Introduction

Remote sensing is defined as the acquisition of information about an object without being in contact with it physically. Information is acquired by detecting and measuring changes that the object imposes on the surrounding field, whether it is an electromagnetic, acoustic, or potential. This could include an electromagnetic field which is emitted or reflected by the object, acoustic waves reflected or perturbed by the object, or perturbations of the surrounding gravity or magnetic potential field due to the presence of the object.

The term ‘remote sensing’ is most commonly used in connection with electromagnetic techniques of information acquisition. These techniques include the whole electromagnetic spectrum from low-frequency radio waves through the microwave, sub millimetre, far infrared, near infrared, visible, ultraviolet, x-ray, and gamma-ray regions of the spectrum.

The arrival of satellites is allowing the acquisition of global and synoptic detailed information about the planets (including the Earth) and their environments. Sensors on Earth-orbiting satellites provide information about global patterns and dynamics of clouds, surface vegetation cover and its seasonal variations, surface morphologic structures, ocean surface temperature, and near-surface wind. The rapid wide coverage capability of satellite platforms allows monitoring of rapidly changing phenomena, particularly in the atmosphere. The long duration and repetitive capability allows the observation of seasonal, annual, and longer-term changes such as polar ice cover, desert expansion, and tropical deforestation. The wide-scale synoptic coverage allows the observation and study of regional and continental-scale features such as plate boundaries and mountain chains.

Sensors on planetary probes (orbitors, flybys, surface stations, and rovers) are providing similar information about the planets and objects in the solar system. Up to now, all the planets in the solar system, except for Pluto, have been visited by one or more spacecraft. The comparative study of the properties of the planets is providing new insight into the formation and evolution of the solar system.

With the increase of satellites launched and placed in the orbit, the remote sensing data is one of the data resources which are effectively used in spatial
estimating models. One faces a variety of sensors, spatial resolution, radiometric resolution, and temporal resolution, and has access to these data easily. It appears inevitable to survey their capabilities and to offer criteria to select, process, and extract useful ones. Therefore, employing images taken by satellites and digitally processing them by using appropriate algorithms can help, while trying to minimize man’s optical error where he cannot clearly visualize the changes and distinguish them. It seems that by applying these images and classifying the techniques one can classify the lands which enjoy surface similarities and similar reflection into one group and pave the way for the first condition that is just the classification of similar lands.

Another reason which emphasized the case of satellite images for agricultural studies is the high frequency and their coverage potentials of them. Thus, one can easily observe very important phenomena such as the land use changes and vegetation mantle varieties. This technique serves as an instrumental role in studying and knowing the natural sources and abnormalities. Surveys at large scales with temporal repetition and on-time preparation of maps (proper mapmaking) can help achieve constant development and identify the environment and factors affecting it. Consequently, one of the effective tools in the environmental and geological studies is to use remote sensing technology. The identification of most of the renewable resources such as soil, water, mines, vegetation, devastating phenomena like floods, desertification, wind and water erosion, sand-hills drift, the salinity of water and soil and deforestation all require getting access to constant development. Accordingly, making use of remote sensing data and using satellite data help reduce costs, save time, improve precision and speed and the need for this technology to develop constantly is increasingly felt. The remote sensing data technology is one of the modern technologies which help to have access to and extract data for the management of earth resources.

In the third world and developing countries where they suffer from the paucity of budget for research and where they do not have access to the data concerning vegetation mantles, especially in the mountainous and remote areas where reaching and to all areas to observe the intended features is difficult or impossible, obtaining data through satellite sensors especially those with higher spectral, radio-metric, and
spatial resolution can create an inexpensive and significant shortcut. To prove the accuracy and purity of the obtained data in certain areas where there is precise and generally accepted data from the farms and fields, one can compare the existing maps with the ones made from the interpretation of data obtained from the satellites. Most of the uses of remote sensing data technology are heavily focused on the estimating and identifying of surface features of soil such as vegetation, humidity, minerals, particle distribution, and salinity in the soils' surface layers and type of salt. Generally speaking, the reflective features of soil vary with the soil without vegetation, soil colour, soil humidity, minerals of soil, particle distribution, soil structure, soil surface irregularities, irrigation conditions, different chemical compounds, and sedimentations remained on the surface of soil (Zinck, 1996). Therefore, making use of remote sensing technology to quickly produce data of land use and natural incidents and temporal changes can play a great role in regional development and planning.

This chapter describes the methodology and methods of image processing for this study and has included error correction and registration of image data, introducing of images satellite, filter of image and image classification.

4.1 Methodology
4.1.1 Procedure

This research was done in the lands under cultivation of dry-land wheat in Malayer region in order to create an experimental regression model between the amount of yield or product and vegetation index. The sampling operation of wheat yield was done randomly by means of GPS (Garmin model) in 1m*1m plot. The main use of model simulation in evaluating lands is the (estimation crop) prediction of the amount of product or yield. Principally, the main idea behind making these kinds of models is based on this principle that there is a relationship or correlation between vegetation indices and estimation crop and we can estimate the quantity of yield production by establishing this kind of correlation. As far as it is concerned with the analysis of yield amount (y), the following formula is used:

\[ Y = f(X_1, X_2, X_3 \ldots) \]

In this formula, Xs are an indicative of independent variable, which are vegetation indices in our research. Basically, vegetation indices are mathematical
conversions which have been designed for spectral assessment of plants in multi-spectral satellite observations (Kabiri, 2004). These indices are mostly used in places where the spectral satellite data have been placed in the confines of red and near infrared bands. These vegetation indices based on having the property of red light, absorption by pigments inside the chlorophyll of plants, act in such a way that they experience minimum reflection in red band and maximum reflection in infrared waves.

This chapter outlines information with regard to methodological aspects of this research study. It consists of a description of the data involved in the study and the process of analyzing data. It can be separated into two sections; the first one is related to data collection procedure and the second one gives a full description of the process of data analysis included in this study, along with the rationale and theoretical framework used for design purposes.

Data Collection: This section is divided into two processes including: A) library studies and B) field work, which are explained in detail in the following section.

**A) Library studies**

These studies include the following procedure: Getting descriptive and statistical information from the Organization of Agriculture in Malayer regarding the agricultural features of the region under study such as the amount of dry-land wheat production in a Hectare, the quantity of other main products of the region, and getting statistical information of the surface under plantation of the region under study.

Getting descriptive and statistical information about climatology or weather conditions including the amount of temperature degree, rainfall amount, evapotranspiration, sunshine hours, and the like in the years 1994-2007 from Metrological Organization of Hamadan and Synoptic station of Malayer.

Providing the essential maps and satellite images of IRS LISS_III in the years of study from spatial organization and Geographical Organization of Iran.

Surveying the governmental reports and executive plans in the agricultural part of the region under study; in addition to this is the study of the similar work done in
Iran and other countries in order to study the comments suggested by researchers and the methodologies implemented with regard to yield estimation

**B) Field operation (work)**

This process consists of two procedures. First, the coordinates \((x,y)\) of 250 points in farm lands and some others from other main products were obtained by GPS. The model used here was GARMIN, which has the ground accuracy of 5 meters. Before starting the operation of obtaining coordinates, calibrating operation was done by two methods comprising the calibration of compass and Altimeter. Then, the obtained coordinates of points \((x,y)\) was transferred to computer by Map Source software. These coordinates assist us to recognize the phenomena and different agricultural products on image satellite in order to do supervise classification as the training points. Second, the point coordinates of dry-land wheat of the region under study was obtained. In this procedure, these 150 points \((x,y)\) were obtained by GPS when the dry-land wheat had the maximum chlorophyll and leaf area. The placed wheat inside the standard plot of 1m\(^2\) harvested accurately and carefully. Then, the points (wheat plants) were transferred to the laboratory, where the leaf area index was measured by leaf area meter (Fisheye model). It should be pointed out that this kind of measurement is called Ground Measured LAI or gLAI in this research. Therefore, one gLAI was calculated for every 150 points. Again, the researcher obtained and measured the coordinates of 150 points of the wheat sample with maximum amount of accuracy by GPS when the dry-land wheat of the region was ripen completely. These measures were called Ground Measured Yield, or it is better to say “gYield”. Thus, now we have a registered coordinate for every point which includes gLAI and its corresponding point, called gYield.

**4.1.2 Data Analysis**

In order to analyze the data, the digital processing of images was done, which include the following processes:

- Pre-processing
- Image Enhancement
- Data Classification
- Post-processing
First; at pre-processing process, before any digital and visual processing was done, radiometric, atmospheric, and geometrical errors were measured by some standard methods and carry out operations on raw data of the present study because a careful study of them was necessary after obtaining data from the geometric and radiometric point of view. Even if there were some corrections on the bands before the study, we should have been informed completely of the errors of these data. For this purpose, the researcher made use of 1:25000 topographical file and map of the region under study plus two satellite images related to two different dates of the region, which was provided by Geographical organization of Iran. Further, the primary calculations of some useful and necessary statistical indices was done including the minimum and maximum of digital number of each band, mean, standard deviation, correlation matrix, variance-covariance matrix, correlation matrix percentage of bands, changes in digital number of each band, which is able to determine the quality and quantity of the data.

Second, after the images were corrected, the operation of image pre-processing for the purpose of image enhancement of most images under study was done. Among these operations, we can refer to the methods of filtering, image stretching, and false colour composite image generation. The main purpose behind these operations is to obtain images with an acceptable resolution for processing.

Third, with regard to this point that the main purpose behind the technology of remote-sensing is the recognition and separation of ground phenomena, this process can be considered as the most important process of the interpretation of satellite data and as the most significant processing in this study. In fact, the separation of similar spectral units and classified division of those having the same spectral behaviour is called satellite data classification. By this method, each digital number is attributed to the classes of land cover, land use, and other phenomena of ground surface. Satellite data classification is divided into digital and visual method. Digital classification method, which is based on the spectral differences of various phenomena, was used in the present study. It does not mean that every phenomenon is separable on every particular band.
The process of classification consists of two stages. The first is the recognition of categories of real-world objects, in the context of remote sensing of the land surface these categories could include, for example, Pastures, Lake and pools, mountains and other land cover types, depending on the geographical scale and nature of study. The second stage in the classification process is the labelling of the entities (normally pixels) to be classified. In digital image classification these labelled are numerical.

Digital classification can be divided into two parts: supervised classification and unsupervised classification. In unsupervised classification, training areas are not considered as the basis for classification. In other words, in this method, the obtained clusters are created based on spectral similarity of pixels.

In supervised classification, it is necessary to get previous information about the phenomena related to the data. In this method, some of the pixels are selected as training sample and then their specifications are transferred to computer by ILWIS software, where it can classify other pixels based on its own specific instruction. Regarding the selection of the related classes, a lot of attention has been focused so that the sample points can have a good scattering and an appropriate uniformity. The number of samples was selected through the formula N*10, which N is an indicative of the number of bands used in the classification. Because the measurer used had four bands, therefore 4*10= 40 was obtained through the formula. As a result, according to the above justification, the minimum number of 40 was necessary for the present classification. It should be pointed out that supervised classification is divided into three kinds but, based on the study of the works done before and Lillesand theory, “maximum likelihood” was recognized to be the best method, which was applied in this research. After doing classification and the process of post-classification steps, which consisted of filtering and entering non-spectral data, assessment and accuracy of the classification was done by confusion matrix. Lastly, Kappa coefficient was also calculated.

4.1.3. Calculation of vegetation indices

Acquiring information about the position of vegetation cover such as its amount and scattering has focused a lot of attention on the part of researchers. On the
other hand, getting information about the continuous changes of vegetation cover by the usual methods is tough, costly, and time-consuming. Therefore, making use of satellite data is taken for granted as the alternate method to provide the possibility of studying expansive vegetation. We are able to combine the minimum number of two bands together and create a compound index, called Vegetation Index (VI), by implementing this method. In fact, the main intention behind the creation of vegetation index was that some of the characteristics of vegetation index such as canopy, biomass, product, leaf area, or the percentage of vegetation could be predicted and evaluated. According to, the studies done by Lee and Antrop (1996) and others, more than 90% of multi-spectral information can be expressed by two spectral bands. Principally, the reflection of vegetation cover in the confine of red light specter (0.43 -0.66 micrometers) is low while it is high in the confine of near infra red (0.7 -1.1 micrometers). In addition, three important properties of leaf including chlorophyll, physiological structure and amount of water can have a significant influence on spectral reflection. With respect to this important point, a combination of spectral bands, red light and near infrared was able to contribute to differentiate vegetation from the surface of water and soil.

As it was already mentioned in chapter I, Leaf Area Index (LAI) is a key biophysical variable influencing surface processes such as photosynthesis, transpiration, and energy balance and it is a required input for various ecological models (Bonan, 1993). According to Grower et al. 1992, it is defined as the research area leaves per unit of grand area and direct measurement approaches include area harvest.

The amounts of obtained LAI in field work were met with the amounts of their corresponding harvested product or yield in SPSS software. Then, a scatter-plot was drawn and the most appropriate line for these points was dragged. As a result, a logarithmic equation was obtained. This had the highest amount of correlation coefficient \( R^2=0.937 \), in comparison with those of other equations. Lastly, the amount of correlation between gYield and gLAI was computed.

\[
y = a \times \ln (gLAI) + b \quad \text{Eq.4.1}
\]
4.1.3.1. Calculation of NDVI

The Normalized Difference Vegetation Index (NDVI) is defined as:

\[ \text{NDVI} = \frac{R_{\text{Nir}} - R_{\text{Vis}}}{R_{\text{Nir}} + R_{\text{Vis}}} \]

According to this formula, \( R_{\text{Nir}} \) and \( R_{\text{Vis}} \) refer to the reflectance values derived from spectral radiances measured by the NIR channel and the visible channel, respectively. It is not an intrinsic physical quantity, but correlate with physical properties such as cover fraction or biomass.

Now, by considering the coordinates of gLAI available in GPS, a vector map (pint map) was created in GIS environment. Then, by taking the above equation into account, NDVI variable was calculated by making use of red bands (R) and infrared bands (NIR).

Lastly, the layers of gLAI and NDVI were crossed together in the context of ILWIS software in order to extract the amounts of NDVI corresponding with gLAI. Then, the extracted amounts were transferred to SPSS software to elicit the information necessary for our analysis.

To derive remotely-sensed LAI, the following empirically derived logarithmic regression model was developed:

\[ s\text{LAI} = a \times \ln(\text{NDVI}) + b \quad \text{Eq 4.2} \]

The logarithmic expression indicated a higher amount of \( R^2 \) than the other available expressions as far as it is concerned with our analysis. Ezekiel and Fox (1959) expressed that the coefficient of determination (\( R^2 \)) is the most direct and unequivocal way of stating the proportion of the variance independent factor, which is associated with the independent factors. As it was mentioned before, the data used for the development of this model were also obtained in growth season in 2007 out of 150 data points (120 points for models and 30 points for pilot study).

The NDVI was used because it seems that it correlates well with canopy (Rondeaux et al., 1996) and has been demonstrated to give satisfactory LAI estimates (Qi et al., 2000). The approach of determining LAI by establishing a relationship between NDVI and LAI is widely used due to its simplicity and ease of computation (Colombo et al., 2003).
4.1.3.2. Calculation of SAVI

Due to this reason that the vegetation density is not 100% in dry-land wheat farms, the effect of background soil on the amount of vegetation index is not significant. On the other hand, the interference between soil reflections and vegetation creates some problems for the study. Some studies have shown that the sensitivity of vegetation index on background soil with average vegetation (50% green vegetation) is the maximum amount (Alavipanah, 2003). Therefore, a lot of efforts have been done so that the spectral dependency of soil brightness and less vegetation coverage create a model, by which vegetation index can be an indicative of the different position of soil and vegetation. Owing to the fact that NDVI is sensitive to the features of background soil and vegetation, especially when the available vegetation is dispersed and has low density, SAVI is used instead to decrease the effect of background soil, and it is less affected by the reflections of soil. This index (SAVI) causes the spectral variance arising from the changes in background soil to reach to its minimum amount. In addition, the adjustment factor of background soil is taken into account in the formula used for calculating SAVI. According to Alavipanah (2005), the adjustment factor of L= 0.5 has been recognized as appropriate for reducing the effect of soil on vegetation with average density. Thus, SAVI index was calculated by the following formula by making use of point or victor map and red (R) and infrared (NIR) band.

\[
\text{SAVI} = \frac{(\text{NIR}-R)}{(\text{NIR}+R+L)} \times (1+L)
\]

In the environment of ILWIS software, the layers of gLAI and its corresponding SAVI were crossed in order to obtain the amount of SAVI, corresponded to gLAI. Then, these amounts were crossed in SPSS software by which the amount of coefficient of determination was obtained ($R^2= 0.976$).

\[
\text{sLAI}_M = a \times \text{Ln (SAVI)} + b \quad \text{Eq.4.3}
\]

4.1.4 Calculation of Correlation Matrix between variables

The amount of SLAI was measured by three indices including NDVI, SAVI, and gLAI and based on that the amount of yield was estimated through putting it in the equation (1). Then, a correlation matrix was established between ground measure yield, measured by the researcher and agricultural office, and the amount obtained from the above calculations.
According to the correlation matrix between NDVI and SAVI variables, the
correlation between LAI and SAVI had a higher degree of correlation and more
amount of correlation coefficient. By taking the result of this correlation into account,
SAVI index was applied for the intention of computing LAI from satellite images.
Then, the amounts of computed LAI from these images, called sLAI, were substituted
to gLAI in formula (1), by which the amount of dry-land wheat yield was estimated.

4.1.5. Accuracy Assessment

The last process for creating a model is the evaluation of its accuracy. After
the model is created, it should be determined whether the obtained model related to
the desired efficiency has the essential accuracy or not. Therefore, the evaluation of
the whole previous procedures should be done in this section. The most popular
method for quantitative evaluation of the accuracy of the model is the selection of
some obvious sample pixels and their comparison with their results obtained from the
model at hand. In order to do this procedure, a parameter called Root Mean Square
Error (RMSE) was used. That is calculated by the following formula:

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - y_i)^2}
\]

It should be pointed out that, in this formula, \( r \) is the amount of error of each
sample and is calculated from this formula:

\[
R_i = (g\text{Yield} - s\text{Yield})
\]

gLAI is the LAI for each of the check point in IRS LIS_III image, which has
been computed by leaf area meter. These data were implemented as obvious data or
ground truth.

sLAI is the LAI for each of the check point in IRS LIS_III image, which has
been calculated by model.

\( n \) is the number of check points, that was used for the calculation of RMSE. It
should be mentioned that RMSE is an average error which expresses that, on average,
how much the available amount of error in the amount of LAI of the points is by
using the model. It is also worth mentioning that, in the process of the evaluation of
the accuracy, some points which have not been used in the calculation related to the
determination of the model’s parameter were applied. Some other parameters were
used for greater accuracy in assessing the model in addition to RMSE such as Squared
Difference between Standard Deviation (SDSD), Simulation Error (SE), ME, and
MSD.
Then, with regard to the confirmation of the accuracy of the models, the obtained formulas were applied in order to estimate LAI and finally dry-land wheat yield in the area unit in the region under study for other years and their results were compared to the results of Bushel measurement. The obtained results from the calculation of Pearson correlation between the estimated yield with model and the amount of measured production indicated that there is a significant and high correlation between them (p=0.000). Lastly, the calculation of RMSE, MSD, SDSD, and Error and Simulation and reporting a low amount can be regarded as the acceptable accuracy of the model in estimating dry-land wheat in the region under study.

4.1.6 Regression Analysis

Regression analysis is a mathematical method for modelling the relationship among two or more variables. Different types of regression analyses include linear regression, logistic regression, and Poisson regression. In AGB estimation research, multiple linear regression analysis is the approach used most often (Roy and Ravan, 1996; Foody et al., 2003; Steininger, 2000; Zheng et al., 2004).

Multiple linear regression analysis is used to predict the value of one variable given the value of other variables. “Linear” refers to the linear relationship between the dependent and independent variables. Multiple linear regressions use the least squares method to fit a line through the data. In the least squares method, the unknown parameters are estimated by minimizing the sum of the squared deviations between the data and the model prediction. The simple form of the multiple linear regression equation is as follows:

\[ Y = \beta_0 + (\beta_1 X_1) + (\beta_2 X_2) + (\beta_3 X_3) + \ldots + (\beta_n X_n) + \epsilon \]

Where:
- \( Y \) = dependent variable,
- \( X_1, X_2, X_3 \) = independent variables,
- \( \beta_0 \) = intercept,
- \( \beta_1, \beta_2, \beta_3, \beta_n \) = slope parameters, and
- \( \epsilon \) = random error term in the model.
Statistics such as $R^2$, Adjusted $R^2$ and Mallows Cp are generally used to determine the best model. The $R^2$ statistic is a measure of the total variation in the data set which is explained by the model. However, the value of $R^2$ always increases when independent variables are added in the model regardless of the remaining degrees of freedom (Salvador and Pons, 1998; Draper and Smith, 1998). Adjusted $R^2$ takes into account the degrees of freedom and it adjusts for the fact that $R^2$ increases as variables are added, thereby ensuring that improvement in $R^2$ due to adding the new term into the model has some real significance and is not because the numbers of variables in the model have reached a saturation point (Draper and Smith, 1998). Adjusted $R^2$ will tend to increase quickly at first and then more slowly as variables are added. Adjusted $R^2$ is defined as

$$R^2_{\text{adj}} = \frac{(n-1)(1-R^2)}{n-p}$$

Where:

- $n$ = number of observations,
- $p$ = number of parameters in a fitted model, including $\beta_0$, and
- $R^2$ = measure of the amount of variation about the mean explained by the fitted equation.

The $C_p$ statistic was initially suggested by C.L. Mallows. This statistic has the following form

$$C_p = \frac{SSR}{s^2-(n-2p)}$$

Where:

- $SSR$ = residual sums of squares from a model,
- $p$ = number of parameters in the model,
- $n$ = number of observations, and
- $s^2$ = residual mean square from the largest postulated equation.

Residual mean square is presumed to be a reliable unbiased estimate of the error variance $\sigma^2$ (Draper and Smith, 1998). When a model does not suffer from lack of fit (i.e., the model is adequate) $E(SSR) = (n-p)\sigma^2$ and $E(SSR/s^2) = n-p$ so that approximately

$$E(C_p) = p$$
Hence adequate models have a $C_p$ value approximately equal to $p$. Random variations can cause adequate models to have $C_p < p$. Models with a considerable lack of fit (biased) often have a $C_p$ value greater than $p$ (Draper and Smith, 1998). Thus according to this statistic, while choosing a model, the model should have $C_p \leq p$.

For a multiple regression to give reliable and unbiased results, certain conditions need to be met. The assumptions of regression are that: there is no error in measurement of the independent variables, the errors are normally distributed, errors are uncorrelated, variance between the variables is constant and the expected value of the variables is zero (Draper and Smith, 1998).

Many studies have investigated the use of multiple linear regressions to predict biomass from remotely sensed data. These studies have estimated biomass with varying degrees of success. Zhen et al., (2004) obtained $R^2$ values of 0.82 to predict biomass across a landscape in northern Wisconsin. Foody et al., (2003) obtained $R^2$ values of 0.30, 0.32 and 0.25 to predict biomass in tropical forests in Thailand, Brazil and Malaysia. Thenkabail et al., (2004) reported $R^2$ values of 0.16 and 0.13 for predicting dry biomass weight in the Congo basin using IKONOS and Landsat ETM+ data. In a study conducted by Steininger, (2000) $R^2$ of 0.75 and 0.30 were obtained for predicting biomass in the tropical forests of Brazil and Bolivia respectively. Some studies have shown an increase in $R^2$ values when exponential transformation of spectral variables was used.

Ardo (1992) obtained $R^2$ values of 0.55, 0.61, 0.5, 0.23, 0.62 and 0.55 for predicting forest volume using natural logarithm of Landsat TM bands 1-5 and 7 respectively for boreal forests of Sweden. Parametric methods are based on the statistical assumption that the data are normally distributed (Jensen, 1996). This assumption does not fit all applications and is difficult to implement in complex landscapes with classes of high variance (Hansen et al., 1996).

4.1.7 Regression Models and Vegetation Indices

The simplest way to estimate crop yield from spectral information is to use linear regression models, and to correlate the radiance and /or reflectance of specific wavelengths with crop yield (Ball and Frazier, 1993). Since the absorption peaks of chlorophyll are in the red and green region, and since the cuticule on leaf surface strongly reflects in the near-infrared region (Campbell, 2002), brightness values of
these spectral regions are highly correlated with the vigor of crops or strength of photosynthetic activity, and therefore with the crop yields.

The hardware and software which were used in this study are as follows:
1. Computer Pentium IV, 852 MHZ with colour monitor 21"
2. Scanner Contex, Model : FSC8010
3. Software R2V for map digitizing
5. GPS Garmin (vista model)
6. Leaf area meter

LISS-III

This sensor was installed on the INdian satellite. Date of image was June 11th, 2007. This sensor has four bands in the visible spectral (RED) range to near infrared (NIR) and a panchromatic band. Visible spatial bands are 23.5 meters and 5.8 meters for pan band. It has 6983 rows and 7041 columns. Cloud percentage at the catch image was zero.

4.2 The Digital Elevation Model

The digital trail model is a digital map which covers all the elevations of the region. Thus, the digital trail model can also be referred to as digital elevation model and is interchangeably used. Burrony (1985) maintains that since the term 'trail' usually suggests more the physical features of land than those of elevations the digital elevation model is more preferably used for the models which deal with data related to 'elevation'. Consequently, the digital elevation model allows us this opportunity to add elevation values to an image where it can be 3-dimensionally displayed. Line contour and elevations derived from the toposheet can be the most appropriate sources of primary data to establish Dem Generation. The elevation data can be digitally applied for the special purpose of Dem Generation or digitally derived and estimated from the paper maps.

To develop a digital elevation model, all the elevations and contour lines are digitalized at a distance of 2 meters and subsidiary lines at distance of 10 meters on
the toposheet with a scale of 150,000 in the software environment of R2V. Then its vector file is sent to the software environment of ILWIS where special expressions are coded on it. In the second stage, the vector map is transformed into a raster format on the 'segment to raster' command where consequently the pixels have similar elevation values with the contour lines and the rest of the pixels remain unidentified. In the third stage, contour interpolation is between the pixels whose values are certainly defined and the calculation of elevation values is for the pixels that have remained unidentified. In this process, the elevation values, for each unidentified pixels between two curves, are calculated based on the smallest difference (4-1 equation). The result of this process is the raster map all of whose pixels enjoy elevation values.

$$H_p = H_1 + \frac{d_1}{d_1 + d_3} \times (H_1 - H_3)$$  \hspace{1cm} \text{Eq. 4.4}

Fig. 4.1: The contour interpolation between curve-lines of the level and the allocating of elevation digit to the unidentified pixels.

To prepare the slope map with the implementation of command in ILWIS environment, the researcher developed the slope map in percentage.

$$\text{SLOPEPCT} = 100 \times \frac{\text{HYP (DX, DY)}}{\text{PIXSIZE (DEM)}}$$  \hspace{1cm} \text{Eq. 4.5}

4.3 Error Correction and Registration of Image Data

When image data is recorded by sensors on satellites and aircraft, it can contain errors in geometry and in the measured brightness values of the pixels. The
latter are referred to as radiometric errors and can result from the instrumentation used to record the data, from the wavelength dependence of solar radiation and from the effect of the atmosphere. Image geometry errors can occur in many ways. The relative motions of the platform, its scanners and the earth, for instance, can lead to errors of a skewing nature in an image product. Non-idealities in the sensors themselves, the curvature of the earth and uncontrolled variations in the position and attitude of the remote sensing platform can all lead to geometric errors of varying degrees of severity.

When an image is utilized, it is frequently necessary to make corrections in brightness and geometry if the accuracy of interpretation, either manually or by machine, is not to be prejudiced. For many applications, only the major sources of error will require compensation whereas in others more precise correction will be necessary.

4.3.1 Sources of Radiometric Distortion

Mechanisms that affect the measured brightness values of the pixels in an image can lead to two broad types of radiometric distortion. First, the relative distribution of brightness over an image in a given band can be different to that in the ground scene. Secondly, the relative brightness of a single pixel from band to band can be distorted compared with the spectral reflectance character of the corresponding region on the ground. Both types can result from the presence of the atmosphere as a transmission medium through which radiation must travel from its source to the sensors, and can be a result of instrumentation effects.

4.3.2 The Effect of the Atmosphere on Radiation

Fig. 4.2 depicts the effect the atmosphere has on the measured brightness value of a single pixel for a passive remote sensing system in which the sun is the source of energy, as in the visible and reflective infrared regions. In the absence of an atmosphere the signal measured by the sensor will be a function simply of the level of energy from the sun, actually incident on the pixel, and the reflectance properties of the pixel itself. However the presence of the atmosphere can modify the situation significantly as depicted in the diagram. Before discussing this in detail it is of value to introduce some definitions of radiometric quantities as these will serve to simplify
explanations and will allow correction equations to be properly formulated. Imagine the Sun as a source of energy emitting at a given rate of Joules per second, or Watts. This energy radiates through space isotropically in an inverse square law fashion so that at a given distance the sun’s emission can be measured as Watts per square meter (given as the power emitted divided by the surface area of a sphere at that distance). This power density is called irradiance, a property that can be used to describe the strength of any emitter of electromagnetic energy.

![Diagram of solar irradiance](image)

**Fig 4.2.** The effect of the atmosphere in determining various paths for energy to illuminate a (equivalent ground) pixel and to reach the sensor. *Source: Richards and Jia (2006)*

We can measure a level of solar irradiance at the earth’s surface. If the surface is perfectly diffuse then this amount is scattered uniformly into the upper hemisphere. The amount of power density scattered in a particular direction is defined by its density per solid angle, since equal amounts are scattered into equal cones of solid angle. This quantity is called radiance and has units of Watts per square meter per steradian (Wm$^{-2}$sr$^{-1}$).

The emission of energy by bodies such as the Sun is wavelength dependent, as seen in Fig. 4.3, so that often the term spectral irradiance is used to describe how
much power density is available incrementally across the wavelength range. Spectral irradiance is typically measured in Wm−2µm−1.

![Energy from perfect radiators (blackbodies) as a function of wavelength.](image)

**Fig. 4.3** Energy from perfect radiators (blackbodies) as a function of wavelength.  
*Source: Richards and Jia (2006)*

### 4.4. Atmospheric Correction

Atmospheric correction might be a necessary pre-processing technique in three cases. In the first, we may want to compute a ratio of the values in two bands of a multispectral image. The computed ratio will thus be a biased estimate of the true ratio. In the second situation, a research worker may wish to relate up-welling radiance from a surface to some property of that surface in terms of a physically based model. To do this, the atmospheric component present in the signal recorded by the sensor must be estimated and removed. The third case is that in which results or ground measurements made at one time (time 1) are to be compared with results achieved at a later date (time 2). Since the state of the atmosphere will undoubtedly vary from time 1 to time 2 it is necessary to correct the radiance values recorded by the sensor for the effects of the atmosphere. In addition to these three cases, it may
well be necessary to correct multispectral data for atmospheric effects even if it is intended for visual analysis rather than any physical interpretation.

4.5 Sources of Geometric Distortion

There are potentially many more sources of geometric distortion of image data than radiometric distortion and their effects are more severe. They can be related to a number of factors, including

(i) The rotation of the earth during image acquisition,
(ii) The finite scan rate of some sensors,
(iii) The wide field of view of some sensors,
(iv) The curvature of the earth,
(v) Sensor non-idealities,
(vi) Variations in platform altitude, attitude and velocity, and
(vii) Panoramic effects related to the imaging geometry.

4.6 Geometric Correction

Two techniques can be used to correct the various types of geometric distortion present in digital image data. One is to model the nature and magnitude of the sources of distortion and use these models to establish correction formulae. This technique is effective when the types of distortion are well characterized, such as that caused by earth rotation. The second approach depends upon establishing mathematical relationships between the addresses of pixels in an image and the corresponding coordinates of those points on the ground (via a map). These relationships can be used to correct the image geometry irrespective of the analyst’s knowledge of the source and type of distortion. This procedure will be treated first since it is the most commonly used and, as a technique, is independent of the platform used for data acquisition. Correction by mathematical modeling is discussed later. Before proceeding, it should be noted that each band of image data has to be corrected. However, since it can often be assumed that the bands are well registered to each other; steps taken to correct one band in an image can be used on all remaining bands.
4.6.1. Geo-referencing the Images

One of the most important geometric corrections is to determine the control points on the earth. By carefully studying the complications such as roads, rivers, residential areas, and junctions, we must make use of points as the bases for control on the earth which are not subject to alteration or change very little during the process of data collection. On the other hand, maps that are used to identify the coordinates of control points should not only conform to the satellite data but also the time of preparing them should be close to the satellite data. For example, in the developing countries, the road web is under development and there might be some roads that are not identified on the new maps but on the old ones; an example of such a situation is the case of research area in Malayer (Fig 4-4).
The geometric matching of images can be done in several ways. The most common method to compare images is the 'image to map' or 'image to image' method (Ben-Dor, 2001). In this method, several ground points of the image are compared with the points of the image or map that is geometrically corrected. Then, a mathematical algorithm is used to correct the image.

To obtain the control points on the earth, updated topographic maps with a scale of 125000 were used. By carefully studying the images and maps, the common
geometric points such as intersections were identified. After that, the common points were transferred from the map to the image. By analyzing the point-error, the points whose error exceeded one pixel were eliminated, and finally, the points with an error less than one pixel were selected as the final control points with which the images were geo-stationary referenced. For all the images, RMSE < 0.5 pixel was obtained.

The location of phenomena on geographical maps is identified through their latitude and longitude. The latitude and longitude of a phenomenon in the world is the difference between the angles and the longitude and the equator. In the geographical coordinate system, measurement is done according to the measurements based on degree, minute, and second where one degree of longitude in the equator equals 111 km, and in the latitude 60 degrees equals 55 km. Consequently, the longitudinal measurements hardly conform to reality, so to make a plane map of the globe's surface, an image system is required. Image systems are mainly based on a cone or cylinder. In World War II, due to the united military operations between allies, an image system was developed which was called UTM (Universal Transfers Mercator) (Ghohroodi, 2004). Since Iranian topographic maps of 1:50,000 have UTM and European 50 Image System, the researcher selected them to record the images.

To evaluate the results of geo-referencing the images in addition to incorporating RMSE<0.5 pixel, a digital layer of regional roads of the topographic maps with a scale of 1:25000 was provided. Then, this layer was transferred onto the images. With naked eyes, the conformity of vector lines with roads like them was evaluated where the results were all acceptable for all the images.

4.6.2 Use of Mapping Polynomials for Image Correction

An assumption that is made in this procedure is that there is available a map of the region corresponding to the image, that is correct geometrically. I then define two cartesian coordinate systems as shown in Fig. 4.5. One describes the location of points in the map (x, y) and the other coordinate system defines the location of pixels in the image (u, v). Now suppose that the two coordinate systems can be related via a pair of mapping functions f and g so that

\[ u = f(x, y) \] 
\[ v = g(x, y) \]

Eq. (4.6a)  
Eq. (4.6b)
If these functions are known then I could locate a point in the image knowing its position on the map. In principle, the reverse is also true. With this ability I could build up a geometrically correct version of the image in the following manner. First I define a grid over the map to act as the grid of pixel centers in the corrected image.

This grid is parallel to, or indeed could in fact be, the map coordinate grid itself, described by latitudes and longitudes, UTM coordinates and so on. For simplicity I will refer to this grid as the display grid; by definition this is geometrically correct. I then move over the display grid pixel centre by pixel centre and use the mapping functions above to find the corresponding pixel in the image for each display grid position. Those pixels are then placed on the display grid. At the conclusion of the process I have a geometrically correct image built up on the display grid utilizing the original image as a source of pixels. While the process is a straightforward one there are some practical difficulties that must be addressed. First, I do not know the explicit form of the mapping functions of (4.6). Secondly, even if we did, they may not point exactly to a pixel in the image corresponding to a display grid location; instead some form of interpolation may be required.

### 4.6.3 Mapping Polynomials and Ground Control Points

Since explicit forms for the mapping functions in (4.6) are not known they are generally chosen as simple polynomials of first, second or third degree. For example, in the case of second degree (or order)

\[
U = a_0 + a_1x + a_2y + a_3xy + a_4x^2 + a_5y^2
\]

\[
V = b_0 + b_1x + b_2y + b_3xy + b_4x^2 + b_5y^2
\]  

---

---

**Fig. 4.5:** Coordinate systems defined for the image and map, along with the specification of ground control points. Source: Richard. Remote Sensing Digital Image Analysis
Sometimes orders higher than three are used but care must be taken to avoid the introduction of worse errors than those to be corrected, as will be noted later. If the coefficients $a$ and $b$ in (4.7) were known then the mapping polynomials could be used to relate any point in the map to its corresponding point in the image as in the foregoing discussion. At present however these coefficients are unknown. Values can be estimated by identifying sets of features on the map that can also be identified on the image. These features, often referred to as ground control points (G.C.P), are well-defined and spatially small and could be road intersections, airport runway intersections, bends in rivers, prominent coastline features and the like. Enough of these are chosen (as pairs – on the map and image as depicted in Fig (4.5) so that the polynomial coefficients can be estimated by substitution into the mapping polynomials to yield sets of equations in those unknowns. Equations (4.7) show that the minimum number required for the second order polynomial mapping is six. Likewise, a minimum of three is required for the first order mapping and ten for the third order mapping. In practice, however significantly more than these are chosen and the coefficients are evaluated using least squares estimation. In this manner any control points that contain significant positional errors either on the map or in the image will not have an undue influence on the polynomial coefficients (Richard.J.and Jia2006).

4.6.4 Re-Sampling

Having determined the mapping polynomials explicitly by use of the ground control points the next step is to find points in the image corresponding to each location in the pixel grid previously defined over the map. The spacing of that grid is chosen according to the pixel size required in the corrected image and need not be the same as that in the original geometrically distorted version. For the moment suppose that the points located in the image correspond exactly to image pixel centers. Then those pixels are simply transferred to the appropriate locations on the display grid to build up the rectified image. This is the case in Fig. 4.6.
Fig. 4.6: Use of the mapping polynomials to locate points in the image corresponding to display grid positions. Source: Richard.J and Jia.2006

4.6.5 Interpolation

As is to be expected, grid centers from the map-registered pixel grid will not usually project to exact pixel centre locations in the image, as shown in Fig. 4.7, and some decision has to be made therefore about what pixel brightness value should be chosen for placement on the new grid. Three techniques can be used for this purpose. Nearest neighbor resampling simply chooses the actual pixel that has its centre nearest the point located in the image, as depicted in Fig. 4.7. This pixel is then transferred to the corresponding display grid location. This is the preferred technique if the new image is to be classified since it then consists of the original pixel brightnesses, simply rearranged in position to give correct image geometry.

Fig. 4.7: Determining display grid pixel brightness by nearest neighbor resampling, are discrete values of U and V.

Bilinear interpolation uses three linear interpolations over the four pixels that surround the point found in the image corresponding to a given display grid position. The process is illustrated in Fig. 4.8. Two linear interpolations are performed along the scan lines to find the interpolant \( \phi (i,j+j') \) and \( \phi (i+1,j+j') \) as shown.
These are given by

\[
\varphi(i, j + j') = j'\varphi(i, j + 1) + (1 - j')\varphi(i, j)
\]

\[
\varphi(i + 1, j + j') = j'\varphi(i + 1, j + 1) + (1 - j')\varphi(i + 1, j)
\]

Where \( \varphi \) is pixel brightness and \((i+i', j+j')\) is the position at which an interpolated value for brightness is required. The position is measured with respect to \((i, j)\) and assumes a grid spacing of unity in both directions. The final step is to interpolate linearly over \( \varphi(i, j + j') \) and \( \varphi(i + 1, j + j') \) to give

\[
\varphi(i + i', j + j') = (1 - i)\{j\varphi(i, j + 1) + (1 - j)\varphi(i, j)\} +
\]

\[
i\{j\varphi(i + 1, j + 1) + (1 - j)\varphi(i + 1, j)\}
\] (4.8)

Cubic convolution interpolation uses the surrounding sixteen pixels. Cubic polynomials are fitted along the four lines of four pixels surrounding the point in the image, as depicted in Fig. 4.9 to form four interpolants. A fifth cubic polynomial is then fitted through these to synthesize a brightness value for the corresponding location in the display grid.

Cubic convolution interpolation, or resampling, yields an image product that is generally smooth in appearance and is often used if the final product is to be treated by photo interpretation. However since it gives pixels on the display grid, with brightnesses that are interpolated from the original data, it is not recommended if classification is to follow since the new brightness values may be slightly different to the actual radiance values detected by the satellite sensors.
To calculate the degree of pixel brightness in this method, the brightness of the nearest pixel is used and its spectral pixel value is attributed to the nearest or adjacent pixel. In this method, the average brightness of the pixel is 16 which are close to the expected pixel calculated in the first map and then this amount is considered as the brightness for the new pixel. In this method, calculation is easier operation time is shorter. The advantage of this method is that the brightness of the calculated pixel changes a bit in comparison to the other methods. Therefore, in this method, after the reference ground operation which is the nearest neighbor was selected as an internal algorithm and all the images were revised by this method.

To evaluate the results of geo-referencing the images in addition to incorporating RMSE<0.5 pixel, a digital layer of regional roads of the topographic maps with a scale of 1:25000 was provided. Then, this layer was transferred onto the images. With naked eyes, the conformity of vector lines with roads like them was evaluated where the results were all acceptable for all the images.

4.7 Image Enhancement Techniques

4.7.1 Human Visual System

There are a number of theories that seek to explain the manner in which the human visual system operates. The facts on which these theories are based are both physical (to do with the external, objective world) and psychological (to do with our internal, conscious world). Concepts such as ‘red’ and ‘blue’ are an individual’s internal or sensory response to external stimuli. Light reaching the eye passes through the pupil and is focused onto the retina by the lens (Fig 4.10).
Fig. 4.10: Simplified diagram of the human eye. *Source: Mather, 2004*

The retina contains large numbers of light-sensitive photoreceptors, termed rods and cones. These photoreceptors are connected via a network of nerve fibres to the optic nerve, along which travel the signals that are interpreted by the brain as images of our environment. There are around 100 million rod-shaped cells on the retina, and 5 million cone-shaped cells. Each of these cells is connected to a nerve, the junction being called a synapse. The way in which these cells respond to light is through alteration of a molecule known as chromospheres. Changes for light reaching chromospheres produce signals that pass through the nerve fibre to the optic nerve.

Signals from the right eye are transmitted through the optic nerve to the left side of the brain, and vice versa. It is generally accepted that the photoreceptor cells, comprising the rods and cones, differ in terms of their inherent characteristics. The rod-shaped cells respond to light at low illumination levels, and provide a means of seeing in such conditions. This type of vision is called Scotopic. It does not provide any colour information, though different levels of intensity can be distinguished. Cone or photopic vision allows the distinction of colours or hues and the perception of the degree of saturation (purity) of each hue as well as the intensity level. However, photopic vision requires a higher illumination level than doe’s Scotopic vision. Colour is thought to be associated with cone vision because there are three kinds of cones, each kind being responsive to one of the three primary colours of light (red, green and blue). This is called the tri-stimulus theory of colour vision. Experiments have shown that the number of blue-sensitive cones is much less than the number of red- or green-sensitive cones, and that the areas of the visible spectrum in which the three kinds of cones respond do, in fact, overlap. There are other theories of colour (Land, 1977; Tyo et al., 2003) but the tri-stimulus theory is an attractive one not merely because it is simple but because it provides the idea that colours can be formed by adding red, green and blue light in various combinations.
A model of ‘colour space’ can be derived from the idea that colours are formed by adding together differing amounts of red, green and blue light. Fig. 4.11 shows a geometrical representation of the RGB (red, green, blue) colour cube. The origin is at the vortex of the cube marked ‘black’ and the axes are black-red, black-green and black-blue. A specific colour can be specified by its coordinates along these three axes. These coordinates are termed (R, G, B) triples. Note that white light is formed by the addition of maximum red, maximum green and maximum blue light. The line joining the black and white vertices of the cube represents colours formed by the addition of equal amounts of red, green and blue light; these are shades of grey. Colour television makes use of the RGB model of colour vision.

Fig. 4.11 *Generation of the hexcone CST.* Three possible RGB cubes are shown at the top and the resulting projections onto the plane perpendicular to the grey line are shown below. Such projections for all possible sub-cubes define the hexcone. The projection of a particular RGB point, P, into one of the hexagons is shown. At P, the intensity is the center grey value, the hue is the angle around the hexagon, and the saturation is the fractional distance from the center to the perimeter. The hue and saturation were defined as simple linear, rather than trigonometric, relations to make the original algorithm efficient (Smith, 1978).
A colour picture is obtained when the amounts of red, green and blue at each point are unequal, and so – in terms of the RGB cube – the colour at any pixel is represented by a point that is located away from the black–white diagonal line.

The RGB colour cube model (fig. 4.11) links intuitively with the tri-stimulus theory of colour vision and also with the way in which a colour television monitor works. Other colour models are available which provide differing views of the nature of our perception of colour. The HSI model uses the concepts of hue (H), saturation (S) and intensity (I) to explain the idea of colour. Hue is the dominant wavelength of the colour we see; hues are given names such as red, green, orange and magenta. The degree of purity of a colour is its saturation. A pure colour is 100% saturated. Intensity is a measure of the brightness of a colour. Figure 5.4 shows a geometrical representation of the HSI model. Hue is represented by the top edge of a six-sided cone (hexcone) with red at 0°, green at 120° and blue at 240°. Pure unsaturated and maximum intensity colour s lie around the top edge of the hexcone. Addition of white light produces less saturated, paler, colour s and so saturation can be represented by the distance from the vertical axis of the hexcone. Intensity (sometimes called value) is shown as a distance above the apex of the hexcone, increasing upwards as shown by the widening of the hexcone. The point marked black has no hue, nor do any of the shades of grey lying on the vertical axis between the black and white points. All these shades of grey, including white and black, have zero saturation. The RGB model of colour is that which is normally used in the study and interpretation of remotely-sensed images, and in the rest of this chapter we will deal exclusively with this model.

Further details of the material covered in this section can be found in Foley et al. (1990, 1994), Smith (1978), Williams and Becklund (1972) and Stimson (1974). Drury (1993) discusses the properties of the human visual system in relation to the choice of techniques for processing remotely sensed images for geological applications.

4.8 False Colour Composite Images

From the composition of three different bands and allocating each colour of the main colour s, Red, Green, and Blue to each band, a colour full image is made up. In a false colour composite image, red is allocated to the infrared band, green colour
to the red band, and blue to the green band; therefore, the mantles of vegetation which enjoy the most reflection and/or radiation in the infrared band is seen in red colour, water in blue and bare soil in brown-gray. If false colour composite images are accurately and properly prepared and the histograms of the bands used are facially similar (similar in appearance), the obtained image will be well-composed and will be subject to a good interpretation. The quality of colour images is more significant when the trivial data are minimized and more useful data are most made use of. Band composites are selected in different methods. One is naked-eye comparison of images obtained from different composites, which is difficult and time-consuming. Another method is based on the statistical criteria of images used in developing colour images. Among the band composite selection methods are the Optimum Index Factor (OIF) Method, Maximum Variance-Covariance Matrix Determination and Main Factor Analysis (Alavipanah.K., 2003).

It has been experientially proved that for the district of the dry land wheat the spectrum can be presented by NIR_R_G which is attributed to blue, red, green, respectively (Figure, 4.12). Thus in this research one of the spectra which is mostly used in training areas was used in the present study.

![False colour composite image (FCC)](image)
4.8.1. Band Composite Determination Indexes

To better use the multi-spectral data, it feels necessary to determine the best band composite. To determine and select the best composition through ranked-eye comparison of images is hard and time-consuming. Therefore, one can use the digital method of parameters called OIF for the two following purposes:

a. To determine the most appropriate band composite for the development of false colour images
b. To determine the most appropriate bands for digital classification

A large number of band composites resulting from spectral bands shall be made and compared. Based on the following formula, the triple composites resulting from the bands used can be calculated

\[
\binom{N}{3} = \frac{N!}{3!(N-3)!}
\]

\[\binom{N}{3}\] is the number of triple band composites and \(N\) is the number of bands. Since the image used enjoys four bands, then we will have:

\[
\binom{4}{3} = \frac{4!}{3!(4-3)!}
\]

The amount of OIF can be obtained in terms of the variance and correlation between the bands,

\[
OIF = \frac{\sum_{i=1}^{3} SD_i}{\sum_{j=1}^{3} CC_j}
\]

Where \(\sum_{j=1}^{3} SD_i\) the total standard deviations of three are bands and \(\sum_{j=1}^{3} CC_j\) is the absolute value of the correlation coefficient between the two bands from the three bands. The triple-composite that enjoys the highest OIF can be selected for 'FCC' since it contains the most information or data. (Alavipanah.K. 2003).

4.9 Contrast Enhancement

Enhancements are used to make it easier for visual interpretation and understanding of imagery. The advantage of digital imagery is that it allows us to
manipulate the digital pixel values in an image. Although radiometric corrections for illumination, atmospheric influences, and sensor characteristics may be done prior to distribution of data to the user, the image may still not be optimized for visual interpretation. Remote sensing devices, particularly those operated from satellite platforms, must be designed to cope with levels of target/background energy which are typical of all conditions likely to be encountered in routine use. With large variations in spectral response from a diverse range of targets (e.g. forest, deserts, snowfields, water, etc.) no generic radiometric correction could optimally account for and display the optimum brightness range and contrast for all targets. Thus, for each application and each image, a custom adjustment of the range and distribution of brightness values is usually necessary. In raw imagery, the useful data often populates only a small portion of the available range of digital values (commonly 8 bits or 256 levels). Contrast enhancement involves changing the original values so that more of the available range is used, thereby increasing the contrast between targets and their backgrounds. The key to understanding contrast enhancements is to understand the concept of an image histogram. A histogram is a graphical representation of the brightness values that comprise an image. The brightness values (i.e. 0-255) are displayed along the x-axis of the graph. The frequency of occurrence of each of these values in the image is shown on the y-axis (CCR, 2008).

By manipulating the range of digital values in an image, graphically represented by its histogram, we can apply various enhancements to the data. There are many different techniques and methods of enhancing contrast and detail in an image; we will cover only a few common ones here.

4.9.1 Linear contrast stretch

The simplest type of enhancement is a linear contrast stretch. In its basic form the linear contrast-stretching technique involves the translation of the image pixel values from the observed range $V_{\text{min}}$ to $V_{\text{max}}$ to the full range of the display device (generally 0–255, which assumes 8-bit display memory). $V$ is a pixel value observed in the image under study, with $V_{\text{min}}$ being the lowest pixel value in the image and $V_{\text{max}}$ the highest. The pixel values are scaled so that $V_{\text{min}}$ maps to a value of 0 and $V_{\text{max}}$ maps to a value of 255. Intermediate values retain their relative positions, so that the observed pixel value in the middle of the range from $V_{\text{min}}$ to $V_{\text{max}}$ maps to 127. Note that we cannot map the middle of the range of the observed pixel values to 127.5
(which is exactly halfway between 0 and 255) because the display system can store only the discrete levels 0, 1, 2... 255.

This involves identifying lower and upper bounds from the histogram (usually the minimum and maximum brightness values in the image) and applying a transformation to stretch this range to fill the full range. In our region images, the minimum value (occupied by actual data) in the histogram is 65 and the maximum value is 162. These 93 levels occupy less than one-third of the full 256 levels available. A linear stretch uniformly expands this small range to cover the full range of values from 10 to 254. This enhances the contrast in the image with light-toned areas appearing lighter and dark areas appearing darker, making visual interpretation much easier. This graphic illustrates the increase in contrast in an image before (above) and after (down) a linear contrast stretch.

Fig 4.13: Original graphic of linear stretch

![Original graphic of linear stretch]

Fig 4.14: Linear Stretched graphic

![Linear Stretched graphic]
The dynamic range of the image is low, and don’t complete details can be seen. The histograms of this image are shown in Figures 4.13 & 4.14. The image showed in fig 4.16 after a linear contrast stretch. The linear stretch maps the dynamic range of the image (65-162 in this case) to the dynamic range of the display (10–254).

4.9.2 Histogram Equalization

The whole image histogram, rather than its extreme points, is used in the more sophisticated methods of contrast enhancement. Hence, the shape as well as the extent of the histogram is taken into consideration. The first of the two methods described here is called histogram equalization. Its underlying principle is straightforward. It is assumed that in a well-balanced image the histogram should be such that each available brightness level contains an approximately equal number of pixel values, so that the histogram of these displayed values is almost uniform (though not all 256 classes are necessarily non-zero). If this operation, called histogram equalization, is performed then the entropy of the image, which is a measure of the information content of the image, will be increased.

Because of the nature of remotely-sensed digital images, whose pixels can take on only the discrete values 0, 1, 2, . . . , 255 it may be that there are ‘too many’
pixel values in one class, even after equalization. However, it is not possible to take some of the values from that over-populated class and redistribute them to another class, for there is no way of distinguishing between one pixel value of ‘x’ and another of the same value. It is rare, therefore, for a histogram of the pixel values of an image to be exactly uniformly distributed after the histogram equalization procedure has been applied.

The experiments show that the effect of the histogram equalization procedure is to spread the range of pixel values present in the input image over the full range of the display device; in the case of a colour monitor. This ranges normally 256 levels for each of the primary colours (red, green, blue). The relative brightness of the pixels in the original image is not maintained. In addition, in order to achieve the uniform histogram the number of levels used is usually reduced. This is because those
histogram classes with relatively few members are amalgamated to make up the target number. In the areas of the histogram that have the greatest class frequencies the individual classes are stretched out over a wider range. The effect is to increase the contrast in the densely populated parts of the histogram and to reduce it in the other, more sparsely populated areas. If there are relatively few discrete pixel values after the equalization process then the result may be unsatisfactory compared to the simple linear contrast stretch. The image shown in Fig. 4.18 after equalization contrast stretch. The equalization stretch maps the dynamic range of the image (65-162 in this case) to the dynamic range of the display (35–253).

4.10 Filtering Techniques

Filtering of digital images is used to remove, reduce or amplify specific frequency components of an image. A digital filter can be used to extract a particular spatial scale component from a digital image. The slowly varying background pattern in the image can be envisaged as a two-dimensional waveform with a long wavelength or low frequency; hence a filter that separates this slowly varying component from the remainder of the information present in the image is called a low-pass filter. Conversely, the more rapidly varying detail is like a two-dimensional waveform with a short wavelength or high frequency.

A filter to separate out this component is called a high-pass filter. These two types of filter are considered separately. Low-frequency information allows the identification of the background pattern, and produces an output image in which the detail has been smoothed or removed from the original (input) image (hence low-pass filtering can be thought of as a form of blurring the image). High-frequency information allows us either to isolate or to amplify the local detail. If the high-frequency detail is amplified by adding back to the image some multiple of the high-frequency component three approaches are used to separate the scale components of the spatial patterns exhibited in a remotely sensed image. The first is based upon the transformation of the frequency domain representation of the image into its scale or spatial frequency components using the Discrete Fourier Transform. While the second method is applied directly to the image data in the spatial domain. A third, more recent, development is that of the discrete wavelet transform, which uses both frequency (scale) and spatial representations of the data (Mather, 2004).
4.10.1 Smoothing Filters

Before the topic of smoothing a two-dimensional image is considered, then necessary to look at a simpler expression of the same problem, which is the smoothing of a one-dimensional pattern. Figures 4.19 & 4.20 showed a plot of grey levels along a cross section from the top left corner (0, 0) to the bottom right corner (511, 511). Figure 4.19 shows the cross-section for the unfiltered image, while Figure 4.20 shows the same cross section after the application of a low pass (smoothing) filter. Clearly, the level of detail has been reduced and the cross section curve is more generalized, though the main peaks are still apparent. Figure 4.21 displays another plot showing grey level value (vertical axis) against position across a scan-line of a digital image. The underlying pattern is partially obscured by the presence of local patterns and random noise. If the local variability, and the random noise, were to be removed then the overall pattern would become more clearly apparent and a general description of trends in the data could then be more easily made. The solid line in Figure 7.2 is a plot of the observed pixel values against position along the scan line, while the dotted line and the broken line represent the output from median and moving-average filters, respectively. These filters are described below. Both produce smoother plots than the raw data curve, and the trend in the data is more easily seen. Local sharp fluctuations in value are removed. These fluctuations represent the high-frequency component of the data and may be the result of local anomalies or of noise. Thus, low-pass filtering is used by Crippen (1989), Eliason and McEwen (1990), and Pan and Chang (1992) to remove banding effects on remotely sensed images. While Dale et al. (1996) uses a low-pass filter in an attempt to smooth away the effects of image-to-image misregistration. Images 4.22 indicated the different kinds of smooth filter in the study area.
Fig. 4.19: Cross section from the top left to the bottom right-hand corner of the image

![Graph](image1.png)

Fig 4.20: Cross section between the same points as used in Figure 4.19 after the application of a smoothing filter. The reduction in detail is clearly apparent.

*Source: Mather, 2004*

![Graph](image2.png)

Fig 4.21: One-dimensional data series showing the effect of median (low-pass) filter and moving average (low-pass) filtering. Mather, 2004
Fig. 4.22: Smooth filters
4.10.2 Sharpening (High-Pass) Filter

High-pass filters do the opposite and serve to sharpen the appearance of fine detail in an image. One implementation of a high-pass filter first applies a low-pass filter to an image and then subtracts the result from the original, leaving behind only the high spatial frequency information.

High-pass filters are used routinely in image processing, especially when high-frequency information is the focus of interest. For instance, Ichoku et al. (1996) use the ‘image minus Laplacian’ filter as part of a methodology to extract drainage-pattern information from satellite imagery.

![Sharpen Filter Image](image)

4.10.3 Edge Detector Filter

A high-pass filtered image that is added back to the original image is a high-boost filter and the result is a sharpened or de-blurred image. The high-pass filtered image can be used alone, particularly in the study of the location and geographical distribution of ‘edges’. An edge is a discontinuity or sharp change in the grey scale value at a particular pixel point and it may have some interpretation in terms of cultural features, such as roads or field boundaries, or in terms of geological structure or relief.
One of the main uses of edge-detection techniques has been in the enhancement of images for the identification and analysis of geological lineaments (O’Leary et al., 1976). Other application of edge-detection techniques includes the determination of the boundaries of homogeneous regions (segmentation) in synthetic aperture radar images in order to segment those images (Quegan and Wright, 1984).

The most commonly used filters operate in the spatial domain and can be divided into low-pass or smoothing filters and high-pass or sharpening filters. Uses of smoothing filters include the suppression of noise and other unwanted effects, such as the banding phenomenon, which affects some IRS LIS_III images. Sharpening filters are used to improve the visual interpretability of the image by, for example, de-blurring the signal. Edge and line detection is seen as an extension of the technique of image sharpening.

Therefore, Filtering in the frequency domain is achieved via the application of the principles of the Fourier transform. While these methods are inherently, more flexible than are spatial domain filters the computational cost of applying them is considerable, and they are often understood less intuitively. Recent developments in computer hardware, especially random access memory and processor speed, mean that frequency-domain methods may become more popular (Mather, 2004).
4.12 Image Classification

Image classification is the process of making quantitative decisions from image data, grouping pixels or regions of the image into classes intended to represent different physical objects or types. The output of the classification process may be regarded as a thematic map rather than as an image. The majority of classification techniques use mainly the radiometric data (pixel value) present in the image, with little or no reference to spatial variation, and these techniques will be described first. These techniques can be thought of as follows.

Suppose we have an n-band image, and the pixel values in each band can take k different value (e.g. k = 256 for 8 bit data). The number of possible coordinates in the n-dimensional pixel-value space kn, a number that can very easily exceed a million (it is over 16 million for the case where n= 3 and k= 256). However, it is extremely unlikely that the image represents a million or more different classes of data, or that we could make use of the information if it did. What we require is some simplification of the data in the n-dimensional pixel-value space, identifying a value within this space as representing a single class of data.

4.11.1 The Classification Process

Traditionally, thematic classification of an image involves several steps, as shown in Fig. 4.25:

- Feature extraction—Transformation of the multispectral image by a spatial or spectral transforms to a feature image. Examples are selection of a subset of bands, a PCT to reduce the data dimensionality, or a spatial smoothing filter. This step is optional, i.e., the multispectral image can be used directly, if desired.
- Training—Selection of the pixels to train the classifier to recognize the desired themes, or classes, and determination of decision boundaries, which partition the feature, space according to the training pixel properties. This step is either supervised by the analyst or unsupervised with the aid of a computer algorithm.
- Labelling—Application of the feature space decision boundaries to the entire image to label all pixels. If the training was supervised, the labels are already associated with the feature space regions; if it was unsupervised, the analyst must now assign labels to the regions. The output map consists of one label for each pixel.
The result is a transformation of the numerical image data into descriptive labels that categorize different surface materials or conditions. By virtue of the labelling process, we have presumably converted the data into a form that has informational value.

A large reduction in data quantity also takes place during classification; the multispectral image, consisting of several to hundreds of bands with at least 8bits/pixel/band, is reduced to a map consisting of as few as a dozen or so category labels.
Fig. 4.25: The data flow in a classification process.
Fig. 4.26: Classification as a data compression technique, the training step of Fig 4.25 has been previously performed to create the codebook. The left column is the encoding stage that takes place at the source transmitter, and the right column is the decoding stage that takes place at the receiver. The decoded image may or may not be a perfect reconstruction, as discussed in the text.

4.11.2 Image Classification Methodologies

In principle, classification of multispectral image data should be straightforward. However to achieve results of acceptable accuracy care is required first in choosing the analytical tools to be used and then in applying them. In the following the classical analytical procedures of supervised and unsupervised classification are examined from an operational point of view, with their strengths and weaknesses highlighted. These approaches are often acceptable; however more often a judicious combination of the two will be necessary to attain optimal results.

4.11.3 Supervised Classification

The underlying requirement of supervised classification techniques is that the analyst has available sufficient known pixels for each class of interest that representative signatures can be developed for those classes. These prototype pixels are often referred to as training data, and collections of them, identified in an image and used to generate class signatures, are called training fields. The step of determining class signatures is frequently called training.
Signatures generated from the training data will be of a different form depending on the classifier type to be used. For parallelepiped classification the class signatures will be the upper and lower bounds of brightness in each spectral band. For minimum distance classification the signatures will be the mean vectors of the training data for each class, while for maximum likelihood classification both class mean vectors and covariance matrices constitute the signatures. For neural network and support sector machine classifier the collection of weights define the boundaries between classes.

While they do not represent class signatures as such they are the inherent properties of the classifier, learnt from training data that allow classes to be discriminated. By having the labelled training data available beforehand, from which the signatures are estimated, the analyst is, in a relative sense, teaching the classification algorithm to recognize the spectral characteristics of each class, thereby leading to the term supervised as a qualification relating to the algorithm’s learning about the data with which it has to work.

As a proportion of the full image to be analyzed the amount of training data would represent less than 1% to 5% of the pixels. The learning phase therefore, in which the analyst plays an important part in the a priori labeling of pixels, is performed on a very small part of the image. Once trained, the classifier is then asked to attach labels to all the image pixels by using the class estimates provided to it.

4.11.4 Steps in Supervised Classification

Supervised classification is the procedure most often used for quantitative analysis of remote sensing image data. It rests upon using suitable algorithms to label the pixels in an image as representing particular ground cover types, or classes. A variety of algorithms is available for this, ranging from those based upon probability distribution models for the classes of interest to those in which the multispectral space is partitioned into class-specific regions using optimally located surfaces. Irrespective of the particular method chosen, the essential practical steps usually include:

1. Decide the set of ground cover types into which the image is to be segmented. These are the information classes and could, for example, be water, urban regions, croplands, rangelands, etc.
2. Choose representative or prototype pixels from each of the desired set of classes. These pixels are said to form training data. Training sets for each class can be established using site visits, maps, air photographs or even photo interpretation of a colour composite product formed from the image data. Often the training pixels for a given class will lie in a common region enclosed by a border. That region is then often called a training field.

3. Use the training data to estimate the parameters of the particular classifier algorithm to be used; these parameters will be the properties of the probability model used or will be equations that define partitions in the multispectral space. The set of parameters for a given class is sometimes called the signature of that class.

4. Using the trained classifier, label or classify every pixel in the image into one of the desired ground cover types (information classes). Here the whole image segment of interest is typically classified. Whereas training in Step 2 may have required the user to identify perhaps 1% of the image pixels by other means, the computer will label the rest by classification.

5. Produce tabular summaries or thematic (class) maps which summarize the results of the classification.

6. Assess the accuracy of the final product using a labeled testing data set.

In practice it might be necessary to decide, on the basis of the results obtained at Step 6, to refine the training process in order to improve classification accuracy. Sometimes it might even be desirable to classify just the training samples themselves to ensure that the signatures generated at Step 3 are adequate. It is our objective now to consider the range of algorithms that could be used in 3 and 4. In so doing it will be assumed that the information classes each consists of only one spectral class, so that the two names will be used synonymously. By making this assumption, problems with establishing sub-classes will not distract from the algorithm development to be given.

4.11.5 Determining the Training Samples

The major step in straightforward supervised classification is the prior identification of training pixels. This may involve the expensive enterprise of field visits, or may require use of reference data such as topographic maps and air photographs. In the latter, a skilled photo interpreter may be required to determine the
training data. Once training fields are suitably chosen they have to be related to the pixel addresses in the satellite imagery. Sometimes training data can be chosen by photo interpretation from image products formed from the multispectral data to be classified. Generally however this is restricted to major cover types and again can require a great deal of photo interpretive skill if more than a simple segmentation of the image is required.

Some image processing systems have digitizing tables that allow map data – such as polygons of training pixels, i.e. training fields– to be taken from maps and superimposed over the image data. While this requires a registration of the map and image, it represents an unbiased method for choosing the training data. It is important however, as with all training procedures based upon field or reference data, which the training data be recorded at about the same time as the multispectral data to be classified. Otherwise, errors resulting from temporal variations may arise.

It is necessary to identify training data at least for all classes of interest and preferably for all apparent classes in the segment of image to be analyzed. In either case, and particularly if the selection of training data is not exhaustive or representative, it is prudent to use some form of threshold or limit if the classification is of the minimum distance or maximum likelihood variety; this will ensure poorly characterized pixels are not erroneously labelled. Limits in minimum distance classification can be imposed by only allowing a pixel to be classified if it is within a pre specified number of standard deviations of the nearest mean. For maximum likelihood classification a limit may be applied by the use of thresholds on the discriminate functions. Having so limited a classification, pixels in the image that are not well represented in the training data will not be classified. This will identify weaknesses in the selection of the training sets, which can then be rectified and the image re-classified. Repeated refinement of the training data and reclassification in this manner can be carried out using a representative portion of the image data.

In the supervised classification, analysts' classification mainly relies on the training samples and their spectral characteristics. Selecting training areas is a combination of science and art and it requires the analysts' close association with the image and its data. It also requires reference and spatial data of the region. The main
purpose in selecting training samples is to provide a statistical collection that
describes the spectral reflection/radiation pattern of each land mantle which is
classified on the image. To reach an acceptable result in classification, the entire
spectral classes must enjoy adequately and well-thought-of sample that represents that
class. It is also required to provide training samples to select the most appropriate
band collection for the classification. The classification is done through calculating
statistical descriptive measures such as the mean and the standard deviation of each
class in the training samples and its calculation in the entire image through each
algorithm of the classifier. Selecting appropriate training samples requires a precise
and accurate classification and the evaluation of classification accuracy is based on
the training and experimental samples. On the other hand, one of the evaluation
methods of accuracy is based on error matrix and the simplest description for
expressing accuracy is through using the overall accuracy. In fact what is considered
important in the evaluation process is the examination of classified image conformity
with the ground reality. To evaluate the accuracy of different classifications and
identifying which classification has less error, it is necessary to provide a sufficient
number of training samples from the respective phenomena where one can easily
evaluate the accuracy of classification by using the error matrix. The training samples
must enjoy a normal distribution and must represent each of the related classes.
Moreover, training samples must enjoy an appropriate number and dispersion as
properly required for each class proportion in the area under study. In fact, the
position and scattering of training areas in the entire image increase the probability
that these areas may represent all the spectral changes of ground phenomena. The
reason for choosing scattered training areas is probably the different conditions for a
phenomenon in different parts of an image. For example, farmland variation, soil
salinity, pastures, soil type, etc. can remarkably affect the spectral reflection of a
class. Therefore, for farmland classes, saline soils, and pastures, the training areas
with required dispersion were chosen. Selecting an adequate number of samples from
each class is required because for classification through majority likelihood method
the calculation of variance-covariance matrix feels necessary. Thus, if the number of
pixels composing a class is sufficient, problems will arise in calculation. The
minimum number of training samples required for each class is $N=10$ and the
maximum $N=100$ ($N$ represents the number of bands used in classification). The
larger the number of training samples, the better the results of spectral classes. On the other hand, the dispersion of a training area for one specific class on the image is better than that of an area with a large number of pixels chosen. For examples, for class X, 20 locations with 2 pixels is much better than one location with 800 pixels (Lillesand, 2004). In the present study, while sampling with the Feature Space Plot (scatter-gram) and later with spectral gram evaluation, by employing an appropriate colour image, through naked eye evaluation of the image, and by using the ground sampling of the areas with GPS, the homogeneous areas on the image with the highest dispersion for each of the training classes were selected and their classification and the training samples were evaluated and corrected.

4.11.6 Selecting Training Samples

In each of the classes and subclasses which enjoyed the same reflection on the image and some of which were selected as the training samples, their coordinate features were extracted and saved in ILWIS environment in dot-file format. This file was then saved in GPS. The dispersion of sites within the units is according to random classification.

![Figure 4.27: The concept of random classified sampling](image)

To enhance the accuracy of sampling, each site was selected in an area which could represent a remarkable surface and which had the least irregularities and the most homogeneity on the surface. The barren and saline lands were selected in such a way that each site could enjoy an area of ten hectares with a bare surface and without any or with the least mantle of vegetation. The dry-farmed wheat sites, gardens, alfalfa farms, and pastures were selected in such a way that they could represent the
truth. In general, an appropriate method for the evaluation of image pixels and ground pixels adjustable with the image is the sampling with 4x4 pixel area (Ben-Dor, 2001). Therefore, in each site (the site for GPS) with a dimension of 4x4 pixel, the central pixel and the four points around it were sampled (Fig. 4.28).

Fig.4.28: Overview from each sample site

4.11.7 Feature Selection

The cost of the classification of a full image segment is reduced if bands or features that do not aid discrimination significantly are removed. After training is complete feature selection can be carried out using the separability measures.

The recommended measures are transformed divergence, if maximum likelihood signatures have been generated or Euclidean distance if the signatures have been prepared for minimum distance classification.

Separability measures can also be used to assess whether any pair of classes are so similar in multispectral space that significant misclassification will occur if they are both used.

Two types of output are available from a classification. One is the thematic (or class) map in which pixels are given a label (represented by a colour or symbol) to identify them with a class. The other output is a table that summarizes the number of pixels in the image found to belong to each class. The table can be interpreted also as a table of areas, in hectares.

4.11.8 Determining the Data Class Available in the Region

In order to convert the spectral classes to data, an analyst must have sufficient data taken from the surface phenomena and different types of mantles. Thus, through
a field work, face to face interviews with the local experts and farmers were conducted where the researcher could get an agricultural calendar. The agricultural calendar of the region with an emphasis on farming seasons when the ground surface is covered with mantles of vegetation is briefly presented in Table 4-1.

Table 4.1: The agricultural mantle and garden status in Malayer in brief

<table>
<thead>
<tr>
<th>Canopy period</th>
<th>Harvest date</th>
<th>Implant date</th>
<th>Land use</th>
</tr>
</thead>
<tbody>
<tr>
<td>15th March - 1st Jul.</td>
<td>10th Jul. to 20th Aug.</td>
<td>4th Dec to 15th Nov.</td>
<td>Wheat/barley</td>
</tr>
<tr>
<td>5th Jun – 1st Aug</td>
<td>20th Aug.</td>
<td>1st May to 15th May</td>
<td>corn</td>
</tr>
<tr>
<td>1st May- 27th Jul.</td>
<td>10th Aug- 30th Aug</td>
<td>-</td>
<td>vine garden</td>
</tr>
<tr>
<td>5th Jun – 5th Aug</td>
<td>28th Aug.----</td>
<td>5th May to 15th May</td>
<td>Potato</td>
</tr>
<tr>
<td>10 May to 1st Jul.</td>
<td>15th Jul. to 30th Jul.</td>
<td>10th March to 25th March</td>
<td>Cereal dry land</td>
</tr>
<tr>
<td>1st May to 20th Dec.</td>
<td>1st Jun.</td>
<td>25th March to 5th May.</td>
<td>Alfalfa</td>
</tr>
</tbody>
</table>

In the months of June and July, wheat, barley, alfalfa and other annual plants enjoy the highest growth and the earth is usually covered by vegetation mantles. From late July, when most of wheat and barley are harvested to early November, the only green mantle of the region is the gardens, alfalfa, and corn plantations, and poor pastures are cleared by the cattle and herds of sheep's having grazed them up. Thus, the topographic maps, field studies, naked-eye interpretation of colour image and 18 classes of data were defined for the study scope-limit. Each class was given a special code or name which was selected in such a way that it could represent each class. The coordinate features of one point and other similar points of each class along with the characteristics of the soil are presented here:

4.11.9 Class Separability

One of the most important stages of classification of images is the study of separability of classes. To get this, the spectral mean and standard deviation of the training samples are compared. The method used in the present study was the Feature space (FS) which was displayed on the monitor with the dispersion and/or intervening of the samples.
4.11.10 Selecting the Best Band Composite

The purpose of this stage is to select bands which have highly a contributing effect on classification and to leave out those which are not effective on classification. In processing the satellite digital data, precision and exactness in selecting appropriate bands is remarkably important for classification.

4.11.11 Maximum Likelihood Classification

Maximum likelihood classification is the most common supervised classification method used with remote sensing image data. This is developed in the following in a statistically acceptable manner.

4.11.12 Bayes’ Classification

Let the spectral classes for an image be represented by

\[ \omega_i, i = 1, \ldots, M \]

where M is the total number of classes. In trying to determine the class or category to which a pixel vector \( x \) belongs it is strictly the conditional probabilities

\[ p(\omega_i | x), i = 1, \ldots, M \]

that is of interest. The measurement vector \( x \) is a column of brightness values for the pixel. It describes the pixel as a point in multispectral space with co-ordinates defined by the brightness’s, as shown in the simple two-dimensional. The probability \( p(\omega_i | x) \) gives the likelihood that the correct class is \( \omega_i \) for a pixel at position \( x \). Classification is performed according to

\[ x \in \omega_i, \text{ if } p(\omega_i | x) > p(\omega_j | x) \text{ for all } j \neq i \quad (4.9) \]

i.e., the pixel at \( x \) belongs to class \( \omega_i \) if \( p(\omega_i | x) \) is the largest. This intuitive decision rule is a special case of a more general rule in which the decisions can be biased according to different degrees of significance being attached to different incorrect classifications. The general approach is called Bayes’ classification.

4.12.13 The Maximum Likelihood Decision Rule

Despite its simplicity, the \( p(\omega_i | x) \) in (4.9) is unknown. Suppose however that sufficient training data is available for each ground cover type. This can be used to estimate a probability distribution for a cover type that describes the chance of finding a pixel from class \( \omega_i \), say, at the position \( x \). Later the form of this distribution function will be made more specific. For the moment however it will be retained in
general terms and represented by the symbol \( p(x|\omega_i) \). There will be as many \( p(x|\omega_i) \) as there are ground cover classes. In other words, for a pixel at a position \( x \) in multispectral space a set of probabilities can be computed that give the relative likelihoods that the pixel belongs to each available class.

The desired \( p(\omega_i|x) \) in (4.9) and the available \( p(x|\omega_i) \) - estimated from training data – are related by Bayes’ theorem (Freund, 1992):

\[
p(\omega_i|x) = p(x|\omega_i)p(\omega_i)/p(x) \tag{4.10}
\]

Where \( p(\omega_i) \) is the probability that class \( \omega_i \) occurs in the image. If, for example, 15% of the pixels of an image happen to belong to class \( \omega_i \) then \( p(\omega_i) = 0.15 \); \( p(x) \) in (4.10) is the probability of finding a pixel from any class at location \( x \). It is of interest to note in passing that

\[
p(x) = \sum_{i=1}^{N} p(x|\omega_i)p(\omega_i),
\]

although \( p(x) \) itself is not important in the following. The \( p(\omega_i) \) is called a priori or prior probabilities, since they are the probabilities with which class membership of a pixel could be guessed before classification. By comparison the \( p(\omega_i|x) \) are posteriori probabilities. Using (4.10) it can be seen that the classification rule of (4.9) is:

\[
x \in \omega_i \text{ if } p(x|\omega_i)p(\omega_i) > p(x|\omega_j)p(\omega_j) \text{ for all } j \neq i \tag{4.11}
\]

where \( p(x) \) has been removed as a common factor. The rule of (4.11) is more acceptable than that of (4.9) since the \( p(x|\omega_i) \) are known from training data, and it is conceivable that the \( p(\omega_i) \) are also known or can be estimated from the analyst’s knowledge of the image. Mathematical convenience results if in (4.11) the definition

\[
g_i(x) = \ln \{p(x|\omega_i)p(\omega_i)\}
\]

\[
= \ln p(x|\omega_i) + \ln p(\omega_i) \tag{4.12}
\]

is used, where Ln is the natural logarithm, so that (4.11) is restated as

\[
x \in \omega_i \text{ if } g_i(x) > g_j(x) \text{ for all } j \neq i \tag{4.13}
\]

This is, with one modification to follow, the decision rule used in maximum likelihood Classification; the \( g_i(x) \) is referred to as discriminant functions.
4.11.14 Thresholds

It is implicit in the foregoing development that pixels at every point in multispectral space will be classified into one of the available classes $\omega_i$, irrespective of how small the actual probabilities of class membership are. This is illustrated for one dimensional data in Fig. 4.29a. Poor classification can result as indicated. Such situations can arise if spectral classes (between 1 and 2 or beyond 3) have been overlooked or, if knowing other classes existed, enough training data was not available to estimate the parameters of their distributions with any degree of accuracy. In situations such as these it is sensible to apply thresholds to the decision process in the manner depicted in Fig. 4.29b. Pixels which have probabilities for all classes below the threshold are not classified.

In practice, thresholds are applied to the discriminant functions and not the probability distributions, since the latter are never actually computed. With the incorporation of a threshold therefore, the decision rule of (4.13) becomes

\[
x \in \omega_i \quad \text{if} \quad g_i(x) > g_j(x) \quad \text{for all } j \neq i \quad (4.14)
\]

\[
\text{and} \quad g_i(x) > T_i \quad (4.15)
\]

where $T_i$ is the threshold seen to be significant for spectral class $\omega_i$. It is now necessary to consider how $T_i$ can be estimated. From (4.14) and (4.15) a classification is acceptable if

\[
\ln p(\omega_i) - \frac{1}{2} \ln |\Sigma_i| - \frac{1}{2} (x - m_i)^\top \Sigma_i^{-1} (x - m_i) > T_i \quad \text{i.e.}
\]

\[
(x - m_i)^\top \Sigma_i^{-1} (x - m_i) < -2T_i - \ln |\Sigma_i| + 2\ln p(\omega_i) \quad (4.16)
\]
Fig. 4.29: a Illustration of poor classification for patterns lying near the tails of the distribution functions of all spectral classes; b Use of a threshold to remove poor classification.

The left hand side of (8.10) has a $\chi^2$ distribution with N degrees of freedom, if $x$ is (Assumed to be) distributed normally (Swain and Davis, 1978). N is the dimensionality of the multispectral space. As a result $\chi^2$ tables can be consulted to determine that value of $(x - m_i)^t \Sigma_i^{-1} (x - m_i)$ below which a desired percentage of pixels will exist (noting that larger values of that quadratic form correspond to pixels lying further out in the tails of the normal probability distribution). This is depicted in Fig. 8.2.

As an example of how this is used consider the need to choose a threshold such that 95% of all pixels in a class will be classified (i.e. such that the 5% least likely pixels for each spectral class will be rejected). $\chi^2$ tables show that 95% of all pixels have $\chi^2$ values (in Fig. 4.29b) less than 9.488. Thus, from (4.16)

$$T_i = -4.744 - 1/2 \ln |\Sigma_i| + \ln p(\omega_i)$$

which thus can be calculated formal knowledge of the prior probability.
4.11.15 Number of Training Pixels Required for Each Class

Sufficient training pixels for each spectral class must be available to allow reasonable estimates to be obtained of the elements of the class conditional mean vector and covariance matrix. For an N dimensional multispectral space the covariance matrix is symmetric of size $N \times N$. It has, therefore, $\frac{1}{2}N(N + 1)$ distinct elements that need to be estimated from the training data. To avoid the matrix being singular at least $N(N + 1)$ independent samples is needed. Fortunately, each N dimensional pixel vector in fact contains N samples (one in each waveband); thus the minimum number of independent training pixels required is $(N+1)$. Because of the difficulty in assuring independence of the pixels, usually many more than this minimum number is selected. Swain and Davis (1978) recommend as a practical minimum that $10 \times N$ training pixels per spectral class be used, with as many as $100 \times N$ per class if possible. For data with low dimensionality (say up to 5 or 6 bands) those numbers can usually be achieved, but for hyper spectral data sets finding enough training pixels per class is extremely difficult.
4.11.16 Minimum Distance Classification

The minimum distance algorithm is also attractive since it is a faster technique than maximum likelihood classification. However because it does not use covariance data it is not as flexible as the latter. In maximum likelihood classification each class is modelled by a multivariate normal class model that can account for spreads of data in particular spectral directions. Since covariance data is not used in the minimum distance technique class models are symmetric in the spectral domain. Elongated classes therefore will not be well modelled. Instead several spectral classes may need to be used with this algorithm where one might be suitable for maximum likelihood classification. The discriminant function for the minimum distance classifier is developed as follows.

Suppose \( m_i, i = 1...M \) are the means of the M classes determined from training data, and \( x \) is the position of the pixel to be classified. Compute the set of squared Euclidean distances of the unknown pixel to each of the class means, defined in vector form as

\[
d(x, m_i) = (x - m_i)(x - m_i)^T = (x - m_i) \cdot (x - m_i), \quad i = 1...M
\]

Expanding the product gives

\[
d(x, m_i) = x \cdot x - 2m_i \cdot x + m_i \cdot m_i.
\]

Classification is performed on the basis of

\[
x \in \omega_i \text{ if } d(x, m_i) < d(x, m_j) \text{ for all } j = i
\]

Note that \( x \cdot x \) is common to all \( d(x, m_j) \) and thus can be removed. Moreover, rather than classifying according to the smallest of the remaining expressions, the signs can be reversed and classification performed on the basis of

\[
x \in \omega_i \text{ if } g_i(x) > g_j(x) \text{ for all } j = I
\]

Where

\[
g_i(x) = 2m_i \cdot x - m_i \cdot m_i, \text{ etc.}
\]

Equation (4.20) defines the discriminant function for the minimum distance classifier. In contrast to the maximum likelihood approach the decision surfaces for this classifier, separating the distinct spectral class regions in multispectral space, are
linear. The higher order decision surface possible with maximum likelihood classification renders it more powerful for partitioning multispectral space than the linear surfaces for the minimum distance approach.

Nevertheless, as noted earlier, minimum distance classification is of value when the number of training samples is limited and, in such a case, can lead to better accuracies than the maximum likelihood procedure.

Minimum distance classification can be performed also using distance measures other than Euclidean (Wacker and Landgrebe, 1972); notwithstanding this, algorithms based upon Euclidean distance definitions are those generally implemented in software packages for remote sensing image analysis, such as Multispec, ENVI, ERMapper, ILWISS and ERDAS IMAGINE.
The major difference between the minimum distance and maximum likelihood classifier lies in the use, by the latter, of the sample covariance information. Whereas the minimum distance classifier labels a pixel as belonging to a particular class on the basis only of its distance from the relevant mean, irrespective of its direction from that mean, the maximum likelihood classifier modulates its decision with direction, based upon the information in the covariance matrix. Furthermore the entry $-\frac{1}{2}\ln |\Sigma_i|$ in its discriminate function shows explicitly that patterns have to be closer to some means than others to have equivalent likelihoods of class membership. As a result substantially superior performance is expected of the maximum likelihood classifier, in general. The following situation however warrants consideration since then there is no advantage in maximum likelihood procedures. It could occur in practice when class covariance is dominated by systematic noise rather than by natural spectral spreads of the individual spectral classes.

4.11.17 The Mahalanobis Classifier

Consider the discriminate function for the maximum likelihood classifier, for the special case of equal prior probabilities. If the sign of this function is reversed it can be considered as a distance squared measure since the quadratic entry has those dimensions and the other term is a constant. Thus we can define

$$d(x,m_i)^2 = \ln |\Sigma_i| + (x - m_i)^t \Sigma_i^{-1} (x - m_i)$$

and classify on the basis of the smallest $d(x,m_i)$ as for the Euclidean minimum distance classifier. Thus the maximum likelihood classifier can be regarded as a minimum distance-like classifier but with a distance measure that is direction sensitive and modified according to class.

Consider the case now where all class covariances are equal – i.e. $\Sigma_i = \Sigma$ for all $i$. Clearly the $\ln |\Sigma_i|$ term is now not discriminating and can be ignored. The distance measure then reduces to

$$d(x,m_i)^2 = (x - m_i)^t \Sigma^{-1} (x - m_i)$$

Such a classifier is referred to as a Mahalanobis distance classifier, although sometimes the term is applied to the more general measure of (4.21). Mahalanobis distance is understood as the square root of (4.22). Under the additional constraint that
\[ \Sigma = \sigma^2 I \] the Mahalanobis classifier reduces, as before, to the minimum Euclidean distance classifier.

The advantage of the Mahalanobis classifier over the maximum likelihood procedure is that it is faster and yet retains a degree of direction sensitivity via the covariance matrix \( \Sigma \), which could be a class average or a pooled variance.

Fig.4.32 : Minimum Mahalanobis Distance Classification
Box classification method

This method is the commonest and easiest classification for remote sensing data, because it is both easy and effective. In this method, sensitivity to class variance can be introduced by considering the limit of the amount in each educational class. The limits with the highest and lowest amount of DN in each band is determined and displayed as four corners in the two-dimensional scatter plot.

Fig. 4.33 : Box Classification
4.11.18 Unsupervised Classification

Unsupervised classification is an analytical procedure based on clustering. Application of clustering partitions the image data in multispectral space into a number of spectral classes, and then labels all pixels of interest as belonging to one of those spectral classes, although the labels are purely symbolic (e.g. A, B, C, ... , or class 1, class 2, ...) and are as yet unrelated to ground cover types. Hopefully the classes will be unimodal; however, if simple unsupervised classification is of interest, this is not essential.

Following segmentation of the multispectral space by clustering, the clusters or spectral classes are associated with information classes – i.e. ground cover types – by the analyst. This a posteriori identification may need to be performed explicitly only for classes of interest. The other classes will have been used by the algorithm to ensure good discrimination but will remain labelled only by arbitrary symbols rather than by class names.

The identification of classes of interest against reference data is often more easily carried out when the spatial distribution of spectrally similar pixels has been established in the image data. This is an advantage of unsupervised classification and the technique is therefore a convenient means by which to generate signatures for spatially elongated classes such as rivers and roads.

In contrast to the a priori use of analyst-provided information in supervised classification, unsupervised classification is a segmentation of the data space in the absence of any information provided by the analyst. Analyst information is used only to attach information class (or ground cover type, or map) labels to the segments established by clustering. Clearly this is an advantage of the approach. However it is a time-consuming procedure computationally by comparison to techniques for supervised classification. When comparing the time requirements of supervised and unsupervised classification it must be recalled that a large demand on user time is required in training a supervised procedure. This is necessary both for determining training data and then identifying training pixels by reference to that data. The corresponding step in unsupervised classification is the posteriori labelling of clusters. While this still requires user effort in determining labelled prototype data not as much
may be required. As noted earlier, data is only required for those classes of interest; moreover only a handful of labelled pixels is necessary to identify a class. By comparison, sufficient training pixels per class are required in supervised training to ensure reliable estimates of class signatures are generated.

A final point that must be taken into account when contemplating unsupervised classification via clustering is that there is no facility for including prior probabilities of class membership. By comparison the decision functions for maximum likelihood classification can be biased by previous knowledge or estimates of class membership.

In the present study, by using the command 'cluster' in ILWIS environment, the researcher classified the images. Then, by drawing the spectral class dispersion, the manner of the class dispersion in a two-dimensional environment was identified.

![Fig. 4.34: Unsupervised Classifications](image)
4.11.19 Feature Selection

Most clustering procedures used for unsupervised classification in remote sensing generate the mean vector and covariance matrix for each cluster found. Accordingly, separability measures can be used to assess whether feature reduction is necessary or whether some clusters are sufficiently similar spectrally that they should be merged.

These are only considerations of course if the clustering is generated on a sample of data, with a second phase used to allocate all image pixels to a cluster. Feature selection would be performed between the two phases.

4.11.20 Determining the accuracy of the maps produced by the satellite images

Using a Testing Set of Pixels

The significance of any map made depends on its accuracy. The maps made with little accuracy enjoy little applicability. To determine the accuracy of the results obtained, one can apply different sampling methods, ground control, and examination of classification pixels and the number of pixels involved in sampling. By using appropriate statistical formulae, classification accuracy can be calculated.

This will allow a degree of confidence to be attached to the results and will serve to indicate whether the analysis objectives have been achieved.

Accuracy is determined empirically, by selecting a sample (desirably an independent random sample) of pixels from the thematic map and checking their labels against classes determined from reference data (desirably gathered during site visits).

Often reference data is referred to as ground truth, and the pixels selected for accuracy checking are called testing pixels. From these checks the percentage of pixels from each class in the image labelled correctly by the classifier can be estimated, along with the proportions of pixels from each class erroneously labelled into every other class. These results are then expressed in tabular form, often referred to as a confusion or error matrix, of the type illustrated in Table 4.2. The values listed in the table represent the number of ground truth pixels, in each case, correctly and incorrectly labelled by the classifier. It is common to average the percentage of correct
classification and regard this overall classification accuracy (in this case 83%), although a better measure globally would be to weight the average according to the areas of the classes in the map.

**Table 4.2 : Illustration of a confusion matrix used in assessing the accuracy of a classification**

<table>
<thead>
<tr>
<th>Thematic Map classes</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>35</td>
<td>2</td>
<td>2</td>
<td>39</td>
</tr>
<tr>
<td>B</td>
<td>10</td>
<td>37</td>
<td>3</td>
<td>50</td>
</tr>
<tr>
<td>C</td>
<td>5</td>
<td>1</td>
<td>41</td>
<td>47</td>
</tr>
<tr>
<td>Number of ground truth pixels</td>
<td>50</td>
<td>40</td>
<td>46</td>
<td>136</td>
</tr>
</tbody>
</table>

Confusion matrix is the common and standard method to determine the accuracy of classification. To determine the accuracy of maps mentioned requires data collected from the ground surface or study areas.

**4.11.21 Error Matrix Table**

Error matrix is an agreeable table from the comparing of ground data with those obtained from the classification when and where the values of the elements may be expressed in percentage or the number of pixels. The diametrical elements of error matrix show the number of correctly classified pixels and the non-diametrical elements, too, show the error pixels that are in fact the pixels related to commission or omission error. Error matrix is a square matrix with the dimensions of n x n where n represents the number of classes available in the classification (Table 4.3). In fact, the purpose of making an error matrix is to compare two groups of data with each other. One group of data is the product of classification and the other is the ground or reference truth.

**4.11.22 Classified Error Matrix**

The diametrical matrix numbers indicate the pixels that are correctly classified, and the rest (off the diameter of the matrix) show the pixels that are wrongly classified, and the total of pixels of each class is in fact representative of the ones chosen for the experimental samples.
### Table 4.3 the Classification finding

<table>
<thead>
<tr>
<th>Ground truth</th>
<th>ClassA</th>
<th>B Class</th>
<th>ClassC</th>
<th>Total</th>
<th>producer's accuracy%</th>
</tr>
</thead>
<tbody>
<tr>
<td>ClassA</td>
<td>70</td>
<td>5</td>
<td>0</td>
<td>75</td>
<td>93</td>
</tr>
<tr>
<td>B Class</td>
<td>3</td>
<td>55</td>
<td>0</td>
<td>58</td>
<td>94</td>
</tr>
<tr>
<td>ClassC</td>
<td>0</td>
<td>0</td>
<td>77</td>
<td>77</td>
<td>100</td>
</tr>
<tr>
<td>Total</td>
<td>73</td>
<td>60</td>
<td>77</td>
<td>210</td>
<td></td>
</tr>
<tr>
<td>Users accuracy%</td>
<td>95</td>
<td>91</td>
<td>100</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### 4.11.23 Overall Accuracy

Overall accuracy is one of the indexes that are used in expressing the accuracy of the results obtained from the different methods of classification applied, and it is calculated through dividing the total elements of the main diameter (Xii) by the total of pixels (N) (Lillesand and Kiefer, 2004). For example, the calculation for Table 4.3 will be as following:

The overall accuracy does not give out any practical information about which class has been correctly classified; thus, for this purpose, two other parameters, producer's accuracy and user's accuracy were applied.

#### 4.11.24 The producer's accuracy

For each class of experimental samples, the product is the proportion of correctly classified pixels (Xii) in each error matrix to the total pixels of the same row (Xi+). For example, for class A, the producer's accuracy was 93%; that is, 93% of the ground truth pixels of A were classified in image as class A, and 7% in the other classes. In general, the producer's accuracy indicates the likelihood of correct classification of experimental samples (reference data) and is indicative of omission error (Jensen, 1996).

#### 4.11.25 The user's accuracy

For each class in the classified image, the product of the proportion of correctly classified pixels (Xii) in every column of error matrix to the total pixels of that column (X+i), and the probability that one classified pixel of the image in class A
of the data is in fact the same as class A data on the ground. For example, for class A, the user's accuracy equaled 95%; that is, 95% of the pixels classified as class A on the ground were the same as class A data, and 5% of the pixels classified as A belonged to other data classes. Therefore, the user's accuracy measures commission error (Tso and Mather, 2001).

In general, the difference between these two types of accuracy is:

'Suppose the producer of a map is standing in area A. The likelihood that the point where he is sanding is the same point on the map is 93% (the producer's accuracy). Now, suppose that the map user chooses area A on the map; the probability that this area on the ground is the same A is 95%.'

By using the error matrix, we can find out the nature of the two error groups including Omission Error and Commission Error.

The commission error refers to the pixels that do not belong to the class X, but they are classified in this class.

The omission error refers to all the pixels that belong to class X, but they are not classified in that class.

Omission error = 1 – the producer's accuracy
Commission error = 1 – the user's accuracy

When interpreting an error matrix of the type shown in Table 4.2 from the point of view of a particular class, it is important to understand that different indications of class accuracies will result according to whether the number of correct pixels for a class is divided by the total number of reference (ground truth) pixels for the class (the corresponding column sum in Table 4.2) or the total number of pixels the classifier attributes to the class (the row sum in Table 4.2). Consider class B in Table 4.2, for example. As noted, 37 of the reference data pixels have been correctly labeled. This represents $37/40 = 93\%$ of the ground truth pixels for the class. We interpret this measure, which Congalton and Green (1999) refer to as the Producer’s accuracy, as the probability that the classifier has labelled the image pixel as B given that the actual (ground truth) class is B. As a user of a thematic map produced by a classifier we are more interested in the probability that the actual class is B given that
the pixel has been labelled B (on the thematic map) by the classifier. This is what Congalton and Green refer to as the User accuracy, and for this example is \( \frac{37}{50} \equiv 74\% \). Thus only 74\% of the pixels labelled B on the thematic map are correct, even though the classifier coped with 93\% of the B class reference data. This distinction is important and leads one to believe that the User accuracy is the figure that should most often be adopted.

Some authors prefer to use the kappa coefficient as a measure of map accuracy (Hudson and Ramm 1987, Congalton and Green 1999). This is defined in terms of the elements of the error matrix; let these be represented by \( x_{ij} \), and suppose the total number of test pixels (observations) represented in the error matrix is \( P \).

Also, let

\[
x_{+i} = \sum_j x_{ij}, \quad \text{(i.e. the sum over all columns for row } i)\\
\]

\[
x_{+j} = \sum_i x_{ij}, \quad \text{(i.e. the sum over all row for columns } j)\\
\]

Then the kappa estimate is defined by

\[
\kappa = \frac{P \sum_k x_{kk} - \sum_k x_{+k} x_{+k}}{P^2 - \sum_k x_{+k} x_{+k}}
\]

Choice of the sample of pixels for accuracy assessment is an important consideration. Perhaps the simplest strategy for evaluating classifier performance is to choose a set of testing fields for each class, akin to the training fields used to estimate class signatures. These testing fields are also labelled using available reference data, presumably at the same time as the training areas. After classification the accuracy of the classifier is determined from its performance on the test pixels. Another approach, with perhaps more statistical significance since it avoids correlated near neighbouring pixels, is to choose a random sample of individual pixels across the thematic map for comparison with reference data. A difficulty that can arise with random sampling in this manner is that it is area-weighted. That is, large classes tend to be represented by a larger number of sample points than the smaller classes; indeed some very small classes may not be represented at all. Assessment of the accuracy of labelling small classes will therefore be prejudiced. To avoid this it is necessary to ensure small
classes are represented adequately. An approach that is widely adopted is stratified random sampling in which the user first of all decides upon a set of strata into which the image is divided. Random sampling is then carried out within each stratum. The strata could be any convenient area segmentation of the thematic map, such as grid cells. However, the most appropriate stratification to use is the actual thematic classes themselves. Consequently, the user should choose a random sample within each thematic class to assess the classification accuracy of that class.

**Fig. 4.35 : Omission and commission error of classification based on MLC**

4.11.26 Post Classification Steps

After the classification of images, the product enjoys a pepper appearence format and the reason is the spectral changes of the image pixels which (the changes) appear when the classification of the image is carried in basic pixel method. For example, in an alfalfa farm, several pixels in the dense vegetation mantles might be classified as bare soil, or in poor pastures some thick vegetation mantles might be classified as rich mantles. Therefore, it is recommended that the final result and produced map be prepared based on the dominant class, so by applying appropriate filters, scattered pixels among the classes are merged so that the final output enjoys homogeneity. To achieve this, different methods can be used and in the present study, the researcher has employed the following ones.
a. Using Filters

One of the instruments of homogenizing classes is using majority filters. Through this method, a moving window with certain coefficients filters the entire image and then the dominant class is introduced. If within the window there is no dominant class, the central pixel will not change. Sometimes, the image, if required, can be filtered several times so that the image can be clearer.

Therefore, filtering is a process in which each pixel value in a raster map is replaced with a new value. The new value is obtained by applying a certain filter to each input pixel and its direct neighbours. These neighbours are usually the 8 adjacent pixels (in a 3 x 3 filter or the 24 surrounding pixels (in a 5 x 5 filter). When you create or define your own filters, any odd sized matrix is allowed (5 x 1, 11 x 23, 25 x 25).

Filters can be used for a number of purposes:

- to enhance 'sharpness' of a satellite image for better visual interpretation,
- to reduce noise in an image prior to a multi-band image classification when classifying rather large areas
- to detect line features or edges in a satellite image,
- to calculate steepness, direction (aspect), and shape (concave, convex) of slopes in a DEM,
- to assign pixels which were classified as unknown during a multi-band image classification the value of the most frequent occurring class around the unknown pixel,
- morphologic filtering on bit maps, etc.

4.11.27 Majority Filter

The majority filters is a standard majority filter which works in a 3x3 environment. Of each 9 pixels considered, the predominant value or class name is assigned to the center pixel in the output map. If no predominant value is found, the value or class name which is encountered first is used as output. When 9 pixel values encountered in the input map are:

$$\begin{bmatrix}
9 & 3 & 9 \\
11 & 5 & 7 \\
7 & 7 & 14 \\
\end{bmatrix}$$

The predominant value is 7; the value for the output pixel is thus 7.
Fig. 4.36: Original satellite image after classification

Fig. 4.37: Majority 3*3 used filter after classification
4.11.28 Undef-Majority filter (MAJUNDEF)

The MAJUNDEF filter is a standard majority filter which works in a 3x3 environment. Of each 9 pixels considered, the predominant value or class name of the other 8 pixels is assigned to the center pixel in the output map, only if the center pixel in the input map is undefined.

If the central pixel in the input map is not undefined, the value or class name remains the same in the output map.

When 9 pixel values encountered in the input map are:

```
9  3  9
11 ?  7
 7  7 13
```

The predominant value is 7; the value for the output pixel is thus 7.

4.11.29 Zero-Majority filter (MAJZERO)

The majzero filter is a standard majority filter which works in a 3x3 environment. Of each 9 pixels considered, the predominant value or class name of the other 8 pixels is assigned to the center pixel in the output map, only if the center pixel in the input map has value zero.

If the central pixel in the input map does not have value 0, the value or class name remains the same in the output map.

When 9 pixel values encountered in the input map are:

```
9  3  9
11 0  7
 7  7 13
```

The predominant (most frequently occurring) value is 7. The value for the output pixel is thus 7.
b. Merging Classes

Due to the heterogeneity of phenomena, it is required to sample one class in several spectral subclasses to obtain a data class. In this situation, after being classified, the subclasses can be merged in one data-class.

c. Incorporating the Secondary Data

Data such as slope maps, aspects and DEM digital elevation model are referred to as professional data that are used during classification and after classification.

In the present study, after the classification, the data were statistically analyzed. The classified image with the highest accuracy and KAPA coefficient were chosen for the post-classification operations.

### Table 4.4: General Characteristics of Training Areas

<table>
<thead>
<tr>
<th>Training Classes</th>
<th>Number of Pixels</th>
<th>Pixels %</th>
<th>Area (in hectares)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PL</td>
<td>190</td>
<td>3.5</td>
<td>10.5</td>
</tr>
<tr>
<td>CO</td>
<td>210</td>
<td>3.9</td>
<td>11.6</td>
</tr>
<tr>
<td>CD</td>
<td>284</td>
<td>5.4</td>
<td>15.7</td>
</tr>
<tr>
<td>S</td>
<td>405</td>
<td>7.5</td>
<td>22.4</td>
</tr>
<tr>
<td>SS</td>
<td>395</td>
<td>7.4</td>
<td>21.8</td>
</tr>
<tr>
<td>FA</td>
<td>271</td>
<td>5.1</td>
<td>15</td>
</tr>
<tr>
<td>OC</td>
<td>243</td>
<td>4.5</td>
<td>13.4</td>
</tr>
<tr>
<td>OC2</td>
<td>292</td>
<td>5.4</td>
<td>16.1</td>
</tr>
<tr>
<td>AL</td>
<td>404</td>
<td>7.5</td>
<td>22.3</td>
</tr>
<tr>
<td>OG</td>
<td>410</td>
<td>7.6</td>
<td>22.6</td>
</tr>
<tr>
<td>OP</td>
<td>311</td>
<td>5.8</td>
<td>17.2</td>
</tr>
<tr>
<td>PA</td>
<td>267</td>
<td>5</td>
<td>14.7</td>
</tr>
<tr>
<td>PA2</td>
<td>295</td>
<td>5.5</td>
<td>16.3</td>
</tr>
<tr>
<td>RE</td>
<td>198</td>
<td>3.7</td>
<td>10.9</td>
</tr>
<tr>
<td>LA</td>
<td>215</td>
<td>4</td>
<td>11.9</td>
</tr>
<tr>
<td>WD</td>
<td>425</td>
<td>7.9</td>
<td>23.5</td>
</tr>
<tr>
<td>WH</td>
<td>353</td>
<td>6.6</td>
<td>19.5</td>
</tr>
<tr>
<td>PO</td>
<td>198</td>
<td>3.7</td>
<td>10.9</td>
</tr>
<tr>
<td>Total</td>
<td>5366</td>
<td>100</td>
<td>296.3</td>
</tr>
</tbody>
</table>