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Remote sensing imagery in vegetation mapping: a review

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Abstract

Aims

Mapping vegetation through remotely sensed images involves various considerations, processes and techniques. Increasing availability of remotely sensed images due to the rapid advancement of remote sensing technology expands the horizon of our choices of imagery sources. Various sources of imagery are known for their differences in spectral, spatial, radioactive and temporal characteristics and thus are suitable for different purposes of vegetation mapping. Generally, it needs to develop a vegetation classification at first for classifying and mapping vegetation cover from remote sensed images either at a community level or species level. Then, correlations of the vegetation types (communities or species) within this classification system with discernible spectral characteristics of remote sensed imagery have to be identified. These spectral classes of the imagery are finally translated into the vegetation types in the image interpretation process, which is also called image processing. This paper presents an overview of how to use remote sensing imagery to classify and map vegetation cover.

Methods

Specifically, this paper focuses on the comparisons of popular remote sensing sensors, commonly adopted image processing methods and prevailing classification accuracy assessments.

Important findings

The basic concepts, available imagery sources and classification techniques of remote sensing imagery related to vegetation mapping were introduced, analyzed and compared. The advantages and limitations of using remote sensing imagery for vegetation cover mapping were provided to iterate the importance of thorough understanding of the related concepts and careful design of the technical procedures, which can be utilized to study vegetation cover from remote sensed images.

Keywords: vegetation mapping • remote sensing sensors • image processing • image classification

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Introduction

Assessing and monitoring the state of the earth surface is a key requirement for global change research (Committee on Global Change Research, National Research Council, 1999; Jung *et al.* 2006; Lambin *et al.* 2001). Classifying and mapping vegetation is an important technical task for managing natural resources as vegetation provides a base for all living beings and plays an essential role in affecting global climate change, such as influencing terrestrial CO_2 (Xiao *et al.* 2004). Vegetation mapping also presents valuable information for understanding the natural and man-made environments through quantifying vegetation cover from local to global scales at a given time point or over a continuous period. It is critical to obtain current states of vegetation cover in order to initiate vegetation protection and restoration programs (Egbert *et al.* 2002; He *et al.* 2005). A good case is demonstrated by the GAP Analysis Program sponsored by US Geological Survey that aims at better conserving plant communities (http://gapanalysis.nbii.gov/). Strong preference has been given to acquire updated data on vegetation cover changes regularly or annually so as to better assess the environment and ecosystem (Knight *et al.* 2006).

Traditional methods (e.g. field surveys, literature reviews, map interpretation and collateral and ancillary data analysis), however, are not effective to acquire vegetation covers because they are time consuming, date lagged and often too expensive. The technology of remote sensing offers a practical and economical means to study vegetation cover changes, especially over large areas (Langley *et al.* 2001; Nordberg and Evertson 2003). Because of the potential capacity for systematic observations at various scales, remote sensing technology extends possible data archives from present time to over several decades back. For this advantage, enormous efforts have been made by researchers and application specialists to delineate vegetation cover from local scale to global scale by applying remote sensing imagery. For example, the International Geosphere–Biosphere Program pioneered a global land cover mapping in the development of the Global Land Cover Characterization (GLCC) Database that was based on 1-km Advanced Very High Resolution Radiometer (AVHRR) in 1992 (http://edcsns17.cr.usgs.gov/glcc/). Similarly, in collaboration with over 30 research teams from around the world, the Joint Research Institute in Italy implemented a similar project, the Global Land Cover 2000 (GLC2000), in 1999 to map global land cover and built up the VEGA2000 dataset by extracting the data from 1-km SPOT4-VEGETATION imagery (http://www-gvm.jrc.it/glc2000/). Two years later, US NASA released the database of global MODIS land cover based on monthly composites from Terra MODIS Levels 2 and 3 data between January and December 2001 (http://duckwater.bu.edu/lc/mod12q1.html). The mapping approaches as well as their strengths and weaknesses of the above global land cover products were highlighted by Jung *et al.* (2006). At a smaller scale, the Pan-European Land Cover Monitoring project, aimed at establishing a 1-km Pan-European Land Cover Database (Fig. 1), was initialized in 1996 to build a land cover database covering the entire European continent through the integrative use of multiple spectral–temporal NOAA–AVHRR satellite imagery and ancillary data (Rounsevell *et al.* 2006).

Besides these datasets at the global and continental scales, there have been numerous efforts taken over regional or national extents to map vegetation. An example is the USGS–NPS Vegetation Mapping, a collaborative program between the U.S. Geological Survey and the National Park Service, which began in 1994 with the aim to produce detailed and computerized maps of the vegetation for ~250 national parks across the United States by processing Airborne Visible and Infrared Imaging Spectrometer (AVIRIS) imagery along with ground sampling references. Remote sensing technology not only can be applied to map vegetation covers over land areas but also in underwater areas with focus on mapping submergent aquatic vegetation (SAV), which is regarded as a powerful indicator of environmental conditions in both marine and fresh water ecosystems (Lathrop *et al.* 2006; Wolter *et al.* 2005).

We will synthesize in this paper a comprehensive review on how the remote sensing technology is utilized to classify and map vegetation cover. A survey of remote sensing sensors as well as their suitability in vegetation mapping will be presented in next section. Image preprocessing and image classification methods commonly adopted in extracting vegetation information from remote sensed images (including hyperspectral imagery application and data fusion) will be illustrated in 'Vegetation extraction from remote sensing imagery'. Classification result evaluation (or accuracy assessment) will be discussed in 'Result evaluation'. Limitations of using imagery to map vegetation covers and related discussions will be concluded in the final section.

Remote sensing sensors

A remote sensing sensor is a key device that captures data about an object or scene remotely. Since objects (including vegetation) have their unique spectral features (reflectance or emission regions), they can be identified from remote sensing imagery according to their unique spectral characteristics. A good case in vegetation mapping by using remote sensing technology is the spectral radiances in the red and near-infrared regions, in addition to others. The radiances in these regions could be incorporated into the spectral vegetation indices (VI) that are directly related to the intercepted fraction of photosynthetically active radiation (Asrar *et al.* 1984; Galio

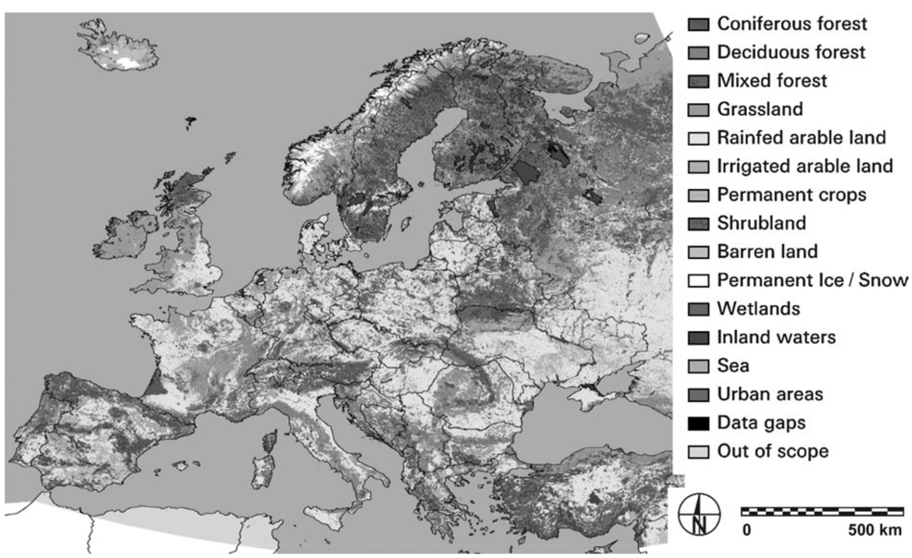

Figure 1 Pan-European Land Cover Monitoring 1 km pan-European land cover derived from NOAA–AVHRR satellite imagery (from http://www.geo-informatie.nl/projects/pelcom/public/index.htm). A colour version of this figure is available online as supplementary data.

et al. 1985). The spectral signatures of photosynthetically and non-photosynthetically active vegetation showed obvious difference and could be utilized to estimate forage quantity and quality of grass prairie (Fig. 2) (Beeri *et al.* 2007).

Over the past half century, remote sensing imagery has been acquired by a range of airborne and space-borne sensors from multispectral sensors to hyperspectral sensors with wavelengths ranging from visible to microwave, with spatial resolutions ranging from sub-meter to kilometers and with temporal frequencies ranging from 30 min to weeks or months. The rough guidelines for definitions of spatial resolution may be defined as following (Navulur 2006): (i) low or coarse resolution is defined as pixels with ground sampling distance (GSD) of 30 m or greater, (ii) medium resolution is GSD in the range of 2.0–30 m, (iii) high resolution is GSD 0.5–2.0 m, and (iv) very high resolution is pixel sizes <0.5 m GSD. Since different sensors have different spatial, temporal, spectral and radiometric characteristics, the selection of appropriate sensors is very important for mapping vegetation cover. The selection of images acquired by adequate sensors is largely determined by four related factors: (i) the mapping objective, (ii) the cost of images, (iii) the climate conditions (especially atmospheric conditions) and (iv) the technical issues for image interpretation. First, the mapping objective concerns what is to be mapped and what mapping accuracy is expected. In general, images with low resolutions may be adopted only when the high level of vegetation classes are to be identified, while the images with relatively higher resolutions are used for fine-detailed classifications of vegetation. Second, remote sensing imagery may be very expensive and the cost of imagery is definitely a consideration when choosing imagery. From the mapping scale point of view, vegetation mapping at a small scale usually requires high-resolution images, while low-resolution images are used for a large-scale mapping. Third, it raises the issue of the feasibility of using data from different sources to obtain a cloud-free image series over an extended period of time (Soudani *et al.* 2006). Lastly, some technical

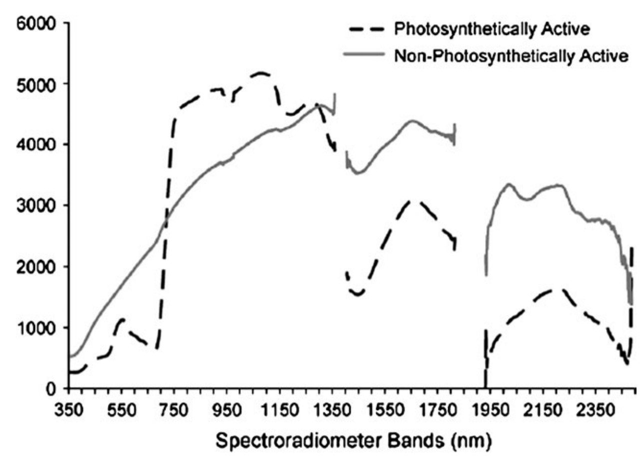

Figure 2 typical spectral signatures of photosynthetically active and non-photosynthetically active vegetation (Beeri *et al.*, 2007).

specifics need to be taken into account regarding image quality, preprocessing and interpretation when choosing suitable candidates of sensors. In the field of vegetation mapping, the most commonly applied sensors include Landsat (mainly TM and ETM+), SPOT, MODIS, NOAA–AVHRR, IKONOS and QuickBird. The characteristics of these sensors are summarized in Table 1 and described below.

Landsat TM and ETM+

The Landsat might have the longest history and widest use for monitoring the earth from space. Since the first Landsat satellite was launched in 1972, a series of more sophisticated multispectral imaging sensors, named TM—Thematic Mapper, have been added ranging from Landsats 4 (1982), 5 (1984), 6 (1993, launch failed) to 7 (1999) (Enhanced Thematic Mapper Plus, ETM+). The Landsat TM and ETM+ imaging sensors have archived millions of images with a nearly continuous record of global land surface data since its inception. Landsat provides medium to coarse spatial resolution images. For example, Landsat ETM+ imagery has a spatial resolution of 30 m for the multispectral bands and 60 m for the thermal infrared band.

Landsat products have been applied in vegetation mapping mainly at regional scales. Since Landsat has a long history of dataset, it is very helpful to map long-term vegetation cover and study the spatiotemporal vegetation changes. For example, nearly 20-year continuous Landsat TM/ETM+ image datasets (19 images) covering western Oregon were used to detect and characterize continuous changes in early forest succession (Schroeder *et al.* 2006). Landsat TM images, striding a long period of time from 1986 to 2002, were used to conduct quantitative analyses of wetland landscape patterns and their dynamic changes in the estuary of the Minjiang River (Zheng *et al.* 2006). Because of the different characteristics of spectral sensors (i.e. TM and ETM+) in the Landsat image series, it is necessary to correct the spectral reflectance between images acquired by those sensors. This is especially necessary in long-term vegetation cover monitoring research where both Landsat TM and ETM+ images are used. Moran *et al.* (2001) proposed an empirical line approach for reflectance factor retrieval from Landsat-5 TM and Landsat-7 ETM+. The correspondence analysis method based on the spectral transformation of individual date images into a component space was applied to two multi-temporal Landsat images of Raleigh, North Carolina for land use and land cover change detection (Cakir *et al.* 2006). Due to the limitation of spatial resolution, Landsat products are usually used to map vegetation at community level. It is a challenging task to use Landsat images for mapping at species level, especially in a heterogeneous environment. However, when integrating with other ancillary data, it becomes possible to map species. An example of a species level of vegetation classification was implemented in the Amanos Mountains region of southern central Turkey using Landsat images, combined with the environmental variables and forest management maps, to produce regional scale vegetation maps with an overall high accuracy (Domaç and Süzen 2006).

Table 1 main features of image products from the different sensors

Products (sensors)	Features	Vegetation mapping applications[a]
Landsat TM	Medium to coarse spatial resolution with multispectral data (120 m for thermal infrared band and 30 m for multispectral bands) from Landsat 4 and 5 (1982 to present). Each scene covers an area of 185 × 185 km. Temporal resolution is 16 days.	Regional scale mapping, usually capable of mapping vegetation at community level.
Landsat ETM+ (Landsat 7)	Medium to coarse spatial resolution with multispectral data (15 m for panchromatic band, 60 m for thermal infrared and 30 m for multispectral bands) (1999 to present). Each scene covers an area of 185 km × 185 km. Temporal resolution is 16 days.	Regional scale mapping, usually capable of mapping vegetation at community level or some dominant species can be possibly discriminated.
SPOT	A full range of medium spatial resolutions from 20 m down to 2.5 m, and SPOT VGT with coarse spatial resolution of 1 km. Each scene covers 60 × 60 km for HRV/HRVIR/HRG and 1000 × 1000 km (or 2000 × 2000 km) for VGT. SPOT 1, 2, 3, 4 and 5 were launched in the year of 1986, 1990, 1993, 1998 and 2002, respectively. SPOT 1 and 3 are not providing data now.	Regional scale usually capable of mapping vegetation at community level or species level or global/national/regional scale (from VGT) mapping land cover types (i.e. urban area, classes of vegetation, water area, etc.).
MODIS	Low spatial resolution (250–1000 m) and multispectral data from the Terra Satellite (2000 to present) and Aqua Satellite (2002 to present). Revisit interval is around 1–2 days. Suitable for vegetation mapping at a large scale. The swath is 2330 km (cross track) by 10 km (along track at nadir).	Mapping at global, continental or national scale. Suitable for mapping land cover types (i.e. urban area, classes of vegetation, water area, etc.).
AVHRR	1-km GSD with multispectral data from the NOAA satellite series (1980 to present). The approximate scene size is 2400 × 6400 km	Global, continental or national scale mapping. Suitable for mapping land cover types (i.e. urban area, classes of vegetation, water area, etc.).
IKONOS	It collects high-resolution imagery at 1 m (panchromatic) and 4 m (multispectral bands, including red, green, blue and near infrared) resolution. The revisit rate is 3–5 days (off-nadir). The single scene is 11 × 11 km.	Local to regional scale vegetation mapping at species or community level or can be used to validate other classification result.
QuickBird	High resolution (2.4–0.6 m) and panchromatic and multispectral imagery from a constellation of spacecraft. Single scene area is 16.5 × 16.5 km. Revisit frequency is around 1–3.5 days depending on latitude.	Local to regional scale vegetation mapping at species or community level or used to validate vegetation cover extracted from other images.
ASTER	Medium spatial resolution (15–90 m) image with 14 spectral bands from the Terra Satellite (2000 to present). Visible to near-infrared bands have a spatial resolution of 15 m, 30 m for short wave infrared bands and 90 m for thermal infrared bands.	Regional to national scale vegetation mapping at species or community level.
AVIRIS	Airborne sensor collecting images with 224 spectral bands from visible, near infrared to short wave infrared. Depending on the satellite platforms and latitude of data collected, the spatial resolution ranges from meters to dozens of meters and the swath ranges from several kilometers to dozens of kilometers.	At local to regional scale usually capable of mapping vegetation at community level or species level. As images are carried out as one-time operations, data are not readily available as it is obtained on an ‘as needs’ basis.
Hyperion	It collects hyperspectral image with 220 bands ranging from visible to short wave infrared. The spatial resolution is 30 m. Data available since 2003.	At regional scale capable of mapping vegetation at community level or species level.

[a] Many sensors provide imagery for producing VI (e.g. NDVI) that is calculated from the bands in the visible and near-infrared regions.

In addition to the limitation caused by the medium spatial resolution of Landsat imagery, the relatively low temporal resolution might also restrict its application in vegetation mapping. Landsat satellites are popular and sun synchronous. It takes ~16 days for the satellites to revisit the last location. This imposes a problem for vegetation mapping using Landsat imagery especially when the interest of period (IOP) falls in a rainy season, during which heavy cloud greatly decreases the image quality. Since IOP usually has limited time window, it is very important to take the mapping purpose as well as the local climate and topography conditions into account for the selection of imagery source.

SPOT

The images acquired by SPOT Earth Observation Satellites are useful for studying, monitoring, forecasting and managing natural resources and human activities. Five SPOT satellites have been launched so far, from SPOT 1 to SPOT 5 in the year of 1986, 1990, 1993, 1998 and 2002, respectively. SPOT imagery comes in a full range of resolutions from 1 km global scale (SPOT vegetation imagery) down to 2.5 m local scale. Two HRV (High Resolution Visible) imaging instruments on SPOT 1, 2 and 3 and the corresponding instruments of HRVIR (High Resolution Visible and Infrared) on SPOT 4 and HRG (High Resolution Geometry) on SPOT 5 scan in either panchromatic or multispectral modes. In addition, SPOT 4 and 5 also have a second imaging instrument referred to as SPOT vegetation (VGT) instrument that collects data at a spatial resolution of 1 km and a temporal resolution of 1 day. SPOT images, particularly SPOT VGT, are very useful for observing and analyzing the evolution of land surfaces and understanding land changes over large areas. Because of the multiple sensor instruments and the revisit frequencies, SPOT satellites are capable of obtaining an image of any place on earth every day and having an advantage of mapping vegetation at flexible scales (regional, national, continental or global).

Huang and Siegert (2006) studied the desertification processes by using time series of SPOT VGT images and produced a land cover map with a special emphasis on the detection of sparse vegetation in north China. A classification system for different land cover types with a special emphasis on the sparse vegetation cover was developed to resolve problems related to the seasonal changes and the highly variable natural conditions. As Huang and Siegert (2006) noted, SPOT VGT imagery is very useful to detect large-scale dynamics of environmental changes due to the wide swath and sensitivity of the images to vegetation growth. From multi-temporal SPOT4 VGT sensor data, Wang *et al.* (2006) built a two-level land cover classification system for identifying Poyang Lake Basin's land cover clusters. At continental scale, Cabral *et al.* (2006) built a dataset of monthly composite images composed of daily SPOT VGT images and developed a method suitable for producing a land cover map of southern hemisphere Africa at a spatial resolution of 1 km. In addition, SPOT imagery is also effective in monitoring the distribution and growth of particular plants. For example, SPOT4 VGT was used to produce a vegetation map and predict the distribution of nest-site habitats of eastern New Zealand falcons (*Falco novaeseelandiae*) in Otago (Mathieu *et al.* 2006). To get more accurate mapping, SPOT images can be integrated with other remote sensing images. Millward *et al.* (2006) used medium-resolution satellite imagery to determine the changes in the landscape of the coastal zone near Sanya in Hainan Province, China. After a search for suitable satellite imagery, they found that an effective way to identify the changes was to integrate data from different sensors (TM and ETM+ images, in addition to SPOT 2 HRV images). Furthermore, SPOT imagery can be even utilized to model biochemical processes. Churkina *et al.* (2005) performed an analysis of annual net ecosystem exchange and the length of the carbon uptake period using the enhanced vegetation index (EVI) of SPOT4 VGT.

MODIS

MODIS (Moderate Resolution Imaging Spectroradiometer) is a key instrument on aboard of the Terra (EOS AM) and Aqua (EOS PM) satellites. Terra MODIS and Aqua MODIS together are able to view the entire earth's surface every 1–2 days. The gathered images from MODIS, including 36 spectral bands with spatial resolutions ranging from 250 to 1 km, are mainly applied to map vegetation dynamics and processes at a large scale. Due to the coarse spatial resolution, vegetation mapping at a local scale or regional scale is not recommended. However, image fusion by combining multiple imagery types can possibly lead to better mapping results. Knight *et al.* (2006) examined the potential for classifying vegetation phenology-based land cover over Albemarle-Pamlico estuarine system using MODIS-NDVI 250 m 16-day composite data. They concluded that a significant value could be added to MODIS imagery through combining and comparing the multi-temporal observations with similar classifications generated from much higher spatial resolution data.

AVHRR

Carried aboard the NOAA's Polar Orbiting Environmental Satellite series, the AVHRR sensor is a broadband, 4- (AVHRR/1), 5- (AVHRR/2) or 6- (AVHRR/3) channel scanning radiometer in the visible, near infrared and thermal infrared portions of the electromagnetic spectrum. AVHRR image data have two spatial resolutions: ~1.1 km for local area coverage (LAC) and 5 km for global area coverage (GAC). They are both widely used to study and monitor vegetation conditions in ecosystems, including forests, tundra, grasslands, agricultural lands, land cover mapping and production of large-scale maps for these subjects. One of the obvious advantages of AVHRR is the low cost and the high probability of obtaining a cloud-free view of the land surface. GLCC, as mentioned previously, was produced based on AVHRR image data. A global 8-km fractional vegetation cover dataset for 1982–2000 was also derived from the NOAA–AVHRR Land Pathfinder normalized difference vegetation index (NDVI) data (Zeng and Rao 2003).

Because AVHRR has an image archive with long history (ever since 1978 when the first AVHRR was launched), it is very useful to study long-term changes of vegetation. In the study of the natural ecosystems of the Northeast Region of Brazil (NEB) where they experienced persistent drought episodes and environmental degradation recently, Barbosa *et al.* (2006) examined the spatial heterogeneity and temporal dynamics of the NEB using a 20-year (1982–2001) time series of NDVI observations derived from AVHRR instrument. Other studies conducted using AVHRR include Julien *et al.* (2006), Gonzalez-Alonso *et al.* (2004) and Al-Bakri and Taylor (2003). Because of the coarse spatial resolution, AVHRR is suitable for a large-scale mapping. At a continental scale, Mayaux *et al.* (1998) mapped the vegetation cover of Central Africa by using the AVHRR LAC and GAC data. Han *et al.* (2005) used AVHRR data to calculate the daily NDVI. In the similar way, Maselli and Chiesi (2006) used AVHRR data to study Mediterranean forest productivity based on the production of NDVI.

AVHRR imagery suffers certain limitations in calibration, geometry, orbital drift, limited spectral coverage and variations in spectral coverage especially in the early period of applications. Its utility has been restricted because its use often introduces substantial errors at various stages of processing and analysis. Nevertheless, many projects (including GLCC) aiming at mapping vegetation covers at continental to global scales have been carried out using AVHRR for years simply because of its low cost and easy access.

IKONOS

IKONOS is a commercial sun-synchronous earth observation satellite launched in 1999 and was the first to collect publicly available high-resolution imagery at 1 and 4 m resolution. It has two imagery sensors, multispectral and panchromatic. Panchromatic sensor collects image at 1 m while the multispectral bands (including blue, green, red and near infrared) have a spatial resolution at 4 m. Both sensors have a swath width of 11 km and 3–5 days of revisit interval. The IKONOS observations are at a spatial scale equivalent to field measurements typically carried out in ecological and land cover research. As such, the IKONOS observations may serve as a source of 'virtual' ground measurements for the lower spatial resolution, global observatories (Goward *et al.* 2003). Ideally, IKONOS can be used to map vegetation cover at a local scale or validate vegetation cover classified from other remote sensing images (Goward *et al.* 2003).

QuickBird

Similar to IKONOS, QuickBird offers highly accurate and even higher resolution imagery with panchromatic imagery at 60–70 cm resolution and multispectral imagery at 2.4 and 2.8 m resolutions. It is the only spacecraft able to offer submeter resolution imagery so far. QuickBird's global collections of images greatly facilitate applications ranging from land and asset management to ecology modeling (including vegetation mapping). QuickBird images are usually used to study special topics in relatively small areas (or at a local scale) since it is impractical to apply QuickBird imagery for applications in large area due to its high cost and rigid technical parameters. Wolter *et al.* (2005) used QuickBird imagery to map SAV at three sites across the Great Lakes and proved that QuickBird sensor data were very useful for classifying SAV. Coops *et al.* (2006) evaluated the applicability of QuickBird multispectral imagery in detecting, mapping and monitoring the forestry damages caused by beetles. The results suggested that QuickBird imagery particularly had a valuable role to play in identifying tree crowns with red attack damages. Similar to IKONOS, images from QuickBird can be used to map vegetation cover at a local scale or used for validation purpose.

Besides aforementioned sensors, there are many others. For example, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) is an imaging instrument flying on Terra. ASTER has been used to obtain detailed maps of land surface, reflectance and elevation in the study of habitat patterns (Tuttle *et al.* 2006). The transmitted charge coupled device and infrared multispectral scanner on aboard of Chinese–Brazilian Earth Resources Satellites, a cooperative program between China and Brazil, acquire images with spatial resolution from 20 to 256 m (Epiphanio 2005; Ponzoni *et al.* 2006). While most sensors aforementioned collect multispectral images with dozens of spectral bands, hyperspectral imagery acquired by some other sensors may have hundreds of spectral bands. Note that the principle for mapping vegetation cover from remote sensing images relies on the unique spectral features of different vegetation types. Thus, hyperspectral imagery contains more vegetation information and can be used for more accurate vegetation mapping. AVIRIS, for example, collects images with 224 spectral bands.

Vegetation extraction from remote sensing imagery

Vegetation extraction from remote sensing imagery is the process of extracting vegetation information by interpreting satellite images based on the interpretation elements such as the image color, texture, tone, pattern and association information, etc. Diverse methods have been developed to do this. Those methods can be broadly grouped either as supervised or as unsupervised depending on whether or not true ground data are inputted as references. General steps involved in vegetation mapping include image preprocessing and image classification. Image preprocessing deals with all preparatory steps necessary to improve the quality of original images, which then results in the assignment of each pixel of the scene to one of the vegetation groups defined in a vegetation classification system or a membership matrix of the vegetation groups if fuzzy classification is adopted.

Image preprocessing

Preprocessing of satellite images prior to vegetation extraction is essential to remove noise and increase the interpretability of image data. This is particularly true when a time series of imagery is used or when an area is encompassed by many images since it is essentially important to make these images compatible spatially and spectrally. The ideal result of image preprocessing is that all images after image preprocessing should appear as if they were acquired from the same sensor (Hall *et al.* 1991). Botanist and ecologist should keep in mind that while image preprocessing is the prerequisite for vegetation extraction from remote sensing images, the preprocessing procedures listed below may not be always needed because some of these preprocessing procedures may have been done by image distribution agencies. Thus, it is recommended to consult with the image distributor and get to know at what level the imagery is (usually including level 0, 1A, 1B, 2A, 2B, 3A, 3B with image quality gradually increased) before imagery purchase. For example, for most sensors, level 3A means that radiometric correction, geometric correction and orthorectification have been processed for the images. Image preprocessing commonly comprises a series of operations, including but not limited to bad lines replacement, radiometric correction, geometric correction, image enhancement and masking (e.g. for clouds, water, irrelevant features) although variations may exist for images acquired by different sensors.

Bad line replacement is to determine the overall quality of the images (e.g. missing data lines) through visually previewing the images band-by-band. The visual review is usually done at full extents while attention is focused on identifying lines or blocks of missing data in each band for further repairing. Image line replacement is a procedure that fills in missing lines with the line above, below or with an average of the two.

Radiometric correction of remote sensing data normally involves the process of correcting radiometric errors or distortions of digital images to improve the fidelity of the brightness values. Factors such as seasonal phenology, ground conditions and atmospheric conditions can contribute to variability in multi-temporal spectral responses that may have little to do with the remote sensed objects themselves (Song and Woodcock 2003). It is mandatory to differentiate real changes from noises through radiometric correction in cases where the spectral signals are not sufficiently strong to minimize the effects of these complicating factors. Several methods are available to make radioactive corrections. Some of them are based on complex mathematical models that describe the main interactions involved. However, the values of certain parameters (i.e. the atmospheric composition) must be known before applying them. Other radiometric correction methods are based on the observations of reference targets (e.g. water or desert land) whose radiometry is known. Whatever radiometric correction methods are, they can be classified into two types: absolute and relative correction (Cohen *et al.* 2003; Coppin *et al.* 2004; Du *et al.* 2002; Elvidge *et al.* 1995). The absolute radiometric correction is aimed toward extracting the absolute reflectance of scene objects at the surface of the earth, requiring the input of simultaneous atmospheric properties and sensor calibration, which are difficult to acquire in many cases (Chen *et al.* 2005; Du *et al.* 2002; Song *et al.* 2001). On the other hand, the relative radiometric correction is aimed toward reducing atmospheric and other unexpected variations among multiple images by adjusting the radiometric properties of target images to match a base image (Hall *et al.* 1991), which proves to be easier to apply. Schroeder *et al.* (2006) and Chen *et al.* (2005) extensively compared the effectiveness of the absolute radiometric correction methods (6S model, MDDV model and DOS model) and the relative radiometric correction methods (MAD model and PIF model) and illustrated the pros and cons of each model.

Geometric correction is aimed to avoid geometric distortions from a distorted image and is achieved by establishing the relationship between the image coordinate system and the geographic coordinate system using the calibration data of the sensor, the measured data of position and altitude and the ground control points. Therefore, geometric correction usually includes the selection of a map projection system and the co-registration of satellite image data with other data that are used as the calibration reference. The outcome of geometric correction should obtain an error within plus or minus one pixel of its true position, which allows for accurate spatial assessments and measurements of the data generated from the satellite imagery. The first-order transformation and the nearest neighbor resampling of the uncorrected imagery are among those popularly adopted methods in geometric correction. The first-order transformation, also known as the linear transformation, applies the standard linear equation ($y = mx + b$) to the X and Y coordinates of the ground control points. The nearest neighbor resampling method uses the value of the closest pixel to assign to the output pixel value and thus transfers original data values without averaging them. Therefore, the extremes and subtleties of the data values are not lost (ERDAS 1999).

Sometimes the images will be more distinguishable for interpretation if image enhancement is performed, which is aimed to emphasize and sharpen particular image features (i.e. particular species of vegetation) for visualization purpose. The traditional image enhancement include gray scale conversion, histogram conversion, color composition, color conversion between red-green-blue (RGB) and hue–saturation–intensity transform (HSI), etc., which are usually applied to the image output for image interpretation. Shyu and Leou (1998) explained the limitations of traditional image enhancement methods and proposed a genetic algorithm approach that was proved more effective than the traditional ones.

In mapping vegetation cover using remote sensing images, especially mapping over large regions, cloud imposes a big noise for identifying vegetation and thus has to be removed or masked. Jang *et al.* (2006) proposed a neural network to detect cloud in SPOT VEGETATION images. Walton and Morgan (1998) used cloud-free space shuttle photograph to detect and remove (mask) unwanted cloud covers in Landsat TM scenes.

Image classification

Image classification, in a broad sense, is defined as the process of extracting differentiated classes or themes (e.g. land use categories, vegetation species) from raw remotely sensed satellite data. Obviously this definition includes the preprocessing of images. We here simply refer to the process following the image preprocessing as image classification. Techniques for extracting vegetation from preprocessed images are grouped into two types: traditional and improved methods.

Traditional methods

The traditional methods employ the classical image classification algorithms, e.g. K-mean and ISODATA for unsupervised classification or the maximum likelihood classification (MLC) for supervised classification. Unsupervised approach is often used in thematic mapping (including vegetation cover mapping) from imagery. It is easy to apply and widely available in image processing and statistical software packages (Langley *et al.* 2001). Two most frequently used methods are the K-mean and the ISODATA clustering algorithms. Both of these algorithms involve iterative procedures. In general, both of them assign an arbitrary initial cluster vector first. The second step classifies each pixel to the closest cluster. In the third step, the new cluster mean vectors are calculated based on all the pixels in one cluster. The second and third steps are repeated until the gap between the iteration is small enough (or smaller than a preset threshold). Unsupervised classification methods are purely relying on spectrally pixel-based statistics and incorporate no priori knowledge of the characteristics of the themes being studied. The benefit of applying unsupervised classification methods is to automatically convert raw image data into useful information so long as higher classification accuracy is achieved (Tso and Olsen 2005). Alternatively, rather than purely spectral, Tso and Olsen (2005) incorporated both spectral and contextual information to build a fundamental framework for unsupervised classification, Hidden Markov Models, which showed improvements in both classification accuracy and visual qualities. Algorithms of unsupervised classification were investigated and compared with regard to their abilities to reproduce ground data in a complex area by Duda and Canty (2002). Despite its easy application, one disadvantage of the unsupervised classification is that the classification process has to be repeated again if new data (samples) are added.

By contrast, a supervised classification method is learning an established classification from a training dataset, which contains the predictor variables measured in each sampling unit and assigns prior classes to the sampling units (Lenka and Milan 2005). The supervised classification is to assign new sampling units to the priori classes. Thus, the addition of new data has no impact on the established standards of classification once the classifier has been set up. MLC classifier is usually regarded as a classic and most widely used supervised classification for satellite images resting on the statistical distribution pattern (Sohn and Rebello 2002; Xu *et al.* 2005). However, MLC shows less satisfactory successes since the MLC assumption that the data follow Gaussian distribution may not always be held in complex areas.

Improved classifiers

It is very common that the same vegetation type on ground may have different spectral features in remote sensed images. Also, different vegetation types may possess similar spectra, which makes very hard to obtain accurate classification results either using the traditional unsupervised classification or supervised classification. Searching for improved classification methods is always a hot research topic. However, strictly speaking, all classification methods are derived from the traditional methods as aforementioned, which provide the basic principles and techniques for image classification. Thus, improved methods usually focus on and expand on specific techniques or spectral features, which can lead to better classification results and thus deserve special attention. Great progress has been made in developing more powerful classifiers to extract vegetation covers from remote sensing images. For example, Stuart *et al.* (2006) developed continuous classifications using Landsat data to distinguish variations within Neotropical savannas and to characterize the boundaries between savanna areas, the associated gallery forests, seasonally dry forests and wetland communities. They proved that continuous classifications were better than MLC classification especially in complex land cover areas.

Extensive field knowledge and auxiliary data may help improve classification accuracy. Studies have shown that classification accuracy can be greatly improved after applying expert knowledge (empirical rules) and ancillary data to extract thematic features (e.g. vegetation groups) (Gad and Kusky 2006; Shrestha and Zinck 2001). In a regional scale vegetation classification conducted in the Amanos Mountains region of southern central Turkey using Landsat images, Domaç and Süzen (2006) incorporated vegetation-related environmental variables and considerably improved classification accuracy when compared with the traditional MLC method. Under many circumstances, however, gathering specific knowledge is an enormous task and obtaining ancillary data is very costly. Therefore, the knowledge-based classifications are not universally applicable.

Sohn and Rebello (2002) developed supervised and unsupervised spectral angle classifiers (SAC), which take account of the fact that the spectra of the same type of surface objects are approximately linearly scaled variations of one another due to the atmospheric and topographic effects. Those SAC helped identify the distances between pairs of signatures for classification and were successfully applied in biotic community and land cover classification (Sohn and Qi 2005). The adoption of VI including the most widely used NDVI and its refined form, EVI, is another method to map vegetation using optical remote sensing devices (deFries *et al.* 1995). The principle of applying NDVI in vegetation mapping is that vegetation is highly reflective in the near infrared and highly absorptive in the visible red. The contrast between these channels can be used as an indicator of the status of the vegetation. In other word, NDVI is a biophysical parameter that correlates with photosynthetic activity of vegetation. In addition to providing an indication of the 'greenness' of the vegetation (Wang and Tenhunen 2004), NDVI is also able to offer valuable information of the dynamic changes of specific vegetation species given that multiple-time images are analyzed. Therefore, NDVI is a good indicator to reflect periodically dynamic changes of vegetation groups (Geerken *et al.* 2005). Particular vegetation groups can be identified through their unique phenology, or dynamic signals of NDVI (Lenney *et al.* 1996), which is also known as 'Multitemporal Image Classification'. Another approach to identify specific vegetation groups is to study time series VI. For example, Bagan *et al.* (2005) applied the combined EVI multi-dataset generated from 16-day interval MODIS data during the growing season of plants as input parameters to match the features of vegetation groups and to classify the images. The classification results were compared with those of the traditional MLC method and the accuracy of the former exceeded that of the latter.

Artificial neural network (ANN) and fuzzy logic approaches are also seen in literature for vegetation classifications. ANN is appropriate for the analysis of nearly any kind of data irrespective of their statistical properties. ANN is very useful in extracting vegetation-type information in complex vegetation mapping problems (Filippi and Jensen 2006), though it is at the expense of the interpretability of the results since ANN deploys a black-box approach that hides the underlying prediction process (Černá and Chytrý 2005). Berberoglu *et al.* (2000) combined ANN and texture analysis on a per-field basis to classify land cover and found the accuracy could be 15% greater than the accuracy achieved using a standard per-pixel ML classification. One disadvantage of ANN, however, is that ANN can be computationally demanding when large datasets are dealt to train the network and sometimes no result may be achieved at all even after a long-time computation due to the local minimum (e.g. for a back-propagation ANN).

A fuzzy classification approach is usually useful in mixed-class areas and was investigated for the classification of suburban land cover from remote sensing imagery (Zhang and Foody 1998), the study of medium-to-long term (10–50 years) vegetation changes (Okeke and Karnieli 2006) and the biotic-based grassland classification (Sha *et al.* 2008). Fuzzy classification is a kind of probability-based classification rather than crisp classification. Unlike implementing per-pixel-based classifier to produce crisp or hard classification, Xu *et al.* (2005) employed a decision tree (DT) derived from the regression approach to determine class proportions within a pixel so as to produce a soft classification. Theoretically, probability-based or soft classification is more reasonable for composite units since those units cannot be simply classified to one type but to a probability for that type. While soft classification techniques are inherently appealing for mapping vegetation transition, there is an unresolved issue of how best to present the output. Rather than imposing subjective boundaries on the end-member communities, transition zones of intermediate vegetation classes between the end-member communities were adopted to better represent the softened classification result (Hill *et al.* 2007).

DT is another approach of vegetation classification by matching the spectral features or combinations of spectral features from images with those of possible end members of vegetation types (community or species level). DT is computationally fast, makes no statistical assumptions and can handle data that are represented on different measurement scales. A global land cover map deduced from AVHRR imagery was produced by Hansen *et al.* (2006) using a DT that has a set of 41 metrics generated from five spectral channels and NDVI for input. The agreements for all classes varied from an average of 65% when viewing all pixels to an average of 82% when viewing only those 1 km pixels consisting of >90% one class within the high-resolution datasets. Other studies integrated soft classification with DT approach (Xu *et al.* 2005). Pal and Mather (2003) studied the utility of DT classifiers for land cover classification using multispectral and hyperspectral data and compared the performance of the DT classifier with that of the ANN and ML classifiers, with changes in training data size, choice of attribute selection measures, pruning methods and boosting. They found that the use of DT classifiers with high-dimensional (hyperspectral data) is limited while good result was achieved with multispectral data. Under some circumstances, DT can be very useful when vegetation types are strictly associated with other natural conditions (e.g. soil type or topography) (He *et al.* 2005). For example, some vegetation species may only grow in areas with elevation higher than a certain level. This can be integrated within DT to assist the classification process from imagery if such ancillary data are available.

In the study of monitoring natural vegetation in Mediterranean, Sluiter (2005) investigated a wide range of vegetation classification methods for remote sensing imagery. Firstly, two methods of random forests and support vector machines were explored, which showed better performances over the traditional classification techniques. Secondly, rather than using the per-pixel spectral information to extract vegetation features, Sluiter applied the spatial domain, viz. both per-pixel spectral information and the spectral information of neighboring pixels to analyze and classify remote sensing imagery. It was found that when a contextual technique named SPARK (SPAtial Reclassification Kernel) was implemented, vegetation classes, which were not distinguished at all by conventional per-pixel-based methods, could be successfully detected. The similar result was also noted by Im and Jensen (2005) who used a three-channel neighborhood correlation image model to detect vegetation changes through the relation of pixels and their contextual neighbors. Based on SPARK, Sluiter (2005) continued integrating spectral information, ancillary information and contextual information and developed a spatiotemporal image classification model called ancillary data classification model (ADCM). The ADCM method increased the overall accuracy as well as individual class accuracies in identifying heterogeneous vegetation classes.

As stated above, there are many classification methods or algorithms developed for image classification applications under a broad range of specific applications. Sometimes, it may increase the quality of classification results when multiple methods (algorithms) are jointly employed. For example, Lo and Choi (2004) proposed a hybrid method that incorporated the advantages of supervised and unsupervised approaches as well as hard and soft classifications for mapping the land cover in Atlanta Metropolitan Area using Landsat 7 ETM+ data. However, cautions should be usually exercised when applying improved classifiers because these methods were often designed and developed under specific challenges to solve unique problems. Moreover, discrimination of vegetation species from single imagery is only achievable where a combination of leaf chemistry, structure and moisture content culminates to form a unique spectral signature. Thus, imagery classification relies on successful extraction of pure spectral signature for each species, which is often dictated by the spatial resolution of the observing sensor and the timing of observation (Asner and Heidebrecht 2002; Varshney and Arora 2004). In short, search for improved image classification algorithms is still a hot field in the remote sensing applications because there are no super classification methods that could apply universally.

Hyperspectral imagery and data fusion

In recent years, more advanced methods reflecting the latest remote sensing techniques used in vegetation mapping are seen in literature. Among them, the applications of hyperspectral imagery and multiple imagery fusion to extract vegetation cover are rapidly developed and thus deserve our special attention.

Vegetation mapping from hyperspectral imagery

Rather than using multispectral imagery, vegetation extraction from hyperspectral imagery is increasingly studied recently. Compared with multispectral imagery that only has a dozen of spectral bands, hyperspectral imagery includes hundreds of spectral bands. Hyperspectral sensors are well suited for vegetation studies as reflectance/absorption spectral signatures from individual species as well as more complex mixed-pixel communities can be better differentiated from the much wider spectral bands of hyperspectral imagery (Varshney and Arora 2004). For example, the hyperspectral imagery from AVIRIS is commonly used in the realm of earth remote sensing. AVIRIS is a unique optical sensor that delivers calibrated images of the upwelling spectral radiance in 224 contiguous spectral channels (bands) with the wavelengths ranging from 400 to 2500 nm. The information within those bands can be utilized to identify, measure and monitor constituents of the earth's surface (e.g. vegetation types) based on molecular absorption and particle scattering signatures. One of the studies using AVIRIS imagery was to classify salt marshes in China and in San Pablo Bay of California, USA (Li *et al.* 2005). The results were satisfactory considering the success in classifying two main marsh vegetation species, *Spartina* and *Salicornia*, which covered 93.8% of the total marsh, although further work was required to correct the false detection of other marsh vegetation species. A similar work was also conducted by Rosso *et al.* (2005) in the study of the structure of wetlands in San Francisco Bay of California by monitoring vegetation dynamics aimed at proposing sustainable management of wetland ecosystems. Hyperspectral data acquired by the Hyperion instrument on board the Earth Observing-1 (EO-1) satellite were evaluated for the discrimination of five important Brazilian sugarcane varieties (Galvâo *et al.* 2005). The results showed that the five Brazilian sugarcane varieties were discriminated using EO-1 Hyperion data, implying that hyperspectral imagery is capable of separating plant species, which may be very difficult by using multispectral images.

Although the general procedures (preprocessing and classification) for hyperspectral images are the same as those required for multispectral images, the processing of hyperspectral data remains a challenge. Specialized, cost effective and computationally efficient procedures are required to process hundreds of bands (Varshney and Arora 2004). To extract vegetation communities or species from hyperspectral imagery, a set of signature libraries of vegetation are usually required (Xavier *et al.* 2006). For certain applications, the vegetation libraries for particular vegetation communities or species might be already available. However, for most cases, the spectral signature library is established using ground truth data with hyperspectral data or through spectrometers. As such, vegetation mapping using hyperspectral imagery must be well designed to collect synchronous field data for creating imagery signatures.

Vegetation mapping through image fusion

The information provided by each individual sensor may be incomplete, inconsistent and imprecise for a given application. Image fusion of remotely sensed data with multiple spatial resolutions is an effective technique that has a good potential for improving vegetation classification. It is important for accurate vegetation mapping to efficiently integrate remote sensing information with different temporal, spectral and spatial resolutions through image fusion. There are many studies focusing on the development of new fusion algorithms (Amarsaikhan and Douglas 2004; Zhang 2004; Zhu and Tateishi 2006). For example, in the study of fusion for high-resolution panchromatic and low-resolution multispectral remote sensing images, Li *et al.* (2006) proposed a frequency buffer model to overcome the difficulty of identifying high-frequency components of panchromatic images and low-frequency components of multispectral images. Based on the statistical fusion of multi-temporal satellite images, Zhu and Tateishi (2006) developed a new temporal fusion classification model to study land cover classification and verified its improved performance over the conventional methods. Behnia (2005) compared four frequently adopted image fusion algorithms, namely principle component transform, brovey transform, smoothing filter-based intensity modulation and HSI and concluded that each of them improves the spatial resolution effectively but distorts the original spectral signatures to certain degrees. To solve the color distortion associated with some existing techniques, Wu *et al.* (2005) developed an enhancement color normalized algorithm to merge lower spatial resolution multispectral images with a higher spatial resolution panchromatic image. Rather than designing new fusion algorithms, Colditz *et al.* (2006) tested various image fusion methods to study their impacts on land cover classification accuracies ranging from common techniques like brovey, hue–saturation–value transform and principal component analysis to more complex approaches like adaptive image fusion, multisensor multi-resolution image fusion technique and wavelet transformation. In brief, image fusion opens a new way to extract high accuracy vegetation covers by integrating remote sensing images from different sensors. However, the challenges of fusion strategy (including developing new fusion algorithms) still require further studies.

Result evaluation

The products of vegetation mapping derived from remote sensed images should be objectively verified and communicated to users so that they can make informed decisions on whether and how the products can be used. Result evaluation, a procedure also called accuracy assessment, is often employed to determine the degree of 'correctness' of the classified vegetation groups compared to the actual ones. A vegetation map derived from image classification is considered accurate if it provides a true representation of the region it portrays (Foody 2002; Weber 2006). Four significant stages have been witnessed in accuracy assessment methods (Congalton 1994). Accuracy assessment in the first stage was done by visual inspection of derived maps. This method is deemed to be highly subjective and often not accurate. The second stage used a more objective method by which comparisons of the area extents of the classes in the derived thematic maps (e.g. the percentage of a specific vegetation group in area) were made with the corresponding extents on ground or in other reference dataset. However, there is a major problem with this non-site-specific approach since the correct proportions of vegetation groups do not necessarily mean the correct locations at which they locate. In the third stage, the accuracy metrics were built on a comparison of the class labels in the thematic map with the ground data for the same locations. Measures such as the percentages of cases correctly (and wrongly) classified were used to evaluate the classification accuracy. The accuracy assessment at the fourth stage made further refinements on the basis of the third stage. The obvious characteristic of this stage is the wide use of the confusion or error matrix, which describes the fitness between the derived classes and the reference data through using the measures like overall accuracy and kappa coefficient. Additionally, a variety of other measures is also available or can be derived from the error matrix. For example, the accuracy of individual classes can be derived if the user is interested in specific vegetation groups.

Although it is agreed that accuracy assessment is important to qualify the result of image classification, it is probably impossible to specify a single, all-purpose measure for assessing classification accuracy. For example, the confusion matrix and its derived measures of accuracy may seem reasonable and feasible. However, they may not be applicable under some circumstances, especially in vegetation mapping at coarse scales (Cingolani *et al.* 2004). One of the problems caused by the pixel-based confusion matrix evaluation is that a pixel at a coarse resolution may include several vegetation types. As shown in Fig. 3, a pixel in imagery represents a composite of three vegetation classes (class *A*, *B* and *C*). Clearly, the eclipse located in the center of the pixel may be the sampling area. Since it is impractical to sample the whole pixel at a large-scale mapping, this pixel would most likely be labeled with class *B* in image classification considering its percentage of the occupied area. Therefore, the vegetation class between the derived (class *B*) and the referenced (class *A*) will not match and this mismatch will introduce classification errors. In this case, the non-site-specific accuracy measures may be more suitable if not for the limitation mentioned previously. Moreover, rather than using field samples to test the classification accuracy, a widely accepted practice is to use finer resolution satellite data to assess coarser resolution products (Cihlar *et al.* 2003), although the high-resolution data are themselves subject to interpretation and possible errors (Defries and Townshend 1999). The result evaluating for image classification still remains a hot debating topic today (Foody 2002).

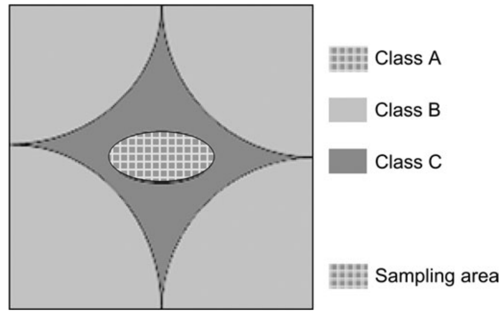

Figure 3 illustration for pixel-based accuracy assessment at coarse scale. The envelope square represents a pixel in imagery. Here problem occurs: ground 'true' vegetation class is *A*, but classified result for the pixel, if correctly classified, would be labeled with *B*. This would lead to a mismatch between ground referenced data and classified result, which is very typical in pixel-based accuracy assessment especially at large-scale vegetation mapping.

Conclusions and discussions

This paper covered a wide array of topics in vegetation classification using remote sensing imagery. First, a range of remote sensing sensors and their applications in vegetation mapping were introduced to facilitate the selection of right remote sensing products for specific applications. Second, the techniques of image preprocessing and various classification methods (traditional and improved) were discussed on how to extract vegetation features from remote sensing images. Particularly, the extraction of vegetation cover through the application of hyperspectral imagery and image fusion was discussed. Third, a section was dedicated to the discussion of result evaluation (accuracy assessment) of image classification. Although the coverage of topics was not inclusive, and not all possible problems were addressed, the basic steps, principles, techniques and methods of mapping vegetation cover from remote sensing imagery were discussed and the supporting references were provided.

In short, remote sensing images are key data sources for earth monitoring programs considering the great advantages that they have (Nordberg and Evertson 2003). For instance, it is more easily obtainable to produce and update vegetation inventories over large regions if aided by satellite imagery and appropriate imagery analysis. A growing number of studies have examined a wide variety of vegetative phenomena (including mapping vegetation cover) by using remote sensed data (Duchemin *et al.* 1999; Geerken *et al.* 2005; Nerry *et al.* 1998; Xavier *et al.* 2006). However, although remote sensing technology has tremendous advantages over traditional methods in vegetation mapping, we should have a clear understanding of its limitations. As stated by Rapp *et al.* (2005), three questions should be asked when using the results of vegetation mapping from remote sensing imagery: how well the chosen classification system represents actual vegetation community composition, how effectively images from remote sensing capture the distinguishing features of each mapping unit within the classification and how well these mapping units are delineated by photointerpreters. In other word, a well-fit vegetation classification system should be carefully designed according to the objective of studies in order to better represent actual vegetation community compositions. More specifically, the following points should be taken into consideration when selecting a right vegetation classification system for better classification accuracy (Rapp *et al.* 2005): (i) refining class definitions to decrease ambiguity, (ii) adding new classes to more adequately describe the complexity of local vegetation patterns and (iii) using a higher level of classification.

Furthermore, because of these limitations, the to-be-classified vegetation types, categorized by physiognomic classification systems (Dansereau 1962), floristic classification systems (Salovaara *et al.* 2005; Thenkabail *et al.* 2003) or site-oriented vegetation classification systems (Degraaf and Chadwick 1984; Harms *et al.* 2001), must produce distinct spectral signatures so that the remote sensed images could be differentiated. However, this is not always true in many cases, especially when a study area is covered by vegetations of complex forms or different stages, which result in similar spectral responses among different vegetation groups or generate spectral variations for the same vegetation group (Sha *et al.* 2008). Difficulties or challenges are often encountered to map vegetation under such circumstances. One solution is to adopt more advanced image classification method such as sub-pixel analysis (Lee and Lathrop 2005). Another way is to choose higher resolutions of imagery acquired by the right remote sensing sensors so as to increase the distinguishable possibility in image classification (Cingolani *et al.* 2004). Nevertheless, higher resolutions of imagery will most likely increase the cost.

Although there are some standard methods for image preprocessing, there are no super image classifiers that can be uniformly applicable to all applications. Thus, it is a challenging task, as well as a hot research topic, to apply effective classifiers or to develop new powerful classifiers suitable for specific applications. Moreover, ancillary data, including field samples, topographical features, environmental characteristics and other digital (geographic information system) data layers, have been proved very helpful to get a more satisfactory result or increase classification accuracy. It is advisable to keep in mind that the technical improvements (designing more advanced classifiers or acquiring high-resolution imagery, etc.) cannot solve all problems that are encountered during vegetation extraction from remote sensed data but will improve the results. It is especially difficult to map vegetations over large areas such as at continental or global scales. Commonly, vegetation cover maps at large scales are compositions of many maps from different sources over a long time. As stated by White (1983), for example, the UNESCO/AETFAT/UNSO vegetation of Africa at a continent scale is the compilation of many national or local maps over a 15-year period. It is not surprising that the overall accuracy of the product is not satisfactory as those national or local maps are based on heterogeneous conceptions of vegetation classification systems and produced at different periods. Therefore, it is very preferable to conduct vegetation classification using the data acquired from the same sources and at the same period and applying the same processing methods for the entire region. The lack of such consistent and identical data (mainly remote sensed data and the reference data) for large regions often limits the production of vegetation maps with good quality.

Supplementary Data

Supplementary material is available online at *Journal of Plant Ecology* online.

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