Chapter 2
Theoretical Background and State of the Art

This chapter provides a short overview of the principles of remote sensing outlines current studies focused on the Euphrates River Basin (ERB) and presents a survey of the literature available on the topics that the thesis covers. Within the confines of this study, remote sensing is defined as the measurement of emitted or reflected electromagnetic radiation, or spectral behaviors, from a target object by a multi-spectral satellite sensor. This thesis contains four main sections: land use/land cover classification, the mapping of irrigated areas, irrigated agriculture mapping (especially crops classification), and land use/land cover change detection mapping. A great number of papers have been published on the above four topics. In this section a small range is given, based on significance and likeness to this thesis, with the goal of providing no wide-ranging survey, but of giving an experience of the techniques, applications and performances found in the literature.

2.1 Remote Sensing Concept

For purposes of this text, discussion has been limited to Earth observation from space. "Remote sensing is the science and art of obtaining information about an object, area or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area or phenomenon under investigation. Using various sensors, we remotely collect data that may be analyzed to obtain information about the objects, areas or phenomena being investigated. The remotely collected data can be of many forms, including variations in force distributions, or electromagnetic energy distributions" (Lillesand et al. 2008). Figure 2.1 illustrates the generalized processes and elements involved in the electromagnetic remote sensing of Earth resources.

Key to the consideration of remotely sensed imagery is the coverage, resolution and density of its spectral, spatial and temporal characteristics. *Spectral coverage* describes which part of the EMS (Fig. 2.2) is being used (e.g., visible, infra-red, thermal, etc.). *Spectral resolution* indicates to the spectral bandwidths in which the

W. Al-Fares, *Historical Land Use/Land Cover Classification Using Remote Sensing*, SpringerBriefs in Geography,
DOI: 10.1007/978-3-319-00624-6_2,

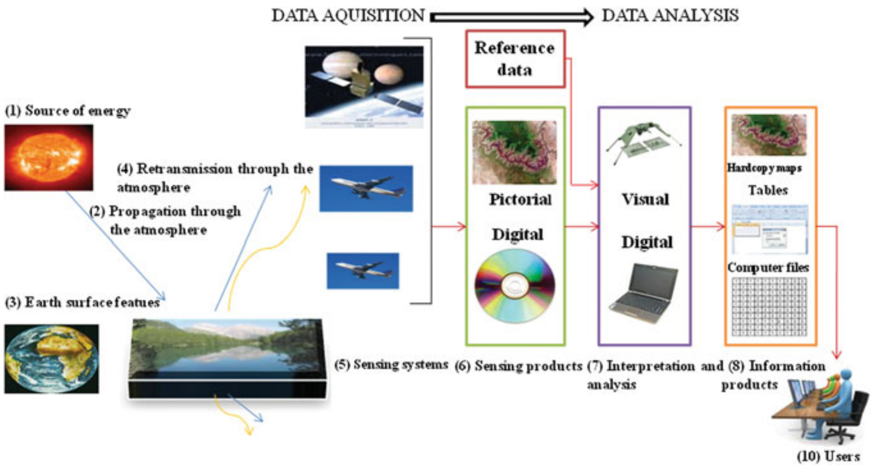

Fig. 2.1 Electromagnetic remote sensing of Earth resources (*Source* modified from Lillesand et al. 2008)

sensor collects information. *Spectral density* indicates to the number of spectral bands in an exacting part of the EMS (e.g., the LANDSAT-MSS has only four bands, while the TERRA-ASTER has 14 bands, etc.). *Spatial coverage* is the area enclosed by the image, while *spatial resolution* indicates to the smallest pixel or picture element recorded. *Temporal coverage* is the acquiring period over which the data is obtainable (e.g., LANDSAT-Sensors have a temporal coverage of 41 years). *Temporal resolution* relates to the time that the data is obtainable over. It is generally low by most remote sensing systems. *Temporal density* refers to the repeat properties of the satellite. A good repeating in gathering the data would, for some applications, offer more availability of cloud free data (McVicar and Jupp 1998). *Radiometric resolution* indicates to the active range or number of potential data file values in each spectral band (the number of bits into which the recorded energy/data is divided). For example, the total *intensity* of the energy for 8-bit data is measured from 0 to the maximum amount of 256 brightness values. Where 0 stands for no energy return, 255 is the maximum return of each pixel (ERDAS 1999).

A multispectral sensor (e.g., MSS) acquires multiple images of the same target Earth surface feature (e.g., water, soil, etc.) at different wavelengths (spectral bands). Each band measures single spectral characteristics about the target (e.g., the fourth near infra-red band of MSS is responsible for detection and recoding the spectral response of the natural vegetation). A spectral band is a data set recorded by the sensor with information from separate parts of the electromagnetic spectrum. One foundation of remote sensing is that LULC-features have different spectral properties and responses (McVicar and Jupp 1998). Analysts generate spectral signatures based upon the detected electromagnetic energy's measurement and place in the electromagnetic spectrum. A spectral signature contains statistics that define the spectral characteristic of a target feature or training samples. Image

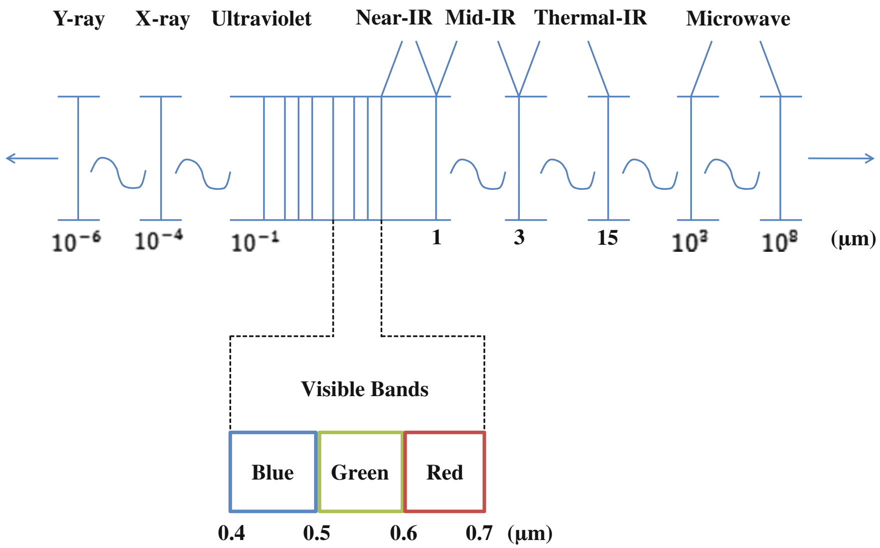

Fig. 2.2 The primary spectral regions of the electromagnetic spectrum that are of interest in Earth remote sensing applications (*Source* modified from Tso and Mather 2009)

interpreters detect the value of these statistics by quantitatively comparing the relation between studied class signatures and the used spectral bands. Spectral signatures are made more sophisticated by superior ground-truth points/measurements and accuracy assessment analysis. By utilizing the sophisticated spectral signatures in multispectral classification and thematic mapping, the interpreter generates new data for analysis (ERDAS 1999). Figure 2.3 shows idealized spectral reflectance plots for two types of vegetation, soils and water types, respectively.

2.2 Remote Sensing Application in Syria

The application of remote sensing in Syria is similar to the situation which exists in other developing countries. Remote sensing technology has been in place for more than two decades but has lacked the expected effectiveness of such technology as used in the countries of the developed world. The General Organization for Remote Sensing (GORS) was established by the Syrian Arab Republic (SAR) in 1986 and is today the most important and highest scientific body in the country competent to conduct remote sensing. It carries out many scientific projects and studies based on the application of remote sensing in Syria, and has utilized these skills even outside the country's borders (e.g., in Sudan). All of these studies have been addressed to the government's institutions and ministries, and thus the basics

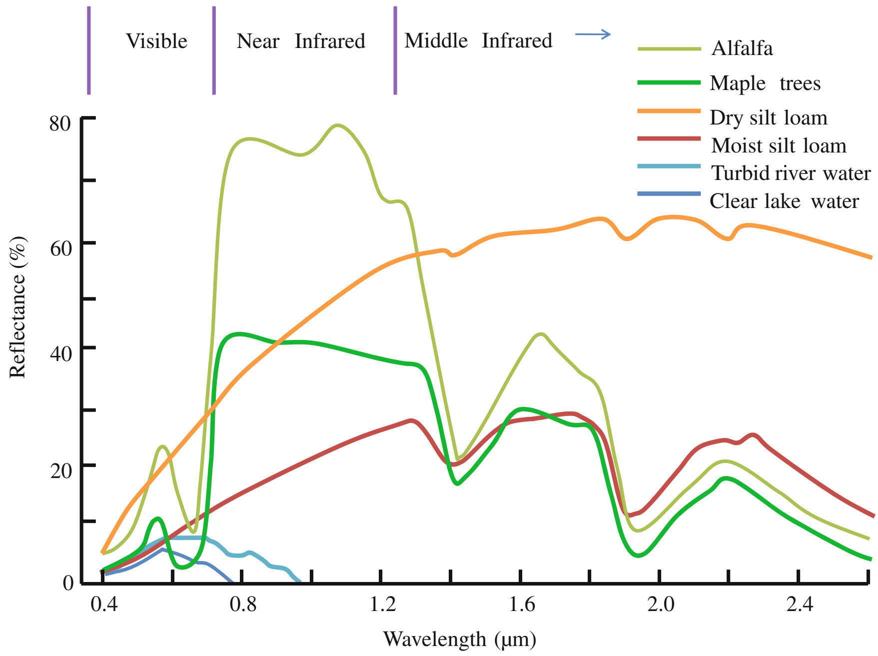

Fig. 2.3 Idealized reflectance plots for different land cover types (*Source* modified from Harrison and Jupp 1989)

and the details of remote sensing techniques has remained almost entirely within the confines of GORS and the researchers who work within this organization.

Plus GORS, there are two other scientific authorities who have published studies based on the use of remote sensing: the Arab Centre for the Studies of Arid Zones and Dry Lands (ACSAD) and the International Centre for Agriculture Research in Dry Areas (ICARDA). Unfortunately, these have refused to cooperate with university and graduate students, requiring several levels of approvals before any research is distributed for academic purposes. The other related international institutions in Syria are the Food and Agriculture Organization (FAO) and the United Nations Development Program (UNDP), which work in co-operation with national institutions mentioned above.

A vital component of the research required for this thesis was a project undertaken by GORS in the provinces of Arraqqa, Deir Azzour and Al-Hasakah. “The Survey of Natural Resources in the Eastern Regions of Syria in Cooperation with the Ministry of Agriculture and Agrarian Reform” was initiated in 2004 and was undertaken over a period of five years. Data was remotely collected from ASTER, IRES, SPOT and an Algerian satellite. The project included:

- A tour of the provinces in question to choose the appropriate areas from which to take spectrometry readings on a variety of crops for the purpose of spectral

profile/characterization, during which different stages of growth were to be distinguished spectrally using satellite images;
- Field testing of the devices to be used in the study (Spectrometer/FieldSpecPro and GPSs);
- The characterization of agricultural crops and land use during May 2005, consistent with the presence of winter crops, and during August 2005, consistent with the presence of summer crops. Some 1,050 sites were identified for the purposes of the study;
- Spectrometry readings on strategic crops (wheat, barley, lentils, sugar beet, cotton, watermelon and maize). These readings were conducted on average once every two weeks through the stages of crop growth;
- Input of field survey data and spectrometry readings to databases through electronic forms prepared for this purpose; and
- The creation of spectral signatures for each crop under study. Analysis of these spectral signatures led to the identification of the optimal time to request satellite images to be used in the estimation of the areas of winter and summer crops.

The project's objectives were: a study and cost estimate on crop area and yield for various strategic crops in Syria compared with traditional methods, and the production of maps of winter and summer crops, allowing the calculation of the level of agriculture in the regions. Many other studies focused on the ERB have proved essential during the development of this thesis.

Other studies were based on remotely sensed data, such (Beaumont 1996; Hirata et al. 2001; Zaitchik et al. 2002; De Pauw et al. 2004; De Pauw 2005; Celis et al. 2007a, b; Udelhoven and Hill 2009).

2.3 Land Use-Land Cover Mapping

2.3.1 The Classification Process

In general, classification of LULC-features using remote sensing data consists of numerous phases (Robinove 1981; Mather 2004; Schowengerdt 2007), as shown in Fig. 2.4:

- *Identifying*: the number and the name of classes that represents the real-world features which have defining priority;
- *Feature extraction*: data are frequently highly correlated between spectral bands. This high correlation might be inappropriate for classification of LULC-features and may reduce classification accuracy. Optionally, one can apply the spatial (e.g., smoothing filter) or spectral (e.g., bands subset) transformation of the multispectral data with the aim to: (1) differentiate between valuable information and noise or non-information; and (2) reducing the dimensionality

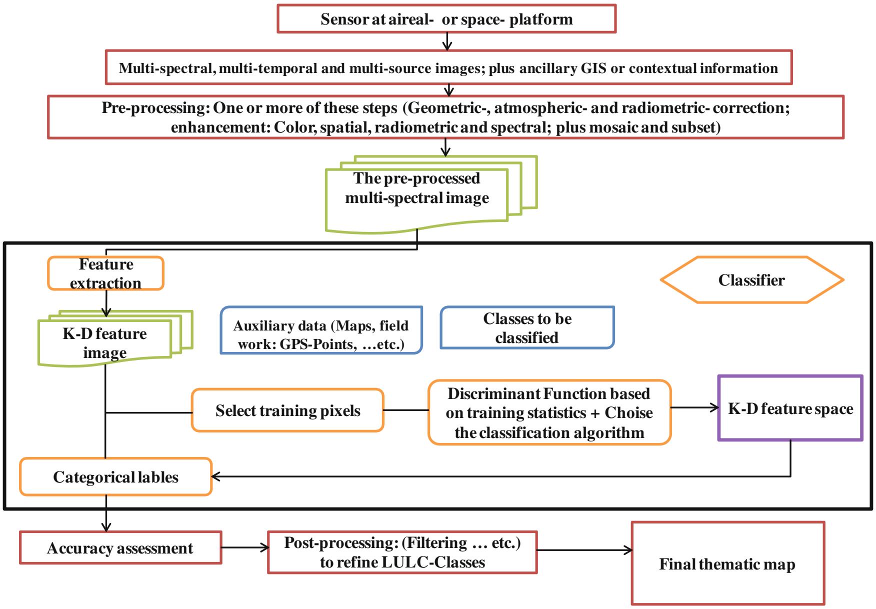

Fig. 2.4 The classification process (*Source* modified from Townshend and Justice 1986, Tutz 2000, Wilkinson 2005 and Schowengerdt 2007)

of the data to shorten the computing time needed by the classifier, and thus to raise the effectiveness of statistical estimators in a statistical classifier;

- *Training*: the term “training” is the choosing of the pixels to train the classifier to identify the preferred *themes*, or *classes*, and the selection of decision boundaries. Here, the drawing of boundaries around geographically located pixels has to be homogeneous, or suitably heterogeneous. This phase can be carried out either supervised or unsupervised; and
- *Labeling*: it is the process of allocating diverse pixels to their most likely class based on the use of the feature space decision boundaries. This process can be supervised or unsupervised. If a pixel is not spectrally alike to any of the available classes, then it can be assigned to an unknown class. There are two kinds of relationships between the object and the class label: one-to-one (producing a *hard classification*); or one-to-many (producing a *fuzzy classification*). The object may be a single pixel or a group of neighboring pixels forming a geographical unit. As a result, a thematic map is produced, presentating every pixel with a class label. The end result is a transformation of the digital image data into descriptive labels that classify unlike Earth surface objects or conditions.

2.3.2 The General Classification Techniques

Researchers have presented various approaches for image classification, which can be divided into three general groups (Fig. 2.5) (Pal and Pal 1993).

Statistical classifiers: these are ideally suitable for data that have information with an assumed theoretical model based distribution within each of the classes. The representative algorithms for this group are: MLC; PPC; k-NNC and MDC. Corresponding literature for these algorithms can be found in Swain and Davis (1978) and Hastie et al. (2001). *Fuzzy mathematical approaches*: Zadeh (1965) presented the concept of fuzzy sets in which unclear knowledge can be used to delineate a result. *Artificial intelligence* (*AI*): here, supervised classification approaches were developed from the starting of the 1970s, with the well-known "Arch Concept Learning" problem presented by Winston (1975). These methods based on the learning from descriptions of a constructive pattern, and therefore gave up the value-attribute based model that was used in other methods. AI-type models were constructed based on semantic networks and on predicate logic.

Liu and Mason (2009) summarized the classification approaches in seven categories: unsupervised classification; supervised classification; hybrid classification; single pass classification; iterative classification; image scanning classification; and feature space partition. In most cases, image classification approaches included: supervised and unsupervised; parametric and nonparametric; hard and soft (fuzzy) classification; per-pixel, sub-pixel, object-oriented and per-field; spectral classifiers, contextual classifiers and spectral-contextual classifiers; or combinative approaches of multiple classifiers (Lu and Weng 2007). This article presents: present practices; remotely sensed data classification troubles and scenarios. It highlighted the main advanced classification approaches, in addition to those techniques that can improve the at-end classification accuracy.

Unsupervised classification: when insufficient ground reference information is available (e.g., field work measurements) about the characteristics of specific classes for classification processes, an unsupervised classification is used to identify natural homogeneous groups (clusters) within the remotely sensed data. Unsupervised classification approaches are based on non-parametric statistical approaches, such as Iterative Self-Organizing Data Analysis Technique (ISO-DATA) (Tou and Gonzalez 1974), K-means-clustering (Johnson and Wichern 1988) algorithms, and the advanced unsupervised neural classification method Self-Organizing feature Mapping (SOM) (Kohonen 1989). In this approach, the

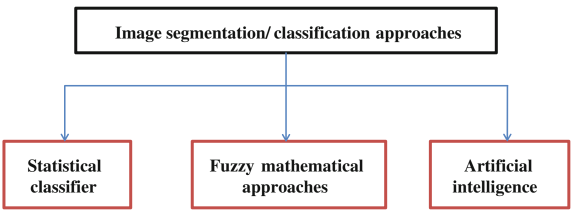

Fig. 2.5 Major approaches for image segmentation/ classification (*Source* modified after Pal and Pal 1993)

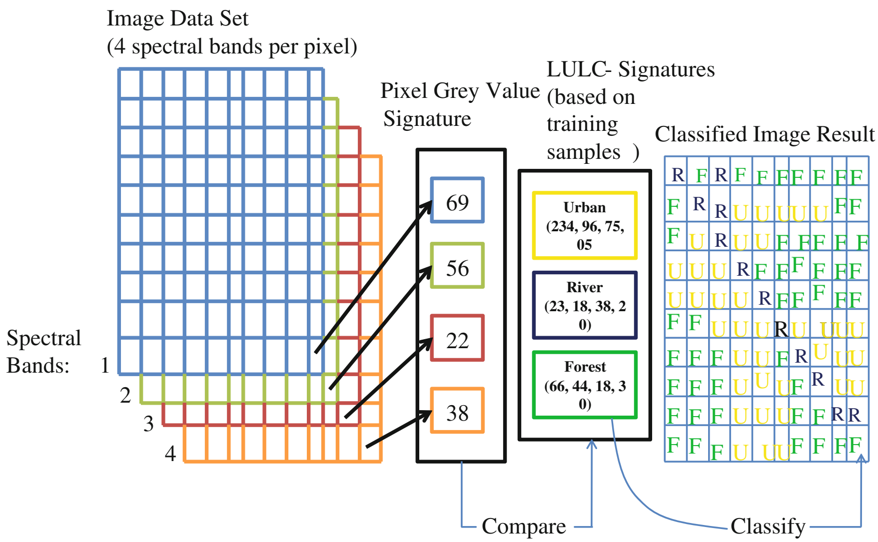

Fig. 2.6 The principal idea of the supervised classification approach for multi-spectral remote sensing (*Source* modified from Eastman 2006)

image processing software groups pixels that have similar properties (in feature space and in adequate representative spectrally-separable clusters for the ground surface features), based on the statistics of the radiometric value/digital number of each pixel. Then the analyst evaluates the classified map with field survey data, aerial photographs and other reference data, and labels these clusters (spectral classes) with its equivalent in the real world to information classes, without having a prior knowledge of the classes. Generally, some clusters must be subdivided or combined to make this equivalence. Results of an unsupervised classification can be used to define the training samples, which are a main input in the supervised classification, or the labeled cluster map can be just accepted as the final map (Schowengerdt 2007).

Supervised classification: supervised approaches, as seen in Fig. 2.6, are based upon training sites, and can assure the former but not the latter; unsupervised approaches can assure the latter but not the former (Tso and Mather 2009). Each image is characterized by *n*-observations (the values in *n*-data bands). Supervised image classification is an approach in which the analyst delineates the training samples (vectors in an *n*-dimensional feature space) on the image which are representative of each interested LULC-class (Mather 2004). A basic step in supervised classification and mapping is the design of a realistic classification scheme, which satisfies a clear definition of separable discrete informational LULC-categories within the available data (Cingolani et al. 2004). Training sites/samples can be created from fieldwork, aerial photography and other existing maps based on analyst knowledge (e.g., Google Earth), and are then used as reference information (Lillesand et al. 2008). Visual interpretation is used to locate the training samples position on the image (Mather 2004). These training samples have to be homogeneous spectrally to represent specific LULC-classes. A supervised algorithm, after the training samples stage, uses the distribution of the training samples for each class to assess density functions in the feature space statistically and to divide the space into class regions (Fukunaga 1990). In other words, the used image's processing software recognizes the spectral signature of each training site based on its statistics, and then classifies the images in different LULC-classes according to the applied classification algorithm (Jensen 2005). Here, the information required from the training data differs from one algorithm to another. The most general and used supervised approaches are: The Maximum Likelihood Classifier (MLC) and the Minimum Distance Classifier (MDC). The advanced supervised classification algorithms are: The Artificial Neural Network (ANN), the Decision Tree Classifier (DTC), the Nearest Neighbor Classifier (NNC) and the Support Vector Machines classifier (SVM).

The supervised approach is more popular but requires more detailed a priori knowledge of the study area and analyst expertise, to identify suitable training sites and the resultant spectra for classification (ERDAS 1999). The characteristics of the training sites selected by the analyst have a great impact on the dependability and the functioning of a supervised classification process. This approach has a more subjective impact on the analyst during the defining of the LULC-categories characteristics and its representative training samples. Supervised classification approaches need more user-data-software interaction, especially in the collection of training data.

A general introduction to pattern recognition and classification is given in the textbooks by Duda et al. (2000) and Bishop (1995, 2006), and in the review paper by Jain et al. (2000). A detailed introduction in the context of remote sensing is given by Richards and Jia (2003).

2.3.3 Remote Sensing Applications in Land Use/Land Cover Mapping

The broad utilization of remote sensing is to extract and represent LULC-information from multispectral imagery as thematic maps, data and GIS-layers (Donnay et al. 2001). Research proves that remote sensing can be considered as a useful tool for studying arid and semi-arid ecosystems (Tucker et al. 1983; Justice and Hiernaux 1986; Townshend and Justice 1986; Maselli et al. 1993; Bastin et al. 1995; Hobbs 1995; Schmidt and Karnieli 2000; Kheiry 2003; Suliman 2003).

In comparison to the more classical classification methodologies such as basic aerial photo interpretation, LULC-mapping using satellite imagery has four distinct advantages: (1) LULC-classes can be mapped faster and often with lower costs; (2) fast and inexpensive updating of LULC-map products is possible, where the satellite imagery are captured for the same geographic area at a high repeat ratio; (3) remotely sensed data are captured in digital forms and can thus be easily jointed with other types of ground feature information through such techniques as GIS; and (4) the large economies of scale offered by digital satellite image processing make it fairly low-cost to map large areas, meaning it is easier and more cost effective to produce large amounts of map products.

Although the optical remote sensing systems such as LANDSAT-MSS/TM/ETM+, ASTER, and SPOT have limitations in obtaining cloud-free imagery and the resulted difficulties in performing spectral classification for specific categories of LULC (Ulaby et al. 1982), they have proven an efficient device for LULC-mapping (Ji 2000). Kanellopoulos et al. 1992 conducted a 20 class classification test on SPOT High-Resolution Visible (HRV) images, and the end-result was proven to be satisfactory. De Colstoun et al. (2003) applied a decision tree on multi-temporal images from the ETM+ to distinguish between 11 features of land cover. The overall accuracy was clearly enhanced by using classifier ensemble techniques, as boosting. The paper from Berberoglu et al. (2007) aimed to evaluate the usefulness of integrating texture measures into MLC and ANN classifications in a Mediterranean environment, using LANDSAT-TM-imagery. The best classification accuracies were reached by using the ANN classifier. The dealing with the measures of texture characteristics were most effectively with the ANN rather than the MLC classifier. Yuan et al. (2009) explained and applying an automated two-module ANN classification system, i.e. an unsupervised SOM network module and a supervised MLP neural network module, using LANDSAT-TM. After an evaluation of the performance of MLC, DA, and ANN in image classification, ANN classifications have the advantages in image accuracy overall and for single land cover classes.

LULC-Classification using the three VNIR- and six SWIR- bands of ASTER-data has been discussed in the past 10 years. The most commonly used approach is separating the ASTER into two sets of images, i.e. 15 and 30 m resolution, where each have three and six spectral bands, respectively. For each set, support vector machine (SVM)-based algorithms (Zhu and Blumberg 2002) or segmentation algorithms (Marcal et al. 2005) were applied for processing of classification. An approach based on *wavelet fusion* was proposed by Bagan et al. (2004). Other studies based on the Principal Component Analysis (PCA) were used to the nine VNIR and SWIR. From the earlier obtained principal components, a supervised MLC was implemented (Gomez et al. 2005). But, most of the approaches referred to have not adopted thermal band data (TIR) in classification processing. Jianwen and Bagan (2005) used ASTER and the Kohonen's Self-Organized neural network feature Map (KSOM) to LULC-classification. It classified 7 % more accurately than MLC. Also, the study showed that the quality of ASTER was good for LULC classification. Yüksel et al. (2008) used ASTER and converted it into Top Of Atmosphere reflectance data (TOA) to generate LULC-maps according to the CORINE-Land cover project, using supervised and the knowledge-based expert classification systems to get a superior accuracy of the classified image.

These optical remotely sensed data can be integrated with recordings from remote sensing active systems such as the microwave sensors (e.g., Synthetic

Aperture Radar SAR), which has the ability to acquire remotely sensed imagery under various weather condition during both day and night. Studies (Solberg et al. 1994; Huang et al. 2007) using SAR and optical sensor data have confirmed clear enhancement in classification accuracies contrary to an optical sensor alone.

Xu and Gong (2007) evaluated the potential of the Earth Observing-1 (EO-1) Hyperion hyper-spectral (HS) data with that of the EO-1 Advanced Land Imager (ALI) multispectral (MS) data for distinguishing various LULC-classes in Fremont, California.

In addition to the progress achieved by the referenced studies, the use of object- or segment-based classification techniques is another new development in the environment of remote sensing image classification. This approach has achieved generally better success with the narrow bands and high spatial resolution data such as IKONOS, SPOT-5, or QUICKBIRD (Willhauck 2000). In several of the followed studies (e.g., Fuller et al. 2002; Marcal et al. 2005; Platt and Rapoza 2008) segment-based classifications were more accurate than conventional pixel-based classifications.

2.4 Land Use/Land Cover Change Detection Mapping

Change detection analysis is important in monitoring and managing the natural resources of the Earth. It gives statistical analysis of the occurred spatial distribution of the LULC-changes of interest (Singh 1989). Some of its applications are: Monitoring shifting agriculture, estimation of deforestation, estimation of desertification, and other environmental changes (Jingan et al. 2005). Natural change can have a wide impact on natural resources. So, in relation to LULC and natural resource and ecosystem management, there is an important need for timely, permanent, and truthful monitoring of changes occurring. But, the problems challenging the change detection process are: where is the change?, how much?, when did it occur?, and how great is its impact on the ecosystem? (Lambin and Linderman 2006). Changes can occur either suddenly or gradually (Bontemps et al. 2008). Here, the remote sensing techniques take on an increasing importance in natural resource monitoring programs and in answering the above questions (Wiens et al. 2009). In the case of LULC-changes, two kinds of change can be classified from previously published literature: conversion and modification (Lambin et al. 2003). LULC-conversion is the change from one cover category to another (e.g., the complete replacement of an agricultural parcel by man-made buildings), while LULC-modification is the modifications of structure or function without a complete change from one category to another (e.g., changes in productivity, biomass, or phenology).

2.4.1 Change Detection Techniques

There are numerous change detection approaches applied on remotely sensed data, as a result of increasing versatility in processing digital data and increasing computing power (Pacifici et al. 2007). Generally applied approaches are: image differencing; and image rationing (Singh 1989). Some of the proposed supervised and unsupervised approaches in the literature are: write function memory insertion; image algebra; multiple-date composite; post-classification comparison; image differencing; image rationing; change vector analysis; etc. (Nelson 1983; Singh 1989; Sohl et al. 2004). Expert systems and neural networks were too used in change detection (Seto and Liu 2003). These approaches use multi-date imagery from multi- and hyper-spectral sensors, so that alterations, in feature or phenomena, be accurately recognized, measured and if needed observed (Jensen 2007), each of which could be spatially, spectrally, or temporally controlled (Lu et al. 2003a). Figure 2.7 illustrates how the various frequently used techniques are located in this framework.

Returning to Fig. 2.7, change detection techniques can be separated into two general groups, depending on whether the technique needs classification before or after change detection process.

1. Techniques which first detect change and then assign classes (e.g., image differencing or PCA)-Unsupervised Approach- Pre-classification method.

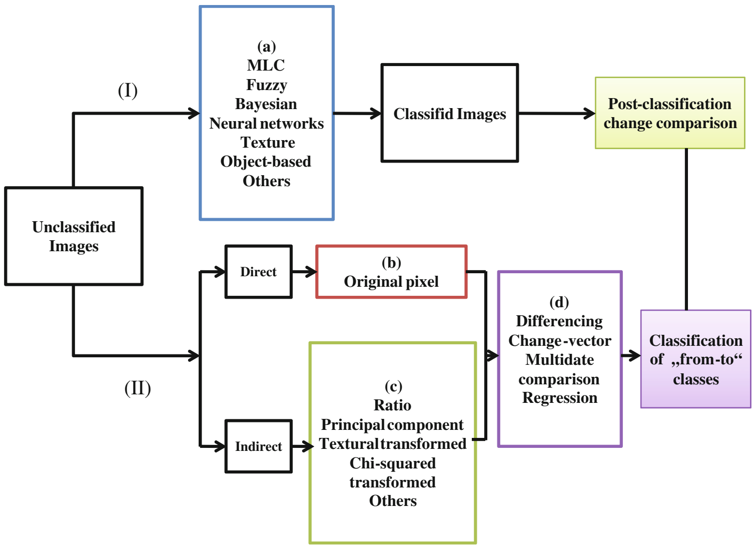

Fig. 2.7 A framework for classifying change detection methods (*Source* modified from Lam 2008)

Many unsupervised change detection approaches deal with the multispectral images to produce an additional image. The most essential basis for these algorithms is the determining of the finest global threshold in the histogram of the so-called generated difference image, where the classifying of change and unchange classes is made on the importance of the resulting spectral change vectors by applying of empirical or theoretical well-founded global threshold strategies. The best global threshold depends on the statistical irregularity of the two images, which are often unknown. Pacifici et al. (2007) reviewed the published techniques in the past decade: the *Image Differencing* (ID), *Normalized Difference Vegetation Index* (NDVI), *Change Vector Analysis* (CVA), *Principal Component Analysis* (PCA), *Image Rationing* (IR), *Expectation Maximization* (EM) (Bruzzone and Fernàndez-Prieto 2000), *Markov Random Field* (MRF) (Bruzzone and Fernàndez-Prieto 2000), Object-Level Change Detection (OLCD) (Hazel 2001), *Reduced Parzen Estimation* (RPE) (Bruzzone and Fernàndez-Prieto 2002), *Maximum a Posteriori Probability* (MPP) decision criterion (Kasetkasem and Varshney 2002), *Multivariate Alteration Detection* (MAD also called *Iteratively Reweighted* MAD (IR-MAD)) (Nielsen 2007), MAD and the combined MAF/MAD (*Maximum Autocorrelation Factor*) transformations, and *Genetic Algorithm* (GA) (Celik 2010).

The above techniques generally do not aim to identify clearly what types of LULC-changes have taken place in an area (e.g., which vegetated areas have been urbanized). They are suitable for applications such as detection of burned areas, or detection of deforestation. However, they are not useful when it is necessary to define the types of changes that have occurred in the studied area, for example, in: observing the shifting in cultivation; urban growth; or where it is required to know all the types of changes that occurred in investigated area.

Advantages: (1) pre-classification is not necessary, so, avoiding the tiring in classification process at the starting; (2) it is regarded as simple and rapid, and can be applied on a great number of images; and (3) the ease in fine-tuning to detect the specific interested changes, and they are, in general, likely to have a higher ability to find slight changes (Yuan et al. 2005). Disadvantages: (1) the detection of image changes, especially if focused on agricultural areas, may be affected by troubles with phenology and cropping. Such troubles could be worsened by inadequate image accessibility and poor quality in moderate zones, and the problems in adjusting poor images (Blaschke 2005); (2) also, these techniques are corrupted by: changes in illumination at two times, changes in atmospheric conditions, and in technical sensor calibration. These make complex a direct evaluation between raw imagery obtained at different times where additional processing steps are required (e.g., radiometric calibration) (Pacifici et al. 2007); and (3) there remains the problem of defining the threshold value at which the change between the two images is measured. Also, it is clear that using unsupervised methods is obligatory in many remote-sensing applications, when appropriate ground truth information is not always available (Bruzzone and Fernàndez-Prieto 2002).

2. Techniques which first assign classes and then detect change (post-classification comparison) Supervised Approach Post classification methods.

In order to overcome the limitations of the first technique, one can use techniques based on a supervised classification of multi-temporal images: *Direct Multi-data Classification* (DMC), *Neural networks* (NNs) (Bishop 1995), *Knowledge-Based Systems* (KBS), *Support Vector Machines* (SVMs) (Vapnik 1998), *Post-Classification Comparison* (PCC) (Del Frate et al. 2005).

The fame of the above techniques may be because they can be freely applied on available created single date classifications, where they are based on separate single-date classifications whose results are later compared with the result of the second independently classified image (Weismiller et al. 1977). This simple technique includes: (1) producing the classified image based on the classification process; and (2) assessment the occurred changes based on the principle of identifying the areas of change as pixel per pixel differences in class membership (Castelli et al. 1999).

Advantages: (1) the ability to clearly identify the kinds of occurred LULC-conversions; (2) the robustness to the various atmospheric and light conditions at the two recording times (Bruzzone and Fernàndez-Prieto 2000); (3) where the two datasets/imagery are separately classified, so it is not needed to normalize these data (Singh 1989); (4) it is more flexible than those used the comparison of multi-temporal raw data; (5) it allows one to make change detection also by using different sensors and/or multi-source data at two times; and (6) the possibility in entering several modifications on the used classifier in classification process (e.g., contextual information as using the texture of an image) would increase the change detection mapping accuracy (Pacifici et al. 2007). Also, the new image classification algorithms, other than the traditional MLC, can be used to increase both accuracy and effectiveness. Disadvantages: (1) requires more human supervision for classifying the images; (2) despite its potential, this category is not relevant to quick change detection, because user supervision is required to pre-classify the images; (3) limitations also include cost in terms of money and implementation time, and generated errors from classification of imagery, where the generation of a suitable training set has the two drawbacks, i.e. the difficulty and the high cost (Bruzzone and Fernàndez-Prieto 2000); and (4) finally, the accuracy of the change thematic map will be equal to the accuracies of each individual classification for each date.

2.4.2 Change Detection in Arid- and Semi-Arid-Environments

Approximately 50 % of the total surface areas of the world are arid and/or semi-arid regions (Meadows and Hoffman 2002). Arid and semi-arid areas feature irregular, low precipitation, dry ecosystems, and have a limited sustained economical potential (Adam et al. 1978). Because of the sensitive nature of these areas, it may only require a small amount of turbulence to cause clear changes within the environment (Okin et al. 2001). As a result, remote sensing is quickly becoming an essential tool to use in the study of these areas (Zhou et al. 1998).

There is a variety of problems that confuse the detection of variations in the reflected EMR: (1) low irregular precipitation and high potential ETP allows only spatially-limited low vegetation cover by the available moisture. As a result, the greater part of the area-averaged reflectance of a pixel is for the soil substrate (Smith et al. 1990a). Associated problems in these regions include the low organic components of the soils, which therefore tend to be bright. These issues join to negate, or reduce, the vegetation signal present within an individual pixel (Huete et al. 1985); (2) the variability of soils (light, dark, etc.), and their spectral responses, over the ecosystem of the study area and over the resulting image also cause problems to the detection of vegetation.

Existing remote sensing algorithms allow the application of LULC-change detection in moderate areas of the world (Berberoglu and Akin 2009). However these algorithms are less able to be applied in the Mediterranean environment because: (1) the high temporal variability of the spectral responses of major LC causes large inter-class spectral variability; (2) the complex mixed spatial frequency of the landscape; and (3) the similar reflectance responses of major LC makes spectral separation hard (e.g., the bright toned, often calcareous soil can have alike reflectance responses to urban areas and alike near-infrared reflectance to a crop canopy) (Berberoglu et al. 2000). Therefore, the observation of land cover change is complicated in Mediterranean environments.

Before mapping LULC-change detection using optical sensors data in arid and/or semi-arid areas, we have to answer this question: at which scale is green vegetation detectable and how can we best distinguish it? Siegel and Goetz (1977) demonstrated that major changes in the reflectance characteristics need a vegetation cover of more than 10 %, and that a vegetation signal has a tendency to be more significant than the soil signal when vegetation coverage is more than 30 %. Hill (2000) argued that this does not mean that vegetation coverage of less than 30 % is not detectable by remote sensing, but affirms that ratio based vegetation indices do not offer the best approximation. Vegetation approximation under the spectral un-mixing concept offers better approximation of the true vegetation coverage (Hurcom and Harrison 1998).

A number of change detection studies, such as (Ray 1995; Kwarteng and Chavez 1998; Ram and Chauhan 2009) rely on the clear difference between agricultural fields or urban areas, and the neighboring arid environment, in order to detect LULC-change. However, for example, the detection of vegetative change (within the same LULC-category) within arid areas is significantly more difficult. Image differencing, especially the vegetation index differencing, is one of the most familiar vegetation change detection approaches, because of its simplicity (Singh 1989; Lu et al. 2003a). Pilon et al. (1988) favored the use of the visible red spectral band information to detect changes for their semi-arid study area. Chavez and Mackinnon (1994) established that the red band differencing process presented improved information about vegetation change rather than NDVI in an arid environment. Lyon et al. (1998) accomplished that the NDVI-vegetation index differencing technique achieved the best when comparing several vegetation indices for change detection.

Serrano et al. (2000) compared different techniques developed to create a homogeneous time series of LANDSAT images from 1984 to 2007 for the Middle Ebro Valley in Spain. Mahmood and Easson (2006) explored the capability of using ASTER imagery integrated with LANDSAT-7-ETM+ imagery of south-western Bangladesh to detect equivalent measurements for change detection studies. The used methods were regression with Discrete Fourier Transform (DFT) and the cross-calibration method using digital number ratios. French et al. (2008) demonstrated and confirmed a method using ASTER-imagery obtained between 2001 and 2003 over the Jornada Experimental Range, to map the LULC-changes in a semi-arid area in southern New Mexico, USA. The results emphasize the importance of multispectral thermal infrared data that contains observations at wavelengths within 8–9.5 µm. Alberga (2009) proposed a technique for probable change detectors in multi-sensor configurations, based on similarity measures that did not rely totally on radiometric values. A chain of such measures was used for automatic change detection of optical and SAR-images and an evaluation of their functioning were carried out to detect the limits of their applicability and their understanding to the occurred changes.

2.5 Remote Sensing for Irrigated Agriculture

Exact information on irrigation spatial coverage is the foundation of many sides of the knowledge of the Earth's systems and global change research. Ozdogan and Gutman (2008) defined irrigation as “agricultural area that receives full or partial application of water to the soil to offset periods of precipitation shortfalls under dry land conditions”. The remote sensing techniques offer a unique approach to the gathering of various data across place and time, facilitating the application of various methods to obtain irrigated area statistics. In addition, time-series remotely sensed data allow the dynamics of irrigated agriculture to be clearly researched, as differing from other land uses (mapping). To date, a number of researchers have used remote sensing to observe irrigated agriculture (Ozdogan 2010). Initial efforts focused on applying remote sensing in mapping and to update irrigated land areas mostly in the US and India (Draeger 1976; Rundquist et al. 1989). More recently, studies on classification irrigated areas were carried out based on advanced classification algorithms (Abuzar et al. 2001). These researchers concluded that irrigation monitoring and mapping using remote sensing were at an advanced phase of improvement (Ozdogan et al. 2006) and that multi-temporal data were more effective rather than single-date data in determining individual irrigated crop classes (Thiruvengadachari 1981). Spatial resolution of used remotely sensed data for irrigation mapping was seen as vital to obtaining sufficient spatial details about the irrigated fields (Pax-Lenney and Woodcock 1997), as was the potential of vegetation indices in classification irrigated fields, if suitable time-series are obtainable. This latter fact was proved in several studies (Martinez-Beltran and Calera-Belmonte 2001).

2.5.1 Remote Sensing Approaches for Vegetation Studies

The optical characteristics of vegetation and different leaves were explained in detail by (Kumar et al. 2001). In general the reflectance of vegetation in the visible wavelengths (0.43–0.66 μm) is small and reflection in near infrared (0.7–1.1 μm) is large (Fig. 2.2). The life cycle in crop plants includes the three major phases: a vegetative stage, reproductive phase and a grain-filling stage. Three features of leaves have an important impact on their reflectance characteristics: pigmentation (e.g., chlorophyll a and b), physiological structure and water content. *Pigments* absorb the energy of the visible wavelengths, where the highest level of absorption from chlorophyll a is located at 430 and 480 nm, while for chlorophyll b it is at 450 and 650 nm. As, the bandwidth of the TM is too wide to detect these thin absorption bands (Bidwell 1974). The reflectance response of *vegetation canopy* is affected by: the vegetated and non-vegetated areas spatial distribution, vegetation classes, leaf area index, distribution of the leaf angle, and bio-chemical and physical vegetation conditions. The *water content* of the leaves and water in the atmosphere decrease overall leaf reflectance and causes some thin absorption features (Irons et al. 1989).

The spectral response of vegetation changes permanently during the growing season and with alterations in moisture content. Appropriate information about these changes assists in the determining of the best time period for field work and in determining biophysical features to be measured. Figure 2.8 illustrates a simplified spectral reaction curve for vegetation from 400 to 2.500 nm. The relationship between the irradiation absorption and the irradiation reflection illustrated in this figure changes with wavelength. The biophysical controls (pigment, cell structure and water) of the irradiation to plant interaction are also affected by differing wavelengths (McCoy 2005).

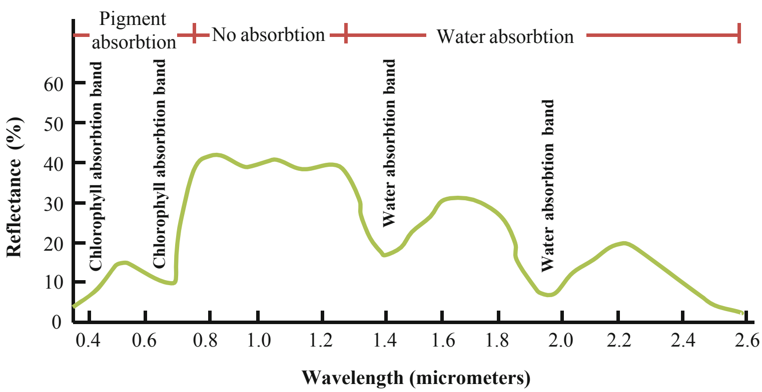

Fig. 2.8 The typical spectral response curve for vegetation showing the characteristic bands that differentiate vegetation spectrally (*Source* modified from Hoffer and Johannsen 1969)

Factors controlling the spectral responses of the vegetation and its reflectance measurements include many natural and technical parameters, such as: atmosphere conditions (e.g., the quantity of occurring sunrays and the proportion of water vapor, change reflectance from plant canopies) (Gao and Goetz 1992); soil background (Mickelson et al. 1998); wind (Lord et al. 1985); viewing angle (Galvao et al. 2004); the altitude of the sensor from plant canopies; and the amount of light.

There is an important relationship between the available images for an individual study area and the plant growth stages, where the growth stage determines which images are suitable for separation between the crops spectrally. So, learning the phenological details about the crops of interest to an individual study area may be required. These phenological details refer to the natural vegetation calendar or a crop calendar. Data for these calendars can be obtained from: literature of previous ecological studies; meeting with qualified field-oriented ecologists; in state or regional bureaus engaged with natural resource management in the region; or from field-work based observation and measurements (e.g., Spectrometer measurements).

Single-date captured remotely sensed data would be inadequate for primarily vegetated areas described by large temporal changeability and typical spatial patterns of highly frequent land cover changes between vegetation canopies. Multi-date remote sensing would be able to cover this problem: when specific data might not be suitable to separate individual LULC-classes, the use of another acquisition date might prove more appropriate for classification. Therefore, the use of the total multi-temporal information gives us a better separation between several classes, and consequently, more classification accuracy (see Fig. 5.23). Crop phenology understanding is very important in crop monitoring and classification (Chen et al. 2008).

2.5.2 Crop Discrimination from Satellite-Based Images

The most frequently practiced utilization of remote sensing for agriculture is the identification of crop types and then classification (Van Niel and McVicar 2000), where crop discrimination is a critical and difficult first step for most agricultural observing activities. The capability of remotely sensed data to identify crop class makes it promising to classify and estimate each crop area, and so calculate the relevant statistics automatically that can used as inputs to crop production forecasting models (Blaes et al. 2005). The application of remote sensing for discrimination between agricultural crop classes and internal crop characteristics has been widely studied throughout the past decade (Senay et al. 2000; Blaes et al. 2005; Satalino et al. 2009). Most of these researchers have focused on increasing classification accuracy through the development of several techniques and methods. In contrast, only small studies have been presented on determining the best time(s) to obtain images in order to distinguish different crops (Van Niel and McVicar 2004).

The temporal information dimension in used remotely sensed data is the most useful factor in natural vegetation and agricultural applications for identifying crop types (Wardlow et al. 2007). This is because agricultural features have great (within-class and within-season) spectral flexibility, that is based on several complex natural and biophysical factors (e.g., crop type/s, soil, water and geographical location). The observation and understanding of these various spectral responses of crops, and comparison with the physical characteristics of remotely sensed data recorded in various dates in the year (building a crop-specific temporal record), would give us the appropriate date(s) during the growing stages in which the crops of interest are spectrally separable. Also, by observing the physical derived spectral indices from remotely sensed data that are sensitive to natural vegetation cover over time, it is possible to discriminate crops (Ozdogan 2010).

Discrimination of crops using remote sensing imagery is generally achieved with supervised or unsupervised classification algorithms (Jensen 2007). Recently, nonparametric algorithms, expert knowledge and ancillary data have been used in the process of cropland classification, improving the overall classification accuracy. One example of this is the establishment of neural networks for crop type identification, which is the most important development in information extraction from remotely sensed data in the last 15 years (Del Frate et al. 2003). Multi-sensor data fusion and classification of time series data are being applied in cropland classification more and more (Chen et al. 2008). The most simple method of distinguishing crops is the classification of images into large-scale classification categories including all agricultural features (Level 1 in LULC-classification) (Campbell 2002). From this level of classification, agricultural features can be classified into cropping and non-cropping regions.

The interaction between crop field scale and pixel size is a significant factor, especially in heterogeneous cropping areas. For instance, large pixel dimensions allow an increasing chance of recording mixed reflectance values. This resulted mixed spectral response is confused by traditional local agricultural management practices, such as found in most areas of the Euphrates River Basin, where crops are sometimes planted in almost 30 m strips (see Fig. 5.29). This is alternated with un-cropped areas (bare soil, stubble, dirt roads, etc.) of similar size to the cropped strips. So, pixels that are not entirely homogeneous (e.g., solely forest, vegetation, wheat crop, etc.), have mean reflectance values (composite spectral response that might match neither feature's spectral response) as a result of more than one feature within the pixel area. Such pixels are known as mixels and are an ever-present problem in cropland classification, reducing their discriminating power (Chen et al. 2008). Spectral Mixture Analysis techniques (SMA) have been developed and used to solve the mixel-problem in remotely sensed data (Fitzgerald et al. 2005). Confusion between natural vegetation and cropland is also another major source of error in crop classification using low spatial and/or spectral resolution remotely sensed data. Sometimes this is also true of high-resolution imagery. This type of confusion is especially common in areas with very complicated traditional local agricultural management practices, which are controlled by natural topography or from land ownership (Loveland et al. 1999). An additional factor to the quantity of this confusion type is the seasonal variation in the NDVI signals caused by seasonal difference in illumination geometry, which imitates a phenological cycle (McIver and Friedl 2002).

In order to support the capability of remotely sensed data to discriminate between the various crops, researchers have investigated many alternatives which have to do with: The sensor-type (e.g., optical or microwave); number of images (e.g., single-date or multi-date); timing of the imagery; digital processing techniques; or ancillary and spatial data integrating in the classification process (Van Niel and McVicar 2000).

2.5.3 Crop Area Estimation from Satellite-Based Images

Crop area measurement and survey are very common practices in agriculture. Photo-interpretation of images can give better information than statistical analysis to evaluate an amount, or area, for a thematic category (Ozdogan and Woodcock 2006). Usually, crop area estimation has been achieved with very costly and hard statistically-based ground surveys that do not determine either the area or the geographical distribution of individual crops. To overcome or decrease these drawbacks, remote sensing, either alone or in combination with ground surveys, were used in crop area estimation (Wardlow and Stephen 2008). Obtaining full efficiency of remote sensing for crop area estimation depends on the landscape characteristics, especially field size compared with the image resolution, where a suitable resolution for a specific landscape is realized when the most image pixels are pure. But, when this relationship is not realized, for example when using MODIS- or MERIS images especially for landscapes with small fields, then sub-pixel classification techniques (e.g., pixel un-mixing) can be used (GEO 2010). Remote sensing has not been widely used for crop area estimation, due to the tradeoff between spatial detail (the scale of the remote sensing data) and area coverage for each image. In addition, there is the relationship between the spatial resolution of the remotely sensed data and the agricultural field sizes. Agricultural fields in most countries in the world are rather small, requiring medium to high spatial resolution data. However, increases in spatial resolution provide a decrease in the temporal availability which in turn lowers the chance of clouds-free coverage. Even if the clouds-free suitable spatial resolution data were obtainable, the increased number of datasets makes the cost high, and the high spatial resolution sensor covers only small geographical areas at a time. This leads to an additional problem, the need for atmospheric corrections in automated image digital processing and classification, as the required images are often gained at diverse times during the growing cycle of a crop. Medium spatial resolution data (e.g., LANDSAT) may be too coarse in countries with very small cultivated fields (e.g., China), but high spatial resolution is more appropriate for use in countries with large cultivated fields, such as the U.S. (Ozdogan and Woodcock 2006). In contrast, lower spatial resolution data (e.g., MODIS) offer wide temporal and geographical coverage at continental and global scales, but need detailed spatial information. The fact that not each pixel in an image represents only single crop type can introduce uncertainty into area estimates because of the mixture (Ozdogan and Woodcock 2006). Where cultivated areas are smaller than the spatial resolution of the image, here, both cultivated and uncultivated areas (e.g., roads, houses, irrigation channels) are integrated in a pixel classified as agriculture or cropland. In agricultural situations, the amount of uncultivated area has been reported to vary from 10 to 40 % (Crapper 1980; Frolking et al. 1999). To relatively solve this mixed pixel problem which occurs especially in high temporal resolution data at low spatial resolution, some contributors have developed techniques that use the concept of *temporal un-mixing* (Adams et al. 1986). It is similar to the traditional *spectral un-mixing* technique, where pure end-members are distinguished by their spectral response. Temporal un-mixing uses end-members defined by their single temporal response to improve the fractional area of each end-member based on its part to the mixed temporal reaction observed by the sensor (Ozdogan 2010).

There are two generally used area estimation methods with remote sensing (Ozdogan and Woodcock 2006). The first method calculates portions/fractions of a thematic category of interest for each pixel (Hansen et al. 2002). The essential drawback here is the accuracy assessment of fractions of the thematic field. However, area estimation by this method is becoming more common (Liu and Wu 2005). A second method is based on generating the thematic map through image classification and then multiplying the area of the pixels with their number in a specific class. The drawback here is the classification accuracy of the thematic map (Ozdogan and Woodcock 2006).

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http://www.springer.com/978-3-319-00623-9

Historical Land Use/Land Cover Classification Using Remote Sensing
A Case Study of the Euphrates River Basin in Syria
Al-Fares, W.
2013, XVIII, 204 p. 96 illus., 86 illus. in color., Softcover
ISBN: 978-3-319-00623-9