THE IDENTIFICATION OF IRRIGATED LAND IN AN INTENSIVELY CULTIVATED AGRICULTURAL AREA IN THE SOUTHWESTERN CAPE BY MEANS OF SATELLITE REMOTE SENSING

H.L. Zietsman
A.C. Vlok
I. Nel

Report to the
WATER RESEARCH COMMISSION
by
INSTITUTE FOR GEOGRAPHICAL ANALYSIS
UNIVERSITY OF STELLENBOSCH
WRC Report No 440/1/96
ISBN 1 86845 247 6

EXECUTIVE SUMMARY

1.1 INTRODUCTION

The ever-increasing demand for water - one of the scarcest natural resources in this country - makes scientifically-based management essential in order to meet all user requirements.

South Africa is not richly endowed with natural water resources. Furthermore, this scarce natural resource is not evenly distributed among the economic growth areas. This is particularly true of agricultural areas. Because of the numerous sectors which make demands on the water supply, it is essential to have systems that constantly monitor water usage. This would make prior planning of future water consumption and allocation possible.

Information on current land use patterns and trends underlies effective management of natural water resources in drainage areas. Conventional methods of data collection used in making an inventory of land use, such as land use surveys, field work and aerial surveys are expensive, cumbersome and time-consuming. Therefore, one has to consider alternative methods of data collection. Modern technology, such as remote sensing and Geographic Information Systems, is in theory able to provide a cost-effective and regular means of collecting information on land use. Research has shown that it is possible to map irrigated areas fast and reasonably accurately with the aid of satellite data. However, the capability of relatively high resolution satellite data to identify irrigated areas has not yet been fully tested in intensively farmed areas, such as the Southwestern Cape. Therefore, there is some doubt as to the degree of success which can be achieved in such complex land use areas.

This study set out to evaluate the potential of SPOT and Landsat TM satellite data to identify vegetation in quantifiable terms, so that the irrigation requirements of the Wolseley-Worcester area of the Upper Breede River Catchment could be determined.

1. AIMS:

(a) To identify, classify and map land cover types with particular emphasis on irrigated land in a section of the Breede River Valley by analysing multi-temporal SPOT and Landsat TM digital imagery;

(b) To refine the results obtained by digital image processing techniques by combining ancillary information such as soil types and slopes with a GIS using polygon overlaying techniques;

(c) To investigate the usefulness of land cover data gathered by the abovementioned techniques for quantifying water abstraction by irrigation through field surveying techniques.

2. RESEARCH METHODOLOGY

The diagram in Figure 1 summarizes the steps and procedures followed to achieve the aims of the study.

3. STUDY AREA

The study area comprises the Breede River Valley in the South Western Cape of South Africa from where the river emerges from the Mitchell's Pass in the vicinity of Wolseley to just north of Worcester. The valley is intensively cultivated and vines, orchards, vegetables and pastures under irrigation are the main crops. Dryland farming of wheat is also significant. The rest of the area is utilized for pine plantations or still under natural veld, mostly Cape Fynbos. Figure 2 shows the location of the study area superimposed on a Landsat TM image.

3. DATA

In order to achieve the goals set for this research four different data sets were required:

(a) SPOT XS

Two quarter images were purchased from the Satellite Application Centre (SAC) at Hartebeesthoek, namely a winter and a summer scene for the 1992/93 growing season. Due to bad weather conditions at the time of the overpass no cloudless spring or autumn scenes were available.

(b) LANDSAT TM

Four quarter images were purchased from SAC, one representing each of the 1992/93 seasons. The details of the imagery are presented in Table 1.

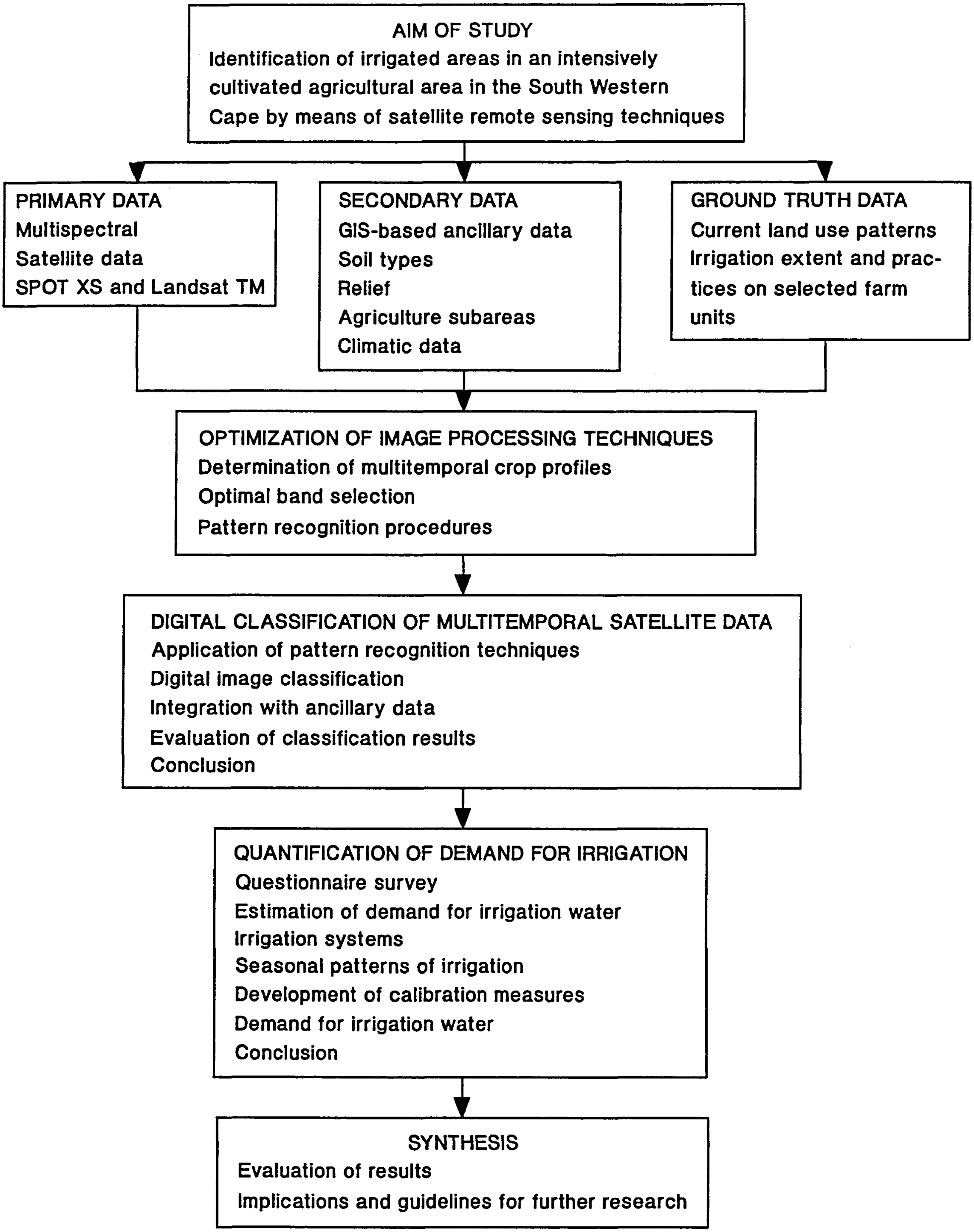

Figure 1: Schematic representation of the research methodology.

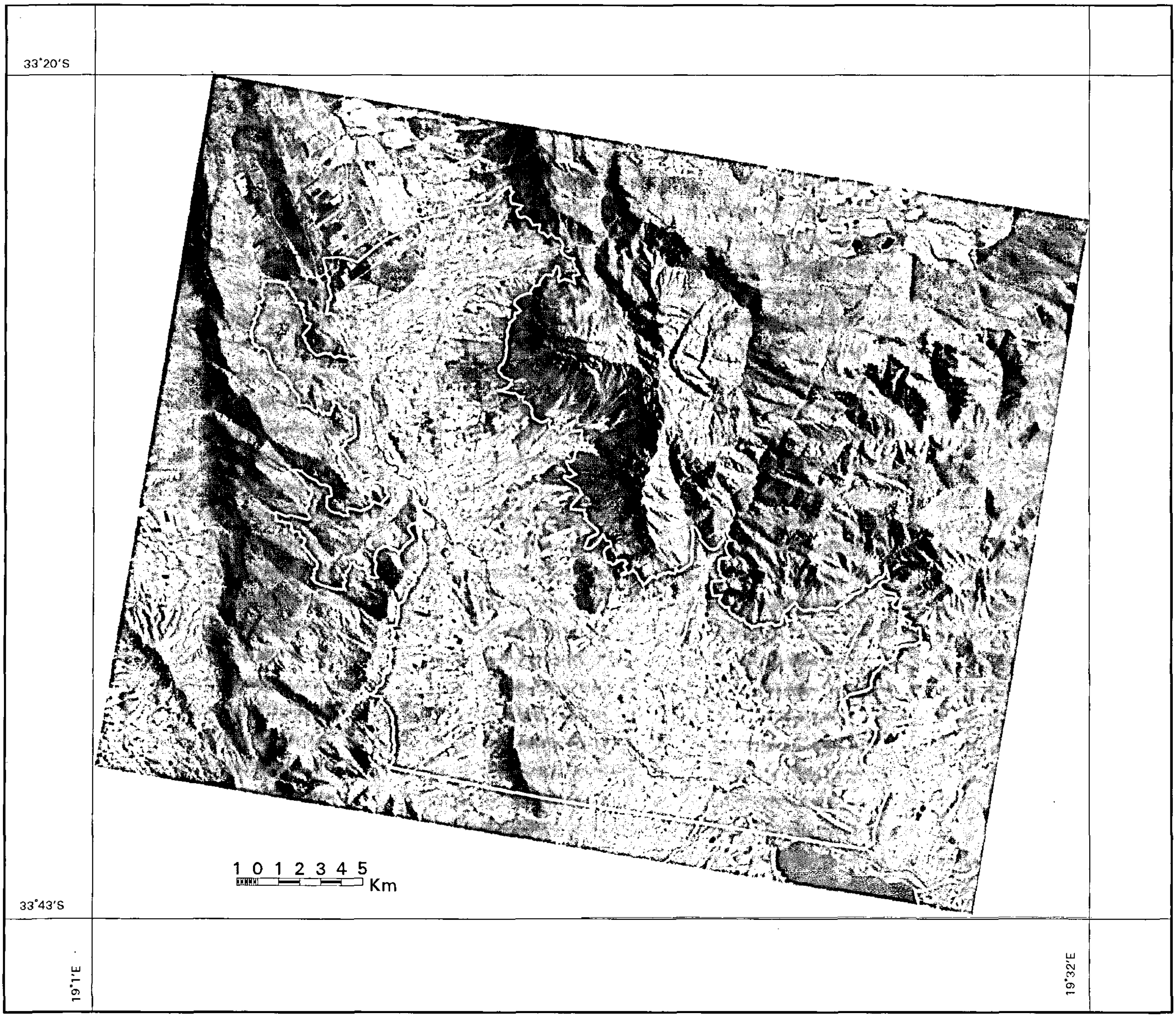

Figure 2: Landsat TM image showing the location of the study area.

Table 1: Imagery purchased for the study.

Satellite: Instrument	SPOT HRV 1		LANDSAT TM			
Acquisition date Season	92/08/13 Winter	93/01/13 Summer	92/04/12 Autumn	92/08/18 Winter	92/10/05 Spring	93/01/25 Summer
Identification Scene:						
Path	119	119	175	175	175	175
Row	417	417	83	83	83	83
CCT ID	4680	4674	3575	4699	4698	4970
Tape format	SISA BIL 6250	SISA BIL 6250	ESA BIL 6250	ESA BIL 6250	ESA BIL 6250	ESA BIL 6250

(c) ANCILLARY GIS DATA

A GIS database was created for the study area containing the data sets as described in Table 2.

The GIS database compiled for the refinement of the results of the image classification consists mainly of two types:

(i) GIS data which served as ground truth
   (a) Data representing the *current generalized agricultural land use patterns* for the entire project study area.
   (b) Data representing *detailed agricultural land use patterns on 22 selected farms* in the project study area.

(ii) GIS-based **ancillary data** used as secondary data sources:
   (a) Data which was representative of the *soil types* in the area and
   (b) *Contour data* for the study area.
   Ancillary data gathered to provide supporting information was used in the study to supplement classifications of areas so that 'incorrect classification' could be corrected.

(d) GROUND TRUTH DATA

Table 3 presents a summary of the land cover classification scheme used for mapping land cover from 1:10000 orthophotos and 1:30000 scale aerial photographs against which satellite derived land cover maps of the entire study area could be evaluated. The land use map created is presented in Figure 3.

Table 2: Geographic themes included in GIS database.

Geographic Theme	Name	Data Type	Unprocessed Data Source
Elevation Contours	contours	line	1:50 000 topographic maps scanned and vectorized by the Department of Water Affairs and Forestry
Selected Farms	farms	polygon	Maps at various small scales from the Department of Agriculture/Personal Information : Individual Farmers
1:50 000 scale map grid	topogrid	polygon	1:50 000 topographic maps from the Chief Directorate: Surveys and Land Information
1:10 000 scale map grid	orthogrid	polygon	1:10 000 orthophotos from the Chief Directorate: Surveys and Land Information
Soil types	soils	polygon	1:50 000 data from the Resources Development Division: Elsenburg, Department of Agriculture
Mean Annual Rainfall (Weather stations)	rainfall	point	Digital data from the Resources Development Division: Elsenburg, Department of Agriculture
Land-use	breemap	polygon	1:50 000 aerial photography and 1:10 000 orthophotos from the Chief Directorate: Surveys and Land Information with Field verification 1:10 000 scale
Drainage regions South-Western Cape	wkaapstr	polygon	Digital data (1:50 000 scale) from the Department of Water Affairs and Forestry
Rivers	rivers	line	Digitized from 1:50 000 topographic maps. Chief Directorate: Surveys and Land Information
Upper Breede River drainage region	catch	polygon	Digital data 1:50 000 scale from the Department of Water Affairs and Forestry
Agricultural Subregions	regions	polygon	Digitized from 1:50 000 scale topographic maps. Chief Directorate: Surveys and Land Information
Towns	towns	point	Digitized from 1:50 000 scale topographic maps. Chief Directorate: Surveys and Land Information

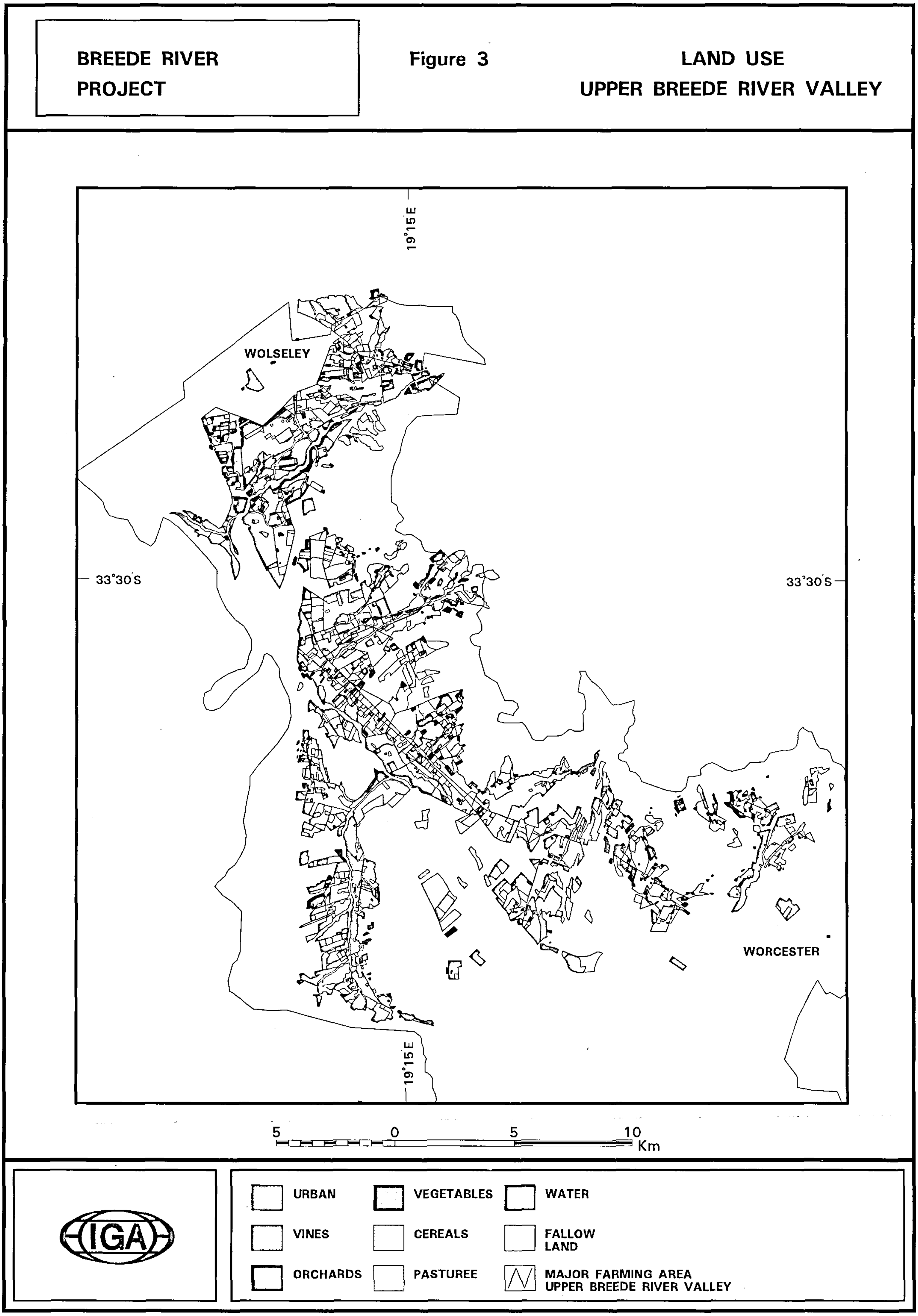

Figure 3: Land use Upper Breede River Valley

Table 3: Land use and land cover classification system used with satellite data: Upper Breede River Valley

Level I	Level II	Item Code LU1	Level III	Item Code LU2
1. Urban or built up	Residential	r		
	Farmstead	f		
2. Agriculture	Vineyard	v	Young vines	yv
	Orchards	b	Bush-trained vines	btv
	Vegetables	v	Trellissed vines	tv
	Cereals: wheat, rye, oats	pc	Young orchards	yo
3. Natural pasture	Natural fynbos	v		
	Natural bush, riparian growth	bs		
4. Forest	Plantation	p		
5. Water area	River, channel, canal	r		
	Dam	d		
6. Bare ground	Natural bareground, sand	bg		
	Fallowland	fa		

Source: Adapted from Lo, 1986

(e) QUESTIONNAIRE SURVEY DATA

A questionnaire survey of 21 farms in the study area provided detailled land use data and information on irrigation practices from which it was possible to compute the amount of irrigation water applied per land cover type.

A schedule of activities and how these related to one another is presented in Table 4.

Table 4: The temporal relationship between the capturing of satellite data, the gathering of ground truth data and the irrigation period in the study area.

Duration of Study	1992													1993	
	Summer			Autumn			Winter			Spring				Summer	
	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec	Jan	Feb
Capturing of satellite data:															
SPOT XS				not available						not available					
Landsat TM															
Gathering of ground truth data															
Irrigation period in the study area															

4. IMAGE PROCESSING

Two image processors were used to analyse the data, namely an older version of Easi Pace on a 386 PC to process the SPOT XS data and the latest version of Erdas Imagine on a SUN workstation to analyse the Landsat TM data. The data were subjected to the following image processing techniques:

(i) Unsupervised classification;

(ii) Principle Component Analysis;

(iii) Normalized and Transformed Normalized Difference Vegetation Indices;

(iv) Supervised classification.

These procedures are discussed in the following sections as applied to the Spot and Landsat TM images respectively.

4.1 SPOT XS

4.1.1 Unsupervised classification: Untransformed SPOT XS data

As a first step in the process of pattern recognition, an unsupervised classification was carried out on the six spectral bands from the summer and winter SPOT XS images.

It is very important to note that the unsupervised classes obtained are spectral classes and do not necessarily have information value with regard to land use or irrigated area . In order to evaluate the information value, it was necessary to compare the spatial appearance of the spectral classes with the spatial land use data which was obtained during the fieldwork phase. This comparison revealed that only four of the sixteen classes represented agricultural land use types. All of the other classes were mainly variations of the natural environment (mountain areas and natural vegetation). It was felt that more than four spectral classes were required in order to accurately map agricultural land use in the study area. In order to separate the four agricultural classes into subgroups, a mask of the spatial occurrence of the four agricultural classes was created and the masked area was subjected to a second 16-class unsupervised classification. This resulted in 10 significant classes - the frequency of six of the initial sixteen classes was too low to use as input during the process of signature generation. The spatial distribution of the spectral classes is shown in Figure 4.

4.1.2 Unsupervised classification: SPOT XS Principal components data

Principal components analysis was used to reduce the volume of data (6-dimensional) to a three-dimensional data matrix which could be shown as a false colour image. The same unsupervised classification procedures were applied on the three principal components for the area lying 500 meters below sea level. Although an attempt was made to identify sixteen classes, only 14 classes could be created because of sample size limitations. The spatial distribution of the 14 classes is shown in Figure 5.

4.1.3 Transformed Normalised Vegetation Index- SPOT XS data

Separate vegetation indices were calculated for the summer and winter SPOT XS-data, respectively. Since the index values could vary between 0 and 255, a threshold value had to be set for each of the seasonal indices which would divide the data into "irrigated" and "non-irrigated" areas (This technique is known as "density slicing"). Experimentation with various threshold values derived from the winter vegetation index showed that it had little value as an technique which could be used to distinguish between irrigated and non-irrigated areas. This is not surprising if one considers that orchards and vines have no leaves in winter. The summer index, on the other hand, showed a clear relationship between the spatial distribution of irrigated crops and high index values. Since, it was not absolutely clear which index value should be used as a threshold value, the summer index values were grouped into classes and these were crosstabulated with the farm survey data. The result revealed that an irrigation map based on a threshold value of 185 succeeded best in distinguishing between irrigated and non-irrigated land use types on the surveyed farms.

4.1.4 Supervised classification: Raw SPOT XS data

The success of a supervised classification is largely dependent on the spectral separability of the target classes, as well as the extent to which the selected training areas are representative of the target classes determined *a priori*.

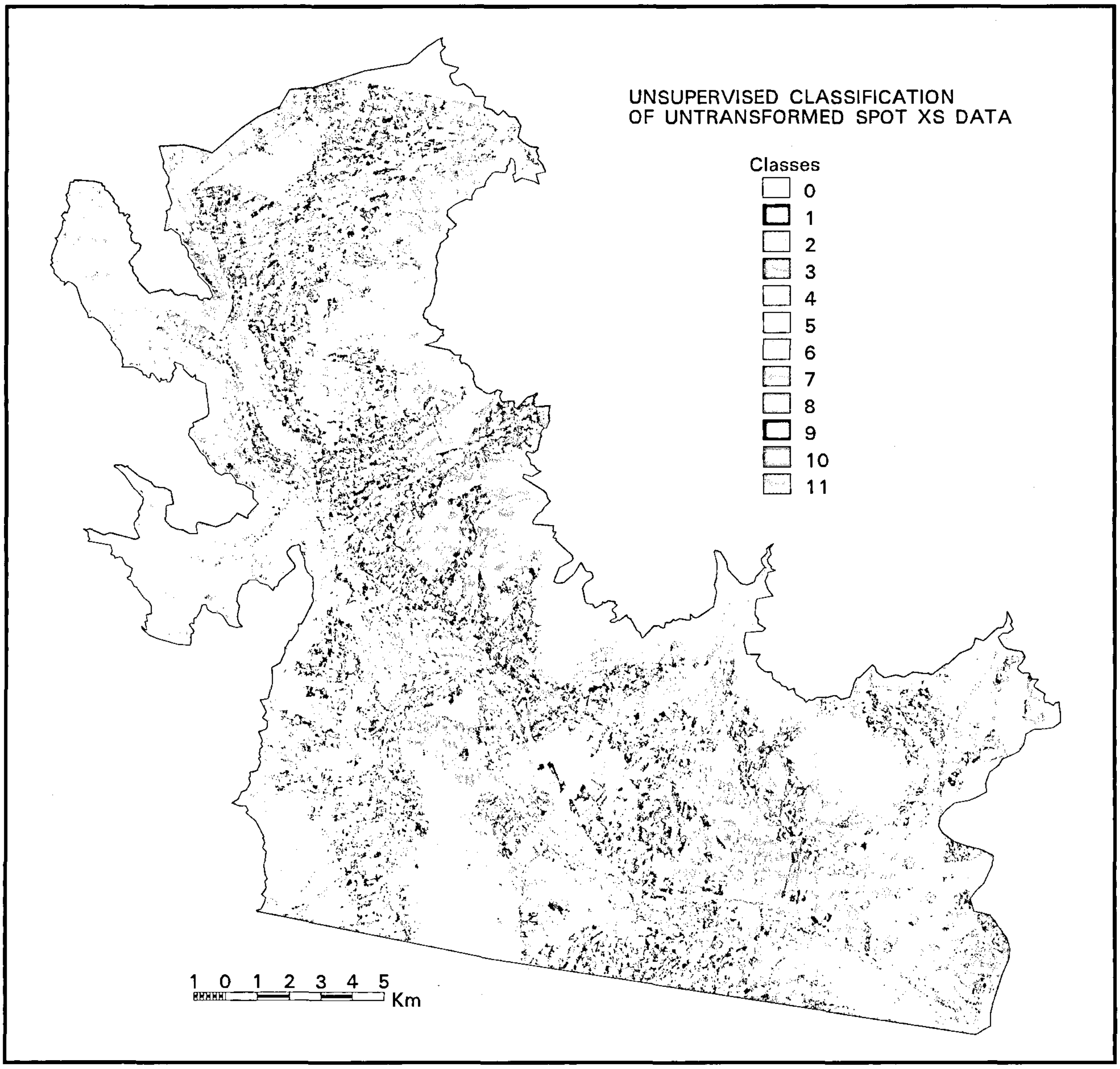

Figure 4: Unsupervised classification of untransformed SPOT XS data.

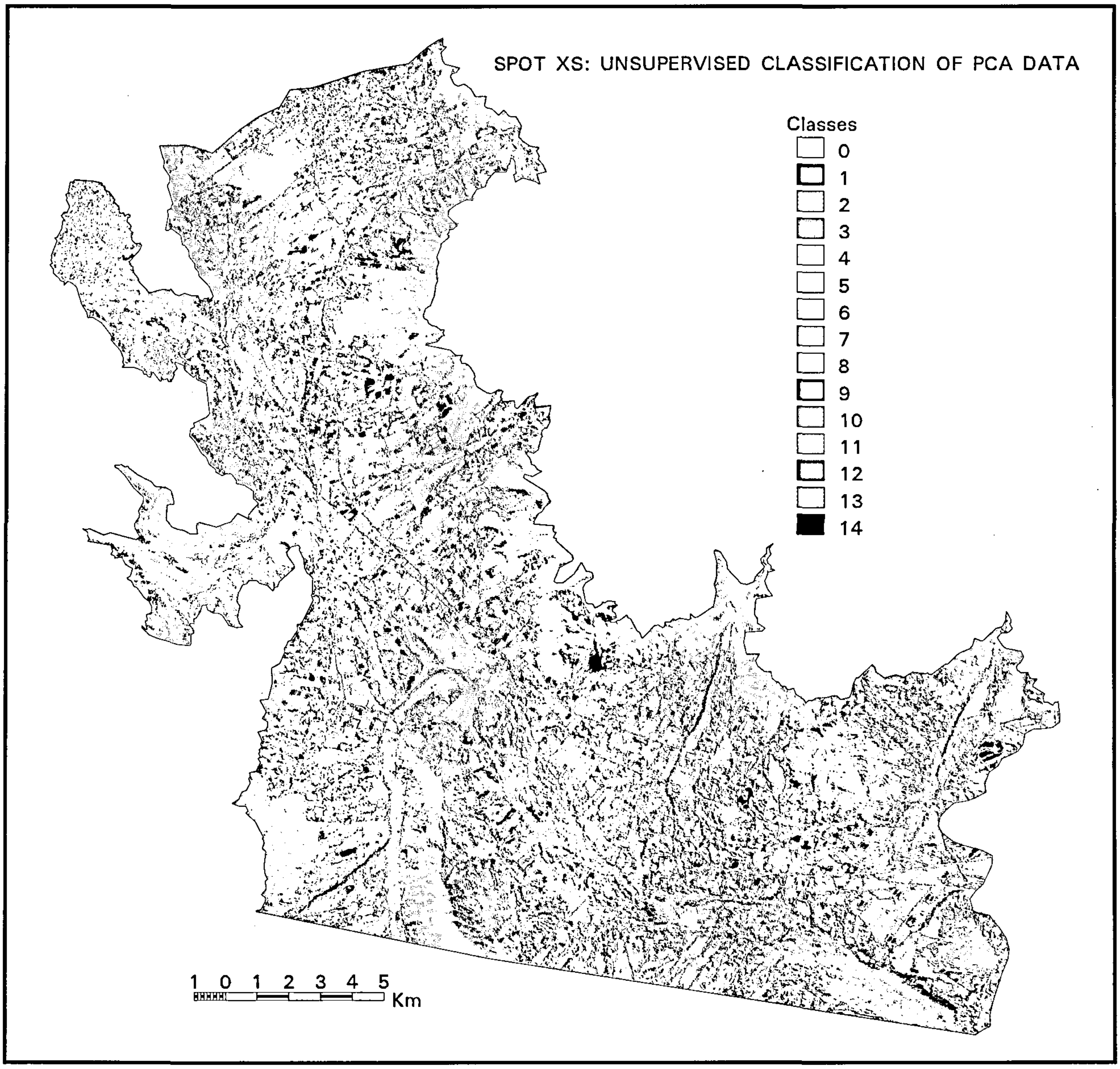

Figure 5: Unsupervised classification of Principal Component SPOT XS data.

Since the chief purpose of this research was to identify irrigated areas and to quantify the extent of the area under irrigation, the training areas had to be representative of the broad spectrum of irrigated crops which are found in the study area.

As a first step in generating the training areas, the different land use types were transferred from PC Arc/Info to the Gems Junior image processing system as separate vector files. The various vector files were then separately transformed in the image processing system into a grid format, so that they could be used as input to generate spectral signatures.

Six separate maximum likelihood classifications in all were conducted on the data. The classifications varied from one another with regard to the number of spectral signatures used and the rigour of the classification parameters (Gaussian threshold values) chosen.

A great deal of time was spent experimenting with strategies to identify vegetable plots. The problem of vegetable classification was exacerbated by the fact that vegetables are cultivated on relatively small units of land and are annual crops. A specific annual vegetable crop might be cultivated for only a few consecutive months, after which the land could lie fallow or the crop could be replaced by one of a wide variety (in terms of the type of crop and spectral characteristics) of vegetables. Using multitemporal analyses in a situation like this was extremely problematic. The project team frequently found that whenever an attempt was made to accommodate the combinations found in the area, the training areas were too small to generate valid and reliable training statistics.

As indicated earlier, the lack of GIS-querying facilities on the Gems Junior image processing system was a limitation because the evaluation of the respective classification attempts could not be done time-efficiently. On the basis of "subjective" visual decisions, classification number five was considered to be the most satisfactory (Figure 6).

4.2 Landsat TM

As stated earlier the Landsat TM dataset consisted of four images, representing land cover conditions during each of the four seasons. Due to its coarser spatial resolution Band 6 was excluded from all subsequent analyses. The four images were combined into a single file consisting of 24 spectral bands. This multi-temporal dataset was used in all analyses discussed in the sections that follow.

4.2.1 Unsupervised classification: Untransformed Landsat TM-data

The Erdas Imagine software besically provides one algorith for unsupervised classification, namely the ISODATA algorithm. This algorithm requires very little input from the user apart from specifying the maximum number of clusters needed, a convergence threshold to stop clustering and a maximum number of iterations to perform. In this particular study it was decided to request 30 clusters after an initial run using only 15 clusters had created a

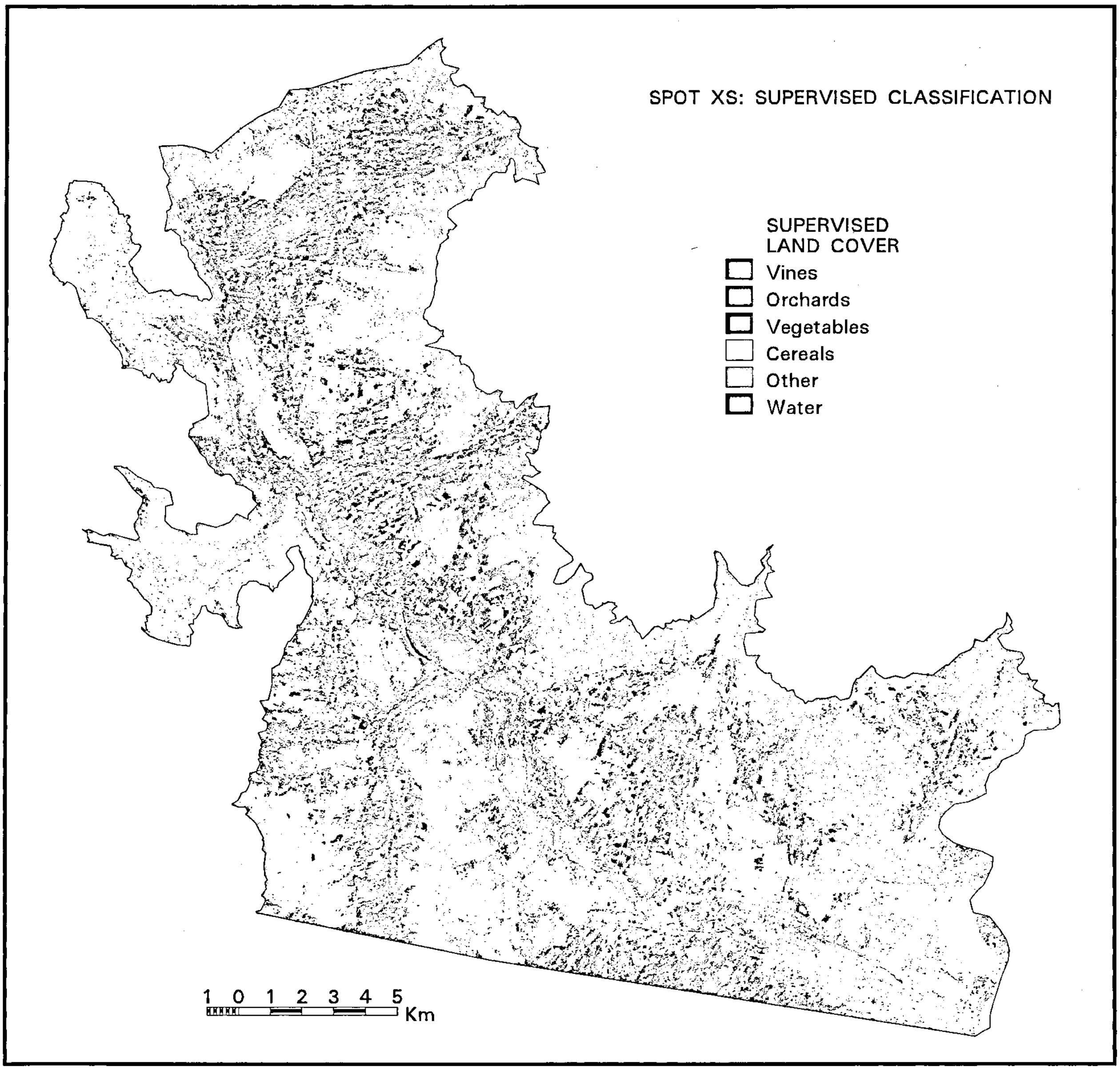

Figure 6: Generalized land cover map from supervised classification of untransformed SPOT XS data.

small number of very large generalized land cover classes. By doubling the number of clusters it was hoped that the classifier would be able to distinguish more subtle differences within agricultural land cover types. That did not take place however and no significant new cultivated classes emerged. Most new classes were subclasses of the mountainous fynbos surrounding the valley. In an attempt to force the classifier to generate more subclasses in the cultivated area of the valley a mask was created which included all land cover classes of interest as produced by the initial 30 class unsupervised classification. The classification was then repeated but only classifying pixels under the mask. The resultant classification is presented in Figure 7.

4.2.2 Unsupervised classification: Landsat Principal Component Data

By using 24 spectral bands in the analyses a large amount of redundancy may be present in the data as many spectral bands are strongly correlated. Most classification algorithms utilize some measure of spectral distance between pixels and classes so that distance values could be contaminated by these intercorrelations as most distances are computed using the pythagoras algorithm which is based on the assumption that the axes are orthogonal. To eliminate this potential problem a Principal Component Analysis was performed on the data as this produces a new set of uncorrelated components. These components were then subjected to an ISODATA unsupervised classification, again specifying a maximum number of 30 clusters. Figure 8 shows the results of the PCA classification.

4.2.3 Unsupervised classification: Landsat Normalized Difference Vegetation Index

Another approach that was followed to extract usefull land cover data from the multi-temporal Landsat TM dataset, was to compute Normalized Difference Vegetation Indices for each of the seasons. These four variables were then subjected to an ISODATA unsupervised classification with 30 clusters. The classified image is presented in Figure 9.

4.2.4 Supervised classification: Raw Landsat TM-data

Supervised classification is a much more labour intensive procedure and requires intensive interaction with the image processing system. The classes needed were dictated by the objectives of the study, which are to identify different agricultural crops with different water requirements. From the farm survey it was evident that the major cover types of interest were vines, orchards, vegetables, cereals and other cultivated crops.

In a supervised approach training areas are needed representing each of the required land cover classes. To complicate matters vegetables are annual crops often cultivated on a rotational basis with cereals or legumes. This means that a particular parcel of land may have vegetables in one or more seasons and some other crop at others or even be left fallow or barren. These patterns produce extremely complex spectral signatures. In this study 21 different combinations and permutations of annual crops were distinguished. To demarcate

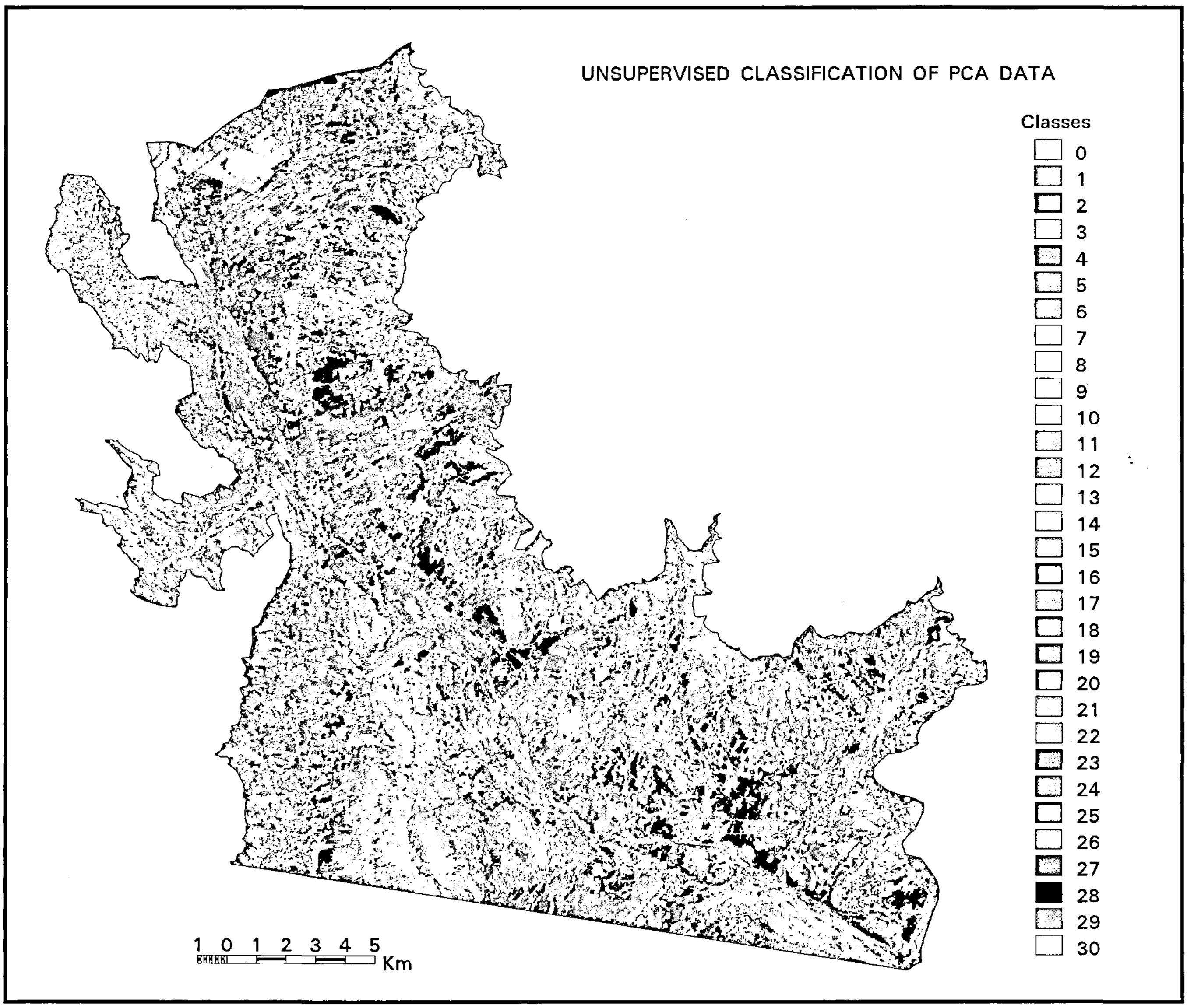

Figure 8: Unsupervised classification of Landsat TM Principal Component data.

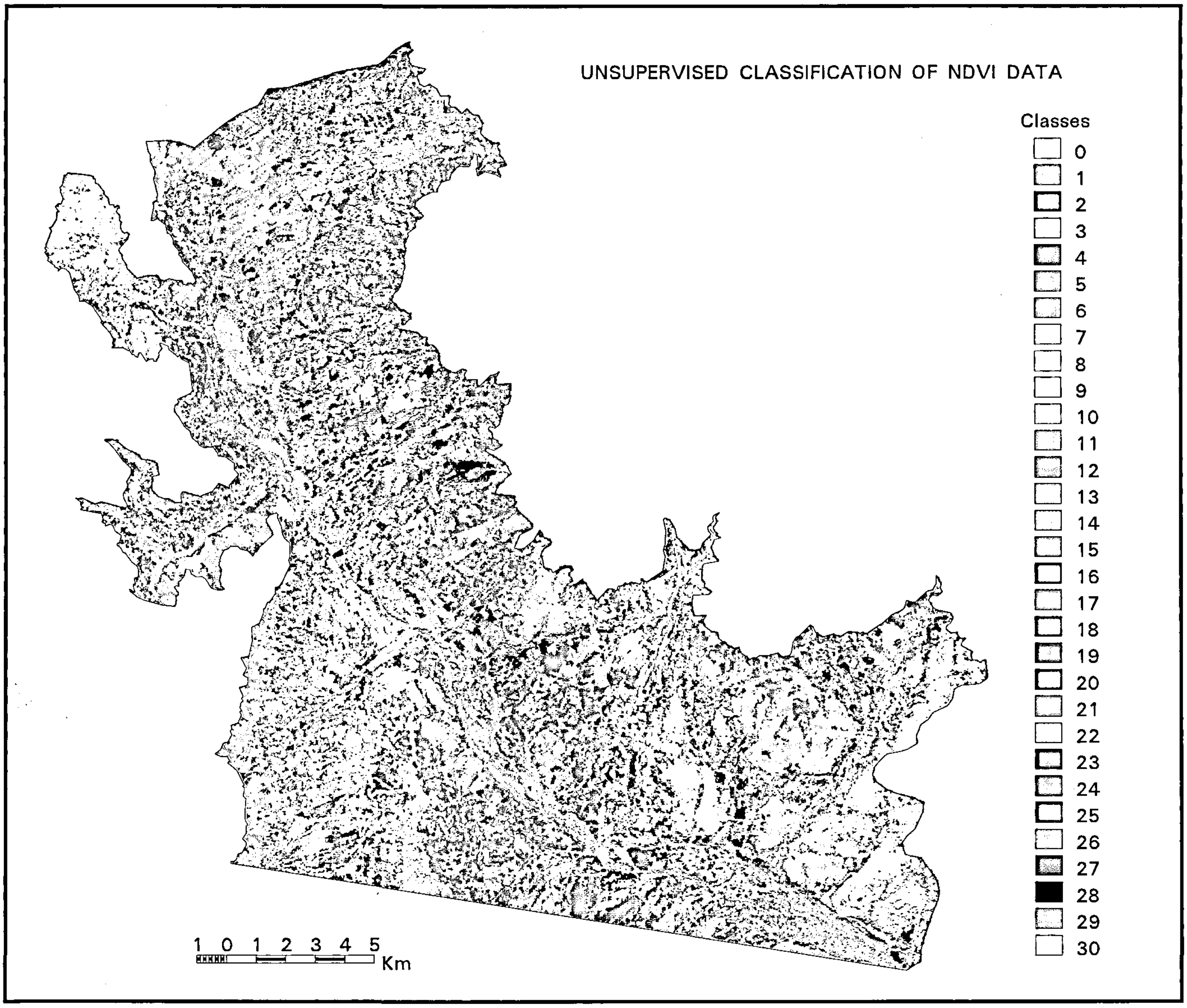

Figure 9: Unsupervised classification of Landsat TM NDVI data.

training areas and compute spectral signatures for each of these combinations was not feasible. Firstly, land parcels are small and fragmented and secondly, ground truthing was restricted to those farms included in the survey. This meant that in many cases there was only one occurence of a particular land cover combination. The problem was resolved by allocating each land cover combination to a single dominant type. In a few cases (4) where no single crop type dominated it was arbitrarily assigned to the first cover type in the combination, thus identifying vegetables, cereals or bare soil. Bare soil or unused land was put into a catch all class called Other.

A total of 104 training areas were finally demarcated on the image after three iterations. These represented vines, orchards, cereals, vegetables, fallow land, pine stands, bare soil, veld, mountain fynbos, riverine bush, water and shadows. Erdas Imagine has a pixel growing facility which allows the analyst to select a single representative starting pixel within a potential training area. The system then searches radially for pixels with similar spectral characteristics. This search can be constraint spectrally and spatially. No spatial limits were imposed but a value not exceeding 30 spectral units deviation were allowed. This spectral constraint produced acceptable training samples in most cases. A maximum-likelihood decision rule was used to classify the image, the results are presented in Figure 10.

5. INTEGRATION OF GIS DATA

Ancillary GIS data were used in the following ways:

(a) To guide the selection of suitable training areas for supervised classification;

(b) To refine the classified images by logical replacement of incorrect classes based on an assessment of:

   (i) Elevations above 500 m contour
   Land cover types were changed to unclassified thereby demarcating the boundaries of the study area.

   (ii) The irrigation potential of soils
   Irrigated land cover types were changed to non-irrigated where soil potential for irrigation was low.

   (iii) Steepness of slopes for agriculture
   Agricultural land cover types were changed to natural vegetation on slopes exceeding 25%.

(c) To evaluate the accuracy of the classified digital imagery.

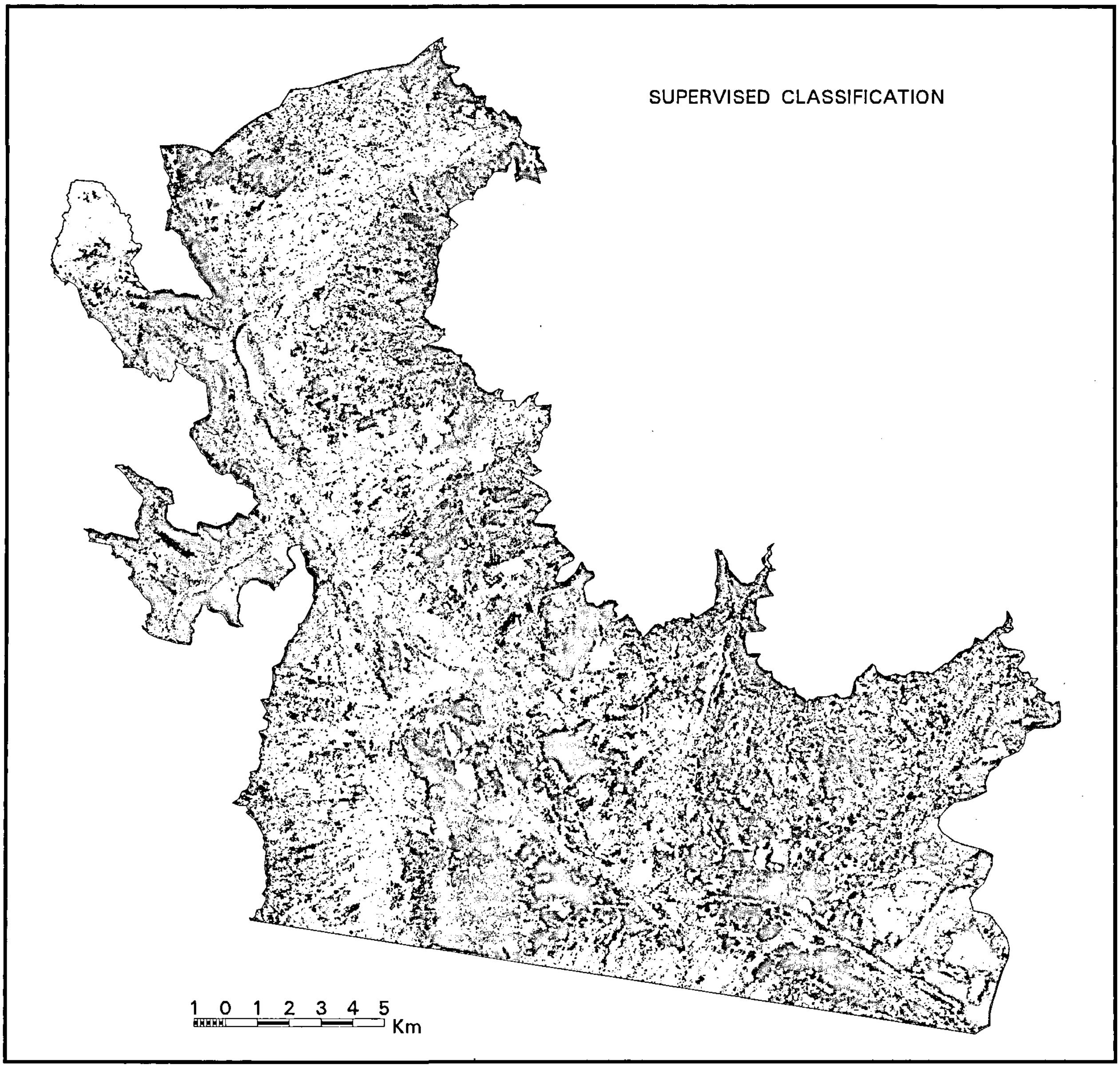

Figure 10: Supervised classification of untransformed Landsat TM data.

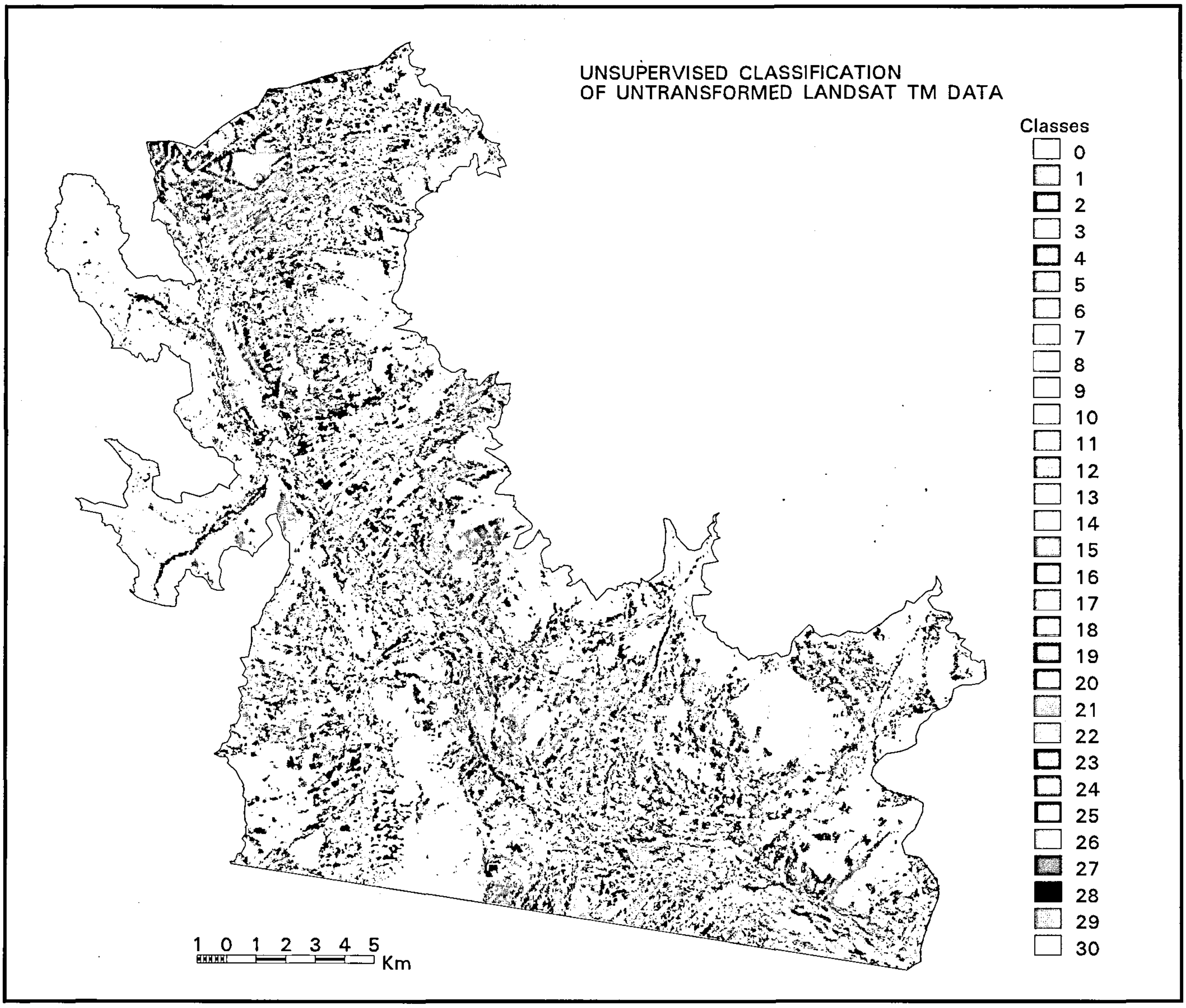

Figure 7: Unsupervised classification of untransformed Landsat TM data.

6. DIGITAL CLASSIFICATION RESULTS

Generally speaking the unsupervised approaches tended to achieve higher levels of accuracies than the supervised classifications, but could not distinguish as many different land cover types. Based on overall accuracies the vegetation indices fared best on average. However, when just considering vines the unsupervised classification in the case of SPOT data and the PCA analysis for Landsat outperformed the other techniques.

To be more specific the results of each of the the applied analytical procedures are evaluated by comparing the derived land cover maps to ground truth data at three levels of detail:

(a) Farm survey data

The mean overall accuracy for SPOT data was 66,4% and for Landsat TM 70,5%. For SPOT data the TNDVI approach fared best (83,4%), but for Landsat data it was the unsupervised classification (73%). The mean accuracies for vines were 70,1% and 84,4% for SPOT and Landsat respectively. In general terms better results were achieved with the analyses of Landsat data.

(b) Land cover map of study area

Classification accuracies were much lower when compared to the land cover map. Overall accuracies dropped to 45,6% and 49,9% for SPOT and Landsat respectively. These weaker results are ascribed to deficiencies of the land cover map. The Landsat analyses again fared better than those applied to the SPOT data.

(c) Irrigated vs Non-irrigated land classes

When land cover types were aggregated to two broad classes overall accuracies of 66,0% and 69,7% were achieved for SPOT and Landsat respectively. Irrigated land cover types were 74,3% and 79,2% correctly classified by the SPOT and Landsat analyses. These results are summarized in Table 5.

It is extremely difficult to make direct comparisons between the results obtained using SPOT XS and Landsat TM imagery. There are many reasons for this. Firstly, two different teams of researchers were involved. This means that levels of expertise in image processing are not comparable, nor the amount of time devoted to the research project due to differences in individual workloads and programmes. Secondly, two different image processing systems were used. SPOT XS data were analysed using an older PC based version of the EASI PACE system, whereas Landsat TM data were processed by a SUN workstation version of Erdas imagine. Although the Erdas software is state-of-the-art it to reduce operator flexibility. Thirdly and probably most importantly, SPOT XS imagery consisted of only two time slices (summer and winter) due to bad weather conditions at the time of image aquisition, whereas Landsat TM imagery covered four seasons. These differences mitigates against any fair comparison.

With these caveats in mind it is not surprizing that the results obtained using Landsat TM imagery outperformed those from the SPOT XS imagery.

Table 5: Comparison of accuracy levels obtained by analysing SPOT XS and Landsat TM imagery.

Analytical Procedure	Farm Survey Data SPOT XS		Landsat TM	
	Overall %	Vines %	Overall %	Vines %
Unsupervised	59,6	83,2	73,0	87,7
P.C.A.	65,4	81,9	68,0	89,4
Vegetation Index	83,4	63,9	70,2	85,7
Supervised	57,0	51,7	71,0	74,9
Average	66,4	70,1	70,5	84,4
Analytical Procedure	**Land Cover Map SPOT XS**		**Landsat TM**	
	Overall %	Vines %	Overall %	Vines %
Unsupervised	52,9	84,0	50,7	71,6
P.C.A.	42,0	74,8	51,8	83,7
Vegetation Index	-	-	53,1	79,4
Supervised	41,8	47,0	43,9	62,3
Average	45,6	68,6	49,9	74,3
Analytical Procedure	**Irrigated/Non-Irrigated Classes SPOT XS**		**Landsat TM**	
	Overall %	Irrigated %	Overall %	Irrigated %
Unsupervised	67,4	84,0	69,0	77,9
P.C.A.	66,3	73,3	67,5	84,2
Vegetation Index	76,6	80,9	69,1	78,8
Supervised	54,0	58,9	73,1	75,8
Average	66,0	74,3	69,7	79,2

Another aspect that needs to be considered in evaluating the results obtained using SPOT XS and Landsat TM imagery pertains to the fact that analyses on the Landsat TM data sets were capable of also distinguishing between more categories of land cover types than the SPOT analyses. In most cases orchards and cereals could also be distinguished with some degree of accuracy.

7. GAUGING DEMAND FOR IRRIGATION WATER

Based on a questionnaire survey of 21 farms in the area the mean volume of irrigation water per hectare applied annually to each of the major land cover types were computed. These conversion factors were applied to the area estimates obtained from the classified image results. Large variations in the estimated demand for irrigation water resulted due to widely different area estimates from each of the classification techniques employed. By analysing the statistics in Table 6 it can be seen that there is a substantial variation between different classification techniques and satellite systems in estimated irrigation demands.

Overall it would seem that the supervised approach produced the most consistent results and is to be preferred.

8. CONCLUSIONS

The overwhelming impression gained during the course of this research was related to the complex nature of the problem. It seems as though the level of complexity has been increased many times in attempting to achieve better results by enhancing spectral, spatial and temporal resolutions. Although data volumes and costs increase proportionately by adding a time dimension spectral signatures become disproportionately even more complex. The analyst not only has a multispectral situation to contend with but also many combinations and permutations of land cover changes on different land parcels as crops are rotated. Planting of annual crops are not simultaneous by all farmers and neither is harvesting or preparation of the land. For crops under irrigation a farmer has even greater latitude. To select appropriate training samples under these conditions is virtually impossible. The fact that only three spectral bands are visible at any one time means that choosing training areas becomes very difficult. These confounding factors point at a need for new approaches which will directly adress the multitemporal and multispectral nature of current satellite imagery. Image processing systems will do well to incorporate more flexible visualization techniques. Much has been written about spatial pattern recognition but little has been adopted by image processing systems. The rate of software development has been disappointingly slow.

Future research in this area should not just look at the use of existing standard image processing techniques but attempt to incorporate or create new and innovative techniques and approaches. The technology has matured to such an extent that it is in danger of calcifying. A wider range of classification algorithms, neural net analysis and the latest in

Table 6: Estimated demand for irrigation water per annum in the study area.

	SPOT			Landsat TM		
UNSUPER-VISED	Hectare	Irrigated	Water usage (m^3 x 1000)	Hectare	Irrigated	Water usage (m^3 x 1000)
Vine	12630	12604	71302	11611	11588	65553
Orchard	-	-	-	5794	5794	41573
Cereal	-	-	-	4008	321	3773
Total	12630	12604	71302	21413	17703	110900
	SPOT			Landsat TM		
PCA	Hectare	Irrigated	Water usage (m^3 x 1000)	Hectare	Irrigated	Water usage (m^3 x 1000)
Vine	12234	12209	69067	22059	22015	124538
Orchard	-	-	-	4018	4018	28835
Cereal	-	-	-	3078	246	2893
Total	12234	12209	69067	29155	26279	156267
	SPOT			Landsat TM		
NDVI	Hectare	Irrigated	Water usage (m^3 x 1000)	Hectare	Irrigated	Water usage (m^3 x 1000)
Vine	23881	23833	134825	18653	18616	105311
Orchard	-	-	-	2442	2442	17523
Cereal	-	-	-	4988	399	4695
Total	23881	23833	134825	26083	21457	127531
	SPOT			Landsat TM		
SUPER-VISED	Hectare	Irrigated	Water usage (m^3 x 1000)	Hectare	Irrigated	Water usage (m^3 x 1000)
Vine	6328	6315	35724	7654	7639	43163
Orchard	2077	2077	14902	1999	1999	14344
Vegetable	1062	1062	3597	1604	1604	5432
Cereal	5230	418	4918	1440	115	1353
Total	14697	9872	59142	12697	11357	64292

computer visualization software should be added to current image processing systems. A tighter integration between image processing and GIS capabilities are also absolutely essential. The artifical boundaries between these two technologies should be eliminated as soon as possible. Despite these shortcomings visual interpretation of imagery supported by digital classification techniques and GIS analytical capabilities provide a very powerful tool for land cover mapping and monitoring.

As far as the use of multitemporal imagery is concerned it appears that the gains are not necessarily of such an order of magnitude that it will be financially feasible in all applications. A careful consideration of the costs and benefits should be made before using a multitemporal approach.

This research was very ambitious in its attempt at handling two different types of images, two different image processing systems, creating a GI database and integrating the ancilliary GIS data, doing a supplementary field survey and employing a multitemporal approach. Although the results obtained were as good as could realistically be expected it would make sense to back track on some of the analyses. Too little time was available to carefully check the selected training samples for their discriminatory abilities. In hindsight much more attention should have been given to an analysis of the multitemporal characteristics of the training samples. This should be done specifically focussing on the richness and diversity of the multitemporal and spectral Landsat TM data.

In conclusion it seems that digital image analysis enhanced with GIS data is a valid means of obtaining land cover information of sufficient quality and accuracy for planning and monitoring catchments and their agricultural water requirements. It remains the most appropriate technology for cost effectively mapping land cover over large areas or obtaining up to date information on land cover changes on a fairly regular basis.

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ACKNOWLEDGEMENT

I would like to thank the following persons and organizations for their contributions to the project.

i) Mr H Maaren, Research Manager of the WRC (Water Research Commission) as well as the WRC for their sponsorship.

ii) Ms A Howman, Institute for Water Quality Studies for her valuable inputs and part in initiating the project.

iii) The Satellite Applications Centre, Mikomtek, CSIR for the provision of all satellite data.

iv) Mr G van Zyl and A Roux of the Department of Water Affairs, Cape Town; the Department of Water Affairs and Forestry, Pretoria and Elsenburg Agricultural Development Institute, for their assistance in obtaining data for the project.

v) Mr N de Jager Department of Agriculture, Worcester and the farmers of the Upper Breede River Valley region for their valuable contributions towards the success of this project.

vi) Mr BHA Schloms Department of Geography, University of Stellenbosch for his contribution towards the soil irrigation potential base map.

vii) Ms I Neethling who took care of the technical production of the report.

viii) The following members of the steering committee are thanked for their inputs:
Ms A Howman
Mr H Maaren
Mr M Silberbauer
Mr T Newby
Mr AG Reynders
Prof IJ van der Merwe
Mr G van Zyl
Prof HL Zietsman
Mr D Huyser
Mr FP Marais.

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CHAPTER 1: THE UPPER BREEDE RIVER PROJECT : PROBLEM, STUDY AREA AND RESEARCH METHODOLOGY

1.1 INTRODUCTION

The ever-increasing demand for water - one the scarcest natural resources in this country - makes scientifically-based advance management essential in order to meet all user requirements.

South Africa is not richly endowed with natural water resources (Department of Water Affairs, 1985). Furthermore, this scarce natural resource is not evenly distributed among the economic growth areas. This is particularly true of agricultural areas. Because of the numerous sectors which make demands on the water supply, it is essential to have systems that constantly monitor water usage. This would make prior planning of future water consumption and allocation possible.

Information on current land use patterns and trends underlies effective management of natural water resources in drainage areas. Conventional methods of data collection used in making an inventory of land use, such as land use surveys, field work and aerial surveys are expensive, cumbersome and time-consuming. Therefore, one has to consider alternative methods of data collection (Lourens, Brown, Seed & Maaren, 1987). Modern technology, such as remote sensing and Geographic Information Systems, is in theory able to provide a cost-effective and regular means of collecting information on land use. Research and a few experimental applications by Menenti & Niewenhuis, 1986; Nieuwenhuis & Bouwmans, 1986; Heller & Johnson, 1979; Zuluaga, 1990; Senguin, Lagonrade, Steinmetz & Vidal, 1990; Visser, 1990; Menenti, 1990; Minderhoud & Nieuwkoop, 1990; Sattar, 1990; Lourens, 1990; Chambouleyron, 1990; Meyer, 1991; Lourens, Brown, Seed & Maaren, 1987; Lourens & Seed, 1989; Ehrlich, Estes & Scepan, 1990 and Thelin, Johnson & Johnson, 1979 have shown that it is possible to map irrigated areas fast and reasonably accurately with the aid of satellite data. The Department of Water Affairs sums it up thus:

> "*Remote Sensing through the use of satellite imagery has already proved to be highly successful for determining areas that are under irrigation and is now considered to be the only technique by which a regular, country-wide survey of such areas can be made economically and in good time*" (Department of Water Affairs, 1986).

However, the capability of relatively high resolution satellite data to identify irrigated areas has not yet been fully tested in intensively farmed areas, such as the Southwestern Cape. Therefore, there is some doubt as to the degree of success which can be achieved in such complex land use areas.

This study set out to evaluate the potential of SPOT and Landsat TM satellite data to identify vegetation in quantifiable terms, so that the irrigation requirements of the Wolseley-Worcester area of the Upper Breede River Catchment could be determined.

1.2 STATEMENT OF THE PROBLEM

Studies on remote sensing in the Southwestern Cape undertaken by the Institute for Geographic Analysis (IGA) and the Hydrological Research Institute had shown its shortcomings in identifying certain classes of land use. This was especially true of irrigated areas (Lourens *et al*, 1987; Lourens, 1990; Meyer, 1991; Vlok, 1989 and Zietsman, 1982). The relatively low resolution of Landsat MSS (80m) appeared to account for the inability of Landsat MSS to distinguish vigorous natural vegetation and irrigated areas. Particularly in intensively farmed areas, Landsat MSS is not capable of separating complex land use classes. Studies by Meyer (1991) and Lourens (1990) suggest that high resolution SPOT XS and Landsat TM data should be used for the study of intensively farmed areas.

There is also a need to do further research in the Southwestern Cape in order to test the capability of high resolution satellites like Landsat TM and SPOT. Research done by Lourens *et al* (1987), Lourens (1990), Heller & Johnson (1979), Kolm & Case (1984), Moreton & Richards (1984) show the advantages that a multitemporal approach holds. High spatial and spectral resolutions combined with seasonal image data should help to ensure more accurate identification of irrigated areas in places that are intensively farmed.

Consultation with the Western Cape Regional Office of the Department of Water Affairs revealed a high demand for accurate land use data in the Southwestern Cape, so that the amount of water used in irrigation in the respective catchment areas could be quantified. The Department contended that "updated land use records and other relevant information needed for the management of catchment areas should be readily available in the form of maps and statistics for every catchment area" (Department of Water Affairs, 1986: 3.11).

Not only was there a dearth of accurate data, but there was no available means by which information could be constantly available for monitoring purposes.

This study should provide a clearer answer as to whether SPOT and Landsat TM data could be utilised to determine the water requirements of irrigation. It would also clearly adjudge the additional advantages of a multitemporal approach in identifying more detailed land cover patterns in the country. This would pave the way for large-scale inventories of land use patterns and the monitoring of change over the course of time. This would eventually make it possible to effect better planning and to make optimal use of scarce natural resources like water and land.

1.3 THE UPPER BREEDE RIVER AS A STUDY AREA

1.3.1 Choice of the study area

The management and planning of South Africa's water resources is done on a regional basis (Department of Water Affairs, 1986). The Republic is primarily divided into 22 catchment areas, which are subdivided into secondary and tertiary catchment areas.

This study focuses on the Upper Breede River Valley - region H100, which forms part of the greater Breede River Valley - region H (Figure 1.1 and 3.3). The study area extends from the part where the Breede River appears in Michell's Pass (19°16' East; 33°25'17" South) to the Papkuils pump station (19°26' East; 33°39'30" South) - an intensively farmed area of the Breede River.

This study area was chosen for the following reasons:

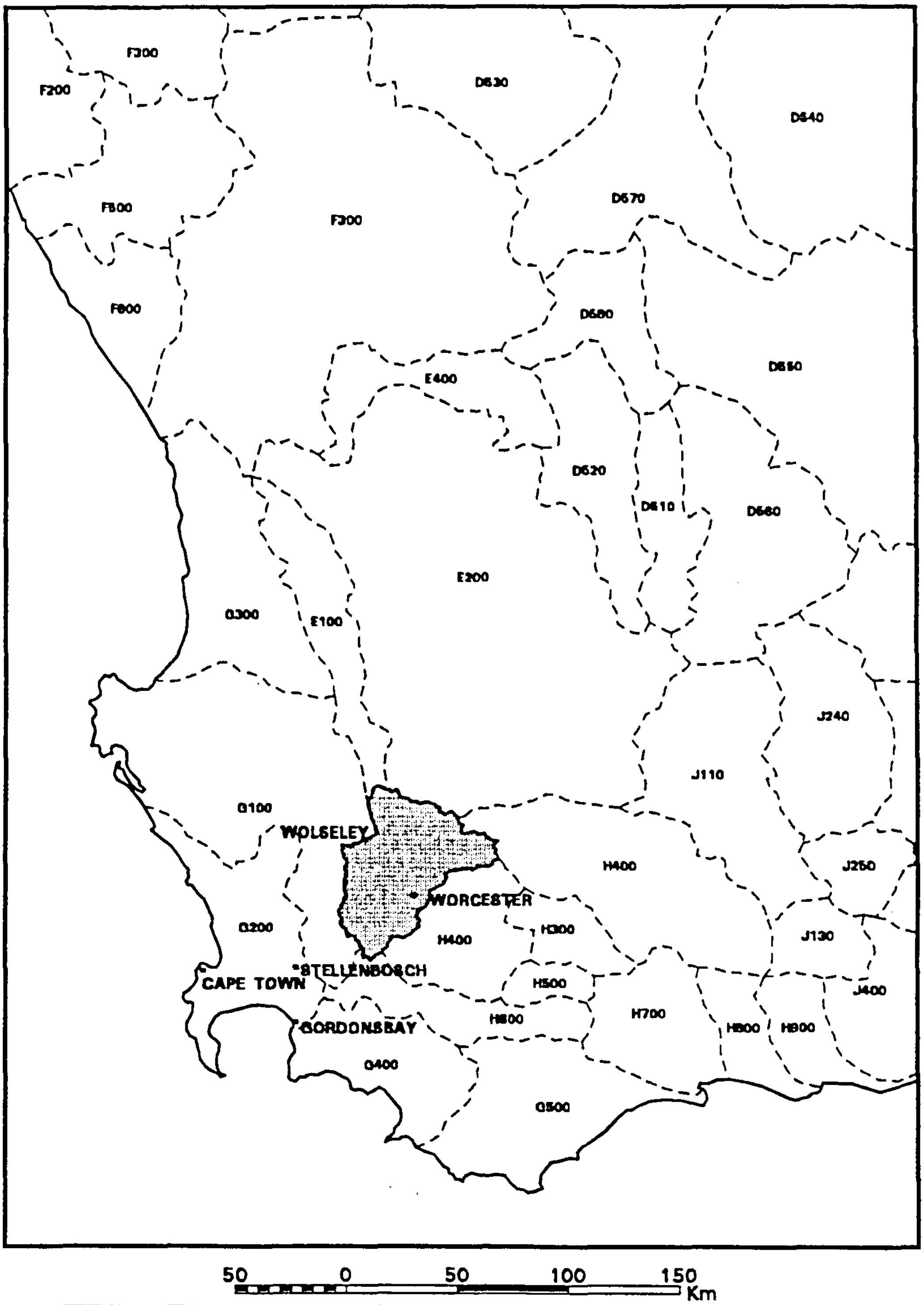
(i) The area is viewed by the Water Research Commission and the Department of Water Affairs as a high priority research area, which forms part of a larger drainage development plan (Department of Water Affairs, 1986).
(ii) Irrigated farming represents the major agricultural land use in the sub-drainage area.
(iii) The area is intensively farmed and has a large variety agricultural land use types which are necessary for the feasibility of the study.
(iv) The area is approximately 100 kms from the University of Stellenbosch. This made field work and surveys relatively easy and inexpensive.

1.3.2 A physiographic review of the study area

An overview of the physical geographic factors is important, because of the influence these factors exercise on the agricultural activities in the study area. Environmental factors have a direct bearing on the cultivation of crops and the concomitant agronomic methods which determine land use patterns.

BREEDE RIVER PROJECT

Figure 1.1 DRAINAGE REGIONS SOUTH WESTERN CAPE



COASTLINE

DRAINAGE REGIONS D530 - J400

REGION H100 UPPER BREEDE RIVER CATCHMENT

1.3.2.1 Morphology of the terrain and drainage

The Upper Breede River drainage area covers a total area of approximately 294 800 ha and is situated between 33°22' and 33°44' S latitude and 19°05' and 19°25' E longitude. The valley is bordered by the Winterhoek mountains in the north, the Elandskloof-Drakenstein- and Slanghoek mountain range in the west and the Witzenberg and Hex River mountains in the north east and east. The Breede River, one of the most important rivers in the Western Cape, which originates in the Agter-Witsenberg, is the principal river in the area. The Breede River has the highest runoff volume of all the rivers in the area. The mean annual runoff is set at 1880 x 10^6 m^3 (Odendaal, 1978). With many of the mountain peaks higher than 1500 m, but a main channel that is less than 250 m above sea level for 90 % of its total length, large differences in relief and tributaries with steep gradients are the dominant features of the Upper Breede River catchment basin.

Figure 1.2 shows the Upper Breede River catchment basin with the most important tributaries which drain into this area. A typical dendrite pattern is to be seen, characteristic of the pattern of drainage which is governed by geological structure.

1.3.2.2 Geology and soil

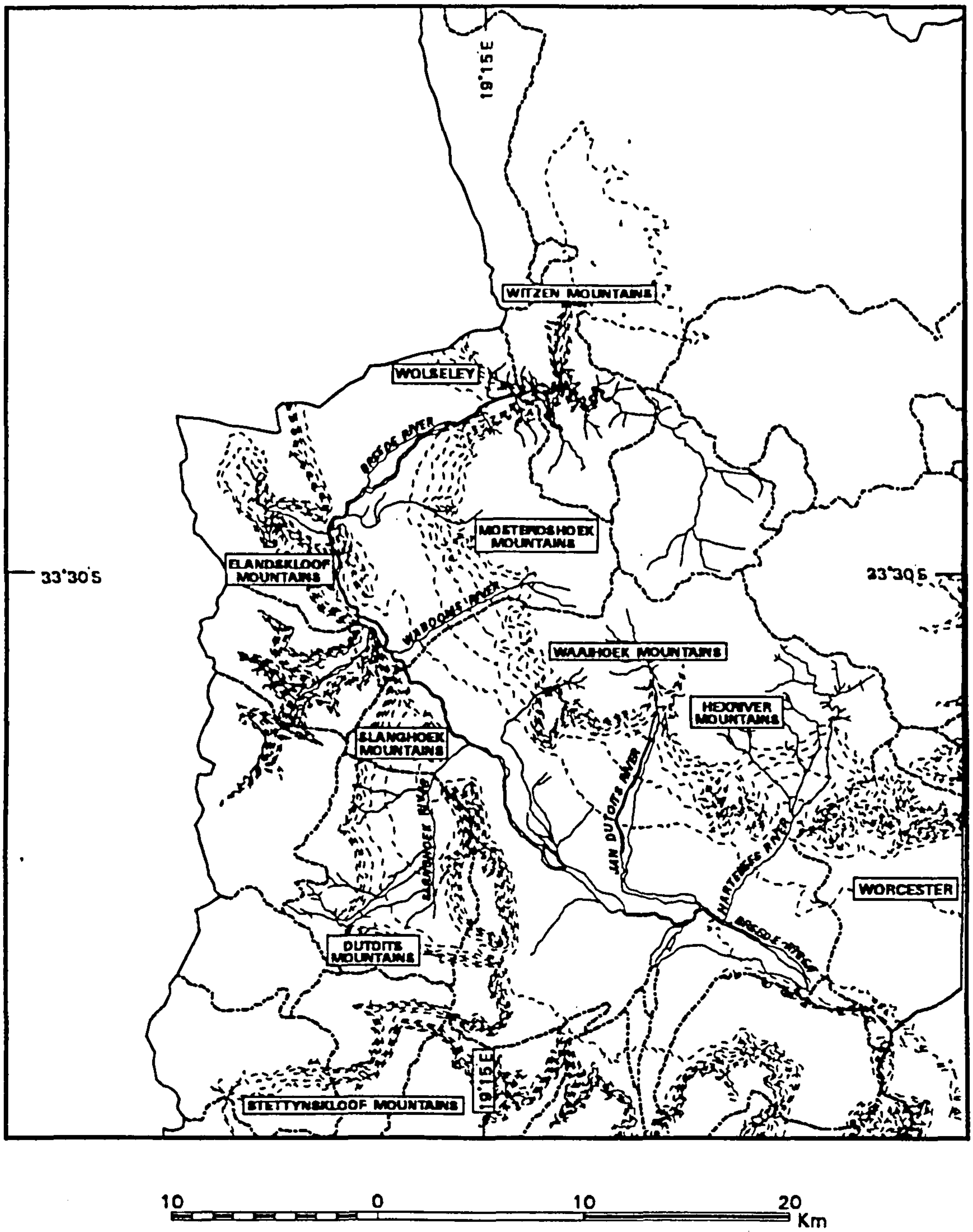
The soil in the Upper Breede River valley consists mainly of alluvial deposits which include the products of the erosion of the surrounding geological formations (Swanevelder, 1965). This soil displays a high degree of variation in colour, structure and composition, even over short distances within the study area. A few comments on the dominant geological formations from which the different types of soil have their origin would, therefore, provide a logical point of departure for an explanation of the appearance and distribution of different forms of soil within the area.

The oldest sedimentary rocks which are found in the area are the Malmesbury group of the *Nama Supergroup* . In the study area, these rocks make up the foothills of the surrounding Witzen-, Waterval-, Olifants- and Hexriver mountain ranges (Swanevelder, 1965). The deposits from these rocks consist mainly of shale and metamorphic products, which have been eroded into clay with a low level of permeability (Feyt, 1988). Rocks from the *Cape Supergroup* (Table Mountain, Bokkeveld and Witteberg series) comprising sandstone shale and quartzite, dominate the landscape of the Southwestern Cape.

The Upper Breede River valley was formed when the sandstone of the Table Mountain group was eroded, revealing the material of the underlying *Malmesbury group*. Alongside

BREEDE RIVER PROJECT

Figure 1.2 THE UPPER BREEDE RIVER



UPPER BREEDE RIVER SYSTEM

SUB-DRAINAGE REGIONS

AREA H100 WATERSHED

CONTOUR LINES BELOW 500 M

the valley, high sandstone mountains remained, known as the Witzen-Mostertshoek mountain range on the eastern side and the Waterval mountains on the western side of the Upper Breede Valley. The land forms which developed from these rock types are mainly sandy and are characterised by the appearance of round sandstone pebbles. The *Bokkeveld series* follows conformably upon the Table Mountain series. The soils which formed from the Bokkeveld series are characteristically olive brown in colour and are also more fertile than those which came from the Table mountain series. The shale in particular has weathered into clay and has high agricultural potential. Products of the erosion of the Table mountain sandstone formation, Witteberg series and Klipheuwel formation respectively form quartzite deposits, finely layered shale and duplex soils with low agricultural potential (Schloms, 1994).

At present, tertiary alluvium covers the largest part of the Upper Breede River Valley. Fast flowing mountain streams in the valley result in the continuous deposit of alluvial material. These fundamental soils are the basis of cultivation of fruit and wine farming in the Upper Breede River valley (Swanevelder, 1965 and Feyt, 1988).

1.3.2.3 Climate

1.3.2.3.1 Rainfall

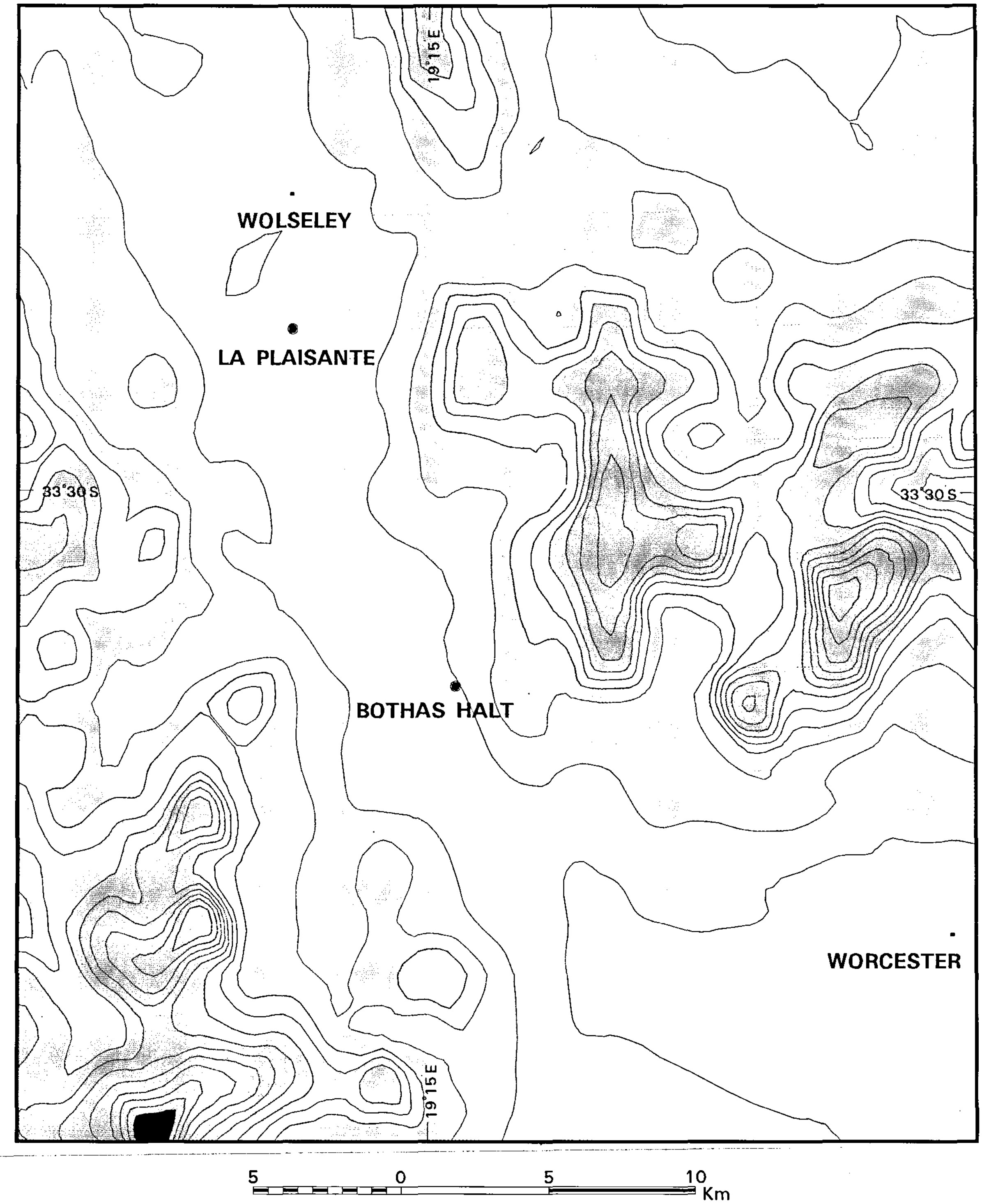
The particular location of the Upper Breede River region, with high mountain ranges and relative closeness of the oceans, means that it is subjected to a unique set of climatological influences. The area that is influenced in summer by the outer tropical high pressure system is characterised by warm, dry summer conditions. In the winter, when the low pressure system of the circumpolar west wind circulation moves over the region, cyclonic rainfall occurs (Odendaal, 1978). However the high mountain ranges which surround the region cause heavy accompanying orographic rainfall to increase the total precipitation to more than 3 000 mm a year in some places (Swanevelder, 1965). The drainage from these high rainfall areas is mainly used for irrigation.

Viewed as a whole, the study area is a winter rainfall area that receives approximately 80% of its rain in winter and 20% of its rain in summer. The rainfall pattern within the study area follows the topography and varies from ±2 400 mm in the mountains at Slanghoek to ±400 mm in the vicinity of Worcester (Figure 1.3).

The rainfall decreases from very good (±3 000 mm per year) in the mountain regions to moderate in the northern valley areas to very poor (±250 mm per year) south-eastwards in the valley.

BREEDE RIVER PROJECT

Figure 1.3 MEAN ANNUAL PRECIPITATION
UPPER BREEDE RIVER VALLEY



IGA

- 200-400 mm
- 401-600 mm
- 601-800 mm
- 801-1000 mm
- 1001-1200 mm
- 1201-1400 mm
- 1401-2000 mm
- 2001-2600 mm
- 2601-3000 mm
- > 3000 mm
- WEATHER STATIONS

The highest rainfall occurs from May to August. Mean monthly rainfall of up to 210 mm occurs in the parts of the valley near the mountains (Figure 1.4).

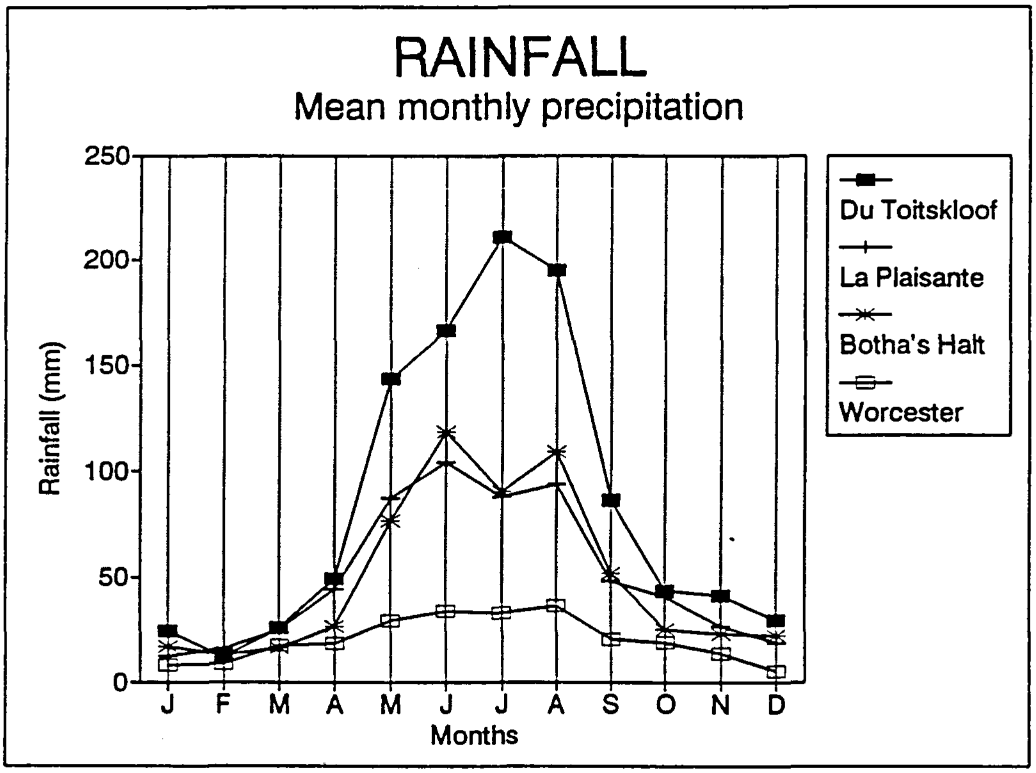


Figure 1.4: Mean monthly rainfall in the Upper Breede River valley as recorded by four weather stations in the area.

In the drier months (October to March), the region is characterised by a very low rainfall, and high summer temperatures are experienced. This rainfall pattern makes the whole region dependent on irrigation water to produce crops during the summer months.

1.3.2.3.2 Temperature

In the study area, summer temperatures are high and average daily temperatures of over 25°C are experienced. The cooler parts are limited to the escarpments on both sides of the valley (Figure 1.5). Heat waves are often experienced and maximum temperatures of over 34°C are recorded five or six times a month on average at the weather stations in the area (Natural Resource Development Programme, Elsenburg, 1990).

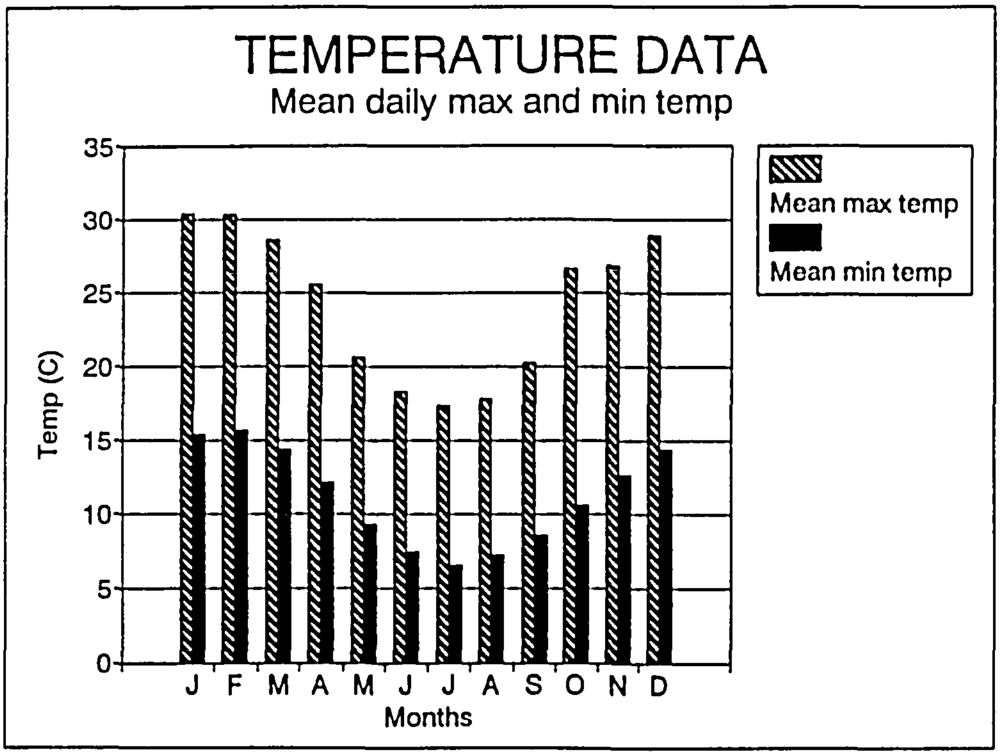


Figure 1.5 Average daily minimum and maximum temperatures in the Upper Breede River Valley.

The mean daily temperatures in winter are moderate and vary between 7°C and 20°C. Frost occurs in the Goudini area and minimum temperatures can drop to below freezing point. Snow sometimes occurs on the mountain peaks, but is shortlived (Odendaal, 1978). Cooler conditions with a lower daily evaporation rate are experienced in the Goudini area. Thus the evaporation tempo differs from warmer parts, such as the Botha-Olifantsberg area.

Wind is generally experienced in the region, with strong to gale force south east (usually in the spring and summer) and northwest (rain) winds in the winter as regular features in the region.

1.3.2.4 Natural vegetation

The region is very intensively farmed and has relatively little natural veld. The vegetation there consists of invaders such as *Acacia saligna* (Port Jackson) and *Acacia mearnsii* (Wattle) trees. However, the mountainous areas have dense plant cover consisting of Cape fynbos (Feyt, 1988).

1.3.3 Cultivation of crops as the primary agricultural activity

The Upper Breede River region is very intensively farmed. The most important irrigated crops in the region are perennial vine and fruit cultivation, which respectively extend over 6257 ha and 1841 ha. The cultivation of vegetables has increased significantly to cover approximately 338 ha. Cereals also occur in the valley and cover a total area of 3381 ha.

Because of the soil and climatic differences in the region, there is a case for dividing the region into three chief production regions: *Wolsley*, *Goudini* (Goudini-Slanghoek-Rawsonville area) and *Botha-Olifantberg* (extending from Brandwacht mountains, Botha's halt, Breede River to Worcester) which cover a total area of 63371 ha (see Figure 1.6).

Wine grapes, fruit and vegetables - mainly potatoes and onions - cover the largest area in the Wolsley island region. Fruit orchards represent approximately 50% of the cultivated areas. Fruit with a low to medium requirement for cold weather, like pears, apples, plums and nectarines are successfully cultivated here. Vines and fruit are largely fully irrigated, while the cultivation of vegetables requires supplementary irrigation. On the lower foothills, cultivated pasture (oats, barley and lucerne) as well as cereal crops (wheat and rye) are grown.

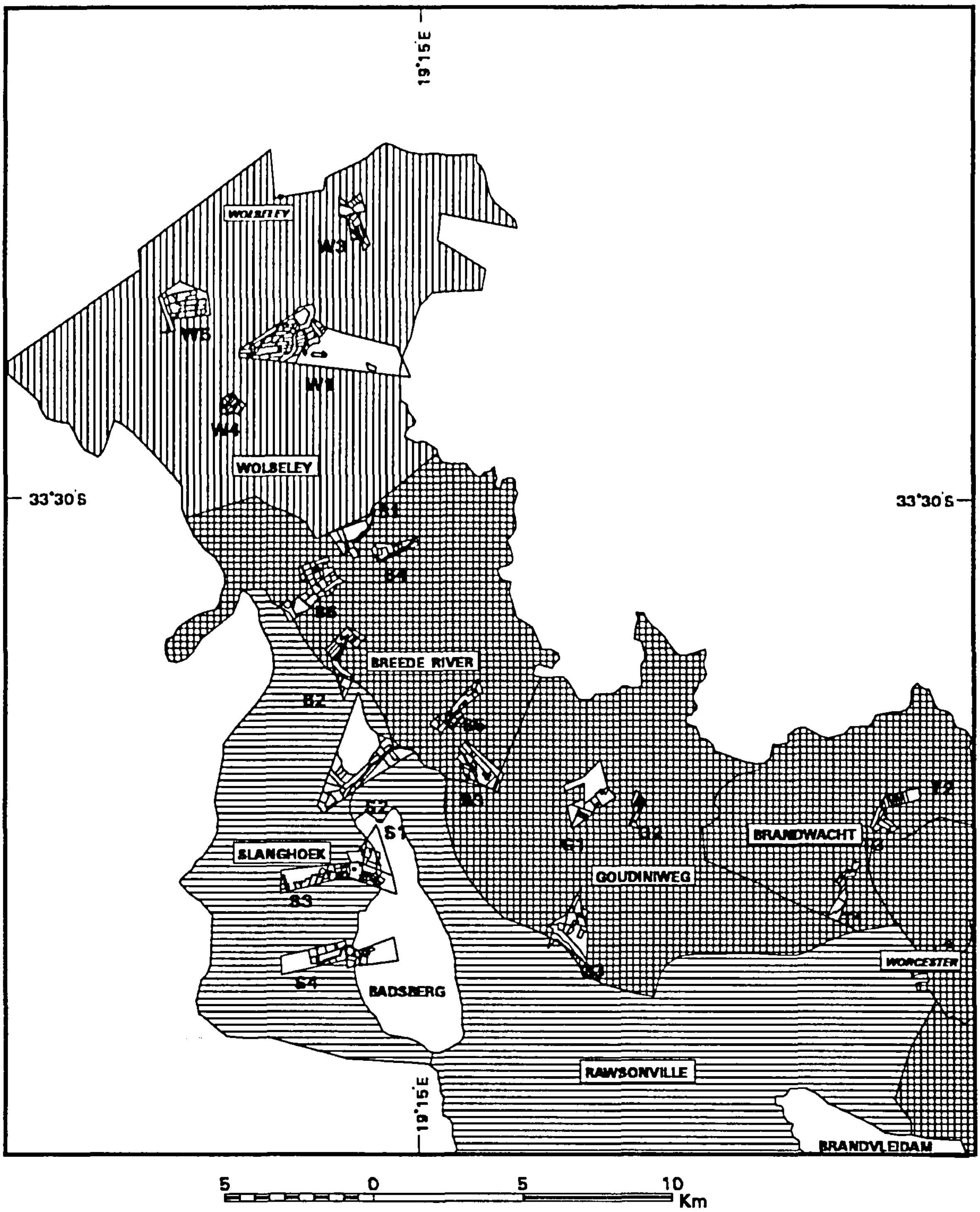
The dominant branches of farming in Goudinin are wine grapes, whereas the farmers at Botha-Olfantsberg grow additional crops like vegetables, cereals, cultivated pasture, fruit and also stone-fruit, on a large scale. North of Worcester (Brandwacht area) table grapes are grown along the Hartbees River, whereas a few olive orchards are found in the foothills of the mountains. All summer crops are irrigated in this area.

1.3.4 Aspects of irrigation

Irrigation farming is the single biggest consumer of water in South Africa (see Figure 1.7). This sector accounts for 50,9% of the total water use in the Republic (Department of Water Affairs, 1986).

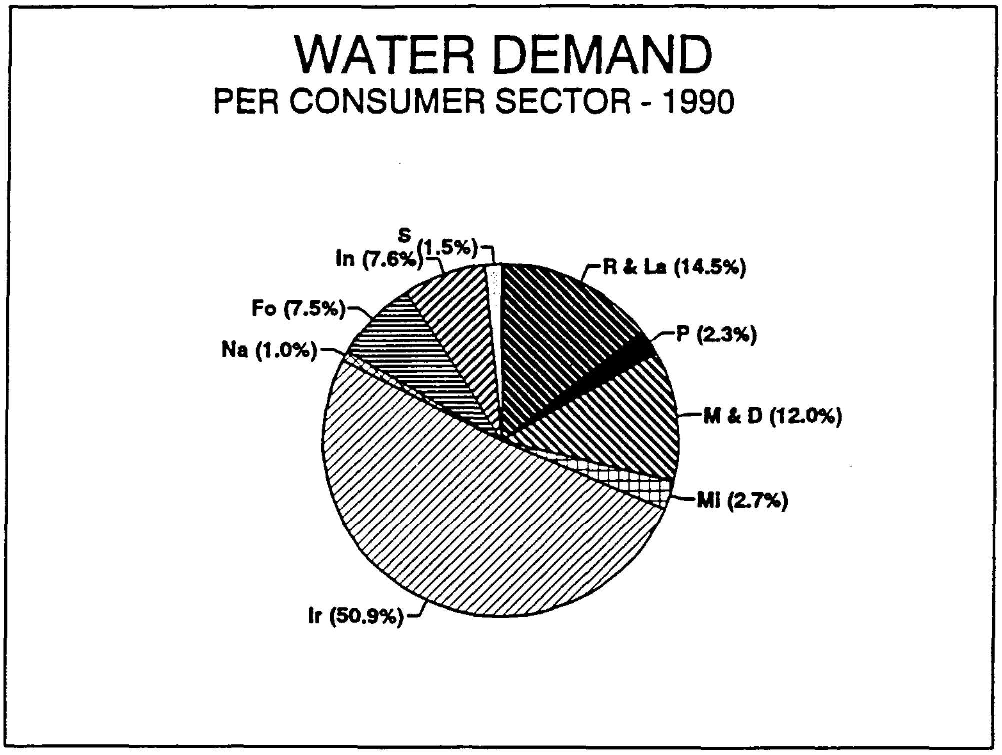
BREEDE RIVER PROJECT

Figure 1.6 MAJOR FARMING AREAS UPPER BREEDE RIVER VALLEY



IGA

WOLSELEY	GOUDINI
BOTHA-OLIFANTSBERG	MAJOR FARMING AREAS WITH SELECTED FARMING UNITS



R & La	Ecological use, river mouths and lakes	Ir	Irrigation
		Na	Nature Conservation
P	Power generation	Fo	Forestry
M & D	Municipal and Domestic	In	Industry
Mi	Mining	S	Stock

Figure 1.7: Water demand per consumer sector in the RSA: 1990.

At present, irrigation farming can be divided into three categories: state water schemes, Irrigation Board schemes and private irrigation schemes. The precise area under irrigation in South Africa is not known, but is estimated at approximately 1,2 million ha (Bloem, Lagrange & Smit, 1992). State water schemes have accurate records on the present extent of irrigation and the volume of water that is required. Irrigation boards have less accurate records. However, almost without exception, the consumption on private farms is estimated since there is seldom any accurate records.

As indicated in Table 1.1, there are eight irrigation boards at present in the Upper Breede River region which serve the various irrigation districts.

Table 1.1: Irrigation Districts in the Upper Breede River Valley.

Farming areas	Irrigation district/ Irrigation boards	Number of members	Recorded area (ha)
Wolseley	Dwars River	35	1876
	Darling bridge	12	288
Goudini	Wagenboom River	10	216
	Waaihoek	10	144
	Jan du Toit's	13	175
Botha-Olifantsberg	Olifantsberg	18	286
	Brandwag	21	322
	Grooteiland	23	432
Total		142	3739

Source: Adapted from Elsenburg, 1990 & Department of Water Affairs, 1994

A total of 3739 ha are on the records of the irrigation boards and are provided with water (Agricultural Development Programme Elsenburg, 1990). However, there is no data available on the present extent of irrigation in the area. A ground survey conducted by the Department of Agricultural Services in 1977 showed that there was 7237 ha of irrigated land below the 300 m irrigation control line (Basson, Pretorius & Robbroeck, 1977). It can therefore be assumed that there is an additional approximately 3 500 ha of irrigable land in the Upper Breede area, which points to the demand for water for further irrigation development.

The *Goudini* area has good supplies of irrigation water. Only the environs of the Hartebees River, which is situated far from the Breede River, experience a shortage of adequate irrigation water. The main sources of irrigation in this area are the Breede River and its tributaries which supply 535 ha with irrigation water. There are few farm dams in the Goudini area - apparently as a result of the absence of clay and suitable dam sites. The Slanghoek, Smalblaar, Holsloot and Platdrif Rivers are important sources of irrigation water. The private water from dams, boreholes and rivers is supplemented by water from three irrigation boards. In the Botha-Olifant area, the Waboom and Bobbejaan Rivers make an important contribution to irrigation requirements. Boreholes and farm dams are also important sources of irrigation water. An area of 1040 ha is on the books of the three irrigation boards (Table 1.1).

The Upper Breede River area is largely dependent on sufficient water for ongoing production. There is still a considerable supply of runoff water available in winter in the Breede River for the erection of dams and has potential for further extension of irrigation in the area (Hulpbronontwikkelingsprogram Elsenburg, 1990). However, continual extension of crop cultivation and crop rotation in this area requires judicious advance planning so that future irrigation requirements can be provided.

1.4 AIMS OF THE STUDY

The importance of irrigation in the Upper Breede River Valley, the lack of up-to-date information on area statistics and the time and cost involved in gathering the required data prompted the Department of Water Affairs and Forestry to investigate the feasibility of using satellite remote sensing technology to solve the problem. This study was therefore initiated to meet the following objectives:

(i) The identification, classification and mapping of agricultural land use types with the aid of digital image processing of seasonal SPOT XS and Landsat TM data.

(ii) A refinement of classification results with the aid of ancilliary data such as slope and soil type through the application of a Geographic Information System (GIS).

(iii) An evaluation of the feasibilty of the land use data generated as a means of quantifying water requirements for irrigation purposes.

It was hoped that a multispectral and multitemporal approach would solve many of the problems experienced in the past to discriminate between vines, orchards, vegetables and other vigorously growing natural land cover types such as riverine bush and wetland reeds. By comparing SPOT XS and Landsat TM imagery an indication could possibly be given as to their relative merits for identifying irrigated land cover types in areas with high land cover fragmentation such as the Southwestern Cape.

1.5 RESEARCH METHODOLOGY

The following steps and procedures (Figure 1.8) were used to achieve the aims of the study:

(i) The creation of a 1:10 000 ground truth map of the land use in the study area.
The present land use pattterns were determined by 1:50 000 scale aerial photographs (Assignment 911 of May 1987) which were enlarged to a 1:30 000

scale, in order to identify the dominant crop types. The boundaries of the crop types were then transferred to 1:10 000 orthophotos. All the information was verified by means of intensive field trips, undertaken during November and December 1992, in order to map the current land use patterns and to obtain additional information which could affect the spectral reflection attributes of the individual blocks of cultivation.

(ii) The capture of land use data with the aid of the ARC/INFO, Geographic Information System (GIS). The ground truth map is also used to evaluate and refine image classification results.

(iii) Collection of three types of ancilliary data, namely soil data, contour data and farm information.

The necessity to have soil data for this project stems from the assumption that this has an important influence on the reflective attributes of individual image elements, and that it is possible that the appearance of certain crop types and associated irrigability are related to certain soil characteristics.
Contour data was used as a criterium to determine the occurrence of certain crops and to delineate slope zones where no irrigation takes place.
In order to quantify the extent of irrigation in the study area, a survey on farming and irrigation practices with regard to the respective types of ground cover was conducted on a number of farm units in the farming subregions.

(iv) The digital capture of various types of ancilliary and supplementary data in a Geographic Information System (GIS).

(v) The digital image processing of multispectral multitemporal SPOT XS and Landsat TM satellite data.

(vi) The refinement of the satellite image classifications through integration of image data with GIS-based ancilliary data.

(vii) Evaluation of the degree of success by comparing the respective image classification results with a ground truth map.

(viii) Quantification of water requirements for irrigation purposes.
With a view to quantification of the extent of irrigation in the study area, questionnaire data was used to calculate an irrigation conversion factor per crop

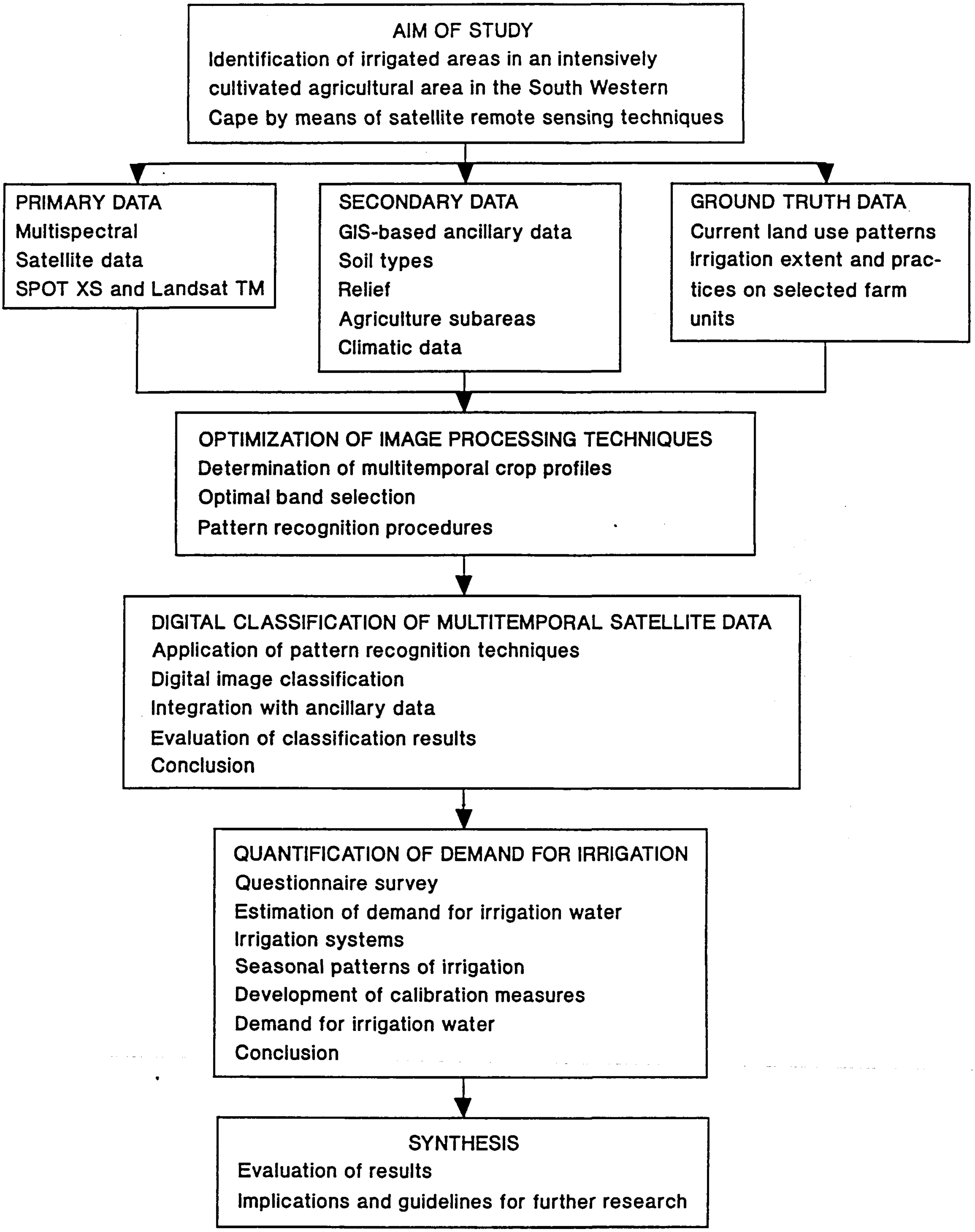


Figure 1.8: Schematic representation of the research methodology.

type for selected farm units. This conversion factor was applied to the land cover area statistics derived from the satellite imagery to estimate the demand for irrigation water.

(ix) The study concludes with a synthesis of the results and presents the implications and guidelines for further research.

1.6 SUMMARY

This chapter provided an orientation regarding identification of irrigated crops in the study area. The scientific basis was land upon which the study could proceed, that was followed by defending the choice of the Upper-Breede River as study area. A physiographical description of the study area was given to reflect the influence of environmental factors on crop production, associated agricultural practices and resulting land use types and patterns. Attention was also given to crop distribution patterns and related aspects of irrigation. The chapter concluded with a summary and diagrammatic representation of the research design followed during the study.

Chapter two will provide a review of perspectives from the literature to guide the rest of the research project.

CHAPTER 2: REMOTE SENSING OF IRRIGATED LAND : PERSPECTIVES FROM THE LITERATURE

2.1 INTRODUCTION

The rising population growth rate, the current restructuring of land use, and a drive towards economic prosperity make heavy demands on limited natural resources. Planning for the optimal development and utilisation of natural resources requires an interdisciplinary approach (Burger, 1992). Therefore planners of resources require readily accessible and accurate methods of obtaining information on the spatial distribution of the features on the earth's surface, as well as a means of processing and interpreting the information.

The identification, determination of the extent and inventory of the earth's natural resources is a huge task of almost mammoth proportions. Nevertheless, the technology of remote sensing makes it possible for man to obtain a regular, constantly updated data base of information on the features of the earth's surface, at a spatial, spectral and temporal resolution which is suitable for planning and monitoring purposes. With reference to Estes, Jansen and Simonett (1980), Simonett (1983: 1) describes the impact of remote sensing technology as:

> *"A reality whose time has come. It is a powerful tool that cannot be ignored because of its information potential and the logic implicit in the reasoning processes employed to analyse remote sensing data."*

The use of computer information systems to combine remote sensing technology with cartography provides resource planners with a extremely powerful means of obtaining, processing and manipulating digital data (Ehlers, Edwards and Bédard, 1989; Ehlers, Greenlee, Smith & Star, 1991; Foody, 1988; Davis & Simonett, 1991 and Star & Estes, 1990). Manore (1990) and Allan (1992) refer to the important role of remote sensing as a primary source of data for Geographic Information Systems (GIS). In the words of Simonett (1983: 1), the potential impact of remote sensing and GIS is that "this coupling can change our perceptions, our methods of analysis, our models and our paradigms".

Developments in spatial and information technology are currently introducing a new dimension in multispectral remote sensing technology. This is reflected in a wide range of reference works and textbooks (Barrett & Curtis, 1982; Colwell, 1983; Campbell, 1987; Elachi, 1987; Lillesand & Kiefer, 1979; Sabins, 1978; Mather, 1987; Lo, 1986; Szekielda, 1988; Swain & Davis, 1978; Harris 1987 and Rees, 1990).

Since the launching of high resolution, so-called "Second Generation Remote Sensing Satellites", Landsat TM in 1984 and SPOT-1 (Systeme Probatoire de l'Observation de la Terre) in 1986, huge volumes of digital data on large areas of the earth's surface are available daily, which can be utilised for land cover mapping and monitoring of resources.

2.2 REMOTE SENSING IN AGRICULTURE

2.2.1 Introduction

Up-to-date and accurate information on the ways in which the earth's surface is utilised, the extent and condition of agricultural resources, as well as information on land use patterns and changes are essential for effective management of agriculture. Although land use maps have already been compiled for large sections of the world, there is an urgent need in developing countries for data which can be used to monitor land use (Lo, 1986; Campbell, 1987; Karteris, 1990 and Toulios, Yassoglou & Moutsoulas, 1990).

There is a need for the timeous provision of the kind of agriculture-specific data that daily marketing activities and management decisions are based on. State involvement in agriculture in the form of bolstering of prices and granting of subsidies requires national and international data on agricultural production. Vlok (1989) points out that early forecasting of yield, information on plant disease and pests, quantification of the effect of shortages and surpluses in ground moisture and the continuous updating of inventories are but a few of the requirements of the present-day agricultural sector.

Community involvement in remote sensing as applied to agriculture is diverse and extends across international boundaries. It draws in scientists, members of national and international government agencies (e.g. the EEC, ESA, ASEAN), national (e.g. USAID, ODA), international (FAO, Worldbank, IFAD), as well as advisory and numerous other organisations which are involved in monitoring and managing natural resources and the environment.

2.2.2 Biological diversity and complexity

Remote sensing as applied to agriculture is problematic because of the dynamic nature and inherent complexity of biological materials (Ahrean, 1991; Fuller & Parsell, 1990 and Meyer, 1991). Guyot (1990: 19) contends that "... the optical properties of vegetation canopies are not static. They not only vary with time as a function of plant status, but also as a function of external and internal factors".

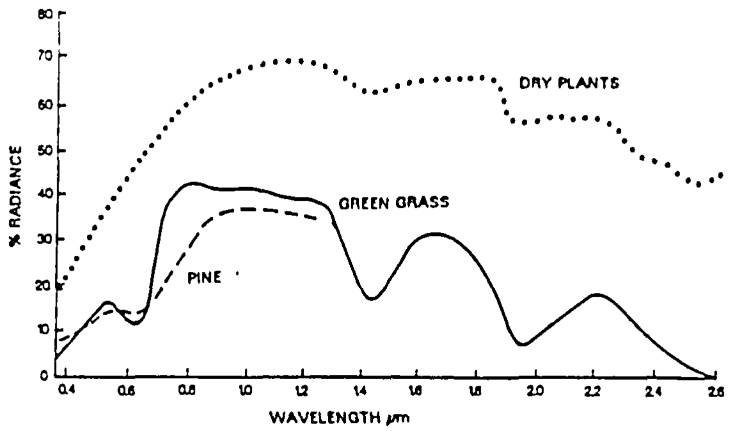
Bauer (1973) ascribes the complex reflectance of the layers of vegetation to the following variables:

i) **Amount of foliage and ground cover** as a result of varying planting dates, soil types, uneven growth patterns and the influence of plant disease;
ii) **Variation in the growth stages** of types of vegetation;
iii) **Differences in agricultural activities** such as use of fertiliser and harvesting practices;
iv) Influence of **plant stress** and/or moisture tension;
v) **Geometric siting of types of vegetation** as a result of varying row widths and orientation; and
vi) **Environmental variables** like atmospheric reflection, absorption and dispersal.

Mackay (1994) adds to these the complexity of biological material and kinds of land/soil types and focuses attention on the influence of external factors such as the morphology and the complexity of the terrain as well as the diversity of types of vegetation. According to Campbell (1987) the optical features of the underlying soil types also play an important role in agricultural applications: "In agricultural scenes, however, reflections from individual plants, or individual rows of plants, are closely intermingled with the bare soil between plants and between rows of plants, so that the reflectances are mixed even at the finest resolutions". Hutchinson (1982) also warns that it is difficult to differentiate between different types of vegetation when the total vegetation cover is less than 30%.

The **reflectance of vegetation** demands further attention, since the identification of specific crop types depends on the unique reflection features of vegetation. According to Malan (1991), the reflection spectrum of vigorous vegetation is dominated by the dispersal of incoming light by the spongy cell structure of leaves (Figure 2.1). In the visible area of the electromagnetic spectrum, reflection is low because of absorption by chlorophyll at wavelengths of 450 nm and 650 nm, resulting in a reflection maximum in the green part of the spectrum at about 540 nm. In the mid-infrared (MIR) part of the spectrum there is absorption by water at 1,4, 1,9 and 2,7 μm. If the plant becomes less vigorous, less chlorophyll is produced and the plant starts turning yellow. The water content of the plant declines simultaneously, with a concomitant increase in the reflectance in the MIR.

Theoretically, every feature of the earth's surface has a unique spectral reaction with regard to electromagnetic radiation. Factors such as absorption, radiance, dispersal and/or reflection determine the nature and quality of a specific reaction (Wolfaard, 1983). This interaction takes place in the atmosphere as well as the on the earth's surface. The sensor



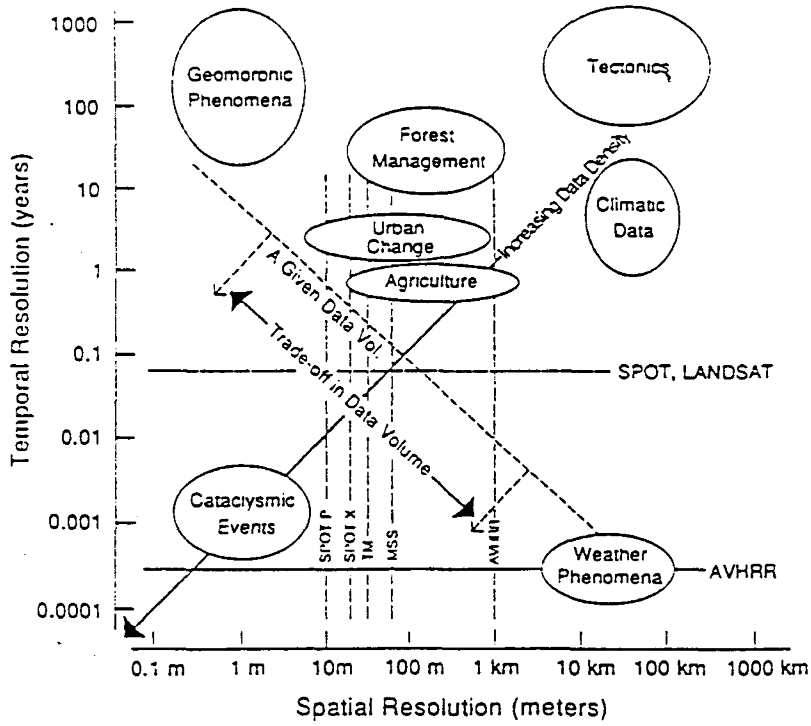
Source: Malan, 1991

Figure 2.1: Typical spectral reflectance of a few vegetation types.

of the earth resource satellite will therefore measure the humidity or reflected energyartificially. Theoretically, the unique spectral features of every vegetation type is reflected by a characteristic spectral curve. This is generally referred to as the '**spectral signature**' of a feature of the earth's surface. The principle of discrimination between different ground cover types like snow, vegetation, water and soil, as described by Harris (1987), Guyot (1990), Myers (1983) and Bauer (1976), constitutes the basic principle of land use classification by means of remote sensing.

Scale and spatial resolution are of the greatest importance in any crop identification or mapping with the aid satellite data (Mackay, 1994). According to Campbell (1987), resolution can be described as the capacity of a satellite sensor to assemble specifically detailed data. **Spectral resolution** refers to the breadth and number of intervals (spectral bands) of wavelengths in the electromagnetic spectrum to which the satellite sensor is sensitive (ERDAS, 1991). The range and number of spectral bands determine the operational application field of a specific satellite sensor. The **temporal resolution** indicates the frequency with which a particular sensor system can collect data during a satellite orbit (Jensen, 1986). Spatial resolution can be described as the dimension of the instantaneous-field-of-view (IFOV), of the sensor system which moves over the terrain and collects spectral data (Curran, 1985). Thus, the spatial resolution determines the size of the elements of the satellite image. According to Campbell (1987: 224) the **radiometric resolution** indicates the capability of a sensor to distinguish between the different signal strengths of the outgoing radiation from the earth's surface, i.e. the number of radiance levels which are captured. For instance, 8 bits could include a range of values from 0-255 levels.

Davis (1991) refers to the specific requirements of agricultural applications for spatial and temporal resolution of remote sensing systems, as opposed to other fields of application.



Source: Davis, 1991

Figure 2.2: The requirements of agricultural applications with respect to spatial and temporal resolution of remote sensing systems compared with those of other users of remotely sensed data.

According to Figure 2.2, the low temporal frequency of data (between 10 and 15 years) from traditional cartographic systems is sufficient for topographic mapping, but not feasible for environmentalists. At the same time, satellite systems like AVHRR, NOAA and Meteosat supply data with a high temporal frequency, but the spatial resolution is not adequate for agricultural applications. There are very specific **temporal and spatial resolution requirements for agricultural applications** (Figure 2.2), which are determined by the terrain, climatic influences and cultural agricultural activities in a particular area. Allan (1990: 9) particularly emphasises the influence of agronomic practices and refers specifically to the influence of individual parcel sizes on the satellite sensor. He specifies that "... agricultural parcels must be at least four times the nominal area of the recording pixel, to be sure that there is no effect from the mixed pixels at the parcel boundaries. It is preferable to have parcels which are ten times the area of the recording pixel." Figure 2.2 refers to the specific temporal requirements for agricultural applications. Allan (1990: 10) considers that "agricultural applications need adequate temporal resolution, in other words the frequency of the temporal sample must be appropriate for the particular application". Adequate temporal resolution is therefore a prerequisite for agricultural monitoring, because of the varying growth stages of crop types over time (Myers, 1983).

2.2.3 Agricultural satellite remote-sensing projects

Remote sensing data has an important role to play in a variety of agricultural projects, which range from micro-level surveys to surveys of global proportions. The wealth of literature, particularly in the last few years is evidence of this trend.

At international level, the first applications of satellite data with the aid of Landsat-MSS data (resolution 80 m) was mainly directed at large-scale land use classification, crop inventories, prediction of crop production and yield forecasting services. The LACIE-project (Large Area Crop Inventory Experiment), which was jointly undertaken by NASA (National Aeronautics and Space Agency), USDA (United Stated Department of Agriculture) and NOAA (National Oceanic and Atmospheric Administration) between 1974 and 1977, was probably one of the most comprehensive agricultural applications (Myers, 1983). The main aim of the project was to capture, process and analyse multitemporal spectral data on wheat harvest at a global scale. Promising results were obtained by the study and forecasts for the USA differed by less than 10% from the real production statistics. Forecasts for the Soviet Union differed from the offical statistics by less than 1%.

The Agreste Project was specifically focussed on smaller European farming units. This project executed between 1973 and 1977 was a joint undertaking of the "Commission of the European Communities" and other research bodies in France and Italy. The study used remotely sensed data for different time slices during the growing season. In addition to the satellite data, it also made use of multispectral scanners mounted on aircraft, spectrometers, radiometers, conventional aerial photography and soil and ancillary laboratory data. Smaller cultivated units and inadequate sensor resolution were the main reasons for the incorrect surface estimates made. The problem was exacerbated whenever atmospheric disturbances - for instance cloud cover - were also experienced. Barrett and Curtis (1982) believe that relatively accurate surface estimates were obtained despite the problems that were experienced. The results of the maximum likelihood classifications made during this project revealed overestimations of 9% and 8% for rice and plantation land use classes, respectively.

Lo (1986) discussed a project in Oregon, USA where an associated classification technique was used in digital image processing of Landsat MSS data to distinguish vegetation from other land use classes in an area of diverse topography. The measure of accuracy achieved was 88,8%. Szekielda (1988) ascribes the high percentage of accuracy in digital image classification to the uniform growth stages of foliage during the sensor survey.

Vlok (1989) describes the "Inventory Technology Development Project" under the auspices of the 'Agriculture and Resources Inventory Surveys through Aerospace Remote Sensing' (AGRISTARS) in which NASA, UDSA and NOAA, and others were involved. The programmme, which lasted five years and cost 300 million Rand, concentrated on effective methods of crop monitoring, utilisation of resources as well as international crop production forecasting. Hilwig (1987) lists the main objectives of the project:

i) early warning crop condition assessment;
ii) foreign commodity production forecasting;
iii) yield model development;
iv) supporting research;
v) soil moisture;
vi) domestic crops and ground cover;
vii) renewable resources inventory; and
viii) conservation and pollution."

The findings of this project of global scope reflect the specific information requirements of resource managers across international boundaries.

According to King & Meyer-Roux (1990), the only large-scale international crop monitoring project at present is that of the US Department of Agriculture. Smaller monitoring projects are constantly being launched in developing countries by the FAO or the USA.

As described earlier, high resolution satellite data were mainly used qualitatively in monitoring programmes in the past. These results were largely dependent on the skill of the data analyst. The more quantitative aspects are only now strongly coming to the fore through the comparison of vegetation indices, application of agricultural meteorological models and development of extensive data bases for crop identification and monitoring programmes (King *et al*, 1990). According to King *et al* agricultural crop identification and monitoring programmes still represent a research phase and will need further imput to become fully operational: "... when we go from surface inventories to production and yield forecasts, **we are still in a research stage** (my emphasis) and we must pursue the efforts initiated with the LACIE and AGRISTARS programmes."

On a local level, agricultural applications have been employed since 1982. The research done by Sandham (1982) and Wolfaardt (1983) focused on the linking of Landsat data with agricultural statistics in the Bronkhorstspruit and Vermaas development area. Van Dyck

(1982) did land use mapping in the Western Transvaal by means of computer manipulation of Landsat data. Sandham (1984) and Van Rensburg (1987) launched a Landsat geo-coding project in the Bethal district, in order to locate grain silos, as well as to create yield forecasting models for the Eastern Transvaal Cooperative. The other remote sensing application research projects, which have been carried in South Africa, are for instance the Heilbron project of Malan and Turner (1982); land use mapping, Boyle (1981) and Scogings and Piper (1984); mapping of forestry areas, (Snyman & Caithness, data unavailable); water quality (Howman and Kempster, 1987); irrigation areas (Lourens, Brown, Seed & Maaren, 1987; Meyer, 1991); oceanographic applications (Shannon & Lutjeharms, 1983; Shannon & Shackleton, 1988); crop and vine identification (Vlok, 1989; Zietsman, 1982; Vlok & Zietsman, 1987); identification and mapping of asbestos mine dumps (Prinsloo, 1992) and veld monitoring in the Ceres-Karoo (Mackay, 1994).

2.2.4 Crop identification

According to Myers (1983: 2153), the level of accuracy of experimental studies on crop identification is generally related to developments in the technical field. The literature suggests that crop identification with the aid of Landsat data can achieve as high a level of accuracy as 90% where the cultivated fields are regular, extensive and homogeneous such as irrigated rice fields in California, potatoes in New Brunswick, Canada; oil-seeds in Western Canada; and fields being prepared for the sowing of winter corn in Kansas, Oklahoma and Texas. The accuracy of the LACIE and AGRISTARS projects confirms this trend.

There is also strong evidence that mapping should preferably be based on multiple timeslices. The argument is that the uniqueness of the crop's so-called 'spectral signature' is to be found in the pattern of temporal changes in the spectral response.

However, a problem of **landscape complexity** occurs in developing countries. Diverse forms of cultivation and small irregular patterns of crop cultivation are often characterised by spectral reflections which are not distinguishable by means of classification of single timeslice Landsat data.

According to Myers (1983), studies done by Bauer *et al* (1978) point to the discrimination between crops of different types by means of multitemporal data. Maize and grain sorghum could be identified with a greater degree of accuracy by utilising multiseasonal data. Myers (1983) cites instances where sets of multitemporal data were used to discriminate between irrigated crop types and dryland crops. These examples underline the fact that plant cover is a dynamic entity which is constantly being affected by cultural and environmental factors.

It is, therefore, essential to quantify the sources of this influence on spectral reflection measurements and to understand their influence (Szekielda, 1990 & Mather, 1990).

More specialised literature sources focus on numerous examples where the identification and quantification of crops is based on digital imaging, **high resolution Landsat TM and SPOT data** (Altamira, Baumgardner & Valenzuela, 1986; Badhwar, Gargantini & Redondo, 1987; Conese & Maselli, 1991; Chou Chen, Batista & Tardin, 1986; Jewell, 1989; Redondo, Lac Prugent, Gargantini & Antes, 1984; Samson, 1993; Schmullius, 1988; Silleos, Misopolinos & Perakis, 1992; Toulios, Yassoglou & Mountsoulos, 1990 and Wheeler, Jarvis, Mitchell, King & White, 1988). The results of the above experimental studies reveal different degrees of accuracy in the identification and quantification of specific crop types.

Badhwar *et al* (1987) found that in a maximum likelihood classification of multitemporal Landsat data summer crop types such as sunflowers, soya beans, maize and pastures in Argentinia had been identified 80-100% correctly. An evaluation of multitemporal SPOT data for crop identification shows that broader land use classes such as grain, pasture, beetroot and vegetables can be classified with an 88% level of correctness.

A study by Toulios *et al* (1990) refers to the potential of false colour composites of SPOT and Landsat TM, to make visual crop identification. Crop types like orchards, vineyards, non-irrigated winter crops, irrigated crops and fallow land can be visually separated from false colour images and can be further interpreted with the aid of ground control data for the specific area.

There are numerous other sources in the literature which concern the **physiological, physical and spectral behaviour of vegetation** (Guyot, 1990; Lo, 1986; Baret, 1988; Szekielda, 1988). An experimental study by Wanjura & Hatfield (1988) utilised Landsat TM data to investigate the optical features of four row orientated crop types, namely cotton, soya beans, grain sorghum and sunflowers and found that plant height correlates strongly with ground cover and Leaf Area Index (LAI). Regression analysis shows that the angle of solar radiation, Leaf Area Index (LAI) and leaf density correlates best with the optical properties of different crop type canopies.

Baumgardner *et al* (1986: 533) sum up identification of agricultural crop types by means of remote sensing as follows:

> *"To discriminate crop species by means of remote sensing, several factors related to the cultural practices for each crop must be considered, such as plant*

and row spacing, geometric arrangement of the plants, fertilization and irrigation practices and growth cycles. The differences in reflectance which allows us to discriminate between vegetative species, are due to the characteristics of the leaves and canopies of different species. All these internal and external factors influence the optical properties of the leaves and canopies. The spectral patterns sensed by the scanners represent the integration of all of them."

In **South Africa** similar trends in crop identification are evident. The identification of crop types where the fields cover large areas and where there is homogeneous morphology appears to be reasonably successful (Malan *et al*, 1983; Sandham *et al*, 1984; van Rensburg, 1980 and Lourens, 1990). However, attempts to identify agricultural crops in the Southwestern Cape with the aid of satellite data have been less successful. Research in this regard, both in the Tulbagh (Lourens & Seed, 1989) and Robertson (Lourens, Brown, Seed & Maaren, 1987) areas showed that not one of the classes - vineyards, orchards, lucerne, pastures, vegetables, maize and wheat - exhibited unique spectral reflections. Lourens and Seed (1989) also found that both orchards and vineyards exhibit strong inherent spectral diversity. This finding confirms the conclusion drawn by Zietsman, (1982) that incorrect vine classification can be ascribed to "variations in farming practices, terrain and morphological conditions."

The problem of inadequate spatial resolution relating to the use of Landsat MSS-data in the **Southwestern Cape** has also been emphasised by Zietsman (1982); Vlok (1988); Lourens, Brown, Seed & Maaren (1987) and Lourens & Seed, (1989). Morain & Williams (1975), Allan (1980) and Townshed & Justice (1980) are but a few of the authors who have highlighted the inadequacies of remote sensing in areas where there are small areas under cultivation and diverse vegetation. Jackson *et al* (1980: 1050) confirm that "Landsat's present 79m instantaneous field of view (IFOV) is compatible with the requirement to map areas of 5 hectares or larger ..." Lourens, Brown, Seed & Maaren (1987) found that in their proposed study area, east of Robertson in the Breede River Valley, only 7% of the selected 'training areas' were larger than the 5 hectare criterion. Vlok and Zietsman (1987), however, point out that it was virtually impossible to find internally homogeneous areas of 4,2 hectares, for the purposes of their study.

An additional aspect of remote sensing which has been elucidated by a number of authors is the differences between the terms **land use** and **land cover** (Campbell, 1987; Lillesand & Kiefer, 1979 and Gong & Howarth, 1988). The influence of this was shown by Lourens (1990) in the Southwestern Cape where newly planted crops were often classified in terms of the reflection properties of the underlying soil. More attention will be given to this important concept later in this chapter.

2.2.5 The identification of irrigated crops and quantification of irrigated area

2.2.5.1 Introduction

The identification of irrigated crops, delineation of the extent of irrigation and monitoring of irrigation development is an integral part of water resources planning and management in South Africa (Conley, 1988). There is a constant and urgent need for accurate, regular and reliable information on current irrigation patterns and trends within geographic drainage areas. Conventional methods of data collection such as panchromatic aerial photography and fieldwork is expensive, cumbersome and inadequate for large-scale monitoring (Conley *et al*, 1989). A number of authors like Maaren (1985), Lourens *et al* (1989), Lourens (1990) and Meyer (1991), refer to the potential multispectral satellite data has to monitor irrigated areas successfully on a regular basis.

According to Lourens (1990: 91), the advantages of multispectral satellite data for the identification of of irrigated areas can be ascribed to:

i) *The synoptic nature of the data.* An image provides a more accurate representation of reality than any map. Thus, it is possible to distinuish cultivated crop areas visually from natural vegetation.
ii) *The extent of the ground coverage.* Landsat TM covers an area of approximately 34 000 km^2. The advantage is that the total catchment basin, agricultural district or farm, can be viewed as a unit on photographic hard copy or on the screen of an image processor.
iii) *A repetative coverage.* Periodic surveys and regular monitoring of an area can be done continuously.
iv) *The practicability and feasibility of the media.* A single satellite image on Computer Compatible Tape, (CCT) or CD, covers the same area as a few hundred aerial photographs, stores them easily in digital format and has the potential to monitor any change quantifiably.
v) *The integration with Geographic Information Systems (GIS).* According to King (1991: 70), the true merits of remote sensing are seen when large quantities of spatial data are integrated with other geographic data. Geographic Information Systems (GIS) are ideal, because they provide powerful methods of input, storage, manipulation, analysis and output of spatial information.

shaped patterns were characteristic of centre-pivot irrigation systems, while pastures exhibited irregular shapes. Combinations of infrared colour photography and false colour composites are viewed by Tinney *et al* (1979: 694) as a more effective method of identifying irrigated areas:

> *"This combined satellite and aircraft approach takes advantage of both the temporal frequency of Landsat Multispectral imagery and the higher spatial resolution of aircraft photography to provide a product more usefull than is available from either source individually".*

The results of the study demonstrate that smaller irrigated areas can also be successfully identified.

In Kansas, USA a single band (Landsat MSS band 2) was used by Williams *et al* (1979) to identify and monitor irrigated areas. A multitemporal visual interpretation technique, based on grey scale colour-shading was successfully used to map irrigated areas. It was also possible to determine the areal extent of the predominant irrigated crops with a high level of accuracy (ranging between 85 and 99%).

Zuluaga (1990) used multitemporal Landsat MSS data in six different areas in Mendoza, Argentinia to distinguish the following land use classes, with the aid of a false colour composite of bands 7, 5, 4: irrigated and non-irrigated areas, desert area and urban areas. Drainage patterns of main drainage channels, which were related to the location of irrigated areas, could also be visually identified from the false colour composites.

A few studies done by Heller *et al* (1979), Thiruvengadachari (1983), Wall *et al* (1984) and Bauer *et al* (1984) and others demonstrate the success of a two-phase approach to quantifying the extent of the irrigation: visual interpretation of satellite data followed by regression estimation. The first phase mainly consists of visual determination of the extent of irrigated areas per stratum, based on land use classes. The second phase involves the assignment of test areas per stratum, followed by land use surveys per stratum to determine the extent of the irrigated areas. The two phases are integrated by means of regression methods in order to quantify statistically the extent of the irrigated areas. Studies by Wall *et al* (1983) and Bauer *et al* (1984) in the state of California showed that the overall estimation achieved a standard deviation of 1,74% at a 99% precision level. The total irrigated surface differed by only 0,4% from the calculations based on a ground survey.

It appears from the literature quoted above that Landsat MSS data has been chiefly utilised internationally for reconnaissance purposes in places where general information is required on the occurrence and distribution of irrigation patterns within drainage areas. General land use pattern recognition, such as cultivated areas, natural vegetation, water surfaces and also the extent of these can be successfully established. The low resolution of Landsat MSS (80 m) was inadequate for the accurate visual interpretation of irrigated areas in European countries such as the Netherlands, which has characteristically complex land use classes. According to Lourens (1990: 27) the work of Van den Brink *et al* confirms this trend: "The use of satellite imagery for land-use studies in the Netherlands was limited due to the poor resolution of MSS imagery".

The launching of Landsat 4 in 1982, followed by Landsat 5 in 1984 with an enhanced spatial resolution, held great promise for the identification of more detailed land cover classes. Landsat TM has a spatial resolution of 30 m and consists of seven spectral bands: three in the visible part of the spectrum - blue (TM 1), green (TM 2) and red (TM 3); one band in the near infrared (TM 4); two bands in the mid-infrared (MIR), (TM 5) and (TM 7) and TM 6 in the thermal infrared part of the spectrum.

Follow-up studies by Van den Brink (1986) show that false colour composites of Landsat TM, in particular combinations of 4, 5, 3 and 4, 5, 6, successfully separate specific agricultural land use patterns, such as forestry, cities and grassed areas. Trommervik (1986) notes Landsat TM's capacity to differentiate between vegetation communities in Norway, using visual interpretation of TM band combinations 4, 5, 6 and 3, 4, 5.

Nikolaos (1988) recommends a false colour combination compiled from TM data to discriminate visually between non-irrigated crops, irrigated crops (maize, cotton, vegetables), rice and fallow land. This method of pattern recognition has been successfully and cost-effectively used to compile an agricultural land use map for the Axios Alluvial Plains in Greece.

Trolier and Philipson (1986) found that enlargements of false colour composites (bands 3, 4, 5) enhance interpretation of the inventory of hydrologically important land use/land cover classes. During this study the land cover and hydrological patterns were identified successfully and cost-effectively.

Landsat TM false colour composites were also used by France & Hedges (1986) for the visual interpretation of hydrologically important land use classes. Various image processing techniques were applied to individual TM bands, as well as to combinations of bands 1, 4, 5; 2, 4, 5 and 3, 4, 5 respectively. A variety of techniques such as linear stretching, principal component analysis and a variety of filtering processes optimise the spectral information of various applications. According to Milford, Mackay (1994: 13) notes in this regard that "the feature that one is interested in is not often directly sensed by satellite, it usually has to be deduced".

According to Gastellu-Etchegorry (1990); Gastellu-Etchegorry (1989); Quarmby & Townshed (1986); Chidley & Drayton (1986); De Gloria (1984) and Gong, Marceau & Howarth (1992), **high resolution SPOT** data is extraordinarily well suited to visual interpretation. SPOT has three spectral bands with 20 m resolution: bands 1, 2, 3 in the green, red and infrared part of the spectrum respectively and a panchromatic band which extends from 0,51 - 0,73 μm with a resolution of 10 m. During an agricultural land use study in Tanzania, Wheeler *et al* (1988) evaluated false colour composites of SPOT and TM and found that SPOT false colour composites could be used to identify specific sub-class attributes correctly. Gastellu-Etchgorry (1990) confirms this finding, saying, "Computer screen displays of SPOT bands and colour composites provided straight recognition of all landscapes of interest" and further "... various vegetative stages could be discriminated with SPOT data within cultivated areas".

During visual photograph interpretation of SPOT panchromatic and multispectral images, De Gloria (1984) found that it was possible to:

i) separate agricultural land use classes successfully,
ii) to identify crop parcels with as little as 20% land cover, and
iii) to determine the extent of crop parcels varying from 1-80 ha in size.

Inter- and intra-field boundaries were successfully identified with the aid of the 10 m panchromatic band.

Chidley & Drayton (1986) refer to various techniques to enhance visually hydrologically important spectral information. During this study photographic forms of principal components were used for visual analysis and mapping of drainage systems, dams and main channels.

Lourens (1990) sees visual analysis using SPOT false colour composites on a 1:50 000 scale as an effective method of monitoring irrigated areas. A number of features like farm boundaries and access routes which are related to locating and monitoring irrigated areas can also visually recognised from SPOT data.

To sum up it seems that the success of visual pattern recognition depends on three important components: the type of data and associated band parameters, as well as the specific objectives of the project and the local knowledge of the interpreter.

2.2.5.3 *Digital image classification for identification and quantification of irrigated areas*

Digital image processing includes classification procedures whereby pixels are assigned to different classes with the aid of special computer algorithms (Campbell, 1987). There are three main approaches to digital image classification: **supervised classification, unsupervised classification**, as well as a **combination of the two methods** (ERDAS, 1991: Campbell, 1987 and Lillesand & Kiefer, 1979).

Digital image classification offers many more advantages than visual interpretation technology: "Digital image-analysis techniques are generally considered faster, provide objective decisions and can readily employ multiband and/or multidate image data, thus allowing crop identification in addition to irrigation identification." Digital image data can also be directly integrated with geographic information systems (GIS). "Raster-based satellite data are becoming an integral component of many GIS programmes" (Parent, 1992). An integrated data base of this kind also has the capacity for data manipulation, statistical analysis and modelling and offers high quality output (Marble, 1990; Manore, 1990).

Authors like Meneti *et al* (1986), Gastellu-Etchegorry (1990), Mausel Kramber & Lee (1990), Khorram, Brockhaus & Gerachi (1988), Schmullius (1988), Chavez & Bowell (1984), Chen, Batista & Tardin (1986), Conese & Maselli (1991) refer to the application of various image processing techniques to the identification and quantification of irrigated areas. Maaren (1985), Lourens (1991) and Meyer (1991) view the following digital image processing techniques as the most important methods of identifying and quantifying irrigated areas:

i) Supervised image classification;
ii) Unsupervised image classification;
iii) The application of regression estimation;
iv) The application of principal component analysis;
v) The use of vegetation indices.

Next, a few perspectives from the literature are given to illustrate the application of each of these image processing techniques.

2.2.5.3.1 The application of supervised classification methods

In a **supervised classification**, land use ground control data are used to cluster image elements. Training sites, consisting of a number of pixels extracted from the image, are selected for each of the clusters which are related to a specific land use class. Next, the statistics (mathematical mean, variance and co-variance) of the training sites are calculated. The so-called 'spectral signature' which represents the unique spectral features of each of the land cover classes is extrapolated to the whole data set in order to effect a classification.

The application of supervised classification techniques to both Landsat and SPOT data for the identification of irrigated areas is widely undertaken (Nikolaos 1988; Azzali, Menenti, Mieuwissen & Visser, 1990; Visser, 1990; Lourens, 1990; Chavez, 1984; Tommervik, 1986; Schmullius, 1988; Lourens *et al*, 1989; Lourens *et al*, 1987; Meyer, 1991). The same basic procedures are generally followed regardless of the type of data. Training sites which are representative of the principal land cover type are delineated and statistically analysed, since the success of a classification depends on the spectral separability of the chosen classes. Lourens (1990) recommends statistical tests, like the transformed divergence limit and Jefferys-Matusita distance for this purpose, which can determine the measure of separabilty between classes. Other applications include the use of parallelepiped, minimum distance from the mean, maximum log-probability and maximum likelihood algorithms.

The selection of training sites, choice of classification techniques and evaluation of classification results is an interactive process. Lillesand & Kiefer (1979: 471) describe it as follows:

> *"In many ways the training effort is more an art than a science. It requires close interaction between the image analyst and the image data. It also necessitates a thorough knowledge of the geographical area to which the data apply. Most importantly, it requires a knowledge of the spectral characteristics of the features being analyzed".*

The success of supervised classification is directly related to the ability of the analyst to select representative training sites (Malan, 1990). Campbell (1987: 315), drawing on the work of Scholtz *et al* & Hixon *et al*, notes:

> *"... the selection of training data may be as important as, or even more important than choice of classification algorithm in determining classification accuracies of agricultural areas in the central United States".*

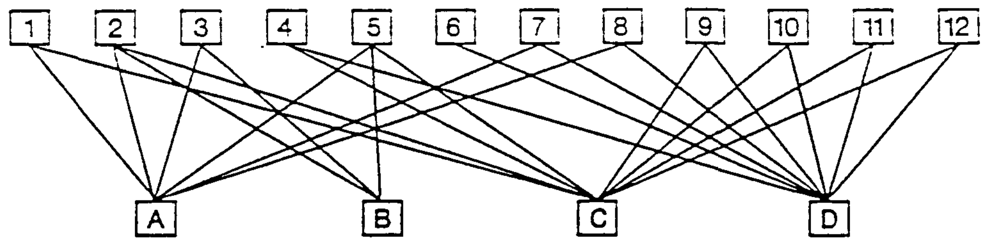
Gong & Howarth (1988) stress the necessity of distinguishing between **land cover** and **land use** during the evaluation of a classification. Land use is viewed as a cultural concept: "To classify land use requires a large amount of human knowledge with respect to texture, shape, size, neighbourhood, proximity and association, as well as pattern", while Lillesand & Kiefer (1979: 119) define land cover as "the type of feature present on the surface of the earth". The following example illustrates the relationship between land use and land cover. Table 2.1 shows typical results of a maximum likelihood classification applied to SPOT data. Land cover classes (1-12) are separated by means of the classification and are evaluated against four types of control data, codes A-D.

From this, it is evident that multiple diverse land cover classes combine to form single land use classes. Figure 2.3 shows the possible relationships between land cover classes and land use classes.

Table 2.1: The relationship between land cover and land use classes .

Code	Land cover class	Code	Land use class
1	Residential roofs	A	Residential
2	Paved surfaces	B	Industrial/Commercial
3	Industrial/Commercial	C	Agriculture
4	Open area	D	Unutilised land
5	Lawn and tree complexes		
6	Cultivated grass types		
7	Deciduous trees		
8	Evergreen trees		
9.	Crops		
10	New crops and pastures		
11	Fallow land		
12	Water surfaces		

Source: Gong, 1988



Source: Gong, 1988

Figure 2.3: The relationship between land cover classes and land use classes.

Lourens *et al* (1987: 15) see the poorer digital classification results obtained in the Robertson area as evidence of the 'human analyst's' superior ability to discriminate as opposed to that of the remote sensor:

> *"The human observer places a certain area of land into a particular land-use class dependent on the nature of the crop being grown there, irrespective of its stage of growth. The satellite on the other hand records only spectral response from the earth's surfaces."*

Authors like Lourens *et al* (1989), Zietsman (1982), Vlok (1988), Lourens (1990) emphasise the influence of diverse land cover classes in intensively cultivated agricultural areas. Lourens (1990) found that in certain agricultural areas in the Southwestern Cape that "the percentage vegetative cover had to exceed a certain threshold for a plant to be identified as vegetation". In the case of newly planted fields, the background medium has the greatest effect on reflectance. This often accounts for poorer classification results, when land cover is compared with land use control data.

In the eighties, the availability of high resolution multitemporal, multispectral SPOT and TM data, with its high volume of data, meant that cost-effectiveness (measured in terms of computer time and the cost of digital data) frequently became an issue. Consequently, the **selection of optimum band combinations** became a critical means of reducing the amount of data and the high dimensionality of satellite data.

Studies done by Karteris (1990), Conese & Maselli (1993), Chaves *et al* (1989), Chou Chen, Batista & Tardin (1986), Mausel, Kramber & Lee (1990), Khorram (1988), Lourens (1991) and Dorfling (1994) focus on the selection of optimal band combinations to attain even higher measures of accuracy in the classification, but with smaller quantities of data.

The following six band selection techniques were identified for use with SPOT and Landsat TM data:

i) Sheffield algorithm (Sheffield, 1985);
ii) Jeffreys-Matusita distance (Chen *et al*, 1986 & Mausel *et al*, 1990);
iii) Divergence (Mausel *et al*, 1990);
iv) Transformed divergence (Mausel *et al*, 1990);
v) Bahattacharyya distance (Mausel *et al*, 1990);
vi) Mutual information analysis (Conese & Maselli, 1993);
vii) Optimum Index Factor (Lourens, 1990).

Lourens (1990) used the Optimum Index Factor (OIF) and the Jeffreys-Matusita mean to determine the total variance in spectral reflectance for the respective irrigated classes within training areas. Various TM band combinations, with the 2-4-5, 2-4-5-7 and 2-3-4-5-7 combinations being seen as the most important, were statistically analysed and subjected to supervised parallelepiped classification in order to identify irrigated areas.

Lourens (1990: 70) viewed the four methods of supervised classification listed below as the most effective techniques of identifying irrigated areas with the aid of **Landsat TM**:

i) Supervised parallelepiped classification conducted on the best four band combination determined by means of the Optimum Index Factor.
ii) Supervised parallelepiped classification conducted on TM bands determined by means of the Jeffries-Matusita mean distance.
iii) Supervised parallelepiped classification of a colour transformed TM image, compiled from selective principal components analysis.
iv) Supervised parallelepiped classification making use of statistics obtained from modified unsupervised clustering.

The application of these methods showed that 70% accuracy had been attained with the TM data in the Mogol River Catchment Basin, Transvaal (Lourens, 1990). Certain crops which exhibit a high land cover, such as groundnuts and tobacco (between harvesting cycles), were classified 85-90% correctly. Overestimation and underestimation could chiefly be ascribed to varying agronomic practices within the study area.

Lourens (1990: 78) recommends the use of the following three techniques in identifying irrigated areas with the aid of **SPOT** data:

i) Supervised parallelepiped classification of the contrast enhanced image;

ii) Density slicing by means of the second principal component;

iii) Supervised parallelepiped classification of "the colour transformed, combined vegetation indices and Euclidean band image".

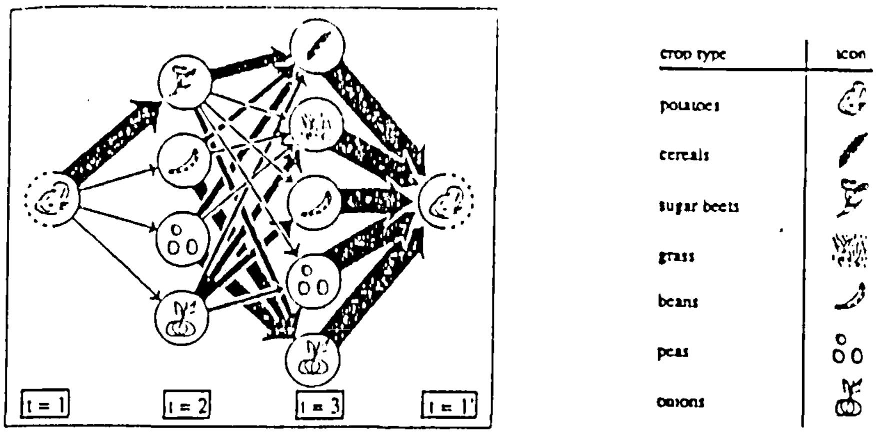
However, the results Lourens (1990) obtained using these techniques exhibited lower classification accuracy than the TM classification. This trend was ascribed to image capture late in the growth season, when the crops within the study area had already reached the drying stage.

Results of an experimental study done by Dorfling (1994) on optimum band selection strategies for multitemporal SPOT data, show that four of the six main band selection strategies identified the 2-3-6 band combination as the optimum band combination, which produced the best supervised classification results. The Sheffield algorithm is recommended as the best band selection strategy, because it is simple to apply, requires minimal computer processing time, and can be done on a personal computer.

Khorram *et al* (1988) considered 1-4-5-7, 3-4-5-7 and 2-3-4 TM band combinations as the optimum band combinations for multitemporal analysis of agricultural land cover in the Catania region of Italy, but they emphasised that "the waveband combination required to classify TM data is dependent upon the cover types to be classified" (Khorram, 1988: 202). Irrigated crop types (including cotton vegetables and maize) were 85% correctly classified using a supervised classification (maximum likelihood algorithm) of TM bands 2-3-4. Approximately 100 ground control areas were used during the study. A high measure of accuracy (90%-95% correct) was attained in the classification of other land use classes, such as wheat, fallow land and forestry areas (Nikolaos, 1988).

A study done by Trolier *et al* (1989) showed that mid-season vineyards in various New York districts could be identified with an 80% degree of accuracy, by using band selection (TM 2-3-4), followed by a supervised maximum likelihood classification.

Middelkoop and Janssen (1991) suggest a method of supervised classification which is based on temporal relationships between land use classes. Prior knowledge of crop rotation practices was gathered in the form of a matrix and empirically analysed to determine the temporal relationships. Figure 2.4 shows the transitional likelihood schema for a three year crop rotation cycle. The width of the arrows is a proportional representation of the transitional probability.

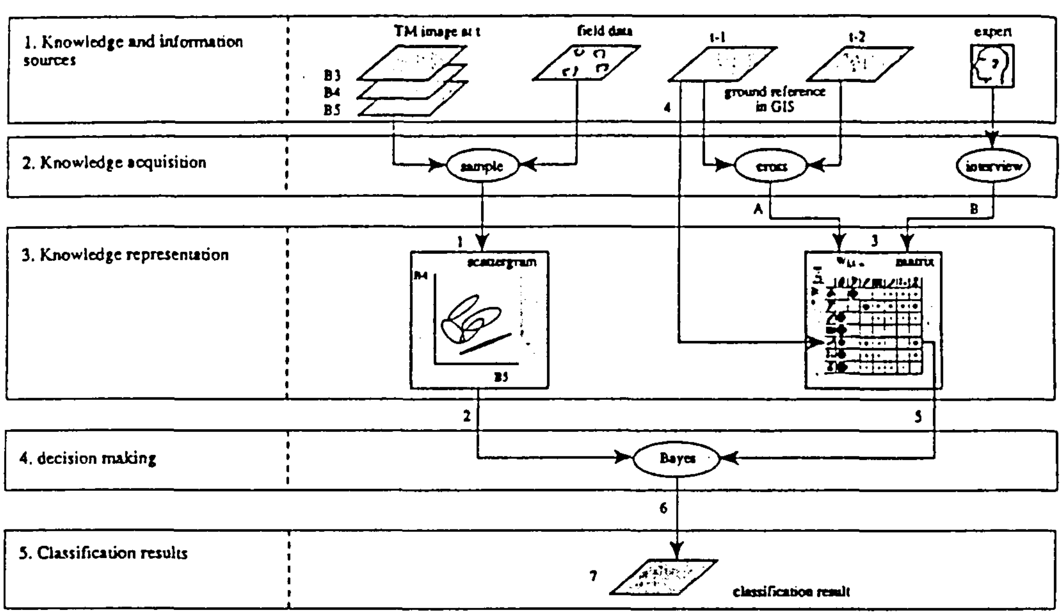


Source: Middelkoop & Janssen, 1991

Figure 2.4: The transitional likelihood schema for a three year crop rotation cycle.

Multispectral TM data, information stored in a Geographic Information System (GIS) and prior knowledge of crop rotation cycles are combined in a Bayes maximum likelihood classification. According to the Bayes decision rule every pixel is assigned to the class with the greatest likelihood value based on the Gaussian assumption (Prinsloo, 1991: 25). A schematic representation of the specific supervised classification procedures is given in Figure 2.5.

Results of the study done in the Netherlands displayed high percentages of classification accuracy (80%). According to the authors, this method of classification enhances the results by 4-20% as compared with classification results based purely on spectral information.



Source: Middelkoop & Janssen, 1991

Figure 2.5: Schema of classification procedure.

2.2.5.3.2 The application of unsupervised classification

During unsupervised classification, remotely sensed data is added to groups by a clustering algorithm (Barrett *et al*, 1982). The spectral data is divided into a pre-determined number of classes and then the computer allocates pixels in terms of the highest class membership likelihood. (PCI, 1988). Thus the classification process is controlled by predetermined statistical parameters. Lo (1986: 299) defines the unsupervised classification method as "the definition, identification, labelling and mapping of uniform spectral classes".

Unsupervised classification techniques are widely applied in the identification of land use types and irrigated areas (Azzali *et al*, 1990; Lourens *et al*, 1987; Lourens, 1990; Fukue *et al*, 1988; Maaren, 1985; Meyer, 1991). Fukue *et al* (1988) did an evaluation of the classification accuracy of various unsupervised classification methods utilised for TM imagery by comparing with results obtained from a conventional supervised classification. Six types of hierarchical clustering methods as well as minimum residual clustering were applied to TM data in order to identify specific land use/land cover classes. This study showed that clustering methods improved classification accuracies by approximately 6% points in comparison with a conventional supervised maximum likelihood analysis. This was particularly the case in intensively farmed agricultural areas in the area around Tokyo, Japan. This method is recommended for use as an alternative where intensive land use/land cover makes the selection of homogeneous "training sites" impossible.

Lourens (1990) applied hierarchical unsupervised classification methods successfully to TM data of the Mogol area to obtain statistics for classes representing actively growing vegetation. However, this method proved unsuccessful as a means of utilising SPOT data. Therefore Lourens (1990) does not recommend unsupervised classification of SPOT data as a means of identifying irrigated crop types.

Many authors consider it best to use **a combination of unsupervised and supervised classification methods** to identify irrigated areas and to quantify their extent (Moreton & Richards, 1984; Lourens *et al*, 1987; Azzali *et al*, 1990; Kolm & Case, 1984; Wall *et al*, 1984). This approach involves carrying out unsupervised clustering on representative heterogeneous subimages in order to determine spectrally separable features. Different areas are selected so that all land use classes are represented in the subimage. This makes it possible to determine important spectral class boundaries. The statistics of the different spectral classes in each of the subimages are determined. Once the derived spectral signatures have been linked with a land cover type, a minimum distance and maximum likelihood supervised classification is done on the entire image. In cases where spectral discrimination between irrigated land use classes can not be determined, the classes are regarded as a single land use class called "irrigated agriculture". (Lourens *et al*, 1987). The principle of extracting subimages (consisting of 512 x 512 pixels) which represent the major land use classes was applied throughout by Lourens (1990). "Techniques were tested on the sub-images and those found to extract irrigated areas well, based on a visual, qualitative assessment, were applied to the entire image" (Lourens 1990: 38).

Azzali (1990: 86) refers to the successful application of a two-phase approach to classification which focuses on the discrimination of crop clusters that exhibit the same growth patterns rather than the identification of individual crop types. An unsupervised classification was done on Landsat TM data to distinguish homongeneous crop groups. The statistical information on the dominant crop type in each of the homogeneous crop groups was then used in a maximum likelihood algorithm. This approach has a number of advantages for quantifying irrigated land by means of satellite data: "... this has implied for a given environment that the water requirement for each class of homogeneous fields can be accurately calculated by means of a crop coefficient which is actually 'canopy-dependent' and not 'crop dependent'" (Azzali, 1990: 98).

2.2.5.3.3 The application of regression analysis

Many authors like Redondo *et al* (1984), Bauer *et al* (1982) en Wall *et al* (1982) have combined supervised classification techniques with regression methods to estimate the extent of irrigation.

The main features of the study are summed up as follows by Lourens (1990):

i) Stratification of the study areas by means of visual interpretation of false colour composites;
ii) Random selection of strata areas to serve as training or control areas;
iii) Classification of the images and adaption of the classification result using a regression estimate.

Maximum likelihood classifications largely utilising statistics for the training areas are carried out. Then, the following equation is used throughout in the estimation of the irrigated area:

$$\hat{Y} = N * [\bar{y} + b(\bar{X} - \bar{x})]$$

where $\hat{Y}$ = estimate of the whole population;
$\bar{y}$ = sample mean of field data;
$\bar{X}$ = population mean of satellite imagery per N 'sample units';
$\bar{x}$ = sample mean of satellite imagery;
N = number of sample units within the population;
b = slope of the regression curve ($y = a + bx$).

The results of the study quoted above showed that there are significant differences in the estimation of areas when satellite data and survey data are used in independent calculations. Consequently the authors recommend that they be combined to attain high levels of accuracy.

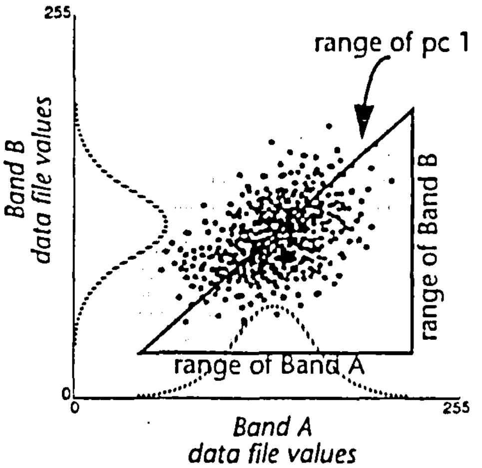
2.2.5.3.4 The application of principal components analysis

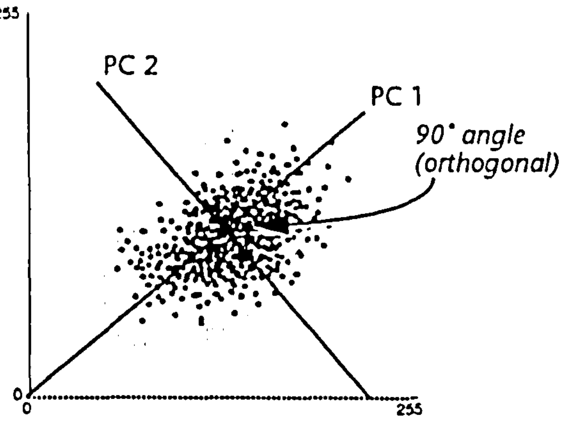
Principal components analysis (PCA) is a data reduction technique, which reduces the dimensionality of multitemporal multispectral satellite data to principal components, each of which contains a part of the total variation of the set of data. The process of principal components analysis is described in ERDAS (1991: 182) as:

> *"... a linear transformation performed on the data - meaning that the coordinates of each pixel in spectral space (the original data file values) are recomputed using a linear equation. The result of the transformation is that the axes in n-dimensional spectral space are shifted and rotated to be relative to the axes of the ellipse".*

Figures 2.6 and 2.7 provide simple graphic illustrations of the technique. Figure 2.6 (a two dimensional scatter diagram) shows the relationship between data values in both bands. In an n-dimensional histogram the ellipse (2 dimensions), becomes ellipsoid (3 dimensions) or hyperellipsoid (more than 3 dimensions), when the distribution profile of each of the bands is normal or near normal.

In a principal component analysis a new axis is calculated for the spectral space during orthogonal linear transformation, and new values are assigned to the points on the scatterplot, accordingly. The main axis of the ellipse is known as the **first principal component** (PC1), and exhibits the highest variance in the data (Figure 2.7). The **second principal component** (PC2) is defined as the vector with the largest diameter, orthogonal to the first principal component and describes the largest data variance which is not captured by the first principal component (Taylor, 1977 cited in ERDAS, 1994). An n-dimensional data structure is therefore defined by N principal components, of which the first three principal components comprise virtually 100% of the total variance in the data.





Source: ERDAS, 1994

Figure 2.6: Two Band Scatterplot. Figure 2.7: First and Second Principal Component.

The value of **principal components analysis** as a means of reducing large volumes of data to increase computer capacity and reduce processing time, has frequently been highlighted in the literature (Altamira, Baumgardner & Venezuela, 1986; Chavez *et al*, 1989; Haralick & Fu, 1983; Kateris, 1990; Singh, 1989; Williamson, 1989; Lourens, 1990; Meyer, 1991 en Dorfling, 1994). Principal components analysis has chiefly been the means of enhancing the image, where detailed land use patterns and surface structure can not readily be identified from the original data. Principal components analysis has also been applied to multitemporal data to identify patterns which relate to seasonal variations in land use (Singh, 1989).

Chavez *et al* (1989: 339), however, have identified a few drawbacks to the application of 'standard' principal components analysis: *"... two problems that can be encountered using the PCA method are that information of interest might be mathematically mapped to one of the unused components and that a colour composite can be difficult to interpret"* and suggest **selective principal components analysis** (SPCA) as a better alternative. During SPCA only highly correlated pairs of band (> 0,90), which are representative of the visual and infrared spectrums, are used as input. This results in a reduction of dimensionality, while the loss of information is minimised. (Chavez *et al*, 1989). Clustering bands in this way means that most of the variation during principal components analysis is encapsulated in the first component, as a result of the high level of correlation between the pairs of bands that are used as input.

Lourens (1990) succesfully applied SPCA to TM data and obtained principal components for each of the TM 1, 2, 3 and TM 5, 7 band clusters respectively. These principal components were combined with a contrast enhanced four band TM image in order to generate a new set of data. Colour tranformation, however, was first applied to the set of data (to create a colour image). Next, parallelepiped classification was done. According to Lourens (1990) this kind of supervised classification showed that irrigated areas could be identified as 'bright red' areas. Evaluation of the eigen-value matrix revealed that the first three principal components constituted 97,5% of the variation in the 1, 4, 5 and 7 TM bands. However, Lourens (1990) does not recommend the inclusion of the thermal band (TM 6) in SPCA, because the resultant classification can not separate irrigated crops from riparian vegetation.

Lourens (1990) found, as Tateishi en Mukouyama (1987) had done, that there is a high correlation in SPOT data between the first principal component and the sum of the three bands, as well as between the second principal component and the Normalised Vegetation Index (NDVI = (SPOT 3 - SPOT 2)/(SPOT 3 + SPOT 2)). According to the authors irrigated areas in the second principal component can be clearly defined within the threshold value of 200-255.

Quarmby & Townshed (1986) draw attention to the high correlation between individual spectral bands in SPOT data (cumulative percentages of 98,6%, 99,7% and 100% were determined for the multispectral SPOT set of data). Each of the bands have a high discrimination potential but it is said of band 2 in particular that *"... the infrared band provides unique information on the variability within vegetated areas"*.

2.2.5.3.5 The application of vegetation-indices

Campbell (1987: 384) defines vegetation indices as "quantitative measures, based upon digital values, that attempt to measure biomass or vegetation vigor". According to Meyer (1991), a **vegetation index** is a variable which is closely related to vegetation features. As the vegetation cover increases from 0% tot 100%, reflection in the visible part of the spectrum decreases, and the reflection of the near infrared (IR) waves will increase. This infrared and red (IR/R) ratio is a measure which is related to the amount of photosynthesis that is taking place in the vegetation.

The research shows that vegetation indices are mainly applied in two types of study. Firstly, the type of study which "... attempts to 'validate' the usefulness of vegetation indices (VI's), establishing that values of the VI's ... are closely related to biological properties of plants such as fractional vegetative cover, canopy density biomass and leaf area index (LAI)" (Campbell, 1987 en Samson, 1993). Secondly, vegetation indices are used as a means of mapping - more of a qualitative application: "Such applications use VI's to assist in image classification, to separate vegetated from non-vegetated areas, to distinguish between different types and densities of vegetation, and to monitor seasonal variations in vegetative vigor, abundance and distribution".

According to Moreton *et al* (1984) and Maaren (1985), vegetation indices are an effective means of identifying irrigated crops in a semi-arid area. An Infra-Red/Red Ratio has been successfully applied by both research teams to separate vigorous vegetation regarded as 'irrigated' areas from non-irrigated areas. According to Turner (1984), the same ratio has been used to distinguish winter grain crops in the Highveld from the surrounding area.

Meyer (1991) obtained a 60% measure of correctness utilising a Transformed Normalised Difference Vegetation Index (TNDVI = ((NDVI + 0,5)) * 0,5) to identify irrigated areas in the Wellington area. With the aid of ancillary data, this percentage was improved to 71%.

Wall *et al* (1984) and Menenti *et al* (1986) have used multitemporal applications, during which threshold values of the IR/R ratios per stratum for every growing season were obtained, to identify irrigated areas, as well as specific crop types that are being irrigated. The above-mentioned application is described as "The Greenness Vegetation Index" by Menenti *et al* (1986).

Lourens (1990) also experimented with the IR/R-Ratio, the Normalised Vegetation Index (NDVI) and the Transformed Normalised Vegetation Index (TNDVI) to distinguish irrigated areas from the surrounding vegetation in the Mogol River Drainage Basin. However, the attempt to determine irrigated areas by density slicing from the TM images was unsuccessful. This tendency was mainly ascribed to external factors like a period of high rainfall at the time of image capture. It was also not possible to determine unique threshold values for irrigated crops from the SPOT data, with the aid of the IR/R relationship. Lourens (1990: 45) found supervised parallelepiped classification of the combined vegetation indices (as recommended by Wall *et al*, 1984) and an Euclidean Band the most effective method of identifying irrigated areas with the aid of SPOT data.

2.2.5.3.6 The application of density slicing

According to Lourens (1990), density slicing on single bands is cited in the literature only in a few cases. In this technique, class limits are determined within the 0-255 series of values by means of which certain features are separated on the image. Pixels representing 'irrigated crops' could be extracted from the image in this way.

2.3.4 Criteria for the evaluation of classification results

Determination of accuracy, an essential step after image classification, employs various types of reference data:

> *"There are no set of formulae for what form of data have to be collected as surface reference data, neither when or where it should be collected" (Lillesand & Kiefer, 1979). These requirements are determined on a project-by-project basis in accordance with predetermined objectives. Surface reference measurements can be either qualitive recording of surface characteristics at selected field sites or quantitative radiometric measurements (Lourens, 1990). Qualitative information recorded in agricultural surveys include: field size, row direction, row spacing, crop height, crop colour, crop type, percentage land cover, planting and harvesting dates, irrigation practices, soil type and slope" (Williams & Poracsky, 1979; De Gloria, 1984; Lourens, 1990).*

The above information is, however, difficult to obtain and often dated. Robinson (1989) contends:

> *"Many of the problems encountered in both agricultural research and in rural development planning in general within the developing world arise primarily from a lack of accurate and up-to-date information. A common complaint has been that existing sources of information are incomplete, poorly organized or based on incompatible criteria".*

Hardy (1980) refers to various statistically-based sampling strategies of capturing reference data. **Purposive sampling** involves the selection of 'typical' cases. This method has the advantage of time and cost effectiveness, involves explicit siting and direct application of research data. There are a few disadvantages of purposive sampling such as subjectivity, doubts on representativeness and the absence of reliability estimates. **Random sampling** involves the application of simple random, systematic, stratified or multifaceted hierarchical sampling (Matthews, 1981).

Reference data is not absolute. Some of the factors to be taken into account include siting errors, ambiguous classes, the effect of scale and mapping size, boundary errors, as well as digital registration errors when digital reference data is registered to an image.

According to Lourens (1990), the most effective methods of determining acccuracy are the determination of errors of omission and commission. The Overall Accuracy, Mean Class Accuracy, Kappa Measure and the Jaccard Coefficient, are measures of association.

Lourens (1990) calculated the Jaccard coefficient for classifications that had been accepted on visual assessment of the sub-images and applied to the entire TM and SPOT images. The surface reference data were used to determine the Jaccard coefficient.
The Jaccard Coefficient (J) was calculated as follows:

$$J = \frac{\text{Positive Matches}}{\text{Positive Matches} + \text{Omission} + \text{Commission}}$$

where:

Positive	Matches	=	Number of hectares mapped in field survey correctly classified.
	Omission	=	Number of hectares mapped in field survey not classified.
	Commission	=	Number of hectares incorrectly classified.

There is increasing recognition of the importance of **ancillary data** in enhancing the accuracy of supervised classification results (Baumann & Greenberg, 1991; Steven, 1987 and Meyer, 1991). According to Meyer (1991: 11), the importance of ancillary data is that of using known information on an area in order to enhance the accuracy of classified results. This prior knowledge can be used to compile maps to be used as ancillary data. Meyer (1991: 12) refers to the application of two types of ancillary data: data on the spatial distribution of urban areas, as well as a map which shows the various soil potential classes for agricultural production in the study area. This data is used to enhance the classification accuracy, by correcting areas which have been incorrectly classified or supplementing information. Results of this study show that ancillary data can enhance the accuracy of the irrigated crop classes by 15%.

Baumann & Greenberg (1991) suggest three approaches to the joint use of ancillary data and spectral data to enhance supervised classification results: pre-classification scene stratification, classification modification and post-classification class sorting. This study by Baumann & Greenberg (1991) focused particularly on the role ancillary topographic data, such as height and slope, could play in enhancing classification results for the purpose of compiling an inventory of land use in the Catskill Region, New York: "Ancillary information such as topographic data is frequently incorporated into multi-spectral data sets as additional data channels and used in conjunction with spectral data". The authors refer to the approach as "postclassification class sorting built on the logical use of ancillary data."

2.4 SUMMARY

Chapter two provided a literature review to guide the research process. As an introduction satellite remote sensing and its applications to agriculture was presented briefly. Literature which focusses on the influence of external environmental factors and required resolutions in terms of temporal and spatial characteristics of satellite sensors for agricultural purposes are highlighted. Relevant international and local crop identification projects are discussed drawing specific attention to the effectiveness of SPOT XS and Landsat TM data for identifying irrigated crops. National and international journals were consulted in order to glean guidelines regarding choice of image processing techniques, selecting optimum spectral band combinations and multi-temporal analytical procedures. The chapter concludes with a review of studies employing ancilliary data in enhancing image classification accuracies.

Chapter three describes the methods used in gathering, capturing, and manipulating data for this research. It focusses on the data capturing processes, data types and functions of the GIS database.

CHAPTER 3: FEATURES OF THE DATABASE : TYPES, FUNCTIONS AND PROCESSING

3.1 INTRODUCTION

The key ingredient in the wise management of natural resources is **information** on the various components of the environment. "We know that the spatial databases we develop today will become the decision tools for tomorrow" (Hartgraves, 1991). In simpler times, one resource could be managed in isolation from the other and information needs were concomitantly simpler and easier to separate. But as population grows and demand for a diversity of resources increases, our understanding of the intricacies of our environment evolves. In this complex environment, we must have the means to collect, store and utilise the information that makes wise decisions possible. Our current information technology has a critical deficiency - the inability to reference and manipulate spatial resource data . A powerful tool is now available to cure that deficiency - **Geographic Information Systems** (GIS). The strength of GIS lies in it its ability to integrate data from a variety of sources and disciplines, such as remote sensing data, using a common geographical frame of reference. Current GIS applications range from simple inventory and query of spatially located objects, to map analysis based on geographic operations, to the support of complex spatial decision making (Ehlers *et al*, 1991; King, 1991; Dangermond, 1991).

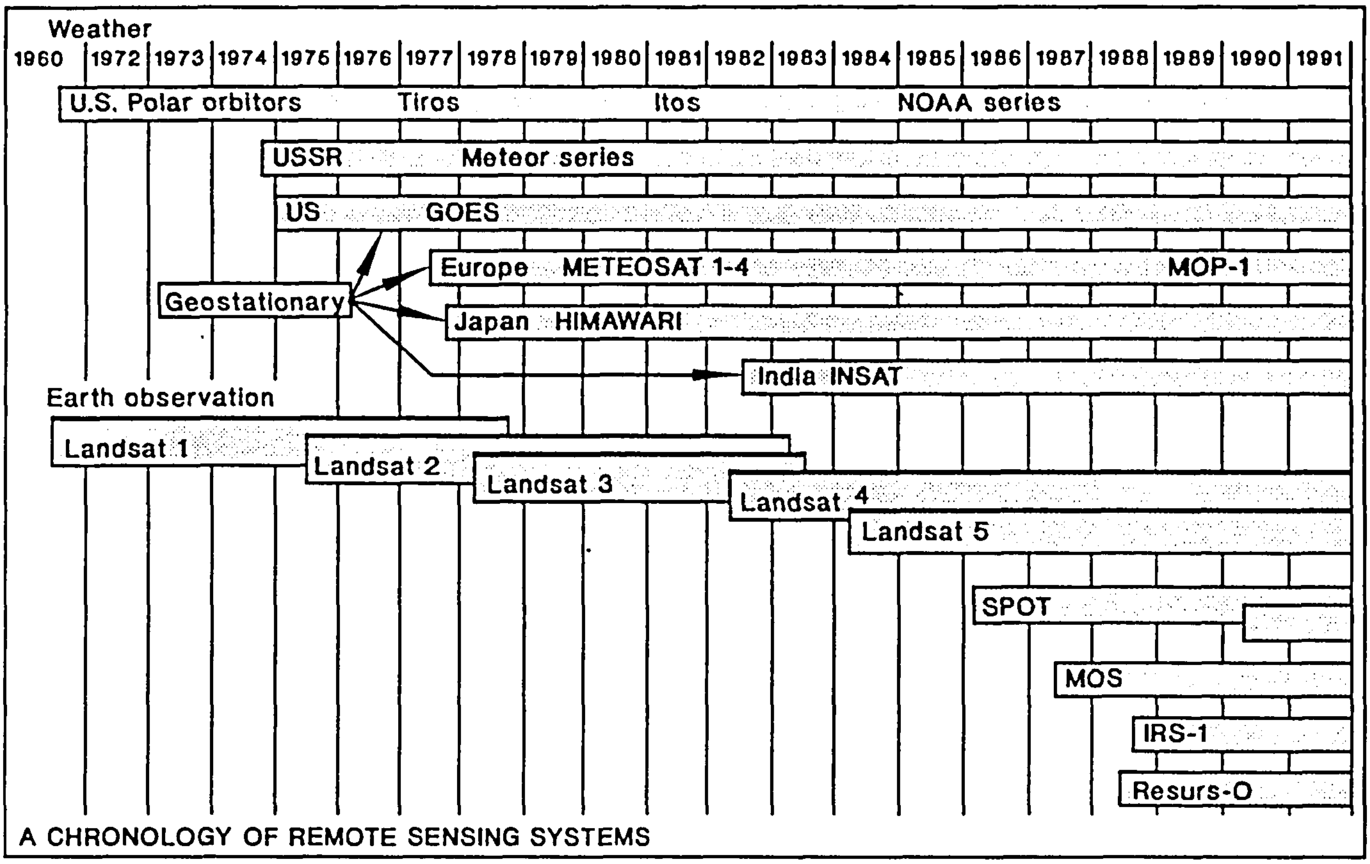
All data required for this research has a spatial component and can be manipulated within a GIS. A systematic spatial database was therefore required to provide baseline data for this study. A vector based Geographic Information System (Arc/Info PC and Workstation version 6.1.2) was used to compile a digital catchment database for the entire study area consisting of various data information overlays which were used in the study as ground truth and ancillary data. This database was used to support various analyses and to evaluate the results of the digital image classifications.

3.2 REVIEW OF EXISTING SATELLITE SYSTEMS

Since 1960 when the term 'remote sensing' was used for the first time by Evelyn Pruitt, satellite remote sensing has become an extremely powerful technique, particularly in the earth sciences (Van Rensburg, 1976). The limitations of the visible part of the electromagnetic spectrum were recognised at an early stage. However, technological breakthroughs made during the Second World War made it possible to extract useful information from other parts of the spectrum and to apply it (Lintz & Simonett, 1976). A new era of remote sensing dawned on 1 April 1960, with the launching of the remote sensing satellite TIROS-1 (Wolfaardt, 1983). This development gave man a new perspective of time and space in the study of features on the surface of the earth:

> *"From 1960 onwards, satellites have greatly enhanced our real-time spatial reach. Now one may see vast sections of the globe instantaneously, in real time"* (Calder, 1991).

The chronological development of the new era of satellite systems since 1960, is presented diagrammatically in Figure 3.1.



Source: Calder N, 1991

Figure 3.1: The chronological development of the 'new era' satellite systems since 1960.

Since then, as a result of the contributions made by the USA and USSR there has been steady development in spatial technology. Two types of satellite systems are delineated in Figure 3.1 namely geostationary satellites and sun-synchronic satellites. Each type is also briefly described.

Geostationary satellites are placed in a geostationary orbit above the equator and record a continuous supply of spectral data from the same place. *Weather satellites* such as the

European Meteosat, GOES-E, GOES-W (USA), GOMS (USSR) and GMS, alias Himawari, (Japan) as well as communication satellites like INSAT (India) are placed in this kind of orbit (Figure 3.1). The satellites are positioned at a height of ±36 000 km and orbits the earth once every day maintaining its predetermined position relative to a fixed point on the earth (Malan, 1991). Meteosat 4 (alias MOP 1), the latest in the series, was launched into space early in 1989. Positioned just above 0° longitude and latitude, it rotates at a rate of 100 revolutions per minute. Radiation is collected by the telescope of the optomechanical sensor by scanning the hemisphere from south to north every 30 minutes. Since February 1977, data have been collected from Meteosat by the CSIR's Satellite Application Centre (SAC) and passed on to the Weather Bureau.

Sun-synchronous satellites move along low orbital paths which vary in height from 750 to 850 km and provide detailed spectral data on features of the earth's surface. The three most common sun-synchronous satellites are the 'National Oceanographic and Atmosphere Administration' (NOAA) meteorological satellite, the American Landsat-series and the French SPOT satellites. The launching and use of Earth observation satellites like Landsat- and SPOT in the seventies and eighties brought a new dimension to remote sensing. Both these satellites move along sun-synchronous orbits i.e. the orientation of the orbital path to the sun is constant. Consequently, a satellite of this kind is always above a particular line of latitude at the same solar time. At every rotation, it will cross the equator at another longitude, as a result of the rotation of the earth (Malan, 1991).

3.3 PRIMARY DATA SOURCES: MULTISPECTRAL SATELLITE DATA

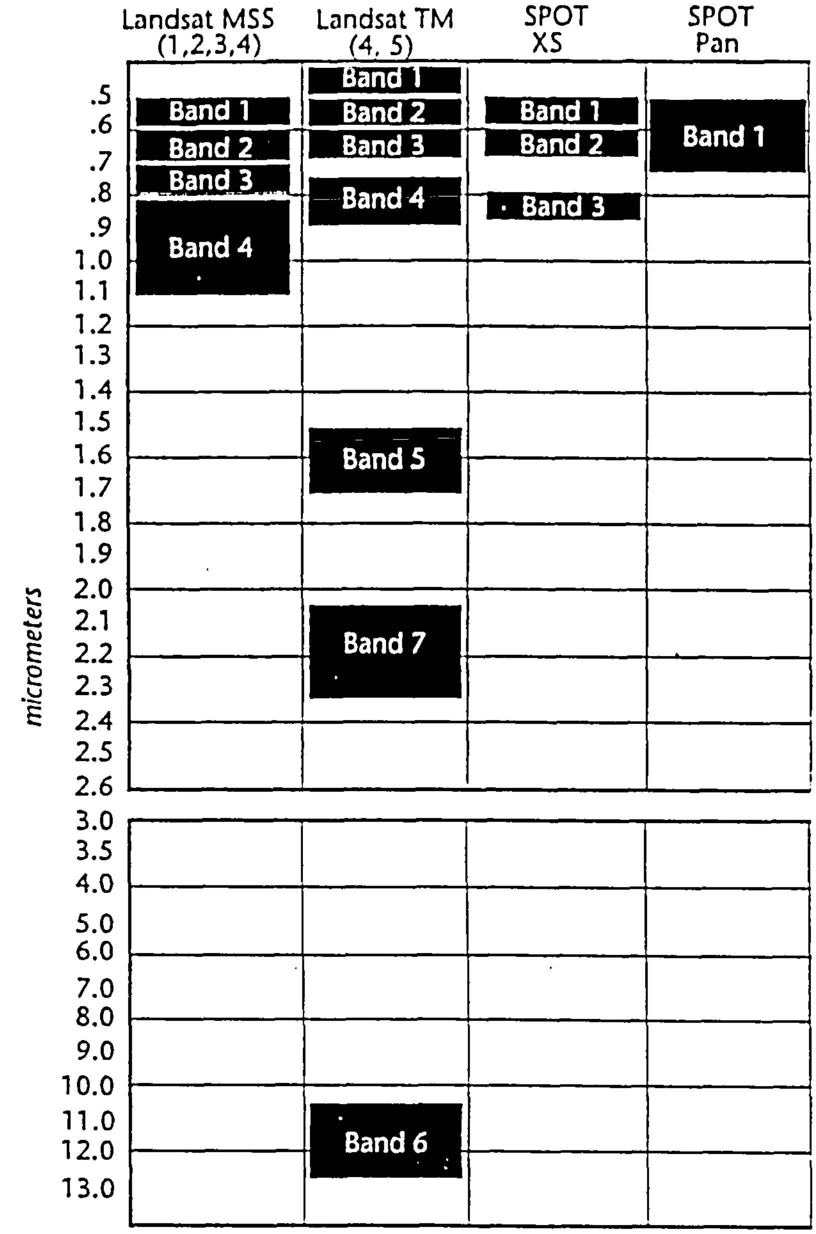
Since this study focuses on the use of data from Landsat TM and SPOT, more detailed attention will be paid to the features of these systems. At present, they constitute the chief source of digital data for studies of the earth's natural resources. Landsat and SPOT have the following features in common:

(i) Both satellite systems have sun synchronous orbits which mean that capturing of data on a certain place always occurs at the same local time.

(ii) Both satellite systems gather electromagnetic radiance in one or more spectral channels. Accordingly, data is simultaneously registered in multiple spectral channels which are known as multispectral images. Single band, monochrome images are termed panchromatic images.

(iii) Both scanners can produce nadir views. Nadir is the area on the ground directly beneath the scanners' detectors (ERDAS, 1991).

Figure 3.2 shows a comparison of the electromagnetic spectrum recorded by Landsat TM, Landsat MSS and SPOT. The data are described in detail in the following sections.



Source: ERDAS, 1991

Figure 3.2: Multispectral Imagery Comparison.

3.3.1 Characteristics of Landsat TM

In 1972, the National Aeronautics and Space Administration (NASA) initiated the first civilian program specializing in the acquisition of remotely sensed digital satellite data. The first system was called ERTS (Earth Resources Technology Satellites), and later renamed to Landsat. There have been several Landsat satellites lauched since 1972. Landsat 1, 2 and 3 are no longer operating, but Landsat 4 and 5 are still in orbit gathering data. Landsat 1, 2 and 3 gathered data with a Multispectral Scanner (MSS) and Landsat 4 and 5 collect data employing both a MSS and Thematic Mapper (TM) (Figure 3.2). TM data was used in this study and are thus discussed in more detail.

The thematic mapper (TM) is a multispectral scanning system much like the MSS, except that the TM sensor records reflected/emitted electromagnetic energy from the visible, reflective-infrared, mid-infrared and thermal-infrared regions of the spectrum. TM has higher spatial, spectral, and radiometric resolutions that MSS.

TM has a swath width of approximately 185 km from a height of 705 km and a repeat coverage cycle of 16 days - 233 orbits. The spatial resolution of TM is 28,5 x 28,5 m for all bands except the thermal band (band 6), which has a spatial resolution of 120 x 120 m. The larger pixel size of this band is necessary for recording an adequate signal strength. However, the thermal band is resampled to 28,5 x 28,5 m to match the other bands. The radiometric resolution is 8-bits, meaning that each pixel has a possible range of data values from 0 to 255 (Campbell, 1987). It is useful for determining vegetation type and health, soil moisture, snow and cloud differentiation, rock type discrimination, etc.

Detectors record electromagnetic radiation (EMR) in seven bands (see Figure 3.2):

(i) Bands 1 (Blue), 2 (Green) and 3 (Red) measure in the visible portion of the EM spectrum. They are useful for identifying cultural features such as roads but also show detail in waterbodies.

(ii) Bands 4 (Reflective-infrared), 5 (Mid-infrared) and 7 (Mid-infrared) can be used in discriminating between land and water.

(iii) Band 6 is in the thermal-infrared portion of the spectrum and is used for thermal mapping (Jensen, 1986; Lillesand and Kiefer, 1987).

Different combinations of the TM bands can be displayed to create different composite effects. The following combinations are commonly used to display TM images:

(i) Bands 3 (red), 2 (green) and 1 (blue-green) can be combined to form a true colour composite, approximately equivalent to a colour aerial photograph in rendition of colours. Experiments with other combinations have shown that bands 2, 3 and 5, 2, 7 and 4, and 4, 2 and 4 are also effective for visual interpretation (Campbell, 1987).

(ii) Bands 4, 3, 2 create a false colour composite. **False colour** composites look like infrared photographs where objects have different colours or contrasts as they would naturally. In an infrared image, vegetation appears red, water appears navy or black, bare soil blueish and so forth.

(iii) Bands 5, 4, 2 create a **pseudo colour** composite. In pseudo colour, features can appear in almost any arbitrary colours. For example, roads could be red, vegetation blue, and water yellow.

3.3.2 Characteristics of SPOT

The first "Systeme Pour l'observation de la Terre" (SPOT) satellite, developed by the French Centre National d'Etudes Spatiales (CNES), was launched in early 1986. The second SPOT satellite was launched in 1990 and the third was launched in 1993. The sensors operate in two modes, multispectral and panchromatic. SPOT is commonly referred to as a pushbroom scanner, meaning that all scanning parts are fixed and scanning is accomplished by the forward motion of the scanner. SPOT pushes 3000/6000 sensors along its orbit. This is different from Landsat which scans with 16 detectors perpendicular to its orbit.

The SPOT satellite can observe the same area on the globe once every 26 days. The SPOT scanner normally produces nadir views, but it does have off-nadir viewing capability. Off-nadir refers to any point that is not directly beneath the detectors, but off at an angle. Using this off-nadir capability, one area on the earth can be viewed as often as every 3 days (Campbell, 1987).

This off-nadir viewing can be programmed from the ground control station and is quite useful for collecting data in a region not directly in the path of the scanner or in the event of a natural or man-made disaster, where timeliness of data acquisition is crucial. It is also very useful in collecting stereo data from which elevation data can be extracted.

The width of the swath observed varies between 60 km for nadir viewing and 80 km for off-nadir viewing at a height of 832 km (Jensen, 1986, after ERDAS, 1991).

SPOT actually has two pushbroom scanners on board and can operate in either a panchromatic or a multispectral mode. SPOT Panchromatic (meaning sensitive to all visible colors) has 10 x 10 m spatial resolution, contains one band with a spectral width of between 0,51 to 0,73 μm - which is similar to a black and white photograph. With its radiometric resolution of 8 bits 256 gray levels can be recorded (Jensen, 1986, after ERDAS, 1991).

SPOT XS, or SPOT multispectral, has a 20 x 20 m spatial resolution, 8-bit radiometric resolution, and records in three spectral bands (Jensen, 1986, after ERDAS, 1991). Table 3.2 lists their characteristics and utility.

Table 3.1: Spectral bands recorded by Landsat TM.

Band	Wavelength μm	General Applications
TM1	0,45-0,52	**Visible blue:** Useful for discriminating between soil and vegetation, identifying forest subtypes, mapping man-made phenomena and differentiating in shallow water areas.
TM2	0,52-0,60	**Visible green:** Good for mapping healthy vegetation and cultural features.
TM3	0,63-0,69	**Visible red:** Very good for differentiating between plant species, demarcating soil and rock type formations as well as cultural features.
TM4	0,76-0,90	**Reflective-infrared:** Used for measuring vegetative biomass, crop mapping and emphasizing land and water contrasts.
TM5	1,55-1,74	**Mid-infrared:** Can be used to discriminate between clouds, snow and ice, but also very useful for measuring moisture stress in drought studies or plant health analyses.
TM6	10,40-12,50	**Thermal-infrared:** Good for studies of thermal pollution orgestermal activities, but also used in crop stress analyses.
TM7	2,08-2,35	**Mid-infrared:** Many geological applications, especially for differentiating eological rock types and soil boundaries, but also useful to determine soil and vegetation moisture content.

Adapted from ERDAS, 1991

Table 3.2: Spectral bands recorded by SPOT XS.

Band	Wavelength μm	General Applications
1	0,50-0,59	**Green:** May be used to map the reflectance of healthy vegetation.
2	0,61-0,68	**Red:** Useful for mapping different plant species and demarcating soil and geological boundaries.
3	0,79-0,89	**Reflective infrared:** Very good for measuring the amount of vegetation biomass present in a scene and thus useful for crop mapping.

Source: ERDAS, 1991

3.4 SATELLITE IMAGERY USED IN THE STUDY

For the purpose of multitemporal image processing, an attempt was made to capture imagery on each of the seasons. However, the availability of seasonal imagery was complicated by weather conditions. No cloud-free SPOT XS imagery was available for the spring season. It later emerged that the SPOT XS autumn imagery was also not cloud-free as had been initially indicated by the Satellite Application Centre. Another disappontment lay in the fact that the last 200 lines of the SPOT XS summer image had not been successfully captured by Hartebeeshoek as a result of technical problems. This meant that the southernmost part of the study area was not included in the image. This smaller image therefore determined the southern boundaries of the other five images. Figure 3.3 shows the study area. There were no problems in the case of LANDSAT TM imagery and four images, representing each of the seasons were obtained.

In total, two SPOT XS and four Landsat images were purchased which reflected the temporal trends in the study period. Table 3.3 could be used for reference purposes and for the identification of the imagery.

Table 3.3: Imagery purchased for the study.

Satellite: Instrument	SPOT HRV 1		LANDSAT TM			
Acquisition date Season	92/08/13 Winter	93/01/13 Summer	92/04/12 Autumn	92/08/18 Winter	92/10/05 Spring	93/01/25 Summer
Identification Scene:						
Path	119	119	175	175	175	175
Row	417	417	83	83	83	83
CCT ID	4680	4674	3575	4699	4698	4970
Tape format	SISA BIL 6250	SISA BIL 6250	ESA BIL 6250	ESA BIL 6250	ESA BIL 6250	ESA BIL 6250

The choice of image data and the capturing date were determined by seasonal growth trends of the crops in the study area. An attempt was made throughout to obtain data representative of the 'peak' season for the analysis of multitemporal imagery. The temporal relationship between the capturing of satellite data, the gathering of ground truth data (fieldwork period) and the irrigation period in the area is shown in Table 3.4. This indicates a close correlation between the crop irrigation period in the study area and the LANDSAT TM spring and summer images, as well as the SPOT summer image and the field survey.

Table 3.4: The temporal relationship between the capturing of satellite data, the gathering of ground truth data and the irrigation period in the study area.

Duration of Study	1992													1993	
	Summer			Autumn			Winter			Spring				Summer	
	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec	Jan	Feb
Capturing of satellite data:															
SPOT XS				not available						not available					
Landsat TM															
Gathering of ground truth data															
Irrigation period in the study area															

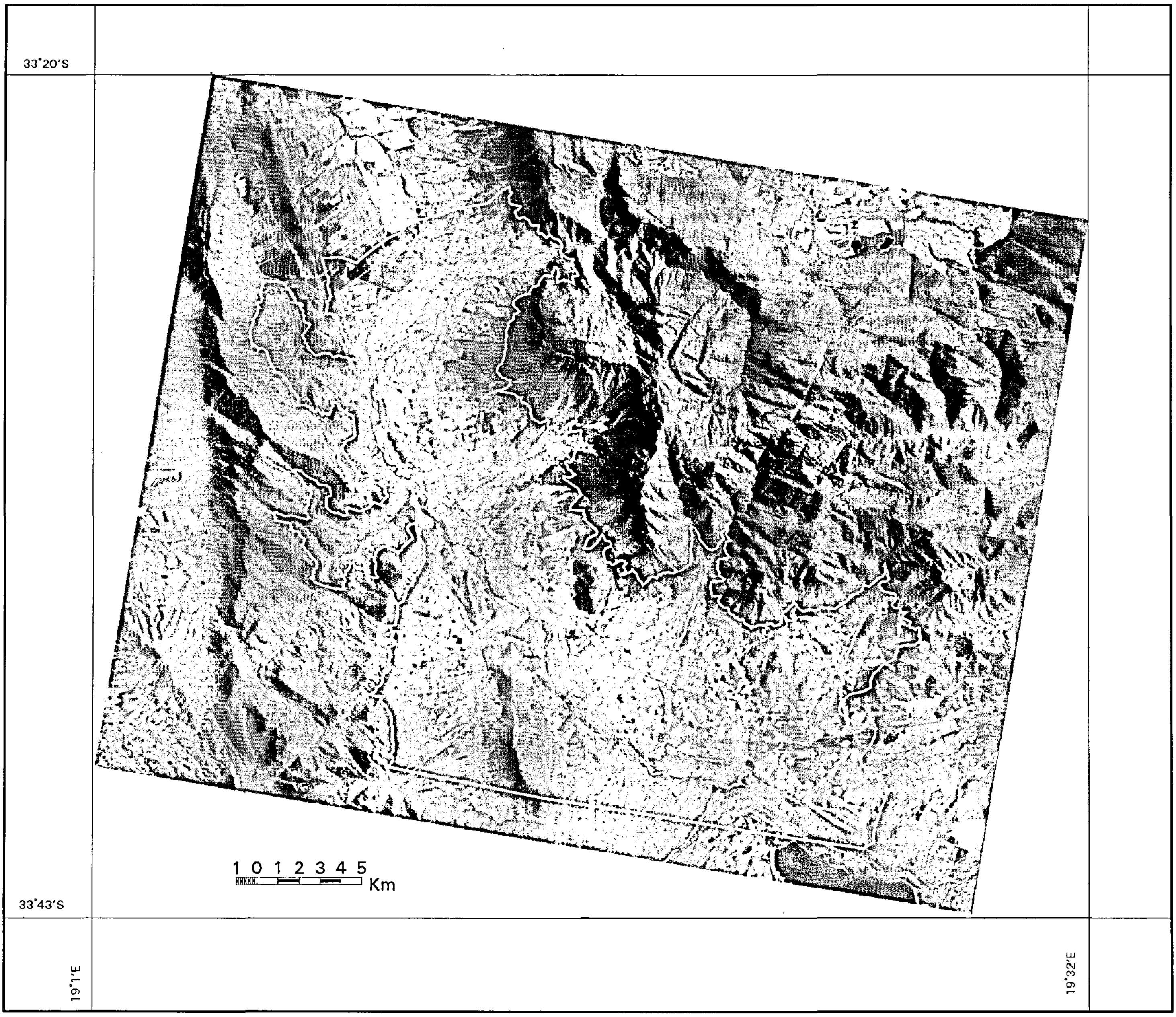


Figure 3.3: Landsat TM image showing the location of the study area.

3.4.1 Preprocessing of data

Unprocessed satellite data is influenced by electronic, geometric, mechanical and radiometric distortions resulting from sensor defects, the motion of the satellite and variations in the topography (Malan, 1990).

In order to determine the 'true' value of the radiance or reflectance of an objects on the surface of the earth or to construct a reliable image of this, these disorting effects have to be reduced by means of data processing, where it is not possible for engineers to exclude them through systems design. The methods which can be used depend on the way which the analyst intends processing the imagery in order to extract the information.

All standard Landsat and SPOT images produced by the Satellite Application Centre (SAC), which were used during the study, were systematically corrected, to correction level 5 in order to eliminate the negative effects of rotation of the earth, non-uniform shutter speed, panoramic distortion, distortion of the curvature of the earth, varying row lengths and aspect ratio on the radiometric and geometric accuracy of the data.

SPOT and LANDSAT TM correction level 5 image data used during the study was thus radiometrically and geometrically corrected. Geometric corrections were applied in both the along-scan and across-scan directions using spacecraft orbital and attitude information. The scene was also corrected to a map projection, but the orientation was not changed. See Table 3.5 for a complete picture of the preprocessing procedures which were carried out at the Satellite Application Centre.

In the case of the LANDSAT TM data, the images were projected geometrically to the Gauss Conform Projection on the 19° East longitude by applying a nearest neighbour resampling technique, with the aid of the Erdas Imagine system. This had to be done so that the vector overlays of the ancillary data taken from the Arc/Info GIS could be registered on this.

3.5 CREATION OF A GIS-DATABASE

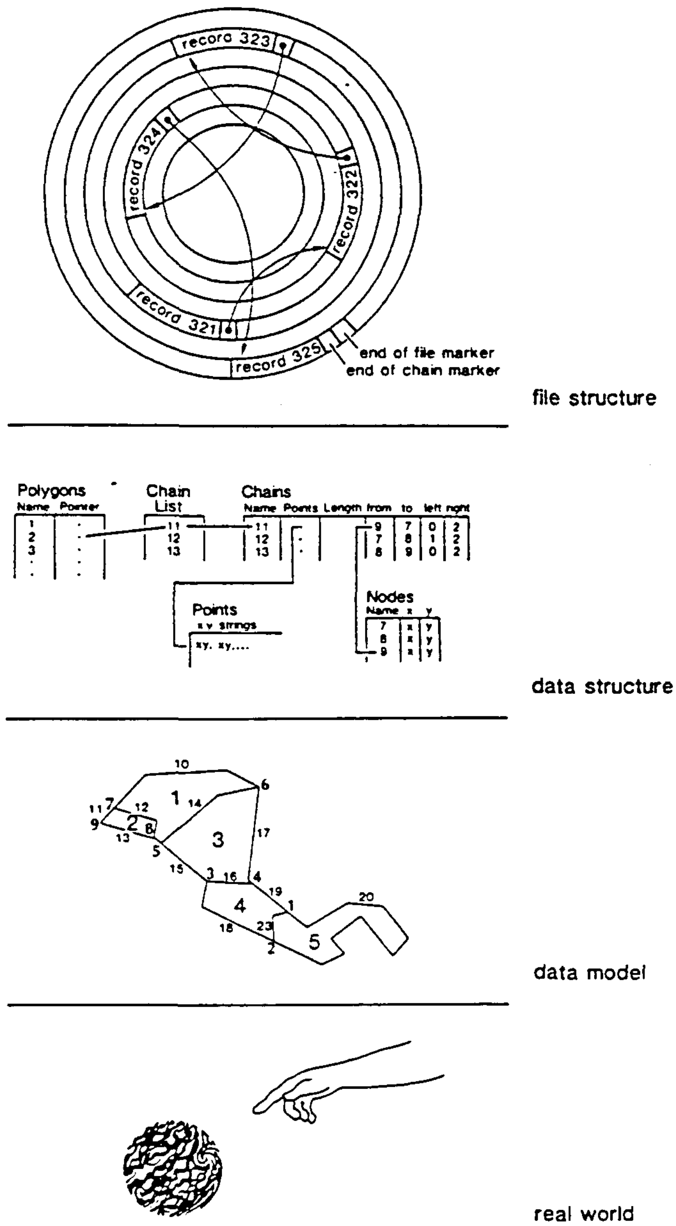
3.5.1 Data model of a GIS

Digital data relating to geographic reality has to be viewed on various levels for manipulating it effectively using a computer. These levels vary from reality on the one hand via abstract conceptualisation to computer orientated storage structures on the other (Zietsman 1993).

Table 3.5: Summary of systematic corrections made by the data provider

Id Satellite	SPOT 1	SPOT 2	Landsat 5	Landsat 5	Landsat 5	Landsat 5
Instrument	HRV 1	HRV 1	TM	TM	TM	TM
Mode	X	X				
CCT ID	4680	4674	3575	4699	4698	4970
Tape Format	SISA BIL 6250	SISA BIL 6250	ESA BIL 6250	ESA BIL 6250	ESA BIL 6250	ESA BIL 6250
Identification Scene:						
Path	119	119	175	175	175	175
Row	417	417	83	83	83	83
Shift	0	0	0	0	0	0
Acquisition Date	920813	930113	920412	920818	931005	930125
Season	Winter	Summer				
Correction Level	5	5	5	5	5	5
Statical calibration	N	N	Y	Y	Y	Y
Haze Removal	N	N	N	N	N	N
Sun Angle Correction	N	N	N	N	N	N
Resampling Code	D	D	C	C	C	C
Map Projection	MTZ 2	MTZ 2	MTZ 2	MTZ 2	MTZ 2	MTZ 2
Orientation	H	H	H	H	H	H
Deconvolution	N	N				
Pixel Size	20	20	30	30	30	30
Scene Centre Coordinates:						
Latitude	-33.42	-33.39	-33.94	-33.94	-33.94	-33.94
Longitude	19.35	19.33	18.73	18.76	18.79	18.74
Line Number	1499	1500	2903	2903	2900	2900
Pixel Number	1598	1638	430	430	435	441

Peuquet (1990) distinguishes four levels: reality, data model, data structure and file structure (Figure 3.4).

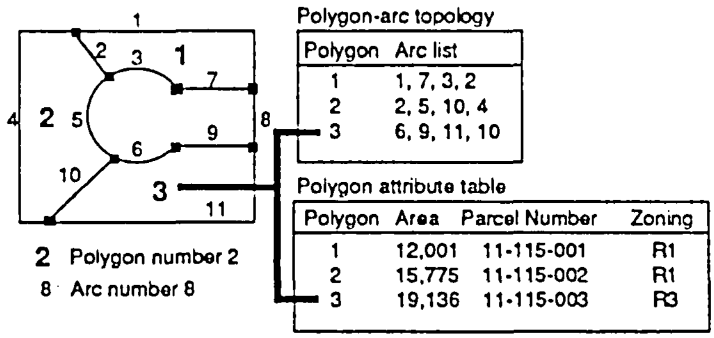


Source: Peuquet, 1990

Figure 3.4: Levels of data abstraction.

The data model on which a specific computer system is based is a conceptualisation of the way in which entities are defined and incorporated in the database (Kriel, 1993). Thus a data model is a conceptual framework which governs the ordering of entities and attributes within a database. In addition to the rules which govern the entities and defines their relationship with each other, the data model establishes the processes and analyses which can be done.

Arc/Info coverages and grids use a georelational data model. This is a hybrid data model that combines spatial data and attribute data in coverages or grids. Descriptive data are stored in Relational Database Management System tables (RDBMS), and are associated or related to spatial features via the feature ID (see Figure 3.5). Other models used in Arc/Info include tins, images and the relational model for tabular data.



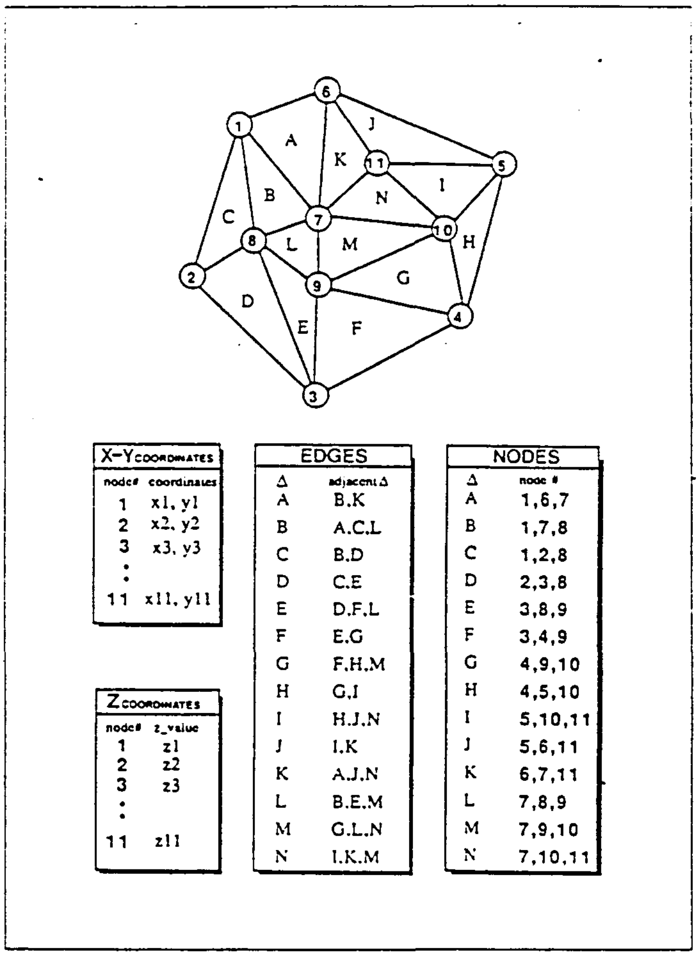
Source: ESRI, 1991

Figure 3.5 The Arc/Info georelational model.

A **tin** (triangulated irregular network) is a representation of a surface, derived from irregularly spaced sample points and breakline features. The tin data set includes topological relationships between points and their proximal triangles. Each sample point has an x, y coordinate and a surface or z value. These points are connected by edges to form a set of non-overlapping triangles that can be used to represent the surface (Figure 3.6). Tins are also called irregular triangular mesh or irregular triangular surface models.

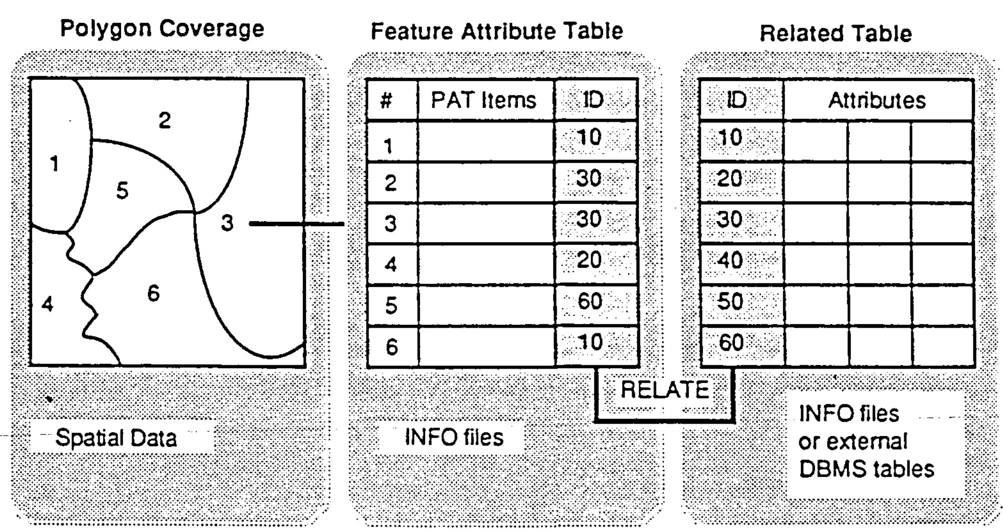
An **image** is a graphic representation or description of an object that is typically produced by an optical or electronic device. Common examples include remotely-sensed data such as satellite data, scanned data and photographs. An image is stored as a raster data set of binary or integer values representing the intensity of reflected light, heat, or another range of values on the electromagnetic spectrum. Remotely-sensed images are digital representations of the earth.

In a **relational database**, data are structured in the form of sets of records so that relations between different entities and attributes can be used for data access and transformation (Figure 3.7).



Source: Aronoff, 1989

Figure 3.6 The structure of a TIN.



Source: ESRI, 1991

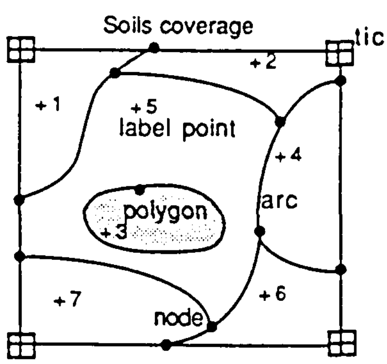
Figure 3.7 A relational database structure.

Three main concepts drive geographic database design in Arc/Info:

(i) *Geographic objects* which are real-world phenomena you wish to represent, such as soil types, agricultural regions, towns and rivers.
(ii) Logically organized groups of geographic objects called layers or *themes*, as defined by the user.
(iii) Feature classes and *attributes* of geographic objects.

A GIS database stores spatial and non-spatial information for particular entities in its database. In the case of Arc/Info these collections are called a coverage. The geographical entities for which data can be entered are classified as points, lines and polygons. All three entity types are represented in the present study. Rainfall stations and soil sampling points from which data was obtained for the study provide examples of point features. Rivers, contours and rainfall isolines are represented by lines, whereas soil types, slope, land use types and agricultural regions are instances of polygon features.

As described earlier, a **coverage** is the primary means of storing and representing geographic features in Arc/Info. A coverage consists of topologically linked geographic features and their associated descriptive data stored as an automated map (Figure 3.8). Coverages are georelational; thus, attribute tables are a major component in the GIS database. Coverages and corresponding attribute tables also serve as important sources of data from which most other geographic sets in the database are derived.



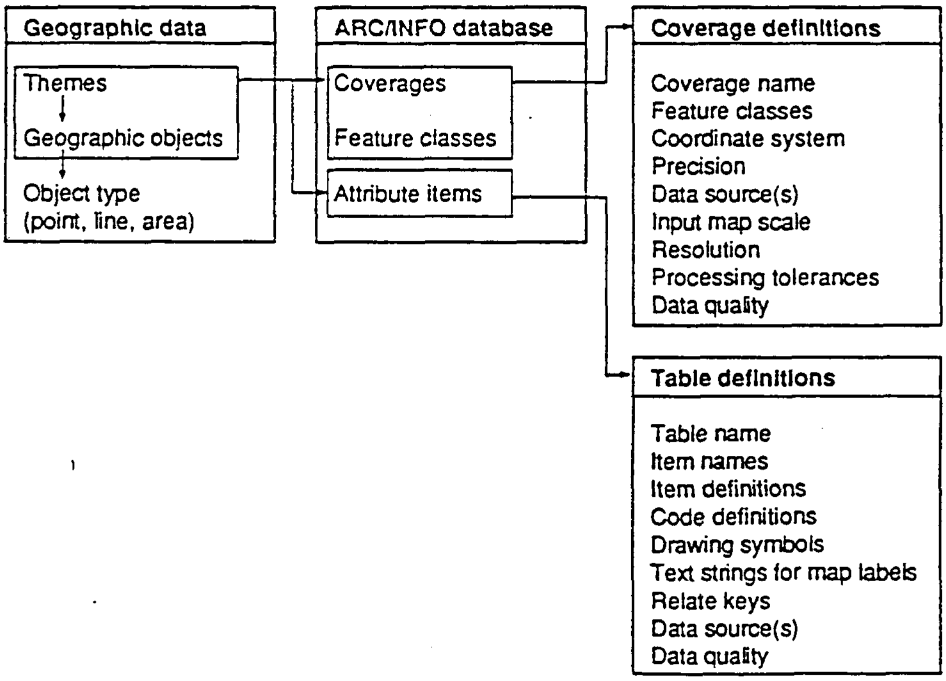
Soils attributes

ID	Soil	Class	Suitability
1	A3	113	HIGH
2	C6	95	LOW
3	B7	212	MODERATE
4	B13	201	MODERATE
5	Z22	86	LOW
6	A6	77	HIGH
7	A1	117	LOW

Source: ESRI, 1991

Figure 3.8: The structure of the coverage data model.

The structure of the coverage data model implies that there are a number of important aspects in automation and maintenance: defining a coordinate system, digitizing coordinates, creating feature topology, building feature attribute tables, and associating attributes with corresponding coverage features (ESRI, 1991). Coverages provide a basis for representing themes or logical collections of real-world geographic objects. Maps represent themes containing objects such as weather stations, land use units and rivers, as points, areas or lines. These and other themes are presented in this study using coverages and corresponding coverage feature classes. As shown in the diagram below, coverage database design defines both the spatial data components as well as the attribute components.



Source: ESRI, 1991

Figure 3.9: Summary of components to be defined for a coverage database.

3.5.2 Collection, storage and registration of data

In this phase of the study, the data were collected and captured. These data formed the basis on which the classification results of the image processing were refined with ancillary data at a later stage and evaluated by means of ground truth data.

The GIS on which the database was created was Arc/Info Version 3.4 D. The system operated on a 386 PC with 80 Mb hard disk and a VGA colour monitor. This system had been effective for initial data capturing, but processing time was slow. The data was then transferred to a 486 PC with 1 Gigabyte hard disk where further data processing and overlay analysis were carried out. This system adequately handled the data volumes involved in the project and imposed few restrictions. The final coverages were then transferred to a Sun Workstation with 32 Mb of memory and 10 gigabytes of disk space, using the UNIX operating system (SUNOS 4.1.2 and Openwindows 3.0). The TIN and GRID modules of Arc/Info Ver. 6.1.2 enabled spatial data modelling and integration of geographic data with classified remotely sensed data. Final maps and image plots were generated from this system.

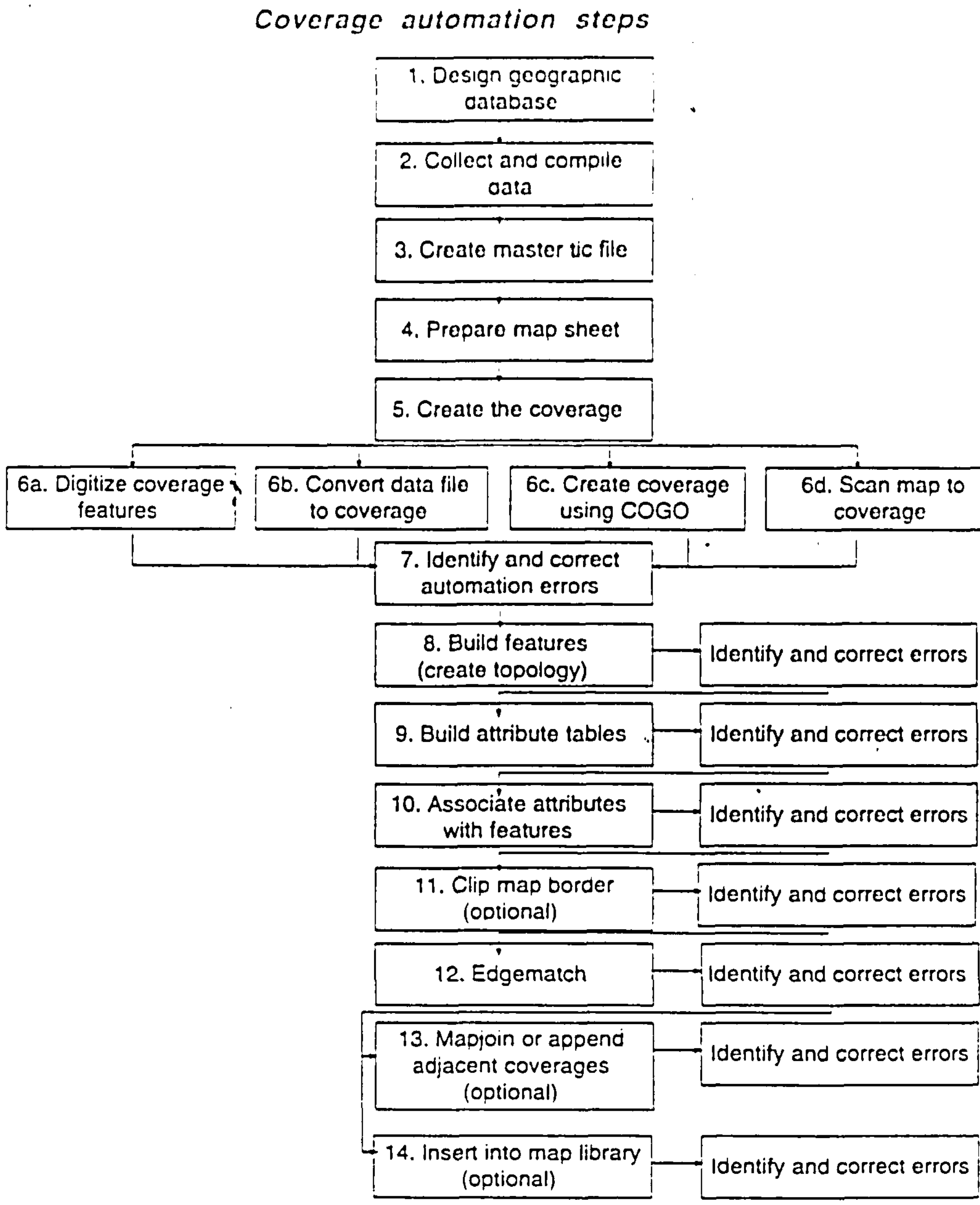
The initial GIS analysis and design was a straightforward process of identifying what geographic themes and attributes were required. Each theme and its attributes were kept as an entirely separate layer in a geo-referenced GIS structure. This allowed for composite layers to be constructed as required, while the base themes remained unchanged. When a geographic theme was identified for inclusion in the GIS, it was captured and stored in the GIS. The data themes used in this study and their source are listed in Table 3.6. The full data dictionary for all geographic data is listed in Addendum A.

Where paper maps were available, information was manually digitized in the relevant projection and the digitized data were then cleaned and edited. In cases where there was a large amount of attribute information, for example soil types, the information was typed into text files. The text files were then imported into INFO data files using TABLES to produce lookup tables. Additional file attribute information, such as the data on irrigation practices on the selected farm units, were joined through a relate-item to the coverage attribute tables, in TABLES by means of the JOIN command.

The process of coverage design and automation that was followed throughout the GIS database design process is summarized in Figure 3.10.

Table 3.6: Geographic themes included in GIS database.

Geographic Theme	Name	Data Type	Unprocessed Data Source
Elevation Contours	contours	line	1:50 000 topographic maps scanned and vectorized by the Department of Water Affairs and Forestry
Selected Farms	farms	polygon	Maps at various small scales from the Department of Agriculture/Personal Information : Individual Farmers
1:50 000 scale map grid	topogrid	polygon	1:50 000 topographic maps from the Chief Directorate: Surveys and Land Information
1:10 000 scale map grid	orthogrid	polygon	1:10 000 orthophotos from the Chief Directorate: Surveys and Land Information
Soil types	soils	polygon	1:50 000 data from the Resources Development Division: Elsenburg, Department of Agriculture
Mean Annual Rainfall (Weather stations)	rainfall	point	Digital data from the Resources Development Division: Elsenburg, Department of Agriculture
Land-use	breemap	polygon	1:50 000 aerial photography and 1:10 000 orthophotos from the Chief Directorate: Surveys and Land Information with Field verification 1:10 000 scale
Drainage regions South-Western Cape	wkaapstr	polygon	Digital data (1:50 000 scale) from the Department of Water Affairs and Forestry
Rivers	rivers	line	Digitized from 1:50 000 topographic maps. Chief Directorate: Surveys and Land Information
Upper Breede River drainage region	catch	polygon	Digital data 1:50 000 scale from the Department of Water Affairs and Forestry
Agricultural Subregions	regions	polygon	Digitized from 1:50 000 scale topographic maps. Chief Directorate: Surveys and Land Information
Towns	towns	point	Digitized from 1:50 000 scale topographic maps. Chief Directorate: Surveys and Land Information



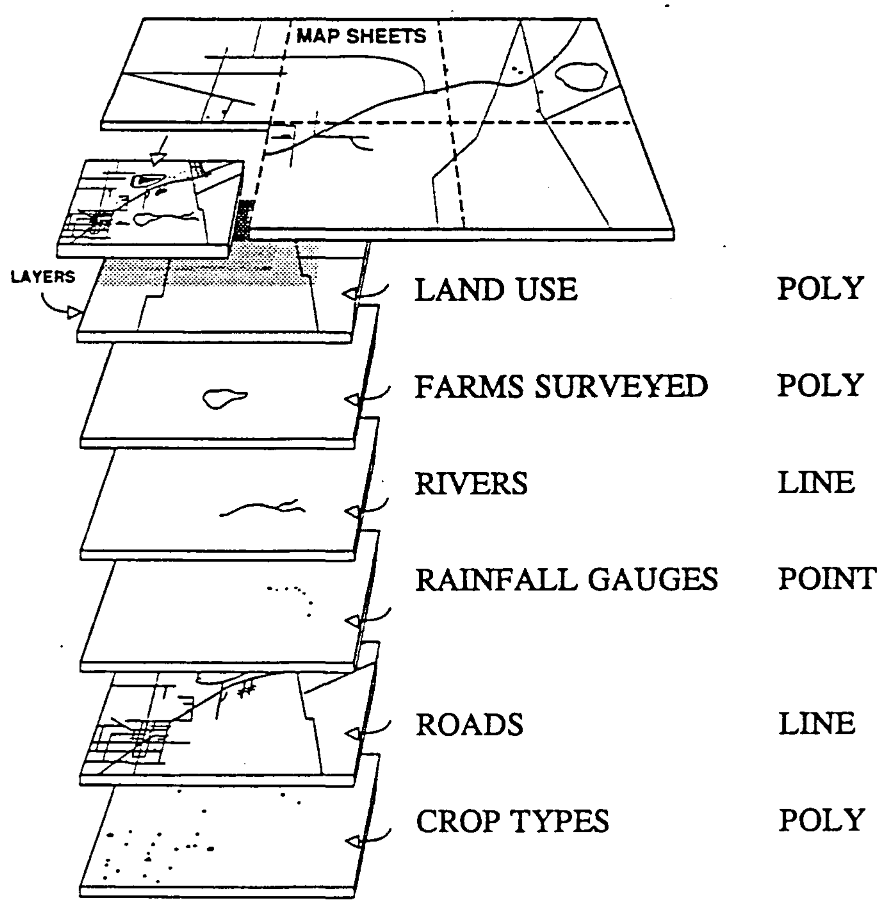
Source: ESRI, 1991

Figure 3.10: Coverage automation steps as used in this study.

The first stage, database design consisted of three major steps: identifying the geographic features, attributes and data layers required; defining the storage parameters of each attribute and ensuring coordinate registration. A master ground control (tic) file was created for the project region to provide base map registration for all layers in the GIS database (Figure 3.10). Data automation followed with the digitizing and/or convention of data from other systems (see Steps 6a-6d) to automate the necessary maps. Then the spatial data were made usable by verifying and editing errors and the creation of topology (see Steps 7 and 8). Before the analysis could be done it was necessary to enter all the attribute data needed for the project, and associate the attributes with spatial features (see Steps 8-10). The final stage of managing the database consisted of converting digitized coverages into real-world coordinates, joining adjacent coverages and maintaining the database.

3.6 THE PROJECT DATABASE

The GIS database used in performing overlay analysis and integration with image data are schematically outlined in Figure 3.11. The database consists of different data layers or themes, where each coverage represents thematic data for the Upper Breede River Valley.



Adapted from ESRI, 1991

Figure 3.11: Schematic representation of the project database.

The GIS database compiled for the refinement of the results of the image classification consists mainly of two types:

(i) GIS data which served as ground truth

(a) Data representing the *current generalized agricultural land use patterns* for the entire project study area.

(b) Data representing *detailed agricultural land use patterns on 22 selected farms* in the project study area.

(ii) GIS-based **ancillary data** used as secondary data sources:
   (a) Data which was representative of the *soil types* in the area and
   (b) *Contour data* for the study area.
   Ancillary data gathered to provide supporting information was used in the study to supplement classifications of areas so that 'incorrect classification' could be corrected.

3.6.1 Ground truth data

In order to create a basis for the subsequent evaluation of satellite image classification, ground truth data had to be gathered on current agricultural land use patterns.

3.6.1.1 Current agricultural land use patterns

Current land use patterns were established from 1:50 000 aerial photographs (Job 911, May, 1987) which were enlarged to a 1:30 000 scale. A transparent film overlay was affixed to the eleven photographs which covered the whole study area and the boundaries of the respective crop types was indicated on these. The predominant land use categories were vineyards, orchards, cultivated pastures (mainly lucerne, oats and grass), wheat, vegetables and natural veld.

The land use boundaries were transferred to orthophotos on a 1:10 000 scale (Dated 1982). Since there had been a five year elapse of time since the aerial survey was done, the land use information had to be verified by means of field checks. During the visits, additional information was gathered on the crops that might influence the spectral reflectance of individual cultivated parcels. This included aspects such as the age of the vines, the presence of trellises and any other factors which would make the parcel "different" from the neighbouring parcels.

One crucial factor in determining the success of land use and land cover mapping lies in the choice of an appropriate classification scheme. A good classification scheme should be easy to use with no ambiguity in defining each land use and land cover category (Lo, 1986: 228). The design of the land use and land cover scheme could take either a functional approach (activity orientated) or a morphological approach (which emphasizes land cover with the use of terms such as arable land, grassland, woodland etc.). With reference to Anderson (1971), Lo (1986) suggested that "... the activity-orientated or functional approach would be more appropriate as a general-purpose classification scheme for use with aerospace imagery."

The 1976 USGS land use and land cover classification system, one of the most widely used classification systems used with remotely sensed images, was adopted for this study. Table 3.7 indicates the land use and land cover classification system on which land use mapping of the Upper Breede River was based.

Table 3.7: Land use and land cover classification system used with satellite data: Upper Breede River Valley

Level I	Level II	Item Code LU1	Level III	Item Code LU2
1. Urban or built up	Residential Farmstead	r f		
2. Agriculture	Vineyard Orchards Vegetables Cereals: wheat, rye, oats	v b v pc	Young vines Bush-trained vines Trellissed vines Young orchards	yv btv tv yo
3. Natural pasture	Natural fynbos Natural bush, riparian growth	v bs		
4. Forest	Plantation	p		
5. Water area	River, channel, canal Dam	r d		
6. Bare ground	Natural bareground, sand Fallowland	 bg fa		

Source: Adapted from Lo, 1986

The above system as adopted for the Upper Breede River Valley has many useful features. First, it is prepared specifically for use with remotely sensed imagery. Its categories are appropriate for information interpreted from aerial images, and it has a hierarchical structure that lends itself for use with images of differing scales and resolutions. Level I (Table 3.7), is tailored for use with broad-scale, coarse-resolution imagery (Landsat imagery or high-altitude aerial photography). Levels II and III are composed of more detailed classes that could be interpreted from large-scale, fine resolution images (Table 3.7). These categories have been used as a framework for the more detailed level III classes. Level III categories were defined by the analyst to meet specific requirements presented by the need to detail the complexity of agricultural land use within the area.

The land use information referred to above was digitized with the aid of the Arc/Info geographic information system (Figure 3.12). Attribute information for Level II and III land use classes were coupled to the polygon overlay as Land use I (LU1) and Land use III (LU2), respectively (Addendum A).

3.6.1.2 Extent of irrigation and -practices on selected farming units

With a view to quantifying the extent of irrigation in the study area, the decision was made to identify farms in the study area where the current irrigation practices and the extent of irrigation could be used to:

(i) evaluate the results of the image processing; and
(ii) calculate irrigation conversion factors per crop type, to provide a basis for the eventual quantification of the demand for irrigation water.

3.6.1.2.1 Selection of farming units

On the advice of an irrigation technician attached to the Worcester office of the Department of Agriculture, the decision was made not to select farms by means of random selection techniques. The reason for this decision was that it was important to select farmers with managerial systems that could provide reliable information.

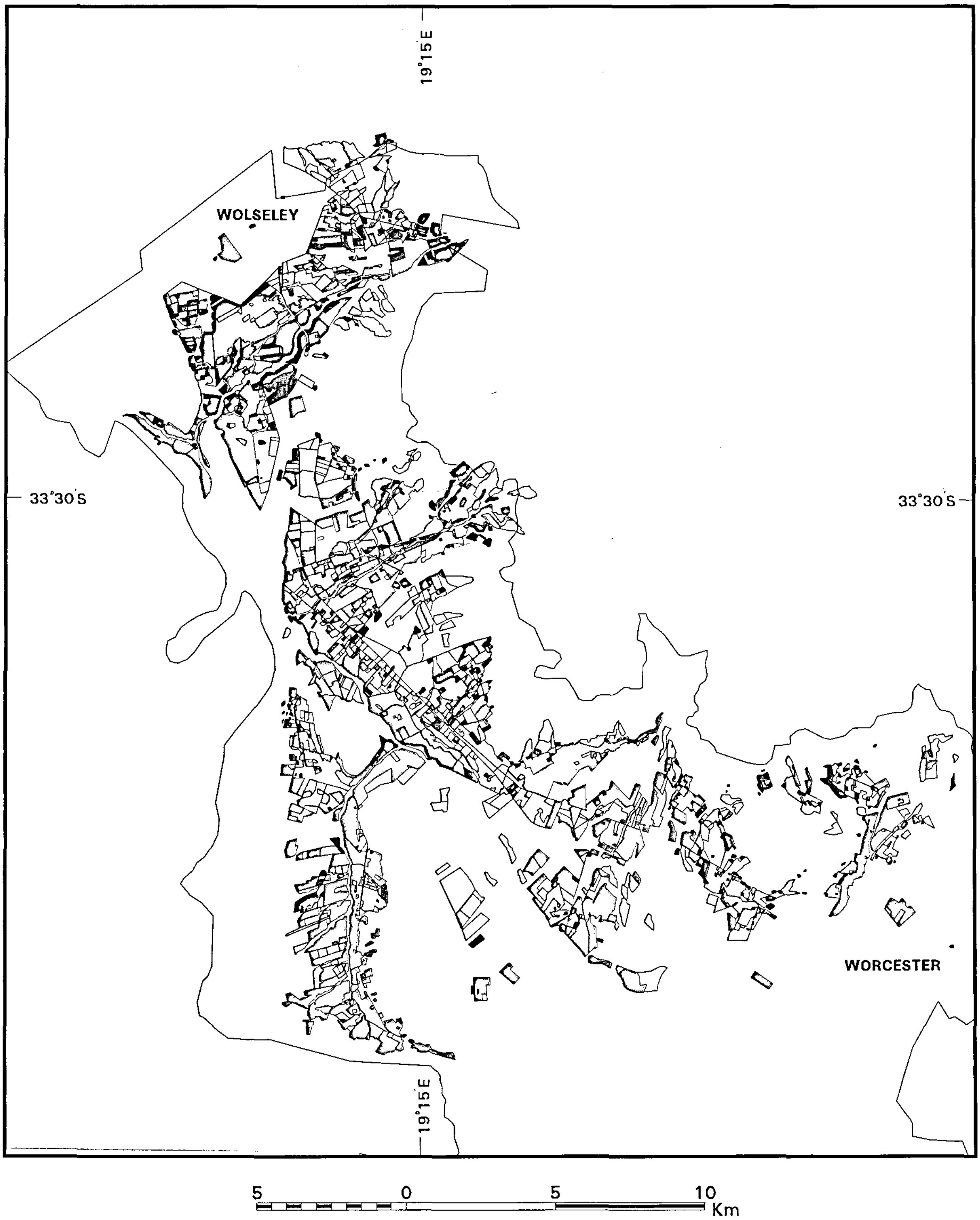
Based on his knowledge of the area, the technician divided the total study into five subsections: Slanghoek, Breede River, Goudini, Worcester and Wolseley (Figure 1.6). Although the delineation was not strictly scientific in the sense that it was not done according to measured climatic parameters, differences in the respective subsections can be ascribed to the adaptations made by the farmers in response to particular climatic environments. Four to six farms, which had a good spatial distribution within each of the farming subsections, were selected. A total of 21 farms, which could be regarded as representative of the various farming and irrigation practices in the study area, were finally identified.

In order to quantify the extent of irrigation, it was necessary to obtain the present boundaries of each of the 21 farms. However, certain problems were experienced because only the historical farm boundaries were available for many of the farms at the respective agricultural information offices (Worcester and Ceres). Farmers had to be asked personally

BREEDE RIVER
PROJECT

Figure 3.12

LAND USE
UPPER BREEDE RIVER VALLEY



IGA

URBAN	VEGETABLES	WATER
VINES	CEREALS	FALLOW LAND
ORCHARDS	PASTUREE	MAJOR FARMING AREA UPPER BREEDE RIVER VALLEY

to delineate the farm boundaries on 1:10 000 scale orthophotos. These boundaries were then digitized by means of Arc/Info (Figure 1.6).

The selection of farming units was, therefore, focused to a large extent on the likelihood that the owner/manager would have the necessary irrigation statistics. These statistics were obtained by means of personal interviews during a survey on the selected farms.

3.6.1.2.2 Questionnaire survey

A survey was conducted on the selected farming units in order to obtain the necessary information on current irrigation trends and associated farming practices. The survey was primarily aimed at establishing which crops were cultivated during the period for which satellite data was available (February 1992 to January 1993), which farming units were irrigated during this period and what the seasonal irrigation pattern looked like (Table 3.4). With this information it was possible to determine the mean volume of irrigation water utilized on a monthly, seasonal and annual basis per crop type per surface area. An example of a completed questionnaire is provided in Addendum B.

During the survey, the initial 1:10 000 scale land use information for each of the selected farming units was refined. The data was digitized using Arc/Info in order to create a farm data overlay (Figure 1.6). Attribute data (Questionnaire data in dBase format) was then linked with each of the land parcels to create a complete database for GIS overlay manipulation and analysis. See Addendum A for a complete picture of the items in the farm database.

3.6.2 Secondary data sources: GIS based ancillary data

In this study, ancillary data made it possible to use prior knowledge on soil types and contour data to improve the final image classification results. GIS-based polygon overlaying and querying techniques make it theoretically possible to refine the classified satellite imagery that had been obtained so that obvious errors could be eliminated.

For the purposes of this project, efforts were made to obtain two types of ancillary data, namely soil data and contour data.

3.6.2.1 Soil types

The requirement for data on soils rests on the assumption that as a background medium soils have an important influence on the reflectance values of pixels and that certain crops will tend to be cultivated on particular soil types.

Boundaries of soil types were digitized from 1:50 000 scale soil maps obtained from the Worcester branch of the Department of Agriculture. The maps cover the same area as that of the following 1:50 000 topographic map sheets: 3319 AC Tulbagh, 3319 AD Ceres, 3319 CA Bainskloof and 3319 CB Worcester. Figure 3.13 depicts the distribution of different soil types in the Upper Breede River Valley.

Additional information pertaining to colour, depth and irrigation potential was also needed in order to select polygons that showed unique soil properties. A pedologist from the Department of Geography at Stellenbosch University prepared an irrigation potential map for the study area. Attributes related to irrigation potential such as soil depth and colour were linked to the polygon coverage (Addendum A). A lookup table was created for categorizing the detailled information to a number of generalized classes (Table 3.8).

Table 3.8: Lookup table for categorizing soil polygons.

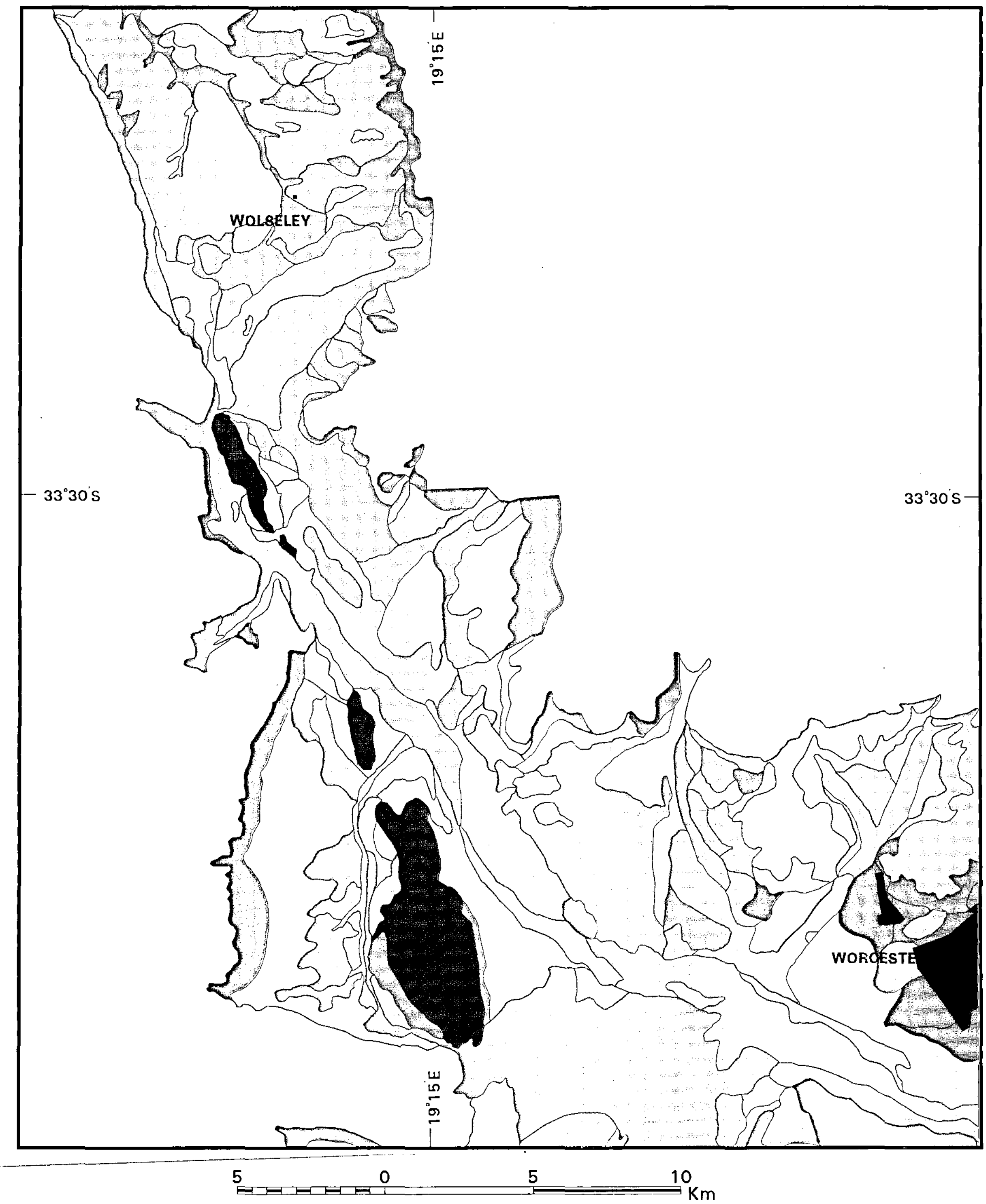
Colour	Code	Depth	Code	Irrigation-potential	Code
Light grey	1	Shallow	1	Low	1
Grey	2	Moderate	2	Medium	2
Dark grey	3	Deep	3	High	3

Source: Schloms, 1994

Using the assigned codes the RESELECT command in Arc/Info was used to separately extract soils of low, medium and high irrigation potential for integrating with the Gem Junior image data. Theoretically intensively irrigated crops should not be found on soils with a low irrigation potential. Figure 3.14 presents the irrigation potential of soils in the Upper Breede River Valley. More attention is devoted in chapter 4 to the integration of this data for refining image classification results.

BREEDE RIVER PROJECT

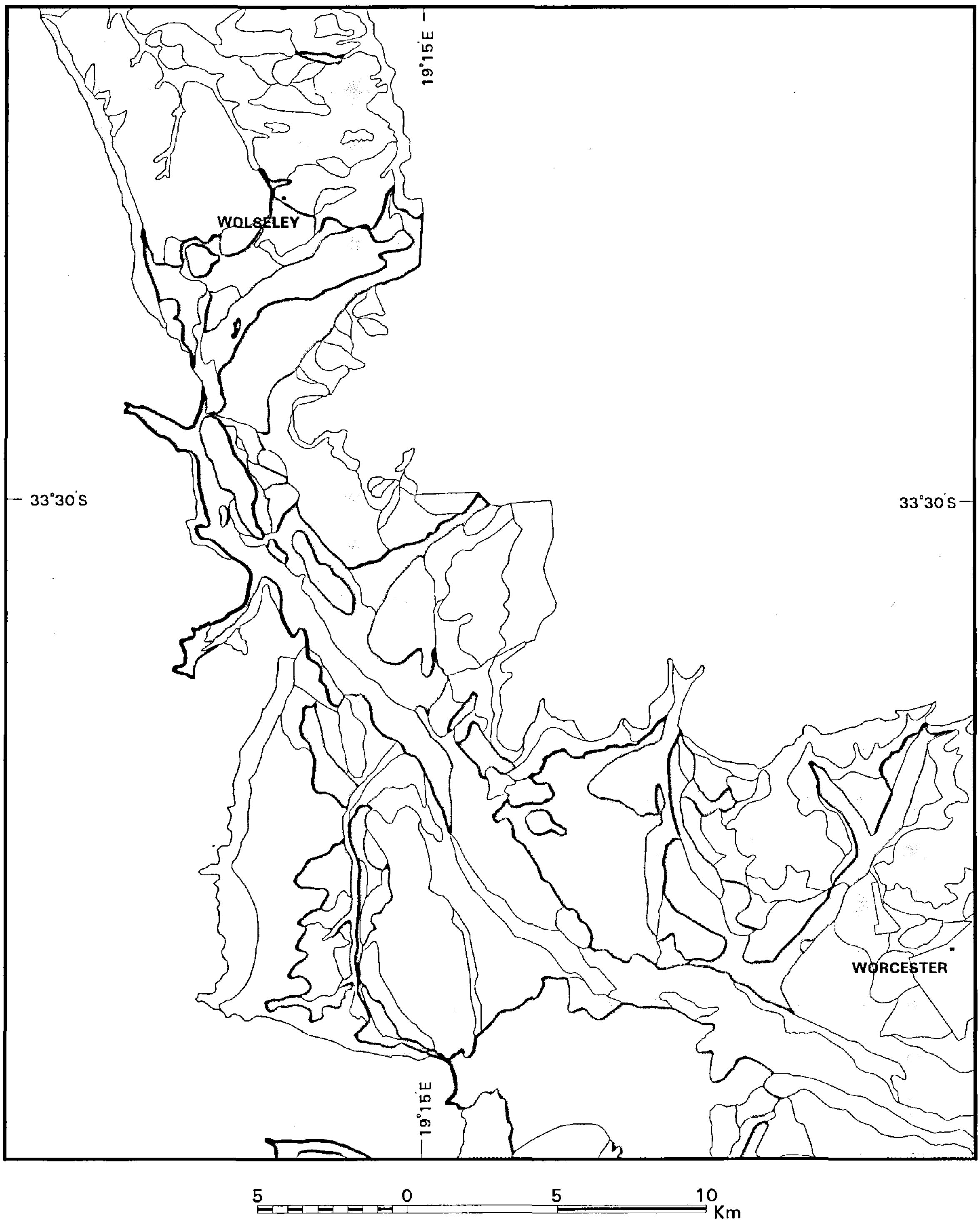
Figure 3.13 SOIL TYPES UPPER BREEDE RIVER VALLEY



IGA

BREEDE RIVER PROJECT

Figure 3.14 SOIL IRRIGATION POTENTIAL UPPER BREEDE RIVER



IGA

LOW IRRIGATION POTENTIAL

MEDIUM IRRIGATION POTENTIAL

HIGH IRRIGATION POTENTIAL

3.6.2.2 Relief

Digital contour data is viewed as an important medium of ancillary data since the appearance and distribution of the different irrigated crops are related to associated altitude parameters such as gradient and aspect. Contour data for the study area was obtained from the Chief Directorate: Surveys and Land Information for 1:50 000 topographic maps 3319 AC Tulbagh, AD Ceres, CA Bainskloof and CB Worcester.

The Department of Water Affairs and Forestry undertook to scan and vectorize the contour data, so that it could be used for computing slopes. This data was also projected to the Gauss Conform Projection with a central meridian of 19° East, by making use of the Clarke 1880 spheroid.

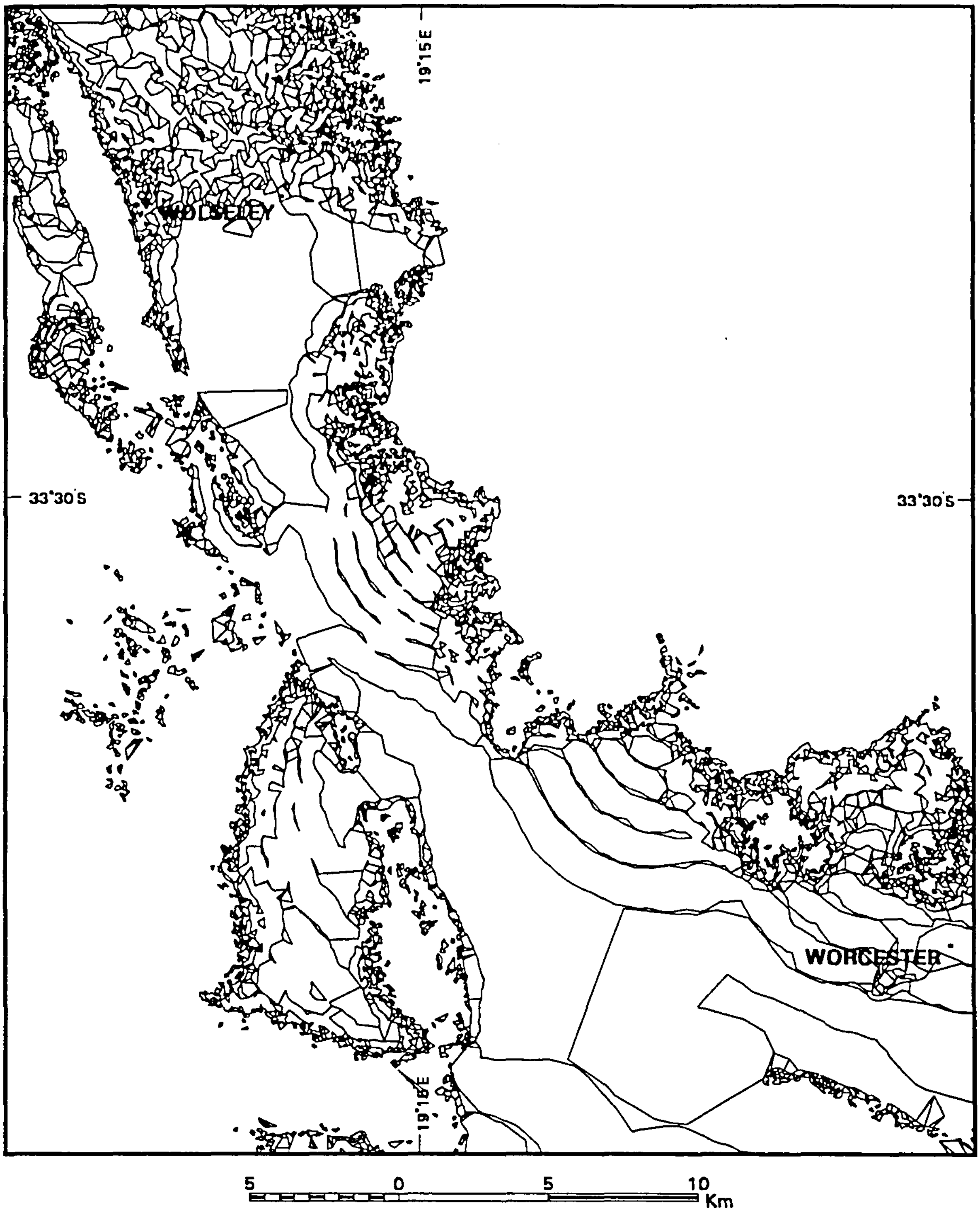
Further surface modelling was done using the Arc/Info TIN (Triangulated Irregular Network) module. TIN has suitable software for surface modelling, analysis and representation. A TIN was created from the digital contour line overlay with the CREATETIN command, after which it was transformed to a polygon overlay with the aid of TINARC (Figure 3.15). Attribute values for percentage slope, aspect and area were calculated during TINARC for each of the polygons. Consultation with the Division of Soil Conservation at Elsenburg revealed that a 20-25% slope is viewed as critical with regard to the cultivation of crops in the area. The next step, therefore, was to create on five slope classes for the study area. In order to create these classes, boundaries between adjacent polygons falling within the same slope class were removed with the aid of DISSOLVE and small polygons were eliminated by means of ELIMINATE. The final slope classes are shown in Table 3.9.

Table 3.9: Slope classes calculated for the study area.

Item name: Percentage-slope %	Slope classes
1-5	class 1
6-10	class 2
11-15	class 3
16-20	class 4
20-25	class 5

BREEDE RIVER PROJECT

Figure 3.15 SLOPE SURFACE MODEL UPPER BREEDE RIVER VALLEY

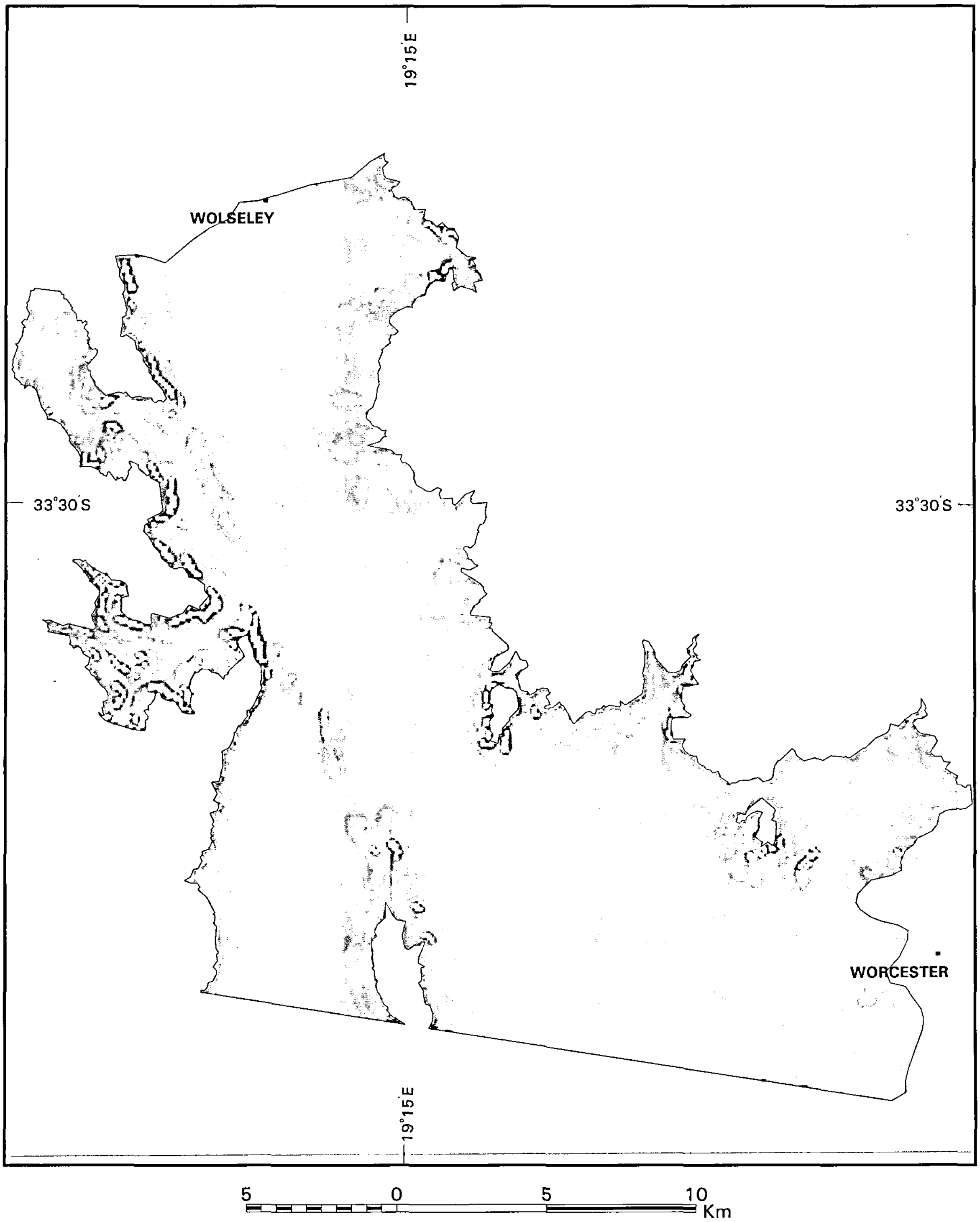


IGA

TIN (TRIANGULATED IRREGULAR NEWORK)
SLOPE POLYGONS
UPPER BREEDE RIVER VALLEY

BREEDE RIVER PROJECT

Figure 3.16 SLOPE CLASSES UPPER BREEDE RIVER VALLEY



IGA

CLASS 0 0% SLOPE	CLASS 2 6-10% SLOPE	CLASS 4 16-20% SLOPE	ABOVE 25% OUTSIDE STUDY AREA
CLASS 1 1-5% SLOPE	CLASS 3 11-15% SLOPE	CLASS 5 20-25% SLOPE	STUDY AREA

Separate polygon overlays were generated for each the gradient classes with the aid of RESELECT rastered so they could be integrated with the results of the image classification. Figure 3.16 depicts the site of the five gradient classes in the study area.

3.7 SUMMARY

In this chapter attention was given to the properties of the database. As an introduction satellite systems were reviewed after which Landsat TM and SPOT were specifically discussed in greater detail. Following from that the creation of the GIS database was described. The purpose of the GIS data is to support the digital image processing phase by providing ancillary data for selecting training areas, evaluating the accuracy of digital land cover classifications and refining the results.

The next chapter will focus on the digital image processing techniques and integration of this ancillary GIS data.

CHAPTER 4: DIGITAL CLASSIFICATION OF MULTITEMPORAL SATELLITE DATA

4.1 INTRODUCTION

As indicated in the previous chapters (particularly in sections 1.2 and 2.2.1) land use mapping from satellite data have in many cases failed to come up to expectation. Lourens, Brown, Seed & Maaren (1987) and Vlok (1989) have shown that the irrigated crops being cultivated in the Western Cape can not be successfully identified and/or mapped with single time-slice Landsat MSS data.

The use of the higher spatial resolution levels of SPOT XS or Landsat TM sensors and a multitemporal approach to obtain better definition of the spectral signatures of crops are two strategies which are often mooted as solutions to the problems experienced with Landsat MSS. However, higher spatial resolution alone does not always fulfil its promise. Studies on vineyards and orchards which have used the higher spatial resolutions of SPOT XS and Landsat TM (Altamira *et al*, 1986; Badhwar *et al*, 1987; Conese *et al*, 1991; Chou Chen *et al*, 1986; Jewell, 1989; Redondo *et al*, 1984; Samson, 1993; Schmullius, 1988; Silleos *et al*, 1992; Toulios *et al*, 1990 and Wheeler *et al*, 1988 and Shimoda *et al*, 1988) provide little evidence that higher spatial resolution will solve the problems of crop mapping in the Western Cape. If pixels are too small the digital data would be very complex, because individual pixels would for example register bare soil between single plants, thus providing a very fine mosaic of differing pixels values. The literature often argues the potential merits of multitemporal applications (Brockhaus *et al*, 1988; Lourens *et al*, 1987; Lourens *et al*, 1989; Lourens *et al*, 1990; Maracci *et al*, 1990 and Silleos *et al*, 1992) but, in practice, multitemporal applications are seldomly used. Heller *et al* (1979), Poracsky *et al* (1979), Badhwar *et al* (1987), Azzali *et al* (1990), Zuluaga (1990), Visser *et al* (1990), Chavez (1984) and Conese *et al* (1991) are the only studies found after a comprehensive review of the literature where the application is similar to this research. Financial considerations may account for the low application rate. Funding provided by the Water Research Commission enabled the Institute for Geographic Analysis to test Misra and Wheelers's (1987) premise that the uniqueness of a crop's spectral signature is a function of the pattern of temporal response rather than merely spectral response at a single time. This involved utilizing digital image processing techniques on the SPOT XS and Landsat TM datasets, respectively.

4.2 DIGITAL IMAGE PROCESSING TECHNIQUES

The techniques used in this chapter to differentiate between irrigated crops and non-irrigated crops can be divided into three basic groups: **pattern recognition, data reduction,** and **data transformation.**

4.2.1 Pattern recognition

The term "pattern" is normally used to refer to a phenomenon which is characterized by spatial or geometric features. As applied to digital image processing, however, the concept "pattern" is rather more complex. The landscape which is scanned by a satellite sensor, represents a variety of natural patterns, for instance, mountains or plains and water masses, as well as man-made features. The sensor system registers a measurement for each of the spectral channels, to which it is sensitive, for every resolution unit within the natural pattern. In mathematical terms, the measurements are viewed as points in an n-dimensional space or an n-dimensional measurement vector. The total surface scanned is termed the measurement space. The main spectral characteristics of the various types of pattern (for example, vineyards, orchards, cereals) are individually extracted from the measurement space (according to pattern type) and are transferred as main feature vectors to main feature space. During the classification process which accompanies pattern recognition, calculations are done on the main feature vectors, after which every measurement vector is assigned to the class (main feature vector) that it fits best in terms of vector characteristics. In pattern recognition terminology, a pattern therefore represents an abstract phenomenon, i.e. a vector which is represented by a set of highly defined measurements (in this case, n spectral radiance values).

4.2.1.1 Classification approaches

There are two general approaches in feature extraction: **supervised classification**, which is mainly concerned with pattern differentiation, and **unsupervised classification** which is based on pattern classification. Mausel (1985: 295) defines supervised classification as follows:

> *"Implementation of a computer algorithm through which the n-dimensional spectral response pattern of a pixel is assigned to a class based on a decision rule where the classes of interest have been defined based on representative training samples of known characteristics. In essence, remote sensing analysts examine environmental areas and attempt to determine the spectral response characteristics associated with specific features of interest (e.g., limestone, marsh, silty water, pine forest, etc.)."*

In essence, the supervised approach determines classes *a priori*, so they must, therefore, be known beforehand. In the next step, training areas are chosen which represent the required classes. The main feature vectors have to be calculated and used as the basis for determining class membership of the areas outside the training areas. If the classes which are adopted as the point of departure are spectrally distinct, and the respective training areas prove to be representative of the land cover types in the whole set of data, the classification should be successful.

The unsupervised approach is defined as follows by Mausel (1985: 294-5):

> *"Implementation of a computer algorithm through which the n-dimensional spectral response pattern is assigned to a class based on a decision rule that analyzes the spectral characteristics inherent in the data rather than using the spectral signatures of specified classes as determined through a training area approach. In essence, this approach groups or clusters spectral values that are close together without concern for the environmental objects that reflect the spectral data."*

The literature does not indicate clearly whether the supervised or the unsupervised approach is better - it seems, however, that the supervised approach is employed more frequently. The research done by Schmidt and Naugle (1985) and Kelton, Shain and Nix (1985) was specifically designed to evaluate the comparative merits of supervised and unsupervised classification. The first group of writers came out in favour of the supervised approach, while the second group favoured the unsupervised approach. The project team decided, therefore, to use both strategies in this study. It seemed that supervised classification would offer a more effective means of identifying irrigated areas and of differentiating between irrigated crops. More accurate classification results in the case of supervised classification would have to be weighed against the advantage of relatively smaller demands on the time of the image processing operator in the case of unsupervised classifications.

4.2.1.2 Data-reduction

Principal components analysis is widely applied in digital image processing as a data reducing technique, whereby the dimensionality of the multispectral data is reduced. The large volume of data poses a real problem in multitemporal applications - the transformation of the n-dimensional spectral data matrix to two or three principal components is an attractive means of overcoming the problem of data volume. Principal components analysis is based on the principle that a large number of linear dependent variables (in this case the n multispectral bands) have to be analysed simultaneously in order to reveal the underlying tendencies in the whole data set. The initial variables are transformed, without loss of information, to uncorrelated variables or components each of which "sums up" a unique part of the whole variance. The first component accounts for the largest proportion of the variance in the original set of data, while the last component (number of components = number of variables) makes the smallest contribution. Normally, the first three components together "sum up" more than 90% of the original variance, and these components are then subjected to supervised and/or unsupervised pattern recognition strategies.

4.2.1.3 Data transformation

Calculating so-called vegetation indices is an example of data transformation. This was initially done using data from the AVHRR sensor of the NOAA satellite series and provides an illustration of how an empirical relationship between measured radiation intensity and biological quantities (in this case, vegetation) can be determined. A number of variations of the basic vegetation index are to be found in the literature but most are based on the ratio which takes account of the radiation intensity in the red (R) and the near infra-red (I) wavelength bands. The ratio (or index) obtained represents that part of the penetrating solar energy which is absorbed by plant chlorophyll, and thus biological activity of plants. The Normalised Difference Vegetation Index NDVI = (I-R)/(I+R) offers a high index value in areas with vigorous vegetation and a low or negative value in areas with sparse or no vegetation. The study made use of two vegetation indices. A Transformed Normalised Difference Vegetation Index in the case of the SPOT data and a Normalized Difference Vegetation Index for the Landsat TM data. The two equations used were:

TNDVI = (((SPOT XS 3 - SPOT XS 2)/(SPOT XS 3 + SPOT XS 2)) + 0,5) * 0,5

NDVI = (TM 4 - TM 3)/(TM 4 + TM 3)

4.3 APPLICATION OF PATTERN RECOGNITION PROCEDURES

In the subsections that follow the focus shifts to the application of image processing techniques outlined in section 4.2. First, the SPOT XS-data are discussed, and then the Landsat TM data. In both cases, the unsupervised procedures and the calculation of vegetation indices are addressed after which the results of supervised procedures are presented.

Before discussing the pattern recognition procedures, however, it is necessary to place the image processing software in perspective. During the initial stages of the project, the Institute for Geographic Analysis operated an old version of the Gems Junior (EASI PACE) image processing system driven by a personal computer. It soon became evident that the demands of the project were so great that the system would be stretched to capacity, and that the relatively slow processing speed would be a limiting factor. Although the Institute was in the process of purchasing a work station based image-processing system (Erdas), the project could not be delayed until finality on the purchase of the Erdas system could be obtained. Consequently, the decision was made to use Gems Junior to process the smaller database (SPOT XS). Later Erdas was purchased and the Landsat TM processing was done using the more sophisticated Erdas software. Although the same basic techniques were applied to the SPOT XS and the Landsat TM data, the Landsat TM analysis could be refined making use of more sophisticated display and querying modules that were available, as well as the extremely useful link between Erdas and Arc/Info. The digital image processing techniques, applied to the SPOT XS-data are presented next.

4.3.1 SPOT XS

4.3.1.1 Unsupervised classification: Untransformed SPOT XS data

As a first step in the process of pattern recognition, an unsupervised classification was carried out on the six spectral bands from the summer and winter SPOT XS images. Unsupervised classification firstly involved application of a technique known as histogramming. This is a non-parametric data reducing technique aimed at accelerating computer processing and essentially creates a four-dimensional histogram or measurement vector (based on radiation values of four spectral bands) for every image element. The software limitation of four spectral bands made it necessary to decide which four of the six bands available would be used. The research done by Dorfling (1994) in the northern region of the study area revealed that the red and near infra-red spectral bands (Bands 2 and 3) of the two seasons would be the appropriate band combinations.

Next, the K-means classification technique was used to divide the four-dimensional histogram data into histogram classes. Software constraints meant only sixteen classes could be created. This constraint can be overcome if the database is divided into sub-scenes with sixteen classes for each separate sub-scene. However, this kind of manipulation was regarded as unnecessary. The initial class means can be specified by the image processing operator or generated by the computer. The latter option was chosen. Computer generation of class means is based on the principle that the range between the minimum and maximum refection value is divided into n classes (n = the number of classes specified by the image processing operator), thus creating classes having similar ranges. Every data value is linked to the class in which the distance squared (in terms of histogram space) between the data value and the class mean is the smallest. New class values are then calculated. This process is continually repeated until the class means change less than a predetermined threshold value or until the desired number of iterations (as specified by the analyst) has been reached. Table 4.1 shows the class means after 33 iterations (threshold value = 3) created for a 16-class classification. The last step in the classification process involves the generation of spectral signatures, or rather main feature vectors. During this last step, the previously determined class means are linked to statistical parameters. The parameters are an essential means of establishing the class to which an image element should most probably be assigned. The following statistics were calculated for each of the main feature vectors:

(i) the mean and the standard deviation;
(ii) the correlation matrix; and
(iii) the parallelipiped limits and Gaussian threshold values.

Table 4.1: Class means of unsupervised K-means classification (SPOT XS data).

Class	Pixel	Channel Means			
	Count	SB2	SB3	WB2	WB3
1	100	33,7	25,8	19,4	13,1
2	217	69,8	34,8	38,6	19,5
3	158	41,3	36,9	20,3	21,3
4	2609	40,6	68,8	18,2	25,7
5	122	40,4	55,3	13,5	13,1
6	2451	38,2	88,7	17,8	33,3
7	8404	55,9	128,3	25,6	39,4
8	733	49,4	52,1	17,9	21,3
9	6255	49,6	80,2	20,7	29,9
10	1051	44,7	65,2	14,9	15,6
11	8646	53,5	101,5	22,6	36,5
12	6759	52,5	64,6	20,0	24,2
13	10691	60,6	72,7	22,5	28,5
14	13369	80,1	103,5	26,7	41,1
15	17109	72,1	84,3	25,6	33,4
16	7487	105,4	113,8	32,1	43,4

SB = Summer Band
WB = Winter Band

After the spectral signatures (main feature vectors) had been generated, the classification of the multitemporal data could begin. A Gaussian maximum likelihood classification was applied for this purpose. This is a parametric technique which, by taking account of the mean vectors and co-variance matrix, can determine the statistical likelihood that a pixel belongs to a specific class. After consideration of the likely membership of each pixel to the individual classes, the pixel are assigned to the most appropriate class or classified as "unknown" if the probability level is smaller than a predetermined threshold value. By assigning a colour code to each of the class codes, the classification can finally be displayed as a thematic map on the monitor.

It is very important to note that the unsupervised classes obtained are spectral classes and do not necessarily have information value with regard to land use or irrigated area . In this regard, Townshed (1980: 90) provides the following warning: "The resultant classes are not guaranteed to be useful: some of the clusters may be meaningless because they contain too wide a variety of ground conditions." In order to evaluate the information value, it was necessary to compare the spatial appearance of the spectral classes with the spatial land use data which was obtained during the fieldwork phase. This comparison revealed that only four of the sixteen classes represented agricultural land use types. All of the other classes were mainly variations of the natural environment (mountain areas and natural vegetation). It was felt that more than four spectral classes were required in order to accurately map agricultural land use in the study area. In order to separate the four agricultural classes into subgroups, a mask of the spatial occurrence of the four agricultural classes was created and the masked area was subjected to a second 16-class unsupervised classification. This resulted in 10 significant classes - the frequency of six of the initial sixteen classes was too low to use as input during the process of signature generation. The class means are shown in Table 4.2, while the spatial distribution of the spectral classes is shown in Figure 4.1. The 10-class evaluation is discussed later in Section 4.4 of this chapter.

4.3.1.2 Unsupervised classification: SPOT XS Principal components data

Principal components analysis was used to reduce the volume of data (6-dimensional) to a three-dimensional data matrix which could be shown as a false colour image. The computer output which was generated in this regard is shown in Addendum C. To sum up, components 1, 2 and 3 respectively explain 65,5%, 27,0% and 3,6% of the variance in the original 6 spectral channels - in total, therefore, 96,1%. The same unsupervised classification procedures (4.3.1.1) were applied on the three principal components for the area lying 500 meters below sea level. Although an attempt was made to identify sixteen classes, only 14 classes could be created because of sample size limitations. The spatial distribution of the 14 classes is shown in Figure 4.2. The interpretation of the findings will also be reserved for Section 4.4.

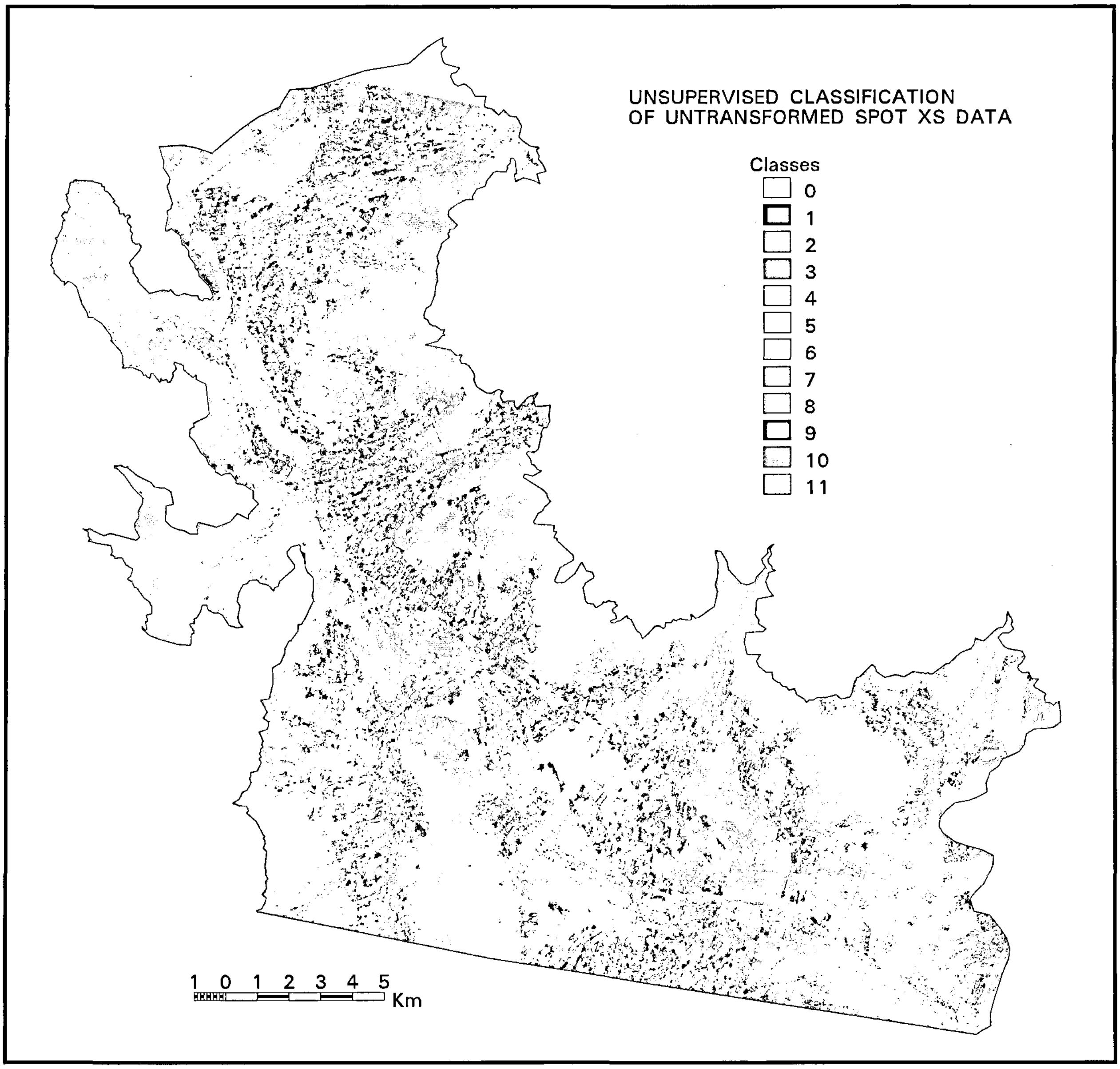


Figure 4.1: Unsupervised classification of untransformed SPOT XS data.

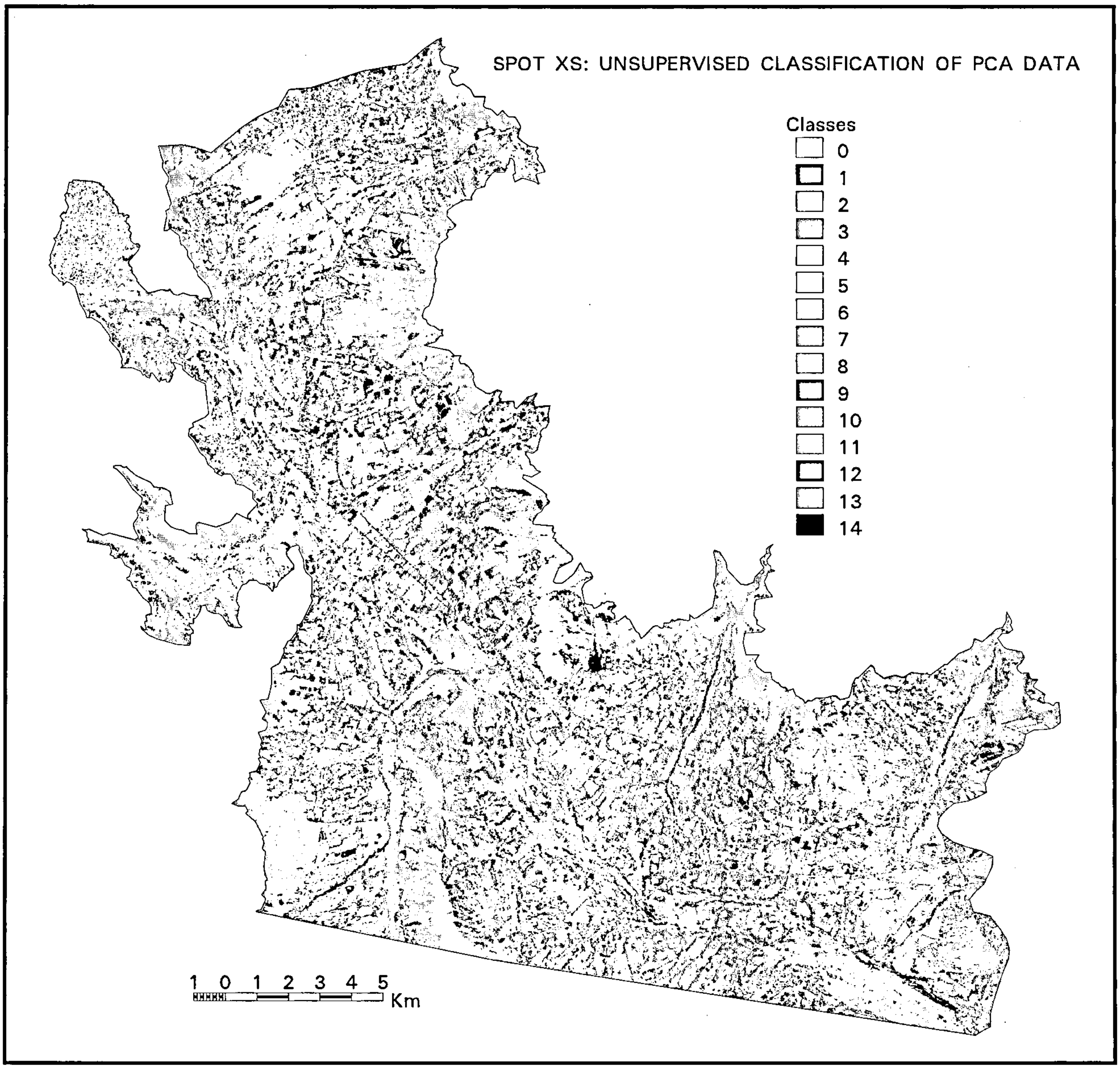


Figure 4.2: Unsupervised classification of Principal Component SPOT-XS data.

Table 4.2: Class means of unsupervised K-means classification on SPOT XS data (area lower than 500 metres above sea level).

Class	Pixel	Channel Means			
	Count	SB2	SB3	WB2	WB3
1	519	44,7	98,2	19,0	29,5
2	2320	52,9	92,5	21,3	34,2
3	3678	48,0	108,8	22,0	37,4
4	4542	64,1	101,6	24,8	37,8
5	7046	56,1	127,4	25,4	39,0
6	4217	79,6	93,4	26,3	38,3
7	5417	78,5	114,5	26,8	41,4
8	5303	90,7	97,3	28,9	40,7
9	3996	102,3	112,4	28,8	45,4
10	1187	120,8	121,6	37,0	42,1

SB = Summer Band
WB = Winter Band

4.3.1.3 Transformed Normalised Vegetation Index- SPOT XS data

Since the calculation and ultimate evaluation of vegetation indices are closely linked, the discussion of these two aspects is reserved for Section 4.4.

4.3.1.4 Supervised classification: Raw SPOT XS data

In section 4.2.1.2 it was pointed out that the success of a supervised classification is largely dependent on the spectral separability of the target classes, as well as the extent to which the selected training areas are representative of the target classes determined *a priori*.

Since the chief purpose of this research was to identify irrigated areas and to quantify the extent of the area under irrigation, the training areas had to be representative of the broad spectrum of irrigated crops which are found in the study area. The farms selected after consultation with an agricultural information official were regarded as representative for the purposes of the study. These farms were divided into training farms and control farms. The land use patterns of the former were to be used as training areas in the supervised classification process, while the latter were to be used as a yardstick to evaluate the ultimate classification.

As a first step in generating the training areas, the different land use types were transferred from PC Arc/Info to the Gems Junior image processing system as separate vector files. Table 4.3 provides a summary of the land use information which was linked to the vectors.

As can be deduced from Table 4.3, an attempt was made to take account of both farming practice (for instance, trellising or not) and plant characteristics (for instance the age of plants) in the selection of training areas. The various vector files were then separately transformed in the image processing system into a grid format, so that they could be used as input to generate spectral signatures. Two problems immediately presented themselves:

(i) The rasterised areas, especially in the case of vegetable types, appeared to be too small to generate reliable and valid training statistics.

(ii) The training areas of individual land use types were not internally homogeneous. This became apparent when the polygon borders of the training areas were superimposed on the false colour image of the study area.

The two problems were addressed by also incorporating the control farms in the signature-generating process. This step, of course, meant that the research team lost their "independent" evaluation tool. However, not even the addition of the control farms produced enough internally homogenous areas to be considered as potential training areas.

It was evident that external factors, other than the qualitative features which the survey had established, greatly influenced the spectral characteristics of the crops cultivated on selected farms. The implication of this was that differentiation between the training areas in terms of the qualitative properties of the farm data (age of crops, trellising, irrigation practises) was not possible. Eventually, greater use was made of more conventional strategies by which training areas are identified in terms of visual homogeneity on false colour displays. The farm survey data continued to be used as a basis, but where it was necessary, training areas outside the boundaries of surveyed farms were included in the training statistics. With the exception of 1987 aerial photographs, there was no supplementary qualitative data available. To sum up, it may be said that the selection of the final training areas was done purely in terms of land use and false colour appearance.

Six separate maximum likelihood classifications in all were conducted on the data. The classifications varied from one another with regard to the number of spectral signatures used and the rigour of the classification parameters (Gaussian threshold values) chosen. Addendum D provides a summary of the broad structure of the respective classification attempts. Although the project team had a fair indication of the proportional area covered by the various land use types, none of the classification attempts made use of Bayesian weighting factors.

Table 4.3: Land use coverages derived from farm survey data base.

			SELECTED VECTOR OVERLAYS																				
			> 2 land-parcels	Vine1	Vine2	Vine3	Vine4	Vine5	Pear1	Pear2	Peach1	Peach2	Prunes	Apples	Rye	Onion	Oats	Cabbage	Potatoes	Pumpkin	Onion	Watermelon	Cabbage
	ITEM	SELECTION CRITERIA																					
	TIPEG	Annual crops													●	●	●	●	●	●	●	●	●
		Perennial crops		●	●	●	●	●	●	●	●	●	●	●									
	ARR_EENJ★ AUG_EENJ○ OKT_EENJ▲ JAN_EENJ□																						
FARMDATABASE		Potatoes	●																□				
		Oats	●														○						
		Cabbage	●															○					□
		Pumpkin	●																	□			
		Rye	●												○								
		Onion	●													○					□		
		Watermelon	●																			□	
	MEERJ	Apples	●											●									
		Pears	●						●	●													
		Peaches	●								●	●											
		Prunes	●										●										
		Tablegrapes	●				●	●															
		Winegrapes	●	●	●																		
	OPLEI	Trellised fruit		●	●		●	●															
		Non-trellised fruit				●			●	●	●	●	●										
	OUD	Younger than 3 years			●			●		●		●											
		Older than 3 years		●		●	●		●		●		●										
	KONTROLE	Training areas		●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●
		Ground-thruth areas																					
	NUMBER OF POLIGONS			45	22	20	11	2	21	2	21	9	2	2	2	2	12	4	5	2	7	3	4

The 48 spectral signatures which were used in the first supervised classification attempt were able to allocate only 52,2% of the pixel to one of the 48 possible classes. Although the unclassified pixel (47,8%), largely corresponded with the mountainous areas of the study area, there were nevertheless large areas of potential irrigated areas which were also included in the null class. A visual analysis of the spatial distribution of the classification unambiguously indicated that nearly half of the spectral signatures resulted in a salt and pepper spatial distribution of classes or that it not only intercepted the target land use types, but also apparently included "unrelated" land use types. This problem was addressed in the subsequent classifications, by applying one or more of the following strategies:

(i) The elimination of the weakest training areas and their spectral signatures;
(ii) Editing to refine the existing training areas;
(iii) More rigorous specification of classification parameters in order to eliminate overlapping between plantations, mountain fynbos, orchards and vineyards;
(iv) The generation of additional training areas for the irrigated areas which had been assigned a null-code.

The 41 spectral signatures of the second classification attempt (Addendum D) resulted in a sizeable improvement. The null-class frequency decreased to 8%. However, of much greater significance was the fact that:

(i) Trellised vineyards could now be differentiated from orchards;
ii) Only a few tree lanes were misclassified as vines;
(iii) The initial problems surrounding the classification of plantations were overcome.

There were only a few subclasses of vineyard that overlapped with orchard classes. However, the differentiation between cereal crops, vegetables and fallow land was not appreciably improved.

The same refinement strategies, referred to earlier, were repeated on classification attempts 3 to 6. Mixed results were obtained. For instance, it became evident that more rigorous classification parameters for vineyard and orchard subclasses, which had been previously overestimated, meant that previously correctly classified orchard and vineyard pixels were incorrectly classified as fynbos and cereal crops.

A great deal of time was spent experimenting with strategies to identify vegetable plots. The problem of vegetable classification was exacerbated by the fact that vegetables are cultivated on relatively small units of land and are annual crops. A specific annual vegetable crop might be cultivated for only a few consecutive months, after which the land could lie fallow or the crop could be replaced by one of a wide variety (in terms of the type of crop and spectral characteristics) of vegetables. Table 4.4 serves to illustrate the dilemma. This table provides a summary of the land use combinations identified on the selected farms in question. The situation in the entire study area is probably even more complex. Using multitemporal analyses in a situation like this was extremely problematic. The project team frequently found that whenever an attempt was made to accommodate the combinations found in the area, the training areas were too small to generate valid and reliable training statistics.

Since the multitemporal nature of the data appeared to be a disadvantage rather than an advantage, as far as vegetable classification is concerned, it was decided that the classification of annual crops would be based on single time slices. The (hopefully) successful annual crop classification that ensued could then be integrated with the multitemporal classification. The problem of small land parcels on which annual crops are cultivated again appeared to be a major obstacle. For the August image hay, onions and cabbage were the only annual crops exceeding the minimum sample size limitation. In the case of the January image signatures could only be generated for onions, potatoes and water melon. The results, of the separate parallelipiped classifications of the seasonal images (August and January) however, showed that the spectral signatures were not unique with regard to the crop types for which they were generated. Because of the gross overestimation, integration of the single season and multitemporal classification was not achieved.

Attention first had to be paid to two land use categories, ie. dams and the null-class, before the supervised classification could be completed. The poor classification of dams and the large number of null-class elements resulted not so much from an inability to define good training areas, as the fact that these were not land uses that would depend on irrigation, and therefore they did not justify the heavy demands made on the analyst's time. The project team were aware of the problem right from the outset and had decided to address it after the final classification.

The joint classification of dams and shadows was resolved by applying density slicing to band 3 of the summer image. Density slicing of the reflection values between 20 and 50 was successful in isolating basically all the water surfaces. Since the threshold limits also included shady parts, the latter had to be removed from the resultant "classification". "Dam surfaces" situated 500 metres above sea level were easily eliminated by means of simple bitmap manipulations, thus only true dams remained. The remaining bitmap surface, i.e. the true water surfaces, were then mapped back into the classification with an appropriate water code.

Table 4.4: Crop combinations of annuals in the Breede River Valley (1992/93).

	Number of units	Season			
		Summer	Autumn	Winter	Spring
1.	2	Fallow	Onions	Onions	Onions
2.	1	Fallow	Fallow	Fallow	Fallow
3.	1	Fallow	Fallow	Pumpkin	Pumpkin
4.	1	Fallow	Fallow	Fallow	Tomatoes
5.	5	Fallow	Fallow	Potatoes	Potatoes
6.	7	Fallow	Fallow	Onions	Onions
7.	1	Fallow	Fallow	Watermelon	Watermelon
8.	1	Fallow	Fallow	Pasture	Pasture
9.	1	Potatoes	Fallow	Fallow	Fallow
10.	2	Rye	Rye	Fallow	Fallow
11.	1	Rye	Rye	Rye	Cabbage
12.	1	Pasture	Pasture	Pasture	Pasture
13.	1	Fallow	Oats	Fallow	Fallow
14.	1	Potatoes	Oats	Oats	Potatoes
15.	6	Oats	Oats	Fallow	Fallow
16.	2	Oats	Oats	Onions	Onions
17.	3	Oats	Oats	Oats	Fallow
18.	1	Oats	Oats	Oats	Potatoes
19.	5	Cabbage	Cabbage	Rye	Cabbage
20.	1	Cabbage	Cabbage	Peas	Peas
21.	1	Lupine	Lupine	Fallow	Fallow

Since the null class was essentially a "class" associated with the fynbos of the mountainous area of the study area, it was decided to use the six fynbos classes of the first unsupervised classification as a refinement tool. Image arithmetic was employed in order to isolate those pixels having a null code in the supervised classification and one of the six fynbos codes in the unsupervised classification. The resulting bitmap was then mapped into the channel containing the supervised classification with a code corresponding with the veld ("other") category.

At this stage the attempt at supervised classification was regarded as completed (Figure 4.3). As indicated earlier, the lack of GIS-querying facilities on the Gems Junior image processing system was a limitation because the evaluation of the respective classification attempts could not be done time-efficiently. On the basis of "subjective" visual decisions,

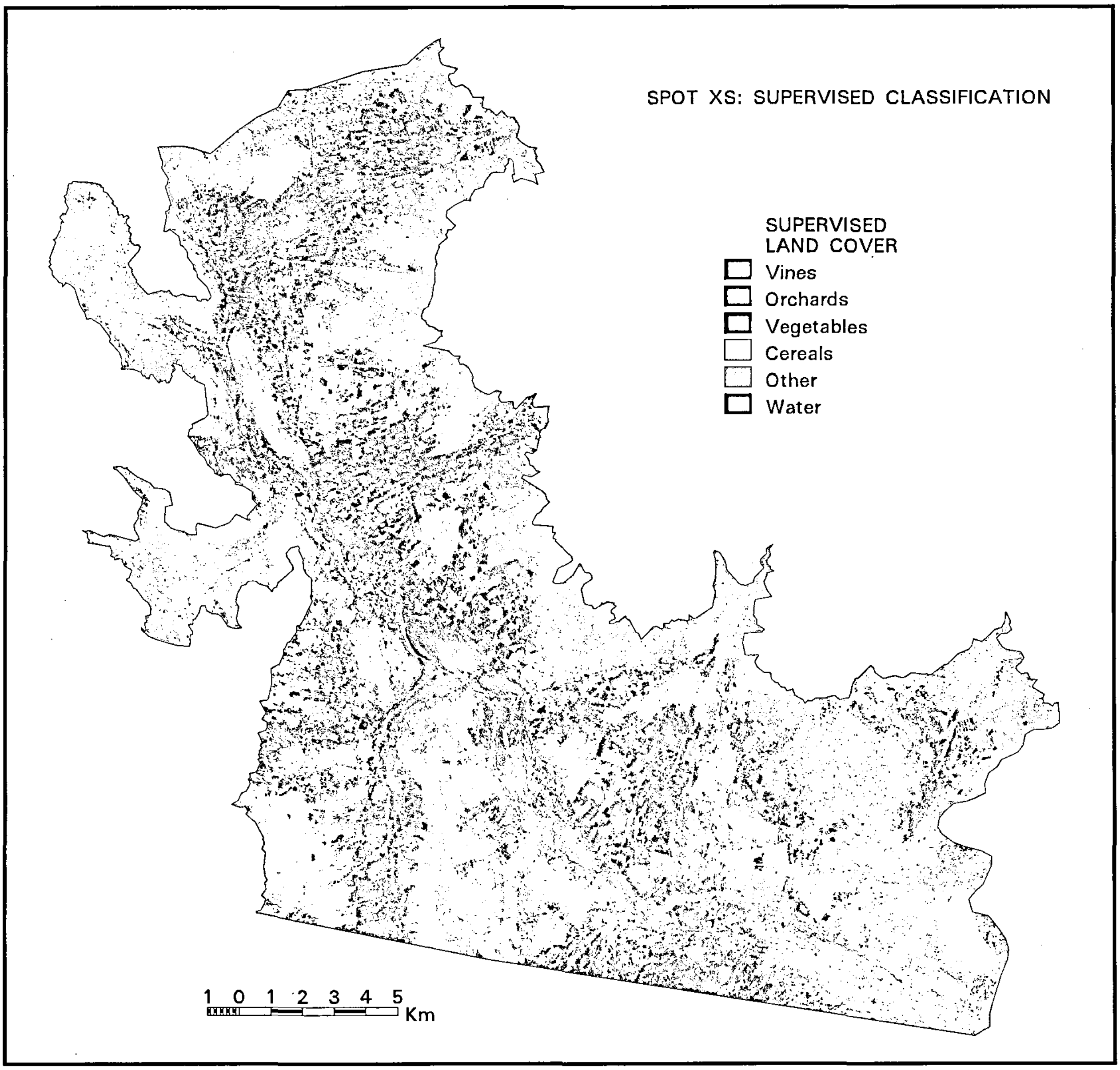


Figure 4.3: Generalized land cover map from supervised classification of untransformed SPOT XS data.

classification number five was considered to be the most satisfactory. The extent to which this classification was successful in correctly classifying the farm data will be the focus of the discussion in section 4.4.2.4.

4.3.2 Landsat TM

As stated earlier the Landsat TM dataset consisted of four images, representing land cover conditions during each of the four seasons. Due to its coarser spatial resolution Band 6 was excluded from all subsequent analyses. The four images were combined into a single file consisting of 24 spectral bands. This multi-temporal dataset was used in all analyses discussed in the sections that follow.

4.3.2.1 Unsupervised classification: Untransformed Landsat TM-data

The Erdas Imagine software besically provides one algorith for unsupervised classification, namely the ISODATA algorithm. This algorithm is discussed by Tou and Gonzalez (1974) and will not be presented here. It requires very little input from the user apart from specifying the maximum number of clusters needed, a convergence threshold to stop clustering and a maximum number of iterations to perform. In this particular study it was decided to request 30 clusters after an initial run using only 15 clusters had created a small number of very large generalized land cover classes. By doubling the number of clusters it was hoped that the classifier would be able to distinguish more subtle differences within agricultural land cover types. That did not take place however and no significant new cultivated classes emerged. Most new classes were subclasses of the mountainous fynbos surrounding the valley. In an attempt to force the classifier to generate more subclasses in the cultivated area of the valley a mask was created which included all land cover classes of interest as produced by the initial 30 class unsupervised classification. The classification was then repeated but only classifying pixels under the mask. The resultant classification is presented in Figure 4.4.

The final unsupervised classification was converted into an Arc/Info GRID format and overlaid with the land use grid of the surveyed farms. On the basis of a combinatorial analysis unsupervised classes were assigned to one of the major land cover types (Addendum E.1). This means that unsupervised classes were amalgamated into fewer land cover types with informational content. The generalized map will be presented and evaluated in a later section.

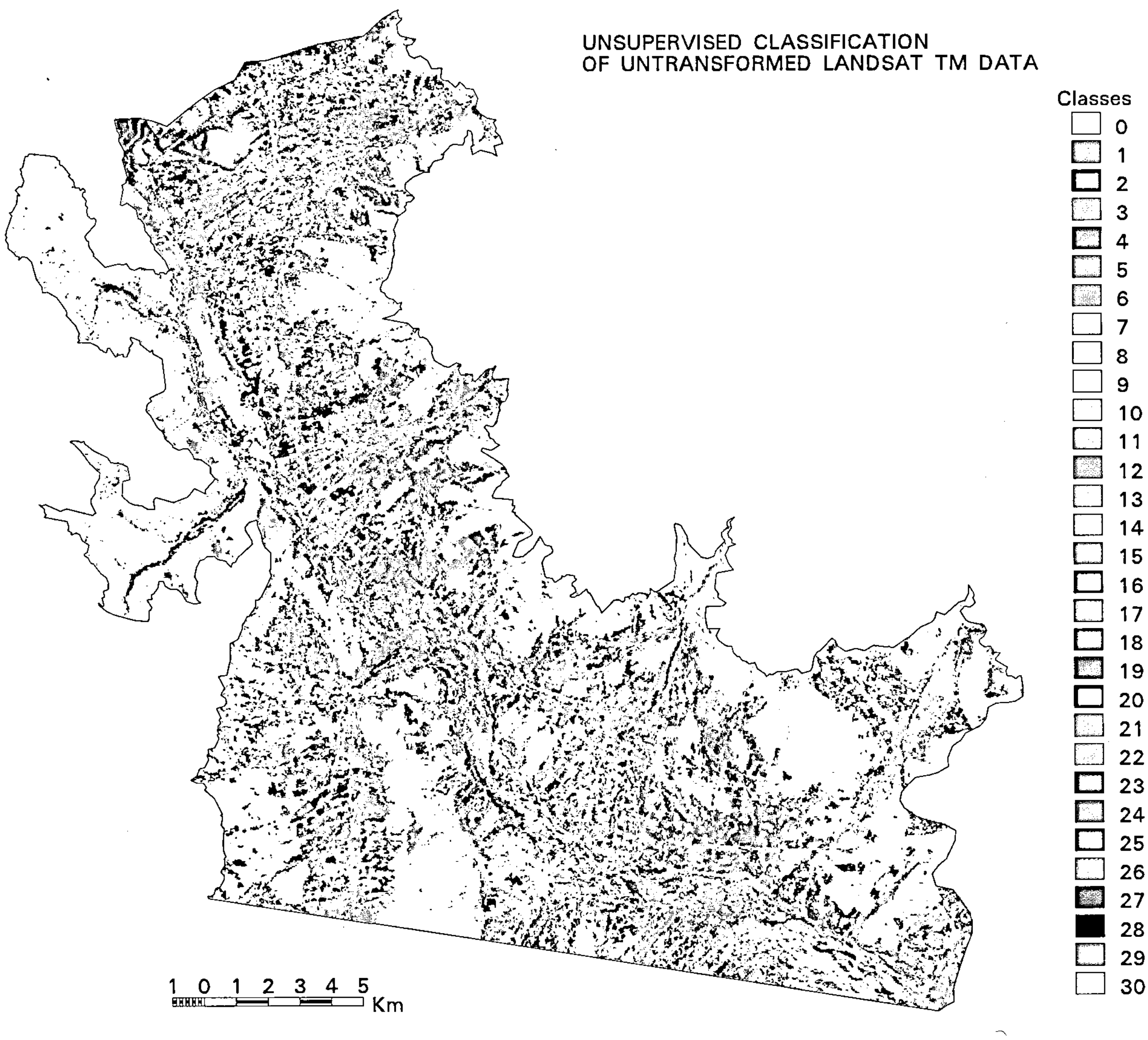


Figure 4.4: Unsupervised classification of untransformed Landsat TM data.

4.3.2.2 *Unsupervised classification: Landsat Principal Component Data*

By using 24 spectral bands in the analyses a large amount of redundancy may be present in the data as many spectral bands are strongly correlated. Most classification algorithms utilize some measure of spectral distance between pixels and classes so that distance values could be contaminated by these intercorrelations as most distances are computed using the pythagoras algorithm which is based on the assumption that the axes are orthogonal. To eliminate this potential problem a Principal Component Analysis was performed on the data as this produces a new set of uncorrelated components. These components were then subjected to an ISODATA unsupervised classification, again specifying a maximum number of 30 clusters. Figure 4.5 shows the results of the PCA classification. This image was converted to Arc/Info GRID format and overlaid with the farm survey land use grid to identify and label classes in a way similar to that described in section 4.3.2.1. Classes were assigned to the land cover type with which they had the highest combinatorial frequency (Addendum E.2). The generalized land cover map will be presented in the section on evaluation of the results.

4.3.2.3 *Unsupervised classification: Landsat Normalized Difference Vegetation Index*

Another approach that was followed to extract usefull land cover data from the multi-temporal Landsat TM dataset, was to compute Normalized Difference Vegetation Indices for each of the seasons. These four variables were then subjected to an ISODATA unsupervised classification with 30 clusters. The classified image (Figure 4.6) was processed in the same way as described in the previous two sections in order to identify land cover types and assign classes to the required generalized land cover categories (Addendum E.3). Also this map will be evaluated in a later section.

4.3.2.4 *Supervised classification: Raw Landsat TM-data*

Supervised classification is a much more labour intensive procedure and requires intensive interaction with the image processing system. The classes needed were dictated by the objectives of the study, which are to identify different agricultural crops with different water requirements. From the farm survey it was evident that the major cover types of interest were vines, orchards, vegetables, cereals and other cultivated crops.

In a supervised approach training areas are needed representing each of the required land cover classes. To complicate matters vegetables are annual crops often cultivated on a rotational basis with cereals or legumes. This means that a particular parcel of land may

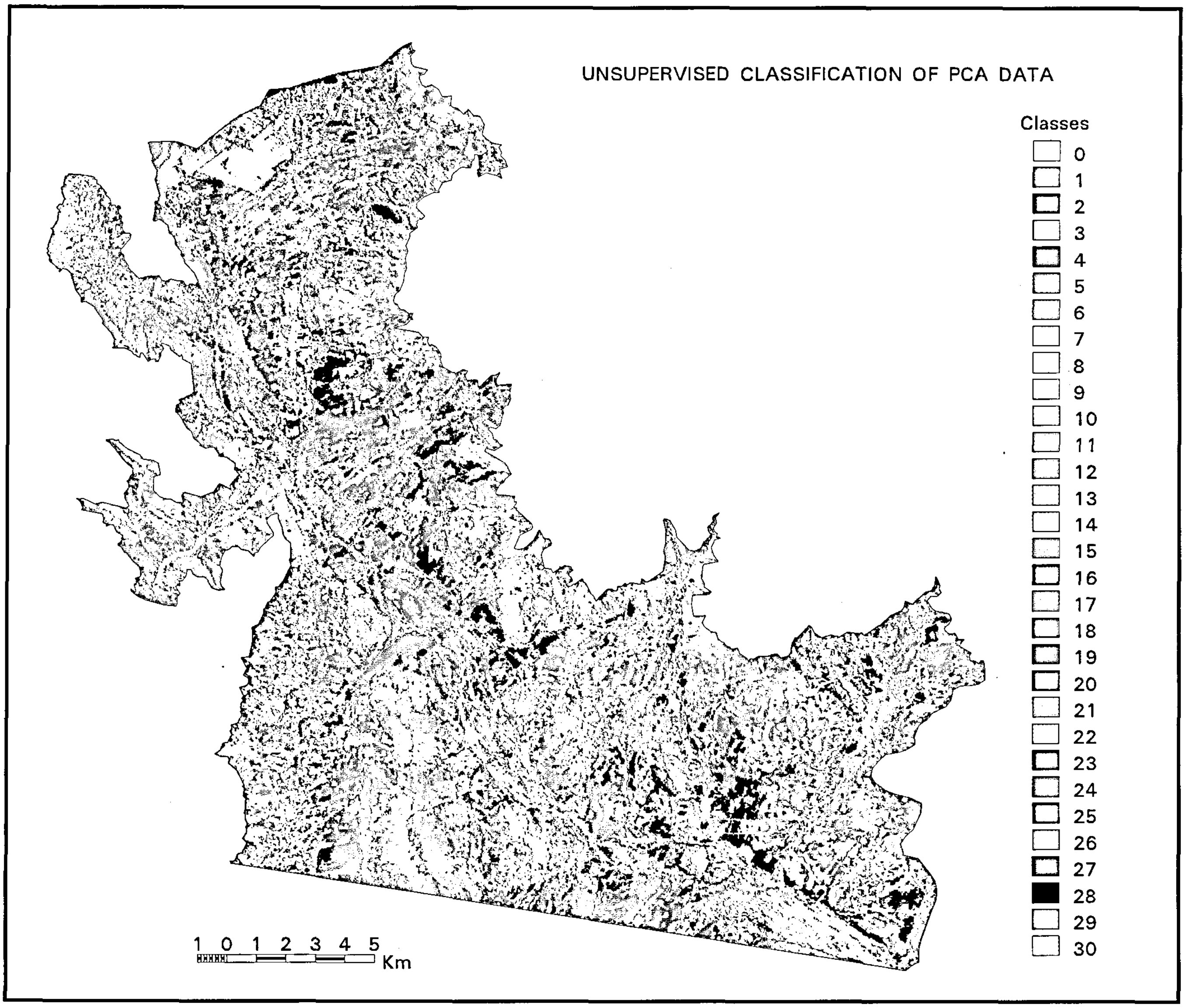


Figure 4.5: Unsupervised classification of Landsat TM Principal Component data.

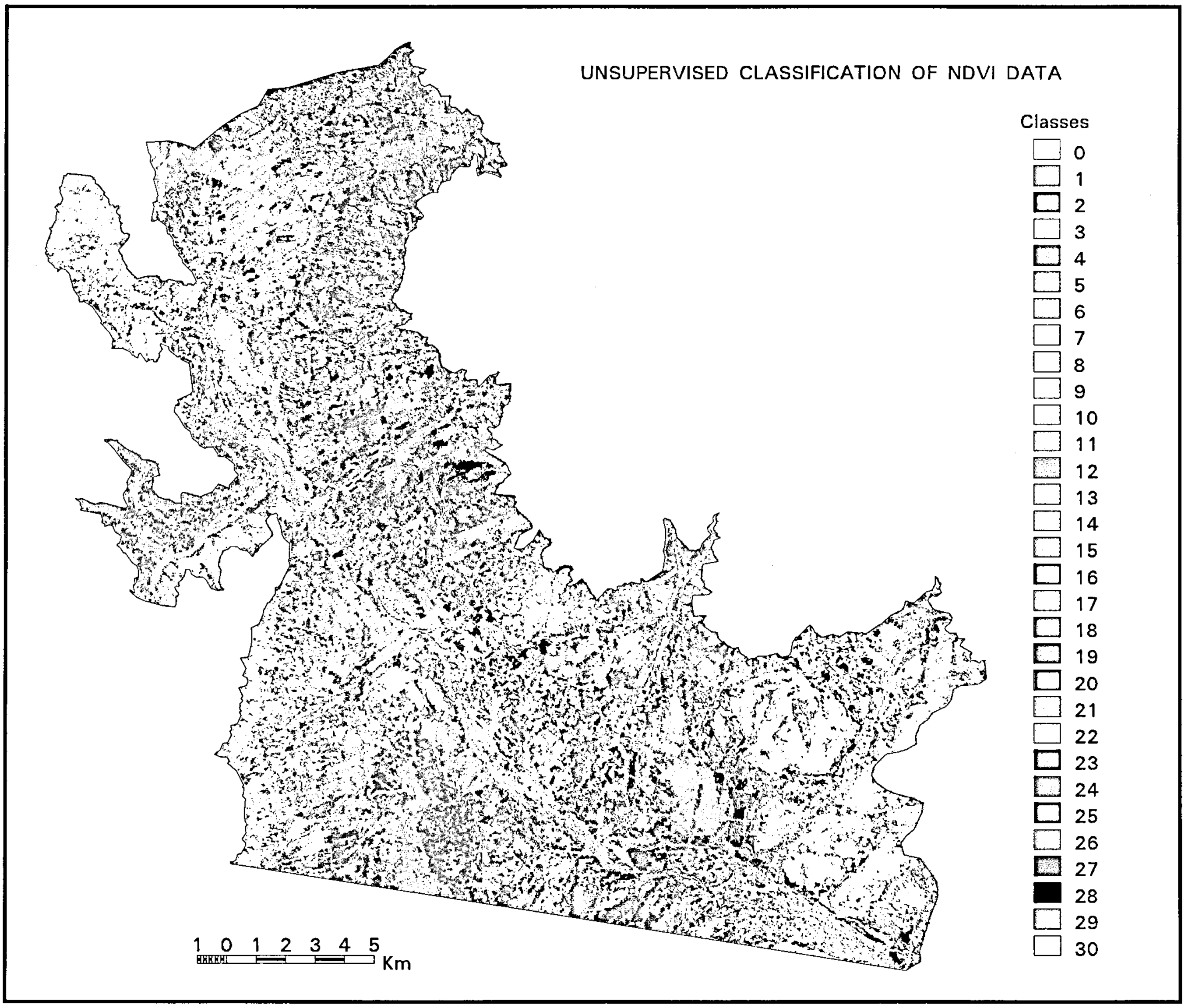


Figure 4.6: Unsupervised classification of Landsat TM NDVI data.

have vegetables in one or more seasons and some other crop at others or even be left fallow or barren. These patterns produce extremely complex spectral signatures. In this study 21 different combinations and permutations of annual crops were distinguished (Table 4.4). To demarcate training areas and compute spectral signatures for each of these combinations was not feasible. Firstly, land parcels are small and fragmented and secondly, ground truthing was restricted to those farms included in the survey. This meant that in many cases there was only one occurence of a particular land cover combination. The problem was resolved by allocating each land cover combination to a single dominant type. In a few cases (4) where no single crop type dominated it was arbitrarily assigned to the first cover type in the combination, thus identifying vegetables, cereals or bare soil. Bare soil or unused land was put into a catch all class called Other.

A total of 104 training areas were finally demarcated on the image after three iterations. See Addendum E.4 for a complete list of signatures and raw cover classes. These represented vines, orchards, cereals, vegetables, fallow land, pine stands, bare soil, veld, mountain fynbos, riverine bush, water and shadows. Erdas Imagine has a pixel growing facility which allows the analyst to select a single representative starting pixel within a potential training area. The system then searches radially for pixels with similar spectral characteristics. This search can be constraint spectrally and spatially. No spatial limits were imposed but a value not exceeding 30 spectral units deviation were allowed. This spectral constraint produced acceptable training samples in most cases. A maximum-likelihood decision rule was used to classify the image, the results are presented in Figure 4.7. Although the statistics show that 25% of the image was not classified, those pixels are mostly outside the actual image falling in the area between the image and the rectangular limits of the scene. A generalized land cover image was produced for later evaluation.

4.4 EVALUATION OF CLASSIFICATION RESULTS AND INTEGRATION WITH ANCILLARY DATA

4.4.1 Basis of Evaluation and Data Integration

The evaluation of both the SPOT XS and the Landsat TM classifications was done by means of comparisons with the farm data which was collected during the farm survey. The comparison involved extracting that part of the classification which corresponded spatially with the farm data and comparing the class codes in the two data sets pixel by pixel. Thus the degree of correspondence between the classification and the farm data could be established, and possible reasons for erroneous classifications obtained. It must, however, be noted that the two sets of data were governed by different classification principles. In the case of the farm survey data, the categorisation was based on land use, while the

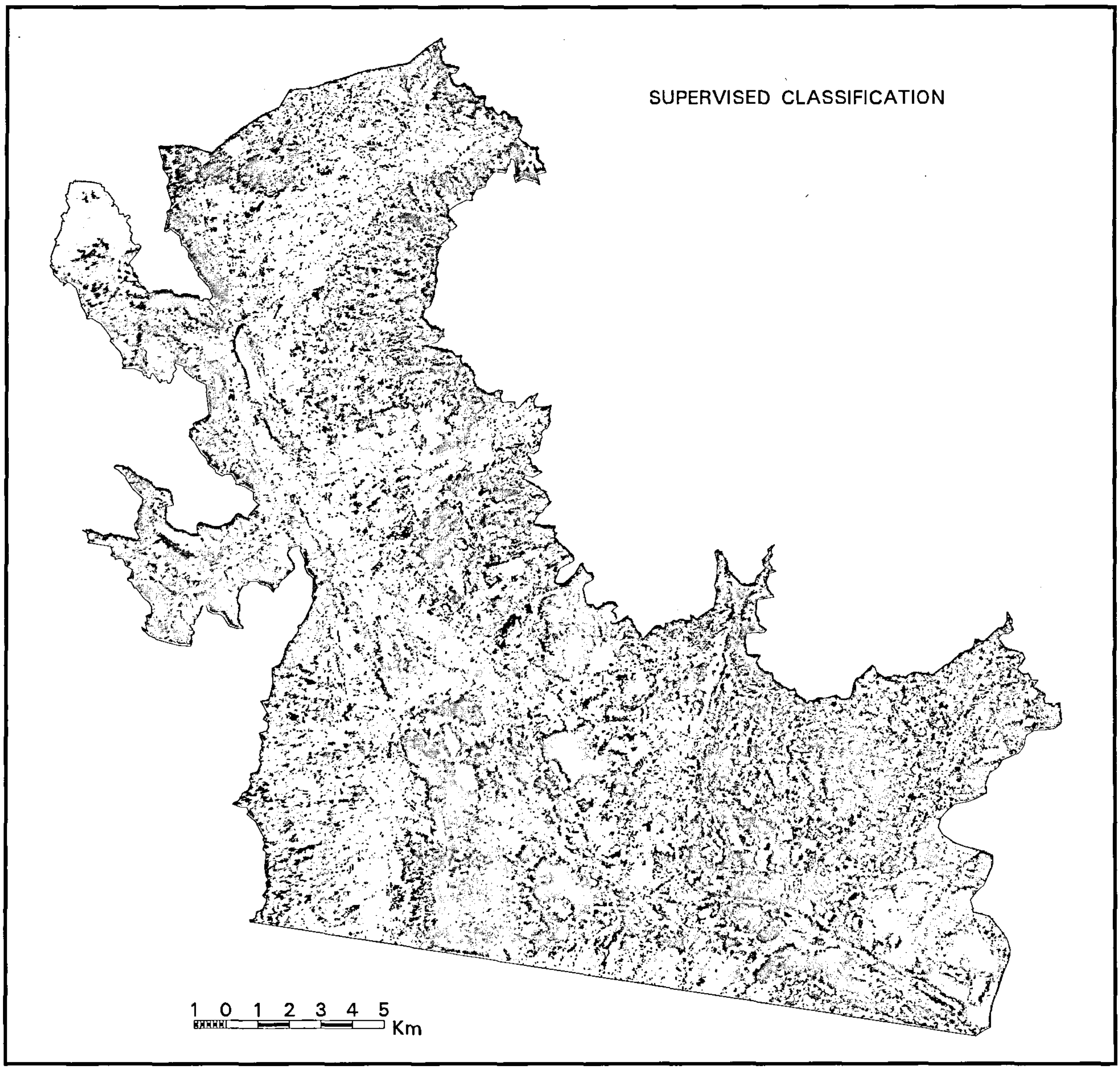


Figure 4.7:—Supervised classification of untransformed Landsat TM data.

satellite images were classified according to the spectral characteristics of land cover types. This difference between the two sets of data could have resulted in a lower level of success than was true in reality. An illustration of this is that a newly planted vineyard with little or no foliage could have been classified as "vineyard" in the farm survey data, while the same "vineyard" would most likely have been classified as "bare ground" in terms of its spectral characteristics.

Apart from its role as an evaluation tool, the farm survey data were used in both the SPOT XS and Landsat TM unsupervised classification in order to invest the spectral classes obtained with informational content. It was necessary to establish how and to what extent the spectral classes corresponded spatially with the land cover types relevant to this study. In other words, the spectral classes had to be labelled in terms of land cover features. This was achieved by crosstabulating the labelled spectral classes with the farm survey data. The dominant land use category associated with each of the spectral classes could be determined objectively by noting the highest cell frequency in each row of the crosstabulation matrix.

With regard to the integration of the ancilliary data, soil potential, height above sea level and slope were the secondary sources of data which could be used to refine the classifications. The integration of the ancilliary data with the classification results was based on a number of assumptions:

(i) No irrigation would take place more than 500 metres above sea level. This assumption was based on a study of the land use patterns and contour lines, as determined on 1:10000 orthophotos of the study area.
(ii) No vineyard or fruit cultivation would be found on slopes with a gradient of more than 25%. This information on agriculture practice was obtained during discussions with the staff of the Soil Conservation Unit, Department of Agriculture, Elsenburg.
(iii) Because of the high capital outlay needed for the establishment of orchards and vineyards, it would not be economically viable to establish such crops on low potential agricultural land. It was therefore decided to view as incorrect any classification of vineyard and orchard which corresponded with land of low agricultural potential. Exceptions to this rule did occur in three areas where orchards and vineyards was identified visually on the false colour images and their presence could be confirmed by checking against aerial and/or orthophotos.

4.4.2 SPOT XS

Because the image-processing system used to process the SPOT XS data did not have GIS-type analytical functions, firstly, only limited integration of the SPOT XS-satellite data was possible with the supplementary data and, secondly, it was an extremely lengthy process. The greatest limitation was the fact that it was not time-efficient to use the farm survey data to it's full extent to select, evaluate or refine spectral signatures.

4.4.2.1 Unsupervised classification: Untransformed SPOT XS data

Table 4.5 presents a crosstabulation which summarises the correspondence between the land use classes of the farm survey data and the results of the unsupervised classification. An analysis of the row frequencies provides an answer to the question: "What land use class corresponds best spatially with the individual unsupervised classification codes?" Row 7 serves as an illustration. The land use class, vines, intercepted 11877 pixels (72,4%) out of a total of 16402 pixels. One may conclude from this that class 7 should be labelled as "vines".

Table 4.5: Crosstabulation of SPOT unsupervised classification and landuse codes from farm survey data.

	Farm Land Use Survey						
	Class	Vines	Orchards	Vegetables	Cereals	Other	Total*
Unsupervised classification	1	1311	480	225	201	77	2294
	2	2494	1248	414	578	3085	7819
	3	65	14	2	3	11	95
	4	390	99	2	20	124	635
	5	2861	1840	25	26	106	4858
	6	2696	815	54	110	205	3880
	7	11877	4072	212	107	134	16402
	8	339	81	46	342	350	1158
	9	4849	905	335	666	196	6951
	10	354	55	184	490	650	1733
	11	682	145	242	674	239	1982
	0	291	40	137	244	288	1000
	Total*	28209	9794	1878	3461	5465	48807

* Number of pixels

An analysis of all the row frequencies produced the interpretation set out in Table 4.6. It may seem strange that this interpretation resulted in only two classes for the unsupervised classification, ie."vines" and "other", with not one of the other land use classes featuring.

In other words, orchards, vegetables and cereals were 0% correctly classified. This peculiarity is the result of classifying land cover types according to the largest absolute number of pixels and not the relative presence. Table 4.7, which gives an indication of the accuracy of the classification provides more perspective.

Table 4.6: Labelling the unsupervised SPOT XS spectral classes.

Classification Code	Label allocated on basis of association with dominant land use type	Number of Pixels
1	Vines	1311
2	Other	3085
3	Vines	65
4	Vines	390
5	Vines	2861
6	Vines	2696
7	Vines	11877
8	Other	350
9	Vines	4849
10	Other	650
11	Vines	682

Table 4.7: Accuracy assessment of SPOT unsupervised classification by comparing with farm survey data.

	SPOT unsupervised Classification						
	N = 47807	Vines	Orchards	Vegetables	Cereals	Other	Total[2]
Farm data	Vines	83,2[1]	0,0	0,0	0,0	11,4	58,4
	Orchards	85,8	0,0	0,0	0,0	14,2	20,4
	Vegetables	63,0	0,0	0,0	0,0	37,0	3,6
	Cereals	56,2	0,0	0,0	0,0	43,8	6,7
	Other	36,7	0,0	0,0	0,0	78,9	10,8
	Total	51,7	0,0	0,0	0,0	8,5	59,6[3]

1) Row % 2) Column % 3) Overall accuracy (%)

The important conclusions which may be drawn from Table 4.7 is that, for "vines" and "other", accuracy levels greater than 80% were achieved by means of the unsupervised technique and the interpretation method applied. However, the overall classification was only 59,6% correct. It was disappointing that irrigated crops like orchards and vegetables did not emerge as dominant classification codes (Figure 4.8). However, it is important to note that the primary goal was not to differentiate between individual crops, but to differentiate between irrigated and non-irrigated crops.

An overall accuracy of 52,9% was obtained when the unsupervised classification was compared with the generalized land cover map. Vines were 84% correctly classified. Most other land cover types were incorrectly assigned to the vine class (Table 4.8). This represents an overestimation of the vine land cover type (Figure 4.9).

Table 4.8: Accuracy assessment of SPOT unsupervised classification by comparing with the land use map.

	Unsupervised Classification						
	N = 622253	Vines	Orchards	Vegetables	Cereals	Other	Total2)
Land use	Vines	84,01)	0,0	0,0	0,0	16,0	24,2
	Orchards	86,1	0,0	0,0	0,0	13,9	7,2
	Vegetables	61,5	0,0	0,0	0,0	38,5	1,3
	Cereals	52,9	0,0	0,0	0,0	47,1	11,0
	Other	58,5	0,0	0,0	0,0	41,5	4,5
	Total	20,3	0,0	0,0	0,0	1,8	52,93)

1) Row %　　2) Column %　　3) Overall accuracy (%)

Table 4.9 and Figures 4.10 and 4.11 reflect the accuracy levels that can be achieved if vines, orchards and vegetables are combined in a generalised land cover class entitled "Irrigated crops". Viewed against the background of the relatively low expenditure of time, required by unsupervised classification, the 83,6% accuracy level obtained for irrigated crops seems very promising. In addition, the overall accuracy increases to 67,4%.

These results were obtained by incorporating the ancilliary data from the GIS data base. This meant that any pixel situated more than 500 metres above sea level, or on a slope with a gradient of more than 25%, or which was associated with low potential irrigated land, did not meet the requirements for the cultivation of vineyards, orchards or vegetables. Pixels which were classified as such could be recoded as non-irrigated crops. However, mention has already been made in Section 4.4.1 that three low potential irrigated areas were regarded as exceptional cases. These conditions did not occur on the surveyed farms so that

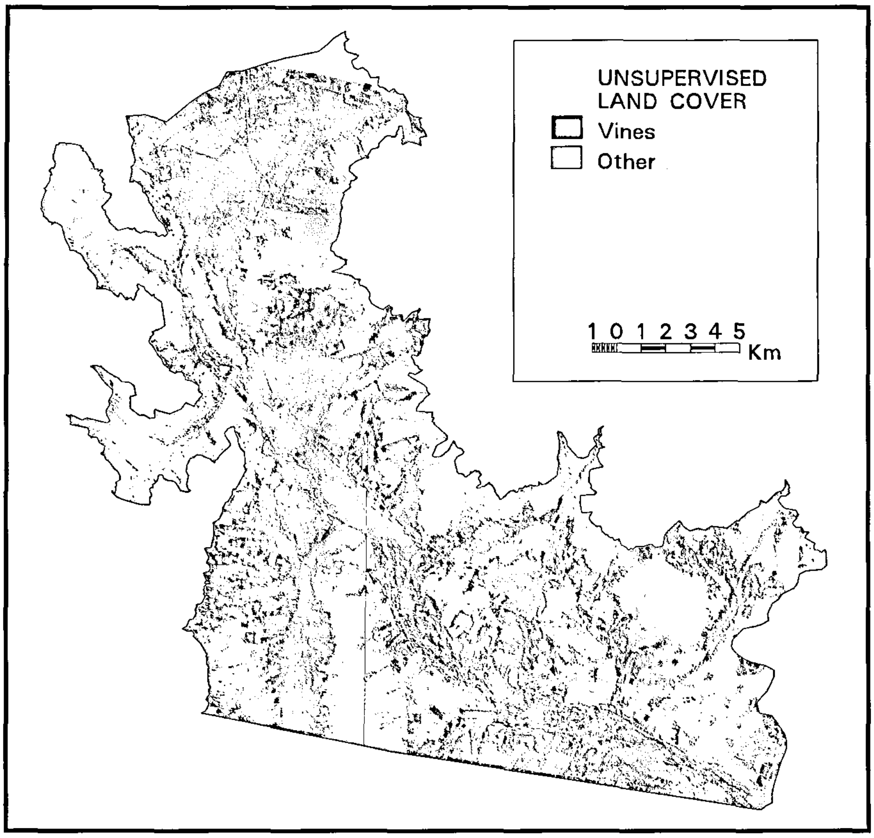


Figure 4.8: Generalized land cover map from unsupervised classification of untransformed SPOT XS data.

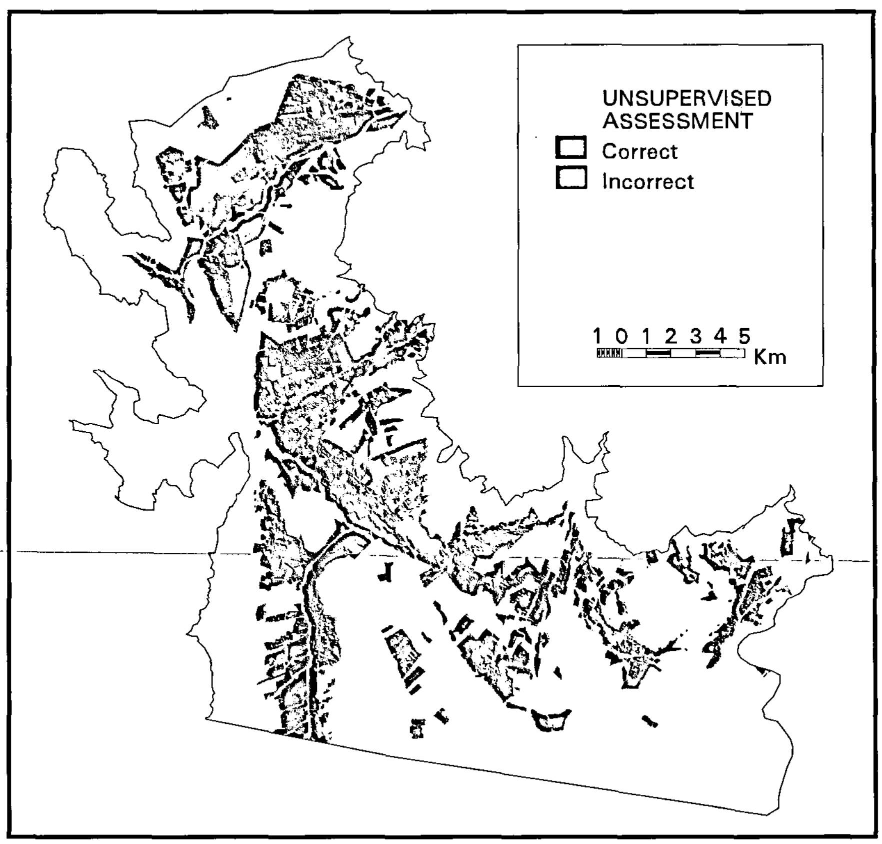


Figure 4.9: Accuracy assessment of generalized land cover map from unsupervised classification of untransformed SPOT XS data.

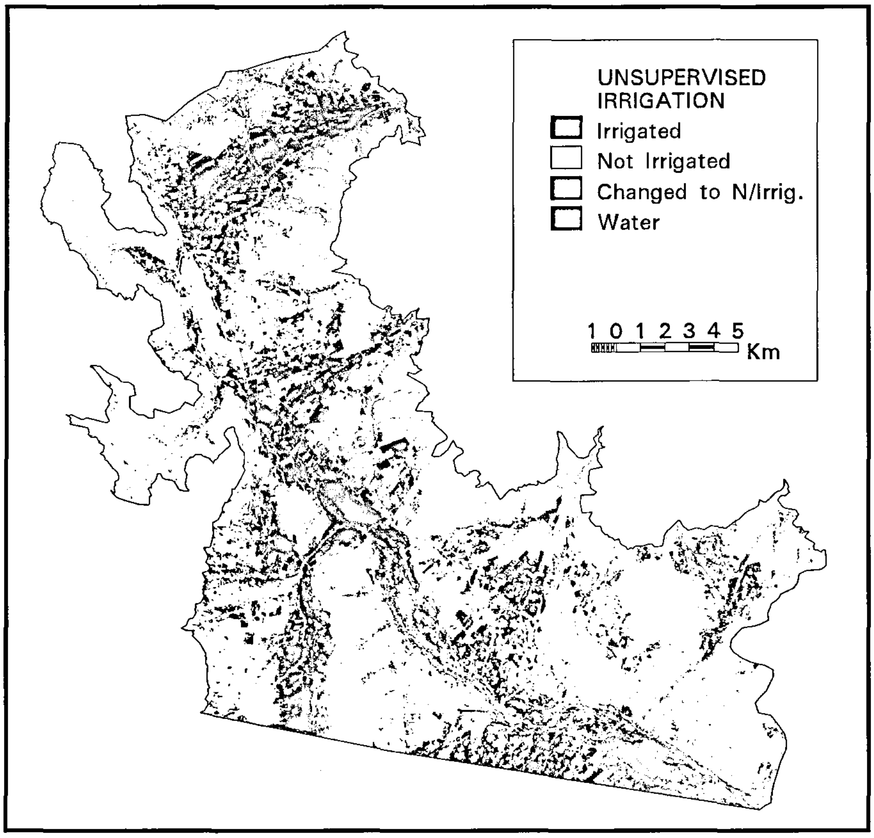


Figure 4.10: Irrigated land cover map from unsupervised classification of untransformed SPOT XS data.

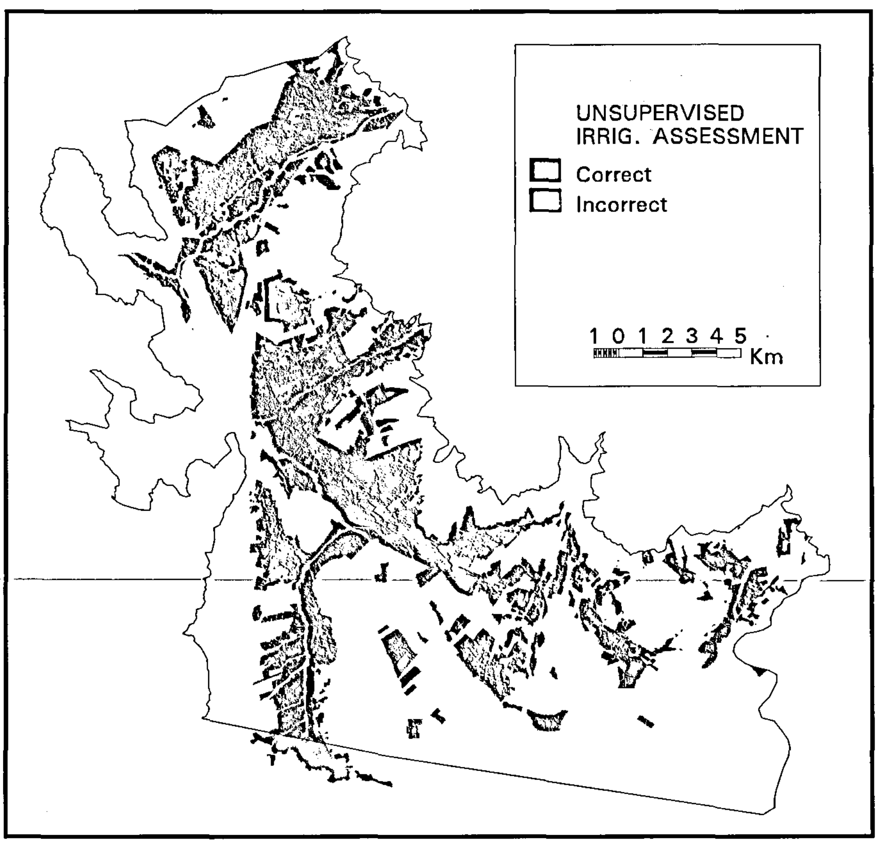


Figure 4.11: Accuracy assessment of irrigated land cover map from unsupervised classification of untransformed SPOT XS data.

the ancilliary data had no refining effect on the comparisons with the farm data. However, the effect of the ancilliary data is very clear in Figure 4.10 and Table 4.9. Both represent the classification of the whole study area.

Classification accuracies of 67,4% were achieved in terms of irrigated land cover types. Irrigated crops were 84% correctly classified whereas only 52,9% of the non-irrigated land cover classes were correct. Table 4.10 shows that 200694 pixels, or 8027,8 ha have been classified as irrigated areas.

Table 4.9: Accuracy assessment of SPOT unsupervised classification of irrigated land compared with land use cover.

	Unsupervised Classification			
	N = 299189	Irrigated	Other	Total[2)]
Land use	Irrigated	83,6[1)]	16,5	67,8
	Non-irrigated	52,9	47,1	22,8
	Other	58,5	41,5	9,4
	Total	74,2	25,8	67,4[3)]

1) Row % 2) Column % 3) Overall accuracy (%)

Table 4.10: Area statistics of final SPOT unsupervised classification.

Class	Unsupervised classification	
	Number of Pixels	Area (Ha)
Irrigated	200694	8027,8
Non-irrigated	840777	33631,1
Ancillary data*	21767	870,7
Water	8347	333,9
Non-classified	25411	1016,4
Total	1096996	43879,9

* Pixels changed from irrigated to non-irrigated by ancillary data

4.4.2.2 Unsupervised classification: SPOT XS principal components data

It was established in Section 4.2.2 that principal components analysis (PCA) is in reality a data reduction technique. As a result of the application of PCA to the six SPOT XS spectral bands, the first three components intercepted 65,5%, 27,0% and 3,6% respectively, that is to say 96,1% in total, of the variance in the original set of data. The fourteen classes which emerged from the unsupervised classification, as applied to the first three principal components, were consequently interpreted in the same way as discussed in section 4.4.2.1 to produce Figure 4.12.

Crosstabulation of the 14 classes with the farm survey data revealed the same trend as that of the unsupervised classification of untransformed data. Once more, it was only "vines" and "other" which emerged as dominant land use classes which could be associated with the classification codes. Since the vines and "other" land use classes together accounted for nearly 75% of the area of the farms, the trend was not altogether unexpected. The conclusions to be drawn from Table 4.11 are that over 80% of the "vines" and "other" were correctly classified, a large proportion (80,6%) of orchards was confused with "vines" and the majority of vegetables (64,4%) and cereals (78,0%) were classified as "other". The overall accuracy was 65,4%.

Table 4.11: Accuracy assessment of SPOT PCA unsupervised classification by comparing with farm survey data.

	PCA Unsupervised Classification						
	N = 72889	Vines	Orchards	Vegetables	Cereals	Other	Total2)
Farm data	Vines	81,91)	0,0	0,0	0,0	18,1	35,8
	Orchards	80,6	0,0	0,0	0,0	19,4	12,4
	Vegetables	35,6	0,0	0,0	0,0	64,4	4,4
	Cereals	22,0	0,0	0,0	0,0	78,0	3,7
	Other	17,6	0,0	0,0	0,0	82,4	43,8
	Total	49,3	0,0	0,0	0,0	50,7	65,43)

1) Row % 2) Column % 3) Overall accuracy (%)

A comparison between the SPOT PCA unsupervised classification and the land use map achieved an accuracy of 42%. Vines were 75% correctly classified, whereas vegetables (45%) and cereals (73,5%) were classified as 'other' land cover types. The map (Figure 4.13) shows the extent of incorrect classifications.

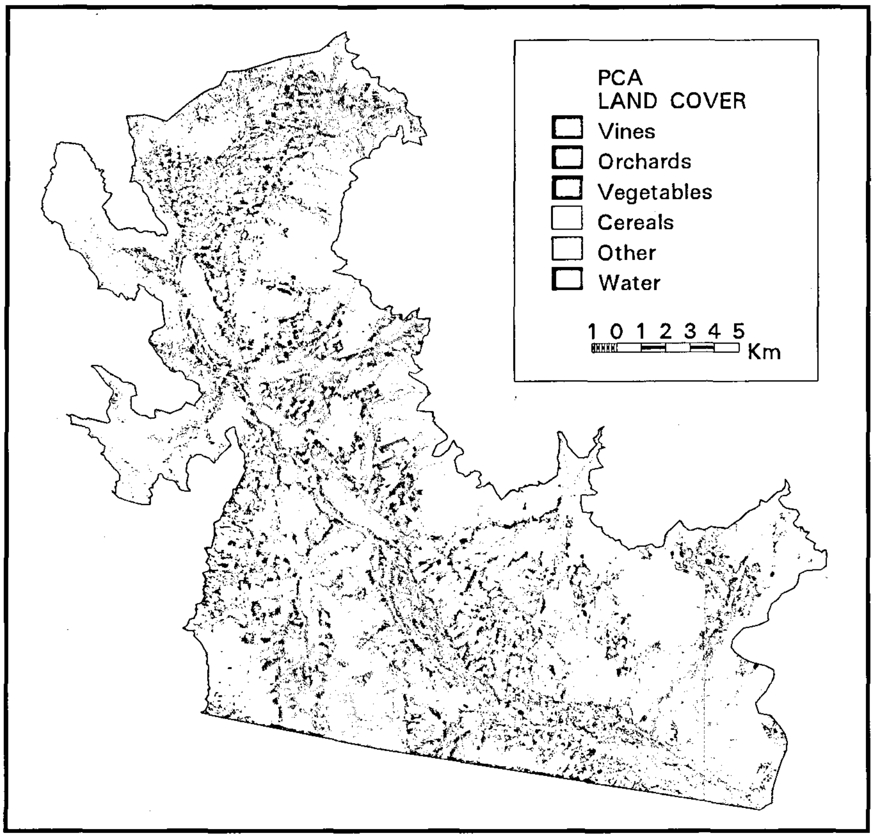


Figure 4.12: Generalized land cover map from unsupervised classification of SPOT XS Principal Component data.

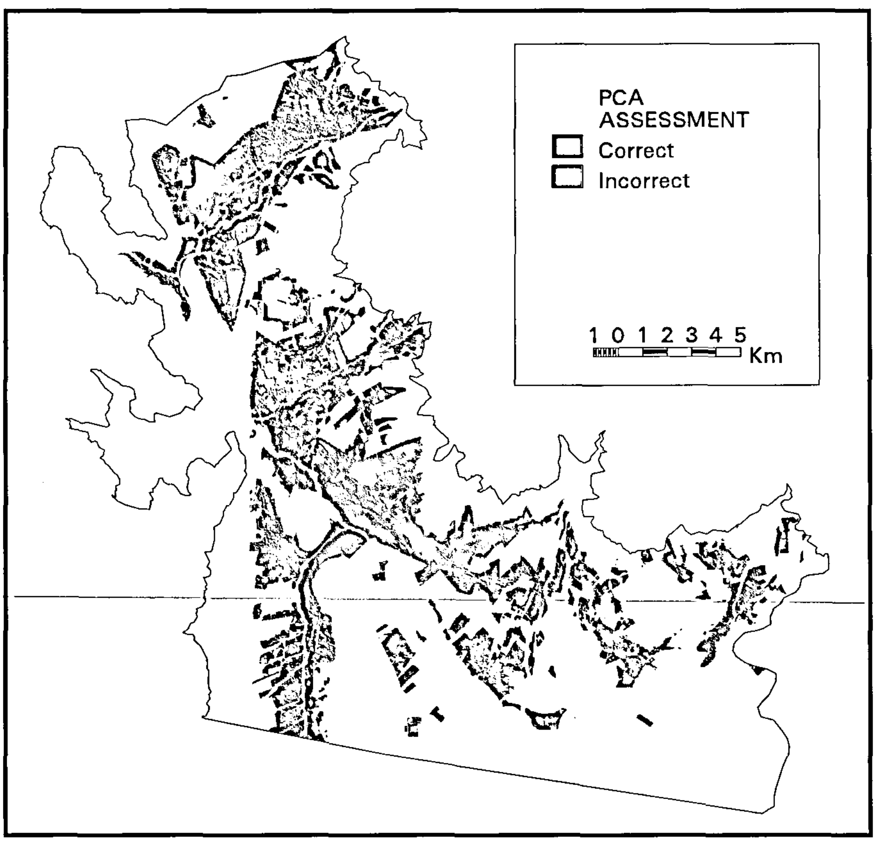


Figure 4.13: Accuracy assessment of generalized land cover map from unsupervised classification of SPOT XS Principal Component data.

Table 4.12: Accuracy assessment of SPOT PCA unsupervised classification by comparing with land use map.

	PCA Unsupervised Classification						
	N = 294543	Vines	Orchards	Vegetables	Cereals	Other	Total2)
Land use	Vines	74,81)	0,0	0,0	0,0	25,2	49,0
	Orchards	73,0	0,0	0,0	0,0	27,0	14,4
	Vegetables	45,0	0,0	0,0	0,0	55,0	2,5
	Cereals	26,5	0,0	0,0	0,0	73,5	24,6
	Other	43,7	0,0	0,0	0,0	56,3	9,5
	Total	59,0	0,0	0,0	0,0	41,0	42,03)

1) Row % 2) Column % 3) Overall accuracy (%)

When overall accuracies are assessed in terms of irrigated land cover types 66,3% of all pixels were correctly assigned, which is only slightly lower than the 67,46% achieved by the unsupervised classification on untransformed data as discussed previously (Table 4.13).

Table 4.13: Accuracy assessment of SPOT PCA unsupervised classification of irrigated land cover types.

	Unsupervised Classification				
	N = 294543	Irrigated	Non-irrigated	Other	Total2)
Land use	Irrigated	73,31)	0,0	26,8	65,9
	Non-irrigated	26,5	0,0	73,5	24,6
	Other	43,8	0,0	56,3	9,5
	Total	59,0	0,0	41,0	66,33)

1) Row % 2) Column % 3) Overall accuracy (%)

The spatial distribution of correctly and erroneously classified pixels is shown in Figure 4.14 and 4.15. The area statistics for the entire study area (after integration with the ancilliary data) are shown in Table 4.14. The most significant conclusion to be drawn from Table 4.14 is that 27798 pixels, or 11111,9 ha, could be identified as irrigated areas on the basis of the classification.

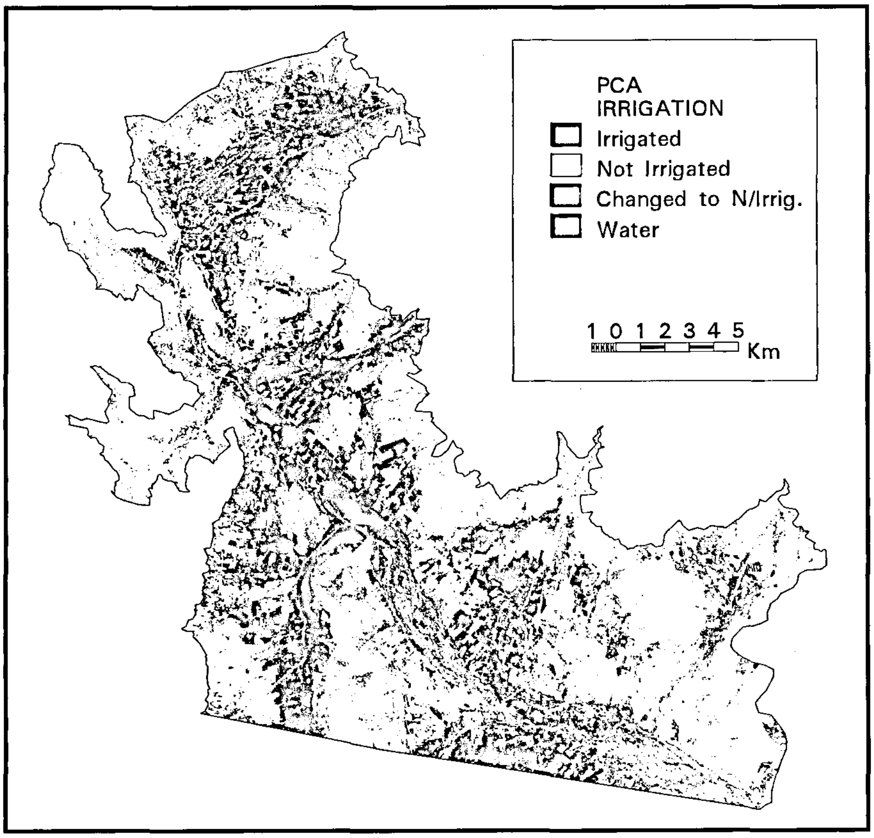


Figure 4.14: Irrigated land cover map from unsupervised classification of SPOT XS Principal Component data.

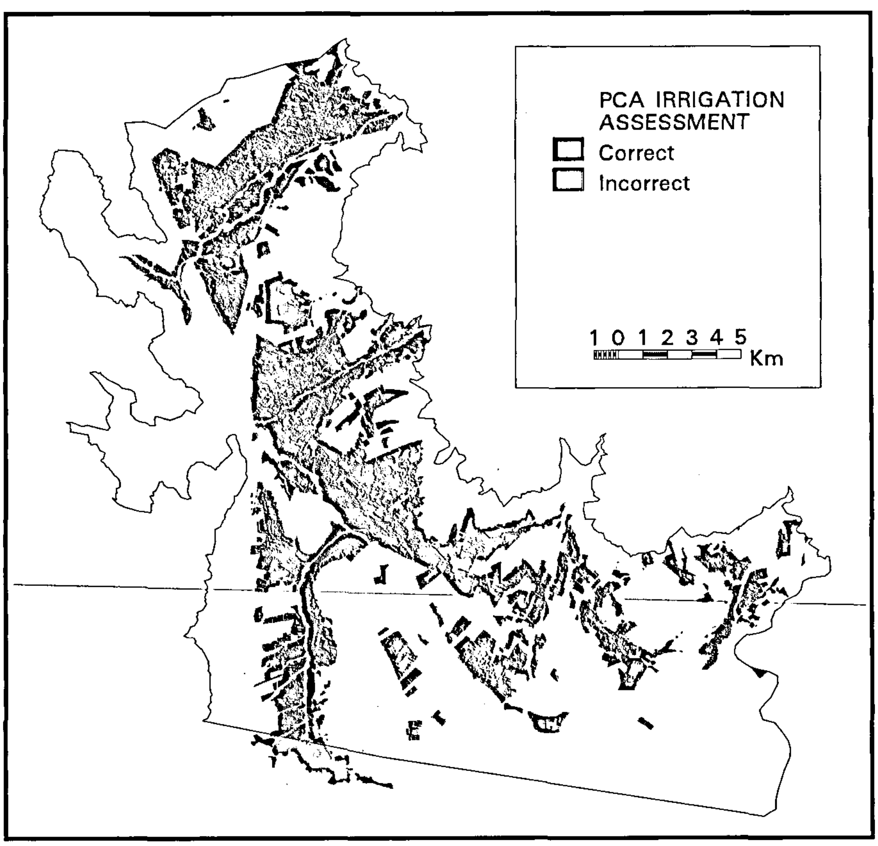


Figure 4.15: Accuracy assessment of irrigated land cover map from unsupervised classification of SPOT XS Principal Component data.

Table 4.14: Area statistics of final SPOT PCA unsupervised classification component data.

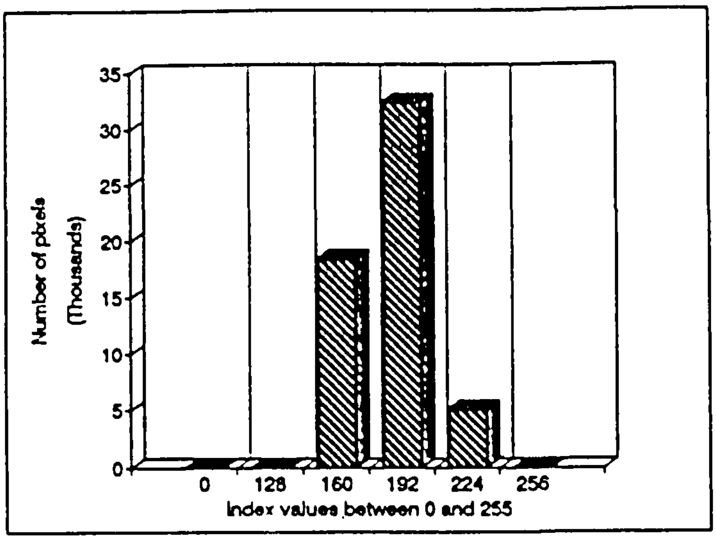
Class	Unsupervised classification	
	Number of Pixels	Area (Ha)
Irrigated	277798	12111,9
Non-irrigated	747509	29900,4
Ancillary data*	27989	119,6
Water	8347	333,9
Non-classified	35353	1414,1
Total	1096996	43879,9

* Pixels changed from irrigated to non-irrigated by ancillary data

In the next section, the focus shifts to the results which were obtained by calculating transformed normalised vegetation indices.

4.4.2.3 Transformed normalised vegetation index: SPOT XS data

Separate vegetation indices were calculated for the summer and winter SPOT XS-data, respectively. Since the index values could vary between 0 and 255, a threshold value had to be set for each of the seasonal indices which would divide the data into "irrigated" and "non-irrigated" areas (This technique is known as "density slicing"). However, Figure 4.16 shows that there were no natural clusters in the set of data. Experimentation with various threshold values derived from the winter vegetation index showed that it had little value as an technique which could be used to distinguish between irrigated and non-irrigated areas. This is not surprising if one considers that orchards and vines have no leaves in winter. The summer index, on the other hand, showed a clear relationship between the spatial distribution of irrigated crops and high index values. Since, it was not absolutely clear which index value should be used as a threshold value, the summer index values were grouped into classes and these were crosstabulated with the farm survey data. The result revealed that an irrigation map (Figure 4.17) based on a threshold value of 185 succeeded best in distinguishing between irrigated and non-irrigated land use types on the surveyed farms. Table 4.15 shows that 83,5% of the vines on the surveyed farms were correctly classified. A high accuracy level (77,8%) was also attained for the land cover types labelled "other". A more negative observation are the large percentage (88,0%) of orchards which were classified as vines. Furthermore, the majority of vegetables (59,2%) and cereals (89,9%) corresponded best spectrally with the class labelled "other". In spite of obvious misclassifications an overall accuracy level of 63,9% was achieved. Generalising the land use categories to "irrigated", "non-irrigated" and "other" improved the overall accuracy to 76,6% (Table 4.16). Taking into account, the low manpower input which was required to calculate the vegetation index, this was a very encouraging result.



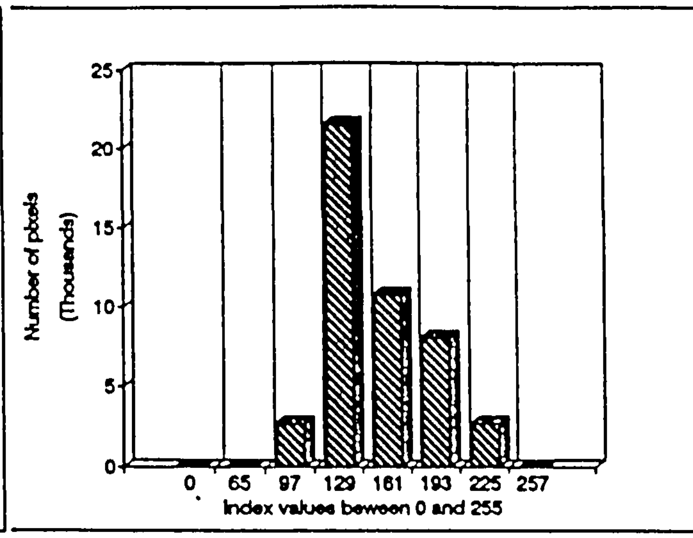


Figure 4.16A: Frequency distribution of winter vegetation index.

Figure 4.16B: Frequency distribution of summer vegetation index.

Table 4.15: Accuracy assessment of SPOT summer vegetation index by comparing with generalised farm survey data.

	SPOT summer vegetation index (Threshold value = 185)						
	N = 72889	Vines	Orchards	Vegetables	Cereals	Other	Total2)
Farm data	Vines	83,51)	0,0	0,0	0,0	16,5	35,8
	Orchards	88,0	0,0	0,0	0,0	12,0	12,4
	Vegetables	40,8	0,0	0,0	0,0	59,2	4,4
	Cereals	10,2	0,0	0,0	0,0	89,9	3,7
	Other	22,2	0,0	0,0	0,0	77,8	43,8
	Total	52,6	0,0	0,0	0,0	47,4	63,93)

1) Row % 2) Column % 3) Overall accuracy (%)

Table 4.16 Accuracy assessment of SPOT summer vegetation index by comparing with farm survey data.

	SPOT summer vegetation index (Threshold value = 185)				
	N = 72889	Irrigated	Non-irrigated	Other	Total[2)]
Farm data	Irrigated	80,9[1)]	0,0	19,1	52,6
	Non-irrigated	0,7	0,0	89,9	3,7
	Other	18,4	0,0	77,8	43,8
	Total	52,6	0,0	47,4	76,6[3)]

1) Row % 2) Column % 3) Overall accuracy (%)

A further experiment with vegetation indices involved combining the indices of two seasons. The rationale behind this was that if the winter index values (no foliage, low index value for vines and orchards) was subtracted from the summer index value (high index values for vines and orchards), the areas with relatively high index values would then represent the areas where vines and fruit trees are cultivated. It was hoped that evergreen growth such as plantations and riverine vegetation could hereby be separated from irrigated crops. However, such an application would also mean that should a field be covered with mature vegetables during both overpasses of the satellite, that area would not be shown as an irrigated area. Since the cultivation of vegetables accounts for a relatively small proportion of the study area, the possible loss of accuracy was overshadowed by the potential advantage of accurately identifying the larger areas of vineyards and orchards.

Although the combined seasonal index produced better results than the winter index, it could not match the accuracy levels of the summer index. The accuracy level of the combined index was up to 7% points lower than that of the summer index.

The integration of the summer vegetation index with the ancilliary data resulted in the classification of 359858 pixels, or rather 14394,3 ha as irrigated areas. These statistics are summarised in Table 4.17, and the spatial accuracy of irrigated and non-irrigated areas are depicted in Figure 4.18.

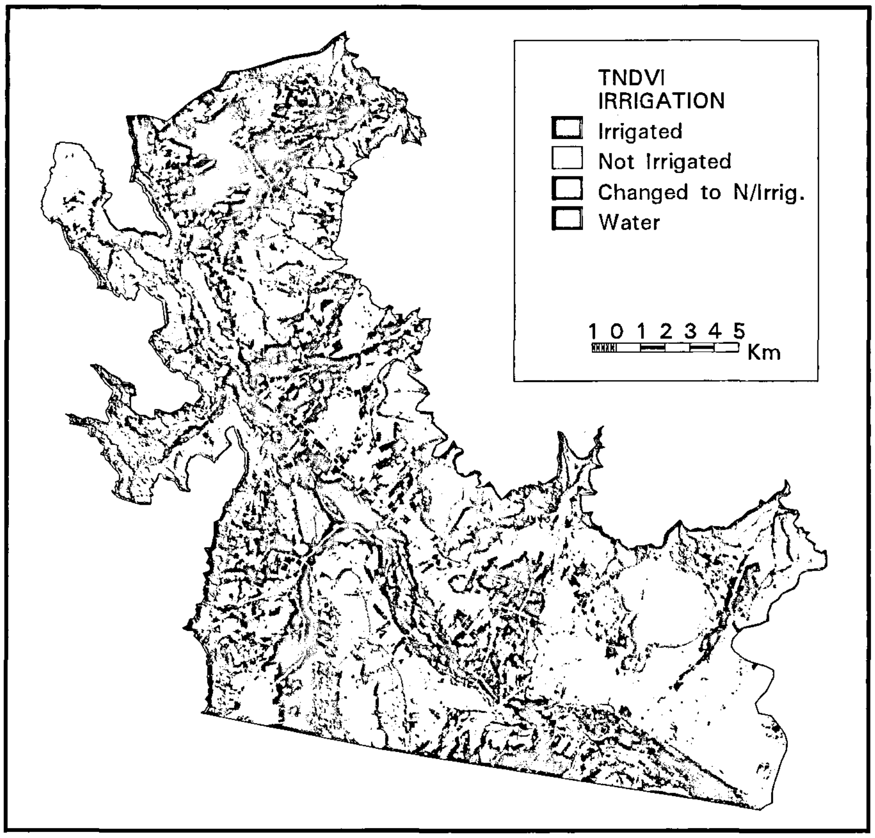


Figure 4.17: Irrigated land cover map from SPOT XS TNDVI data.

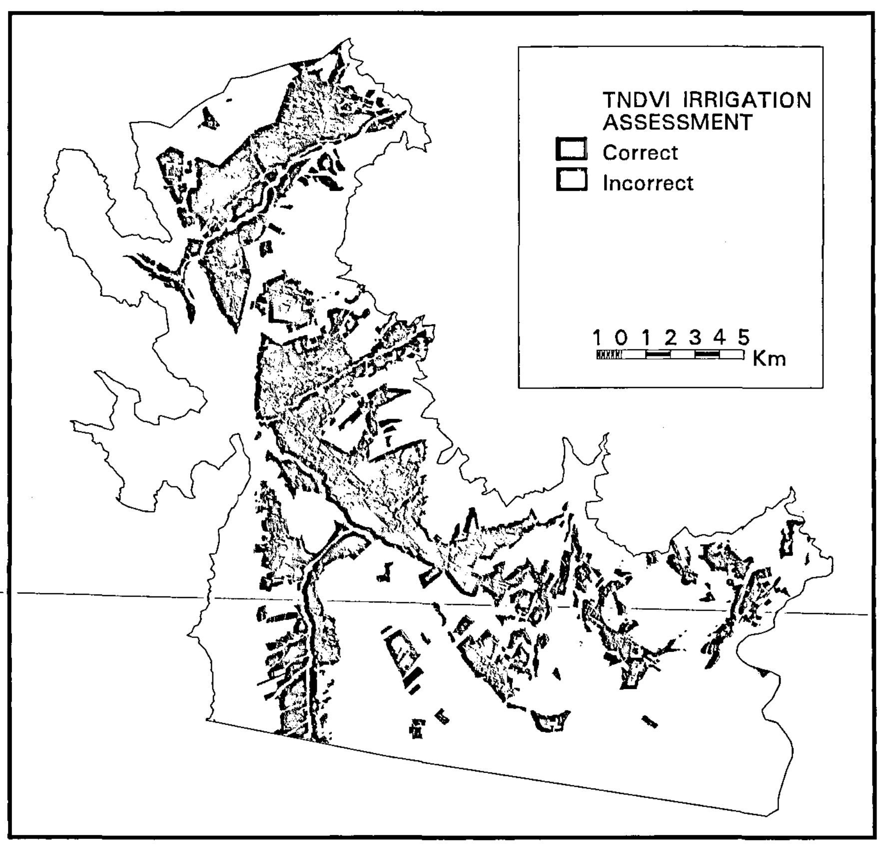


Figure 4.18: Accuracy assessment of irrigated land cover map from SPOT XS TNDVI data.

Table 4.17: Area statistics of final SPOT summer vegetation index.

Class	Summer vegetation index	
	Number of Pixels	Area (Ha)
Irrigated	359858	14394,3
Non-irrigated	478662	19146,5
Ancillary data*	250129	10005,2
Non-classified	8347	333,9
Total	1096996	43879,9

* Pixels changed from irrigated to non-irrigated by ancillary data

4.4.2.4 Supervised classification: Untransformed SPOT XS-data

The results obtained using a supervised approach analysing SPOT XS data did not live up to expectations. This situation may be ascribed to the agricultural complexity of the study area, which made selection of internally homogeneous training areas virtually impossible. In comparison with the farm survey data an overall accuracy level of 57% was achieved which is slightly lower than that obtained with the unsupervised approach. Vines were 52% correctly classified, whilst orchards, vegetables, cereals and the 'other' class were respectively 35%, 11%, 44% and 72% correctly classified (Table 4.18). In spite of low classification accuracies it was possible to distinguish classes such as orchards, vegetables and cereals with a certain degree of certainty (Figure 4.19). This was not possible with the other approaches.

Table 4.18: Accuracy assessment of supervised SPOT classification by comparing with the farm data.

	Supervised Classification						
	N = 77402	Vines	Orchards	Vegetables	Cereals	Other	Total 2)
Farm data	Vines	51,7 1)	8,9	3,3	5,8	30,3	36,4
	Orchards	31,8	34,6	2,6	3,7	27,4	12,6
	Vegetables	18,1	1,1	10,8	22,4	47,5	2,4
	Cereals	8,1	3,6	12,7	43,3	32,3	4,4
	Other	8,3	4,3	1,8	13,9	71,7	44,2
	Total	18,8	4,4	0,3	1,8	31,7	57,0 3)

1) Row % 2) Column % 3) Overall accuracy (%)

Accuracy levels declined when evaluated against the land cover map of the study area. An overall accuracy of only 42% was recorded whilst individual categories corresponded very weakly with those of the map (Figure 4.20). Vines were 47% correctly classified whereas orchards, vegetables, cereals and other cover types had accuracies of 28%, 10,7%, 38,9% and 53,4% respectively (Table 4.19). This statistical analysis probably reflects the lower accuracies of the land use map.

Table 4.19: Accuracy assessment of SPOT supervised classification by comparing with the land use map.

	Supervised Classification						
	N = 308178	Vines	Orchards	Vegetables	Cereals	Other	Total
Farm data	Vines	47,0 1)	7,6	4,4	9,6	31,2	49,2 2)
	Orchards	31,9	27,8	2,5	6,5	31,4	14,5
	Vegetables	23,8	3,1	10,7	18,5	43,9	2,7
	Cereals	11,2	2,9	7,8	38,9	39,2	24,4
	Other	18,5	6,4	5,6	17,2	53,4	9,2
	Total	23,1	4,0	0,3	9,4	4,9	41,8 3)

1) Row % 2) Column % 3) Overall accuracy (%)

By once again assessing accuracy in terms of irrigated and non-irrigated land cover types the overall accuracy improves to 54%. The irrigated class is 59% correctly classified and

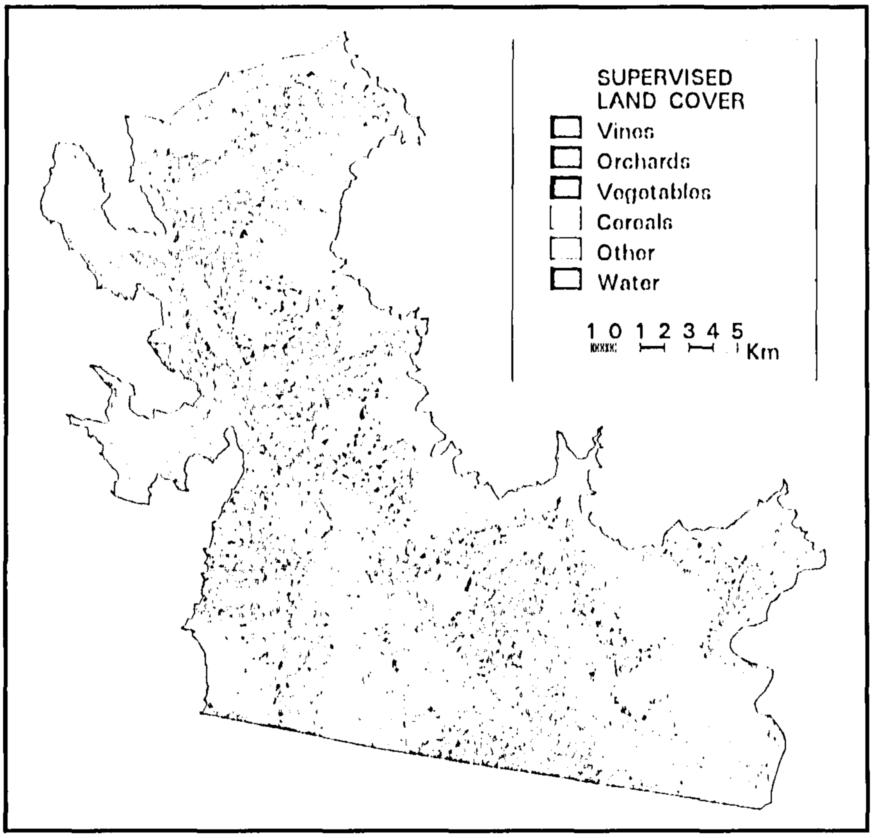


Figure 4.19: Generalized land cover map from supervised classification of untransformed SPOT XS data.

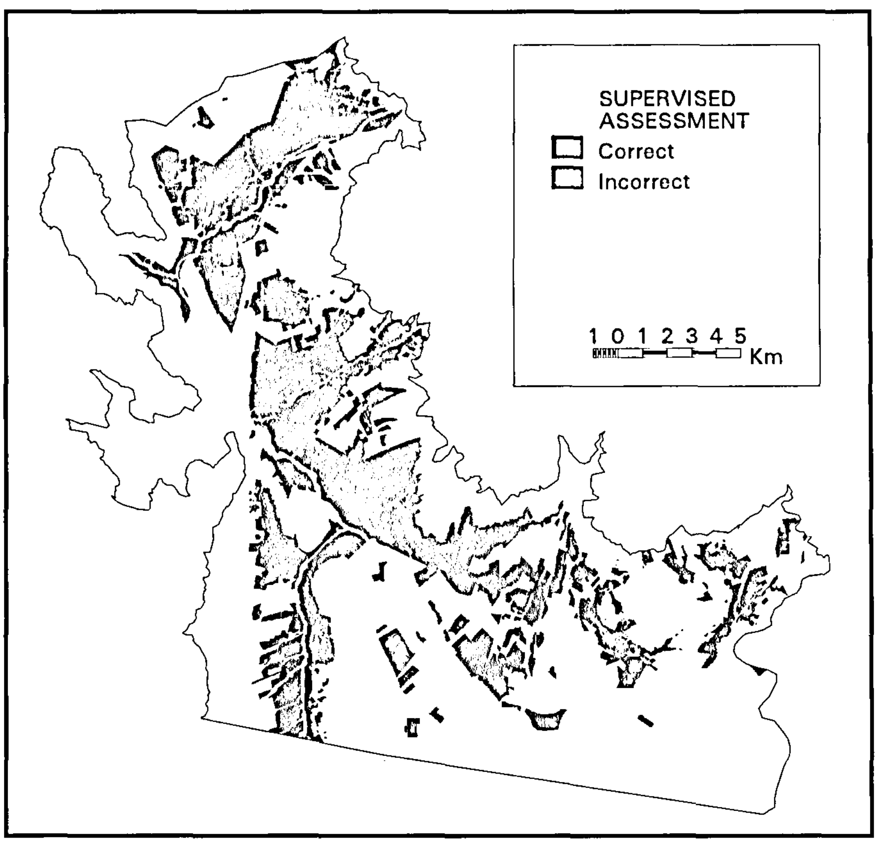


Figure 4.20: Accuracy assessment of generalized land cover map from supervised classification of untransformed SPOT XS data.

the non-irrigated 39% (Table 4.20). The map shows a more conservative distribution of irrigated land cover types than that of other analytical procedures employed (Figures 4.21 and 4.22). The computed area statistics are presented in Table 4.21.

Table 4.20: Accuracy assessment of the SPOT supervised classification for irrigated land cover types.

		Supervised Classification			
	N = 308178	Irrigated	Non-irrigated	Other	Total2)
Land use	Irrigated	58,91)	9,2	31,8	67,0
	Non-irrigated	22,0	38,9	39,2	24,6
	Other	33,0	19,1	59,7	8,3
	Total	47,64	17,4	36,0	54,03)

1) Row % 2) Column % 3) Overall accuracy (%)

Table 4.21: Area statistics of final SPOT supervised classification.

Class	Unsupervised classification	
	Number of Pixels	Area (Ha)
Irrigated	850044	34001,8
Non-irrigated	212255	8490,2
Ancillary data*	24355	974,2
Water	8347	333,9
Non-classified	1995	79,8
Total	1096996	43879,9

* Pixels changed from irrigated to non-irrigated by ancillary data

4.4.3 Landsat TM

The procedure followed to evaluate the accuracy of the classified images entailled crosstabulating the generalized land cover codes of the images with those of the land use classes as obtained from a field survey of a selected number of farms in the study area. In all cases the classified TM imagery was converted to Arc/Info GRID formats and then compared with the gridded farm data and the landuse map of the study area using the

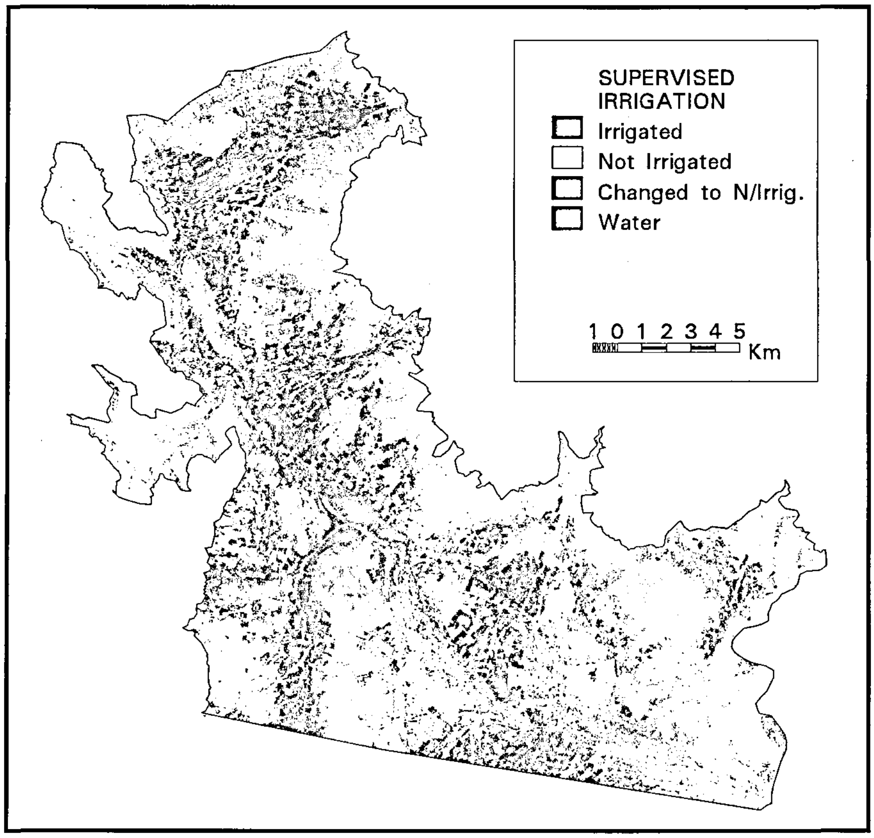


Figure 4.21: Irrigated land cover map from supervised classification of untransformed SPOT XS data.

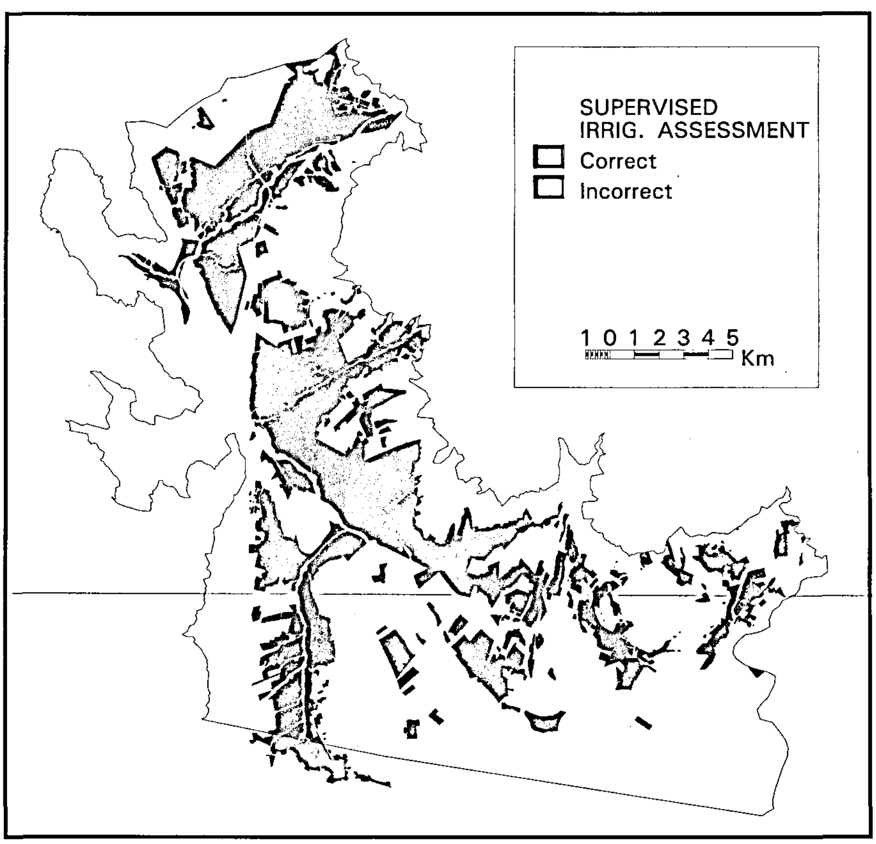


Figure 4.22: Accuracy assessment of irrigated land cover map from supervised classification of untransformed SPOT XS data.

CAND operator. The resulting INFO VAT-files were exported to Borland's Reflex programme for crosstabulating and computing percentages.

4.4.3.1 Unsupervised classification: Raw Landsat TM-data

Table 4.22 shows that the unsupervised classification produced exceptionally good results when checked against the surveyed farm data. An overall accuracy of 73% was achieved. Vines were 87,7% correctly classified and as this is the major agricultural activity in the area it is of particular significance. Orchards were not well classified as only 59,7% were correctly identified. Orchards are mainly confused with vines. The classifier did not classify any land as vegetable crops. Cereals were also not well distinguished (only 54,6% correct).

When evaluating the classification results by comparing with the land use map of the study area somewhat similar trends are observed (Table 4.23). As can be expected the overall accuracy is much lower (50,7%). Vines remain the class with the highest accuracy (71,6%), followed by orchards (47,9%). The statistics show that the vine class included high proportions of all other cover types, indicating substantial errors of commission.

Table 4.22: Accuracy assessment of Landsat unsupervised classification by comparing with farm survey data.

		Unsupervised Classification					
	N = 18398	Vines	Orchards	Vegetables	Cereals	Other	Total2)
Farm data	Vines	87,71)	9,6	0,0	1,1	1,6	62,1
	Orchards	38,5	59,7	0,0	1,1	0,7	21,6
	Vegetables	68,9	2,6	0,0	16,2	12,3	4,0
	Cereals	37,3	7,4	0,0	54,6	0,7	7,7
	Other	40,8	15,6	0,0	12,1	31,6	4,5
	Total	70,2	20,2	0,0	6,3	3,1	73,03)

1) Row % 2) Column % 3) Overall accuracy (%)

Table 4.23: Accuracy assessment of Landsat unsupervised classification by comparing with the land use map.

	Unsupervised Classification						
	N = 145304	Vines	Orchards	Vegetables	Cereals	Other	Total[2)]
Land use	Vines	71,6[1)]	10,0	0,0	5,2	13,2	47,1
	Orchards	37,8	47,9	0,0	4,2	10,1	13,8
	Vegetables	53,6	4,9	0,0	20,0	21,5	2,6
	Cereals	41,7	6,5	0,0	29,8	22,0	23,3
	Other	41,5	18,7	0,0	13,3	26,5	13,2
	Total	55,5	15,4	0,0	12,3	16,8	50,7%[3)]

1) Row % 2) Column % 3) Overall accuracy (%)

A land cover map produced from the classification confirmed that vines are overestimated (Figure 4.23). This is bourne out by the accompanying map (Figure 4.24), which shows where the incorrect classifications had occured.

To take this evaluation a step further land cover classes were generalized into three classes, i.e. irrigated, non-irrigated and water. This map was subjected to a logical cleanup process whereby pixels classified as belonging to an irrigated land cover type (vines, orchards and vegetables) were recoded to a non-irrigated class based on ancilliary GIS-data. The criteria used were as discussed in the introductory section (4.4.1). Table 4.24 and Figures 4.25 and 4.26 presents the results of this process. From this analysis it was found that 77,9% of all irrigated land cover types are correctly classified and the overall accuracy level is at 69,0%. The cleanup procedure improved the overall accuracy level by 2 percentage points.

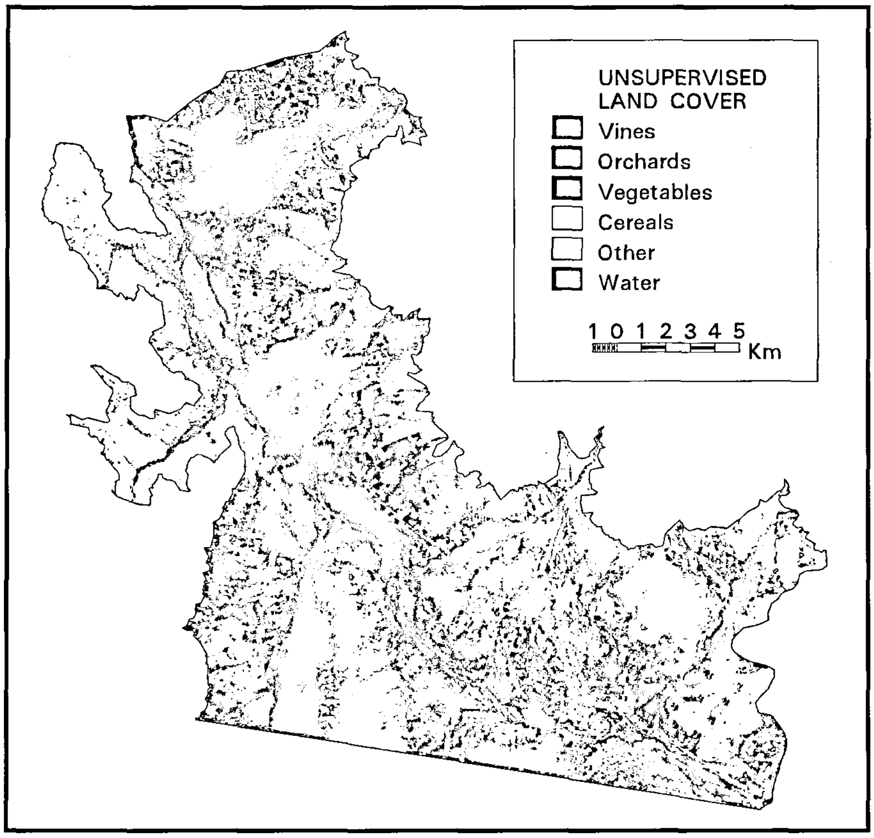


Figure 4.23: Generalized land cover map from supervised classification of untransformed Landsat TM data.

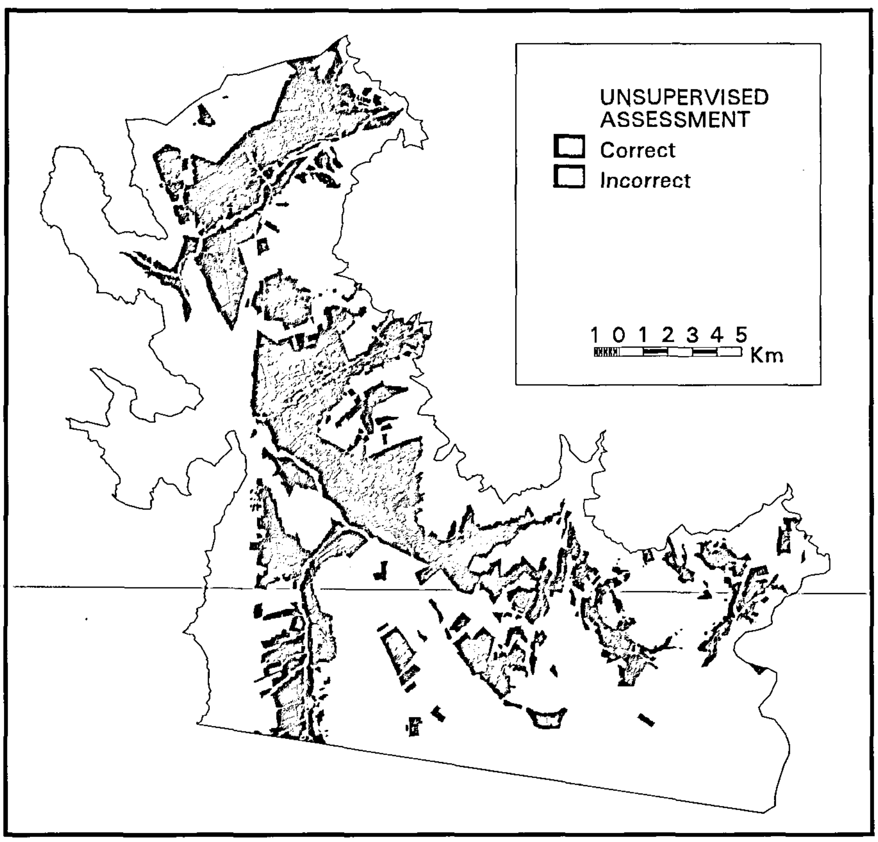


Figure 4.24: Accuracy assessment of generalized land cover map from unsupervised classification of untransformed Landsat TM data.

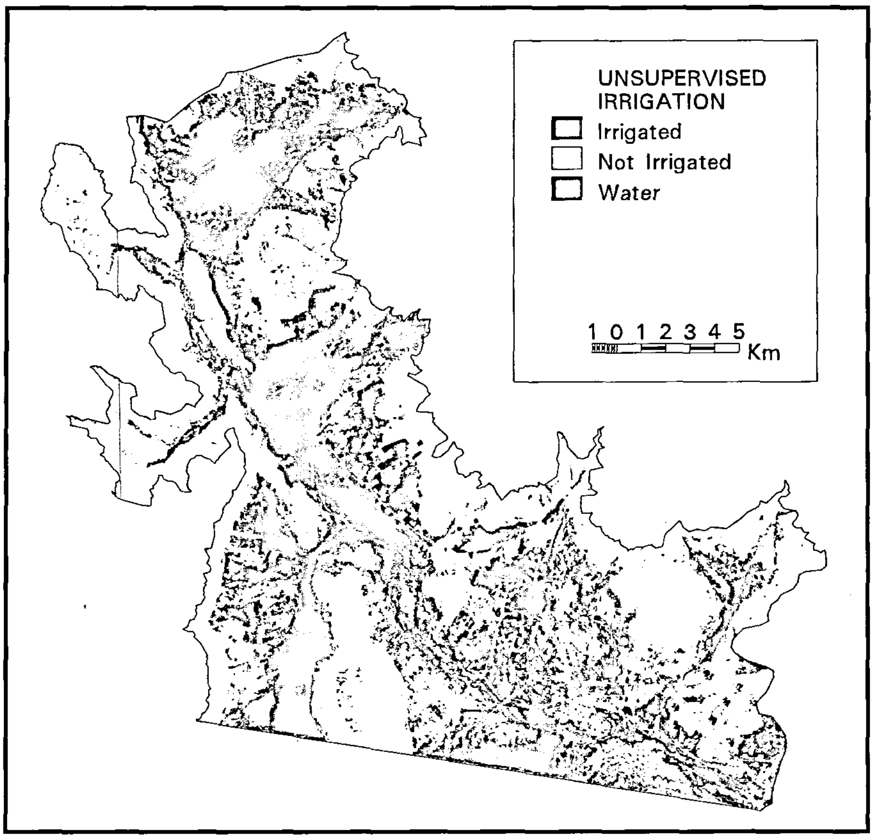


Figure 4.25: Irrigated land cover map from unsupervised classification of untransformed Landsat TM data.

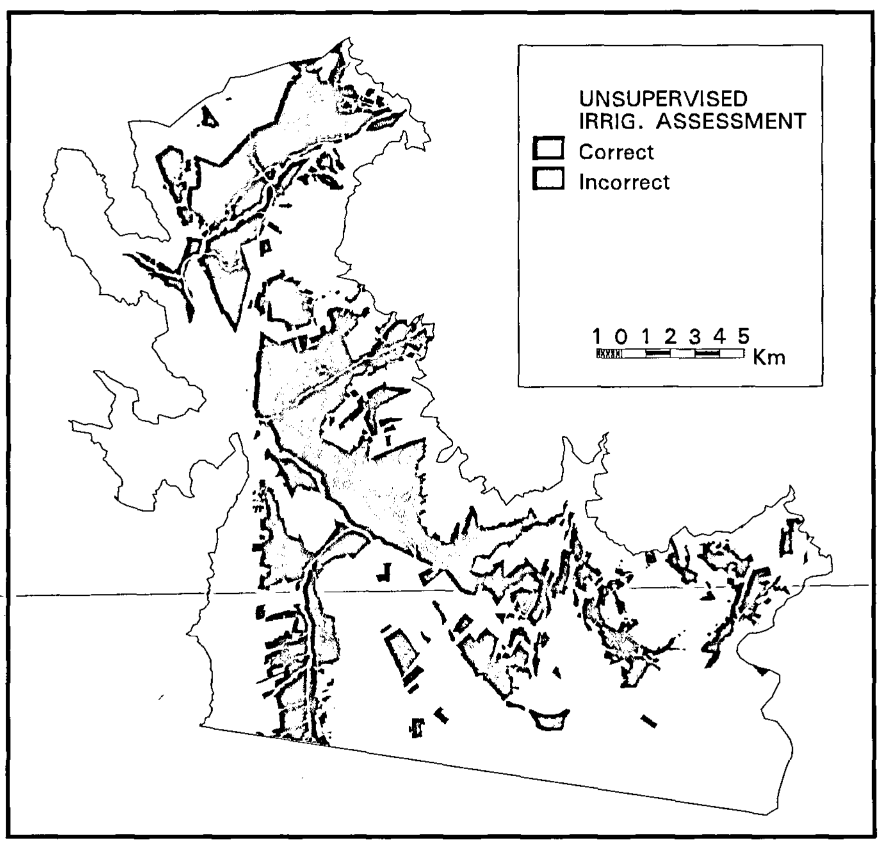


Figure 4.26: Accuracy assessment of irrigated land cover map from unsupervised classification of untransformed Landsat TM data.

Table 4.24: Accuracy assessment of Landsat unsupervised classification for irrigated land cover types.

	Unsupervised Classification				
	N = 149801	Irrigated	Non-irrigated	Other	Total2)
Land use	Irrigated	77,91)	20,7	1,4	61,6
	Non-irrigated	42,7	56,1	1,2	35,4
	Other	18,7	42,3	39,0	3,0
	Total	63,6	33,9	2,4	69,03)

1) Row % 2) Column % 3) Overall accuracy (%)

4.4.3.2 Unsupervised classification: Principal component analysis data

The unsupervised classification of the PCA data proved slightly less successful in overall terms and has an accuracy level of 68% in comparison with the 73% of the unsupervised classification of the untransformed data (Table 4.25). However, vines were more accurately classified (89,4%) but at a cost to orchards and cereal land cover types. The generalized land cover map produced from the PCA classification (Figure 4.27) shows that the PCA approach overestimated vines enormously. This is confirmed by the marginal percentages in Table 4.25 according to which the PCA classification designated 73,9% of all pixels to the vine class, whereas vines only made up 57,8% of the farm survey pixels.

In comparison with the land cover map for the whole study area the classification has an overall accuracy level of only 51,8%. Although vines were well classified and has an accuracy of 83,7% all other land cover types were very badly identified (orchards 32,4%, cereals 26,0% and vegetables 0,0%) (Table 4.26). The map (Figure 4.28) and marginal percentages in Table 4.26 confirms the gross overestimation of vines by this particular classifications. Vines are overestimated by 16 percentage points.

The evaluation of classification accuracy in terms of the irrigated land cover types has an overall level of 67,5% which is slightly lower than that obtained by the unsupervised classification of the untransformed TM data. As far as irrigated land cover is concerned the accuracy level is higher (84,2%), but much lower for other categories (Table 4.27). This emphasizes the tendency of the procedure to overestimate vines and is bourne out by an inspection of the relevant maps (Figures 4.29 and 4.30).

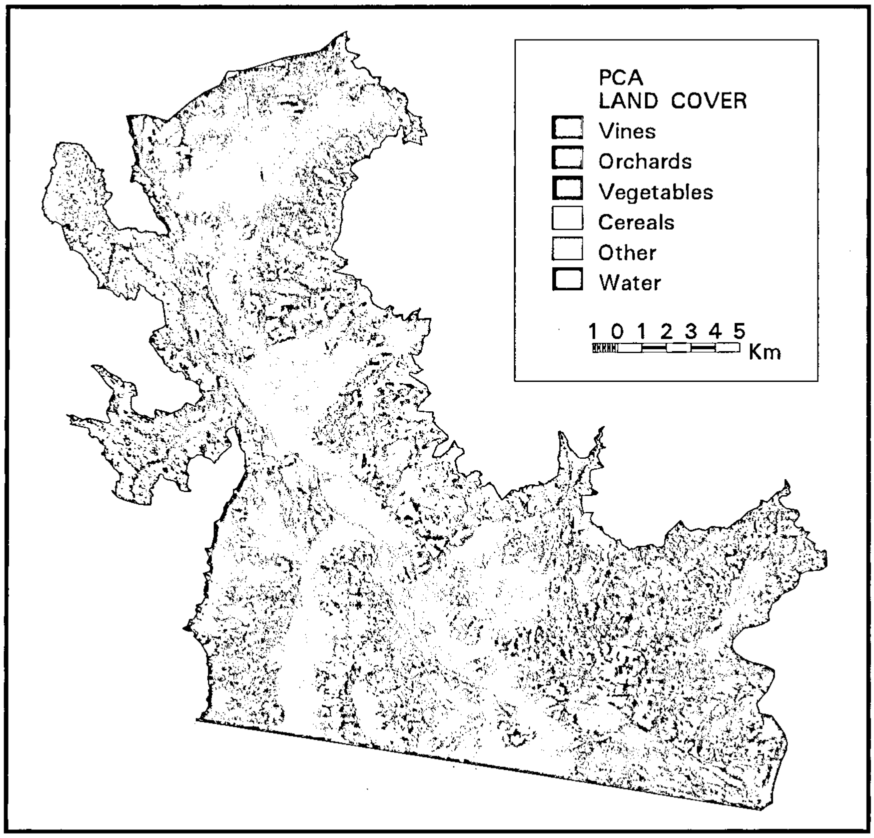


Figure 4.27: Generalized land cover map from unsupervised classification of Landsat TM Principal Component data.

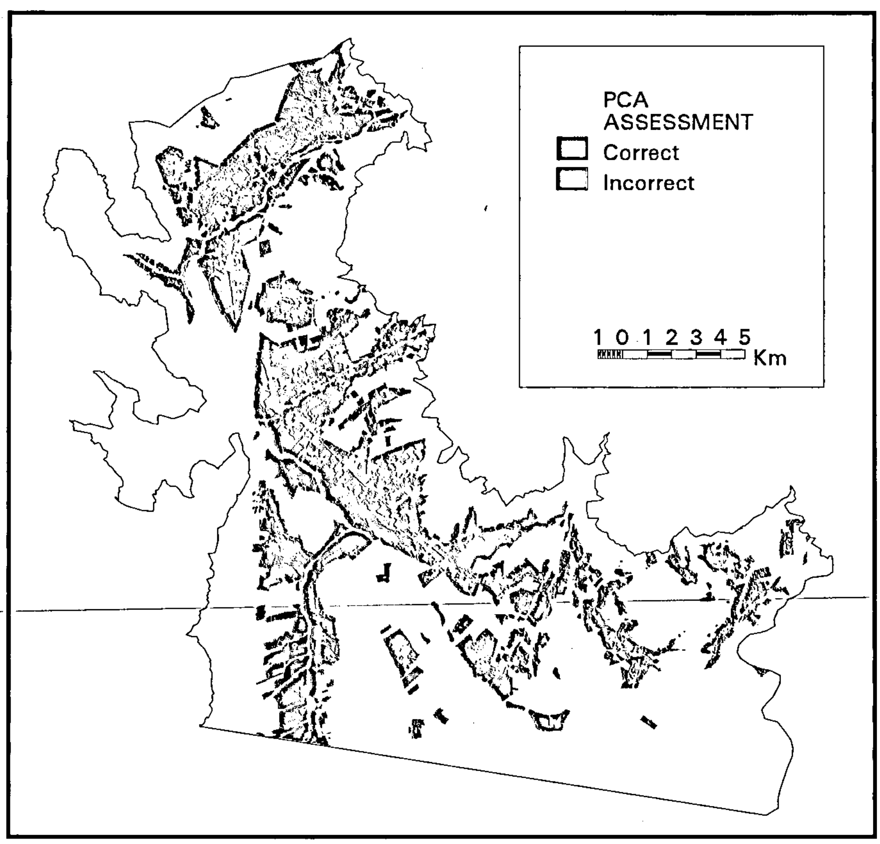


Figure 4.28: Accuracy assessment of generalized land cover map from unsupervised classification of Landsat TM Principal Component data.

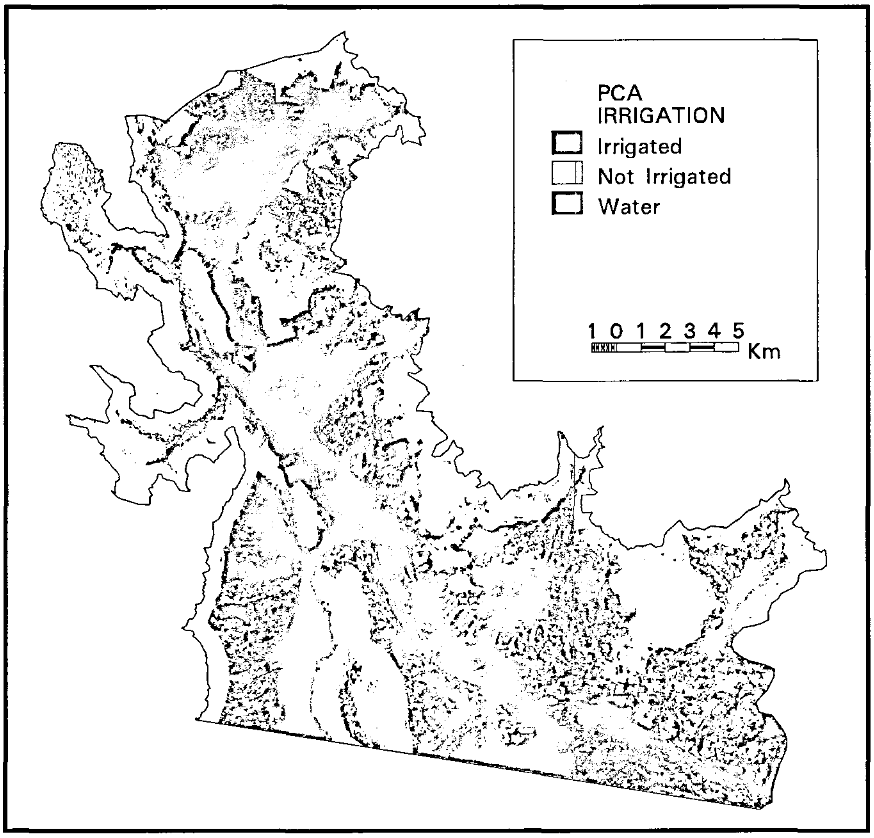


Figure 4.29: Irrigated land cover map from unsupervised classification of Landsat TM Principal Component data.

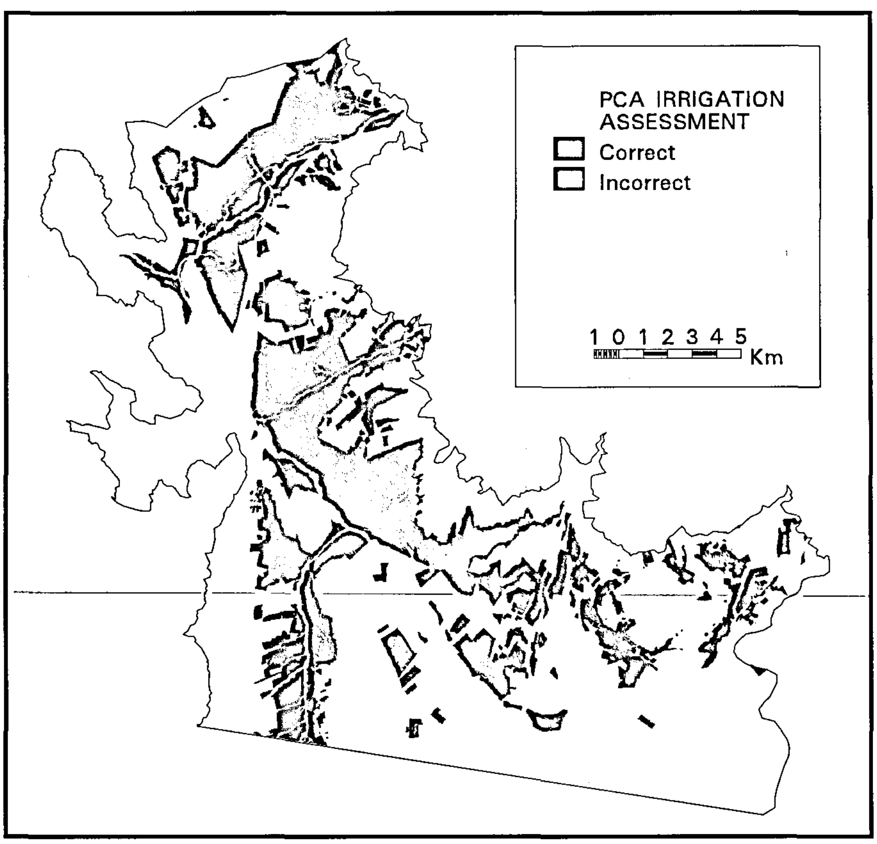


Figure 4.30: Accuracy assessment of irrigated land cover map from unsupervised classification of Landsat TM Principal Component data.

Table 4.25: Accuracy assessment of Landsat PCA unsupervised classification by comparing with farm survey data.

	PCA Unsupervised classification						
	N = 21754	Vines	Orchards	Vegetables	Cereals	Other	Total2)
Farm data	Vines	89,41)	4,5	0,0	1,1	5,0	57,8
	Orchards	55,0	39,3	0,0	1,0	4,6	20,0
	Vegetables	71,7	0,6	0,0	18,5	9,2	3,9
	Cereals	61,7	2,0	0,0	27,8	8,6	7,3
	Other	35,5	2,8	0,0	3,2	58,6	10,9
	Total	73,9	10,9	0,0	3,9	11,2	68,03)

1) Row % 2) Column % 3) Overall accuracy (%)

Table 4.26: Accuracy assessment of Landsat PCA unsupervised classification by comparing with the land use map.

	PCA Unsupervised classification						
	N = 145304	Vines	Orchards	Vegetables	Cereals	Other	Total2)
Land use	Vines	83,71)	4,5	0,0	5,1	6,6	47,1
	Orchards	59,5	32,4	0,0	3,0	5,0	13,8
	Vegetables	67,6	1,9	0,0	20,6	9,9	2,6
	Cereals	59,1	2,7	0,0	26,0	12,1	23,3
	Other	66,7	9,6	0,0	9,5	14,1	13,2
	Total	72,0	8,6	0,0	10,7	8,7	51,83)

1) Row % 2) Column % 3) Overall accuracy (%)

Table 4.27: Accuracy assessment of Landsat PCA unsupervised classification for irrigated land cover types.

	PCA Unsupervised Classification				
	N = 149811	Irrigated	Non-irrigated	Other	Total 2)
Land use	Irrigated	84,2 1)	14,4	1,4	61,6
	Non-irrigated	53,0	45,8	1,2	35,4
	Other	30,0	31,0	39,0	3,0
	Total	71,5	26,0	2,5	67,5 3)

1) Row %   2) Column %   3) Overall accuracy (%)

4.4.3.3 Unsupervised classification: NDVI data

This classification on the NDVI values of four seasons performed slightly better than the principal component analysis but did not reach the same overall level of accuracy achieved by the unsupervised classification on untransformed Landsat TM data. Its overall accuracy was 70,2%, that of vines 85,7%, orchards 41,7% vegetables a dismal 8,5%, cereals 54,8% and other 76,2% (Table 4.28). In comparisong with the former approaches vines are less accurately classified, but orchards slightly better than that of the PCA classification. By interpreting the marginal percentages it becomes evident that vines are not overestimated to the same degree as in the PCA classification. According to the farm data 57,8% of land surveyed is under vines, but the figure obtained from the NDVI classification is 66,1%, a difference of only 8,3% points. Recall that the comparative figure for the PCA classification was 16,0% points. The map confirms this conclusion (Figure 4.31).

Table 4.28: Accuracy assessment of Landsat NDVI unsupervised classification by comparing with farm survey data.

	NDVI Unsupervised classification						
	N = 21758	Vines	Orchards	Vegetables	Cereals	Other	Total2)
Farm data	Vines	85,7 1)	3,1	0,4	1,4	9,3	57,8
	Orchards	49,8	41,7	0,6	1,2	6,7	20,0
	Vegetables	59,2	1,0	8,3	12,5	19,0	4,8
	Cereals	29,1	4,5	0,3	54,8	11,3	6,4
	Other	17,2	3,0	0,0	3,6	76,2	11,0
	Total	66,1	10,8	0,8	5,6	16,7	70,2 3)

1) Row % 2) Column % 3) Overall accuracy (%)

An assessment of the NDVI classification by comparing it with the land use map of the study area (Figure 4.32) shows that an overall accuracy level or 53,1% was achieved. Vines were 79,3% correctly classified but other cover types fared badly (Table 4.29).

Table 4.29: Accuracy assessment of Landsat NDVI unsupervised classification by comparing with the land use map.

	NDVI Unsupervised classification						
	N = 143416	Vines	Orchards	Vegetables	Cereals	Other	Total2)
Land use	Vines	79,4 1)	2,8	0,0	4,8	13,0	47,2
	Orchards	59,8	28,8	0,0	3,1	7,5	13,8
	Vegetables	49,2	2,5	0,0	16,1	22,8	2,3
	Cereals	38,9	2,6	0,0	21,3	1,3	23,3
	Other	58,6	6,0	0,0	14,0	20,3	13,2
	Total	64,5	6,8	0,0	13,5	15,1	53,1 3)

1) Row % 2) Column % 3) Overall accuracy (%)

As far as irrigated land cover types are concerned (Table 4.30) the NDVI procedure performed slightly better than the PCA approach and attained an overall accuracy of 69,1%. Although the overall level is higher, vines has a lower level of accuracy than that of the PCA classification (78,8% versus 89,4%), however non-irregated cover types were

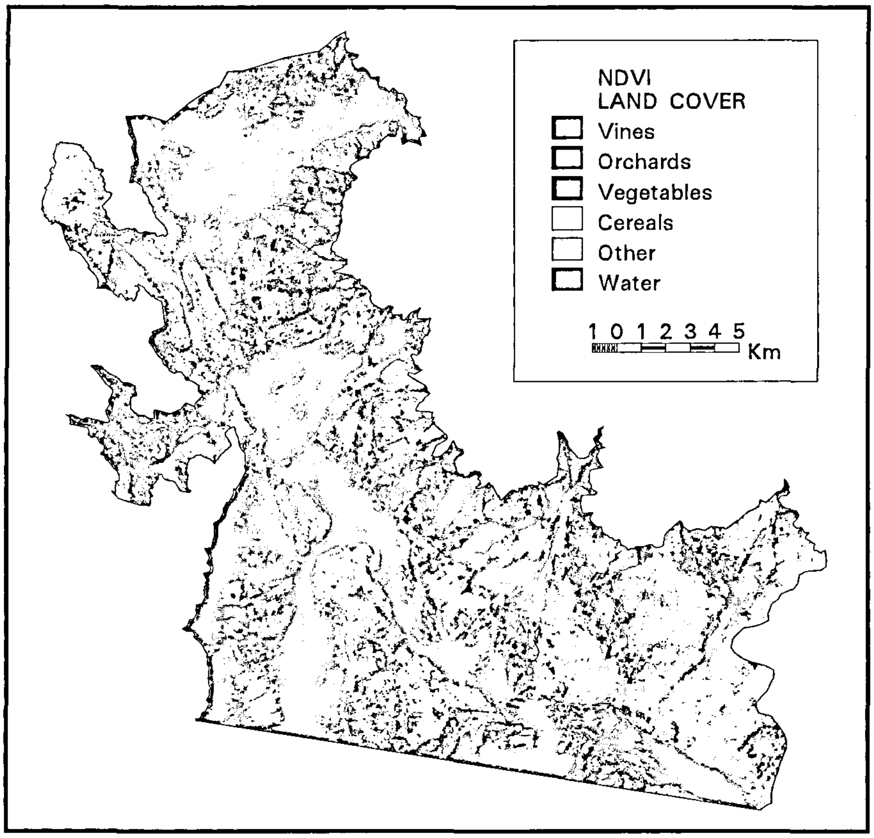


Figure 4.31: Generalized land cover map from unsupervised classification of Landsat TM NDVI data.

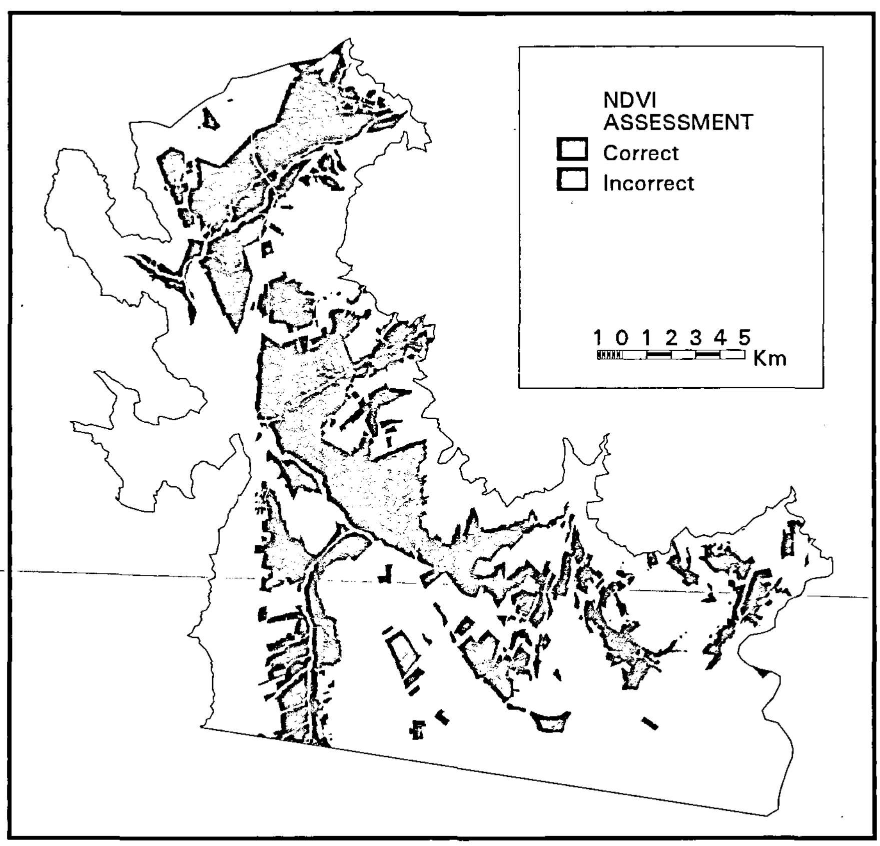


Figure 4.32: Accuracy assessment of generalized land cover map from unsupervised classification of Landsat TM NDVI data.

more accurately distinguished. The NDVI is less prone to overestimate irrigated areas than the PCA classification (Figures 4.33 & 4.34).

Table 4.30: Accuracy assessment of the Landsat NDVI unsupervised classification for irrigated land cover types.

	NDVI Unsupervised Classification				
	N = 149801	Irrigated	Non-irrigated	Other	Total[2]
Land use	Irrigated	78,8[1]	19,8	1,3	61,5
	Non-irrigated	43,5	55,5	1,0	35,4
	Other	21,3	50,8	27,9	3,1
	Total	64,6	33,4	2,0	69,1[3]

1) Row % 2) Column % 3) Overall accuracy (%)

4.4.3.4 Supervised classification: Untransformed Landsat TM-data

Very high expectations were nurtured concerning the ability of a multi-temporal supervised approach for classifying cultivated land cover types. Unfortunately the results did not fully live up to these expectations. Some comments will be made in a later section about possible reasons for this outcome. In comparison with the results of the unsupervised approaches discussed previously this method achieved an overall accuracy of 71% which is slightly lower than that which was achieved by the unsupervised classification of untransformed data. Vines were 75% correctly classified, orchards 56,7%, vegetables 54,7%, cereals 57,9% and other 90,7% (Table 4.31). So despite a slightly lower overall accuracy the supervised approach managed to also classify other land cover types with much higher levels of accuracy than did the unsupervised approaches. With the exception of the NDVI method it could also distinguish vegetables to some extent. Another favourable aspect about the supervized classification is that it did not overestimate vines to the detriment of other land cover types. It actually underestimated vines by 6,7% points and orchards by 4,3% points. This tendency is also to be seen on the generalized land cover map (Figure 4.35).

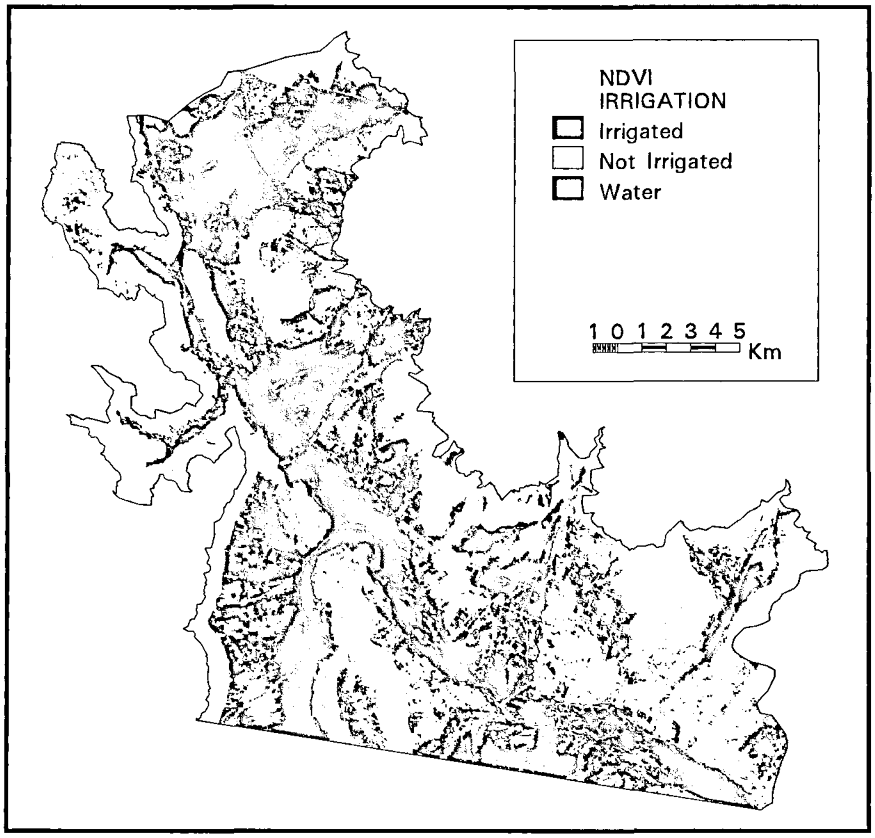


Figure 4.33: Irrigated land cover map from unsupervised classification of Landsat TM NDVI data.

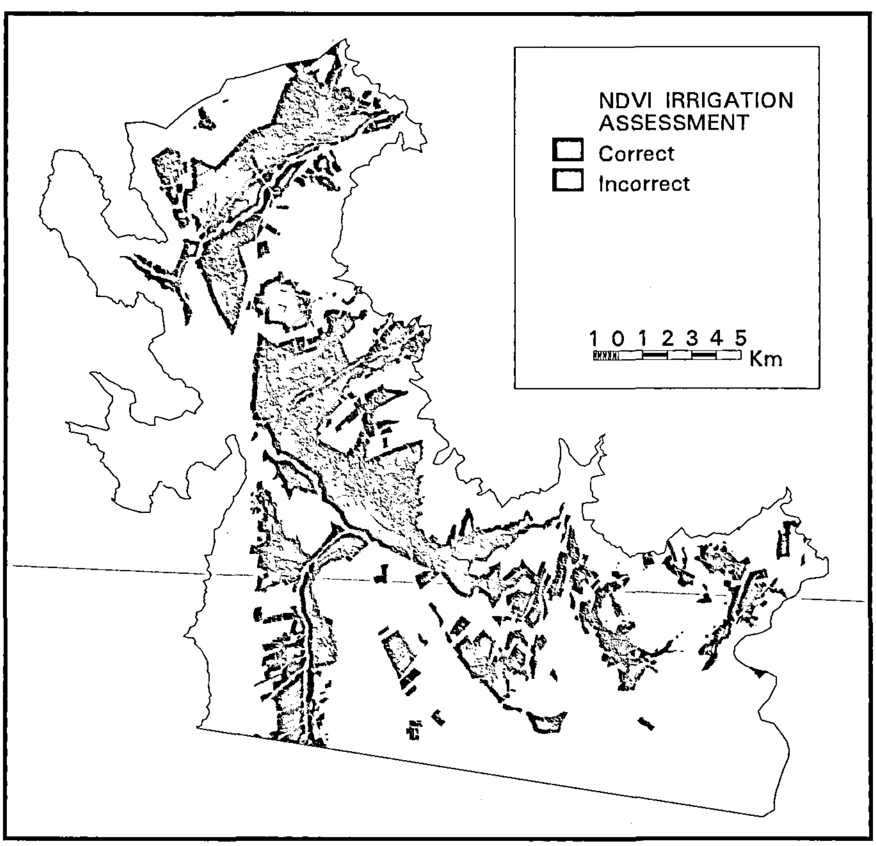


Figure 4.34: Accuracy assessment of irrigated land cover map from unsupervised classification of Landsat TM NDVI data.

Table 4.31: Accuracy assessment of Landsat supervised classification by comparing with farm survey data.

	Supervised classification						
	N = 21758	Vines	Orchards	Vegetables	Cereals	Other	Total[2)]
Farm data	Vines	74,9[1)]	6,9	7,1	1,9	9,1	57,8
	Orchards	28,9	56,7	5,2	2,5	6,8	20,0
	Vegetables	23,6	1,5	54,7	4,5	15,7	3,9
	Cereals	10,6	2,5	11,6	57,9	17,4	7,3
	Other	2,6	0,8	0,5	5,3	90,7	11,0
	Total	51,1	15,7	8,2	5,9	18,4	71,0[3)]

1) Row % 2) Column % 3) Overall accuracy (%)

When the results of the supervised classification are tested against the land cover map of the area substantially lower accuracies are recorded as was the case with the other classification procedures (Figure 4.36). However, the results appear to be much less positive. For instance, an overall level of accuracy of only 44% is attained (Table 4.32). The accuracy with which vines were classified is 62,3%, orchards 40,7%, vegetables 29,5%, cereals 12,8% and other 49,9%. Obviously these statistics are much lower than the actual case and supports the view that the land use map is not an accurate measure of ground truth. It has a certain level of generalization that masks internal heterogeneiety of land cover types and is based on a land use classification which is quite different from a land cover classification. The results may reflect inherent weaknesses of the land use map rather than of the land cover classification. This view is supported by the consistently lower performance of all classification methods when testing against the land use map rather than against farm survey data.

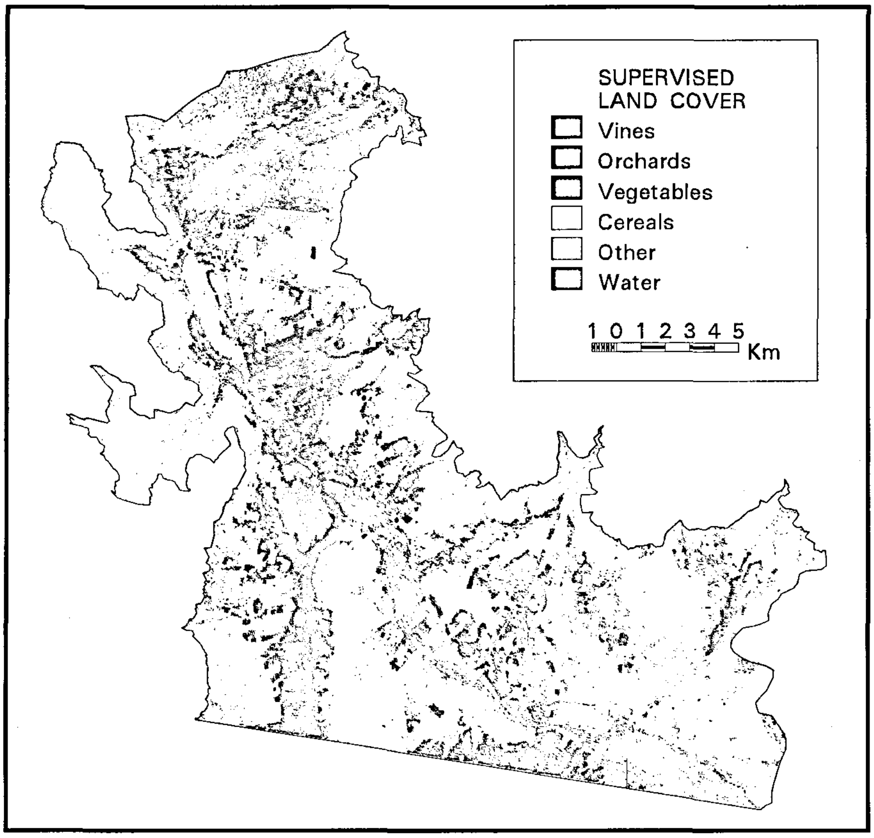


Figure 4.35: Generalized land cover map from supervised classification of untransformed Landsat TM data.

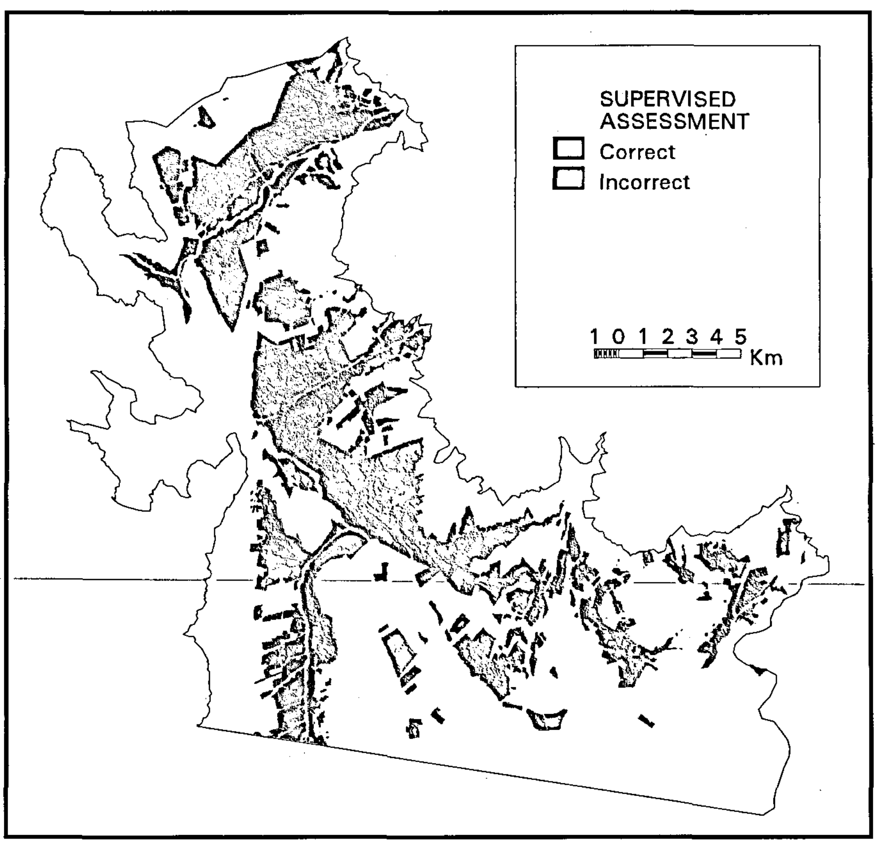


Figure 4.36: Accuracy assessment of generalized land cover map from supervised classification of untransformed Landsat TM data.

Table 4.32: Accuracy assessment of the Landsat supervised classification by comparing with the land use map.

	Supervised classification						
	N = 149704	Vines	Orchards	Vegetables	Cereals	Other	Total2)
Land use	Vines	62,31)	7,1	9,3	2,6	18,6	45,7
	Orchards	35,5	40,7	6,6	1,8	15,3	13,4
	Vegetables	24,2	2,2	29,5	11,6	32,4	2,5
	Cereals	13,5	1,7	6,4	12,8	65,7	22,6
	Other	32,1	7,2	6,1	4,6	49,9	12,8
	Total	41,0	10,1	8,1	5,2	32,6	43,93)

1) Row %   2) Column %   3) Overall accuracy (%)

The assessment of the supervised classification in terms of irrigated land cover types reveals that the method achieved an overall accuracy level of 73% which is much higher than that of the other methods (Table 4.33). Irrigated cover types were 75,8% correctly classified and non-irrigated types 71,3%. These accuracy levels are very good and compared favourably with other methods. Although the irrigated cover types have a lower accuracy level, the non-irrigated is substantially more accurately classified. For the purpose of eventually computing irrigation requirement this distinction is important. The maps show that irrigated land cover types have a much more spatially restricted extent than found on the maps produced by the other unsupervised approaches (Figures 4.37 and 4.38).

Table 4.33: Accuracy assessment of the Landsat supervised classification for irrigated land cover types.

	Supervised Classification				
	N = 149718	Irrigated	Non-irrigated	Other	Total2)
Land use	Irrigated	75,81)	22,8	1,4	61,6
	Non-irrigated	27,5	71,3	1,2	35,4
	Other	9,6	51,1	39,3	3,0
	Total	56,7	40,8	2,4	73,13)

1) Row %   2) Column %   3) Overall accuracy (%)

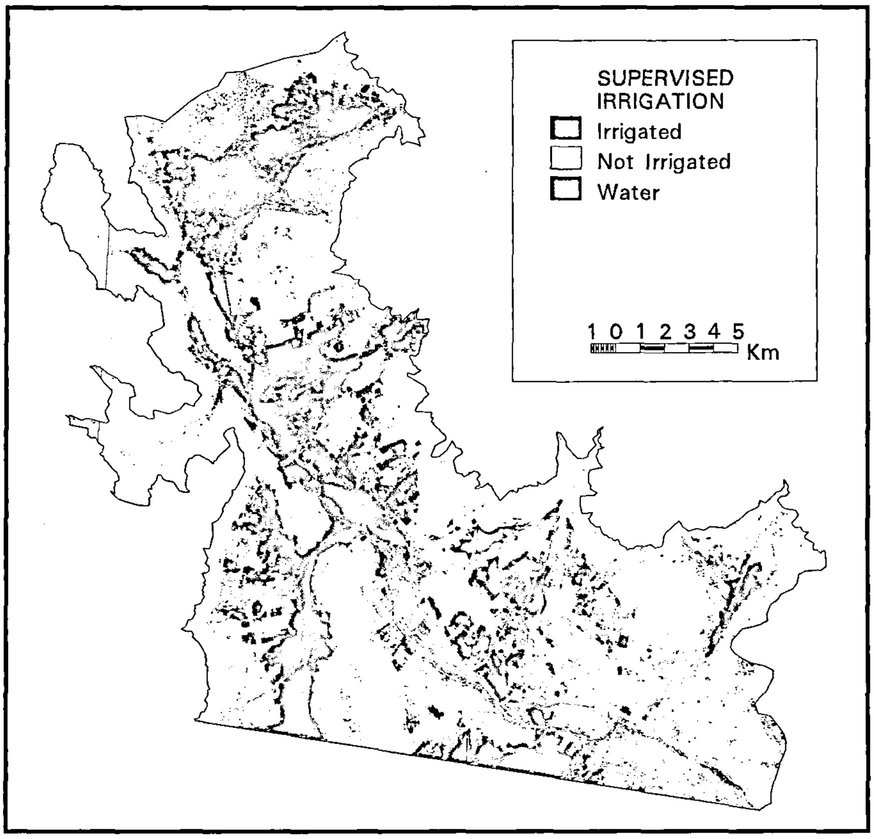


Figure 4.37: Irrigated land cover map from supervised classification of untransformed Landsat TM data.

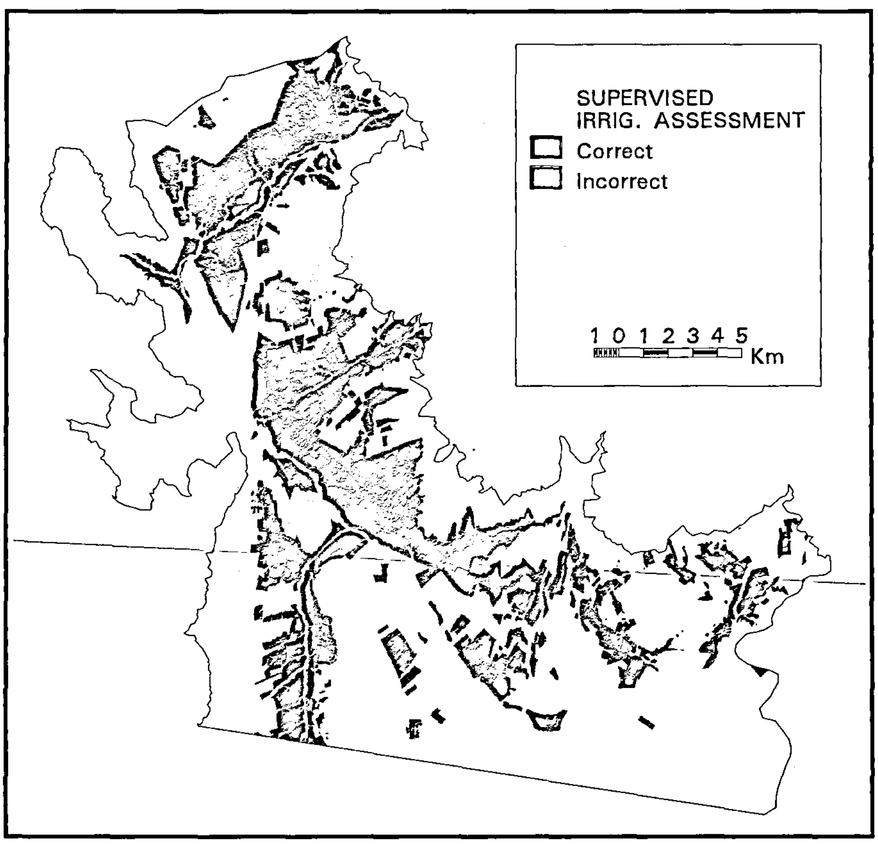


Figure 4.38: Accuracy assessment of irrigated land cover map from supervised classification of untransformed Landsat TM data.

4.5 SPOT XS versus Landsat TM

It is extremely difficult to make direct comparisons between the results obtained using SPOT XS and Landsat TM imagery. There are many reasons for this. Firstly, two different teams of researches were involved. This means that levels of expertise in image processing are not comparable, nor the amount of time devoted to the research project due to differences in individual workloads and programmes. Secondly, two different image processing systems were used. SPOT XS data were analysed using an older PC based version of the EASI PACE system, whereas Landsat TM data were processed by a SUN workstation version of Erdas imagine. Although the Erdas software is state-of-the-art it was used for the first time and not all the software functionality was known, which tended to reduce operator flexibility. Thirdly and probably most importantly, SPOT XS imagery consisted of only two time slices (summer and winter) due to bad weather conditions at the time of image aquisition, whereas Landsat TM imagery covered four seasons. These differences mitigates against any fair comparison.

With these caveats in mind it is not surprizing that the results obtained using Landsat TM imagery outperformed those from the SPOT XS imagery (Table 4.34). On average overall accuracies at the farm level of detail were 4,0% points higher (66,4% versus 70,5%). In the case of vines as a single land cover type the average levels of accuracies obtained are even more pronounced. Across all four analytical procedures SPOT achieved an average accuracy of 70,1% whereas the comparable figure for Landsat was 84,4% - a difference of 14,3% points. These trends are consistent across all three levels of generalization. At the regional scale of comparison accuracies obtained by analysing Landsat TM imagery were on average 4% higher. Differences are somewhat muted by the greater amount of uncertainty inherent in the ground truth land cover map. When comparing irrigated and non-irrigated land cover classes Landsat TM achieved overall average accuracies of 69,7% and SPOT XS 66,0%, a difference of about 4% points. By considering only irrigated and non-irrigated land classes the differences in performance levels are not worth mentioning.

Another aspect that needs to be considered in evaluating the results obtained using SPOT XS and Landsat TM imagery pertains to the fact that analyses on the Landsat TM data sets were capable of also distinguishing between more categories of land cover types than the SPOT analyses. In most cases orchards and cereals could also be distinguished with some degree of accuracy.

Table 4.34: Comparison of accuracy levels obtained by analysing SPOT XS and Landsat TM imagery.

Analytical Procedure	Farm Survey Data			
	SPOT XS		Landsat TM	
	Overall %	Vines %	Overall %	Vines %
Unsupervised	59,6	83,2	73,0	87,7
P.C.A.	65,4	81,9	68,0	89,4
Vegetation Index	83,4	63,9	70,2	85,7
Supervised	57,0	51,7	71,0	74,9
Average	66,4	70,1	70,5	84,4
Analytical Procedure	**Land Cover Map**			
	SPOT XS		Landsat TM	
	Overall %	Vines %	Overall %	Vines %
Unsupervised	52,9	84,0	50,7	71,6
P.C.A.	42,0	74,8	51,8	83,7
Vegetation Index	-	-	53,1	79,4
Supervised	41,8	47,0	43,9	62,3
Average	45,6	68,6	49,9	74,3
Analytical Procedure	**Irrigated/Non-Irrigated Classes**			
	SPOT XS		Landsat TM	
	Overall %	Irrigated %	Overall %	Irrigated %
Unsupervised	67,4	84,0	69,0	77,9
P.C.A.	66,3	73,3	67,5	84,2
Vegetation Index	76,6	80,9	69,1	78,8
Supervised	54,0	58,9	73,1	75,8
Average	66,0	74,3	69,7	79,2

4.6 SUMMARY

This chapter forms the core of the research on identifying and mapping irrigated land cover types in the Breede River Valley using digital image processing techniques and GIS analyses. It presented a theoretical and applied perspective on the many difficult issues involved and highlighted successes and failures. An objective assessment of the results indicated that although a fair degree of accuracy is achievable there still remains a challenge to improve the accuracy levels further. In conclusion the technology is available and the goals are achievable given the time and resources to investigate alternative strategies and procedures.

In the next chapter the results obtained will be put to practical use by estimating water demand based on the land cover information derived from the analyses.

CHAPTER 5: QUANTIFICATION OF DEMAND FOR IRRIGATION WATER

5.1 INTRODUCTION

The importance of intensive agriculture under irrigation was discussed in chapter one. Viticulture, orchards, vegetables and pastures are heavily reliant upon additional water from irrigation due to typical Mediterranean hot dry summer conditions in the valley. Most irrigation water is supplied by the Breede River and its tributaries and the state built the Brandvlei dam with a series of canals in order to provide much needed irrigation water to the farming community. However, the demand for water is growing as farmers expand their irrigated acreages and urban requirements increase over time. In order to plan ahead and get a more accurate estimate of the demand for irrigation water, the Department of Water Affairs and Forestry who are charged with the task of monitoring and managing water resources need a way of keeping pace with these changes. The potential of using remote sensing was specifically investigated with that objective in mind. The purpose of this chapter is to describe the methods followed by which demand for irrigation water was estimated.

5.2 QUESTIONNAIRE SURVEY

A questionnaire survey was undertaken covering 21 farms in the valley as described in section 3.6.1.2.1. The purpose of the questionnaire was to obtain current information on irrigation practices. The questionnaire was structured in such a way so as to determine the actual amount of water applied per crop type per annum. Accurate data is crucial and therefore farmers who kept fairly good records were purposefully selected as described previously. In spite of this the data obtained still showed some serious flaws. One specific question (no. 7) was misinterpreted by some respondents, who provided information on row spacing of crops and not distances between irrigation lines. These figures were usable for micro irrigation systems but obviously incorrect for sprinkler systems. Another question relating to the length of time irrigated (no. 5) also appeared to ellicit incorrect responses. An irrigated block often is serviced by more than one subirrigation system, so that the whole block is not irrigated simultaneously for the full length of time specified, but sequentially irrigated one section after another. This means that the total duration of irrigation should in some cases be reduced by the number of subsections involved. Apart from these problems other obvious discrepancies in the rate of water delivery by different nozzel sizes and irrigation systems also occurred. These errors were corrected as far as possible and some general adjustments had to be made to compensate for those systematic errors that were introduced by weaknesses in the questionnaire's design.

5.3 ESTIMATION OF DEMAND FOR IRRIGATION WATER

The sections that follow give a detailled account of the procedures used in deriving conversion factors for estimating water demand from land cover data acquired by satellite remote sensing techniques.

As a necessary background the section is introduced by first describing the nature of irrigation in the study area in terms of types of irrigation systems used and the seasonal patterns followed, after which calibration methods are esplained.

5.3.1 Irrigation systems

Based on the farm survey data vines are mostly irrigated by sprinkler systems, as 47,8% of all vineyards and 45,8% of the area under vines are irrigated in this way. Micro irrigation is a close second in importance with 39,5% of the vineyards and 43% of the vine area under this type of irrigation system. Drip irrigation is only used in 12,6% of all vineyards comprizing 11,2% of the area under vines. Orchards on the other hand are mostly irrigated by micro systems (62,5% of all orchards and 64,3% of the acreage). Sprinkle system are still important and 35,2% of all orchards are irrigated by this type of system. This represents 33,9% of the area under orchard. Land cover types such as vegetables and cereals for pastures also utilize sprinkler systems. According to the survey 100% of. all orchards and vegetables are under irrigation. The figures for vines are 99,8% and partures (8%).

Additional information obtained from the farm survey related to the spacing of irrigation lines and sprays as well as their rates of water delivery. These statistics were required in order to compute irrigated water utilization per land cover type.

5.3.2 Seasonal patterns of irrigation

As the Breede River valley falls in the winter rainfall region it is characterized by warm dry summer months. Irrigation commences in October and reaches its peak between the months of December and February. Of all the water applied to vines and orchards throughout the year more than half (55,1%) are used during this period in more or less equal monthly amounts. Irrigation of both vines and orchards follow a similar seasonal pattern. Vegetables deviate somewhat in that 25% of all irrigated water for vegetables are applied in January and 22,1% in February. So the irrigation season for vegetables is shorter and more intense. Vines are the major users of irrigation water (67,9%), followed by orchards (29,8%) and vegetables (2,1%).

5.3.3 Development of calibration measures

In order to use remotely sensed land cover data for estimating the amount of water required for irrigation purposes, conversion factors are needed. These conversion factors were computed from the farm survey data. Firstly, the rate of water utilization per irrigated land parcel was computed as m^3 per hectare per hour based on the spacing of irrigation lines (rw) and sprays or nozzles along each line (ss) and the rate of water delivery per spray per hour (sl), using the formula:

$$m^3/ha/hr = (sl * 10) / (rw * ss)$$

Secondly, by multiplying this rate of water delivery with the number of hours irrigated per month the monthly use of water per hectare was calculated per land parcel. These values were then multiplied by the number of hectares under irrigation to arrive at a total amount of irrigation water used per month. The annual total amount per type of irrigation system and land cover type was subsequently computed. Based on that data an average rate of irrigation water actually applied by the farmers during one growing season was computed per land cover type. Table 5.1 shows the results obtained. According to the so-called 'Green Book' extimated annual irrigation requirements for crops in the Wolseley area are as follows: Vines 2430 m^3/ha to 4490 m^3/ha; Orchards 4920 m^3/ha to 7460 m^3/ha; Vegetables (potatoes) 1890 m^3/ha to 1015 m^3/ha depending on the planting season; and Pastures 12640 m^3/ha to 1489 m^3/ha (Green, 1985: 403-409). The rates obtained from the survey appeared plausible and were subsequently applied to the land cover classifications for estimating total irrigation demand in the study area.

Table 5.1: Rate of irrigation water used in cubic meters per hectare per year.

Cover	Hectare	% Irrigated	Drip	Micro	Sprinkle	Mean m^3/ha
Vine	1131	99,8	3481,4	5794,6	6057,1	5657,1
Orchard	392	100,0	7374,6	6998,0	7499,0	7174,9
Vegetable	61	100,0	-	-	3387,1	3387,1
Cereal	11	8,0	-	-	11766,8	11766,8

5.3.4 Demand for irrigation water

In this section the demand for irrigation water is quantified by applying the conversion factors to estimated land cover acreages as obtained by the different classification techniques. The area of each land cover type was first adjusted by the percentage which is irrigated and this adjusted figure was then multiplied by the conversion factor to obtain irrigation demands (Table 5.2). By analysing the statistics in Table 5.2 it can be seen that there is a substantial variation between different classification techniques and satellite systems in estimated irrigation demands. This variability is a direct result of differences in the land cover acreages obtained.

Table 5.2: Estimated demand for irrigation water per annum in the study area.

	SPOT			Landsat TM		
UNSUPER-VISED	Hectare	Irrigated	Water usage (m^3 x 1000)	Hectare	Irrigated	Water usage (m^3 x 1000)
Vine	12630	12604	71302	11611	11588	65553
Orchard	-	-	-	5794	5794	41573
Cereal	-	-	-	4008	321	3773
Total	12630	12604	71302	21413	17703	110900

	SPOT			Landsat TM		
PCA	Hectare	Irrigated	Water usage (m^3 x 1000)	Hectare	Irrigated	Water usage (m^3 x 1000)
Vine	12234	12209	69067	22059	22015	124538
Orchard	-	-	-	4018	4018	28835
Cereal	-	-	-	3078	246	2893
Total	12234	12209	69067	29155	26279	156267

	SPOT			Landsat TM		
NDVI	Hectare	Irrigated	Water usage (m^3 x 1000)	Hectare	Irrigated	Water usage (m^3 x 1000)
Vine	23881	23833	134825	18653	18616	105311
Orchard	-	-	-	2442	2442	17523
Cereal	-	-	-	4988	399	4695
Total	23881	23833	134825	26083	21457	127531

	SPOT			Landsat TM		
SUPER-VISED	Hectare	Irrigated	Water usage (m^3 x 1000)	Hectare	Irrigated	Water usage (m^3 x 1000)
Vine	6328	6315	35724	7654	7639	43163
Orchard	2077	2077	14902	1999	1999	14344
Vegetable	1062	1062	3597	1604	1604	5432
Cereal	5230	418	4918	1440	115	1353
Total	14697	9872	59142	12697	11357	64292

For example, water demand computed for classifications based on SPOT data vary from a low of 59142475 m^3 to a high of 134825660 m^3 - this is a difference of 128%. The Landsat TM classifications showed even greater variations, ranging from 64292635 m^3 to 156267310 m^3 - a difference of 143%. The supervised classifications produced the smallest absolute difference between the satellite systems, i.e. 5150161 m^3 followed by the vegetation index approach (7294290 m^3). In relative terms the latter outperformed the former with a difference of 5,7% points relative to 8,7% points. Overall it would seem that the supervised approach produced more consistent result and is to be prefered.

5.4 SUMMARY

This short chapter reviewed the methodology of converting land cover data to estimated demands for irrigation water. It evaluated the quality of data obtained from a questionnaire survey on irrigation practices and water usage by farmers in the Upper Breede River valley and applied these statistics to satellite derived land cover data to estimate demand for irrigation water. From these analyses it became clear that land cover areas estimated by various analytical procedures using SPOT XS and Landsat TM imagery can produce grossly different results. This emphasizes the importance of obtaining reliable area estimates. It appears as though a supervized classification approach provides a more consistent result and should be selected in preference to other approaches even though it involves much more time and work to apply.

CHAPTER 6: SYNTHESIS : SATELLITE MONITORING OF IRRIGATED LAND

6.1 INTRODUCTION

When the first earth resource satellite was launched in 1972 expectations were very high that this new observation platform and ability to remotely sense phenomena on the earth would be the answer to man's quest for a cost effective and efficient means of gathering information about his living environment in a systematic, regular and accurate way. Literally thousands of studies followed on virtually all aspects of the process as new hard- and software systems were developed and new methods and techniques were tested and tried.

It is probably not too unfair to say that from an initial euphoria interests in satellite remote sensing has gradually declined as the limitations of the technology and the difficulty of the tasks gradually dawned on potential users. The promise of a final breakthrough and an intuitive belief in the eventual success of this operational field has kept many scientists and engineers committed to the task of improving satellite sensors and digital processing systems. It was hoped that higher spatial and spectral resolutions would lead to higher levels of accuracy in land cover mapping. Although this was achieved to some extent it still did not provide the levels of accuracy required in all cases especially where detailed large scale mapping was concerned.

In an attempt to overcome these limitations another dimension was added to the equation namely that of time. It made sense to argue that higher levels of accuracy and a finer discrimination between land cover types would be achieved by analysing the multitemporal as well as the multispectral characteristics of phenomena. To further enhance the final product existing information on topography and soils could be employed by integrating data held in a GIS with that obtainable from standard digital image analytical techniques. In theory this sounds very attractive but what are the practical pitfalls and how achievable are these goals? In general terms those are the questions that this research project attempted to find answers to. The results of which are assessed in this chapter.

6.2 EVALUATION OF RESULTS

6.2.1 Stated objectives

To recap this study focussed on the ability to discriminate between land cover types that are irrigated *vis a vis* those that are not under irrigation in an intensively cultivated area of the Breede River valley between Wolseley and Worcester in the South Western Cape of South

Africa. It is an area with a variety of land cover types ranging from natural rangeland through dryland cereals to intensively nurtured orchards, vines and vegetables under irrigation. The water resources of the valley are increasingly under pressure and forward planning of their utilization and allocation to various user categories are becoming an issue. The Department of Water Affairs and Forestry are facing similar situations in many other parts of the country and are desperately seeking methods for obtaining accurate land cover data on which to base their water management decisions.

Consequently the following three objectives were researched:

(i) To identify, classify and map agricultural land cover types by digital analysis of multitemporal and multispectral SPOT XS and Landsat TM images.

(ii) To refine image classification results by incorporating ancilliary GIS data such as altitude, slope and soil properties.

(iii) To evaluate the usefulness of the land cover information for quantifying water requirements of irrigation.

6.2.2 Data sets: SPOT XS and Landsat TM

Implicit in the use of two different digital sources of data are a comparison of the results obtained. Digital satellite data may be cheaper than other data sets such as those captured by aerial photography or gathered through field surveying, but become very expensive when a multitemporal approach is used. As a secondary objective this study used both SPOT XS and Landsat TM data sets in order to investigate their relative merits for the purpose in hand. The question of efficiency was also a stake especially as far as LANDSAT TM imagery was concerned as there are seven spectral channels to choose from and it may not be necessary to use all seven channels of data. Intercorrelations between spectral bands means that there are high redundancy in these multitemporal and multispectral data sets. If the most important spectral bands can be identified a potential user could save a conserable amount of financial and other resources by not purchasing and analysing all bands. Unfortunately this objective could not be fully pursued. Due to unfavourable weather conditions only a summer and a winter image was available for the SPOT XS data set. This meant that the Landsat TM data set with an image for each of the seasons had a much finer temporal resolution than the SPOT data set and were not fully comparable. Nevertheless an extensive literature survey on the subject and a short study done by Dorfling (1994), revealed that certain band combinations do tend to provide equally good results and can be considered in order to achieve greater efficiencies. Landsat

TM bands 2-3-4 or 2-3-7 or 1-4-5-7 or 3-4-5-7 appear to capture most of the information required for successful crop discrimination.

6.2.3 Image processing techniques applied

Improved spectral and temporal resolutions result in increased complexity. In order to handle these complex data sets and extract useful information many analytical techniques were applied and compared. These were unsupervised and supervised classification, Principal Component Analysis and various vegetation indices. It was once again not possible to apply all techniques equally to both SPOT XS and Landsat TM data sets. There are basically two reasons for this, namely due to differences in the two data sets as alluded to in a previous section (No spring and autumn SPOT images) and the fact that two different image processing systems were used (Gems Junior for SPOT and Erdas Imagine for Landsat TM). This situation developed as a result of untimely software acquisitions *vis a vis* the planned phasing of the project.

In the case of SPOT imagery a histogram migrating means or K-means unsupervised classification technique was employed, whereas the ISODATA algorithm was used on the Landsat TM data. Although both these techniques require a user to specify the number of classes and a threshold value, the version of the Easi Pace software which was used only allows a maximum of 16 classes. In comparison Erdas does not have that restriction thus a value of 30 was used. The end result is that although unsupervised classification techniques were used on both SPOT and Landsat they differed which means that different results can not be ascribed to differences in the satellite systems or the data sets.

The supervised classifications are also very difficult to compare because different training areas were used and Erdas has a pixel growing algorithm which ensures higher internal homogeneity within training samples. Not only did the locations of training samples differ but also the number of training samples, their sizes and ultimately the number of signatures generated. A previous study by Zietsman and Vlok (1993) showed that choice of training samples are crucial in the eventual success of a supervised classification or not. Maximum likelihood classifications were used without specifying *a priori* probabilities.

In order to reduce the dimensionality of the data Principal Component analyses were carried out on the SPOT and Landsat data sets respectively. Six spectral bands in the SPOT data were compressed to three after which an unsupervised K-means clustering was done. In comparison the Landsat data set had 24 spectral bands, these were transformed to 6 components and then clustered using the ISODATA unsupervised classification technique.

As there were only two seasons of SPOT imagery Transformed Normalized Difference Vegetation Indices were computed for each. These indices were subtracted from one another in an attempt to demarcated areas of greatest change in vegetative growth. The results were not satisfactory therefore the summer TNDVI image was thresholded and irrigated areas delimited. In the case of the Landsat TM data sets Normalized Difference Vegetation Indices were computed for each of the four seasons. These NDVI images were then subjected to an unsupervised classification. Thus different approaches limit any comparisons between SPOT and Landsat results in terms of using vegetation indices for demarcating irrigated land cover types.

6.2.4 Classification results

The results of each of the applied analytical procedures were evaluated by comparing the derived land cover maps with ground control data at three levels of detail. At the most detailed level comparisons were made with land cover as obtained from field surveys done in conjunction with a questionnaire survey of 21 selected farms. At a more generalized level land cover classifications were compared with a land cover map of the whole study area as compiled from aerial photographs by interpretation and field checking. Finally, all land cover classes were collapsed into two classes denoting irrigated and non-irrigated land and again compared for the region as a whole.

As far as the analyses of the SPOT imagery were concerned the techniques were only able to distinguish between vines and natural vegetation. With the exception of the supervised classification other cultivated crops types such as orchards, cereals and vegetables could not be distinguished. At the farm level overall accuracies ranged from a low of 42 % for the unsupervised PCA to a high of 60 % for the unsupervised classification of untransformed data. Although these figures appear rather low, vines were classified quite accurately ranging from about 75% to 83% for the PCA and unsupervised classifications of untransformed data respectively. When comparing land cover classifications to the land cover map of the area, the results are somewhat lower but that was to be expected due to possible generalizations and inaccuracies in the ground control data itself. Vines were still quite accurately classified (60% to 83%) but the overall level of accuracy declined to between 40% and 45%. Accuracies again improved by aggregating land cover types into two broad groups (Irrigated and Non-irrigated). Overall accuracies of between 42% and 76% were recorded, whilst irrigated cover types showed accuracy levels of 58% to 87%. Generally speaking the TNDVI approach fared best as far as overall accuracy was concerned but the unsupervised classification managed to classify vines most accurately. The supervised classification disappointed but was the only technique to distinguish between the major crop types albeit not very well.

Interestingly the different analytical procedures all fared more or less equally well when applied to the Landsat TM imagery. Overall accuracies were much higher than those obtained in the analyses of the SPOT data, reflecting the advantages of using more spectral bands and more time slices. Overall accuracies ranged from 70% to 73% at the farm level with the unsupervised classification of untransformed data performing best. However, vines were most accurately classified using the PCA approach (89%). On the other hand the supervised classification did not perform much weaker and has the added advantage of distinguishing between more land cover types than the other techniques. When evaluating the results against the land cover map of the region accuracy levels were also lower as in the case of the SPOT analyses. In conclusion it is clear that Landsat TM imagery can be used quite successfully to map irrigated and non-irrigated land cover types. Overall accuracies of close to 70% were achieved and high values of up to 84% for irrigated cover types were recorded.

6.2.5 Integration of GIS data

Ancilliary data can be used in various ways to improve digital land cover classifications of remotely sensed images. There are basically two approaches, i.e. to include the data as extra channels of information for classification purposes or to follow a post classification refinement using the GIS data and analytical capabilities. This study followed the latter approach. By clipping the study area out of the image based on a preselected altitude of 500 m all pixels above the 500 m contour were reclassified to null values, that is to say designated as unclassified. Furthermore all pixels on slopes exceeding 25 degrees were reclassified as natural vegetation as no agricultural cultivation occurs on such steep slopes. In the case of the broad land cover categorization between irrigated and non-irrigated land pixels classed as irrigated cover types were reclassed to non-irrigated types when found on soils of low agricultural potential. It was not possible to assess the extent to which these reclassification had improved or degenerated the results by comparing the data at the farm level as none of these conditions had occurred on the selected farms in the survey. At a broad regional level the improvements were noticeable and did change calculated areas under irrigation substantially.

6.2.6 Gauging demand for irrigation water

A questionnaire survey of 21 farms were conducted to obtain information on irrigation practices in the study area. Based on that survey the mean volume of irrigation water per hectare applied annually to each of the major land cover types was established. Using these mean values and information on the proportional area of each land cover type which is under irrigation total demand for irrigation water was estimated. This was done by applying computed conversion factors to the land cover areas obtained from the different classification techniques. Due to widely different area estimates demands for irrigation water also varied substantially. SPOT XS and Landsat TM estimates differed greatly as did different classification techniques. However, the supervised classifications produced the most consistent results.

6.3 IMPLICATIONS AND GUIDELINES FOR FURTHER RESEARCH

The overwhelming impression gained during the course of this research was related to the complex nature of the problem. It seems as though the level of complexity has been increased many times in attempting to achieve better results by enhancing spectral, spatial and temporal resolutions. Although data volumes and costs increase proportionately by adding a time dimension spectral signatures become disproportionately even more complex. The analyst not only has a multispectral situation to contend with but also many combinations and permutations of land cover changes on different land parcels as crops are rotated. Planting of annual crops are not simultaneous by all farmers and neither is harvesting or preparation of the land. For crops under irrigation a farmer has even greater latitude. To select appropriate training samples under these conditions is virtually impossible. The fact that only three spectral bands are visible at any one time means that choosing training areas becomes very difficult. These confounding factors point at a need for new approaches which will directly adress the multitemporal and multispectral nature of current satellite imagery. Image processing systems will do well to incorporate more flexible visualization techniques. Much has been written about spatial pattern recognition but little has been adopted by image processing systems. The rate of software development has been disappointingly slow.

Future research in this area should not just look at the use of existing standard image processing techniques but attempt to incorporate or create new and innovative techniques and approaches. The technology has matured to such an extent that it is in danger of calcifying. A wider range of classification algorithms, neural net analysis and the latest in computer visualization software should be added to current image processing systems. A tighter integration between image processing and GIS capabilities are also absolutely essential. The artifical boundaries between these two technologies should be eliminated as soon as possible. Despite these shortcomings visual interpretation of imagery supported by digital classification techniques and GIS analytical capabilities provide a very powerful tool for land cover mapping and monitoring.

As far as the use of multitemporal imagery is concerned it appears that the gains are not necessarily of such an order of magnitude that it will be financially feasible in all applications. A careful consideration of the costs and benefits should be made before using a multitemporal approach.

This research was very ambitious in its attempt at handling two different types of images, two different image processing systems, creating a GI database and integrating the ancilliary GIS data, doing a supplementary field survey and employing a multitemporal approach. Although the results obtained were as good as could realistically be expected it would make sense to back track on some of the analyses. Too little time was available to carefully check the selected training samples for their discriminatory abilities. In hindsight much more attention should have been given to an analysis of the multitemporal characteristics of the training samples. This should be done specifically focussing on the richness and diversity of the multitemporal and spectral Landsat TM data.

In conclusion it seems that digital image analysis enhanced with GIS data is a valid means of obtaining land cover information of sufficient quality and accuracy for planning and monitoring catchments and their agricultural water requirements. It remains the most appropriate technology for cost effectively mapping land cover over large areas or obtaining up to date information on land cover changes on a fairly regular basis.

REFERENCES

Ahrean S C & C Wee 1991: Data space volumes and classification optimization of SPOT and Landsat TM data. *Photogrammetric Engineering and Remote Sensing* 57, 1: 61-65.

Allan J A 1980: Remote sensing in land and land use studies. *Geography* 65, 1: 35-43.

Allan J A 1990: Sensors, Platforms and Applications : Acquiring and Managing Remotely Sensed Data. In J A Clark & M D Steven (eds.): *Applications of Remote Sensing in Agriculture*, 3-18. Butterworths, London.

Allan J W 1992: Remote Sensing - an art, a science on just another GIS input? *Mapping Awareness & GIS in Europe* 55, 5: 4-9.

Altamira J A V, M F Baumgardner & C R Venezuela 1986: Assessment of TM thermal infrared band contribution in land cover/land use multispectral classification. Symposium on Remote Sensing for Resources Development and Environmental Management, ITC Enschede, August 1986.

Azzali S, M Menenti, I Meuwissen & T N M Visser 1990: Mapping of crop coefficients in an Argentinian irrigation scheme using remote sensing techniques. In Menenti M (ed.): *Remote Sensing in Evaluation and Management of Irrigation*, 79-102. Institute Nacional de Ciencia y Téchica Hídricas, Mendoza.

Badhwar G D, C E Gargantini & F V Redondo 1987: Landsat classification of Argentina summer crops. *Remote Sensing of Environment* 21: 111-117.

Baret F, G Guyot, A Begue, P Maurel & A Podaire 1988: Complementarity of middle infrared with visible and near infrared reflectance for monitoring wheat canopies. *Remote Sensing of Environment* 26: 213-225.

Barrett E C & L F Curtis 1982: *Introduction to Environmental Remote Sensing*. Chapman and Hall, London.

Barrett E C & R W Herschy 1985: A European perspective on satellite remote sensing for hydrology and water management. *Hydrologic Applications of Space Technology*. Proceeding of the Coaca Beach Workshop, Florida.

Barrett E C & R W Herschy 1989: Opportunities for satellite remote sensing in hydrology and water management. *Geocarto International* 4, 2: 11-18.

Basson D le R, P F Pretorius & T P C Robbroeck 1977: Bo-Breërivierontwikkeling : 'n Ondersoek na watervoorsiening uit Dwarsrivier, Mitchellspasdam en kanale. Department of Water Affairs Planningreport no. PO 810/01/0177.

Bauer E H, D J Baggett, S L Wall, R W Thomas & C Stow 1984: Results of an irrigated lands assessment for water management in California. *IEEE Transactions on Geoscience and Remote Sensing* 22, 6: 536-539.

Bauer M E & J E Cipra 1973: Identification of agricultural crops by computer processing of ERTS MSS data. The Laboratory for Applications of Remote Sensing. LARS Information Note 030173. West Lafayette, Indiana, Purdue University.

Baumann P R & J B Greenberg 1991: Postclassification class sorting in creating a general land cover inventory. Department of Geography, SUNY College, Oneonta.

Bloem A A, L F Lagrange & C J Smit 1992: Besproeiing : Waterinfiltreerbaarheid van Suid-Afrikaanse gronde. *SA Waterbulletin* 18, 6: 8-11.

Boyle T P 1981: Investigation into landuse mapping using remote sensing data. M.Sc-Thesis, Department of Survey and Mapping, University of Natal, Durban.

Brockhaus J S, Khorram & A Gerachi 1988: Multi-temporal resource complex analysis of Cantinia province, Italy, from Landsat-TM data. *Proc. of IGARSS '88 Symposium*, Edinburgh, Scotland.

Bucheim M P & Lillesand T M 1989: Semi-Automated training field extraction and analysis for efficient digital image classification. *Photogrammetric Engineering and Remote Sensing*, 55, 9: 1347-1355.

Burger A M 1992: Water, ons lewensaar. *South African Panorama* 37, 4: 46-51.

Calder N 1991: Making sense of the images. *Geographical Magazine Supplement.* World Publications, London.

Campbell J B 1987: *Introduction to remote sensing.* The Guilford Press, New York.

Chambouleyron J L 1990: Irrigation and remote sensing in the Province of Mendoza Argentina. In Menenti M (ed.): *Remote sensing in evaluation and management of irrigation.* Instituto Nacional de Ciercia y Técnica Hídricas, Mendoza.

Chavez P S & A Y Kwateng 1989: Extracting spectral contrast in Landsat TM image data using selective principal component analysis. *Photogrammetric Engineering and Remote Sensing* **55**, 3: 347-348.

Chavez P S & J A Bowell 1984: Comparison of the spectral information content of landsat TM and SPOT for three different sites in the Phoenix Arizona region. *Photogrammetric Engineering and Remote Sensing* **54**, 12: 1699-1708.

Chen S C, G T Batista & A T Tardin 1986: Landsat TM band combinations for crop discrimination. Symposium on Remote Sensing for Resources Development and Environmental Management, ITC Enschede, August 1986.

Chidley & Drayton 1986: The use of SPOT-simulated imagery in hydrological mapping. *International Journal of Remote Sensing* **7**, 6: 791-799.

Colwell R N (ed.) 1983: *Manual of remote sensing* Vol I & II. American Society of Photogrammetry, Falls Church, Virginia.

Conese C & F Maselli 1991: Use of multitemporal information to improve classification performance of TM scenes in complex terrain. *ISPRS Journal of Photogrammetry and Remote Sensing* **46**, 6: 187-198.

Conese C & F Maselli 1993: Selection of optimum bands from TM scenes through mutual information analysis. *ISPRS Journal of Photogrammetry and Remote Sensing* **48**, 3: 2-11.

Conley A H & J J Olivier 1989: Planning a GIS : An application in the field of national water management. Proceedings of a workshop at the SAGIS '89 Conference, Pietermaritzburg.

Conley A H 1988: *Remote Sensing in national water management : A future vision.* Department of Water Affairs, Pretoria.

Conley A H 1988: Remote Sensing in national water management : A future vision. Proceedings of a Colloquium on Remote Sensing (November 1988). Department of Water Affairs, Pretoria.

Curran P J 1985: *Principles of remote sensing.* Longman, New York.

Dangermond J 1991: Where is the technology leading us? In M Heit & A Shortreid (eds.): GIS applications in natural resources, 11-17. *Supplement to GIS World*, GIS World Inc, Fort Collins, USA.

Davis P W, D A Quattrochi, M K Ridd, N S Lam, S J Walsh, J C Michaelson, J Franklin, D A Stow, C J Johannsen & C A Johnston 1991: Environmental analysis using integrated GIS and remote sensed data : Some research needs and priorities. *Photogrammetric Engineering and Remote Sensing* 57, 6: 689-697.

De Gloria S D 1984: Evaluation of stimulated SPOT imagery for the interpretation of agricultural resources in California. *SPOT simulations handbook.* Proceedings of the 1984 SPOT Symposium, Scottsdale, Arizona.

Department of Water Affairs 1986: Bestuur van die waterhulpbronne van die Republiek van Suid-Afrika. Government Printer, Pretoria.

Dorfling J 1994: Optimum spektrale bandkombinasies en multitemporele multispektrale SPOT satellietdata : 'n Toepassing in landbouidentifikasie in die Bo-Breëriviergebied. Unpublished BA-Honours Report, University of Stellenbosch, Stellenbosch.

Ehlers M, D Greenlee, T Smith & J Star 1991: Integration of remote sensing and GIS : data and data access. *Photogrammetric Engineering and Remote Sensing* 57, 6: 669-675.

Ehlers M, G Edwards & Y Bédard 1989: Integration of remote sensing with Geographic Information Systems : A necessary evolution. *Photogrammetric Engineering and Remote Sensing* 55, 11: 1619-1627.

Ehrlich D, Estes J and Scepan J 1990: 'Improving crop type determination using satellite imagery: A study for the regione del Veneto, Italy. *Geocarto International* 2: 35-47.

Elachi C 1987: *Introduction to the physics and techniques of remote sensing.* New York, John Wiley & Sons.

Elsenburg Agricultural Development Institute 1990: Hulpbronontwikkelingsprogram : Winterreënstreek, Elsenburg.

ERDAS 1991: *Field Guide*, 2nd Edition, Version 8.1 ERDAS Inc, Atlanta, Georgia.

Feyt P A 1988: 'n Grondopname van die Wolseley-eilande. Department of Agriculture and Water. Afdeling Hulpbronne, Winterreënstreek, Elsenburg.

Foody G M 1988: Incorporating remotely sensed data into a GIS : The problem of classification evaluation. *Geocarto International* 3: 13-16.

Fukue K, H Shimoda, Y Matumae, R Yamaguchi & T Sakata 1988: Evaluations of unsupervised methods for landcover/use classifications of Landsat TM data. *Geocarto International* **3**, 2: 37-44.

Fuller R M & R J Parsell 1990: Classification of TM imagery in the study of land use in lowland Britian : practical considerations for operational use. *International Journal of Remote Sensing* **11**, 10: 1901-1917.

Gastellu-Etchegorry 1989: An assessment of SPOT capability for cartographic applications in Indonesia. *International Journal of Remote Sensing* **10**, 11: 1763-1774.

Gastellu-Etchegorry 1990: An assessment of SPOT XS and Landsat MSS data for digital classification of near-urban land cover. *International Journal of Remote Sensing* **11**, 2: 225-235.

Gong P & P J Howarth 1990: An assessment of some factors influencing multispectral land cover classification. *Photogrammetric Engineering and Remote Sensing* **56**, 5: 597-603.

Gong P J & P J Howarth 1988: Land cover to land use conversion : a Knowledge-based approach. Department of Geography, University of Waterloo Ontario, Canada.

Gong P, J Marceau & P J Howarth 1992: A comparison of spatial feature extraction algorithms for land use classification with SPOT HRV data. *Remote Sensing of Environment* **40**: 137-151.

Gonzalez R C, R E Woods 1992: *Digital Image Processing*. Addison-Wesley Publishing Company. Reading, Massachusetts.

Green G C (ed.) 1985: *Estimated irrigation requirements of crops in South Africa, Part I*. Soil and Irrigation Research Institute, Department of Agriculture and Water Supply, Pretoria.

Guyot G 1990: Optical properties of vegetation canopies. In J A Clark & M D Steven (eds.): *Applications of Remote Sensing in Agriculture*, 19-43. Butterworths, London.

Haralick R M & K S Fu 1983: Pattern recognition and classification. In R N Colwell (ed.): *Manual of remote sensing* Vol I, 793-805. American Society of Photogrammetry, Falls Church, Virginia.

Hardy J R 1980: The aquisition of ground data for surveys based on remotely sensed data. In G Fraysse (ed.): *Remote Sensing Application in Agriculture and Hydrology*, 249-255. AA Balkema for Commission of the European Communities EUR 611.

Harris R 1987: *Satellite remote sensing : an introduction*. Routledge and Kegan Paul, London.

Hartgraves C R 1991: GIS and sustainable development in natural resources management. In Heit & Shortreid (eds.): GIS applications in natural resources, 1-17. *Supplement to GIS World*, GIS World Inc, Fort Collins, USA.

Heller H C & K A Johnson 1979: Estimating irrigated land acreage from Landsat imagery. *Photogrammetric Engineering and Remote Sensing* **45**, 10: 1379-1386.

Hilwig F W 1987: Methods for the use of remote sensing in Agro-ecological characterization and environmental monitoring. In A H Bunting (ed.): *Agricultural environments, characterization classification and mapping*, 221-245. CAB International, Wallingford.

Hutchinson C F 1982: Techniques for combining Landsat and ancillary data for digital classification improvement. *Photogrammetric Engineering and Remote Sensing* 8, 1: 123-130.

Jarvis C, R B King, J R Wheeler, A J B Mitchell & R J White 1988: Evaluation of Landsat TM and SPOT imagery for agricultural land use planning in less developed countries. *Proc. of IGARSS '88 Symposium*, Edinburgh, Skotland, 1988.

Jensen J R 1986: *Introductory digital image processing : a remote sensing perspective*. Prentice-Hall, Englewood Cliffs, New Jersey, USA.

Jewell N 1989: An evaluation of multi-date SPOT data for agriculture and land use mapping in the United Kingdom. *International Journal of Remote Sensing* **10**, 6: 939-951.

Kateris M A 1990: The utility of digital TM data for natural resources classification. *International Journal of Remote Sensing* **11**, 9: 1589-1598.

Kelton K, W A Shain & L Nix 1985: Supervised and unsupervised methods of spectral classification of vegetative types in the South Carolina Coastal Plain. *ACSM-ASPRS FALL Convention Technical Papers*, 440-449.

Kettig R L & D A Landgrebe 1976: Classification of multispectral image data by extraction and classification of homogeneous objects. *IEEE Transactions of Geoscience Electronics* GE - **14**, 1: 19-26.

Khorram S, J A Brockhaus & A Gerachi 1988: A regional assessment of land-use/land-cover types in Sicily with TM data. *International Journal of Remote Sensing* **12**, 1: 67-78.

Khorram S, J Brochaus & A Gerachi 1988: Multitemporal resource complex analysis of Cantina province, Italy from Landsat TM data. *Proceedings of IGARSS '88 Symposium*, Edinburgh, Scotland, 13-16 September 1988.

King C, J Meyer-Roux 1990: Remote sensing in agriculture : From research to applications. In J A Clark & M D Steven (eds.): *Applications of remote sensing in Agriculture*, 397-403. Butterworths, London.

King G O 1991: Geography and GIS technology. *Journal of Geography* 90, 1: 66-72.

Kolm K E & H L Case 1984: The identification of irrigated crop types and estimation of acreages from Landsat Imagery. *Photogrammetric Engineering and Remote Sensing* 50, 10: 1479-1490.

Kriel G 1993: Die ontwikkeling en aanwending van 'n Geografiese Inligtingstelsel vir beplanning en bestuur deur plaaslike owerhede : Die Munisipaliteit Stellenbosch. MA-Thesis, University of Stellenbosch, Stellenbosch.

Lillesand T M and R W Kiefer 1979: *Remote sensing and image interpretation.* John Wiley and Sons, New York.

Lintz J & Simonett 1976: *Remote sensing of environment.* Londen: Addison-Wesley Publishing Co.

Lo C P 1986: *Applied remote sensing*. Longman House, Brunt Hill, Harrow, USA.

Lonergan A T, C D Elphinstone & L P Fatti 1987: Approaches to the classification of remote sensing data. *Proceedings of Earth Data Information Systems* (EDIS 87) Symposium 22-23 September 1987, Pretoria.

Lourens U 1990: Using Landsat TM to monitor irrigated land at the individual farm level. In M Menenti (ed.): *Remote Sensing in Evaluation and Management of Irrigation*, Instituto Nacional de Ciencia y Técnica Hídricas, Mendoza.

Lourens U W & A Seed 1989: Upper Tulbagh Valley : Estimating changes in the extend of irrigated area with the aid of image processing. Department of Water Affairs Report no. N/G102/00/RIH/0489. Pretoria.

Lourens U W 1990: A comparison of satellite data types and techniques for mapping irrigated land. Department of Water Affairs. Institute for Hydrological Research, Pretoria. Report no. TR 144, Pretoria.

Lourens U, B Brown, A Seed & H Maaren 1987: Mapping irrigated land use in the Breede River catchment with the aid of satellite imagery. *Proceedings of Earth Data Information Systems* (EDIS 87) Symposium, 22-23 September 1987, Pretoria.

Maaren H 1985: Use of satellite remote sensing in mapping irrigated land-use. Colloquium Papers - Remote sensing applications in water resources. Department of Water Affairs. Institute for Hydrological Research, Pretoria.

Mackay C 1994: The Application of integrated remotely sensed and geographic data to facilitate rangeland mapping and condition assessment in the Ceres Karoo region of Southern Africa. M.Sc-Thesis, University of Stellenbosch, Stellenbosch.

Malan O G & B Turner 1983: The Heilbron Crop Mapping Project. The identification of Agricultural Crops in the Heilbron area by use of Satellite Imagery. Part 2 : Winter Crops 1981. CSIR Special Report FIS 303. National Physical Research Laboratory, Pretoria.

Malan O G 1991: Inleiding tot Afstandswaarneming. Unpublished papers, University of Stellenbosch, Stellenbosch.

Manore M 1990: Remote sensing and GIS - together at last! *GEOS* 1990 **12**: 17-22.

Manore M J & R J Brown 1990: Remote Sensing/GIS integration in the Canadian crop information system. *Geocarto International* 5, 1: 74-76.

Maracci G & D Aifadopoulou 1990: Multi-temporal remote sensing study of spectral signatures of crops in the Thessaloniki test site. *International Journal of Remote Sensing* **11**, 9: 1609-1615.

Mather P M 1990: Theoretical problems in image classification. In J A Clark & M C Steven (eds.): *Applications of remote sensing in agriculture*, 127-136. Butterworths, London.

Matthews J A 1981: *Quantitative and statistical approaches to Geography - a Practical manual.* Pergamon Press, Oxford.

Mausel P W, W J Kramber & J K Lee 1990: Optimum band selection for supervised classification of multispectral data. *Photogrammetric Engineering and Remote Sensing*. **56**, 1: 55-60.

Menenti M & G J A Niewenhuis, 1986: Remote sensing in the water management practice. *Netherlands Journal of Agricultural Science* **34**, 3: 317-328.

Menenti M 1990: The role of remote sensing, GIS and models in irrigation management. In M Menenti (ed.): *Remote Sensing in Evaluation and Management of Irrigation*, 193-204. Instituto Nacional de Ciencia y Técnica Hídricas, Mendoza.

Menenti M, S Azzali, D A Collado & S Leguizamon 1986: Multitemporal analysis of Landsat Multispectral Scanner (MSS) and Thematic Mapper (TM) data to map crops in the Po valley (Italy) and in Mendoza (Argentina). *Symposium on Remote Sensing for Resources Development and Environmental Management.* I T C Enchede, August 1986.

Meyer K C 1991: Identifisering van besproeide oppervlaktes in 'n diverse landbou-omgewing met behulp van satellietafstandswaarneming. Unpublished BA-Honours Report, University of Stellenbosch, Stellenbosch.

Middelkoop H & L F Janssen 1991: Implementation of temporal relationships in knowledge based classification of satellite images. *Photogrammetric Engineering & Remote Sensing.* 57, 7: 937-945.

Minderhoud P & J van Niewkoop 1990: Application of remote sensing in the evaluation and improvement of irrigation water management. In M Menenti (ed.): *Remote sensing in evaluation and management of irrigation*, 207-224. Instituto Nacional de Ciencia y Técnica Hídricas, Mendoza.

Morain S A & D L Williams 1975: Wheat production estimated using satellite images. *Agronomy Journal* 67, 3: 361-364.

Moreton G E & J A Richards 1984: Irrigated crop inventory by classification of satellite image data. *Photogrammetric Engineering and Remote Sensing* 50, 6: 729-737.

Murray Biesenbach & Badenhorst Consulting Engineers 1988: A pilot study of the irrigated areas served by the Breede River (Robertson) irrigation canal. Part 1 : Technical Report. Department of Water Affairs. Water Research Commission publication no. 184/1/89, Pretoria.

Myers, V I 1983: Remote sensing applications in agriculture. In R N Colwell (ed.): *Manual of remote sensing* Vol II, 2111-2218. American Society of Photogrammetry, Falls Church, Virginia.

Nellis M D 1984: A Remote Sensing approach for modelling water resource use. *Water Resources Bulletin* 20, 5: 789-793.

Nieuwenhuis C, G J A Miltenburg & J W Thunnisen 1990: Applications of remote sensing and Geographical information systems in water management. In J A Clark & M D Steven (eds.): *Applications of remote sensing in agriculture*, 111-126. Butterworths, London.

Nieuwenhuis G J A & J M M Bouwmans 1986: Application of multispectral scanning remote sensing in agricultural water management problems. *Symposium on Remote Sensing for Resources Development and Environmental Mangement*, ITC Enschede, August 1986.

Nieuwenhuis G J A & M Menenti 1986: Application of thermal infrared remote sensing in water management of humid and arid areas. *Geocarto International* 1: 35-46.

Nikolaos S 1988: Visual and digital classification of Landsat TM data for soil, physiography and land use mapping in Axios alluvial plain, Thessaloniki, Greece. *Geocarto International* 4: 55-65.

Odendaal J P le G 1978: Die hoofkanale van die Breërivier en Bergrivier : 'n Geomorfologiese ondersoek. MA-Thesis, University of Stellenbosch, Stellenbosch.

Parent P 1992: Satellite imagery offers utilities - a New look in database development. *GIS World* 5, 3: 58-60.

PCI 1988: *PACE multispectral analysis manual.* Version 4.1. PCI Inc, Richmond Hill, Ontario, Canada.

Peuquet D J & D F Marble 1990: *Introductory readings in Geographic Information Systems.* Taylor & Francis, London.

Poracsky J & T H L Williams 1979: Mapping irrigated lands in Western Kansas from Landsat. *Satellite Hydrology.* American Water Resources Association. Geological Survey, Reston, Virginia.

Prinsloo H B 1992: Die gebruik van afstandwaarneming vir die opsporing en kantering van asbesmynhope en besoedeling. Unpublished MA-Thesis, University of Potchefstroom, Potchefstroom.

Quarmby N A & J R G Townshed 1986: Preliminary analysis of SPOT HRV multispectral products of an arid environment. *International Journal of Remote Sensing* 7, 12: 1869-1877.

Redondo F V, C Lac Prugent, C Gargantini & M Artes 1984: Crop identification and area estimation : an approach to evaluate Argentine main crop areas using Landsat data. *Proceedings of the 18th International Symposium on Remote Sensing of Environment.* Paris, France 1-5 October, 1984.

Rees W G 1990: *Physical principles of remote sensing.* Cambridge University Press.

Robinson G M, D A Gray & P A Furley 1989: Developing a geographic information system (GIS) for agricultural development in Belize, Central America. *Applied Geography* 9: 81-94.

Sabins F F 1978: *Remote sensing : Principles and applications*. San Francisco, W H Freeman.

Saltor M A 1990: Necessity of remote sensing to improve the irrigation management system in Bangladesh. In M Menenti (ed.): *Remote sensing in evaluation and management of irrigation*, 225-230. Instituto Nacional de Ciencia y Técnica Hídricas, Mendoza.

Samson S A 1993: Two indices to characterize temporal pattenrs in the spectral response of vegetation. *Photogrammetric Engineering and Remote Sensing* 59, 4: 551-517.

Sandham L A & P A J van Rensburg 1987: Landsat as an aid in evaluating the adequacy of a grain silo network. *Remote Sensing of Environment* 21, 2: 229-241.

Sandham L A 1984: Landsat-ondersteunde oesskattings as beplanningshulpmiddel vir uitbreidings aan 'n graansilonetwerk in Suidoos-Transvaal. Unpublished M.Sc-Thesis, Rand Afrikaans University, Johannesburg.

Schardt M & Stibig H J 1986: Digital classification of forested areas using simulated TM- and SPOT- and Landsat S/TM-data. *Proceedings of Symposium on Remote Sensing for Resources Development and Environmental Management*, Enschede, 1986.

Schloms B H A 1994: Departement Geografie, Universiteit van Stellenbosch. (Personal communication).

Schmidt L T & B I Naugle 1985: A comparison of classification techniques using thematic mapper and multi-spectral scanner data for land cover classification. *ACSM-ASPRS FALL Convention Technical Papers*, 683-695.

Schmullius C 1988: Large area TM landcover classification of 'Mittlerer Oberrhein' country, SW Germany, and its use for regional planning and crop surveys. *Proceedings of IGARSS '88 Symposium*, Edinburgh Skotland, 13-16 September.

Scogings D A & S T Piper 1984: A pilot study to evaluate the feasibility of constructing half year medium scale landcover maps of selected non-urban areas of Natal using remote sensing data. Department of Survey and mapping, University of Natal, Durban.

Seed A 1985: Use of image processing technology in hydrology. Colloquium Papers - Remote Sensing applications in water resources. Department of Water Affairs. Institute for Hydrological Research, Pretoria.

Senguin B, J P Lagouarde, S Steinmetz & A Vidal 1990: Monitoring crop water use in irrigated areas with thermal infrared remote sensing data. In M Menenti (ed.): *Remote sensing in evaluation and management of irrigation*, 59-78. Instituto Nacional de Ciercia y Técnica Hídricas, Mendoza.

Shannon L V & J R E Lutjeharms 1983: Oceanographic applications of satellite imagery in South Africa. *Proceedings of the Earth Data Information Systems Symposium* (Edis 83) held in Pretoria 1983. South African Society for Photogrammetry, Remote Sensing and Cartography, Cape Town.

Shannon L V & L Y Shackleton 1988: Remote sensing in the marine environment. South African National Scientific Programmes Report No. 152. Foundation for Research Development, CSIR, Pretoria.

Sheffield C 1985: Selecting band combinations from multispectral data. *Photogrammetric Engineering and Remote Sensing* 51, 6: 681-687.

Shimoda H, K Fukue, R Yamaguchi, Z Zhang & T Sakata 1988: Accuracy of landcover classification of TM and SPOT Data. *Proceedings of IGARSS '88 Symposium*, Edinburgh, Scotland, 13-16 Sept. 1988.

Silleos N, N Misopolinos & K Perakis 1992: Relationships between remote sensing spectral indices and crops discrimination. *Geocarto International* 2: 41-51.

Simonett D S 1983: The development and principles of remote sensing. In R N Colwell (ed.): *Manual of remote sensing* Vol I, 1-30. American Society of Photogrammetry, Falls Church, Virginia.

Singh A 1989: Review Article : Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing*, 10, 6: 989-1003.

Snyman C H & Caithness (date unavailable): Pilot study on forest mapping. Aerial Agricultural Services (Pty) Ltd.

Star J & J Estes 1990: *Geographic Information Systems : An introduction*. Prentice Hall, Englewood Cliffs, New Jersey.

Steven M D 1987: Ground truth : an underview. *International Journal of Remote Sensing* 8, 7: 1032-1038.

Stow D A, D Collins & D McKinsey 1990: Land use change detection based on multi-date imagery from different satellite sensor systems. *Geocarto International* 3: 3-12.

Swain P H & S M David (eds.). 1978: *Remote Sensing : The quantative approach.* New York : McGraw-Hill.

Swanevelder D J 1965: 'n Geografiese opname van die Breërivier-Opvangsgebied met klem op die landelike grondgebruik. D.Phil.-dissertation, University of Stellenbosch, Stellenbosch.

Szekielda K H 1988: *Satellite monitoring of the earth.* John Wiley & Sons, New York.

Tateishi R & Y Mukouyama 1987: Land Cover classification using Spot data. *Geocarto International* 2: 17-29.

Thelin G P, T L Johnson & R A Johnson 1979: Mapping irrigated cropland on the high plains using Landsat. *Satellite hydrology*, American Water Resources Association, U.S. Geological Survey, Reston, Virginia.

Thiruvengadachari S 1983: Remote sensing of tank irrigated areas in Tamil Nadu State, India. *International Journal of Remote Sensing* 4, 3: 545-554.

Tinney L, J Holloway, J Braggett & J Estes 1979: A multistage mapping approach for an irrigated croplands inventory. *Satellite hydrology*, American Water Resources Assosiation, U.S. Geological Survey, Reston, Virginia.

Tommervik H 1986: Comparison of SPOT-simulated and Landsat TM imagery in vegetation mapping. *Symposium on Remote Sensing for Resources Development and Environmental Management*, ITC Enschede, August 1986.

Toulios L G, N Y Yassoglou & M Moutsoulas 1990: Land-use mapping in West Messinia, Greece, using satellite imagery. *International Journal of Remote Sensing*, 11, 9: 1645-1661.

Townshed J R G & C O Justice 1980: Unsupervised classification of Landsat MSS data for mapping spatially complex vegetation. *International Journal of Remote Sensing* 1, 2: 105-120.

Trolier L J & W R Philipson 1986: Visual analysis of Landsat thematic mapper images for hydrologic land use and cover. *Photogrammetric Engineering and Remote Sensing* 52, 9: 1531-1538.

Trollier L J, W R Philipson & W R Philpot 1989: Landsat TM analysis of vineyards in New York. *International Journal of Remote Sensing* **10**, 7: 1277-1281.

Turner B 1987: Landsat MSS-temporal-spectral profiles of crops and grass on the Highveld. *Proceedings of Earth Data Information Systems Symposium* (EDIS 87). South African Society for Photogrammetry, Remote Sensing and Cartography, Cape Town.

Van den Brink J W, R Beck & H Rijks 1986: Thematic mapping by satellite - a new tool for planning and management. *Symposium on Remote Sensing for Resources Development and Environmental Management*, ITC Enschede, August 1986.

Van Dyck S S 1982: Bodembenuttingskartering vir 'n gedeelte van Wes-Transvaal deur rekenaarmanipulasie van Landsatdata. Unpublished M.Sc-Thesis, Rand Afrikaans University, Johannesburg.

Van Rensburg P A J 1976: 'n Gevallestudie met versyferde multispektrale Landsat-data. *SA Geograaf* **7**, 2: 117-125.

Van Rensburg P A J 1980: The accuracy of thematic maps generated from Landsat MSS data using computer-aided analysis techniques : a case study. *South African Geographical Journal* **62**, 1: 44-61.

Visser T N M 1990: Use of satellite data and geographic information systems in the appraisal of irrigation performance. In M Menenti (ed.): *Remote sensing in evaluation and management of irrigation*, 147-165. Instituto Nacional de Ciencia y Técnica Hídricas, Mendoza.

Vlok A C & H L Zietsman 1993: Digital analysis of satellite imagery : An art or a science? *South African Geographer* **20**, 1/2: 23-36.

Vlok A C 1989: Die identifisering en kartering van wingerde in Suidwes-Kaapland met behulp van Landsatgegewens. Unpublished MA-Thesis, University of Stellenbosch, Stellenbosch.

Vlok, A C & H L Zietsman 1987: Vineyard identification using Landsat Digital image processing. *Proceedings of Earth Data Information Systems* (EDIS 87) Symposium, 22-23 September 1987, Pretoria.

Wall S L, R W Thomas, C Brown, L E Eriksson & Bauer 1982: A Landsat-based inventory procedure for the estimation of irrigated land in arid areas. *International Symposium on Remote Sensing of Environment 1st Thematic Conference: Remote Sensing of Arid and Semi-arid Lands*, Kaïro, Egipte, Januarie 1982.

Wanjura D F & Hatfield 1988: Vegetative and optical characteristics of four-row crop canopies. *International Journal of Remote Sensing* 9, 2: 249-258.

Webster, K B, J R Lucas, R J Musgrove & A L Higher 1979: Selected irrigation acreage estimates in northern Florida from Landsat data. *Satellite hydrology*. American Water Resources Association, U.S. Geological Survey, Reston, Virginia.

Westmoreland S & D A Stow 1992: Category identification of changed land-use polygons in an integrated image processing Geographic Information System. *Photogrammetric Engineering and Remote Sensing* 58, 11: 1593-1599.

Wheeler J R, C Jarvis, A J B Mitchell, R B King & J R White 1988: Evaluation of Landsat TM and SPOT imagery for agricultural land use planning in less developed countries. *Proceedings of IGARSS '88 Symposium*, Edinburgh, Skotland, 13-16 September 1988.

Wheeler J R, C Jarvis, A J B Mitchell, R B King & R J White 1988: Evaluation of Landsat TM and SPOT imagery for agricultural land use planning in less developed countries. *Proceedings of IGARSS '88 Symposium*, Edinburgh, Scotland, 13-16 September 1988.

Williams T H L & J Poracsky 1979: Mapping irrigated lands in western Kansas from Landsat. *Satellite hydrology*. American Water Resources Association, U.S. Geological Survey, Reston, Virginia.

Williamson H D 1989: The discrimination of irrigated orchard and vine crops using remotely sensed data. *Photogrammetric Engineering and Remote Sensing*, 55, 1: 77-82.

Wolfaard P J 1983: Interskakeling van Landsat-syferdata en landboustatistiek vir die Vermaasontwikkelingsgebied. D.Litt et Phil-dissentation, Rand Afrikaans University, Johannesburg.

Zhou Q 1989: A method for intergrating remote sensing and Geographic Information Systems. *Photogrammetric Engineering and Remote Sensing* 55, 5: 591-596.

Zietsman H L 1982: Grondgebruikkantering van Suidwes-Kaapland met behulp van Landsat gegewens. Publication no. 11. Institute for Geographical Analysis, University of Stellenbosch, Stellenbosch.

Zuluaga J M 1990: Remote sensing applications in irrigation management in Mendoza, Argentina. In M Menenti (ed.): *Remote sensing in evaluation and management of irrigation*, 37-58. Instituto Nacional de Ciencia y Técnica Hídricas, Mendoza.

ADDENDUM A

This appendix contains the data dictionary for all geographic themes used in this research project. Each theme is described and listed in alphabetic order. The datafiles that are listed are subsets of either Arc Attribute Tables (AAT), Polygon Attribute Tables or Point Attribute Tables (PAT).

Datafile name: CATCH.PAT

Type: polygon

Description: This coverage represents the Major Drainage Regions in the South Western Cape. The data had been obtained from the Institute for Geographical Analysis, University of Stellenbosch and reprojected to the Gauss Conform Projection with a Central Meridian of 19° East.

Definition:

COL	ITEM NAME	WIDTH	OUTPUT	TYPE	N.DEC
1	AREA	4	12	F	3
5	PERIMETER	4	12	F	3
9	CATCH_	4	5	B	-
13	CATCH_ID	4	5	B	-
17	NAME	10	10	C	0
27	SHADE	10	10	N	0
69	LUCODE	10	N	0	

Datafile name: CONTOURS.AAT

Type: line

Description: This coverage represents the elevation contours (below 500 m) in the study area. The dataset was scanned and vectorized by the Department of Water Affairs and Forestry. The data was then projected into the Gauss Conform Projection with a Central Meridian of 19° East. The additional ITEM ELEVATION contains data on the height (m) represented by each of the lines.

Definition:

COL	ITEM NAME	WIDTH	TYPE	N.DEC
1	FNODE_	11	N	0
12	TNODE_	11	N	0
23	LPOLY_	11	N	0
34	RPOLY_	11	N	0

45	LENGTH	13	N	0
58	CONTOURS_	11	N	0
69	CONTOURS_ID	11	N	0
80	ELEVATION	10	N	0

Datafile name: FARMS.PAT

Type: polygon

Description: This coverage represents the landuse patterns and farm boundaries of the selected farms in the study area. This data was digitized from 1:10 000 scale orthophoto's, mapjoined and is in the Gauss Conform Projection with a Central Meridian of 19° East. Additional attribute file information from the questionare survey were joined to this file with the common item 'BLOCKNR'.

Definition:

COL	ITEM NAME	WIDTH	TYPE	N.DEC
1	AREA	13	N	6
14	PERIMETER	13	N	6
27	FARMS_	11	N	0
38	FARMS_ID	11	N	0
49		5	C	0
54	PLNR	3	C	0
57	BLOKNR	1	C	0
59	TIPEG	1	C	0
60	APR_EENJ	2	C	0
62	AUG_EENJ	2	C	0
64	OKT_EENJ	2	C	0
66	JAN_EENJ	2	C	0
68	MEERJ	2	C	0
70	OPLEI	1	C	0
71	OUD	1	C	0
72	TIPE_DEK	1	C	0
73	APR_DEK	2	C	0
75	AUG_DEK	2	C	0
77	OKT_DEK	2	C	0
79	JAN_DEK	2	C	0
81	BESPROEI	1	C	0
82	STELSEL	1	C	0
83	FEB_BS	2	N	0

85	MRT_BS	2	N	0
87	APR_BS	2	N	0
89	MEI_BS	2	N	0
91	JUN_BS	2	N	0
93	JUL_BS	2	N	0
95	AUG_BS	2	N	0
97	SEP_BS	2	N	0
99	OKT_BS	2	N	0
101	NOV_BS	2	N	0
103	DES_BS	2	N	0
105	JAN_BS	2	N	0
107	SL	8	N	2
115	RW	5	N	2
120	SS	5	N	2
125	KONTROLE	2	C	0
127	LUCODE	10	N	0

Datafile name: LANDUSE.PAT

Type: polygon

Description: This coverage represents the current landuse pattern (February 1992 - January 1993) in the study area. Information for this coverage was obtained from 1:30 000 scale aerial photographs, 1:10 000 scale orthophoto's, intensive fieldwork and verification. The data was then digitized and mapjoined and is in the Gauss Conform Projection with a Central Meridian of 19° East.

Definition:

COL	ITEM NAME	WIDTH	TYPE	N.DEC
1	AREA	13	N	6
14	PERIMETER	13	N	6
27	BREEMAP_	11	N	0
38	BREEMAP_ID	11	N	0
49	LU1	10	C	0
59	LU2	10	C	0
69	LUCODE	10	N	0

Datafile name: ORTHOGRID.PAT

Type: polygon

Description: This dataset contains lines demarcating the 1:10 000 scale orthophoto sheets, used in this study. It also contains the labels for all the map sheets used in this study. The coverage is in the Gauss Conform Projection with a Central Meridian of 19° East.

Definition:

COL	ITEM NAME	WIDTH	OUTPUT	TYPE	N.DEC
1	AREA	4	12	F	3
5	PERIMETER	4	12	F	3
9	ORTHOGRID_	4	5	B	-
13	ORTHOGRID_ID	4	5	B	-
17	NAME	20	20	C	0

Datafile name: RAINFALL.PAT

Type: point

Description: This coverage contains presipitation data for the entire study area as obtained from the Resource Management Section, at Elsenburg Agricultural Development Institute. A TIN was built from these points and the isohyets generated from the TIN. The coverage was projected to the Gauss Conform Projection with a Central Meridian of 19° East.

Definition:

COL	ITEM NAME	WIDTH	OUTPUT	TYPE	N.DEC
1	AREA	4	12	F	3
5	PERIMETER	4	12	F	3
9	REENDATA_	4	5	B	-
13	REENDATA_ID	4	5	B	-
17	ALTITUDE	4	5	B	-
21	MAP	4	8	F	3
25	MEDAP	4	8	F	3
29	JANMED_MAXT	4	8	F	3
33	JANMED_MINT	4	8	F	3
37	JANMED_RAIN	4	8	F	3
41	FEBMED_MAXT	4	8	F	3
45	FEBMED_MINT	4	8	F	3
49	FEBMED_RAIN	4	8	F	3
53	MARMED_MAXT	4	8	F	3

57	MARMED_MINT	4	8	F	3
61	MARMED_RAIN	4	8	F	3
65	APRMED_MAXT	4	8	F	3
69	APRMED_MINT	4	8	F	3
73	APRMED_RAIN	4	8	F	3
77	MAYMED_MAXT	4	8	F	3
81	MAYMED_MINT	4	8	F	3
85	MAYMED_RAIN	4	8	F	3
89	JUNMED_MAXT	4	8	F	3
93	JUNMED_MINT	4	8	F	3
97	JUNMED_RAIN	4	8	F	3
101	JULMED_MAXT	4	8	F	3
105	JULMED_MINT	4	8	F	3
109	JULMED_RAIN	4	8	F	3
113	AUGMED_MAXT	4	8	F	3
117	AUGMED_MINT	4	8	F	3
121	AUGMED_RAIN	4	8	F	3
125	SEPMED_MAXT	4	8	F	3
129	SEPMED_MINT	4	8	F	3
133	SEPMED_RAIN	4	8	F	3
137	OCTMED_MAXT	4	8	F	3
141	OCTMED_MINT	4	8	F	3
145	OCTMED_RAIN	4	8	F	3
149	NOVMED_MAXT	4	8	F	3
153	NOVMED_MINT	4	8	F	3
157	NOVMED_RAIN	4	8	F	3
161	DECMED_MAXT	4	8	F	3
165	DECMED_MINT	4	8	F	3
169	DECMED_RAIN	4	8	F	3

Datafile name: REGIONH100.PAT

Type: polygon

Description: This coverage represents the Upper Breede River Catchment (H100). The catchment boundary is represented by the extend of the line H100 as represented by this coverage. The data has been obtained from the Department of Water Affairs, South Western Cape Region. It was then reprojected to the Gauss Conform Projection with a Central Meridian of 19° East.

Definition:

COL	ITEM NAME	WIDTH	OUTPUT	TYPE	N.DEC
1	AREA	4	12	F	3
5	PERIMETER	4	12	F	3
9	REGION_	4	5	B	-
13	REGION_ID	4	5	B	-
17	D_REG	4	4	C	-

Datafile name: REGIONS.PAT

Type: polygon

Description: This coverage represents the main Agricultural Regions within the study area. The dataset was drawn by hand from 1:250 000 topographic mapsheet and then digitized. This data is in the Gauss Conform Projection with a Central Meridian of 19° East.

Definition:

COL	ITEM NAME	WIDTH	TYPE	N.DEC
1	AREA	13	N	6
14	PERIMETER	13	N	6
27	REGIONS_	11	N	0
38	REGIONS_ID	11	N	0
49	REGIONNAME	20	C	0
69	REGIONCODE	10	C	0
79	SYMBOL	5	N	0

Datafile name: RIVERS.AAT

Type: line

Description: This coverage represents the Breede River and its major contributaries in the research area. The dataset was digitized from 1:50 000 scale topographic mapsheets published by the Chief Directorate of Surveys and Mapping. They were mapjoined and projected to the Gauss Conform Projection with a Central Meridian of 19° East.

Definition:

COL	ITEM NAME	WIDTH	OUTPUT	TYPE	N.DEC
1	FNODE_	4	5	B	-
5	TNODE_	4	5	B	-
9	LPOLY_	4	5	B	-
13	RPOLY_	4	5	B	-

17	LENGTH	4	12	F	3
21	RIVERS_	4	5	B	-
25	RIVERS_ID	4	5	B	-
29	NAME	20	20	C	-

Datafile name: SLOPES.PAT

Type: polygon

Description: This coverage represents the slopes (below 500 m) for the study area as calculated by the TIN. A polygon coverage was generated from the TIN with TINARC containing values for percentage slope. The coverage was projected to the Gauss Conform Projection with a Central Meridian of 19° East.

Definition:

COL	ITEM NAME	WIDTH	OUTPUT	TYPE	N.DEC
1	AREA	8	18	F	5
9	PERIMETER	8	18	F	5
17	SLOPES	4	5	B	-
21	SLOPES_ID	4	5	B	-
25	PERCENT_SLOPE	4	12	F	3
29	ASPECT	4	12	F	3
33	SAREA	8	18	F	5
41	SLOPE	6	6	N	0

Datafile name: SOILS.PAT

Type: polygon

Description: This coverage represents the different soil types in the study area. The dataset was digitized from 1:50 000 scale mapsheet-overlays obtained from the Department of Agriculture, mapjoined and is in the Gauss Conform Projection with a Central Meridian of 19° East. This dataset contains additional information on soil-irrigation potential, soildepth and associated soilcolour.

Definition:

COL	ITEM NAME	WIDTH	TYPE	N.DEC
1	AREA	13	N	6
14	PERIMETER	13	N	6
27	SOILS_	11	N	0
38	SOILS_ID	11	N	0

49	GRD1	12	C	0
61	GRD	12	C	0
73	KLEUR	10	N	0
83	DIEPTE	10	N	0
93	BESPROEI	10	N	0

Datafile name: STUDYAREA.PAT

Type: polygon

Description: This coverage represents the extend of the study area. The outer boundary of this coverage was defined by the extent of the drainage region, satellite imagery and contour data. This dataset is in the Gauss Conform Projection with a Central Meridian of 19° East.

Definition:

COL	ITEM NAME	WIDTH	OUTPUT	TYPE	N.DEC
1	AREA	4	12	F	3
5	PERIMETER	4	12	F	3
9	STUDYAREA_	4	5	B	-
13	STUDYAREA_ID	4	5	B	-
17	GEBIED	4	4	I	-

Datafile name: TOPOGRID.PAT

Type: polygon

Description: This dataset contains lines demarcating the 1:50 000 scale topographic mapsheets used in this study. It also contains the labels for the map sheets used in this study. The coverage is in the Gauss Conform Projection with a Central Meridian of 19° East.

Definition:

COL	ITEM NAME	WIDTH	OUTPUT	TYPE	N.DEC
1	AREA	4	12	F	3
5	PERIMETER	4	12	F	3
9	TOPOGRID_	4	5	B	-
13	TOPOGRID_ID	4	5	B	-
17	NAME	10	10	C	0

Datafile name: TOWNS.PAT

Type: point

Description: This coverage represents the location of the major towns in the study area. It was generated in ARC/INFO from geographic coordinates and projected to the Gauss Conform Projection with a Central Meridian of 19° East.

Definition:

COL	ITEM NAME	WIDTH	OUTPUT	TYPE	N.DEC
1	AREA	4	12	F	3
5	PERIMETER	4	12	F	3
9	TOWNS_	4	5	B	-
13	TOWNS_ID	4	5	B	-
17	NAMES	20	20	C	-

Datafile name: WCREGION.PAT

Type: polygon

Description: This coverage represents the major drainage regions in the South Western Cape. The data had been obtained from the Institute for Geographical Analysis, University of Stellenbosch and reprojected to the Gauss Conform Projection with a Central Meridian of 19° East.

Definition:

COL	ITEM NAME	WIDTH	TYPE	N.DEC
1	AREA	13	N	6
14	PERIMETER	13	N	6
27	WCREGION_	11	N	0
38	WCREGION_ID	11	N	0
49	D_REG	4	C	0

Datafile name: WEATHERST.PAT

Type: point

Description: This coverage represents the location of the three Weather Stations, La-Plaisante, Botha's Halt and Worcester, in the study area. All climatic data used in this study were derived from these stations. The coverage was generated from geographical coordinates in ARC/INFO and then projected to the Gauss Conform Projection.

Definition:

COL	ITEM NAME	WIDTH	TYPE	N.DEC
1	AREA	13	N	6
14	PERIMETER	13	N	6
27	WEATHERST_	11	N	0
38	WEATHERST_ID	11	N	0
49	STATION	15	C	0

UNIVERSITEIT VAN STELLENBOSCH
UNIVERSITY OF STELLENBOSCH

GEWAS- EN BESPROEIINGSOPNAME IN DIE SO-BREËRIVIERGEBIED

Plaasnaam : WAVERLEY WB

DIE ONDERSTAANDE VRAE HET BETREKKING OP DIE INDIVIDUELE BLOKKE PER PLAAS WAT MET EENJARIGE OF PERMANENTE GEWASSE BEPLANT IS.

Voordat die vraelys ingevul word, moet 'n nommer aan elke blok toegeken word en die ligging van die blok moet op 'n kaart van die plaas aangedui word. Die vraelysopnemer sal u daarmee behulpsaam wees en u van die nodige kaarte voorsien.

Met die uitsondering van vrae 5 en 6 moet u slegs die relevante kode vanuit die geskakeerde ruimte kies.

1. Dui aan watter blokke met *eenjarige* en watter met *permanente* gewasse beplant was gedurende April 1992 tot Januarie 1993.

Eenjarig = 1 Meerjarig = 2

DIE VOLGENDE VRAAG HET SLEGS BETREKKING OP DIE BLOKKE WAT IN VRAAG 1 AS EENJARIG (KODE 1) AANGEDUI IS.

2. Gebruik die onderstaande kodes om aan te dui met watter tipe gewas die blok gedurende die volgende vier datums beplant was :

April 1992
Augustus 1992
Oktober 1992
Januarie 1993

Aartappels = 1 Babala = 2 Boontjies = 3 Erte = 4
Gars = 5 Hawer = 6 Kool = 7 Koring = 8
Lupine = 9 Pampoen = 10 Rog = 11 Serradella = 12
Skorsies = 13 Spanspek = 14 Tamaties = 15 Uie = 16
Waatlemoen = 17

Ander = 18 (Spesifiseer asseblief die gewastipe sowel as die bloknommer).

KWEEK / GRAS = 18

DIE VOLGENDE VRAAG HET SLEGS BETREKKING OP BLOKKE WAT IN VRAAG 1 AS PERMANENTE GEWASSE (KODE 2) AANGEDUI IS.

3. Dui met behulp van die onderstaande kodes aan waarmee die blok beplant is.

Appelkose = 1 Appels = 2 Lusern = 3 Olywe = 4
Pere = 5 Perskes = 6 Pruime = 7 Sitrus = 8
Tafeldruive = 9 Wyndruive = 10

Ander = 11 (Spesifiseer asseblief die gewastipe sowel as die bloknommer).

3.1 Watter van die wingerd- en boordblokke is opgelei?

Opgelei = 1 Nie- opgelei = 2

3.2 Gee 'n aanduiding van die ouderdom van die wingerd- en boordblokke.

Jonger as 1 jaar = 1 1 tot 3 jaar = 2 Ouer as 3 jaar = 3

3.3 Was die blokke op enige stadium gedurende April 1992 tot Januarie 1993 met dekgewasse beplant?

Ja = 1 Nee = 2

BLOKNOMMER

	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
1.	2	2	2	2	2	2	2	1	1	1	1	2	1	1	2	2	1									
2. April 1992								6	6	0	0		0	0			9									
Augustus 1992								6	6	0	0		0	0			9									
Oktober 1992								6	6	16	16		18	10			0									
Januarie 1993								6	0	16	16		18	10			0									
3.	6	10	10	10	10	10	10					10			10	10										
3.1	2	1	1	1	1	1	1	2	2	2	2	1	2	2	1	1										
3.2	3	3	3	3	3	3	3					3			3	1										
3.3	2	2	2	2	2	2	2					2			2	2										

[illegible] watter winter-dekgewastipe 'n permanente blok (bv boord en wingerd) tydens die volgende datums beplant was:

GEEN

	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
April 1992																									
Augustus 1992																									
Oktober 1992																									
Januarie 1993																									

Hawer = 1 Koring = 2 Lupine = 3 Lusern = 4

Ander = 5 (Spesifiseer asseblief die gewastipe sowel as die bloknommer).

....

4. Dui asseblief aan of die individuele blokke besproei word al dan nie.

Besproei = 1 Nie-besproei = 2

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
1	1	1	1	1	1	1	2	2	1	1	1	2	1	1	1	2								

4.1 Dui asseblief op 'n blokbasis aan watter besproeiingstelsel u gebruik.

Drup = 1 Mikro = 2 Sprinkel = 3 Vloed = 4 Spilpunt = 5

Ander = 6 (Spesifiseer asseblief enige ander besproeiingstelsel, asook die bloknommer waar dit aangewend word).

....

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
2	2	2	2	2	3	3			3	3	3		3	3	3									

4.2 Volg u 'n vaste besproeiingspatroon ?

Ja = 1 Nee = 2

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
1	1	1	1	1	1	1			1	1	1		1	1	1									

Indien nee, verskaf asseblief die relevante bloknommer sowel as verduidelikende kommentaar in die toegelate ruimte.

....
....
....
....

MET BEHULP VAN DIE VOLGENDE VRAAG PROBEER ONS PER GEWASBLOK VASSTEL WANNEER U BESPROEI EN HOEVEEL U BESPROEI.

5. Dui vir elk van die besproeide blokke aan hoeveel uur per maand u gedurende die volgende maande besproei het :

	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
Februarie 1992	24	48	48	48	48	4	4	0	0	8	8	4	0	8	4	4	0								
Maart 1992	20	40	40	40	40	4	4	0	0	0	0	4	0	0	4	4	0								
April 1992	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	4	0								
Mei 1992	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0								
Junie 1992	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0								
Julie 1992	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0								
Augustus 1992	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0								
September 1992	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0								
Oktober 1992	20	40	40	40	40	4	4	0	0	0	0	0	0	8	4	4	0								
November 1992	20	40	40	40	40	4	4	0	0	0	0	0	0	8	4	4	0								
Desember 1992	24	48	48	48	48	4	4	0	0	0	0	0	0	8	4	4	0								
Januarie 1993	24	48	48	48	48	4	4	0	0	0	0	0	0	8	4	4	0								

DIE VOLGENDE VRAE HET SLEGS BETREKKING OP GEWASBLOKKE WAT DEUR DRUP, MIKRO-EN SPRINKELBESPROEIINGSTELSEL BEDIEN WORD. (SOOS AANGEDUI IN VRAAG 4.2)

6. Wat is die spuitlewering van die besproeiingstelsel in (liter/uur)?
7. Wat is die rywydte (in meter) per gewasblok ?
8. Gee 'n aanduiding van die spuitspasiering (in meter).
9. Dui die oppervlakte (in hektaar), van die gewasblok aan.

	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
6.	50	32	32	32	32	2273	2273			1000	1000	2273		1000	2275	1000									
7.	5	2,74	2,74	2,74	2,74	12	12			12	12	12		12	12	12									
8.	3	1,8	1,8	1,8	1,8	12	12			12	12	12		12	12	12									
9.																									

Baie dankie vir u samewerking.

ADDENDUM C

Principal Component Analysis : SPOT XS

Input Channels: 6 7 8 9 10 11
Output Channels: 12 13 14
Eigen Channels: 1 2 3
Sampling Window: 0 0 1920 1520
Sample size: 10837

Channel means:

66,94	66,96	92,99	35,52	25,61	35,52

Channel deviations:

12,82	18,73	21,16	5,44	6,02	8,68

Coveriance matrix for input channels:

164,27					
231,98	350,77				
113,93	143,00	447,86			
45,25	59,43	48,23	29,62		
49,27	66,76	50,34	30,79	36,29	
50,36	74,40	116,51	22,37	20,59	75,33

Eigenvalues of covariance matrix:

,723E+03	,298E+03	,399E+02	,350E+02	,621E+01	,160E+01

Eigenvectors of covariance matrix (arranged in rows):

,416	,591	,624	,135	,146	,222
-,338	-,563	,742	-,046	-,061	,114
,123	,127	,238	-,326	-,289	-,850
-,079	,211	-,033	-,552	-,665	,449
,813	-,509	-,046	,074	-,258	,088
,180	-,120	-,017	-,750	,619	,080

Scaling (whitening) values:

Eigen Channl	Output Channl	Min	Unscaled Max	Range	Scale Factor	Bias Value
1	12	-79,181	171,696	251,877	1,016	80,477
2	13	-92,101	58,383	151,485	1,690	155,646
3	14	-33,416	47,934	82,350	3,109	103,880
4		-33,599	27,081	61,679	4,150	139,451
5		-16,843	19,383	37,226	6,877	115,830
6		-6,755	6,941	14,695	17,421	117,671

SUPERVISED CLASSIFICATION

CLASSIFICATION 1

CLASS	SIGNATURE SEGMENT	CLASS CODE	THRESHOLD VALUE	NUMBER OF PIXELS	% IMAGE	AREA HA
ORCHARD	232	1	3	3200	0.11	128
	233	2	3	8546	0.29	341.84
	234	3	3	1694	0.06	67.76
	235	4	3	8768	0.3	350.72
	236	5	3	2836	0.1	113.44
	237	6	3	4334	0.15	173.36
	238	7	3	28701	0.98	1148.04
TOTAL				58079	1.99	2323.16
VINES	239	10	3	6475	0.22	259
	240	11	3	18997	0.65	759.88
	241	12	3	32213	1.1	1288.52
	242	13	3	6113	0.21	244.52
	243	14	3	2974	0.1	118.96
	244	15	3	18515	0.63	740.6
	245	16	3	12039	0.41	481.56
	246	17	3	7297	0.25	291.88
	247	18	3	11763	0.4	470.52
	248	19	3	4076	0.14	163.04
	249	20	3	11947	0.41	477.88
	250	21	3	53175	1.82	2127
	251	22	3	7412	0.25	296.48
	252	23	3	17592	0.6	703.68
TOTAL				210588	7.19	8423.52
TABLE GRAPES	253	24	3	4239	0.15	169.56
	254	25	3	3319	0.11	132.76
	255	26	3	91482	3.13	3659.28
TOTAL				99040	3.39	3961.6
VEGETABLES	256	30	3	11533	0.4	461.32
	257	31	3	42492	1.46	1699.68
	258	32	3	6111	0.21	244.44
	259	33	3	20097	0.69	803.88
	260	34	3	7643	0.26	305.72
	261	35	3	103881	3.56	4155.24
TOTAL				191757	6.58	7670.28
PASTURE	262	40	3	6293	0.22	251.72
	263	41	3	7362	0.25	294.48
	264	42	3	28749	0.99	1149.96
	265	43	3	19864	0.68	794.56
	266	44	3	79018	2.71	3160.72
	267	45	3	18484	0.63	739.36
	268	46	3	34463	1.18	1378.52
	269	47	3	11547	0.4	461.88
	270	48	3	12060	0.41	482.4
TOTAL				217840	7.47	8713.6
FYNBOS	271	50	3	225185	7.72	9007.4
BUSH	272	51	3	336919	11.54	13476.76
RIVERINE	273	52	3	32345	1.11	1293.8
PLANTATION	274	53	3	2404	0.08	96.16
WATER	275	54	3	34213	1.17	1368.52
BARE SOIL	276	55	3	14068	0.48	562.72
SAND	277	56	3	12416	0.43	496.64
FALLOW LAND	278	57	3	7136	0.24	285.44
PASTURE/ GRASS	279	58	3	81250	2.78	3250
WATER						
MOUNTAIN FYNBOS						
PLANTATION						
PLANTATION						
PLANTATION						
FALLOW LAND						
PLANTATION						
TOTAL OTHER				745936	25.55	29837.44
% IMAGE CLASSIFIED				1523240	52.19	60929.6
% IMAGE UNCLASSIFIED				1395160	47.81	55806.4
NUMBER OF CLASSES					48	

CLASSIFICATION 2

CLASS	SIGNATURE SEGMENT	CLASS CODE	THRESHOLD VALUE	NUMBER OF PIXELS	%IMAGE	AREA HA
ORCHARD	232	1	3	3378	0.12	135.12
	233	2	3	8639	0.3	345.56
	234	3	3	1699	0.06	67.96
	235	4	3	14413	0.5	584.32
	287	65	2	1901	0.07	76.04
	237	6	3	4419	0.15	176.76
	288	66	2	13187	0.45	527.48
TOTAL				47836	1.63	1913.44
VINES	239	10	3	10247	0.35	409.88
	240	11	3	24986	0.86	999.44
	241	12	3	46489	1.59	1859.56
	242	13	3	6708	0.23	268.32
	243	14	3	3736	0.13	149.44
	245	16	3	14885	0.51	595.4
	247	18	3	16084	0.55	643.36
	248	19	3	4554	0.16	182.16
	249	20	3	13094	0.45	523.76
TOTAL				140783	4.83	5631.32
TABLE GRAPES	253	24	3	5199	0.18	207.96
	254	25	3	3566	0.12	142.64
TOTAL				8765	0.3	350.6
VEGETABLES						
	259	33	3	27632	0.95	1105.28
	260	34	3	14278	0.49	571.12
TOTAL				41910	1.44	1676.4
PASTURE	262	40	3	6293	0.22	251.72
	263	41	3	7504	0.26	300.16
	264	42	3	33678	1.15	1347.12
	265	43	3	20638	0.71	825.52
	267	45	3	18832	0.65	753.28
	268	46	3	66882	2.29	2675.28
	269	47	3	12856	0.44	514.24
	270	48	3	13795	0.47	551.8
TOTAL				180478	6.19	7219.12
FYNBOS	271	50	3	227716	7.8	9108.64
BUSH	272	51	3	334888	11.48	13395.52
RIVERINE	273	52	3	35095	1.2	1403.8
PLANTATION						
WATER	275	54	3	31095	1.07	1243.8
BARE SOIL	276	55	3	21036	0.72	841.44
SAND	277	56	3	28936	0.99	1157.44
FALLOW LAND	278	57	3	13765	0.47	550.6
PASTURE/ GRASS						
WATER	283	61	2	599739	20.55	23989.56
MOUNTAIN FYNBOS	282	60	2	28371	0.97	1134.84
PLANTATION	284	62	2	3806	0.13	152.24
PLANTATION	285	63	2	2577	0.9	103.08
PLANTATION	286	64	2	2762	0.9	110.48
FALLOW LAND	289	67	2	3632	0.12	145.28
PLANTATION						
TOTAL OTHER				1333418	47.3	53336.72
% IMAGE CLASSIFIED				1165210	60.07	46608.4
% IMAGE UNCLASSIFIED				2918400	39.93	116736
NUMBER OF CLASSES					41	

CLASSIFICATION 3

ASS	SIGNATURE SEGMENT	CLASS CODE	THRESHOLD VALUE	NUMBER OF PIXELS	%IMAGE	AREA HA
ORCHARD	232	1	3	3630	0.12	145.2
	233	2	3	12367	0.42	494.68
	234	3	3	1724	0.06	68.96
	235	4	2	2400	0.08	96
	237	5	2	1953	0.07	78.12
	237	6	3	4556	0.16	182.24
TOTAL				26630	0.91	1065.2
VINES	239	10	3	6970	0.24	278.8
	240	11	3	20880	0.72	835.2
	241	12	2	7648	0.26	305.92
	242	13	3	6139	0.21	245.56
	243	14	3	2976	0.1	119.04
	244	15	3	20443	0.7	817.72
	245	16	2	2598	0.09	103.92
	246	17	3	8173	0.28	326.92
	247	18	3	19156	0.66	766.24
	248	19	3	5232	0.18	209.28
	249	20	2	1973	0.07	78.92
	251	22	3	7764	0.27	310.56
	252	23	2	3290	0.11	131.6
TOTAL				113242	3.89	4529.68
TABLE GRAPES	253	24	2	1312	0.04	52.48
	254	25	2	1276	0.04	51.04
TOTAL				2588	0.08	103.52
VEGETABLES						
	258	32	2	1509	0.05	60.36
	259	33	3	26509	0.91	1060.36
	260	34	3	12662	0.43	506.48
TOTAL				40680	1.39	1627.2
PASTURE	262	40	3	6293	0.22	251.72
	263	41	3	8272	0.28	330.88
	264	42	3	35359	1.21	1414.36
	265	43	3	20930	0.72	837.2
	266	44	2	18327	0.63	733.08
	267	45	3	18836	0.65	753.44
	268	46	3	86091	2.95	3443.64
	269	47	3	12820	0.44	512.8
	270	48	3	12715	0.44	508.6
TOTAL				219643	7.54	8785.72
FYNBOS	271	50	3	224338	7.69	8973.52
BUSH						
RIVERINE	273	52	2	13801	0.47	552.04
PLANTATION						
WATER	275	54	3	38161	1.31	1526.44
BARE SOIL	276	55	3	33256	1.14	1330.24
SAND	277	56	2	2135	0.07	85.4
FALLOW LAND						
PASTURE/ GRASS						
WATER						
MOUNTAIN FYNBOS	282	60	3	137547	4.71	5501.88
PLANTATION	284	62	2	3806	0.13	152.24
PLANTATION	285	63	2	2577	0.09	103.08
PLANTATION	286	64	2	2762	0.09	110.48
FALLOW LAND	289	67	2	18327	0.63	733.08
PLANTATION						
TOTAL OTHER				476710	16.33	19068.4
% IMAGE CLASSIFIED				876905	29.51	35076.2
% IMAGE UNCLASSIFIED				2057235	70.49	82289.4
NUMBER OF CLASSES					43	

CLASSIFICATION 4

CLASS	SIGNATURE SEGMENT	CLASS CODE	THRESHOLD VALUE	NUMBER OF PIXELS	% IMAGE	AREA HA
ORCHARD	232	1	3	3228	0.11	129.12
	233	2	3	7905	0.27	316.2
	234	3	3	1845	0.06	73.8
	235	4	3	15078	0.52	603.12
	236	5	3	2836	0.1	113.44
	237	6	3	4411	0.15	176.44
	238	7	3	32197	1.1	1287.88
TOTAL				67500	2.31	2700
VINES	239	10	3	6531	0.22	261.24
	240	11	3	19949	0.68	797.96
	241	12	3	35340	1.21	1413.6
	242	13	3	5340	0.18	213.6
	243	14	3	3055	0.1	122.2
	244	15	3	28618	0.98	1144.72
	245	16	3	14373	0.49	574.92
	246	17	3	7266	0.25	290.64
	247	18	3	16053	0.55	642.12
	248	19	3	4255	0.15	170.2
	249	20	3	11335	0.39	453.4
	251	22	3	7417	0.25	296.68
	252	23	3	19552	0.67	782.08
TOTAL				179084	6.12	7163.36
TABLE GRAPES	253	24	3	4604	0.16	184.16
	254	25	3	3484	0.12	139.36
TOTAL				8088	0.28	323.52
VEGETABLES						
	258	32	2	1917	0.07	76.68
	259	33	3	21415	0.73	856.6
	260	34	3	10520	0.36	420.8
TOTAL				33852	1.16	1354.08
PASTURE	262	40	3	6293	0.22	251.72
	263	41	3	7394	0.25	295.76
	264	42	3	29604	1.01	1184.16
	265	43	3	21196	0.73	847.84
	266	44	3	87367	2.99	3494.68
	267	45	3	15880	0.54	635.2
	268	46	3	44479	1.52	1779.16
	269	47	3	11031	0.38	441.24
	270	48	3	11144	0.38	445.76
TOTAL				234388	8.02	9375.52
FYNBOS	271	50	3	216181	7.41	8647.24
BUSH						
RIVERINE	273	52	2	11882	0.41	475.28
PLANTATION						
WATER	275	54	3	399292	13.68	15971.68
BARE SOIL	276	55	3	30494	1.04	1219.76
SAND	277	56	3	121872	4.18	4874.88
FALLOW LAND						
PASTURE/GRASS						
WATER						
MOUNTAIN FYNBOS	282	60	3	136901	4.69	5476.04
PLANTATION	284	62	3	11929	0.41	477.16
PLANTATION	285	63	3	9416	0.32	376.64
PLANTATION	286	64	3	10919	0.37	436.76
FALLOW LAND	289	67	2	2973	0.1	118.92
PLANTATION	291	68	3	85384	2.93	3415.36
		80			45.76	
		81			13.01	
TOTAL OTHER				1037243	35.54	41489.72
% IMAGE CLASSIFIED				1560155	53.46	62406.2
% IMAGE UNCLASSIFIED				1358245	46.54	54329.8
NUMBER OF CLASSES					45	

ADDENDUM E.1: Assignment of unsupervised Landsat classes to general land cover types

Rows: Unsupervised Classes Columns: Land use

	Orchards	Vines	Vegetables	Cereals	Other	All
0						17282
1		7				7
2	23	20			6	49
3	49	44		2	23	118
4	296	60		6	15	377
5	74	31		34	20	159
6	1157	308		4	2	1471
7	234	105	3	13	27	382
8	68	63	1	16	20	168
9	489	1343	9	9		1850
10	135	1074	8	14	4	1235
11	474	462	15	30	16	997
12	213	2482	30	24	2	2751
13	12	49	12	47	18	138
14	9	37	21	105	10	182
15	8	23		142	16	189
16	133	1273	48	1		1455
17	172	646	15	13	11	857
18	63	267	46	88	32	496
19	9	71	7	30	9	126
20	21	19	64	182	16	302
21	97	1742	59	31	2	1931
22	4	23	5	205	43	280
23	40	143	69	94	51	397
24		11	19	31		60
25	2	12	13	112	15	154
26	9	75	21	16	32	153
27	46	248	69	99	177	639
28	114	599	120	64		897
29	21	69	43	8	104	245
30	7	117	49	2	158	333
All*	3979	11423	745	1422	829	35680

*Number of pixels

ADDENDUM E.2: Assignment of unsupervised Landsat PCA classes to general land cover types

Rows: PCA Classes	Columns: Land use					
	Orchards	Vines	Vegetables	Cereals	Other	All
0						13922
3	1					1
4	6	1				7
5	4					4
6		10				10
9					11	11
10	4	4		1	28	37
11		1				1
12		11			71	82
13		2	5		63	70
14		84	53		22	159
15		2	41		51	94
16		1	5			6
17	1617	516	5	31	46	2215
18	12	51	1	7	105	177
19	2	25		2	14	43
20	59	123	2	70	100	355
21	2	48		1	62	113
22	16	99	1	32	176	324
23	477	866	57	236	99	1737
24	1125	4538	54	32	10	5759
25	98	403	59	393	192	1145
26	22	79	7	9	340	457
27	515	4692	209	110	14	5540
28	44	133	157	439	76	849
29	142	291	69	85	488	1075
30	118	594	227	130	418	1487
All*	4353	12589	848	1578	2386	35680

*Number of pixels

ADDENDUM E.3: Assignment of unsupervised Landsat NDVI classes to generalized land cover types

Rows: NDVIGRD Classes — Columns: Land use

	Orchards	Vines	Vegetables	Cereals	Other	All
0						13922
2	3	16				19
3				1		1
4		4				4
5	3	7			2	12
6	5	43	1		74	123
7	19	99	51	4	12	185
9	25	51	86	4		166
10	44	76	29	4	19	172
11	11	137	27	5	216	396
12	1	7		1	13	22
13	40	94	66	6	265	471
14	19	113	10	96	194	432
15	46	46	5	3		100
16	13	71	26	110	6	226
17	75	320	62	19	502	978
18	74	99	9	1	7	190
19	139	463	31	31	553	1217
20	68	198	91	37	39	433
21	267	2339	185	27	8	2826
22	203	680	26	70	172	1151
23	29	99	39	472	73	712
24	1	36	21	29	3	90
25	25	202	47	147	47	550
26	535	2397	8	16	9	2965
27	198	3887	121	16	1	4223
28	11	5	65	181	8	270
29	646	754	26	54	92	1572
30	1771	346	5	59	71	2252
All*	4353	12589	1037	1393	2386	35680

*Number of pixels

ADDENDUM E.4: Raw land cover classes of supervised classification on Landsat TM data

Signature	No. of Pixels	Land cover type	% of image
0	557904	Unclassified	25,62
1	8475	Orchards 1	0,39
2	4462	Orchards 2	0,20
3	446	Orchards 3	0,02
4	5402	Orchards 4	0,25
5	109061	Orchards 5	0,50
6	1822	Orchards 6	0,08
7	145	Orchards 7	0,01
8	1009	Orchards 8	0,05
9	180	Orchards 9	0,01
10	1130	Orchards 10	0,05
11	68	Orchards 11	0,00
12	36	Orchards 12	0,00
13	2272	Orchards 13	0,10
14	10859	Vines 1	0,50
15	442	Vines 2	0,02
16	6059	Vines 3	0,28
17	112	Vines 4	0,01
18	5768	Vines 5	0,26
19	2107	Vines 6	0,10
20	1267	Vines 7	0,06
21	9488	Vines 8	0,44
22	10445	Vines 9	0,48
23	3175	Vines 10	0,15
24	17014	Vines 11	0,78
25	36381	Vines 12	1,67
26	220	Vines 13	0,01
27	17055	Vines 14	0,78
28	769	Vines 15	0,04
29	8183	Pine 1	0,38
30	6038	Pine 2	0,28
31	14705	Pine 3	0,68
32	7090	Pine 4	0,33
33	10318	Pine 5	0,47
34	11026	Pine 6	0,51
35	0	Bare soil 1	0,00
36	0	Bare soil 2	0,00
37	0	Bare soil 3	0,00
38	10989	Bare soil/Cereal 1	0,50
39	2521	Bare soil/Cereal 2	0,12
40	3361	Bare soil 6	0,15
41	80	Bare soil 7	0,00
42	2578	Bare soil/Cereal 3	0,11
43	1248	Bare soil/Cereal 3	0,06
44	2577	Fallow 1	0,12
45	1624	Fallow 2	0,07
46	5252	Fallow 3	0,24
47	15854	Fallow 4	0,73
48	5917	Fallow 5	0,27
49	3135	Falow 6	0,14
50	3654	Veld 1	0,17
51	36812	Veld 2	1,69
52	53022	Veld 3	2,43

53	104356	Veld 4/Shadow	4,79
54	129859	Shadow/Veld 1	5,96
55	13007	Shadow/Veld 2	0,60
56	53078	Shadow/Veld 4	2,44
57	688	Veld 4	0,03
58	71214	Shadow/Veld 3	3,27
59	92216	Veld 5	4,23
60	61310	Bush/Riverine 1	2,82
61	31448	Bush/Riverine 2	1,44
62	50656	Mountain veld 1	2,33
63	148681	Mountain veld 2	6,83
64	19804	Veld 6	0,91
65	5341	Veld 7	0,25
66	62216	Veld 8	2,86
67	10656	Bush/Riverine 3	0,49
68	3742	Water 1	0,17
69	162	Water 2	0,01
70	1036	Water 3	0,05
71	34482	Veld 9	1,58
72	63586	Veld 10	2,92
73	4481	Veld 11	0,21
74	26735	Veld 12	1,23
75	1408	Pine 7	0,06
76	931	Veld 13	0,04
77	11620	Veld 14	0,53
78	124	Veld 15	0,01
79	36369	Fallow 7	1,67
80	4739	Veld 16	0,22
81	753	Veld 17	0,03
82	11564	Bare soil 9	0,53
83	59473	Bare soil 10	2,73
84	4138	Cereal1	0,19
85	89707	Bare soil 8	4,12
86	9359	Cereal2	0,43
87	56	Cereal3	0,00
88	1725	Bare soil 11	0,08
89	0	Cereal4	0,00
90	0	Cereal5	0,00
91	35	Cereal6	0,00
92	94	Cereal7	0,00
93	353	Cereal8	0,02
94	466	Cereal9	0,02
95	1766	Vegetables1	0,08
96	6443	Vegetables2	0,30
97	24926	Vegetables3	1,14
98	31	Vegetables4	0,00
99	0	Vegetables5	0,00
100	26	Vegetables6	0,00
101	0	Vegetables7	0,00
102	0	Vegetables8	0,00
103	46	Vegetables9	0,00
104	1337	Vegetables10	0,06

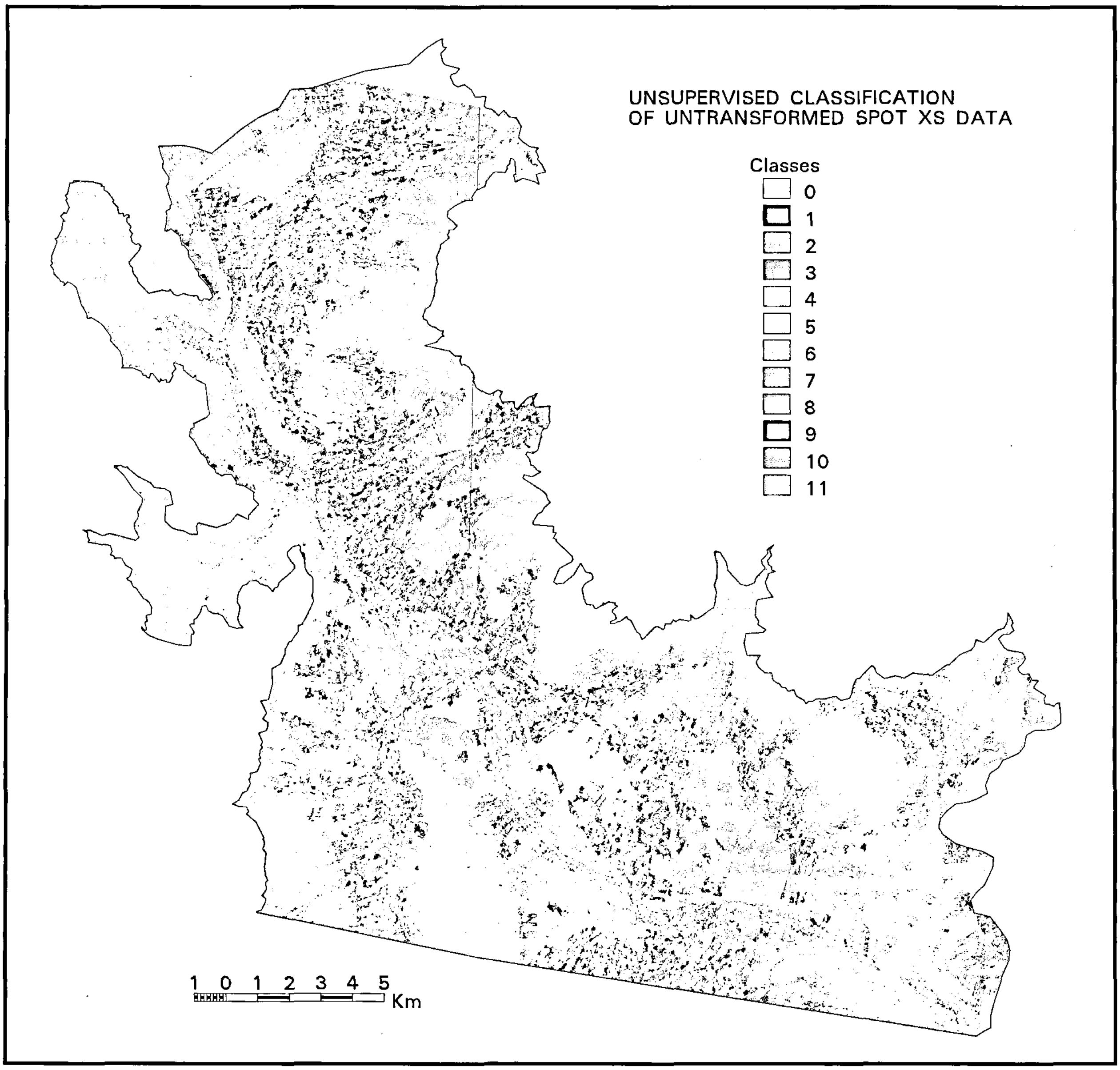


Figure 4.1: Unsupervised classification of untransformed SPOT XS data.

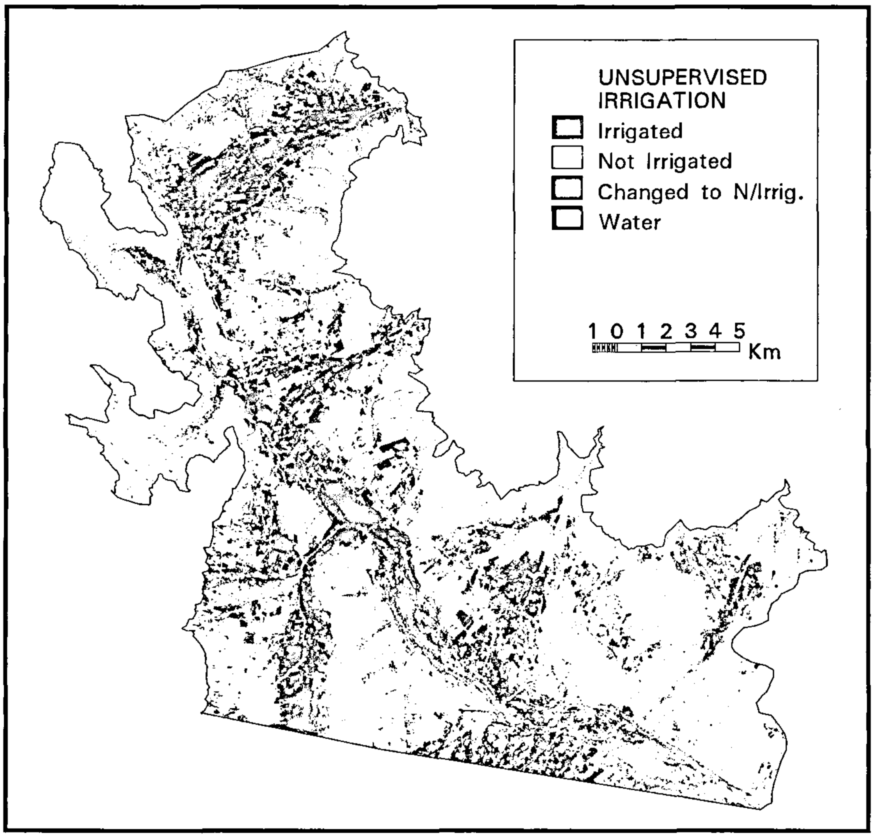


Figure 4.10: Irrigated land cover map from unsupervised classification of untransformed SPOT XS data.

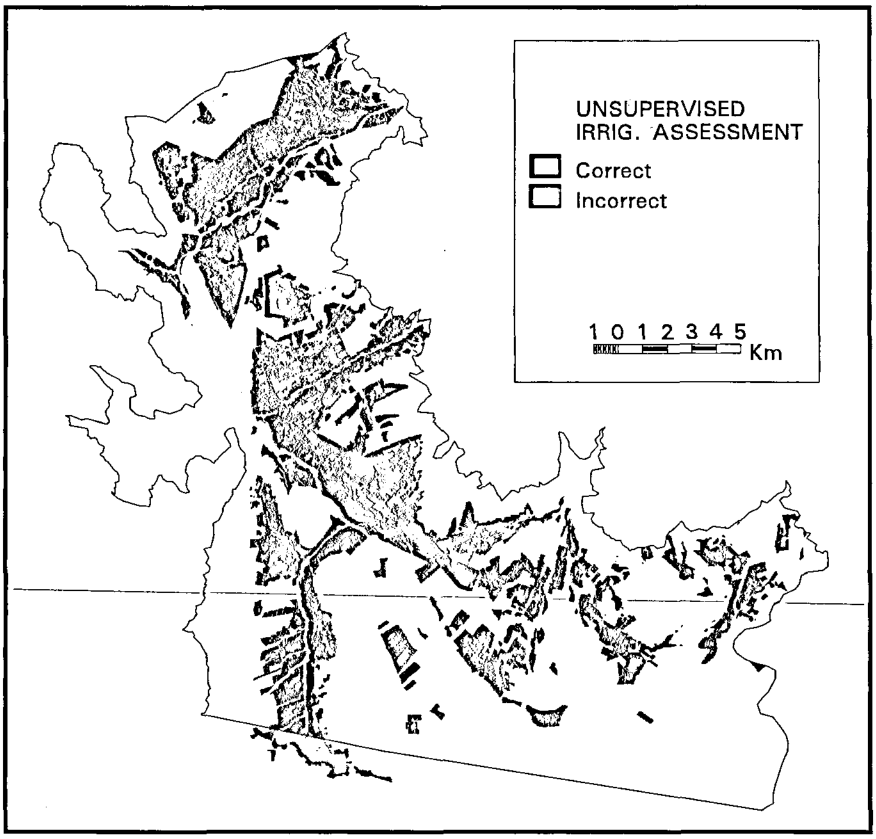


Figure 4.11: Accuracy assessment of irrigated land cover map from unsupervised classification of untransformed SPOT XS data.

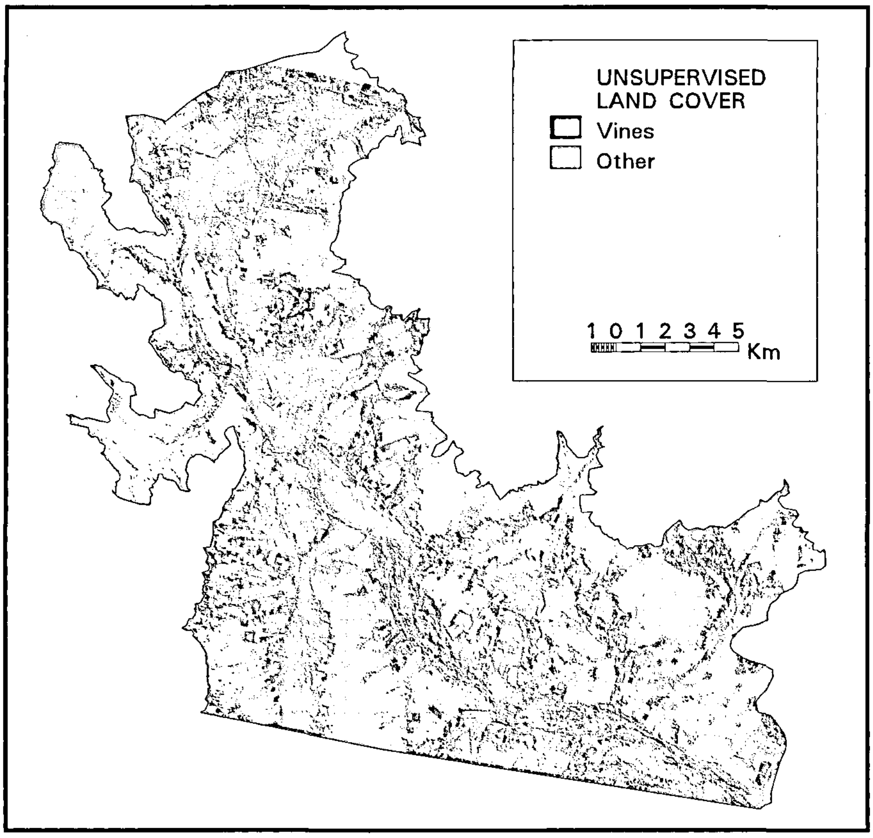


Figure 4.8: Generalized land cover map from unsupervised classification of untransformed SPOT XS data.

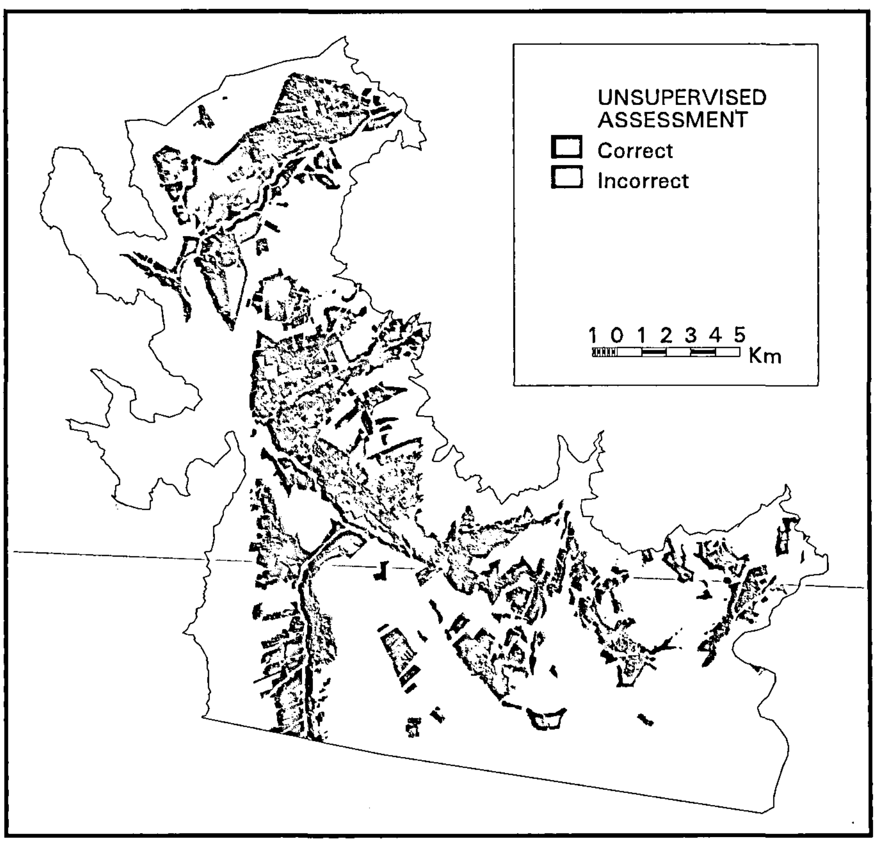


Figure 4.9: Accuracy assessment of generalized land cover map from unsupervised classification of untransformed SPOT XS data.

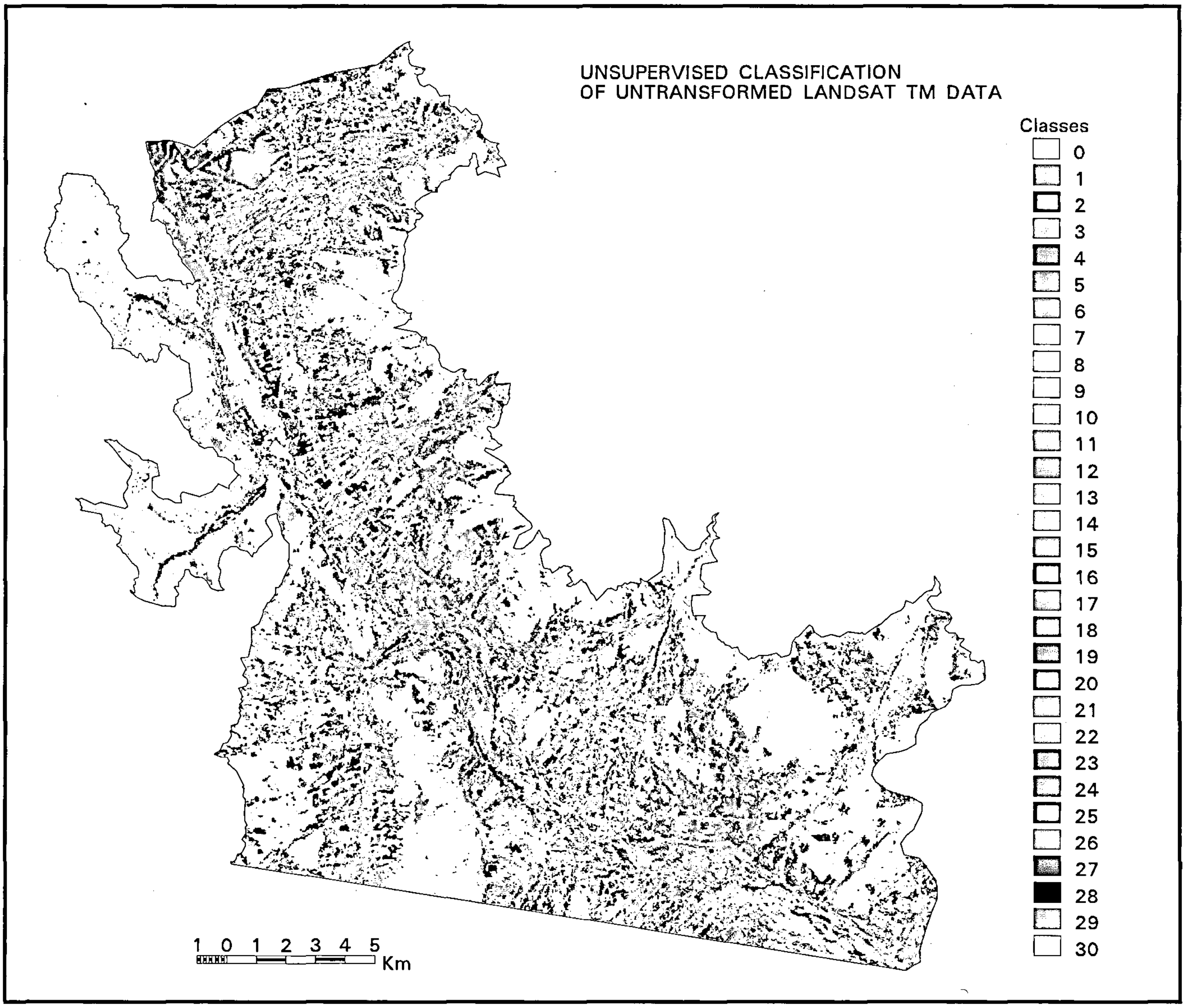


Figure 4.4: Unsupervised classification of untransformed Landsat TM data.

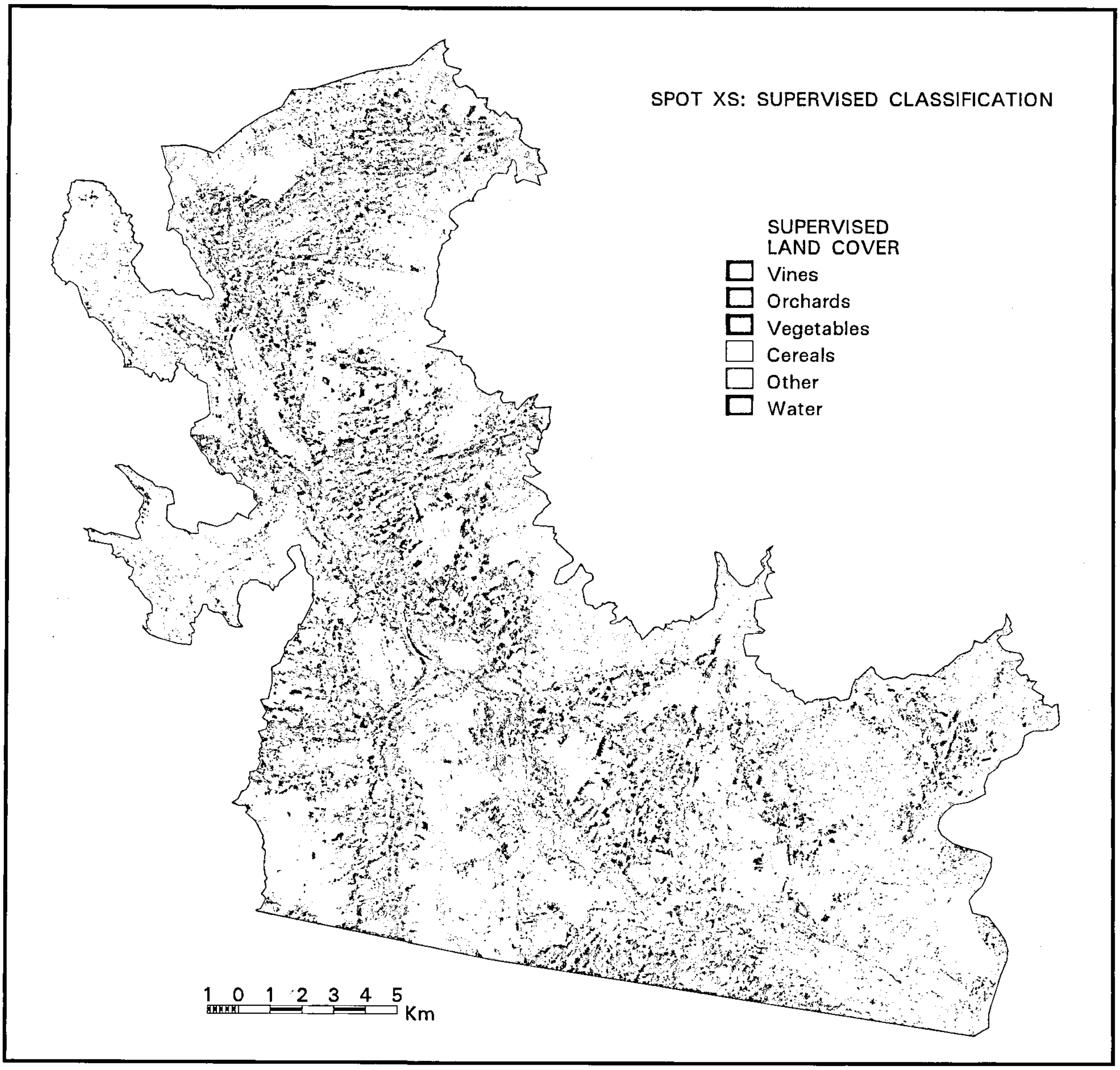
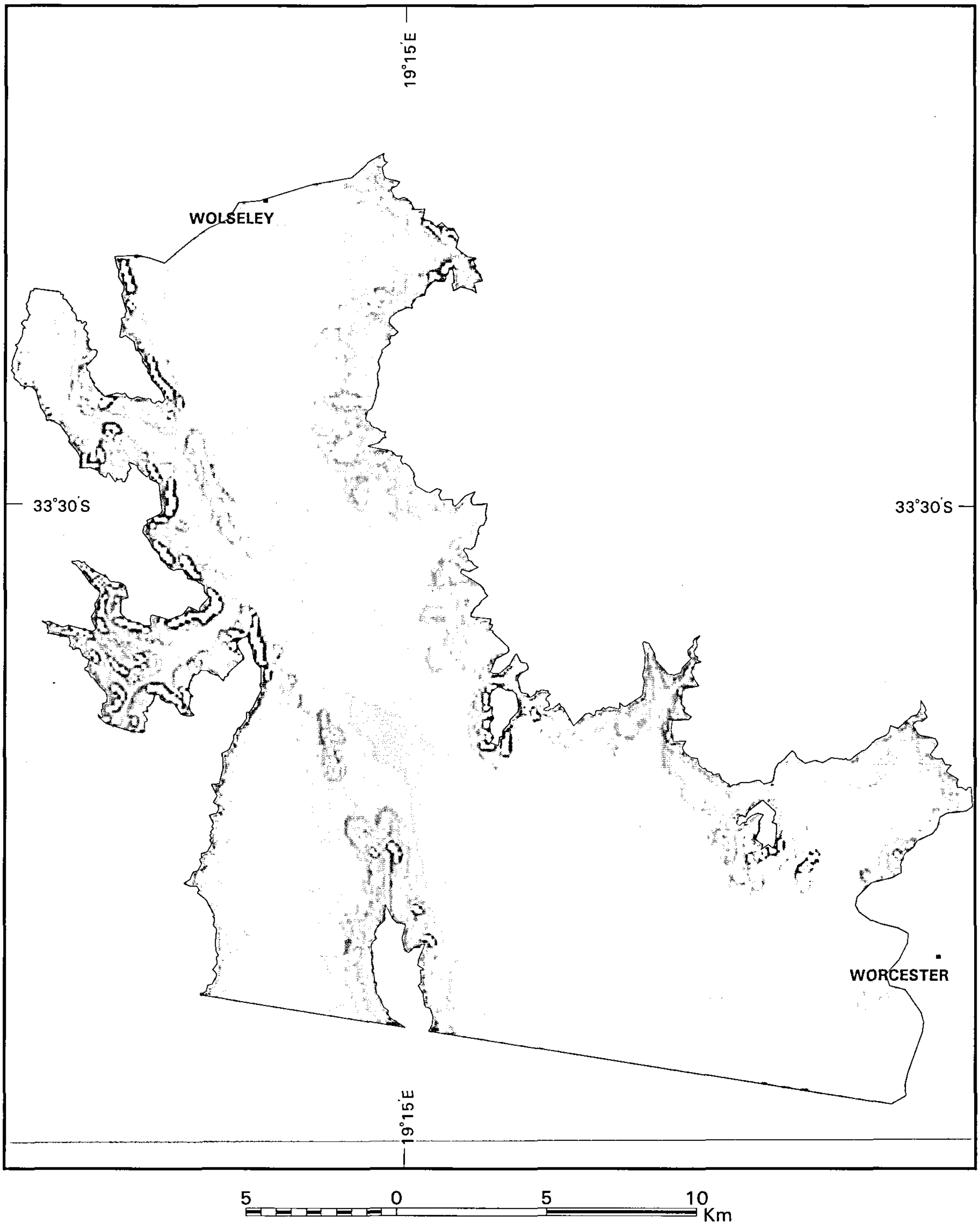


Figure 4.3: Generalized land cover map from supervised classification of untransformed SPOT XS data.

BREEDE RIVER PROJECT

Figure 3.16 SLOPE CLASSES UPPER BREEDE RIVER VALLEY

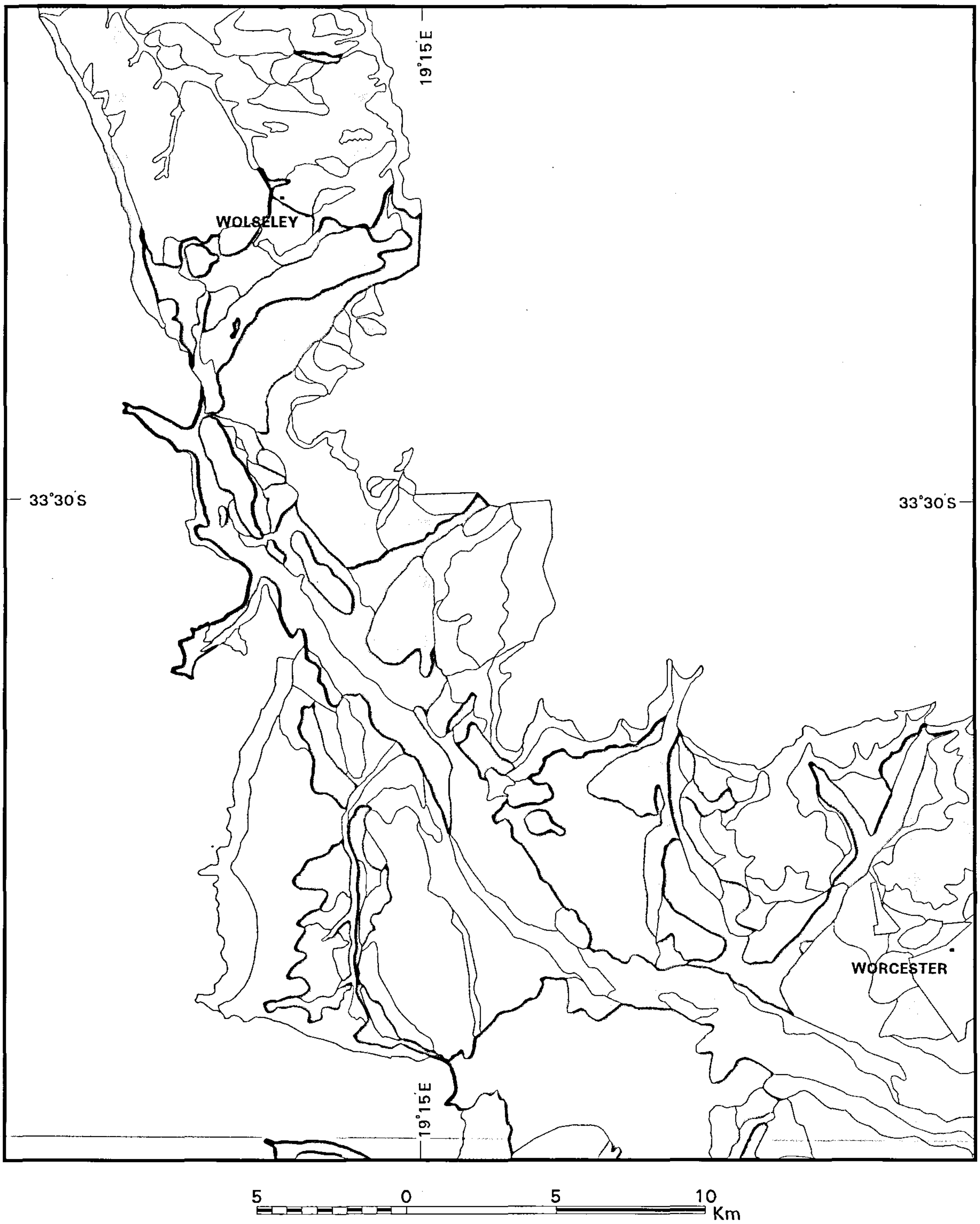


IGA

CLASS 0 0% SLOPE	CLASS 2 6-10% SLOPE	CLASS 4 16-20% SLOPE	ABOVE 25% OUTSIDE STUDY AREA
CLASS 1 1-5% SLOPE	CLASS 3 11-15% SLOPE	CLASS 5 20-25% SLOPE	STUDY AREA

BREEDE RIVER PROJECT

Figure 3.14 SOIL IRRIGATION POTENTIAL UPPER BREEDE RIVER



IGA

LOW IRRIGATION POTENTIAL

MEDIUM IRRIGATION POTENTIAL

HIGH IRRIGATION POTENTIAL

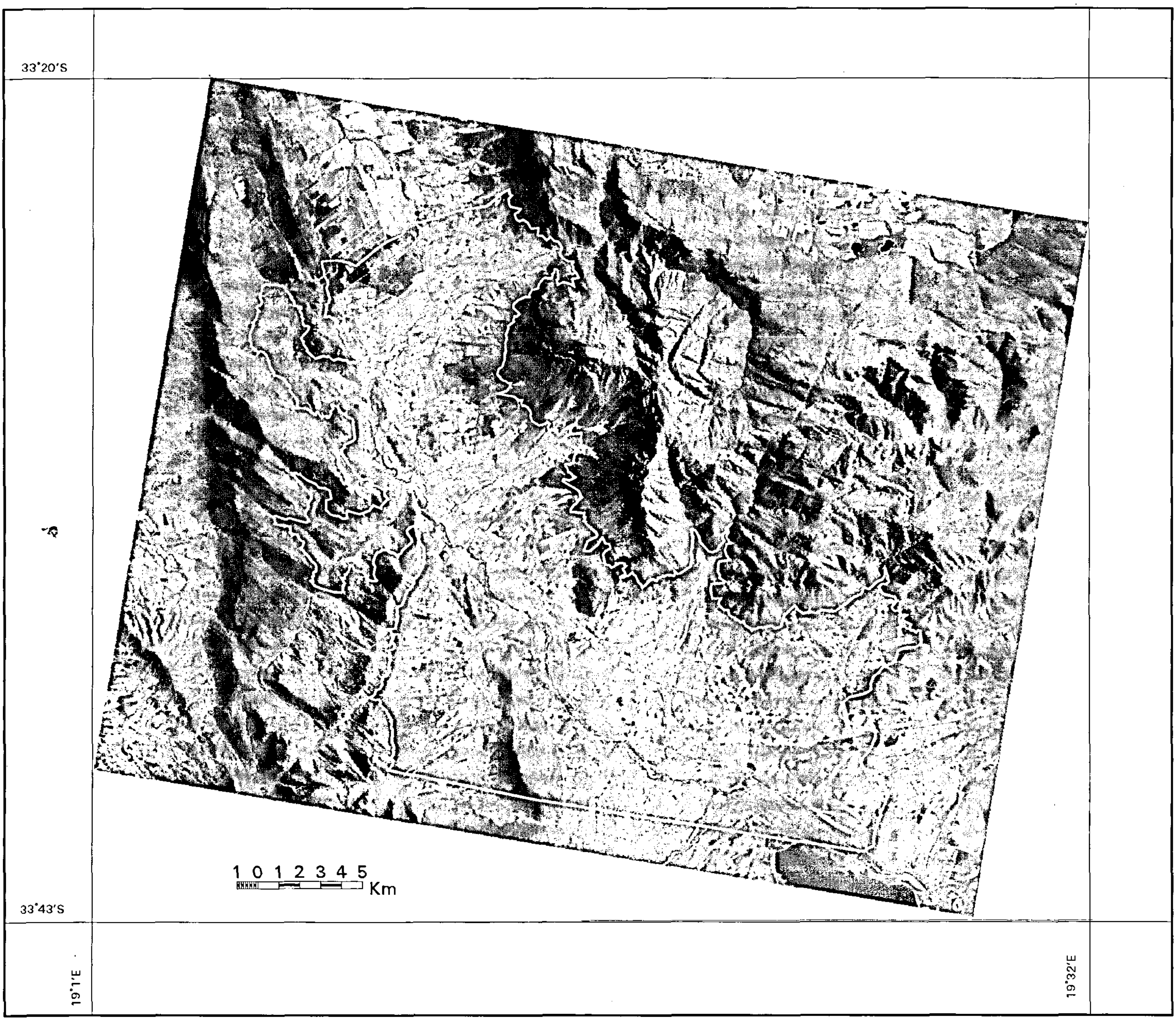
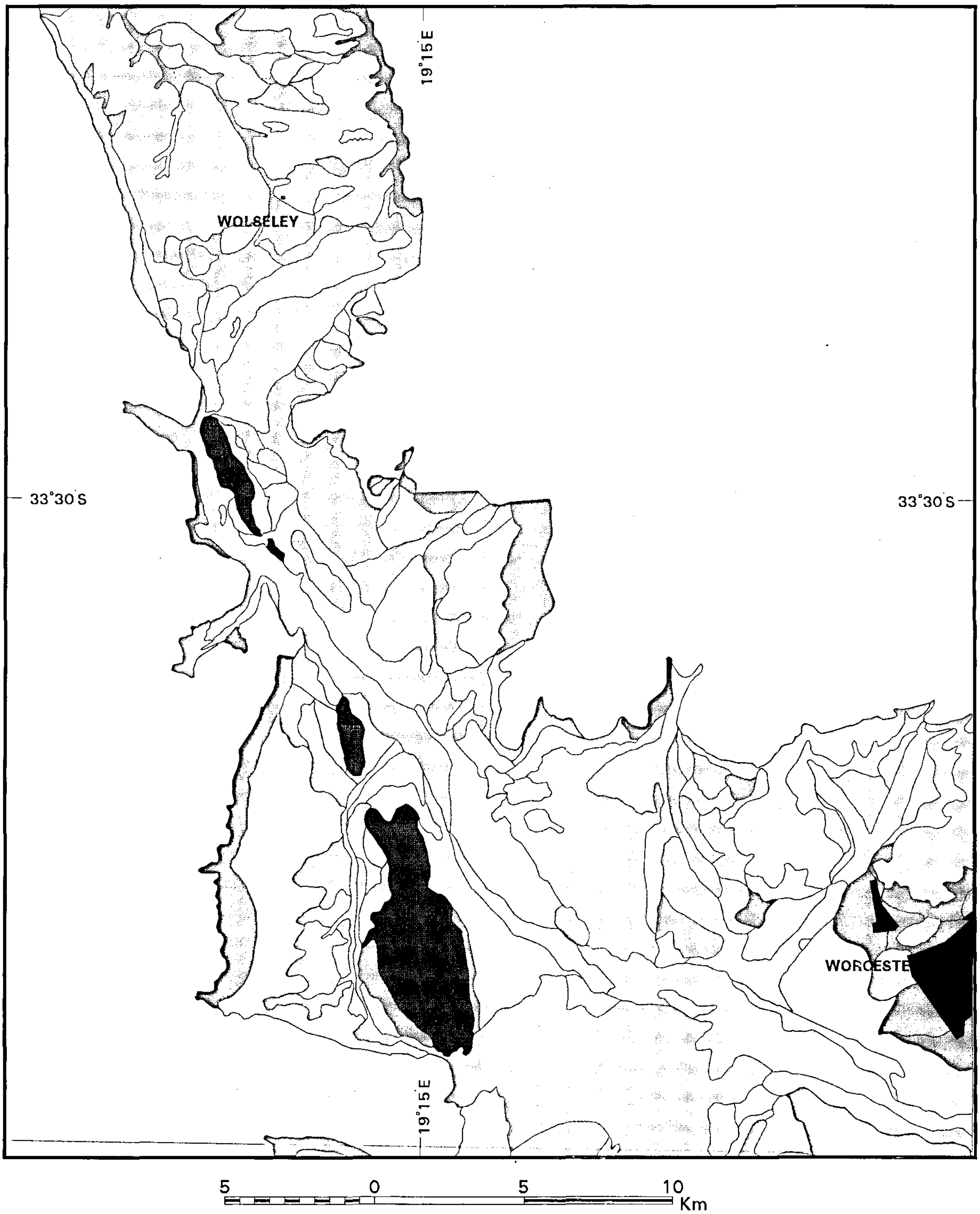


Figure 2: Landsat TM image showing the location of the study area.

BREEDE RIVER PROJECT

Figure 3.13 SOIL TYPES UPPER BREEDE RIVER VALLEY



IGA

GROUP A GLENROSA	GROUP D GLENROSA STERKSPRUIT SWARTLAND	GROUP G SHORTLANDS STERKSPRUIT	GROUP I WESTLEIGH DUNDEE LONGLANDS	GROUP L TALUS
GROUP B HUTTON	GROUP E KROONSTAD LONGLANDS ESTCOURT	GROUP H OAKLEAF FERNWOOD DUNDEE	GROUP J FERNWOOD	GROUP R BOULDERS
GROUP C CLOVELLEY			GROUP K GRAVEL	

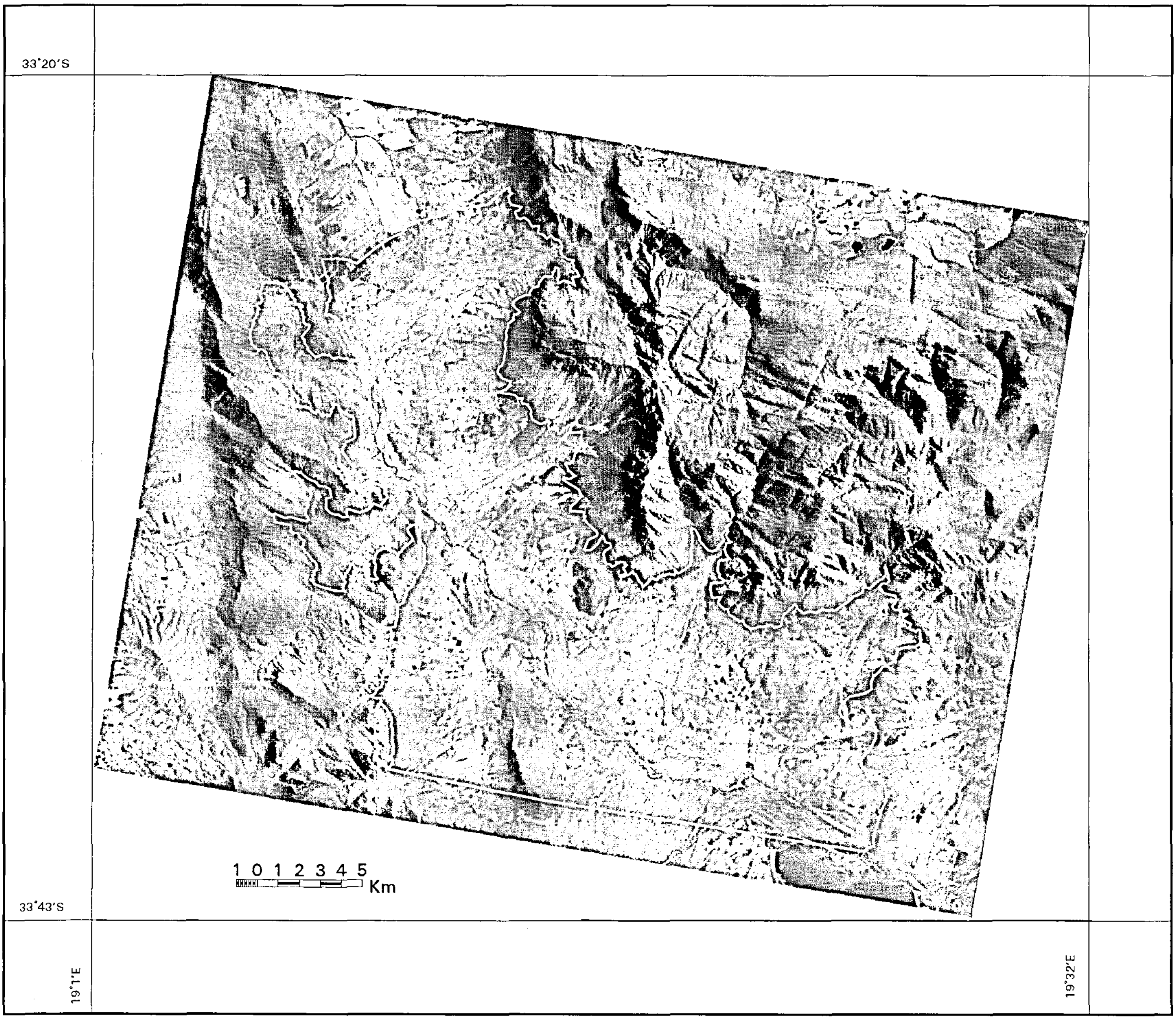
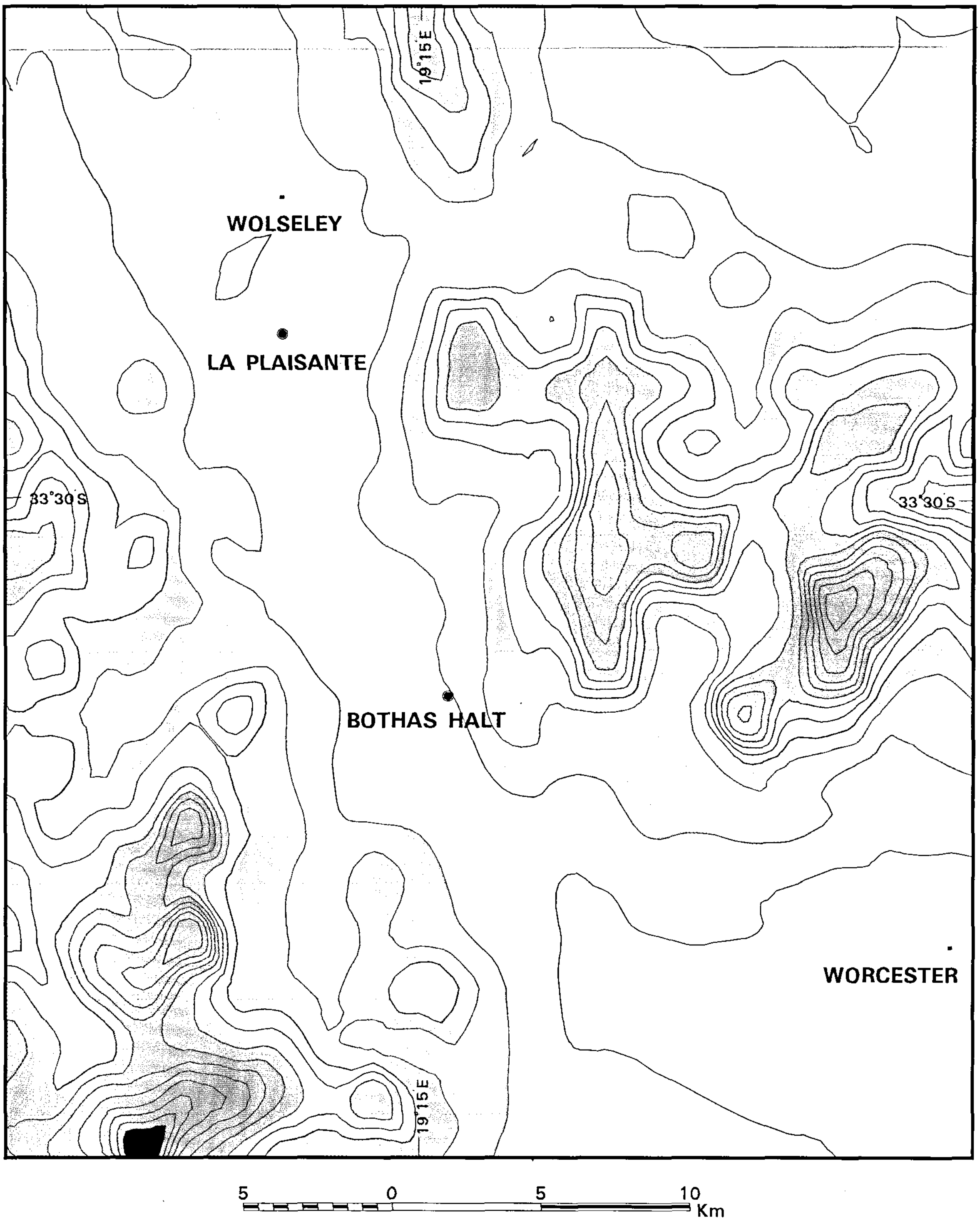


Figure 3.3: Landsat TM image showing the location of the study area.

BREEDE RIVER PROJECT

Figure 1.3 MEAN ANNUAL PRECIPITATION UPPER BREEDE RIVER VALLEY



200-400 mm
401-600 mm
601-800 mm
801-1000 mm
1001-1200 mm
1201-1400 mm
1401-2000 mm
2001-2600 mm
2601-3000 mm
> 3000 mm
WEATHER STATIONS

IGA

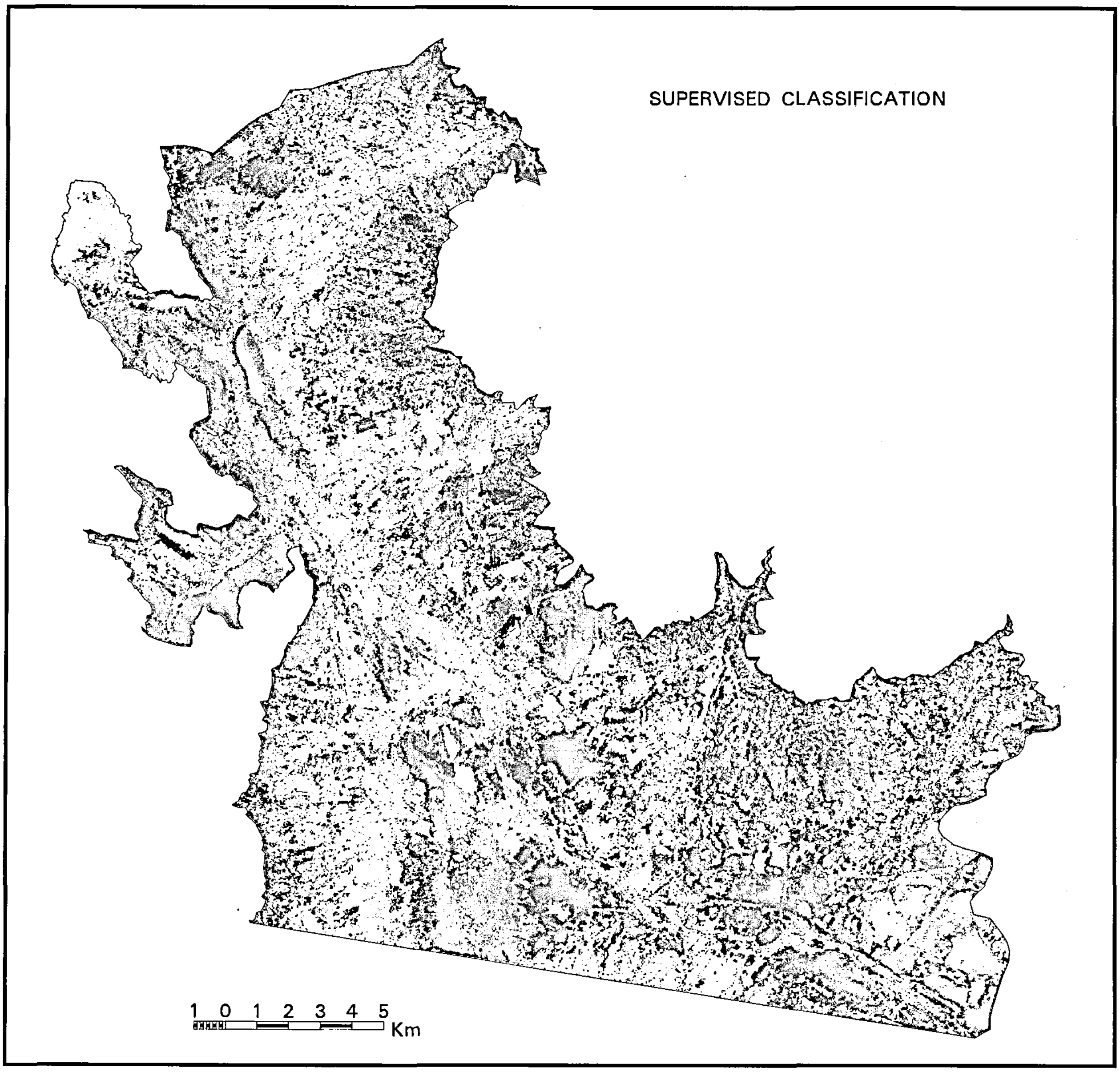


Figure 10: Supervised classification of untransformed Landsat TM data.

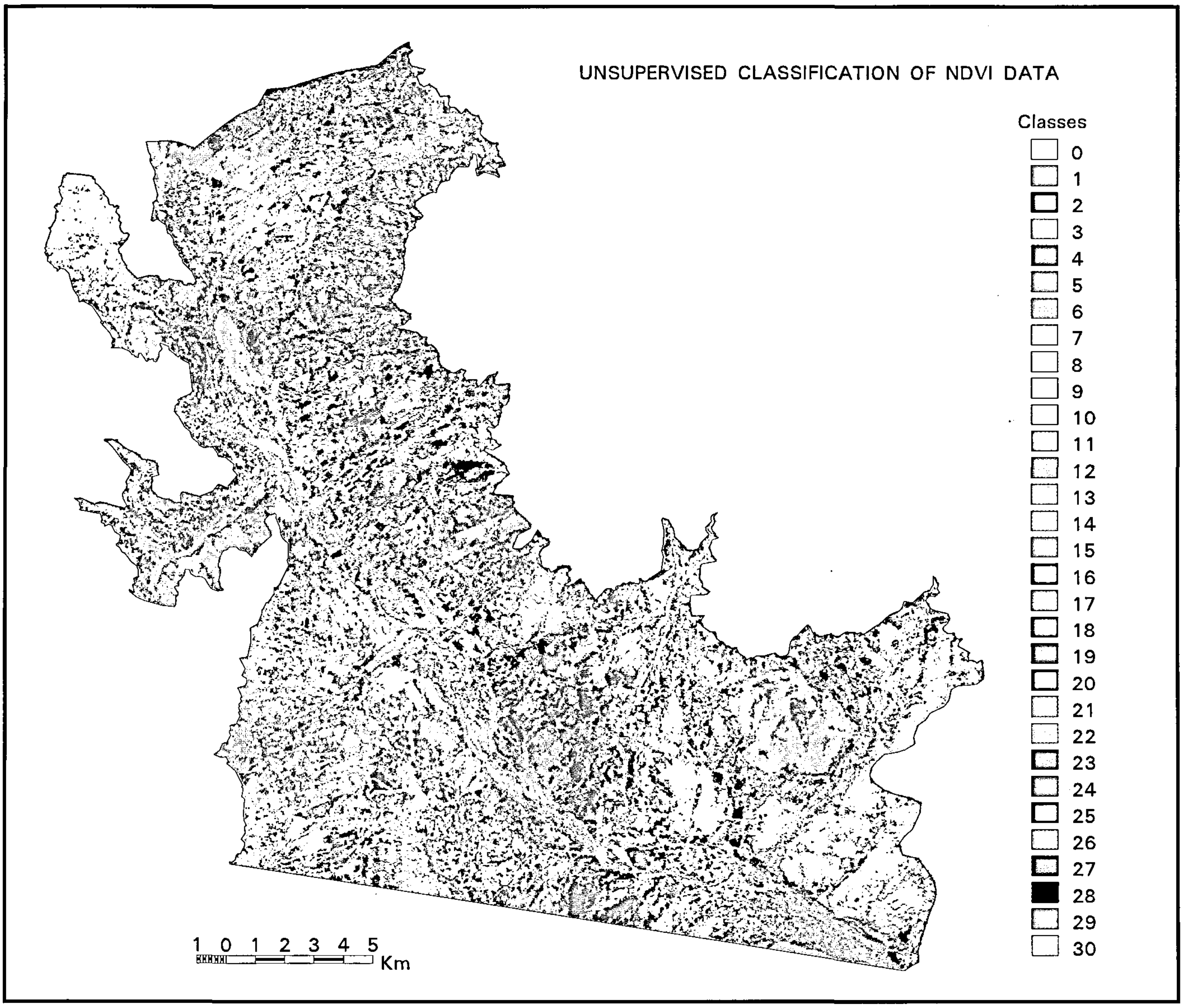


Figure 9: Unsupervised classification of Landsat TM NDVI data.

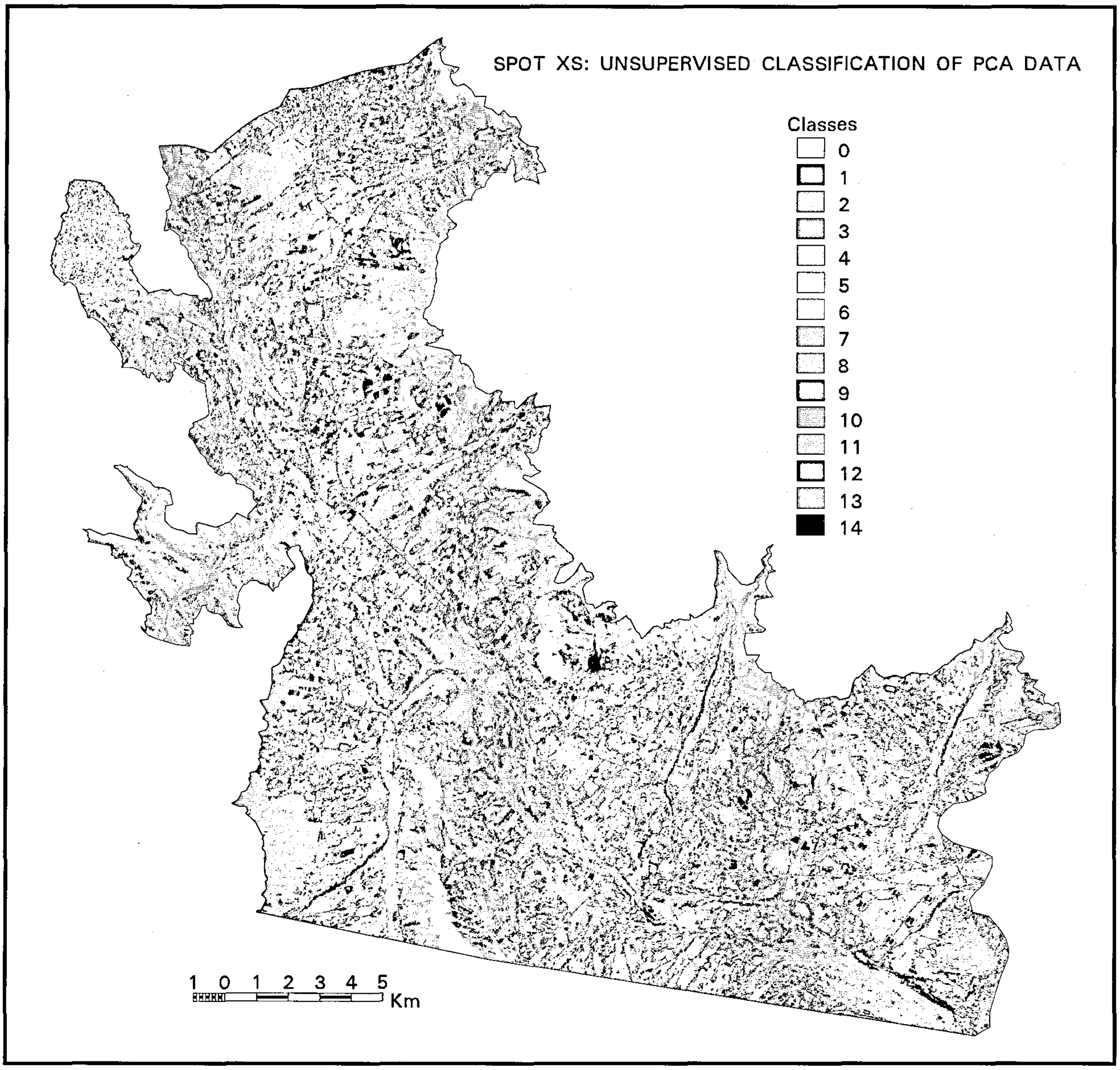


Figure 5: Unsupervised classification of Principal Component SPOT XS data.

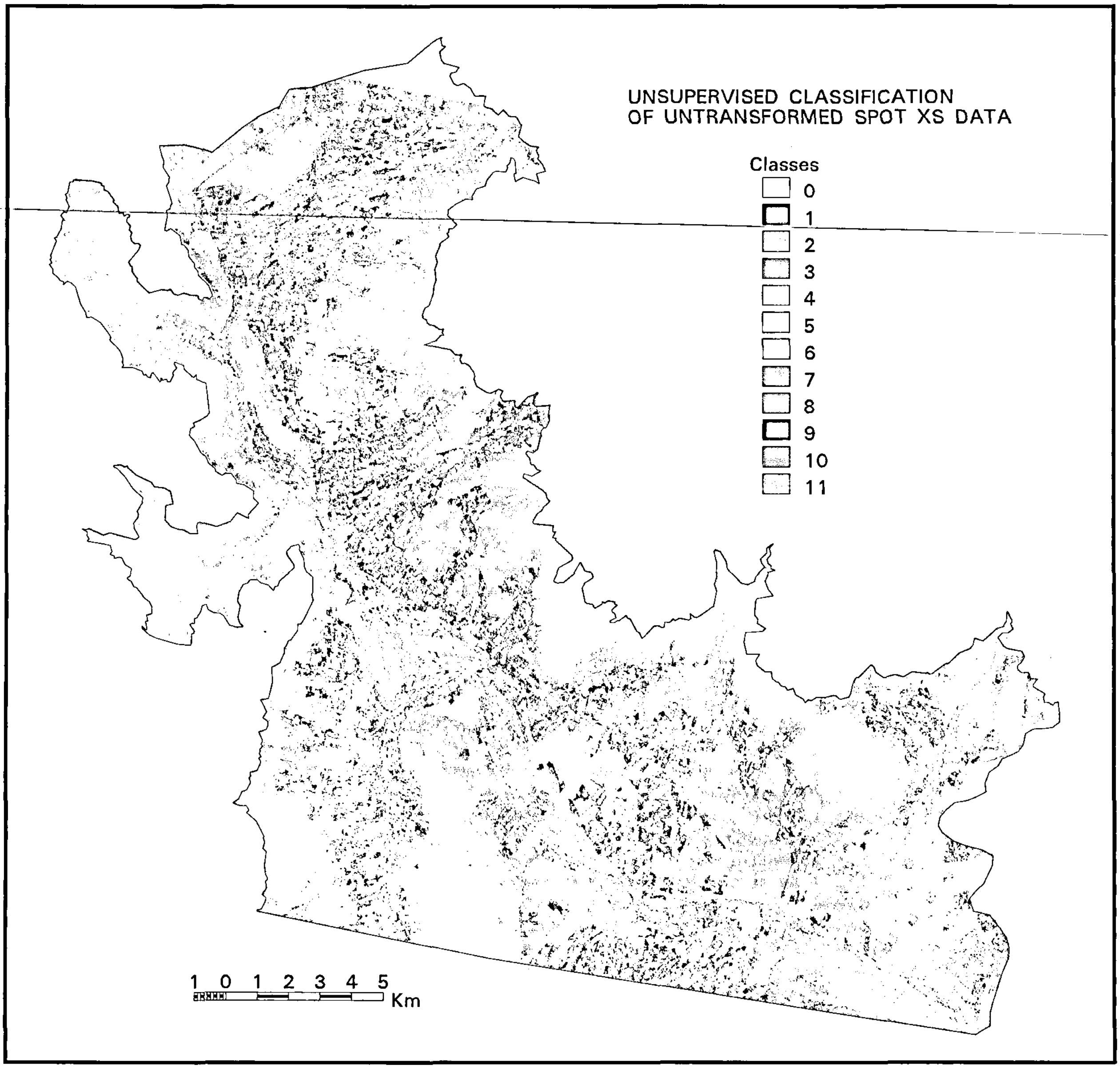


Figure 4:—Unsupervised classification of untransformed SPOT XS data.

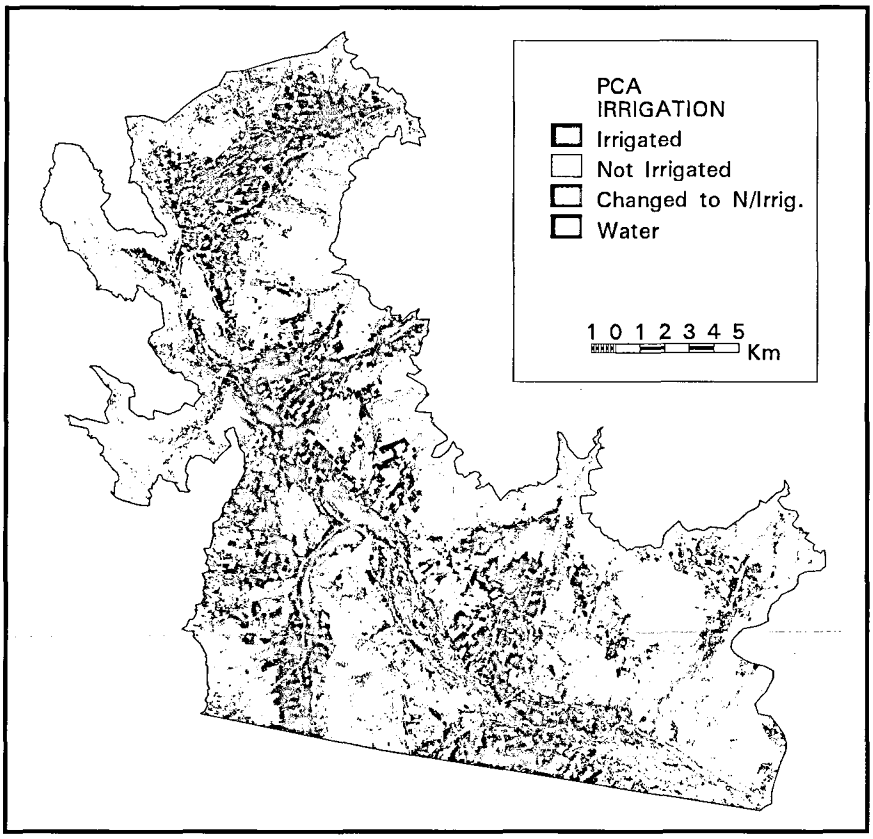


Figure 4.14: Irrigated land cover map from unsupervised classification of SPOT XS Principal Component data.

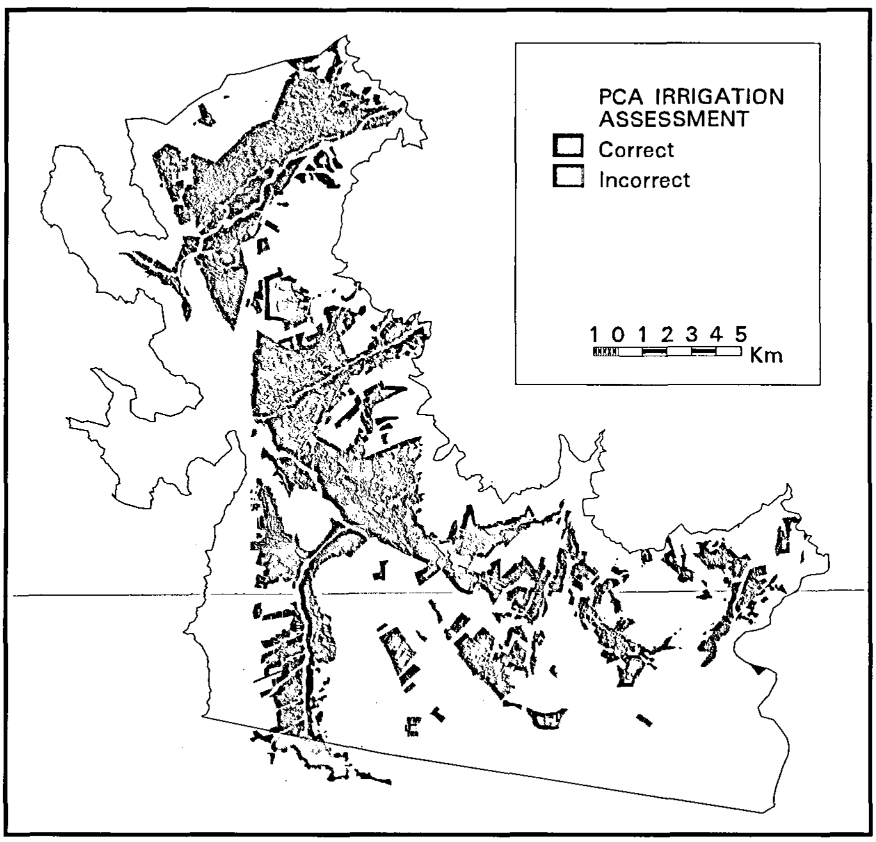


Figure 4.15: Accuracy assessment of irrigated land cover map from unsupervised classification of SPOT XS Principal Component data.

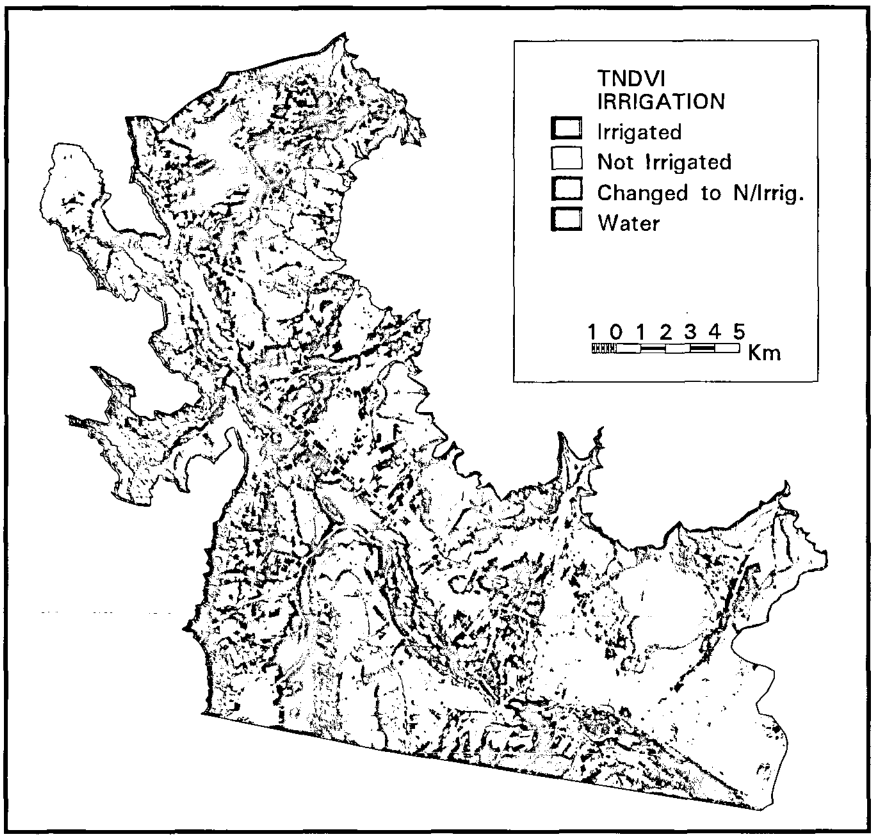


Figure 4.17: Irrigated land cover map from SPOT XS TNDVI data.

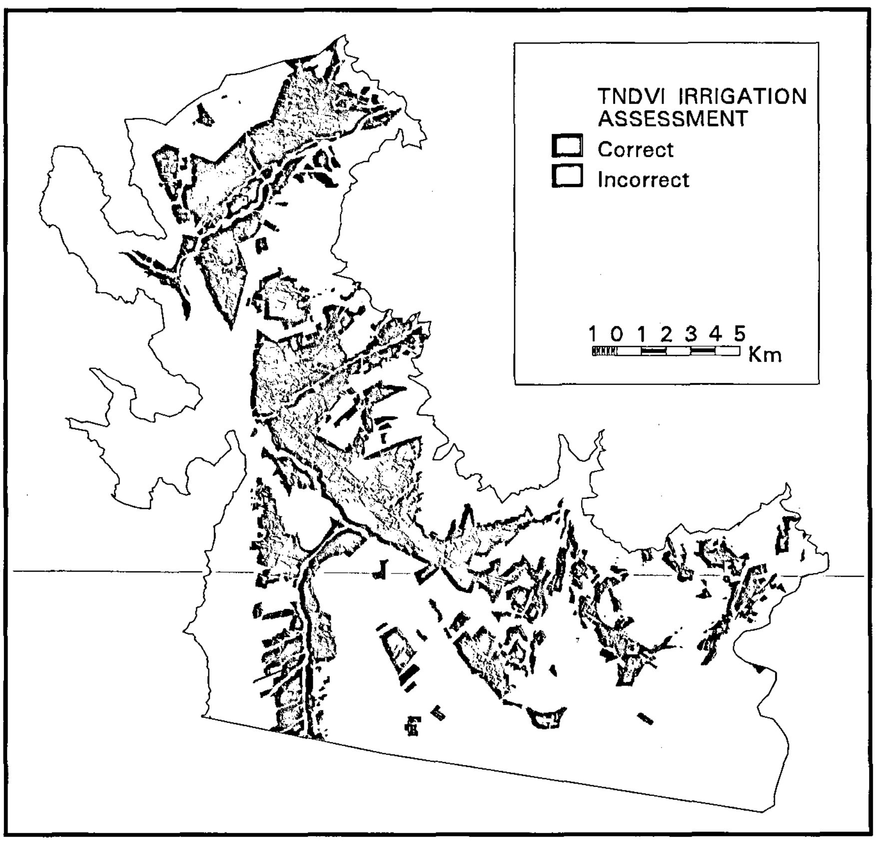


Figure 4.18: Accuracy assessment of irrigated land cover map from SPOT XS TNDVI data.

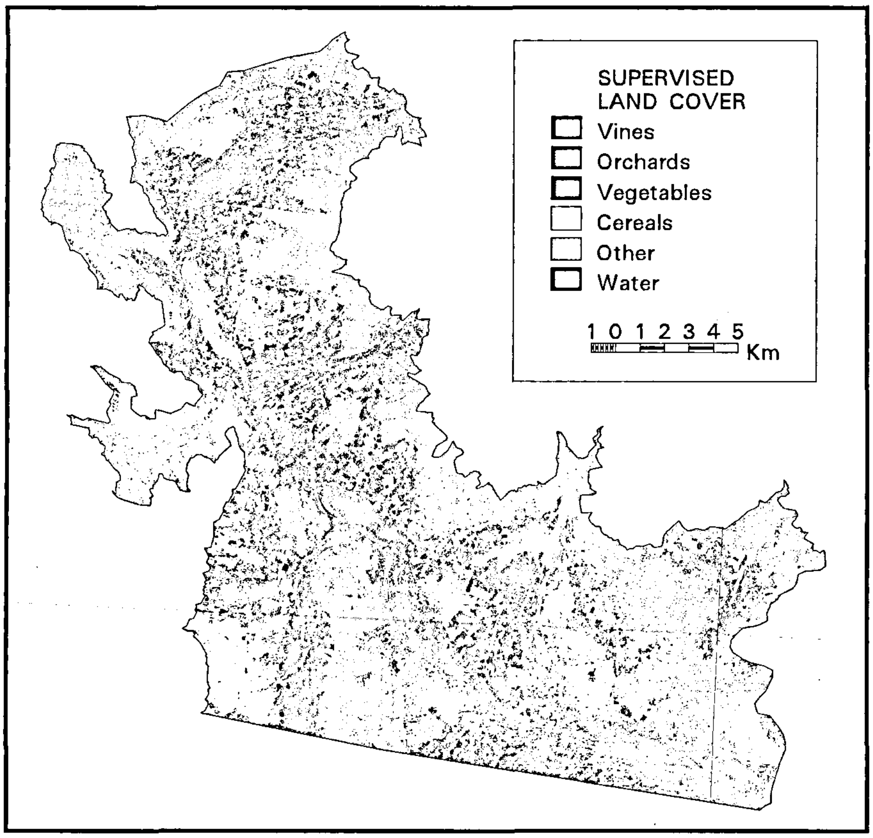


Figure 4.19: Generalized land cover map from supervised classification of untransformed SPOT XS data.

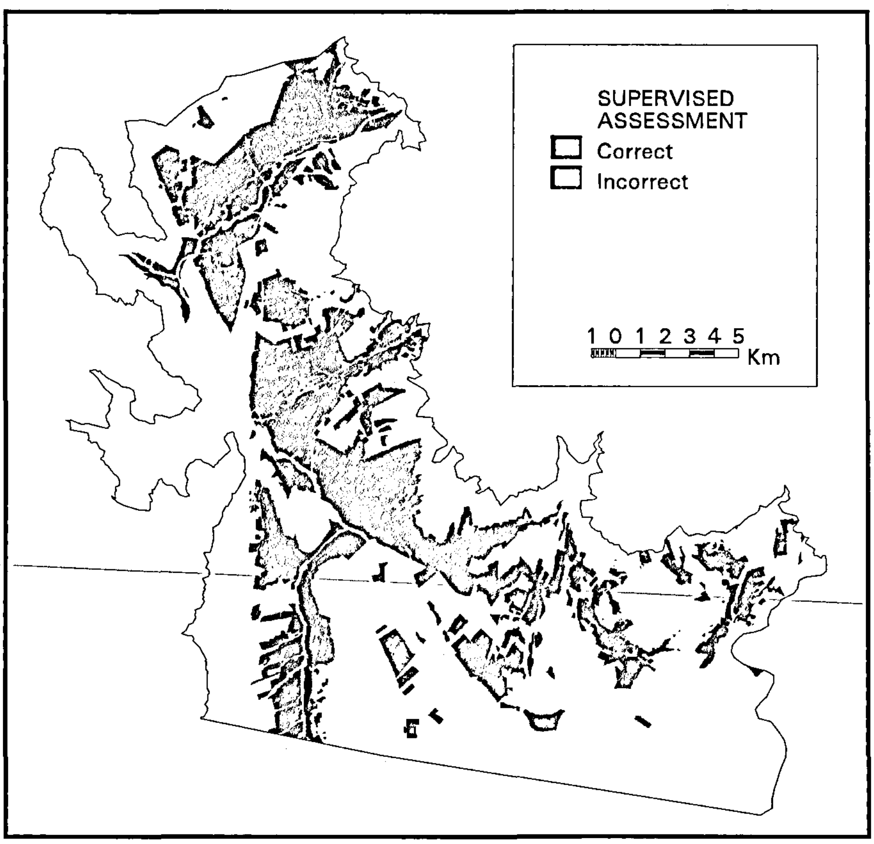


Figure 4.20: Accuracy assessment of generalized land cover map from supervised classification of untransformed SPOT XS data.

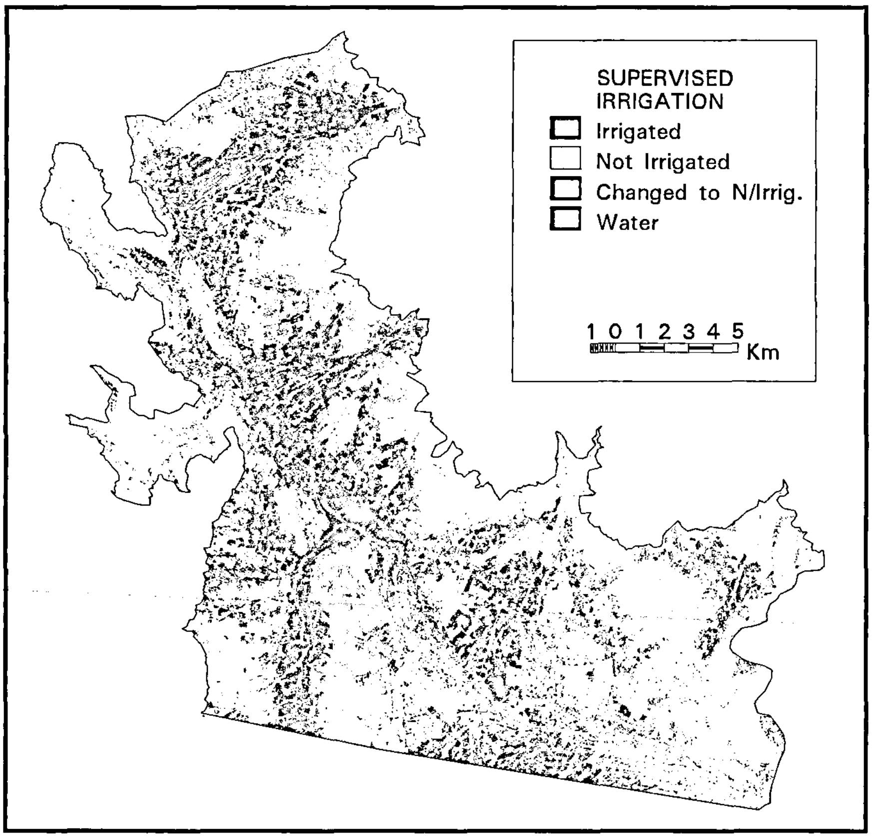


Figure 4.21: Irrigated land cover map from supervised classification of untransformed SPOT XS data.

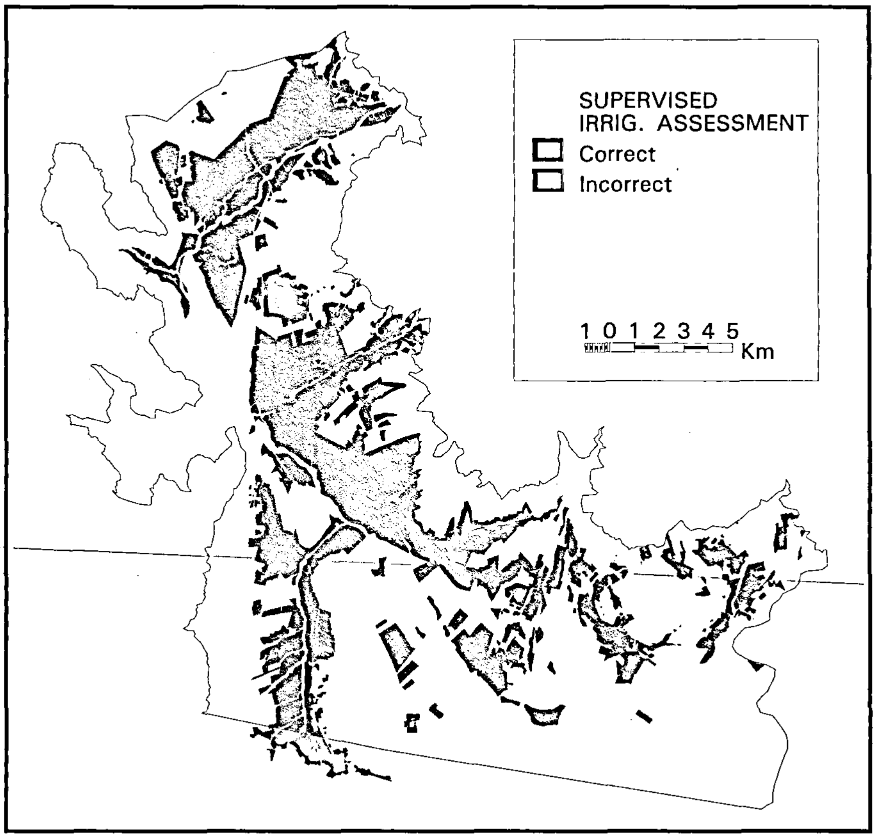


Figure 4.22: Accuracy assessment of irrigated land cover map from supervised classification of untransformed SPOT XS data.

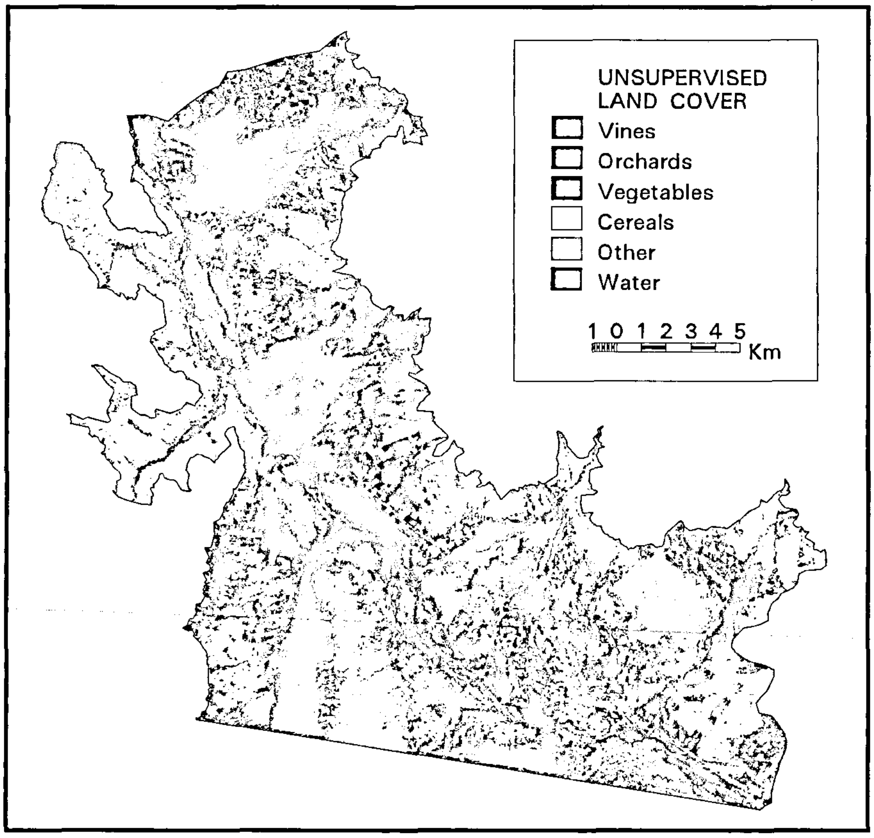


Figure 4.23: Generalized land cover map from supervised classification of untransformed Landsat TM data.

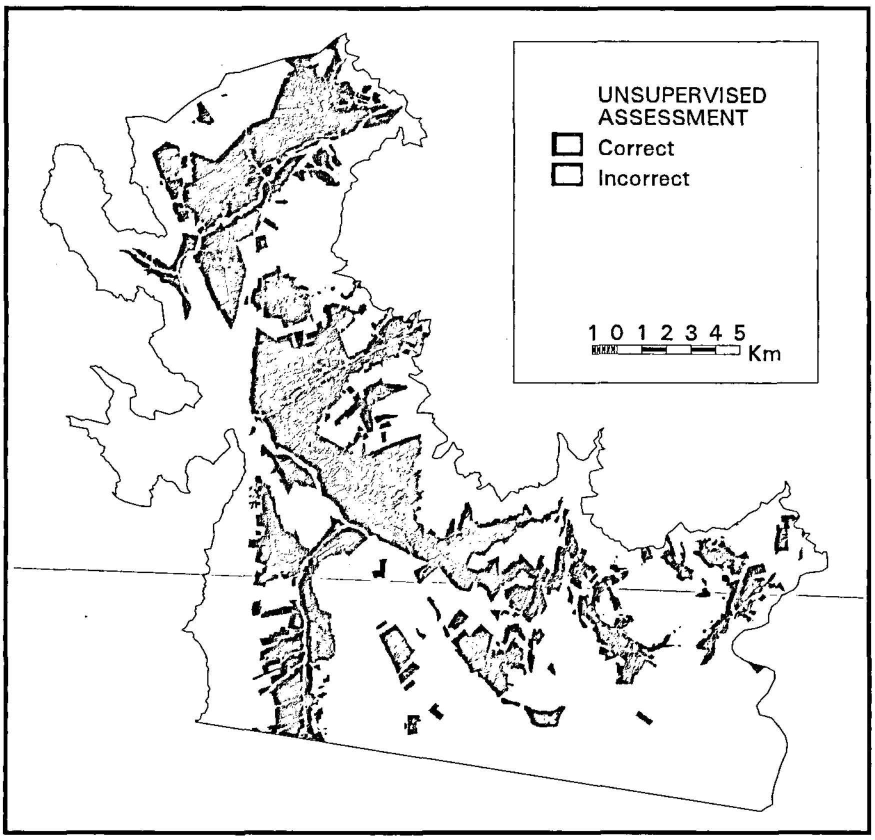


Figure 4.24: Accuracy assessment of generalized land cover map from unsupervised classification of untransformed Landsat TM data.

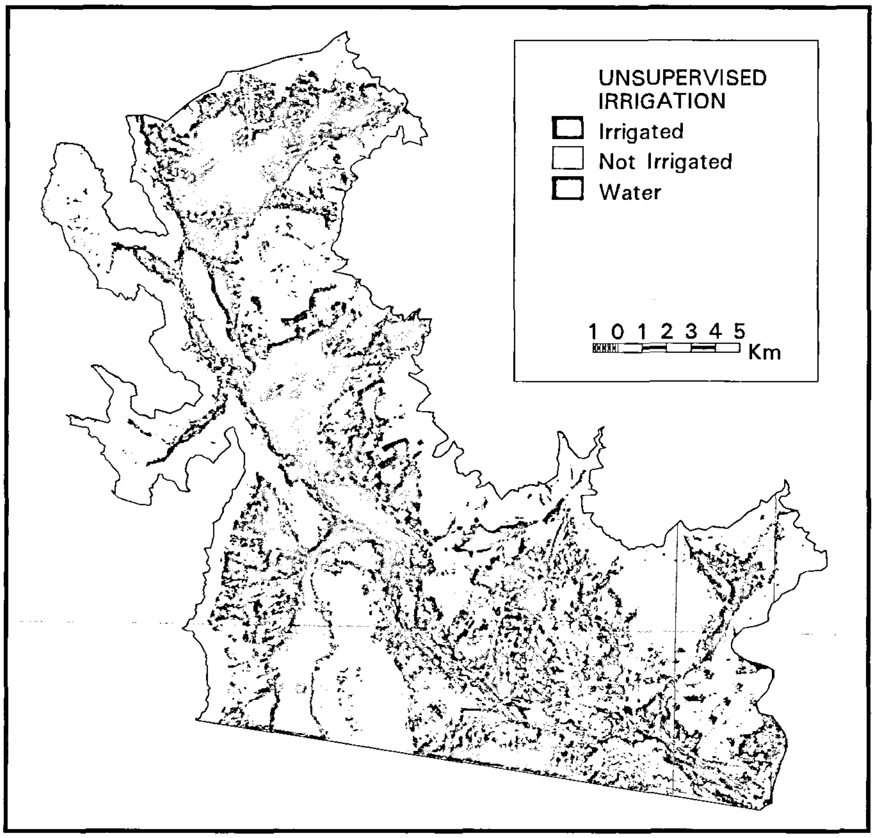


Figure 4.25: Irrigated land cover map from unsupervised classification of untransformed Landsat TM data.

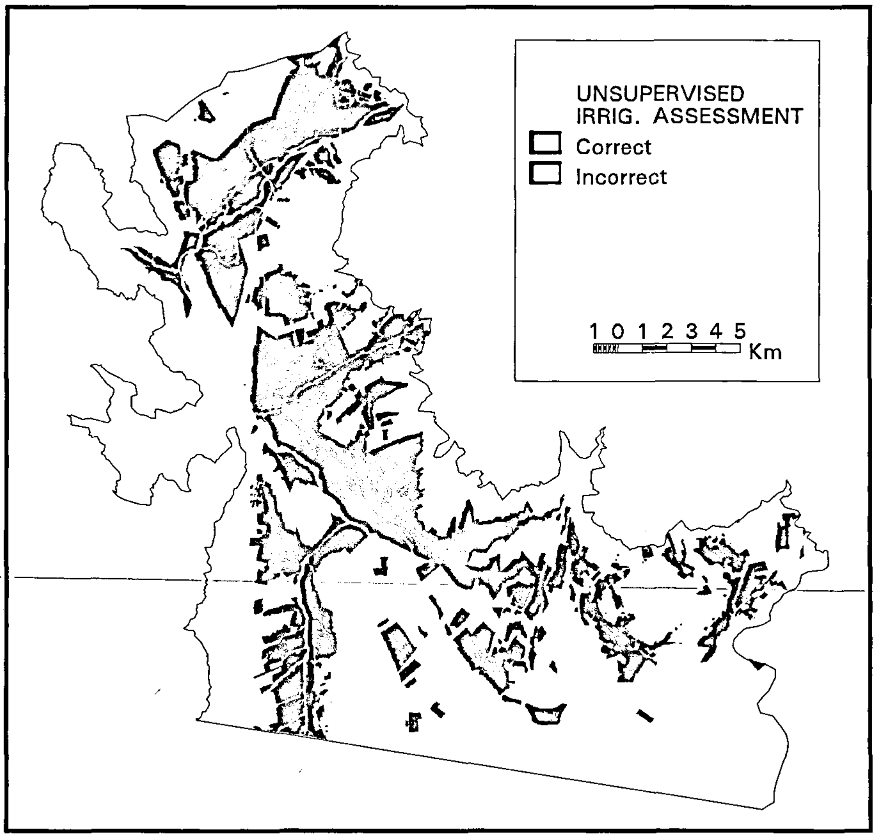


Figure 4.26: Accuracy assessment of irrigated land cover map from unsupervised classification of untransformed Landsat TM data.

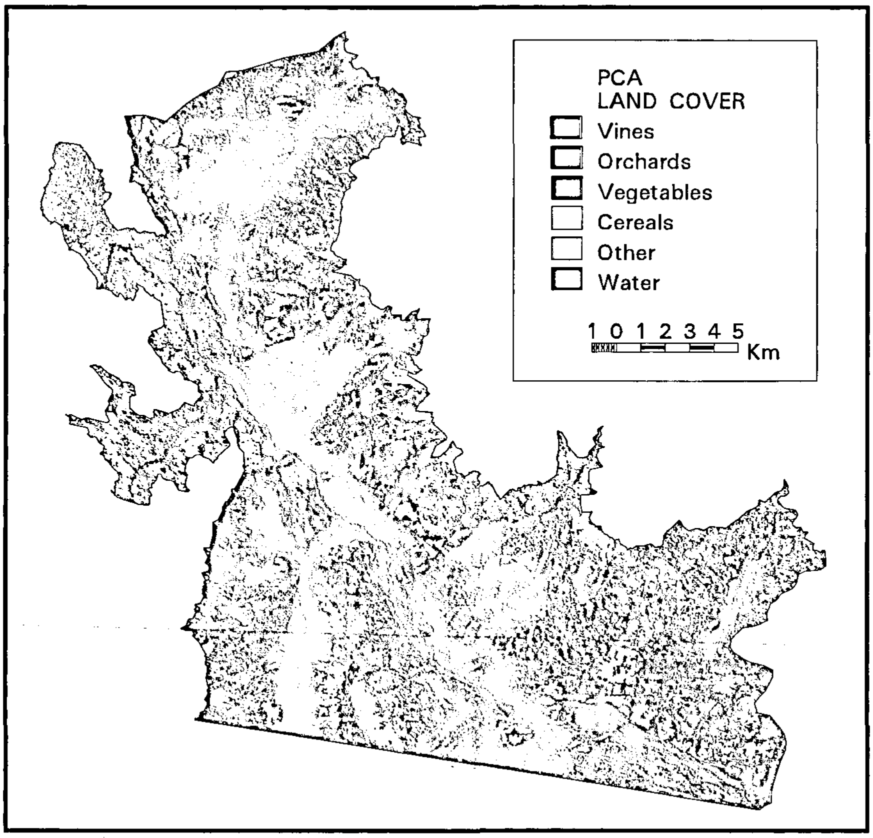


Figure 4.27: Generalized land cover map from unsupervised classification of Landsat TM Principal Component data.

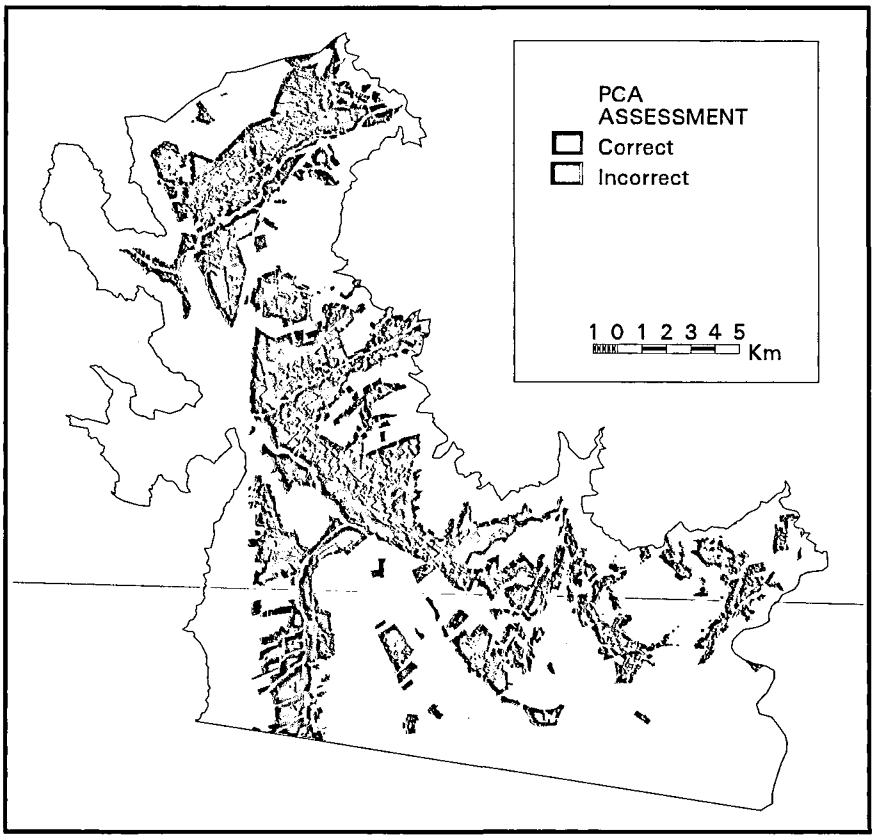


Figure 4.28: Accuracy assessment of generalized land cover map from unsupervised classification of Landsat TM Principal Component data.

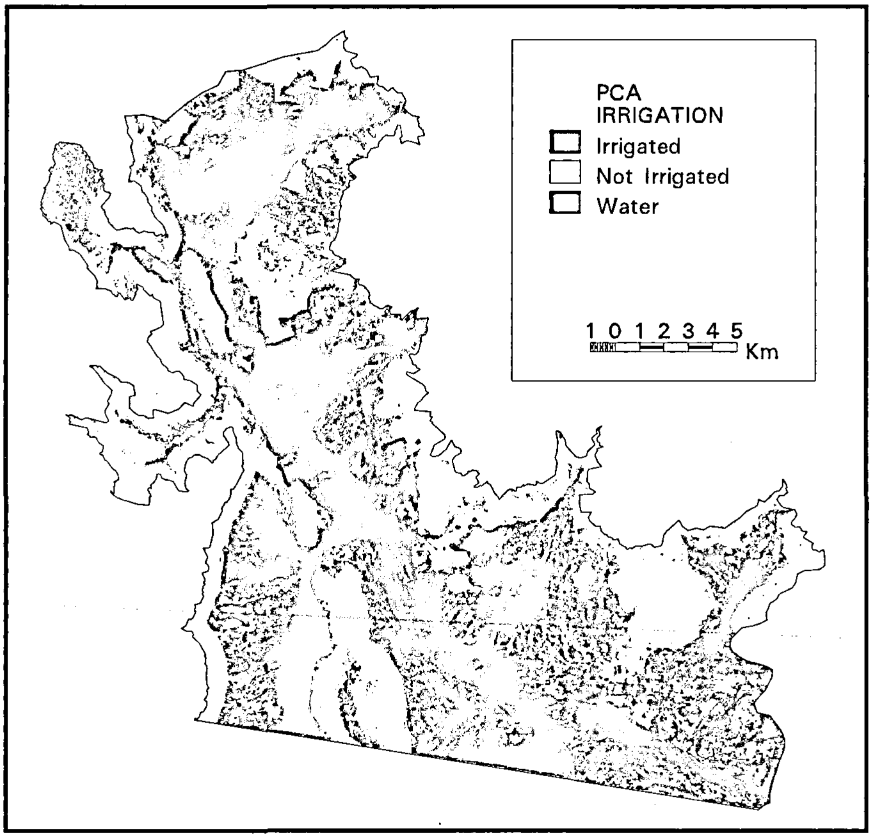


Figure 4.29: Irrigated land cover map from unsupervised classification of Landsat TM Principal Component data.

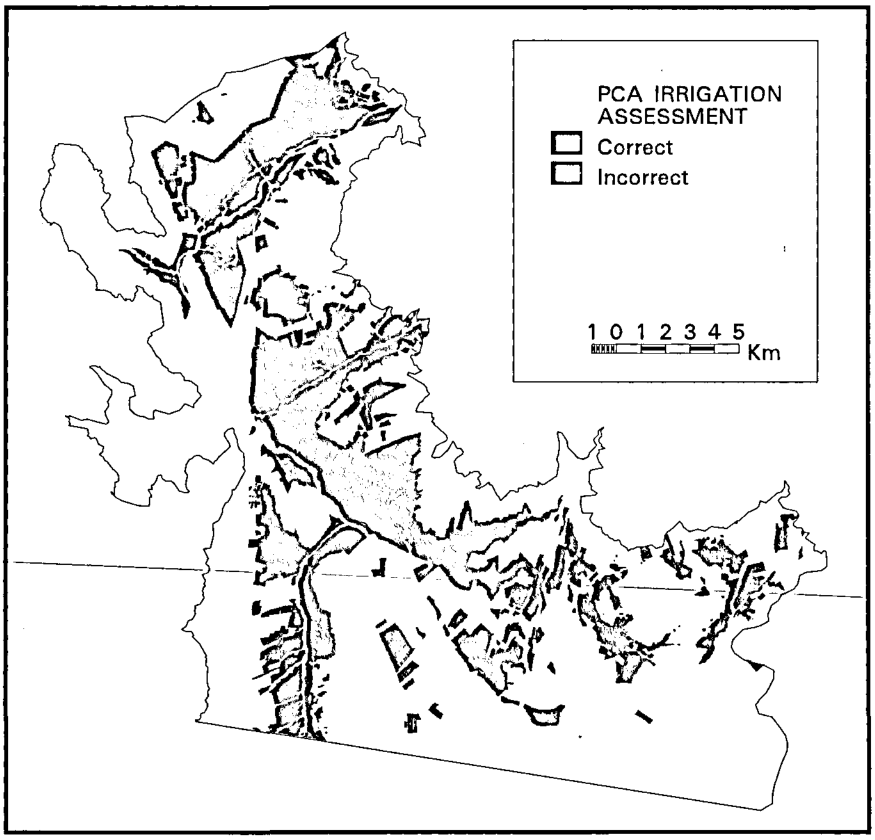


Figure 4.30: Accuracy assessment of irrigated land cover map from unsupervised classification of Landsat TM Principal Component data.

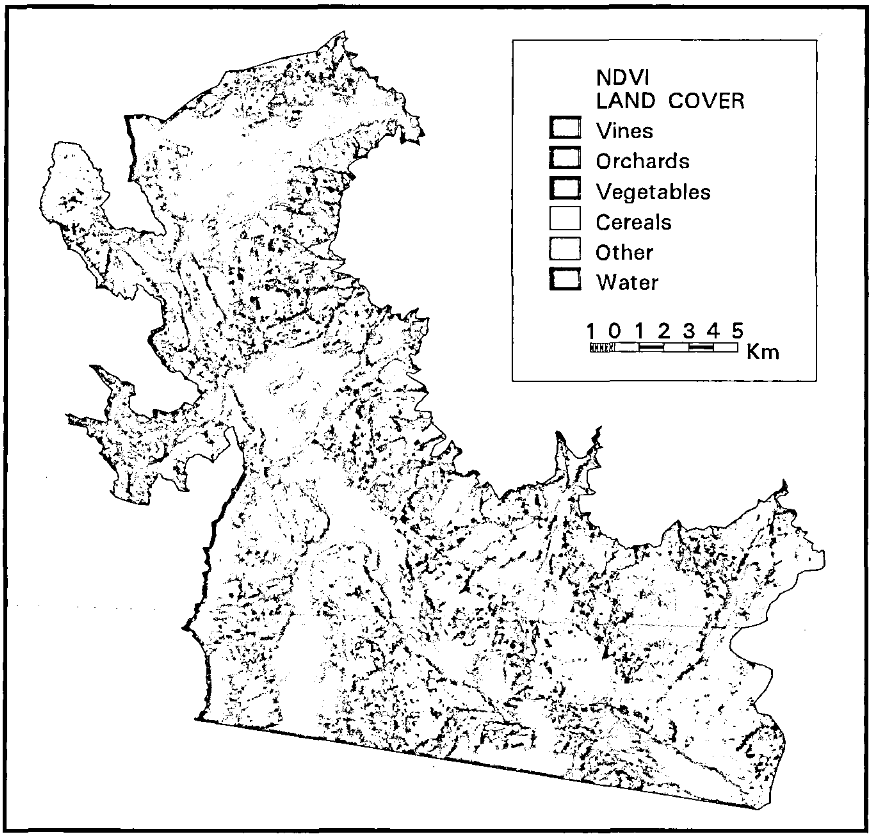


Figure 4.31: Generalized land cover map from unsupervised classification of Landsat TM NDVI data.

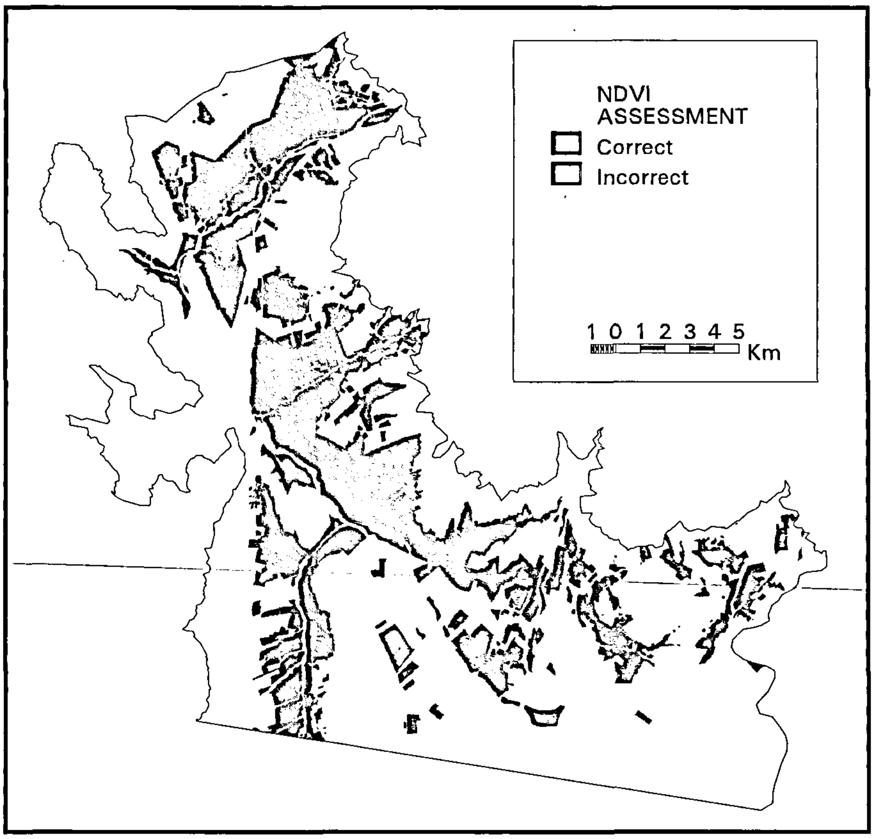


Figure 4.32: Accuracy assessment of generalized land cover map from unsupervised classification of Landsat TM NDVI data.

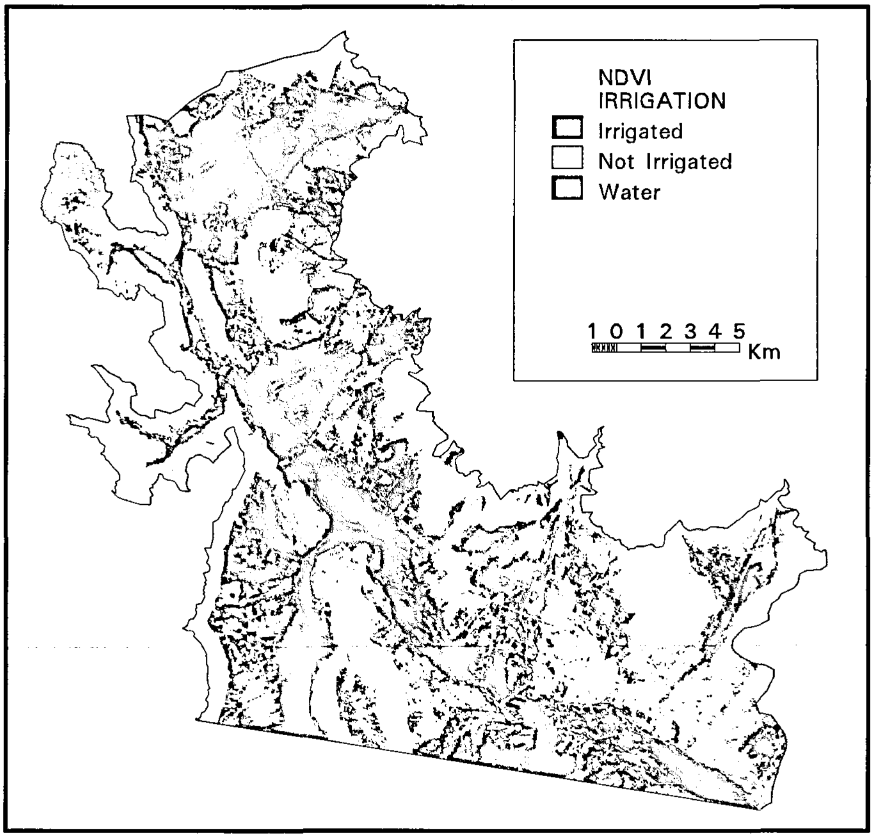


Figure 4.33: Irrigated land cover map from unsupervised classification of Landsat TM NDVI data.

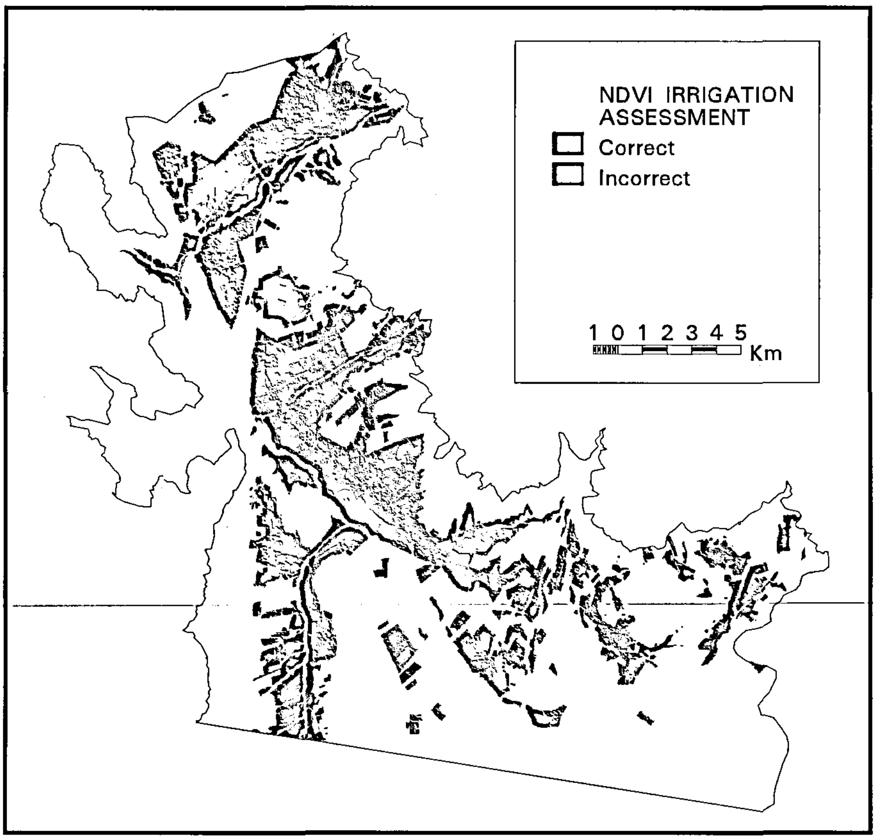


Figure 4.34: Accuracy assessment of irrigated land cover map from unsupervised classification of Landsat TM NDVI data.

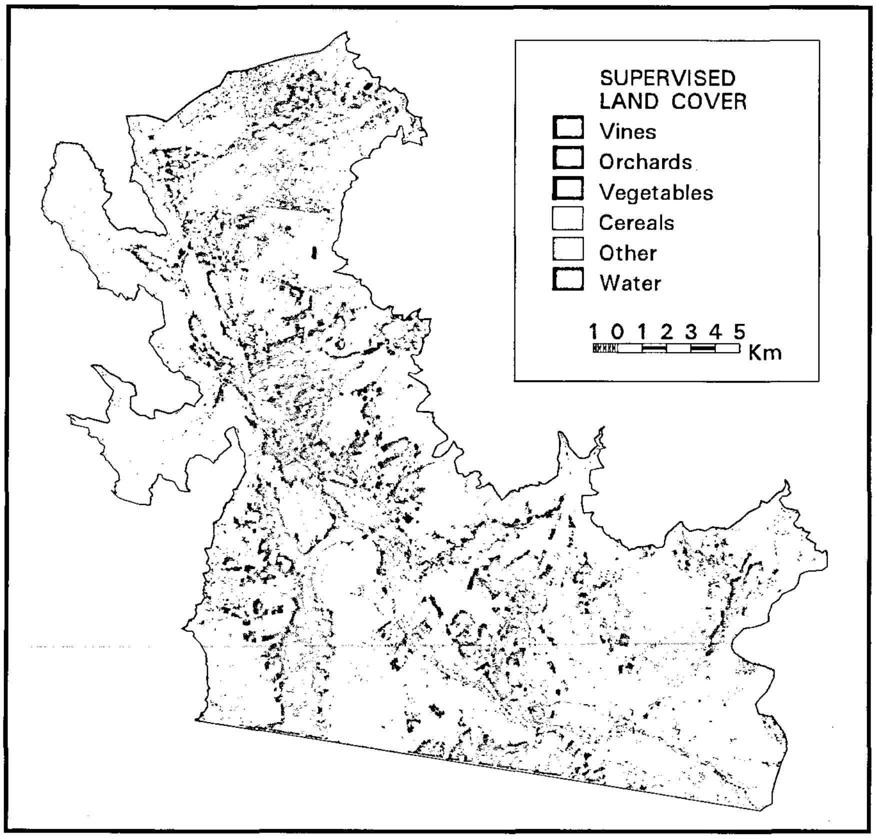


Figure 4.35: Generalized land cover map from supervised classification of untransformed Landsat TM data.

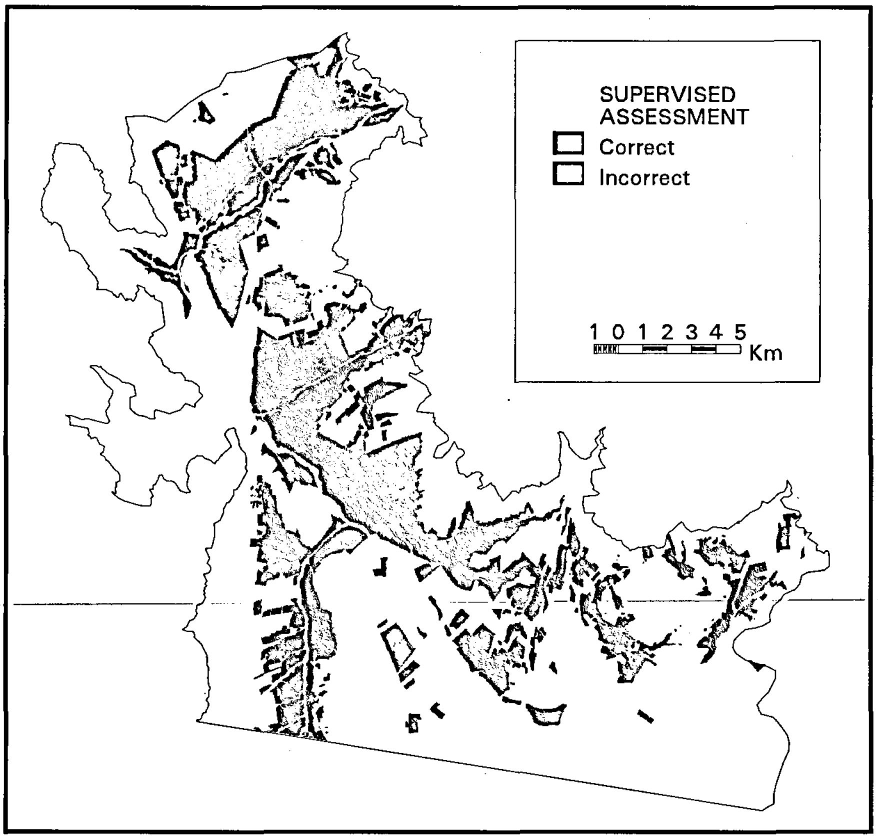


Figure 4.36: Accuracy assessment of generalized land cover map from supervised classification of untransformed Landsat TM data.

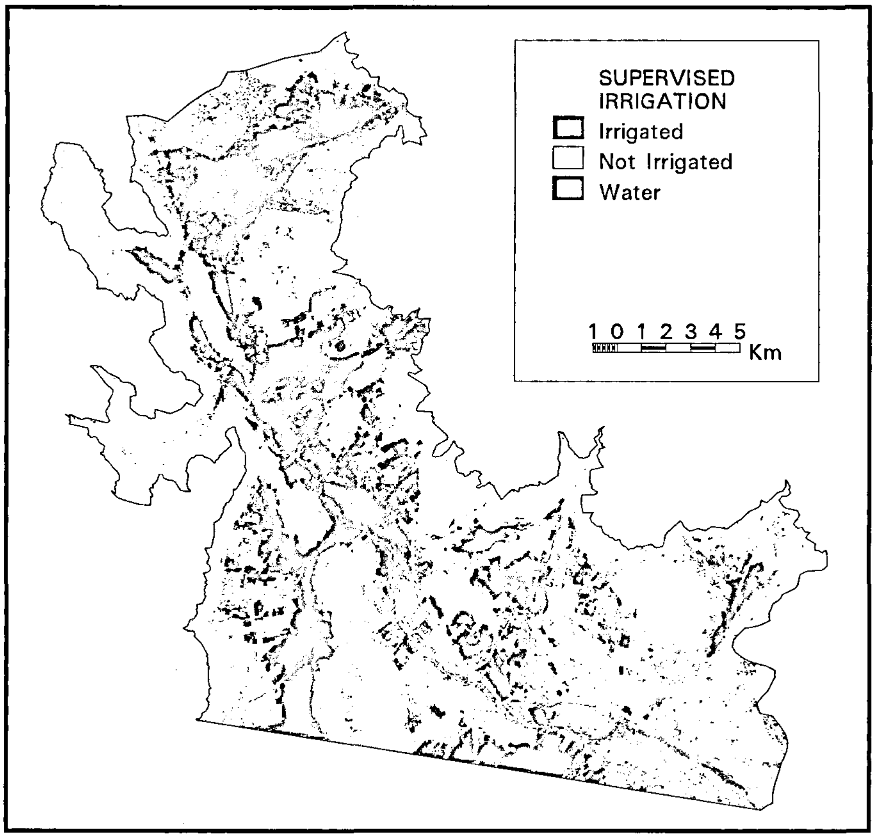


Figure 4.37: Irrigated land cover map from supervised classification of untransformed Landsat TM data.

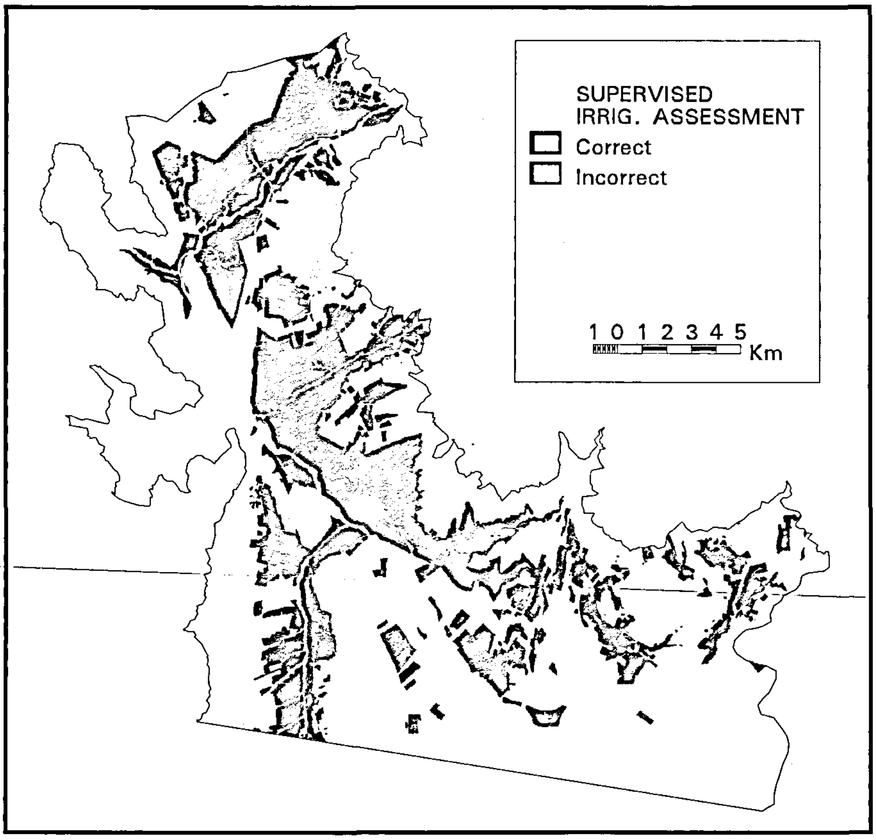


Figure 4.38: Accuracy assessment of irrigated land cover map from supervised classification of untransformed Landsat TM data.