure 10. Detailed view of the Nekouabad Right crop classifcation.

- It is difficult to classify rice (class 2) properly, because the young rice appears to be similar to vegetable (class 5) and alfalfa (class 1) at this stage of the growing season.

- There is a large overlap in the properties of classes 18 (mountains), 19 (hot surfaces/roads) and 20 (urban). Since these categories are not of practical use to the study of crop patterns and crop water requirements it is better to combine them

Table 4 Confusion matrix for the classification with 20 categories.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Acc
1	19	57		1																	25 %
2	1	72			4	5				94	1										41 %
3			68									4									94 %
4				189																	100 %
5	1	35		20	41	107	1	6		3											19 %
6		73		1	9	43	7			59											22 %
7				10		35	179			24									74	8	54 %
8	5			34		34		70	12			48						3			34 %
9									7			4		134	212						2 %
10					19					155	3										88 %
11										12	72										86 %
12	1		3		3			4	2			81		2				2			83 %
13													103			9					92 %
14									525					541	103	1					46 %
15									11						0			71		160	0 %
16																234					100 %
17																	1305				100 %
18								5	8	4				223				2786	328	1102	63 %
19																			273	3	99 %
20					3			2	43			2		83	2			37	1	129	43 %
Rel%	70	30	96	74	52	19	96	80	1	44	95	58	100	55	0	96	100	96	40	9	

avg accuracy	59 %
avg reliability	61 %
overall accuracy	62 %

Post-classification

The final classification was derived by merging a number of classes in accordance with the conclusions drawn from the confusion matrix as given in Table 4. Classes 9 (cultivated), 14 (bare soil) and 15 (fallow) were merged into a single class 14 (bare soil), while classes 18 (mountains), 19 (hot surface/roads) and 20 (urban) were merged into class 18 (heterogeneous). Finally, classes 1 (alfalfa), 2(rice), 5 (vegetable) and 10 (irrigated) were collected into a single class 1 (lightgreen young vegetation). The number of classes is then reduced from 20 to 13. Table 5 shows the effect of this on the overall reliability and accuracy. The overall accuracy has gone up to 88%.

Table 5 Confusion matrix with number of classes reduced from 20 to 13. Classes 9,14,15 mapped into 14 (bare soil), Classes 1,2,5,10 mapped into 1 (lightgreen vegetation) and classes 18,19,20 into 18 (heterogeneous mountains, urban).

	1	3	4	6	7	8	11	12	13	14	16	17	18	acc
1	501		21	112	1	6	4							78 %
3		68						4						94 %
4			189											100 %
6	141		1	43	7									22 %
7	24		10	35	179								82	54 %
8	5		34	34		70		48		12			3	34 %
11	12						72							86 %
12	4	3				4		81		4				84 %
13									103		9			92 %
14								4		1533	1		231	87 %
16											234			100 %
17												1305		100 %
18								2		359			4659	93 %
rel%	73	96	74	19	96	88	95	58	100	80	96	100	94	

avg rel %	82
avg acc%	79
overall %	88

The resulting classification is shown in Figure 11. The overall accuracy has gone up at the cost of a number of classes. Further reduction will improve the accuracy. However, a balance has to be found between the number of categories and the acceptable reliability. Reduction also depends on the type of application. For example, the distinction between classes "bare soil", "heterogeneous", "saline soil" and "gypsum soil" may be irrelevant when strictly agricultural applications are considered, so these classes could have been combined in that case.

Table 5 shows that there is still an overlap in the vegetation classes. For example class 1 is still mixed with 6,7,8,11 and 12. The orchard classification reliability is still only 19%. However, it is clear from Table 5 that there is very little overlap between the vegetation classes and the non-vegetation classes. This is exactly what one would expect in this kind of arid to semi-arid environment where no vegetation can survive without some form of irrigation. Therefore even if there is some inaccuracy involved in the classification of the vegetation types, the total amount of vegetation can be assessed accurately. The last section discusses the comparison between the various methods used to determine the total irrigated area.

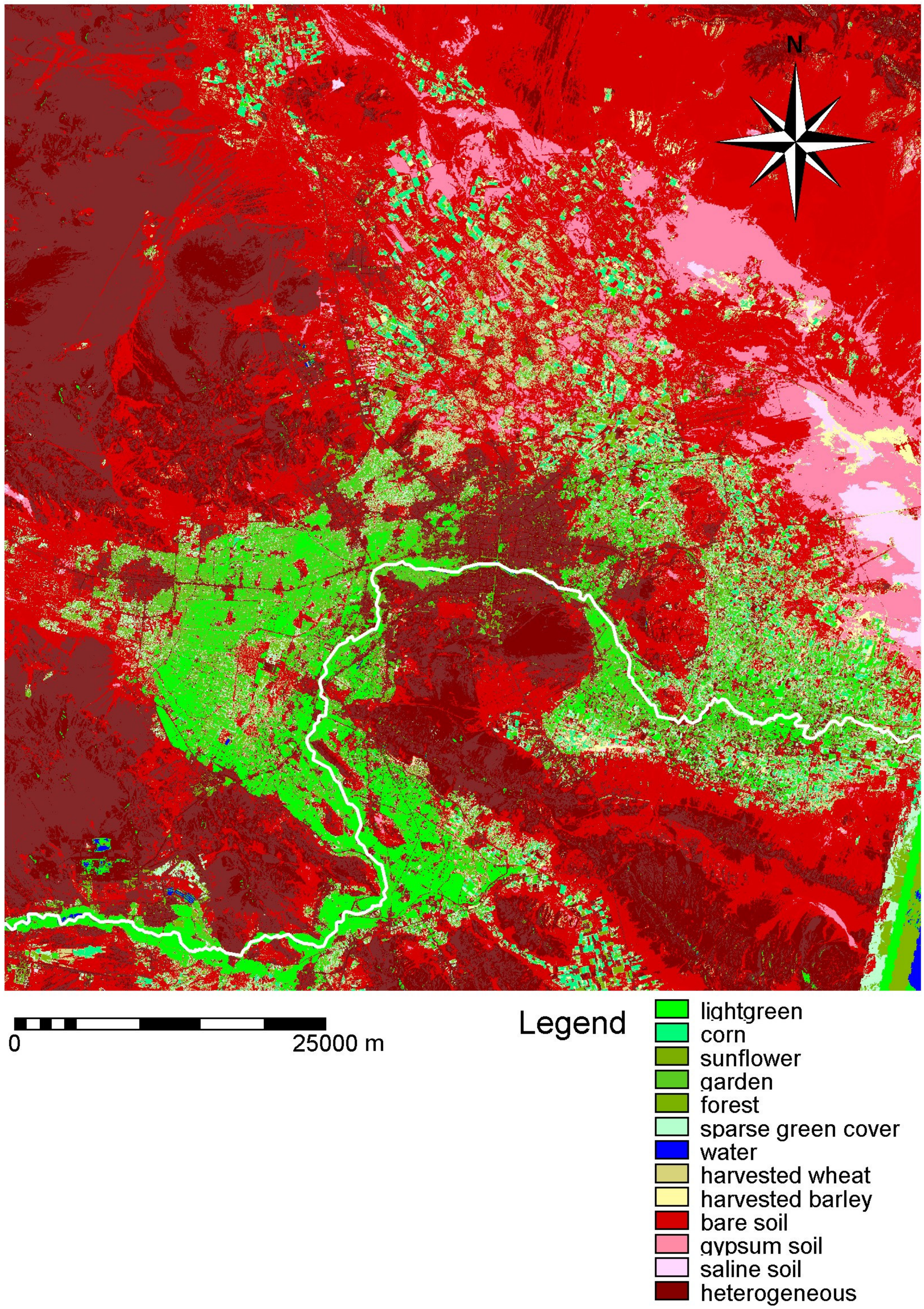

Figure 11. Classification with number of classes reduced to 13.

Total Irrigated Area Statistics

The areas for each class or crop type can be found through some simple GIS crossing operations. Table 6 below shows the results. The classification based on 13 classes has been taken to subdivide crops and soil types. Classes 12 and 13 are not part of the instantaneous irrigated area (cropped area) as viewed by the satellite and these were therefore taken out of the sum for the cropped area. Moreover, a comparison with other satellite methods, which make use of the NDVI, can then be made.

It should also be noted that there is a large area classified as sparse green cover. A number of pixels in this category are probably of mixed origin: part vegetation, part bare soil or road. This category therefore introduces another uncertainty in the total irrigated area assessment, probably leading to a slight overestimation of the irrigated area estimates.

The irrigated area estimates of Table 6 have been compared with estimates made in other studies. All data have been compiled in Table 7.

Table 6. Area per class for the irrigation districts fully covered by the image. Also shown are the total irrigated areas and the gross areas of the districts (July, 2000).

	area	borkhar (ha)	lenjanat (ha)	nekleft (ha)	nekright (ha)	absright (ha)	absleft (ha)	total (ha)
1	alfalfa/rice/irrigated	1600	4741	9894	6587	3020	4147	29990
3	corn	2853	1054	85	240	961	2086	7279
4	sunflower	3501	1362	4832	1852	2098	4894	18539
6	garden	2669	856	6994	1612	2003	2923	17056
7	forest	505	305	574	278	266	279	2208
8	sparse green cover	5547	2290	4168	1714	3315	6493	23528
11	water	15	198	45	16	1	3	280
	irrigated area	**16691**	**10805**	**26593**	**12300**	**11663**	**20825**	**98878**
12	harvested wheat	8533	1797	951	728	1484	4194	17686
13	harvested barley	992	68	30	128	381	1242	2841
14	bare soil	40972	9116	5520	2897	4753	14324	77583
16	gypsum soil	8827	14	43	77	83	1231	10276
17	saline soil	117	1	18	20	44	11	209
18	heterogeneous	7828	5970	5725	4384	3582	7118	34606
	non-irrigated	**67269**	**16965**	**12287**	**8234**	**10325**	**28119**	**143201**
	total area	**83960**	**27771**	**38880**	**20535**	**21988**	**48944**	**242079**

Table 7 Comparison of total area calculations with those by NOAA/AVHRR methods and district agricultural statistics.

satellite	borkhar	lenjanat	nekleft	nekright	absright	absleft
	ha	ha	ha	ha	ha	ha
1 Landsat 7 2/7/00	16691	10805	26593	12300	11663	20825
2 landsat 7 1/8/99	15915		27912	12922	12382	22874
3 Landsat 7 1/8/99	25920	11673	28867	13859	14547	27605
4 NOAA Jul_Aug, 1999	17980	13251	25974	13608	12555	22948
5 NOAA Jul_Aug, 1995	15992	11844	25015	13225	11701	20760
avg	18500	11893	26872	13183	12570	23002
stdev	4230	1013	1533	610	1175	2782
stdev%	23	9	6	5	9	12
6 agric.statistics			40141	15203	11688	27172
7 agric.statistics			27268	11376	9296	21612
8 NOAA 95			30313	16631	16247	38754
9 agric.statistics			48000	13500	15000	15000

1. Landsat 7 ETM (2nd July, 2000) study presented in this report
2. Based on analysis of NDVI values of Landsat 7 image (1st Aug, 1999) (Gieske et al., 2002)
3. Landsat 7 ETM (1st Aug, 1999) Classification by A.R. Mamanpoush
4. NOAA/AVHRR upscaled from Landsat (Gieske et al., 2002)
5. NOAA/AVHRR uspcaled from Landsat (Gieske et al., 2002)
6. District Agricultural Statistics 1994-1995 (Sally et al., 2001)
7. District Agricultural Statistics 1999-2000 (Sally et al., 2001)
8. NOAA/AVHRR 1995 cropped area (Droogers et al., 2001)
9. Command areas, District Agricultural Statistics (Sally et al., 2001)

The results should be interpreted with some care, because different definitions of irrigated area are used. Methods 1-3 use single satellite images (instantaneous situation). Methods 4 and 5 use satellite image averages of two months. Methods 6 and 7 use a combination of GIS methods and District Agricultural Statistics to arrive at cropped area values, which are defined as the combined areas for summer and winter crops. Cropped area should therefore in practice be larger than the irrigated areas determined from the satellite images. Finally method 9 gives the Design Command Area figures.

The results show that the variability of methods 1-5 is much less than the range in values of methods 6-8. The explanation for the difference between 6 and 7 lies in the trend observed by Sally et al. (2001). However, not much of a trend is visible in the remote sensing analysis (methods 1-5), based on 1995, 1999 and 2000 figures.

To be able to make a better comparison with the cropped area statistics, the Agricultural District figures have been separated into summer and winter crop areas. Winter crops are mainly wheat and barley. Table 8 below shows that the areas derived from the Agricultural District figures are consistently lower than those determined by the remote sensing method. The District values are only 60-70% of the remote sensing results. It is therefore recommended to continue with the remote sensing method, during various parts of the year to check both on winter and summer crop statistics. Detailed crop comparison is less useful at this stage in view of these large differences in values for total irrigated areas.

Table 8. Areas separated into winter and summer crops for comparison with Landsat and NOAA methods.

1995/96	areas		Jul-Aug	
	winter	summer	NOAA	
Nek LB	11335	28493	25015	
Nek RB	4353	10649	13225	
Abs LB	14838	13185	20760	
Abs RB	6383	5671	11701	
Borkhar	6502	7542	15992	
Lenjanat	4839	6512	11844	
Total	48250	72052	98537	73 %

1998/99	areas		1/8/99	
	winter	summer	Landsat	
Nek LB	7635	19633	27912	
Nek RB	3958	9997	12922	
Abs LB	14584	11967	22874	
Abs RB	6273	5147	12382	
Borkhar	6371	6931	15915	
Lenjanat	4232	6502	11673	
Total	43054	60177	103678	58 %

Discussion

Data on cropping patterns, cropping calendars and estimated cropping intensities are available at the Provincial Offices of the Ministry of Agriculture. These data are typically organized by village and then aggregated into administrative districts. Because the boundaries of these districts are not coinciding with the irrigation system command areas, problems arise in the compilation of crop data for each command area (Sally et al., 2001)

NOAA/AVHRR, Landsat 7 and other satellites such as TERRA (with high resolution ASTER and medium resolution MODIS) and many others can be used to determine instantaneous irrigated areas (Gieske et al. 2002) and assessment of irrigation performance (Droogers et al., 2001).

The subject of this paper is to make a crop and land cover classification by means of a Landsat 7 ETM image of 2nd July 2000, and compare the results with those obtained earlier from district level statistics (Sally et al., 2001). Although standard methods of classification are applied here, considerable care was taken to discuss the classification methods in detail in view of the training aspects of the IAERI-IWMI Zayandeh Rud Project.

The date of the image fell in the transition period where the first crops were harvested and many fields were being prepared for the second crop. The image therefore shows a picture of a dynamic system in transition from winter to summer crops.

In a number of field trips ground truth was obtained with a GPS instrument, which made it possible to position the image to an accuracy of about 15 m with respect to a coordinate system, and which also allowed identification of the visited fields. The supervised classification method was chosen to classify the image. After establishing a training set of 20 classes, the image was classified with the Minimum Distance method (threshold 0).

Subsequent analysis with a confusion matrix showed that several classes are poorly distinguished on the image, and the number of classes was reduced to 13. For example the classes of “bare soil”, “cultivated soil” and “fallow soil” were combined into a single class “bare soil”. Similarly there is not enough difference between the classes “irrigated”, “rice”, “vegetable” and “alfalfa” at this stage of the growing season to reliably separate them. Hence a single class “light green young vegetation” was created. Finally, the classes “mountains”, “hot surface/roads” and urban turned out to be too heterogeneous, thus causing large overlap of the classes. A single class “heterogeneous” was created.

The resulting classification was used to obtain independent crop statistics, and independent estimates of the irrigated areas in the main districts covered by the image. The main conclusion is that the values for the size of the irrigated areas from the district level statistics are consistently 60-70% of the values obtained through remote sensing methods. Because of these large differences and because the classes used in the remote sensing method are different from those used in the district statistics, detailed crop by crop comparison is not yet possible. It is recommended to continue with this kind of remote sensing techniques, coupled with regular field visits to obtain the essential ground truth.

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Appendix A Definitions of classification methods

The following classification methods are commonly available (after ILWIS3, 2001):

- Box classifier, using a multiplication factor
- Minimum distance, using a threshold distance
- Minimum Mahalanobis distance, using a threshold distance
- Maximum Likelihood, using a threshold distance

The expression ***class mean*** is used for the means of training pixels in a class and the expression ***feature vector*** is used for the spectral values of a pixel to be classified.

Box classifier

For each class, a multi-dimensional box is drawn around the class mean and the size of the box is calculated as:

size=(class mean ± standard deviation per band)* multiplication factor

- if a feature vector falls inside a box, then the corresponding class name is assigned.
- if a feature vector falls within two boxes, the class name of the box with the smallest product of standard deviations is assigned.
- if a feature vector does not fall within a box, the undefined value is assigned.

Minimum Distance

For each feature vector, the distances towards class means are calculated.

- the shortest Euclidian distance to a class mean is found;
- if this shortest distance to a class mean is smaller than the user-defined threshold, then this class name is assigned to the output pixel.
- else the undefined value is assigned.

Minimum Mahalanobis distance

For each feature vector, the distances towards class means are calculated. For each class, the variance-covariance matrix is calculated and the minimum Mahalanobis distance is then calculated as:

$$D_i(x) = y^T V_i^{-1} y$$

For an explanation of the parameters, see Maximum Likelihood classifier.

- the shortest distance to a class mean is found;
- if this shortest distance to a class mean is smaller than the user-defined threshold, then this class name is assigned to the output pixel.
- else the undefined value is assigned.

Maximum Likelihood

For each feature vector, the distances towards class means are calculated. For each class, the variance-covariance matrix is calculated.

The formula used in Maximum Likelihood reads:

$$D_i(x)=\ln[\det(V_i)]+y^T V_i^{-1} y$$

where

D_i	distance between feature vector x and a class mean based on probabilities
M	number of bands
V_i	the M x M variance-covariance matrix of a class
Det(V_i)	determinant of V_i
V_i^{-1}	the inverse of matrix V_i
y	$x-m_i$; is the distance towards a class mean
y^T	the transposed of y

- the shortest distance D to a class mean is found;
- if this shortest distance to a class mean is smaller than the user-defined threshold, then this class name is assigned to the output pixel.
- else the undefined value is assigned.

APPENDIX B Interpretation of a confusion matrix (after ILWIS3, 2001)

Consider the following example of a confusion matrix:

		CLASSIFICATION RESULTS							
		forest	bush	crop	urban	bare	water	unclass	ACC
TEST	forest	440	40	0	0	30	10	10	0.83
SET	bush	20	220	0	0	40	10	20	0.71
	crop	10	10	210	10	50	10	60	0.58
	urban	20	0	20	240	100	10	40	0.56
	bare	0	0	10	10	230	0	10	0.88
	water	0	20	0	0	0	240	10	0.89
	REL	0.90	0.76	0.88	0.92	0.51	0.86		

Average accuracy = 74.25%
Average reliability = 80.38%
Overall accuracy = 73.15%

Explanation:

- Rows correspond to classes in the ground truth map, i.e. the test set.
- Columns correspond to classes in the classification result.
- The *diagonal elements* in the matrix represent the number of correctly classified pixels of each class, i.e. the number of test set pixels with a certain class name that obtained this same class name during classification. In the example above, 440 pixels of 'forest' in the test set were correctly classified as 'forest' in the classified image.
- The *off-diagonal elements* represent misclassified pixels or the classification errors, i.e. the number of ground truth pixels that ended up in another class during classification. In the example above, 40 pixels of 'forest' in the test set, were classified as 'bush' in the classified image.
- Non-diagonal row elements represent ground truth pixels of a certain class which were excluded from that class during classification. Such errors are also known as *errors of omission* or exclusion. For example, 50 ground truth pixels of 'crop' were excluded from the 'crop' class in the classification and ended up in the 'bare' class.

  Non-diagonal column elements represent ground truth pixels of other classes that were included in a certain classification class. Such errors are also known as

errors of commission or inclusion. For example, 100 ground truth pixels of 'urban' were included in the 'bare' class by the classification.
- The figures in column *Unclassified* represent the ground truth pixels that were found not classified in the classified image.

Accuracy: The figures in column *ACC* present the accuracy of classification: it is the fraction of correctly classified ground truth (or test set) pixels of a certain ground truth class. For each class of test set pixels (row), the number of correctly classified pixels is divided by the total number of test pixels in that class; for example for the 'forest' class, the accuracy is 440/530 = 0.83 meaning that approximately 83% of the 'forest' ground truth pixels also appear as 'forest' pixels in the classified image.

Reliability: The figures in row *REL* present the reliability of classes in the classified image: it is the fraction of correctly classified ground truth (or test set) pixels of a certain class in the classified image. For each class in the classified image (column), the number of correctly classified pixels is divided by the total number of pixels, which were classified as this class. For example for the 'forest' class, the reliability is 440/490 = 0.90 meaning that probably 90% if the 'forest' pixels in the classified image are correct compared to the ground truth pixels.

The *average accuracy* is calculated as the sum of the accuracy figures in column ACC divided by the number of classes in the test set. The *average reliability* is calculated as the sum of the reliability figures in column REL divided by the number of classes in the test set. The *overall accuracy* is calculated as the sum of all correctly classified pixels (diagonal elements) divided by the total number of test pixels.

From the example above, you can conclude that the test set classes 'crop' and 'urban' were difficult to classify as many of such test set pixels were excluded from the 'crop' and the 'urban' classes, thus the areas of these classes in the classified image are probably underestimated. On the other hand, class 'bare' in the image is not very reliable as many test set pixels of other classes were included in the 'bare' class in the classified image, thus the area of the 'bare' class in the classified image is probably overestimated.

Appendix C Feature Class Statistics

1 alfalfa

Band	Mean	StDev	Nr	Pred	Total
1:	97.9	12.8	78	89	726
2:	91.9	19	69	81	726
3:	96.1	39.9	39	72	726
4:	139.9	11.8	34	132	726
5:	127.7	30.3	40	107	726
6:	152.7	9.5	101	144	726
7:	72.8	25.9	65	54	726

2 rice

Band	Mean	StDev	Nr	Pred	Total
1:	83.7	3.8	97	82	546
2:	75.7	4.7	79	73	546
3:	64.6	7.7	61	60	546
4:	112.3	13.5	26	123	546
5:	94.5	8.3	34	98	546
6:	141.7	1.9	160	142	546
7:	53.7	5.7	64	52	546

3 corn

Band	Mean	StDev	Nr	Pred	Total
1:	137.1	8.1	44	140	609
2:	152	11.8	31	161	609
3:	215.6	18.9	27	226	609
4:	129.6	7.3	43	132	609
5:	207.3	12.4	27	212	609
6:	174.5	3.3	104	177	609
7:	139	9.5	32	140	609

4 sunflower

Band	Mean	StDev	Nr	Pred	Total
1:	119.2	4.1	39	121	277
2:	123.8	4.6	35	125	277
3:	167.7	6.9	26	167	277
4:	105.6	5.3	46	101	277
5:	150.1	5	36	149	277
6:	164.9	2	74	166	277
7:	96.1	5.7	32	94	277

5 vegetable

Band	Mean	StDev	Nr	Pred	Total
1:	105.1	6.5	7	102	62
2:	101	8	5	97	62
3:	105.8	12.9	5	100	62
4:	87.1	9.9	6	82	62
5:	91.9	20.2	6	79	62
6:	151.2	3.9	20	149	62
7:	63.3	16	7	51	62

6 garden

Band	Mean	StDev	Nr	Pred	Total
1:	98.1	10.2	29	91	289
2:	92.6	13.9	32	81	289
3:	98.7	25.4	17	78	289
4:	105.4	6.2	22	102	289
5:	114.6	19	17	103	289
6:	156	7.7	40	150	289
7:	74.5	20.1	14	56	289

7 forest

Band	Mean	StDev	Nr	Pred	Total
1:	98.6	5.4	37	95	448
2:	88.7	7.7	31	82	448
3:	96.5	12.3	20	83	448
4:	80.5	14.1	29	87	448
5:	104.2	15.1	22	116	448
6:	163.5	4.5	56	165	448
7:	72.9	12.2	22	67	448

8 e green cover

Band	Mean	StDev	Nr	Pred	Total
1:	124.7	9.1	36	123	590
2:	128.6	14.6	23	125	590
3:	165.8	27.8	16	144	590
4:	107.7	14.4	33	118	590
5:	170.3	23.3	17	154	590
6:	173.2	5.2	114	177	590
7:	126.9	17.2	21	119	590

9 cultivated

Band	Mean	StDev	Nr	Pred	Total
1:	133.4	9.4	48	130	810
2:	139.1	10.8	50	149	810
3:	181.2	15.6	51	184	810
4:	95.4	7.6	58	95	810
5:	174.3	12.5	40	174	810
6:	182.2	8	73	183	810
7:	150.9	11.5	47	149	810

10 irrigated

Band	Mean	StDev	Nr	Pred	Total
1:	99.6	10.5	21	98	380
2:	95.1	12.9	17	92	380
3:	102.2	24.3	17	78	380
4:	75.5	6.1	28	75	380
5:	85.7	24.3	16	66	380
6:	149.9	11.6	56	143	380
7:	61.2	21	20	44	380

11 water

Band	Mean	StDev	Nr	Pred	Total
1:	92.1	5.6	26	89	139
2:	76.2	7.6	23	73	139
3:	67	17.6	23	55	139
4:	34.3	12.7	42	26	139
5:	37.9	16.6	28	29	139
6:	141.9	7.8	38	137	139
7:	29.9	11.9	26	24	139

12 harv. wheat

Band	Mean	StDev	Nr	Pred	Total
1:	142.4	16.6	6	156	38
2:	155.2	23.2	4	174	38
3:	207.8	39.7	3	237	38
4:	121.6	11.3	8	131	38
5:	203.7	28.1	3	188	38
6:	175.9	7.7	20	179	38
7:	154.3	24.6	5	171	38

13 harv. barley

Band	Mean	StDev	Nr	Pred	Total
1:	162.3	22.1	11	170	194
2:	184.5	29.4	9	173	194
3:	242	40.2	116	255	194
4:	148.4	7.9	22	141	194
5:	232.6	31.8	41	255	194
6:	175.6	6.5	52	177	194
7:	167.9	29.8	13	178	194

14 bare soil

Band	Mean	StDev	Nr	Pred	Total
1:	138.4	4.5	66	134	505
2:	142.9	7.2	44	134	505
3:	184.7	11.7	34	172	505
4:	92.7	5.5	67	86	505
5:	177.1	10.5	46	169	505
6:	183.7	2.2	113	183	505
7:	156.5	8.9	53	153	505

15 fallow

Band	Mean	StDev	Nr	Pred	Total
1:	147.6	4.1	7	151	40
2:	163.4	4.9	5	168	40
3:	222.6	7.4	5	214	40
4:	113.2	3.5	6	110	40
5:	203.3	5.8	5	198	40
6:	184.1	1.2	14	183	40
7:	182.4	5.1	5	184	40

16 gypsum soil

Band	Mean	StDev	Nr	Pred	Total
1:	167.9	5.8	94	167	1154
2:	190	7.2	77	196	1154
3:	252.8	4.3	806	255	1154
4:	131.4	4.6	116	134	1154
5:	240.4	11.3	134	255	1154
6:	181.2	2.5	178	181	1154
7:	215	10.9	45	223	1154

17 saline

Band	Mean	StDev	Nr	Pred	Total
1:	213.2	16.1	260	230	6264
2:	235.1	21.7	1446	255	6264
3:	254.8	1.3	5925	255	6264
4:	154.7	16.2	581	168	6264
5:	246.6	5.2	603	255	6264
6:	183.8	5.7	1370	181	6264
7:	153.5	33.2	188	133	6264

18 mountains

Band	Mean	StDev	Nr	Pred	Total
1:	133.9	10.1	60	127	769
2:	135	14.1	46	130	769
3:	170.9	23.1	32	165	769
4:	87.2	12.4	56	83	769
5:	173	29.2	30	154	769
6:	174.3	8.6	108	185	769
7:	149.6	25.2	32	136	769

19 hot surface /roads

Band	Mean	StDev	Nr	Pred	Total
1:	117.6	2.8	112	118	744
2:	111.6	3.7	89	112	744
3:	129.2	5	68	130	744
4:	61.9	2.6	129	63	744
5:	109.6	6.1	55	110	744
6:	191	2	142	192	744
7:	95.4	5.8	57	93	744

20 urban

Band	Mean	StDev	Nr	Pred	Total
1:	139.9	8.2	88	138	1341
2:	136.7	10.5	64	134	1341
3:	163.3	15.4	43	162	1341
4:	87.1	6.8	86	83	1341
5:	148	17.7	43	142	1341
6:	174.7	2	278	174	1341
7:	132	17.3	41	130	1341

The following reports have been published in the IAERI-IWMI Research Report series.

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2. **Exploring field scale salinity using simulation modeling, example for Rudasht area, Esfahan Province, Iran.** (2000) P. Droogers, M. Akbari, M. Torabi, E. Pazira.
3. **An overview of the hydrology of the Zayandeh Rud Basin.** (2000) H. Murray-Rust, H. Sally, H.R. Salemi, A. Mamanpoush.
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13. **Water Supply and Demand Forecasting for the Zayandeh Rud.** (2002). H.R. Salemi and H. Murray-Rust.
14. **Water Resources Development and Water Utilization in the Zayandeh Rud Basin, Iran.** (2002). H. Murray-Rust, H.R. Salemi and P. Droogers.
15. **Groundwater resources modeling of the Lenjanat aquifer system.** (2002). A. Gieske and M. Miranzadeh.