CROP AREA ESTIMATION FOR THE NORTHERN WEST BANK, PALESTINE USING SATELLITE REMOTE SENSING

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ABSTRACT

This paper investigates the use of satellite data for crop area estimation in the northern part of the West Bank, Palestine. The satellite data were obtained by the SPOT HRV (High Resolution Visible) on 19 May 1994. The satellite data were geometrically corrected to the Palestine Grid using 1: 50,000 Israeli topographic maps. The study investigated the ability of SPOT HRV data to produce accurate crop area estimation of the northern part of the West Bank that is characterized with small field sizes and complex physical environment. The study area was divided into five strata and training data were selected using field survey, aerial photographs, maps, and interviewing farmers.

A land cover classification scheme appropriate to the study area was designed. Twenty three land cover classes were produced from the SPOT HRV classification. Land cover classes were developed to produce thematic land use classes. The classification accuracy obtained from SPOT HRV image classification was 81%. Classification results were assessed by using the known land use information obtained from the field during the training stage. The results were analyzed on stratum and crop type basis. Remote sensing and thematic agricultural perspectives were used in the analysis.

Results of the study suggest that it is possible to improve image classification accuracy by using better spatial and spectral resolution imagery and the integration of remote sensing data with agricultural data using the Geographical Information Systems (GIS).

تقدير مساحات المحاصيل الزراعية في شمالي الضفة الغربية– فلسطين، بواسطة بيانات الإستشعار عن بعد

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ملخص

يتناول هذا البحث استخدام بيانات الصور الفضائية في تقدير مساحات المحاصيل الزراعية في شمالي الضفة الغربية في فلسطين. التقطت الصور الفضائية بواسطة القمر الصناعي سبوت في التاسع عشر من أيار عام 1994م. تم تصحيح الصور هندسيا على أساس شبكة تربيع فلسطين من خلال خرائط طبوغرافية إسرائيلية مقياس رسمها 1:50000.

بحثت الدراسة في مدى قدرة نظام سبوت الإستشعاري في إنتاج تقديرات دقيقة لمساحات المحاصيل الزراعية لشمالي الضفة الغربية التي تتميز بصغر مساحة الحقول الزراعية من جهة، وتعقد بيئتها الطبيعية من جهة أخرى. قسمت منطقة الدراسة الى خمس طبقات، وتم اختيار مناطق التدريب عن طريق المسح الميداني، والصور الجوية، والخرائط، ومقابلة المزارعين.

تم وضع نظام تصنيف مناسب لمنطقة الدراسة وإنتاج 23 صنف من غطاءات الأراضي من صورة سبوت الفضائية، ثم تم تطوير تلك الأصناف ووضعها في أصناف استعمالات أراضي موضوعية. بلغت نسبة دقة التصنيف الكلية 81% ، وقيمت نتائج التصنيف من خلال بيانات ميدانية تم جمعها اثناء مرحلة إختيار بيانات التدريب، ثم خضعت النتائج للتحليل على أساس الطبقة الواحدة ونوع المحصول من منظور الإستشعار عن بعد والزراعة على حد سواء.

توصي نتائج الدراسة بأن هناك إمكانية لتحسين دقة التصنيف عن طريق إستخدام ميز مكاني وميز موجي أفضل، ودمج البامانت الإستشعارية بالبيانات الزراعية من خلال نظم تامعلومات الجغرافية.

1. Introduction

Agriculture in the West Bank is the main economic sector from which the Palestinians live. About 30% of the surface area of the West Bank is devoted to agriculture and about 15% of the labour sector work in agriculture. Agriculture contributes with the Palestine gross national product (GNP). Also 25% of the Palestinian exports come from agriculture (Applied Research Institute-Jerusalem 1998 (ARIJ)).

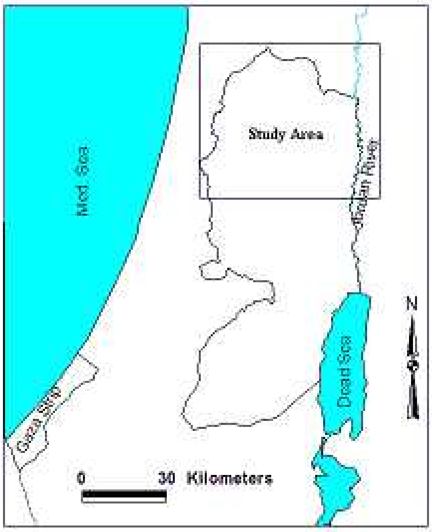
During the last three decades the agricultural sector was exposed to many different policies from the Israeli occupation. Also the political conditions in the West Bank and Gaza Strip affect agriculture. This situation led to the disappearance of some crop types such as watermelon and so the crop type structure was affected. The repeated Israeli military closure of the West Bank also affected the agricultural sector by preventing produce from the West Bank being sold in Israel. These dramatic changes and their effects on agriculture in the West Bank need to be monitored and evaluated using a cost and time effective methodology.

The absence of reliable agricultural data and the weakness of the agricultural laws and services require more investment in research studies in agriculture in order to be able to initiate a strategic plan for sustainable agricultural development (Ministry of Agriculture 1998).

The aims of the study are to investigate the ability of satellite remote sensing to produce an agricultural database for the northern part of the West Bank (Figure 1), and to investigate the role of satellite remote sensing in producing accurate crop area estimates for the major agricultural crops grown in the study area.

Spot HRV (High Resolution Visible) data were used in the study. Spot Satellite Program was undertaken by the French government in 1978, while the first satellite, Spot-1 in the program was launched in 1986, followed by Spot-2 in 1990 and Spot-3 in 1993. The sensor for these satellites consists of two identical HRV imaging systems: a 10 m resolution panchromatic mode over the range 0.51-0.73 µm or a 20 m resolution multispectral mode over the ranges 0.50-0.59 µm, 0.61-0.68 µm, and 0.79-0.89 µm. Spot-4 was launched in 1998 carrying two imaging systems: the High Resolution Visible and Infrared (HRVIR) sensors and the Vegetation instrument. Finally, Spot-5 was launched in 1999 carrying two imaging systems: the High Resolution Geometric (HRG) instrument (5 m resolution),and the High Resolution Stereoscopic (HRS) instrument. The HRS facilitates the preparation of digital elevation models (Lillisand, M., and Kiefer, W., 2000)

Figure 1: Study Area



2. Image Pre-Processing

Errors and distortions occur into the data acquisition process and can affect the quality of the remotely sensed data SPOT- XS (multispectral) are dealt with in this process. These errors can be in the spatial, spectral, temporal and radiometric resolutions (Duggin and Robinove, 1990; Lunetta *et al.*, 1991).

The following processes were applied to the three spectral channels of the SPOT HRV data before the data were analyzed. These were: **merging SPOT panchromatic (PAN) data with SPOT XS data of the study area, geometric correction, contrast stretching, digitization of the study area boundaries and, and image stratification.**

Merging different types of remotely sensed data is usually done by analysts to obtain more effective visual display, improve the spatial resolution of the data, improve the spectral resolution, and increase classification accuracy. SPOT PAN (10 m resolution) can be merged with SPOT XS (20 m resolution) data (Jensen *et al.*, 1990). SPOT-PAN can also be merged with Landsat TM data (30 m resolution) (Hallada, 1986; Welch and Ehlers, 1987; Chavez and Bowell, 1988). Multispectral data can also be merged with active microwave (Sabins, 1987; Harris *et al.*, 1990), and digitized aerial photographs with SPOT-XS or TM data (Chavez, 1986; Grasso, 1993).

SPOT-PAN images of the study area has been geometrically rectified to the UTM (Universal Transverse Mercator) projection at 10 m and merged with a geometrically rectified SPOT XS data of the same geographic area. The SPOT-PAN data span the spectral region from 0.51-0.73 μm. Therefore, it is a record of both green and red energy. It can be substituted directly for either the green (SPOT XS1) or red (SPOT XS2) bands. In this study, the PAN band is substituted for the red SPOT XS band for the sub-scenes 1, 2, 4, and 5. While for the sub-scenes 3 and 6 the SPOT XS bands remained without substitution keeping the original spectral coverage of SPOT XS. The result is a display that contains the spatial detail of the SPOT-PAN data (10 m) and the spectral detail of the 20 m SPOT XS data. This method has the advantage of not changing the radiometric characteristics of both the SPOT-PAN and SPOT XS data (Jensen, 1996).

3. Image Classification

In this study, a multispectral classification method is used. SPOT HRV XS sensor has three bands: SPOT XS1 (0.50 - 0.59μm), SPOT XS2 (0.61 - 0.68μm), SPOT XS3 (0.79 - 0.89 μm). SPOT HRV PAN (0.51 - 0.73μm) is used instead of the red band for the purpose of the classification of four of the six sub-scenes (Figure 2).

There are two image classification techniques that have been widely used for agricultural land cover mapping. New techniques such as artificial neural networks have been tested for agricultural applications but these are still experimental methods. For a study of a new area it is important to select a classification method that is well tried and tested.

1) Supervised classification
2) Unsupervised classification

A third method can be recognized called the *hybrid approach* which involves the use of ancillary data such as maps, reports, and statistics.

A supervised classification approach named the *Maximum Likelihood Classifier* was applied to the SPOT HRV data for the study area. A set of training sites representing 23 land cover classes was selected from the whole study area (northern West Bank).
The applied land cover classification scheme was taken directly from the field survey, maps, and aerial photographs (environmental classes) before studying the different world classification schemes. There are different classification schemes developed compatible with remotely sensed data. The most common schemes are:
-United States Geological Survey Land Use/ Land Cover Classification System (USGS).
- United States Fish and Wildlife Service Wet Land Classification System.
- NOAA Coast Watch Land Cover Classification System.
- The World Land Utilization Survey Classification (WLUS).
- The Second Land Utilization Survey Classification.
- Department of Environment (DoE) Developed Area Classification.
- The National Land Use Classification (NLUC).
- The National Gazetteer Pilot Study (NGPS).

These classification schemes do not concentrate on the same issues. Some of them emphasize on resources (land cover), others emphasize on human activity on land (land use). For example, the USGS is resource oriented (land cover) in contrast with various man activity (land use) oriented systems (Anderson *et al.*, 1976). On the other hand, the SLUC (Standard Land Use Coding Manual) is land use oriented and dependent on *in situ* observation land use information (Rhind and Hudson, 1980).

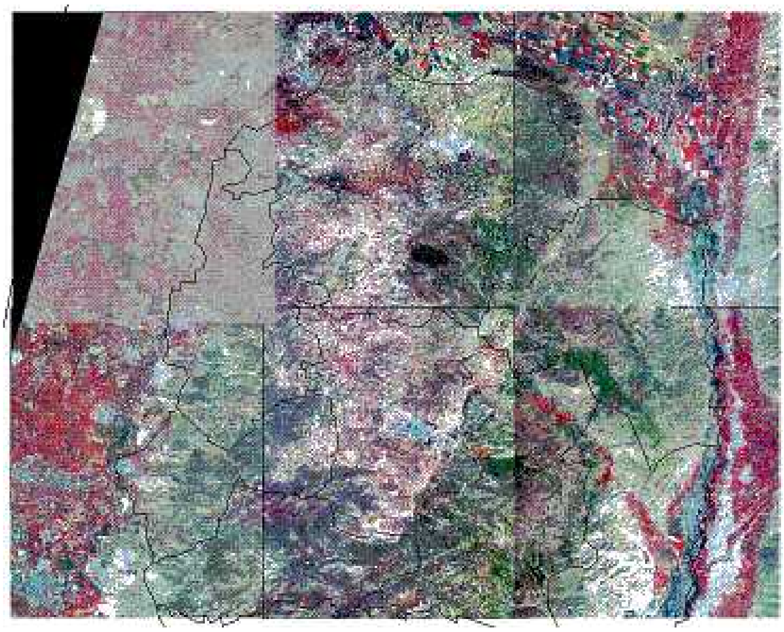
These classification systems insist on a hard boundary between the classes despite the fact that remote sensor data records signatures of a mixture of different types of features, especially at the edges of these features. This means that when adopting one of these existing nationally recognized classification systems, this fact should be taken into consideration.

In order to develop a suitable land use/ land cover system to be used with remote sensing techniques, the training sites were selected directly from the fieldwork, aerial photographs taken in 1995 and maps were adapted to the USGS classification system. The training sites represent the actual environmental and functional situation in the field at the time of the field work (August, September 2005). For example, ploughed fields are labeled as *ploughed land* because the crop type is not known at the time of the survey. The environmental and functional classes are then compared with the USGS classification system where every field class fell in the appropriate USGS classification level. For example, olive trees are located in class2 (agricultural land, cropland) and so on. The resultant classification scheme derived from both the training sites and the USGS system is seen in table (1).

Table (1): Land Cover Classification System Used in the Study

Main Categories (Level I)	Level II	Level III	Level IV
1. Urban or Built-up Land			
2. Agricultural Land	21. Crop Land and Pasture	211. Field Crops 212. Trees Crops	2111. Cereals 2112. Horticultural Crops (Vegetables) 21121. Rain-fed Horticulture 21122. Irrigated Horticulture 2113. Ploughed Land 2114. Greenhouses 2121. Olive Trees 2122. Citrus Trees 2123. Fruit Trees; Bushes 2124. Mixed Trees
3. Forest Land	31. Mixed Forest Land		
4. Range Land	41. Bare Soil; Bushes 42. Bare Soil; Rough Grass 43. Natural Vegetation 44. Natural Vegetation, Rocks 45. Rough Grass, Bushes		
5. Barren Land	51. Rocky Land, Quarries 52. Flat Bad Land		
6. Wet Land	61. Non-forested Wet Land		

Figure 2: False color Composite of the six Spot Sub-Scenes Used in the Study



3.1 Training Area Selection

This stage of supervised image classification is a fundamental one because it is the main difference between the supervised and the unsupervised classification. Training sites must be representative of the land cover types that exist in the image. Before training data were collected, the following factors that may affect land cover/ land use in the study area were taken into consideration:

1) Terrain characteristics and elevation,
2) Slope and aspect and,
3) Type of farming practice.

Based on the above mentioned factors, five different semi-regions or strata can be recognized in the study area:

1) area of Tulkarem
2) area of Jenin
3) area of Nablus
4) the upper eastern slopes (Shafa el-Ghour) and,
5) the Jordan Valley (Al-Ghour)

Administratively, area one represents the semi-district of Tulkarem, area two represents the semi-district of Jenin, and the other three areas are included in the semi-district of Nablus.

Environmental and topographic variations create the problem of anisotropic reflectance. Bishop, M. and Colby, J. (2002) studied this problem using imagery acquired over the Western Himalaya. The Minnaert correction procedure was evaluated using a single Minnaert constant (k).
In order to overcome environmental variations, mainly the problem of anisotropic reflectance in mountainous areas of the northern West Bank, training areas for different land cover types were (when possible) selected to represent all these environments, and each sub-scene was classified separately. For example, olive trees on the steep sloping lands would not have the same spectral signatures of that on the relatively flat lands because density of the different crop densities and

surface illumination. So, training sites were selected from both sloping and flat environments. Another serious problem arose during the training stage; it is that *farmers do not keep records of their agricultural activities in previous years*. When farmers were asked about the type of crop that they grew in their fields in the image acquisition data, they did not give precise answers. To solve this problem, it was necessary to have a full cultural and environmental understanding of the agricultural status in each region. This problem is serious for the dramatically changeable land use/ land cover types, mainly horticultural and cereal crops.

The training data were obtained from the following sources:

1) Israeli maps for the year 1998
2) Aerial photographs taken in 1995
3) Interviewing farmers
4) Corona photographs

The farmers did not give precise answers about the type of crop grown in their fields in May 1994 because none of them kept records for that year or for any other year and the long period between the field data collection date and the image acquisition data. This problem is likely to affect the quality of training data. It was also found that in the irrigated areas (Tulkarem and Al-Ghour), farmers do not follow any clear crop calendar. They sometimes plant the same crop type three times a year. The reason for that is because they use chemical fertilizers very intensively. Secondly, in the purely dry farming areas (area four), they follow a very distinct crop calendar: winter crops (wheat or barely), spring crops (okra or sorghum; these crops resist drought), winter crops. Thirdly, in the mixed farming areas (Jenin and Nablus), they mainly plant winter cereals (wheat and barely) and spring crops (okra, tomatoes, onion, chickpeas, courgetts, and cucumber). Fortunately, the image acquisition season (May) is suitable to differentiate between two main types of crops; cereals and horticulture (vegetables). So, the land cover type at the time of the field work is considered appropriate.

3.1.1. Training Classes Included in Classification and their Annotation Key

1. Supervised Training Classes: Table 2 shows the classes that were chosen from the previously mentioned sources (field, aerial photos and farmers' interview) for the supervised classification of the northern part of the West Bank.

Table (2): Land cover classes chosen for the supervised image classification

No.	Class	Key	Notes
1	Arable Crops	AC	Particularly wheat and barely
2	Horticulture	H1	It includes Spring dry farming crops (relatively low leaf area index crops) such as okra and tomatoes
3	Horticulture	H	It includes irrigated crops (relatively high leaf area index crops) such as cabbage, cauliflower, tomatoes, egg-plants and potatoes
4	Greenhouse	GH	Mostly planted with vegetables
5	Olive Trees 1	OT1	It includes densely planted areas existing in the relatively flat land or the margins of the plains

6	Olive Trees 2	OT2	It includes sparsely planted olive land mixed with some fruit trees mainly almonds, apricots, figs and vineyards
7	Olive Trees 3	OT3	It includes sparse olive land mixed with rough grass and bushes. It exists in the mountainous areas
8	Citrus Trees	CT	It includes orange, clementine, and some lemon and grapefruit
9	Fruit Trees & Bushes	FT;B	It includes fruit trees such as figs, apricots, and grapes mixed with bushes and some olive trees
10	Mixed Forest	MF	It includes both coniferous and deciduous woodland (the coniferous woodland is the dominant)
11	Rough grass & Bushes	RG;B	It includes unmanaged grass and bushes existing in the mountainous land
12	Rocks & Natural Vegetation	R;NV	It includes rocky land partially covered with natural vegetation. It mainly exist on the eastern slopes
13	Rocky Land	RL	It includes rocks and quarries
14	Badland	BL	It includes bare salty land. It exists in the Jordan Valley
15	Built-up Areas	BUA	

2. Unclassified Areas: These classes represent the areas that are not considered in the supervised training set. In other words, the supervised classification left some areas of the image unclassified. These areas are treated as independent classes because they occupy areas (not discrete pixels). Identification of the informative classes of these areas is achieved by:

a) spatial recognition: a comparison of each unclassified area with the available reference data such as large scale aerial photographs and maps is made, then given a grade of probability.
b) spectral recognition: a statistical report including the minimum, the maximum, the mean, the standard deviation and a variance/ covariance matrix for each unclassified area is produced. This statistical report is compared with the statistical report of each supervised training area and given a grade of probability.
c) textural recognition: texture or roughness of these unknown areas is compared with those of supervised training areas, then given a grade of probability.
d) Grade average probability of the three probabilities (spectral, spatial, and textural) is calculated for each unknown area, and then assigned to the class it fits best or create a new class for it. The weight of each factor can be decided according to its importance in the study area.

3.1.2 Bands Used for Image Classification

Kavzoglu, T. and Mather, P. (2002) invistigated methods known as feature selection techniques to select the optimum inputs of an artificial neural network (ANN) analysis. Statistical separability measures were employed to determine the best band combination for two multispectral, multitemporal and multisensor image datasets. The Mahalanobis distance classifier was employed in the determination of the best subset solution.

The data available for this study are three bands (green, SPOT-PAN, and the near infrared, sharpened image) from SPOT sub- scenes that cover the two middle and western parts of the study area. The Jordan Valley region was covered by SPOT HRV XS sub-scenes. The rest of the study area is covered by SPOT HRV XS that has been fused with the SPOT-PAN band. In practice this is achieved by substituting the red band by the panchromatic band which has the effect of improving the visual interpretability. To investigate the effect of the fusion of SPOT HRV XS data with the SPOT-PAN data correlation between bands of the two data has been studied. It was found that correlation between the three spectral bands of the pan-sharpened SPOT HRV image is still lower than that of the SPOT HRV XS image. This can be explained by the higher scattering of the visible bands in the Jordan Valley for its low altitude.

To understand the efficiency of the SPOT XS wavebands in image classification, the training statistics for each band have been studied and analyzed both statistically and graphically. The aim of this analysis is to determine degree of between-class separability in the training data. Using statistical methods, combinations of bands are normally ranked according to their potential ability to discriminate each class from all others using *n* bands at a time (3 bands).
The more the bands are analyzed in the classification, the more the cost and perhaps the greater the amount of redundant spectral information being used (Jensen, 1996). ***Divergence*** is one of the widely used statistical methods for band selection and analysis (Swain and Davis, 1978) when only two training area statistics are analyzed. But when there are more than two classes, the ***average divergence*** is computed. This involves computing the average over all possible pairs of classes, while holding the subset of bands constant. Divergence is computed using the mean and covariance matrices of the class statistics collected in the training phase of the supervised classification.

In this study, the average divergence is used to check the separability among different land cover classes. For non-overlapping distributions a value of 2 was given to Jeffries-Matusita distance and the transformed divergence (Rees, 1999). The following table illustrates the average separability among the different land cover classes over the 6 sub-scenes of the study area:

Table (3): Divergence Statistics for the Study Area Land Cover Classes

	Minimum Divergence	Maximum Divergence	Average Divergence
Tulkarem	0.24	2.00	1.73
Jenin	0.80	2.00	1.85
Jordan Valley (north)	0.51	2.00	1.86
Qalqilia	0.55	1.99	1.76
Nablus	0.82	2.00	1.90
Jordan Valley (south)	0.27	2.00	1.84

Above 1.50 is good, 1-1.50 is intermediate, and below 1 is poor

The divergence method for the study area was evaluated using the green, the panchromatic, and the infrared SPOT band contributions at one time.

It can be seen from the above table that the average separability of all the training classes for the six sub-scenes is between 1.73-1.90 when ***Bahattacharyya Divergence*** is used and between 1.85-1.95 when ***Transformed Divergence*** is used. It can be seen also that the spectral separability varies from one scene to another for the different land cover/ land use types. The lowest separability with different levels is recorded between the following classes:

- Olive Trees1 (OT1), Olive Trees2 (OT2), Olive Trees3 (OT3)
- Olive Trees1 (OT1), Mixed Forest (MF) in stratum 3.
- Badland classes (BL1, 2 and 3), Built-up Areas (BUA) in stratum 5.
- Rough Grass and Bushes (RG; B), Citrus Trees (CT) is stratum 2.
- Olive Trees (OT), Rough Grass and Bushes (RG; B)

This overlap between these classes may result in either overestimation or underestimation of these land cover types, and so influence the final classification accuracy.

So, it was thought to have the classes that have the same thematic meaning generalized as follows:

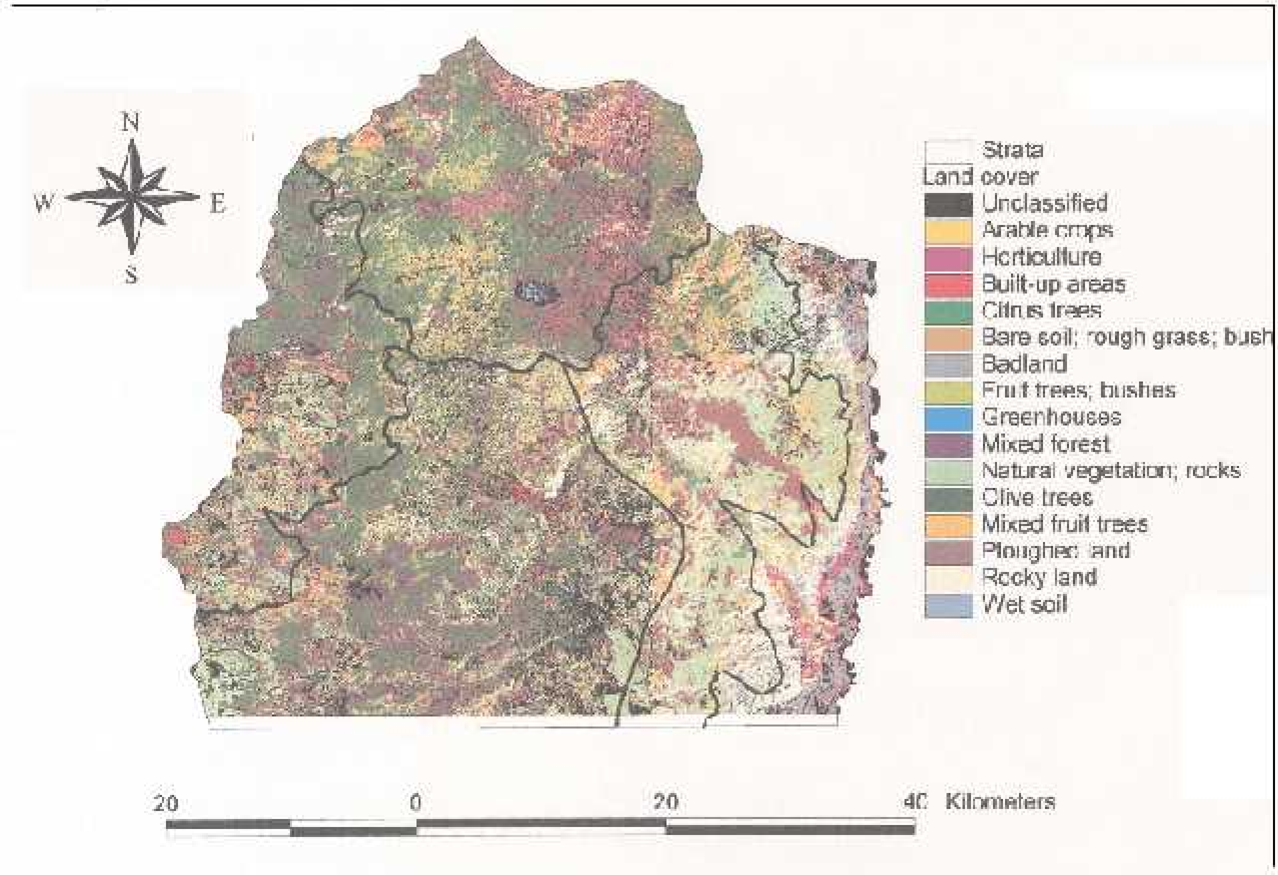
- OT1, OT2, and OT3 classes became OT class
- BL1, BL2, and BL3 classes became BL class
- BS; RG, B; RG, and BS; B classes became B; RG class
- H; H1 classes became H class

The resultant land cover classes after the training data analysis and development are shown in table (4).

Table (4): Land Cover Classes after Development

No.	Land Cover Class	Annotation Key
1	Unclassified	UC
2	Arable Crops	AC
3	Horticulture	H
4	Citrus Trees	CT
5	Olive Trees	OT
6	Fruit Trees; Bushes	FT; B
7	Mixed Trees	MT
8	Greenhouse	GH
9	Wet Soil	WS
10	Ploughed Land	PL
11	Mixed Forest	MF
12	Built-up Areas	BUA
13	Bad Land	BL
14	Rocky Natural Vegetation Land	RNVL
15	Rough Grass; Bushes	RG; B
16	Rocky Land	RL

Figure 3: Spot HRV Classified Image for the Year 1994



4. Land Cover Area Estimation

As the study area lies in 6 sub-scenes, the classified sub-scenes need to be mosaiced to form one continuous image. The classified sub-scenes were merged in one image containing the whole study area. The resultant image mosaic is converted to grid and the dimension of each grid is 10.036 m x 10.036 m or 100.72 m². In order to obtain number of pixels for each land cover type on both the study area and individual stratum levels, the mosaic is clipped to the boundaries of the study area as well as the boundaries of each individual stratum producing a land use map for the study area. By multiplying the numbers of pixels in each land cover class by its area (100.72 m²), the area for each land cover class is obtained on both the stratum and the whole study area levels. Table 5 shows land cover estimation for the study area after class development and generalization.

Table (5): Developed Land Cover Class Area Estimation of the Study Area

No	Land Cover Class	Hectare Area (dunam)	% of Total Area
1	Unclassified	220684	9.30
2	Arable Crops	171786	7.24
3	Horticulture	213824	9.01
4	Olive Trees	405300	17.08
5	Citrus Trees	69053	2.91
6	Fruit Tree and Bushes	14475	0.61
7	Mixed Trees	70239	2.96
8	Mixed Forest	140004	5.90
9	Built-up Areas	51968	2.19
10	Badland	790109	3.33
11	Rocks and Natural Vegetation	298754	12.59
12	Rough Grass and Bushes	345976	14.58
13	Rocky Land	289737	12.21
	TOTAL	2372950	100

Further development of the previously mentioned classes was done as shown in table 6.

Table (6): Final SPOT HRV XS Area Estimates for Agricultural Crops
Northern the West Bank (dunam)

Stratum	Olive and Fruit trees	Citrus Trees	Horticulture	Arable Crops	Non-Agricultural
1	89233	9520	16800	4429	188832
2	181732	15982	104849	61289	158633
3	209980	25910	24107	23949	273718
4	21637	10060	28237	72176	315701
5	326	443	19712	9938	177450

5. Image Classification Accuracy Assessment

Classification accuracy assessment of derived land use/ land cover maps from remotely sensed data is important especially when these maps and statistics are to be used by decision makers. Accuracy assessment is also important to identify the sources of errors. There are two main types of accuracy assessment for crop classification (Mead & Szajgin, 1982):
1) site specific assessment, and, 2) non-site specific assessment.

In this study, the site specific method is preferred because location is fundamental in geographical studies. To get reference information to compare with the remote sensing classification map and fill the error matrix with values, the test reference information is collected before and after the classification. As time and cost are important in using remote sensing for large geographical areas, a stratified random sample was used to collect the appropriate number of samples for each agricultural category.

In previous studies, the optimum sample size used to assess the accuracy of individual categories in remote sensing classification map varied considerably. Hay (1979) and Congalton (1991) suggest that a minimum of 50 samples for each category could be a good rule, while Gurney (1981) suggests 400 pixels for each class. The size of the study area, number of classes included in classification, the relative importance of certain categories and variability of different categories should also be taken into consideration (Jensen, 1996).

In this study, special care is paid for the most valuable categories. These categories are:

1) Olive Trees (OT)
2) Horticultural Crops (H)
3) Citrus Trees (CT) and
4) Arable Crops (AC)

Taking into consideration the previous studies as well as time, cost, and the field characteristics, test pixels and test areas in this study were determined as follows. First, crops existing in plain land mainly horticulture, arable crops, and citrus trees were assessed on a polygon basis. This means that the whole polygon is taken for assessment what ever the size of it is. The relatively large fields were selected (more than 1 ha or 100 pixels because most fields are relatively small). Secondly, crops existing in the upland mainly olive trees and fruit trees in addition to the non-agricultural categories were assessed on cluster basis. 200 pixels were selected for each land use category to be assessed. Finally, because the number of pixels selected for accuracy assessment is not the same for all classes, results were converted to percentages.

There are three types of accuracy assessments that can be made to classified image, the overall classification accuracy, the producer's accuracy and the user's accuracy. The overall accuracy is the sum of the major diagonal divided by the total number of the sample units in the entire error matrix. The producer's accuracy refers to the number of pixels which have been correctly identified as a land use type, while the user's accuracy refers to the actual number or percentage of pixels of a certain class on the classified image that exists on the ground (Congalton & Green, 1998). Classification accuracy assessment was made on both stratum and whole study area levels. Table 7 shows the study area classification accuracy assessment results.

Table (7): overall accuracy of the five strata

Strata	Accuracy %
Jenin	77
Tulkarem	81
Nablus Mountains	78
Eastern Slopes	84
Jordan Valley	87

Table (8): SPOT HRV XS classification accuracy assessment
of the study area (northern the West Bank)

Land Use	Producer’s Accuracy (%)	User’s Accuracy (%)	Overall Accuracy (%)
AC	86	90	86
H	79	80	79
CT	88	79	88
OT;FT	67	68	67
MF	88	77	88
GH	88	88	88
R;NV	71	86	71
RL	91	88	91
BUA	87	88	87
PL	84	89	84
RG;B	71	71	71
BL	74	91	74

OVERALL CLASSIFICATION ACCURACY OF THE STUDY AREA =
(86+79+88+67+88+88+71+91+87+ 84+71+74)/1200 = 974/1200 = 81%

6. Discussion of Classification Accuracy Assessment Results

In this study, the classification accuracy assessment is carried out at different levels; the stratum level, the crop type level in each stratum. Accuracy results show:

1) The overall accuracy in stratum five is the highest (87%). Accuracy ranges from 73% to 97%. The lowest accuracy is for the Badland class because it is spectrally overlapped with the Built-up Areas class. The relatively high accuracy achieved for this stratum is probably due to the relatively small number of classes existing in the area and the good spectral separebility among land cover types. Citrus trees and Horticulture in this stratum are overlapped and 16% of the citrus pixels are assigned as horticulture and so the user’s accuracy of horticulture is decreased from 96% to 83%. This may mean that the classification overestimated horticulture at the expense of citrus trees.

2) In stratum four, the overall accuracy comes in the second highest place among the five strata (84%). The lowest accuracy in this stratum is for the Rough Grass & Bushes and Olive &Fruit Trees classes. Olive trees are confused with arable crops which is unreasonable because these two categories at this time of the year (May) are spectrally different. The reason for this error is the land use change between the image acquisition date (1994) and the field data collection (1998). Some arable lands in the plain areas were planted with olives (young trees). These fields were labeled as olives at the time of the field survey (1998). Rough grass and bushes are also confused with horticulture in this stratum. 13% of the rough grass pixels were assigned to horticulture. This is due to the increasing land cover complexity when moving from the east to the west (from the Jordan valley to the center of the Nablus Mountains).

3) The overall accuracy in stratum three, which represents the core or the center of the Nablus Mountains, is 78%. The lowest accuracy is for the Olive & Fruit trees and Rough Grass & Bushes classes. These two categories in this area are confused. Where17% of the rough grass pixels mainly

Sarcopoterium Spinosum is assigned to olives and fruits, only 1% of olive pixels assigned as rough grass and bushes. The complex land cover, the mountainous landscape (topography), slope and aspect, and the impurity of land cover types may explain the relatively low accuracy of these classes in this stratum.

4) In stratum two, the overall accuracy is 81%. The lowest level of accuracy was also for Olive & Fruit Trees and Rough Grass & Bushes classes. In addition to the reasons mentioned in the previous point, certain types of bushes existing in this stratum are responsible for the spectral overlapping between these two categories on one hand, and between citrus trees and bushes. Some areas of this stratum are covered with *Tistacia Lentiscus* and *Quercus Calliprinos* bushes. *Tistacia Lentiscus* is a kind of bush about two meters tall with evergreen waxy leaves, while *Quercus Calliprinos* is an oak tree.

5) Finally, the overall accuracy of stratum one is 77%. The lowest accuracy was for Horticulture and Rough grass & Bushes classes. Horticulture is confused with citrus trees. The reason for such overlapping is the relatively high Leaf Area Index (LAI) of both classes in such an irrigated area. The rough grass is overlapped with the natural vegetation class that mainly covers the south eastern part of this stratum.

Sources of errors and the relatively low accuracy of some land use types in certain areas can be investigated through viewing the different sources of data and the steps followed in image classification and assessment, the classification scheme, and the characteristics of the study area:

a) The reference data used in this study were the ground data, aerial photographs and satellite images, and Israeli topographic maps.

- The ground data collection for image classification and assessment was far from the image acquisition date (1994). This time separation affected and complicated the field data collection process, especially because farmers do not keep records of their previous activities in the field. They hardly remember the type of crop they grew at the image acquisition date.

- The season and the date of the Israeli aerial photographs used were not ideal for agricultural data collection. They were acquired in autumn and winter where the fields are prepared for cultivation or freshly sown. Although the possibility of getting agricultural data on seasonal crops was limited, these photographs were useful for training and testing the relatively constant agricultural types as olives and citrus trees. CORONA satellite photographs were also useful for collecting agricultural data in the uplands regions where olive trees are the dominant land use, however they are old photographs acquired in 1970. For more efficient field data collection, aerial photographs for the same season and the year of the satellite image are vital for detailed accuracy assessment.

- The 1: 50 000 Israeli topographic maps were used along with the 1: 40 000 CORONA prints for overviewing only, while the large scale CORONA prints were used for field data labeling. So, these maps were of a limited use in the field data collection. Large scale maps showing field boundaries are also recommended for field data collection and labeling because even vertical aerial photographs can contain considerable errors especially away from the NADIR point.

b) The classification scheme used in this study is for land cover. On the other hand, the reference data used for accuracy assessment is for land use data (thematic data). This difference between the applied classification and the reference data affected the accuracy of a certain classes such as the olive trees class and the rough grass class. It was not possible to make field measurements of percentages of crop crown closure to solve this problem.

c) Despite the relatively high spatial resolution of SPOT HRV XS data, the limited spectral resolution mainly the absence of the middle or the short-wave infrared reduced spectral separability especially in the rough textured areas (the uplands).

d)The complex topography of the study area may have affected the classification accuracy. The area is characterized by large topographic variations (elevation, slope and aspect). This situation increased the effect of topographic shadowing on the spectral separability of a certain land use types mainly olives, mixed forest and the ploughed land in the strata 1 to 4.

7. Conclusion

The overall classification accuracy obtained from the SPOT HRV XS images for the study area was 81%. The best accuracy was for stratum five and four (87% and 84% respectively).

The classification also produced fifteen land cover classes after the development of the first image classification scheme applied (23 classes were merged into 15 classes) with more than 80% accuracy.

Despite the spectral overlap of some land use types in some parts of the study area, the results of SPOT HRV image classification northern the West Bank were promising.

To increase the accuracy of image classification and field area estimates it is important to have aerial photographs for the same year and season as the satellite image. This solves the problem of accessibility to some areas and compensates for the absence of agricultural records at the field level. Also, high resolution satellite data such as IKONOS may solve this problem.

Finally, the results of the study and the inferences drawn from them are only tentative. Additional studies with much larger samples would be desirable to further test the validity of the findings.

References

- Anderson, J. R., Hardy, E. E., Roach, J. T., and Witmer, R. E. (1976) “A land use and land cover classification system for use with remote sensor data”. **United States Geological Survey** Professional paper 946, 28 pp., USA.
- Applied Research Institute- Jerusalem (ARIJ) (1998) **Water resources and irrigated agriculture in the West Bank**. Bethlehem, Palestine.
- Bishop, M, and Colby, J. (2002), “Anisotropic reflectance correction of Spot-3 HRV imagery”, **Int. Journal of Remote Sensing**, 23, 2123-2125.
- Chavez, P. S. & Bowel, J. A. (1988) “Comparison of the spectral information content of Landsat Thematic Mapper and SPOT for three different sites in the Phoenix, Arizona Region”. **Photogrammetric Engineering and Remote Sensing**, 54(12): 1699-1708.

- Congalton, R. J., Balogh, M., Bell, C., Green, K., Milliken, J. A. and Ottan, R. (1998) “Mapping and monitoring agricultural crops and other land cover in the Lower Colorado River Basin”. **Photogrammetric Engineering & Remote Sensing**, vol. 64, no. 11, 1107-1113.
- Congalton, R. G. & Grass, K. (1998) **Assessing the Accuracy of Remotely Sensed Data: Principles and Practices**. Lewis Publishers, CRC Press, Inc.
- Congalton, R. G. (1991) “A review of assessing the accuracy of classifications of remotely sensed data”. **Remote Sensing of Environment**, 37: 35-46.
- Duggin, M. J. & Robinove, C. J. (1990) “Assumptions implicit in remote sensing data acquisition and analysis”. **Int. Journal of Remote Sensing**, vol. 11, no. 10, 1669-1694.
- Grasso, D. N. (1993) “Applications of HIS colour transformation for 1: 24,000 scale geologic mapping: A low cost SPOT alternative”. **Photogrammetric Engineering and Remote Sensing**, 59(1): 73-80.

- Gurney, C. M. (1981) “The use of contextual information to improve land cover classification of digital remotely sensed data”. **Int. Journal of Remote Sensing**, vol. 2, no. 4, 379-388.
- Hallada, W. A. (1986) “Cover photo”. **Photogrammetric Engineering and Remote Sensing**, 52(10): 1571-1579.
- Harris, J. R., Murray, R., and Hirose, T. (1990) “HIS transform for the integration of radar imagery with other remotely sensed data”. **Photogrammetric Engineering and Remote Sensing**, 56(12): 1631-1641.
- Hay, A. M. (1979) “Sampling designs to test land use map accuracy”. **Photogrammetric Engineering and Remote Sensing**, 45: 529-533.
- Jensen, J. R. (1996) **Introductory Digital Image Processing-A Remote Sensing Perspective**. (2^{nd} ed.), Prentice Hall, New Jersey, USA.
- Jensen, J. R., Ramsey, E. W., Holmes, J. M., Michel, J. E., Savitsky, B., and Davis, B. A. (1990) “Environmental Sensitivity Index (ESI) mapping for oil spills using remote sensing and geographical information system technology”. **Int. Journal of Geographical information Systems**, 4(2): 181-201.
- Kavzoglu, T. and Mather, P. (2002), “The role of feature selection in artificial neural network application”, **Int. Journal of Remote Sensing**, 23, 2919-2937.
- Lillisand, M., and Kiefer, W., (2000) **Remote Sensing and Image Interpretation**. (4^{th} ed.), John Wiley & Sons Inc., New York, USA.
- Mead, A. A. & Szajgin, J. (1982) “Landsat classification accuracy assessment procedures”. **Photogrammetric Engineering and Remote Sensing**, 48:139.

- Palestine Ministry of Agriculture (1998) **Development plan for the period 1999-2001**. Ramalla, Palestine.
- Sabins, M. J. (1987) **‘Convergence and consistency of fuzzy C-Means/ ISODATA Algorithms’**, IEEE transactions pattern analysis & machine intelligence, 9: 661-668.
- Welch, R. & Elhers, M. (1987) “Merging multiresolution SPOT HRV and Landsat TM data”. **Photogrammertic Engineering of Remote Sensing**, 53(3): 301-303.