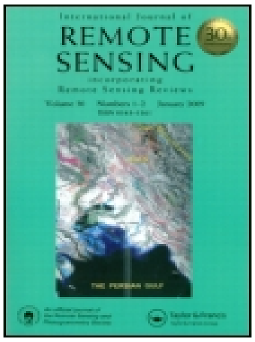

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Review article

A survey of image classification methods and techniques for improving classification performance

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Image classification is a complex process that may be affected by many factors. This paper examines current practices, problems, and prospects of image classification. The emphasis is placed on the summarization of major advanced classification approaches and the techniques used for improving classification accuracy. In addition, some important issues affecting classification performance are discussed. This literature review suggests that designing a suitable image-processing procedure is a prerequisite for a successful classification of remotely sensed data into a thematic map. Effective use of multiple features of remotely sensed data and the selection of a suitable classification method are especially significant for improving classification accuracy. Non-parametric classifiers such as neural network, decision tree classifier, and knowledge-based classification have increasingly become important approaches for multisource data classification. Integration of remote sensing, geographical information systems (GIS), and expert system emerges as a new research frontier. More research, however, is needed to identify and reduce uncertainties in the image-processing chain to improve classification accuracy.

1. Introduction

Remote-sensing research focusing on image classification has long attracted the attention of the remote-sensing community because classification results are the basis for many environmental and socioeconomic applications. Scientists and practitioners have made great efforts in developing advanced classification approaches and techniques for improving classification accuracy (Gong and Howarth 1992, Kontoes *et al.* 1993, Foody 1996, San Miguel-Ayanz and Biging 1997, Aplin *et al.* 1999a, Stuckens *et al.* 2000, Franklin *et al.* 2002, Pal and Mather 2003, Gallego 2004). However, classifying remotely sensed data into a thematic map remains a challenge because many factors, such as the complexity of the landscape in a study area, selected remotely sensed data, and image-processing and classification approaches, may affect the success of a classification. Although much previous research and some books are specifically concerned with image classification (Tso and Mather 2001, Landgrebe 2003), a comprehensive up-to-date review of classification approaches and techniques is not available. Continuous

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emergence of new classification algorithms and techniques in recent years necessitates such a review, which will be highly valuable for guiding or selecting a suitable classification procedure for a specific study.

The foci of this paper are on providing a summarization of major advanced classification methods and techniques used for improving classification accuracy, and on discussing important issues affecting the success of image classifications. Common classification approaches, such as ISODATA, K-means, minimum distance, and maximum likelihood, are not discussed here, since the readers can find them in many textbooks.

2. Remote-sensing classification process

Remote-sensing classification is a complex process and requires consideration of many factors. The major steps of image classification may include determination of a suitable classification system, selection of training samples, image preprocessing, feature extraction, selection of suitable classification approaches, post-classification processing, and accuracy assessment. The user's need, scale of the study area, economic condition, and analyst's skills are important factors influencing the selection of remotely sensed data, the design of the classification procedure, and the quality of the classification results. This section focuses on the description of the major steps that may be involved in image classification.

2.1 *Selection of remotely sensed data*

Remotely sensed data, including both airborne and spaceborne sensor data, vary in spatial, radiometric, spectral, and temporal resolutions. Understanding the strengths and weaknesses of different types of sensor data is essential for the selection of suitable remotely sensed data for image classification. Some previous literature has reviewed the characteristics of major types of remote-sensing data (Barnsley 1999, Estes and Loveland 1999, Althausen 2002, Lefsky and Cohen 2003). For example, Barnsley (1999) and Lefsky and Cohen (2003) summarized the characteristics of different remote-sensing data in spectral, radiometric, spatial, and temporal resolutions; polarization; and angularity. The selection of suitable sensor data is the first important step for a successful classification for a specific purpose (Phinn 1998, Jensen and Cowen 1999, Phinn *et al.* 2000, Lefsky and Cohen 2003). It requires considering such factors as user's need, the scale and characteristics of a study area, the availability of various image data and their characteristics, cost and time constraints, and the analyst's experience in using the selected image.

Scale, image resolution, and the user's need are the most important factors affecting the selection of remotely sensed data. The user's need determines the nature of classification and the scale of the study area, thus affecting the selection of suitable spatial resolution of remotely sensed data. Previous research has explored the impacts of scale and resolution on remote-sensing image classification (Quattrochi and Goodchild 1997). In general, a fine-scale classification system is needed for a classification at a local level, thus high spatial resolution data such as IKONOS and SPOT 5 HRG data are helpful. At a regional scale, medium spatial resolution data such as Landsat TM/ETM+, and Terra ASTER are the most frequently used data. At a continental or global scale, coarse spatial resolution data such as AVHRR, MODIS, and SPOT Vegetation are preferable.

Another important factor influencing the selection of sensor data is the atmospheric condition. The frequent cloudy conditions in the moist tropical regions are often an obstacle for capturing high-quality optical sensor data. Therefore, different kinds of radar data serve as an important supplementary data source. Since multiple sources of sensor data are now readily available, image analysts have more choices to select suitable remotely sensed data for a specific study. A combination of multisensor data with various image characteristics is usually beneficial to the research (Lefsky and Cohen 2003). In this situation, economic condition is often an important factor that affects the selection of remotely sensed data and the time and labour that can be devoted to the classification procedure, thus affecting the quality of the classification results.

2.2 *Selection of a classification system and training samples*

A suitable classification system and a sufficient number of training samples are prerequisites for a successful classification. Cingolani *et al.* (2004) identified three major problems when medium spatial resolution data are used for vegetation classifications: defining adequate hierarchical levels for mapping, defining discrete land-cover units discernible by selected remote-sensing data, and selecting representative training sites. In general, a classification system is designed based on the user's need, spatial resolution of selected remotely sensed data, compatibility with previous work, image-processing and classification algorithms available, and time constraints. Such a system should be informative, exhaustive, and separable (Jensen 1996, Landgrebe 2003). In many cases, a hierarchical classification system is adopted to take different conditions into account.

A sufficient number of training samples and their representativeness are critical for image classifications (Hubert-Moy *et al.* 2001, Chen and Stow 2002, Landgrebe 2003, Mather 2004). Training samples are usually collected from fieldwork, or from fine spatial resolution aerial photographs and satellite images. Different collection strategies, such as single pixel, seed, and polygon, may be used, but they would influence classification results, especially for classifications with fine spatial resolution image data (Chen and Stow 2002). When the landscape of a study area is complex and heterogeneous, selecting sufficient training samples becomes difficult. This problem would be complicated if medium or coarse spatial resolution data are used for classification, because a large volume of mixed pixels may occur. Therefore, selection of training samples must consider the spatial resolution of the remote-sensing data being used, availability of ground reference data, and the complexity of landscapes in the study area.

2.3 *Data preprocessing*

Image preprocessing may include the detection and restoration of bad lines, geometric rectification or image registration, radiometric calibration and atmospheric correction, and topographic correction. If different ancillary data are used, data conversion among different sources or formats and quality evaluation of these data are also necessary before they can be incorporated into a classification procedure. Accurate geometric rectification or image registration of remotely sensed data is a prerequisite for a combination of different source data in a classification process. Many textbooks and articles have described this topic in detail (Jensen 1996, Toutin 2004). Therefore, it is not discussed here.

If a single-date image is used in classification, atmospheric correction may not be required (Song *et al.* 2001). When multitemporal or multisensor data are used, atmospheric calibration is mandatory. This is especially true when multisensor data, such as Landsat TM and SPOT or Landsat TM and radar data, are integrated for an image classification. A variety of methods, ranging from simple relative calibration and dark-object subtraction to calibration approaches based on complex models (e.g. 6S), have been developed for radiometric and atmospheric normalization and correction (Markham and Barker 1987, Gilabert *et al.* 1994, Chavez 1996, Stefan and Itten 1997, Vermote *et al.* 1997, Tokola *et al.* 1999, Heo and FitzHugh 2000, Song *et al.* 2001, Du *et al.* 2002, McGovern *et al.* 2002, Canty *et al.* 2004, Hadjimitsis *et al.* 2004). Topographic correction is another important aspect if the study area is located in rugged or mountainous regions (Teillet *et al.* 1982, Civco 1989, Colby 1991, Meyer *et al.* 1993, Richter 1997, Gu and Gillespie 1998, Hale and Rock 2003). A detailed description of atmospheric and topographic correction is beyond the scope of this paper. Interested readers may check relevant references to identify a suitable approach for a specific study.

2.4 *Feature extraction and selection*

Selecting suitable variables is a critical step for successfully implementing an image classification. Many potential variables may be used in image classification, including spectral signatures, vegetation indices, transformed images, textural or contextual information, multitemporal images, multisensor images, and ancillary data. Due to different capabilities in land-cover separability, the use of too many variables in a classification procedure may decrease classification accuracy (Hughes 1968, Price *et al.* 2002). It is important to select only the variables that are most useful for separating land-cover or vegetation classes, especially when hyperspectral or multisource data are employed. Many approaches, such as principal component analysis, minimum noise fraction transform, discriminant analysis, decision boundary feature extraction, non-parametric weighted feature extraction, wavelet transform, and spectral mixture analysis (Myint 2001, Okin *et al.* 2001, Rashed *et al.* 2001, Asner and Heidebrecht 2002, Lobell *et al.* 2002, Neville *et al.* 2003, Landgrebe 2003, Platt and Goetz 2004) may be used for feature extraction, in order to reduce the data redundancy inherent in remotely sensed data or to extract specific land-cover information.

Optimal selection of spectral bands for classifications has been extensively discussed in previous literature (Mausel *et al.* 1990, Jensen 1996, Landgrebe 2003). Graphic analysis (e.g. bar graph spectral plots, co-spectral mean vector plots, two-dimensional feature space plot, and ellipse plots) and statistical methods (e.g. average divergence, transformed divergence, Bhattacharyya distance, Jeffreys–Matusita distance) have been used to identify an optimal subset of bands (Jensen 1996). Penaloza and Welch (1996) explored the fuzzy-logic expert system for feature selection. Peddle and Ferguson (2002) examined three approaches (exhaustive search by recursion, isolated independent search, and sequential dependent search) for optimizing the selection of multisource data, and found that these approaches were applicable to a variety of data analyses. In practice, a comparison of different combinations of selected variables is often implemented, and a good reference dataset is vital. In particular, a good representative dataset for each class is key for implementing a supervised classification. The divergence-related algorithms are often used to evaluate the class separability and then to refine the training samples for each class.

2.5 *Selection of a suitable classification method*

Many factors, such as spatial resolution of the remotely sensed data, different sources of data, a classification system, and availability of classification software must be taken into account when selecting a classification method for use. Different classification methods have their own merits. The question of which classification approach is suitable for a specific study is not easy to answer. Different classification results may be obtained depending on the classifier(s) chosen. A detailed summarization of major classification methods is provided in §4.

2.6 *Post-classification processing*

Traditional per-pixel classifiers may lead to 'salt and pepper' effects in classification maps. A majority filter is often applied to reduce the noises. Most image classification is based on remotely sensed spectral responses. Due to the complexity of biophysical environments, spectral confusion is common among land-cover classes. Thus, ancillary data are often used to modify the classification image based on established expert rules. For example, forest distribution in mountainous areas is related to elevation, slope, and aspects. Data describing terrain characteristics can therefore be used to modify classification results based on the knowledge of specific vegetation classes and topographic factors. In urban areas, housing or population density is related to urban land-use distribution patterns, and such data can be used to correct some classification confusions between commercial and high-intensity residential areas or between recreational grass and crops. Although commercial and high-intensity residential areas have similar spectral signatures, their population densities are considerably different. Similarly, recreational grass is often found in residential areas, but pasture and crops are largely located away from residential areas, with sparse houses and a low population density. Thus, expert knowledge can be developed based on the relationships between housing or population densities and urban land-use classes to help separate recreational grass from pasture and crops. Previous research has indicated that post-classification processing is an important step in improving the quality of classifications (Harris and Ventura 1995, Murai and Omatu 1997, Stefanov *et al.* 2001, Lu and Weng 2004).

2.7 *Evaluation of classification performance*

Evaluation of classification results is an important process in the classification procedure. Different approaches may be employed, ranging from a qualitative evaluation based on expert knowledge to a quantitative accuracy assessment based on sampling strategies. To evaluate the performance of a classification method, Cihlar *et al.* (1998) proposed six criteria: accuracy, reproducibility, robustness, ability to fully use the information content of the data, uniform applicability, and objectiveness. In reality, no classification algorithm can satisfy all these requirements nor be applicable to all studies, due to different environmental settings and datasets used. DeFries and Chan (2000) suggested the use of multiple criteria to evaluate the suitability of algorithms. These criteria include classification accuracy, computational resources, stability of the algorithm, and robustness to noise in the training data. Classification accuracy assessment is, however, the most common approach for an evaluation of classification performance, which is detailed in §3.

3. Classification accuracy assessment

Before implementing a classification accuracy assessment, one needs to know the sources of errors (Congalton and Green 1993, Powell *et al.* 2004). In addition to errors from the classification itself, other sources of errors, such as position errors resulting from the registration, interpretation errors, and poor quality of training or test samples, all affect classification accuracy. In the process of accuracy assessment, it is commonly assumed that the difference between an image classification result and the reference data is due to the classification error. However, in order to provide a reliable report on classification accuracy, non-image classification errors should also be examined, especially when reference data are not obtained from a field survey.

A classification accuracy assessment generally includes three basic components: sampling design, response design, and estimation and analysis procedures (Stehman and Czaplewski 1998). Selection of a suitable sampling strategy is a critical step (Congalton 1991). The major components of a sampling strategy include sampling unit (pixels or polygons), sampling design, and sample size (Muller *et al.* 1998). Possible sampling designs include random, stratified random, systematic, double, and cluster sampling. A detailed description of sampling techniques can be found in previous literature such as Stehman and Czaplewski (1998) and Congalton and Green (1999).

The error matrix approach is the one most widely used in accuracy assessment (Foody 2002b). In order to properly generate an error matrix, one must consider the following factors: (1) reference data collection, (2) classification scheme, (3) sampling scheme, (4) spatial autocorrelation, and (5) sample size and sample unit (Congalton and Plourde 2002). After generation of an error matrix, other important accuracy assessment elements, such as overall accuracy, omission error, commission error, and kappa coefficient, can be derived. Previous literature has defined the meanings and provided computation methods for these elements (Congalton and Mead 1983, Hudson and Ramm 1987, Congalton 1991, Janssen and van der Wel 1994, Kalkhan *et al.* 1997, Stehman 1996, 1997, Congalton and Green 1999, Smits *et al.* 1999, Congalton and Plourde 2002, Foody 2002b, 2004a). Meanwhile, many authors, such as Congalton (1991), Janssen and van der Wel (1994), Smits *et al.* (1999), and Foody (2002b), have conducted reviews on classification accuracy assessment. They have assessed the status of accuracy assessment of image classification, and discussed relevant issues. Congalton and Green (1999) systematically reviewed the concept of basic accuracy assessment and some advanced topics involved in fuzzy-logic and multilayer assessments, and explained principles and practical considerations in designing and conducting accuracy assessment of remote-sensing data. The Kappa coefficient is a measure of overall statistical agreement of an error matrix, which takes non-diagonal elements into account. Kappa analysis is recognized as a powerful method for analysing a single error matrix and for comparing the differences between various error matrices (Congalton 1991, Smits *et al.* 1999, Foody 2004a). Modified kappa coefficient and tau coefficient have been developed as improved measures of classification accuracy (Foody 1992, Ma and Redmond 1995). Moreover, accuracy assessment based on a normalized error matrix has been conducted, which is regarded as a better presentation than the conventional error matrix (Congalton 1991, Hardin and Shumway 1997, Stehman 2004).

The error matrix approach is only suitable for 'hard' classification, assuming that the map categories are mutually exclusive and exhaustive and that each location belongs to a single category. This assumption is often violated, especially for classifications with coarse spatial resolution imagery. 'Soft' classifications have been performed to minimize the mixed pixel problem using a fuzzy logic. The traditional error matrix approach is not appropriate for evaluating these soft classification results. Accordingly, many new measures, such as conditional entropy and mutual information (Finn 1993, Maselli *et al.* 1994), fuzzy-set approaches (Gopal and Woodcock 1994, Binaghi *et al.* 1999, Woodcock and Gopal 2000), symmetric index of information closeness (Foody 1996), Renyi generalized entropy function (Ricotta and Avena 2002), and parametric generalization of Morisita's index (Ricotta 2004) have been developed. However, one critical issue in assessing fuzzy classifications is the difficulty of collecting reference data. More research is thus needed to find a suitable approach for evaluating fuzzy classification results.

In summary, the error matrix approach is the most common accuracy assessment approach for categorical classes. Uncertainty and confidence analysis of classification results has gained some attention recently (McIver and Friedl 2001, Liu *et al.* 2004), and spatially explicit data on mapping confidence are regarded as an important aspect in effectively employing classification results for decision making (McIver and Friedl 2001, Liu *et al.* 2004).

4. Advanced classification approaches

In recent years, many advanced classification approaches, such as artificial neural networks, fuzzy-sets, and expert systems, have been widely applied for image classification. Cihlar (2000) discussed the status and research priorities of land-cover mapping for large areas. Franklin and Wulder (2002) assessed land-cover classification approaches with medium spatial resolution remotely sensed data. Books by Tso and Mather (2001) and Landgrebe (2003) specifically focus on image-processing approaches and classification algorithms. In general, image classification approaches can be grouped as supervised and unsupervised, or parametric and non-parametric, or hard and soft (fuzzy) classification, or per-pixel, subpixel, and per-field. Table 1 provides brief descriptions of these categories. For the sake of convenience, this paper groups classification approaches as per-pixel, subpixel, per-field, contextual-based, knowledge-based, and a combination of multiple classifiers. Table 2 lists major advanced classification approaches that have appeared in recent literature. A brief description of each category is provided in the following subsection. Readers who wish to have a detailed description of a specific classification approach should refer to cited references.

4.1 *Per-pixel classification approaches*

Traditional per-pixel classifiers typically develop a signature by combining the spectra of all training-set pixels for a given feature. The resulting signature contains the contributions of all materials present in the training pixels, but ignores the impact of the mixed pixels. Per-pixel classification algorithms can be parametric or non-parametric. The parametric classifiers assume that a normally distributed dataset exists, and that the statistical parameters (e.g. mean vector and covariance

Table 1. A taxonomy of image classification methods.

Criteria	Categories	Characteristics	Example of classifiers
Whether training samples are used or not	Supervised classification approaches	Land cover classes are defined. Sufficient reference data are available and used as training samples. The signatures generated from the training samples are then used to train the classifier to classify the spectral data into a thematic map.	Maximum likelihood, minimum distance, artificial neural network, decision tree classifier.
	Unsupervised classification approaches	Clustering-based algorithms are used to partition the spectral image into a number of spectral classes based on the statistical information inherent in the image. No prior definitions of the classes are used. The analyst is responsible for labelling and merging the spectral classes into meaningful classes.	ISODATA, K-means clustering algorithm.
Whether parameters such as mean vector and covariance matrix are used or not	Parametric classifiers	Gaussian distribution is assumed. The parameters (e.g. mean vector and covariance matrix) are often generated from training samples. When landscape is complex, parametric classifiers often produce 'noisy' results. Another major drawback is that it is difficult to integrate ancillary data, spatial and contextual attributes, and non-statistical information into a classification procedure.	Maximum likelihood, linear discriminant analysis.
	Non-parametric classifiers	No assumption about the data is required. Non-parametric classifiers do not employ statistical parameters to calculate class separation and are especially suitable for incorporation of non-remote-sensing data into a classification procedure.	Artificial neural network, decision tree classifier, evidential reasoning, support vector machine, expert system.
Which kind of pixel information is used	Per-pixel classifiers	Traditional classifiers typically develop a signature by combining the spectra of all training-set pixels from a given feature. The resulting signature contains the contributions of all materials present in the training-set pixels, ignoring the mixed pixel problems.	Most of the classifiers, such as maximum likelihood, minimum distance, artificial neural network, decision tree, and support vector machine.
	Subpixel classifiers	The spectral value of each pixel is assumed to be a linear or non-linear combination of defined pure materials (or endmembers), providing proportional membership of each pixel to each endmember.	Fuzzy-set classifiers, subpixel classifier, spectral mixture analysis.

Table 1. (*Continued.*)

Criteria	Categories	Characteristics	Example of classifiers
Which kind of pixel information is used	Object-oriented classifiers	Image segmentation merges pixels into objects and classification is conducted based on the objects, instead of an individual pixel. No GIS vector data are used.	eCognition.
	Per-field classifiers	GIS plays an important role in per-field classification, integrating raster and vector data in a classification. The vector data are often used to subdivide an image into parcels, and classification is based on the parcels, avoiding the spectral variation inherent in the same class.	GIS-based classification approaches.
Whether output is a definitive decision about land cover class or not	Hard classification	Making a definitive decision about the land cover class that each pixel is allocated to a single class. The area estimation by hard classification may produce large errors, especially from coarse spatial resolution data due to the mixed pixel problem.	Most of the classifiers, such as maximum likelihood, minimum distance, artificial neural network, decision tree, and support vector machine.
	Soft (fuzzy) classification	Providing for each pixel a measure of the degree of similarity for every class. Soft classification provides more information and potentially a more accurate result, especially for coarse spatial resolution data classification.	Fuzzy-set classifiers, subpixel classifier, spectral mixture analysis.
Whether spatial information is used or not	Spectral classifiers	Pure spectral information is used in image classification. A 'noisy' classification result is often produced due to the high variation in the spatial distribution of the same class.	Maximum likelihood, minimum distance, artificial neural network.
	Contextual classifiers	The spatially neighbouring pixel information is used in image classification.	Iterated conditional modes, point-to-point contextual correction, frequency-based contextual classifier.
	Spectral-contextual classifiers	Spectral and spatial information is used in classification. Parametric or non-parametric classifiers are used to generate initial classification images and then contextual classifiers are implemented in the classified images.	ECHO, combination of para metric or non-parametric and contextual algorithms.

Table 2. A summary of major advanced classification methods.

Category	Advanced classifiers	References
Per-pixel algorithms	Neural network	Chen *et al.* 1995, Foody *et al.* 1995, Atkinson and Tatnall 1997, Foody and Arora 1997, Paola and Schowengerdt 1997, Foody 2002a, Ozkan and Erbeck 2003, Foody 2004b, Erbek *et al.* 2004, Kavzoglu and Mather 2004, Verbeke *et al.* 2004
	Decision tree classifier	Hansen *et al.* 1996, Friedl and Brodley 1997, DeFries *et al.* 1998, Friedl *et al.* 1999, DeFries and Chan 2000, Pal and Mather 2003, Lawrence *et al.* 2004
	Spectral angle classifier	Sohn *et al.* 1999, Sohn and Rebello 2002
	Supervised iterative classification (multistage classification)	San Miguel-Ayanz and Biging 1996, 1997
	Enhancement-classification approach	Beaubien *et al.* 1999
	MFM-5-Scale (Multiple-Forward-Mode approach to running the 5-Scale geometric-optical reflectance model)	Peddle *et al.* 2004
	Iterative partially supervised classification based on a combined use of a Radial Basis Function network and a Markov Random Field approach	Fernández-Prieto 2002
	Classification by progressive generalization	Cihlar *et al.* 1998
	Support vector machine	Brown *et al.* 1999, Huang *et al.* 2002, Hsu and Lin 2002, Zhu and Blumberg 2002, Keuchel *et al.* 2003, Kim *et al.* 2003, Foody and Mathur 2004a, b, Mitra *et al.* 2004
	Unsupervised classification based on independent component analysis mixture model	Lee *et al.* 2000, Shah *et al.* 2004
	Optimal iterative unsupervised classification	Jiang *et al.* 2004
	Model-based unsupervised classification	Koltunov and Ben-Dor 2001, 2004
	Linear constrained discriminant analysis	Du and Chang 2001, Du and Ren 2003
	Multispectral classification based on probability density functions	Erol and Akdeniz 1996, 1998
	Layered classification	Jensen 1996
	Nearest-neighbour classification	Hardin 1994, Collins *et al.* 2004, Haapanen *et al.* 2004
	Selected pixel classification	Emrahoglu *et al.* 2003

Table 2. (*Continued.*)

Category	Advanced classifiers	References
Subpixel algorithms	Imagine subpixel classifier	Huguenin *et al.* 1997
	Fuzzy classifier	Foody 1996, Maselli *et al.* 1996, Zhang and Foody 2001, Shalan *et al.* 2003
	Fuzzy expert system	Penaloza and Welch 1996
	Fuzzy neural network	Foody 1996, 1999, Kulkarni and Lulla 1999, Zhang and Foody 2001, Mannan and Ray 2003
	Fuzzy-based multisensor data fusion classifier	Solaiman *et al.* 1999
	Rule-based machine-version approach	Foschi and Smith 1997
	Linear regression or linear least squares inversion	Settle and Campbell 1998, Fernandes *et al.* 2004
Per-field algorithms	Per-field or per-parcel classification	Lobo *et al.* 1996, Aplin *et al.* 1999a, Dean and Smith 2003
	Per-field classification based on per-pixel or subpixel classified image	Aplin and Atkinson 2001
	Parcel-based approach with two stages: per-parcel classification using conventional statistical classifier and then knowledge-based correction using contextual information	Smith and Fuller 2001
	Map-guided classification	Chalifoux *et al.* 1998
	Object-oriented classification	Herold *et al.* 2003, Geneletti and Gorte 2003, Thomas *et al.* 2003, van der Sande *et al.* 2003, Benz *et al.* 2004, Gitas *et al.* 2004, Walter 2004
	Graph-based, structural pattern recognition system	Barnsley and Barr 1997
	Spectral shape classifier	Carlotto 1998

Table 2. (*Continued.*)

Category	Advanced classifiers	References
Contextual-based approaches	ECHO (Extraction and Classification of Homogeneous Objects)	Biehl and Landgrebe 2002, Landgrebe 2003, Lu *et al.* 2004
	Supervised relaxation classifier	Kontoes and Rokos 1996
	Frequency-based contextual classifier	Gong and Howarth 1992, Xu *et al.* 2003
	Contextual classification approaches for high and low resolution data, respectively and a combination of both approaches	Kartikeyan *et al.* 1994, Sharma and Sarkar 1998
	Contextual classifier based on region-growth algorithm	Lira and Maletti 2002
	Fuzzy contextual classification	Binaghi *et al.* 1997
	Iterated conditional modes	Keuchel *et al.* 2003, Magnussen *et al.* 2004
	Sequential maximum *a posteriori* classification	Michelson *et al.* 2000
	Point-to-point contextual correction	Cortijo and de la Blanca 1998
	Hierarchical maximum *a posteriori* classifier	Hubert-Moy *et al.* 2001
	Variogram texture classification	Carr 1999
	Hybrid approach incorporating contextual information with per-pixel classification	Stuckens *et al.* 2000
	Two stage segmentation procedure	Kartikeyan *et al.* 1998
Knowledge-based algorithms	Evidential reasoning classification	Peddle *et al.* 1994, Wang and Civco 1994, Peddle 1995, Gong 1996, Franklin *et al.* 2002, Peddle and Ferguson 2002, Lein 2003
	Knowledge-based classification	Kontoes and Rokos 1996, Hung and Ridd, 2002, Thomas *et al.* 2003, Schmidt *et al.* 2004
	Rule-based syntactical approach	Onsi 2003
	Visual fuzzy classification based on use of exploratory and interactive visualization techniques	Lucieer and Kraak 2004
	Multitemporal classification based on decision fusion	Jeon and Landgrebe 1999
	Supervised classification with ongoing learning capability based on nearest neighbour rule	Barandela and Juarez 2002

Table 2. (*Continued.*)

Category	Advanced classifiers	References
Combinative approaches of multiple classifiers	Multiple classifier system (BAGFS: combines bootstrap aggregating with multiple feature subsets)	Debeir *et al.* 2002
	A consensus builder to adjust classification output (MLC, expert system, and neural network)	Liu *et al.* 2002b
	Integrated expert system and neural network classifier	Liu *et al.* 2002b
	Improved neuro-fuzzy image classification system	Qiu and Jensen 2004
	Spectral and contextual classifiers	Cortijo and de la Blanca 1998
	Mixed contextual and per-pixel classification	Conese and Maselli 1994
	Combination of iterated contextual probability classifier and MLC	Tansey *et al.* 2004
	Combination of neural network and statistical consensus theoretic classifiers	Benediktsson and Kanellopoulos 1999
	Combination of MLC and neural network using Bayesian techniques	Warrender and Augusteihn 1999
	Combining multiple classifiers based on product rule, staked regression	Steele 2000
	Combined spectral classifiers and GIS rule-based classification	Lunetta *et al.* 2003
	Combination of MLC and decision tree classifier	Lu and Weng 2004
	Combination of non-parametric classifiers (neural network, decision tree classifier, and evidential reasoning)	Huang and Lees 2004
	Combined supervised and unsupervised classification	Thomas *et al.* 2003, Lo and Choi 2004

matrix) generated from the training samples are representative. However, the assumption of normal spectral distribution is often violated, especially in complex landscapes. In addition, insufficient, non-representative, or multimode distributed training samples can further introduce uncertainty to the image classification procedure. Another major drawback of the parametric classifiers lies in the difficulty of integrating spectral data with ancillary data. The maximum likelihood may be the most commonly used parametric classifier in practice, because of its robustness and its easy availability in almost any image-processing software.

With non-parametric classifiers, the assumption of a normal distribution of the dataset is not required. No statistical parameters are needed to separate image classes. Non-parametric classifiers are thus especially suitable for the incorporation of non-spectral data into a classification procedure. Much previous research has indicated that non-parametric classifiers may provide better classification results than parametric classifiers in complex landscapes (Paola and Schowengerdt 1995, Foody 2002b). Among the most commonly used non-parametric classification approaches are neural networks, decision trees, support vector machines, and expert systems. In particular, the neural network approach has been widely adopted in recent years. The neural network has several advantages, including its non-parametric nature, arbitrary decision boundary capability, easy adaptation to different types of data and input structures, fuzzy output values, and generalization for use with multiple images, making it a promising technique for land-cover classification (Paola and Schowengerdt 1995). The multilayer perceptron is the most popular type of neural network in image classification (Atkinson and Tatnall 1997). However, the variation in the dimensionality of a dataset and the characteristics of training and testing sets may lessen the accuracy of image classification (Foody and Arora 1997). Bagging, boosting, or a hybrid of both techniques may be used to improve classification performance in a non-parametric classification procedure. These techniques have been used in decision trees (Friedl *et al.* 1999, DeFries and Chan 2000, Lawrence *et al.* 2004) and a support vector machine (Kim *et al.* 2003) to enhance classifications.

4.2 *Subpixel classification approaches*

Most classification approaches are based on per-pixel information, in which each pixel is classified into one category and the land-cover classes are mutually exclusive. Due to the heterogeneity of landscapes and the limitation in spatial resolution of remote-sensing imagery, mixed pixels are common in medium and coarse spatial resolution data. The presence of mixed pixels has been recognized as a major problem, affecting the effective use of remotely sensed data in per-pixel classifications (Fisher 1997, Cracknell 1998). Subpixel classification approaches have been developed to provide a more appropriate representation and accurate area estimation of land covers than per-pixel approaches, especially when coarse spatial resolution data are used (Foody and Cox 1994, Binaghi *et al.* 1999, Ricotta and Avena 1999, Woodcock and Gopal 2000). A fuzzy representation, in which each location is composed of multiple and partial memberships of all candidate classes, is needed. Different approaches have been used to derive a soft classifier, including fuzzy-set theory, Dempster–Shafer theory, certainty factor (Bloch 1996), softening the output of a hard classification from maximum likelihood (Schowengerdt 1996), IMAGINE's subpixel classifier (Huguenin *et al.* 1997), and neural networks (Foody 1999, Kulkarni and Lulla 1999, Mannan and Ray 2003). The fuzzy-set technique

(Foody 1996, 1998, Maselli *et al.* 1996, Mannan *et al.* 1998, Zhang and Kirby 1999, Zhang and Foody 2001, Shalan *et al.* 2003) and spectral mixture analysis (SMA) classification (Adams *et al.* 1995, Roberts *et al.* 1998b, Rashed *et al.* 2001, Lu *et al.* 2003) are the most popular approaches used to overcome the mixed pixel problem. One major drawback of subpixel classification lies in the difficulty in assessing accuracy, as discussed in §3.

SMA has long been recognized as an effective method for dealing with the mixed pixel problem. It evaluates each pixel spectrum as a linear combination of a set of endmember spectra (Adams *et al.* 1995, Roberts *et al.* 1998a). The output of SMA is typically presented in the form of fraction images, with one image for each endmember spectrum, representing the area proportions of the endmembers within the pixel. Endmember selection is one of the most important aspects in SMA, and much previous research has explored the approaches (Smith *et al.* 1990, Adams *et al.* 1993, Roberts *et al.* 1993, Settle and Drake 1993, Bateson and Curtiss 1996, Tompkins *et al.* 1997, Garcia-Haro *et al.* 1999, Mustard and Sunshine 1999, Van der Meer 1999, Maselli 2001, Dennison and Roberts 2003, Theseira *et al.* 2003, Small 2004). Previous research has demonstrated that SMA is helpful for improving classification accuracy (Adams *et al.* 1995, Robert *et al.* 1998a, Shimabukuro *et al.* 1998, Lu *et al.* 2003) and is especially important for improving area estimation of land-cover classes based on coarse spatial resolution data.

4.3 *Per-field classification approaches*

The heterogeneity in complex landscapes results in high spectral variation within the same land-cover class. With per-pixel classifiers, each pixel is individually grouped into a certain category, and the results may be noisy due to high spatial frequency in the landscape. The per-field classifier is designed to deal with the problem of environmental heterogeneity, and has shown to be effective for improving classification accuracy (Aplin *et al.* 1999a,b, Aplin and Atkinson 2001, Dean and Smith 2003, Lloyd *et al.* 2004). The per-field classifier averages out the noise by using land parcels (called 'fields') as individual units (Pedley and Curran 1991, Lobo *et al.* 1996, Aplin *et al.* 1999a,b, Dean and Smith 2003). Geographical information systems (GIS) provide a means for implementing per-field classification through integration of vector and raster data (Harris and Ventura 1995, Janssen and Molenaar 1995, Dean and Smith 2003). The vector data are used to subdivide an image into parcels, and classification is then conducted based on the parcels, thus avoiding intraclass spectral variations. However, per-field classifications are often affected by such factors as the spectral and spatial properties of remotely sensed data, the size and shape of the fields, the definition of field boundaries, and the land-cover classes chosen (Janssen and Molenaar 1995). The difficulty in handling the dichotomy between vector and raster data models affects the extensive use of the per-field classification approach. Remotely sensed data are acquired in raster format, which represents regularly shaped patches of the Earth's surface, while most GIS data are stored in vector format, representing geographical objects with points, lines and polygons.

An alternate approach is to use an object-oriented classification (Thomas *et al.* 2003, Benz *et al.* 2004, Gitas *et al.* 2004, Walter 2004), which does not require the use of GIS vector data. Two stages are involved in an object-oriented classification: image segmentation and classification. Image segmentation merges pixels into objects, and a classification is then implemented based on objects, instead of individual pixels. In the process of creating objects, scale determines the occurrence or absence of an object class, and the size of an object affects a classification result. This approach has proven to be able to provide better classification results than per-pixel classification approaches, especially for fine spatial resolution data. The eCognition method is so far the most commonly used object-oriented classification (Benz *et al.* 2004, Wang *et al.* 2004).

4.4 *Contextual classification approaches*

In addition to object-oriented and per-field classifications, contextual classifiers have also been developed to cope with the problem of intraclass spectral variations (Gong and Howarth 1992, Kartikeyan *et al.* 1994, Flygare 1997, Sharma and Sarkar 1998, Keuchel *et al.* 2003, Magnussen *et al.* 2004). Contextual classification exploits spatial information among neighbouring pixels to improve classification results (Flygare 1997, Stuckens *et al.* 2000, Hubert-Moy *et al.* 2001, Magnussen *et al.* 2004). A contextual classifier may use smoothing techniques, Markov random fields, spatial statistics, fuzzy logic, segmentation, or neural networks (Binaghi *et al.* 1997, Cortijo and de la Blanca 1998, Kartikeyan *et al.* 1998, Keuchel *et al.* 2003, Magnussen *et al.* 2004). In general, pre-smoothing classifiers incorporate contextual information as additional bands, and a classification is then conducted using normal spectral classifiers, while post-smoothing classification is conducted on classified images previously developed using spectral-based classifiers. The Markov random field-based contextual classifiers, such as iterated conditional modes, are the most frequently used approaches in contextual classification (Cortijo and de la Blanca 1998, Magnussen *et al.* 2004), and have proven to be effective in improving classification results.

4.5 *Knowledge-based classification approaches*

As different kinds of ancillary data, such as digital elevation model, soil map, housing and population density, road network, temperature, and precipitation, become readily available, they may be incorporated into a classification procedure in different ways. One of the approaches is to develop knowledge-based classifications based on the spatial distribution pattern of land-cover classes and selected ancillary data. For example, elevation, slope, and aspect are related to vegetation distribution in mountainous regions. Data on terrain features are thus useful for separation of vegetation classes. Population, housing, and road densities are related to urban land-use distribution, and may be very helpful in the distinctions between commercial/industrial lands and high-intensity residential lands, between recreational grassland and pasture/crops, or between residential areas and forest land. Similarly, temperature, precipitation, and soil data are related to land-cover distribution at a large scale. Effectively using these relationships in a classification procedure has proven effective in improving classification accuracy. A critical step is to develop the rules that can be used in an expert system or a knowledge-based classification approach. This approach is now increasingly becoming attractive because of its capability of accommodating multiple sources of data. Hodgson *et al.* (2003) summarized three methods employed to build rules for image classification: (1) explicitly eliciting knowledge and rules from experts and then refining the rules, (2) implicitly extracting variables and rules using cognitive methods, and (3) empirically generating rules from observed data with automatic induction methods. GIS plays an important role in developing knowledge-based classification approaches because of its capability of managing different sources of data and spatial modelling.

4.6 *Combination of multiple classifiers*

Different classifiers, such as parametric classifiers (e.g. maximum likelihood) and non-parametric classifiers (e.g. neural network, decision tree), have their own strengths and limitations (Tso and Mather 2001, Franklin *et al.* 2003). For example, when sufficient training samples are available and the feature of land covers in a dataset is normally distributed, a maximum likelihood classifier (MLC) may yield an accurate classification result. In contrast, when image data are anomalously distributed, neural network and decision tree classifiers may demonstrate a better classification result (Pal and Mather 2003, Lu *et al.* 2004). Previous research has indicated that the integration of two or more classifiers provides improved classification accuracy compared to the use of a single classifier (Benediktsson and Kanellopoulos 1999, Warrender and Augusteihn 1999, Steele 2000, Huang and Lees 2004). A critical step is to develop suitable rules to combine the classification results from different classifiers. Some previous research has explored different techniques, such as a production rule, a sum rule, stacked regression methods, majority voting, and thresholds, to combine multiple classification results (Steele 2000, Liu *et al.* 2004).

4.7 *A summary of classification approaches*

Although many classification approaches have been developed, which approach is suitable for features of interest in a given study area is not fully understood. Classification algorithms can be per-pixel, subpixel, and per-field. Per-pixel classification is still most commonly used in practice. However, the accuracy may not meet the requirement of research because of the impact of the mixed pixel problem. Subpixel algorithms have the potential to deal with the mixed pixel problem, and may achieve higher accuracy for medium and coarse spatial resolution images. For fine spatial resolution data, although mixed pixels are reduced, the spectral variation within land classes may decrease the classification accuracy. Per-field classification approaches are most suitable for fine spatial resolution data. When using multisource data, such as a combination of spectral signatures, texture and context information, and ancillary data, advanced non-parametric classifiers, such as neural network, decision tree, and knowledge-based classification, may be more suited to handle these complex data processes, and thus have gained increasing attention in the remote-sensing community in recent years. Selection of a suitable classifier requires consideration of many factors, such as classification accuracy, algorithm performance, and computational resources (DeFries and Chan 2000). Flygare (1997) summarized three criteria—the aim of classification, available computer resources, and effective separation of the classes. In practice, the spatial resolution of the remotely sensed data, use of ancillary data, the classification system, the available software, and the analyst's experience may all affect the decision of selecting a classifier. A comparative study of different classifiers is often conducted to find the best classification result for a specific study (Zhuang *et al.* 1995, Atkinson *et al.* 1997, Cortijo and de la Blanca 1997, Flygare 1997, Michelson *et al.* 2000, Hubert-Moy *et al.* 2001, Keuchel *et al.* 2003, Pal and Mather 2003, Erbek *et al.* 2004, Lu *et al.* 2004, Olthof *et al.* 2004, Pal and Mather 2004, South *et al.* 2004). In many cases, contextual-based classifiers, per-field approaches, and machine-learning approaches provide a better classification result than MLC, although some tradeoffs exist in classification accuracy, time consumption, and computing resources.

5. Use of multiple features of remotely sensed data

As discussed previously, remote-sensing data have many unique spatial, spectral, radiometric, temporal and polarization characteristics. Making full use of these characteristics is an effective way to improve classification accuracy. Generally speaking, the feature of spectral response is the most important information used for land-cover classification. As high spatial resolution data become readily available, textural and contextual information become significant in image classification. Table 3 summarizes major research efforts for improving classification accuracy by using different characteristics of remote-sensing data.

5.1 *Use of spatial information*

Spatial resolution determines the level of spatial detail that can be observed on the Earth's surface. As fine spatial resolution data (mostly better than 5 m spatial resolution), such as IKONOS and QuickBird, become more easily available, they are increasingly employed for different applications (Sugumaran *et al.* 2002, Goetz *et al.* 2003, Herold *et al.* 2003, Hurtt *et al.* 2003, van der Sande *et al.* 2003, Xu *et al.* 2003, Zhang and Wang 2003, Wang *et al.* 2004). A major advantage of these fine spatial resolution images is that such data greatly reduce the mixed-pixel problem, providing a greater potential to extract much more detailed information on land-cover structures than medium or coarse spatial resolution data. However, some new problems associated with fine spatial resolution image data emerge, notably the shadows caused by topography, tall buildings, or trees, and the high spectral variation within the same land-cover class. These disadvantages may lower classification accuracy if classifiers cannot effectively handle them (Irons *et al.* 1985, Cushnie 1987). Increased spectral variation is common with the high degree of spectral heterogeneity in complex landscapes. The huge amount of data storage and severe shadow problems in fine spatial resolution images lead to challenges in the selection of suitable image-processing approaches and classification algorithms. Last, but not least, high spatial resolution imagery is much more expensive and requires much more time to implement data analysis than medium spatial resolution images. In order to make full use of the rich spatial information inherent in fine spatial resolution data, it is necessary to minimize the negative impact of high intraspectral variation. Spatial information may be used in different ways, such as in contextual-based or object-oriented classification approaches, or classifications with textures. The combination of spectral and spatial classification is especially valuable for fine land-cover classification systems in the areas with complex landscapes. As contextual-based and object-oriented classification approaches have been discussed previously, the following only focuses on the use of textures in image classification.

Many texture measures have been developed (Haralick *et al.* 1973, Kashyap *et al.* 1982, He and Wang 1990, Unser 1995, Emerson *et al.* 1999) and have been used for image classifications (Gordon and Phillipson 1986, Franklin and Peddle 1989,

Table 3. Approaches to using multiple features of remotely sensed data for improving classification accuracy.

Method	Features	References
Use of textures	First-, second-, and third-order statistics in the spatial domain; texture features from the texture spectrum and from grey level different vector	Nyoungui *et al.* 2002
	Grey-level co-occurrence matrices (GLCM)	Baraldi and Parmiggiani 1995, Kurosu *et al.* 2001, Narasimha Rao *et al.* 2002, Podest and Saatchi 2002, Butusov 2003
	Co-occurrence matrices, grey-level difference, texture-tone analysis, features derived from Fourier spectrum, and Gabor filters	Augusteijn *et al.* 1995
	GLCM, grey level difference histogram, sum and different histogram	Soares *et al.* 1997, Shaban and Dikshit 2001
	Fractal information	Chen *et al.* 1997, Low *et al.* 1999
	Triangulated primitive neighbourhood method	Hay *et al.* 1996
	Semivariogram	Carr and Miranda 1998
	Geostatistical analysis	Lloyd *et al.* 2004, Zhang *et al.* 2004
	Gabor filtering	Angelo and Haertel 2003
Fusion of multisensor or multiresolution data	AIRSAR and TOPSAR	Crawford *et al.* 1999
	SPOT MS and PAN data	Shaban and Dikshit 2002, Shi *et al.* 2003
	TM and aerial photographs	Geneletti and Gorte 2003
	TM and radar	Ban 2003, Haack *et al.* 2002
	TM and IRS-1C-PAN data	Teggi *et al.* 2003
	TM and SPOT PAN data	Yocky 1996
	SPOT and radar	Pohl and van Genderen 1998
	Hyperspectral and radar	Chen *et al.* 2003
	IRS LISS III and PAN	Ray 2004
Use of multitemporal data	Using multitemporal optical images	Wolter *et al.* 1995, Lunetta and Balogh 1999, Oetter *et al.* 2000, Liu *et al.* 2002a, Guerschman *et al.* 2003, Tottrup 2004
	Using multitemporal SAR images	Pierce *et al.* 1998, Chust *et al.* 2004
	Using multitemporal optical and SAR images	Brisco and Brown 1995
Image transforms	Fuzzy partition method	Wu and Linders 2000
	Stepwise regression analysis	Wu and Linders 2000
	Principal component analysis	Wu and Linders 2000
	Tasselled cap	Oetter *et al.* 2000
	Rotational transformation	Nirala and Venkatachalam 2000
	Wavelet transform	Myint 2001
	Spectral mixture analysis	Adams *et al.* 1995, Roberts *et al.* 1998a,b, Rashed *et al.* 2001, Phinn *et al.* 2002, Rashed *et al.* 2003, Lu and Weng 2004
	Gaussian mixture discriminant analysis	Ju *et al.* 2003
	Normalized difference built-up index	Zha *et al.* 2003

Table 3. (*Continued.*)

Method	Features	References
Fine spatial resolution data	IKONOS or QuickBird	Sugumaran *et al.* 2002, Goetz *et al.* 2003, Herold *et al.* 2003, Hurtt *et al.* 2003, van der Sande *et al.* 2003, Xu *et al.* 2003, Zhang and Wang 2003, Wang *et al.* 2004
	ADAR digital multispectral image	Thomas *et al.* 2003
	Aerial photography and lidar data	Hodgson *et al.* 2003
	Colour infrared aerial images	Erikson 2004
Hyper-spectral data	AVIRIS	Benediktsson *et al.* 1995, Jimenez *et al.* 1999, Okin *et al.* 2001, Kokalya *et al.* 2003, Segl *et al.* 2003, Platt and Goetz 2004
	HyMap hyperspectral digital data	Schmidt *et al.* 2004
	DAIS hyperspectral data	Pal and Mather 2004
	EO-1 Hyperion	Apan *et al.* 2004
	Data obtained from FieldSpec Pro FR spectroradiometer	Thenkabail *et al.* 2004a

Marceau *et al.* 1990, Kartikeyan *et al.* 1994, Augusteijn *et al.* 1995, Groom *et al.* 1996, Jakubauskas 1997, Nyoungui *et al.* 2002, Podest and Saatchi 2002, Narasimha Rao *et al.* 2002, Lloyd *et al.* 2004). Franklin and Peddle (1990) found that textures based on a grey-level co-occurrence matrix (GLCM) and spectral features of a SPOT HRV image improved the overall classification accuracy. Gong *et al.* (1992) compared GLCM, simple statistical transformations (SST), and texture spectrum (TS) approaches with SPOT HRV data, and found that some textures derived from GLCM and SST improved urban classification accuracy. Shaban and Dikshit (2001) investigated GLCM, grey-level difference histogram (GLDH), and sum and difference histogram (SADH) textures from SPOT spectral data in an Indian urban environment, and found that a combination of texture and spectral features improved the classification accuracy. Compared to the obtained result based solely on spectral features, about 9% and 17% increases were achieved for an addition of one and two textures, respectively. They further found that contrast, entropy, variance, and inverse difference moment provided higher accuracy and the best sizes of moving window were 7×7 and 9×9. Use of multiple or multiscale texture images should be in conjunction with original spectral images to improve classification results (Kurosu *et al.* 2001, Shaban and Dikshit 2001, Narasimha Rao *et al.* 2002, Podest and Saatchi 2002, Butusov 2003). Recently, the geostatistic-based texture measures were found to provide better classification accuracy than using the GLCM-based textures (Berberoglu *et al.* 2000, Lloyd *et al.* 2004). For a specific study, it is often difficult to identify a suitable texture because texture varies with the characteristics of the landscape under investigation and the image data used. Identification of suitable textures involves determination of texture measure, image band, the size of moving window, and other parameters (Franklin *et al.* 1996, Chen *et al.* 2004). The difficulty in identifying suitable textures and the computation cost for calculating textures limit the extensive use of textures in image classification, especially in a large area.

5.2 *Integration of different sensor data*

Images from different sensors contain distinctive features. Data fusion or integration of multisensor or multiresolution data takes advantage of the strengths of distinct image data for improvement of visual interpretation and quantitative analysis. In general, three levels of data fusion can be identified (Gong 1994)—pixel (Luo and Kay 1989), feature (Jimenez *et al.* 1999), and decision (Benediktsson and Kanellopoulos 1999). Data fusion involves two major procedures: (1) geometrical co-registration of two datasets and (2) mixture of spectral and spatial information contents to generate a new dataset that contains the enhanced information from both datasets. Accurate registration between the two datasets is extremely important for precisely extracting information contents from both datasets, especially for line features, such as roads and rivers. Radiometric and atmospheric calibrations are also needed before multisensor data are merged.

Many methods have been developed to integrate spectral and spatial information in previous literature (Gong 1994, Pohl and Van Genderen 1998, Chen and Stow 2003). Solberg *et al.* (1996) broadly divided data fusion methods into four categories: statistical, fuzzy logic, evidential reasoning, and neural network. Dai and Khorram (1998) presented a hierarchical data fusion system for vegetation classification. Pohl and Van Genderen (1998) provided a literature review on methods of multisensor data fusion. The methods, including colour-related techniques (e.g. colour composite, intensity-hue-saturation or IHS, and luminance-chrominance), statistical/numerical methods (e.g. arithmetic combination, principal component analysis, high pass filtering, regression variable substitution, canonical variable substitution, component substitution, and wavelets), and various combinations of these methods were examined. IHS transformation was identified to be the most frequently used method for improving visual display of multisensor data (Welch and Ehlers 1987), but the IHS approach can only employ three image bands, and the resultant image may not be suitable for further quantitative analysis such as classification. Principal component analysis is often used for data fusion because it can produce an output that can better preserve the spectral integrity of the input dataset. In recent years, wavelet-merging techniques have shown to be another effective approach to generate a better improvement of spectral and spatial information contents (Li *et al.* 2002, Simone *et al.* 2002, Ulfarsson *et al.* 2003). Previous research indicated that integration of Landsat TM and radar (Ban 2003, Haack *et al.* 2002), SPOT HRV and Landsat TM (Welch and Ehlers 1987, Munechika *et al.* 1993, Yocky 1996), and SPOT multispectral and panchromatic bands (Garguet-Duport *et al.* 1996, Shaban and Dikshit 2002) can improve classification results. An alternate way of integrating multiresolution images, such as Landsat TM (or SPOT) and MODIS (or AVHRR), is to refine the estimation of land-cover types from coarse spatial resolution data (Moody 1998, Price 2003).

5.3 *Use of multitemporal data*

Temporal resolution refers to the time interval in which a satellite revisits the same location. Higher temporal resolution provides good opportunities to capture high-quality images. This is particularly useful for areas such as moist tropical regions, where adverse atmospheric conditions regularly occur. The use of different seasons of remotely sensed data has proven useful for improving classification accuracy, especially for crop and vegetation classification (Brisco and Brown 1995, Wolter *et al.* 1995, Lunetta and Balogh 1999, Oetter *et al.* 2000, Liu *et al.* 2002a, Guerschman *et al.* 2003) because of different phenologies of vegetations and crops. For example, Lunetta and Balogh (1999) compared single- and two-date Landsat 5 TM images (spring leaf-on and fall leaf-off images) for a wetland mapping in Maryland, USA and Delaware, USA and found that multitemporal images provided better classification accuracies than single-date imagery alone. An overall classification accuracy of 88% was achieved from multitemporal images compared to 69% from single-date imagery.

5.4 *Use of data transformation techniques*

The spectral characteristics of land surfaces are the fundamental principles for land-cover classification using remotely sensed data. The spectral features include the number of spectral bands, spectral coverage, and spectral resolution (or bandwidth). The number of spectral bands used for image classification can range from a limited number of multispectral bands (e.g. four bands in SPOT data and seven for Landsat TM), to a medium number of multispectral bands (e.g. ASTER with 14 bands and MODIS with 36 bands), and to hyperspectral data (e.g. AVIRIS and EO-1 Hyperion images with 224 bands). The large number of spectral bands provides the potential to derive detailed information on the nature and properties of different surface materials on the ground, but the bands also create difficulty in image processing and high data redundancy due to high correlation in the adjacent bands. High-dimension data also require a larger number of training samples for image classification. An increase in spectral bands may improve classification accuracy, but only when those bands are useful in discriminating the classes (Thenkabail *et al.* 2004b). In previous research, hyperspectral data have been successfully used for land-cover classification (Benediktsson *et al.* 1995, Hoffbeck and Landgrebe 1996, Platt and Goetz 2004, Thenkabail *et al.* 2004a, b) and vegetation mapping (McGwire *et al.* 2000, Schmidt *et al.* 2004). As spaceborne hyperspectral data such as EO-1 Hyperion become available, research and applications with hyperspectral data will increase.

Image transformation is often used to reduce the number of image channels so the information contents are concentrated on a few transformed images (Jensen 1996). Several techniques have been developed to transform the data from highly correlated bands into a dataset. Vegetation indices, principal component analysis, tasselled cap, and minimum noise fraction, are among the most commonly used ones (Oetter *et al.* 2000, Wu and Linders 2000). Wavelet transform and spectral mixture analysis have also been used in recent years (Roberts *et al.* 1998a, Rashed *et al.* 2001, Lu and Weng 2004).

6. Use of GIS in improving classification performance

Ancillary data, such as topography, soil, road, and census data, may be combined with remotely sensed data to improve classification performance. Hutchinson (1982) discussed the strengths and limitations of remote-sensing and GIS data integration. Harris and Ventura (1995) and Williams (2001) suggested that ancillary data may be used to enhance image classification in three ways, through pre-classification stratification, classifier modification, and post-classification sorting. Table 4 summarizes major approaches for combining various ancillary data and remote-sensing imagery for image classification improvement.

Table 4. Summary of major approaches using ancillary data for improving classification accuracy.

Method	Features	References
Use of ancillary data	DEM	Maselli *et al.* 2000
	Topography, land use, and soil maps	Baban and Yusof 2001
	Road density	Zhang *et al.* 2002
	Road coverage	Epstein *et al.* 2002
	Census data	Harris and Ventura 1995, Mesev 1998
Stratification	Based on topography	Bronge 1999, Baban and Yusof 2001
	Based on illumination and ecological zone	Helmer *et al.* 2000
	Based on census data	Oetter *et al.* 2000
	Based on shape index of the patches	Narumalani *et al.* 1998
Post-classification processing	Kernel-based spatial reclassification	Barnsley and Barr 1996
	Using zoning and housing density data to modify the initial classification result	Harris and Ventura 1995
	Using contextual correction	Groom *et al.* 1996
	Using filtering based on co-occurrence matrix	Zhang 1999
	Using polygon and rectangular mode filters	Stallings *et al.* 1999
	Using expert system to perform post-classification sorting	Stefanov *et al.* 2001
	Using knowledge-based system to correct misclassification	Murai and Omatu 1997
Use of multisource data	Spectral, texture, and ancillary data (such as DEM, soil, existing GIS-based maps)	Gong 1996, Solberg *et al.* 1996, Bruzzone *et al.* 1997, Benediktsson and Kanellopoulos 1999, Bruzzone *et al.* 1999, Tso and Mather 1999, Franklin *et al.* 2002, Amarsaikhan and Douglas 2004

Previous research has shown that topographic data are valuable for improving land-cover classification accuracy, especially in mountainous regions (Janssen *et al.* 1990, Meyer *et al.* 1993, Franklin *et al.* 1994). This is because land-cover distribution is related to topography. In addition to elevation, slope and aspect derived from DEM data have also been employed in image classification. These DEM-derived variables may be used in the image-preprocessing stage for topographic correction or normalization so the impact of terrain on land-cover reflectance can be removed (Teillet *et al.* 1982, Leprieur *et al.* 1988, Ekstrand 1996, Richter 1997, Gu and Gillespie 1998, Dymond and Shepherd 1999, Tokola *et al.* 2001). Furthermore, topography data are useful at all three stages in image classification—as a stratification tool in pre-classification, as an additional channel during classification, and as a smoothing means in post-classification (Senoo *et al.* 1990, Maselli *et al.* 2000). For vegetation classification in mountainous areas, the integration of DEM-related data and remotely sensed data has been proven effective for improving classification accuracy (Senoo *et al.* 1990, Franklin 2001). Bolstad and Lillesand (1992) found that a rule-based classification with Landsat TM, soil, and terrain data yielded higher land-cover classification accuracy than a standard spectral-based classification. In urban studies, DEM data are rarely used to aid image classification due to the fact that urban regions often locate in relatively flat areas. Instead, data related to human systems such as population distribution and road density are frequently incorporated in urban classifications (Mesev 1998, Epstein *et al.* 2002, Zhang *et al.* 2002). Use of soil and road network maps, in conjunction with a SPOT image, was found to have improved classification accuracy (Kontoes and Rokos 1996). Another important use of ancillary data is in post-classification processing for modifying the classification image based on the established expert rules as discussed previously.

Previous literature has reviewed the methods for integration of remote sensing and GIS (Ehlers *et al.* 1989, Ehlers 1990, Trotter 1991, Hinton 1996, Wilkinson 1996). Three strategies for the integration can be distinguished (Ehlers *et al.* 1989, Hinton 1999): (1) separated GIS and image analysis systems with data exchange, (2) 'seamlessly' interwoven systems with a shared user interface and various forms of tandem processing, and (3) a totally integrated system. As multisource data become easily available, the integration of remote sensing and GIS is emerging as an appealing research direction that can be applied to image classification. Different approaches, such as evidential reasoning classification (Peddle *et al.* 1994, Wang and Civco 1994), knowledge-based techniques (Srinivasan and Richards 1990, Amarsaikhan and Douglas 2004), fuzzy contextual classification (Binaghi *et al.* 1997), and a combination of neural network and statistical approaches (Benediktsson and Kanellopoulos, 1999, Bruzzone *et al.* 1997, 1999) have been used for classification of multisource data. However, difficulties still exist in data integration due to the differences in data structures, data types, spatial resolution, geometric characteristics, and the levels of generation (Wang and Howarth 1994). GIS plays a critical role in handling multisource data. The major roles of GIS lie in (1) managing multisource data, (2) converting different data formats into a uniform format and evaluating the data quality, and (3) developing suitable models for classification.

7. Discussions

7.1 *Uncertainty in image classification*

Uncertainty research in GIS has made good progress in the past decade, but in remote sensing, it had not obtained sufficient attention until recent years (Mowrer and Congalton 2000, Hunsaker *et al.* 2001, Foody and Atkinson 2002). Uncertainties generated at different stages in a classification procedure influence classification accuracy, as well as the area estimation of land-cover classes (Canters 1997, Friedl *et al.* 2001, Dungan 2002). Understanding the relationships between the classification stages, identifying the weakest links in the image-processing chain, and then devoting efforts to improving them are keys to a successful image classification (Friedl *et al.* 2001, Dungan 2002). For example, the limitation of remote-sensing data in spatial and radiometric resolutions and the atmospheric conditions at the image acquisition time may cause uncertainty of remotely sensed data *per se*. Similarly, geometric rectification or image registration between multisource data may lead to position uncertainty, while the algorithms used for calibrating atmospheric or topographic effects may cause radiometric errors. Dungan (2002) found that five types of uncertainties exist in remotely sensed data: positional, support, parametric, structural (model), and variables. Friedl *et al.* (2001)

summarized three primary sources of errors: errors introduced through the image-acquisition process, errors produced by the application of data-processing techniques, and errors associated with interactions between instrument resolution and the scale of ecological processes on the ground.

Uncertainty study is especially important when coarse spatial resolution images such as AVHRR and MODIS are used, due to the existence of the many mixtures among land-cover classes. Uncertainty may be modelled or quantified in different ways such as fuzzy and probabilistic classification techniques, or via visualization (van der Wel *et al.* 1997, Gahegan and Ehlers 2000, Crosetto *et al.* 2001, Lucieer and Kraak 2004). In particular, different visualization techniques, such as geovisualization and interactive visualization, have proven helpful for uncertainty study in image classification (MacEachren and Kraak 2001, Bastin *et al.* 2002, Lucieer and Kraak 2004). More research on uncertainty is needed to improve image classification performance.

7.2 *Impact of spatial resolution*

Spatial resolution is an important factor that affects classification details and accuracy (Chen *et al.* 2004) and influences the selection of classification approaches (Atkinson and Curran 1997, Atkinson and Aplin 2004). The size of ground objects relative to the spatial resolution of a sensor is directly related to image variance (Woodcock and Strahler 1987). Strahler *et al.* (1986) described H- and L-resolution (high- and low-resolution) scene models based on the relationships between the sizes of the scene elements and the resolution cell of the sensor. The scene elements in the H-resolution model are larger than the resolution cell and can, therefore, be directly detected. In contrast, the elements in the L-resolution model are smaller than the resolution cells, and are not detectable. When the objects in the scene become increasingly smaller relative to the resolution cell size, they may no longer be regarded as individual objects. Hence, the reflectance measured by the sensor can be treated as a sum of interactions among various classes of scene elements as weighted by their relative proportions (Strahler *et al.* 1986). Medium spatial resolution data such as Landsat TM/ETM+ or coarse spatial resolution data such as AVHRR and MODIS are attributed to the L-resolution model. Mixed pixels are common in these data. Fisher (1997) summarized four causes of the mixed pixel problem: (1) boundaries between two or more mapping units, (2) the intergrade between central concepts of mappable phenomena, (3) linear subpixel objects, and (4) small subpixel objects.

Different approaches have been developed to reduce the impact of the mixed pixel problem. The first method is to use spectral mixture analysis to decompose the digital number (DN) or reflectance values into the proportions of selected components (Roberts *et al.* 1998a, Mustard and Sunshine 1999, Lu *et al.* 2003). The fraction images are related to biophysical characteristics, and thus have the potential for improving classification (Roberts *et al.* 1998a, Lu *et al.* 2003). The second method is to implement data fusion through the use of higher spatial resolution (e.g. SPOT panchromatic band) and multispectral data (e.g. Landsat TM) (Yocky 1996, Shaban and Dikshit 2002) in order to enhance the information contents from both datasets. Moreover, it may also be appropriate to directly use fine spatial resolution data such as IKONOS and QuickBird data (Sugumaran *et al.* 2002, van der Sande *et al.* 2003, Zhang and Wang 2003, Wang *et al.* 2004). Another potential approach is to use multiscale data to implement calibration of classification results through modelling.

7.3 *Selection of suitable variables*

Remotely sensed data have their own limitations. For example, Landsat TM images have a limited number of spectral bands with broad wavelengths, which may be difficult for distinguishing subtle changes in the Earth's surface. In contrast, hyperspectral images with a substantially large number of bands and with narrow wavelengths may improve classification accuracy (Jimenez *et al.* 1999, Segl *et al.* 2003), but the large volume of data often generates a challenge for image processing and classification. On the other hand, the complexity of forest stand structure and associated canopy shadows may lead to DN saturation, especially in optical-sensed data (Steininger 2000, Lu *et al.* 2003). The long-wavelength radar data can penetrate the canopy structure to a certain depth and can provide information on vegetation stand structures (Leckie 1998, Santos *et al.* 2003), thus reduce the DN saturation problem. In practice, making full use of the multiple features of different sensor data, implementing feature extraction, and selecting suitable variables for input into a classification procedure are all important. Similarly, incorporating ancillary data in a classification procedure is an effective way to improve classification accuracy. A critical step is to develop approaches to identify the best appropriate variables that are most useful in separating land-cover classes (Peddle and Ferguson 2002). To date, very limited research has explored how to identify variables from multisource data to improve classification accuracy.

8. Summary

Image classification has made great progress over the past decades in the following three areas: (1) development and use of advanced classification algorithms, such as subpixel, per-field, and knowledge-based classification algorithms; (2) use of multiple remote-sensing features, including spectral, spatial, multitemporal, and multisensor information; and (3) incorporation of ancillary data into classification procedures, including such data as topography, soil, road, and census data. Accuracy assessment is an integral part in an image classification procedure. Accuracy assessment based on error matrix is the most commonly employed approach for evaluating per-pixel classification, while fuzzy approaches are gaining attention for assessing fuzzy classification results. Uncertainty and error propagation in the image-processing chain is an important factor influencing classification accuracy. Identifying the weakest links in the chain and then reducing the uncertainties are critical for improvement of classification accuracy. The study of uncertainty will be an important topic in the future research of image classification.

Spectral features are the most important information for image classification. As spatial resolution increases, texture or context information becomes another important attribute to be considered. Classification approaches may vary with different types of remote-sensing data. For example, with high spatial resolution data such as IKONOS and SPOT 5 HRG, the severe impact of the shadow problem resulting from topography and vegetation stand structures and the wide spectral variation within the land-cover classes may outweigh the advantages from high spatial resolution if a per-pixel, spectral-based classification is used for these image classifications. Under this circumstance, a combination of spectral and texture information can reduce this problem and per-field or object-oriented classification algorithms outperform per-pixel classifiers. For medium and coarse spatial resolution data, however, spectral information is a more important attribute than spatial information because of the loss of spatial information. Since mixed pixels create a problem in medium and coarse resolution imagery, per-pixel classifiers repeatedly have difficulty dealing with them. Subpixel features, such as fraction images of SMA or fuzzy membership information, have been used in image classification. Moreover, image data have been integrated with ancillary data as another means for enhancing image classification. When multisource data are used in a classification, parametric classification algorithms such as MLC are typically not appropriate. Advanced non-parametric classifiers, such as neural network, decision tree, evidential reasoning, or the knowledge-based approach, appear to be the choices.

Although spatial information is remarkably useful for fine spatial resolution data, how to effectively derive and use it in image classification remains a research topic. Texture, shape, and context information are currently most frequently used. However, even with the most widely used texture information, there is still much uncertainty in the determination of texture measures, image channel, window size, and other parameters. More research is necessary to develop a guideline for selecting textures suitable for different biophysical environments.

Integration of remote sensing and GIS is significant in classification improvement. Remote-sensing data are more uniform than ancillary data, which vary in data format, accuracy, spatial resolution, and coordinate systems. GIS is an essential tool to implement pre-processing procedures before data integration, such as conversion of data format and coordinate systems, data interpolation, and evaluation of data quality. As various sensor data with different resolutions emerge, remote sensing/GIS integration may provide new insights in image classification for its capability in handling the scale issue. Comparison and testing of different classification algorithms for various applications are also necessary. Evaluation of uncertainties caused by the use of multisource data is becoming an important research topic.

The success of an image classification depends on many factors. The availability of high-quality remotely sensed imagery and ancillary data, the design of a proper classification procedure, and the analyst's skills and experiences are the most important ones. For a particular study, it is often difficult to identify the best classifier due to the lack of a guideline for selection and the availability of suitable classification algorithms to hand. Comparative studies of different classifiers are thus frequently conducted. Moreover, the combination of different classification approaches has shown to be helpful for improvement of classification accuracy (Benediktsson and Kanellopoulos 1999, Steele 2000, Lunetta *et al.* 2003). It is necessary for future research to develop guidelines on the applicability and capability of major classification algorithms.

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