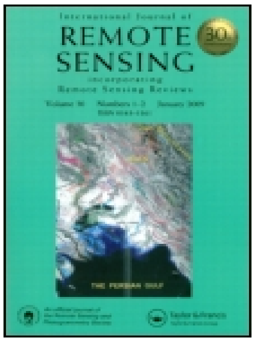

International Journal of Remote Sensing

ISSN: 0143-1161 (Print) 1366-5901 (Online) Journal homepage: http://www.tandfonline.com/loi/tres20

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

D. Lu & Q. Weng

To cite this article: D. Lu & Q. Weng (2007) A survey of image classification methods and techniques for improving classification performance, International Journal of Remote Sensing, 28:5, 823-870, DOI: 10.1080/01431160600746456

To link to this article: https://doi.org/10.1080/01431160600746456

Published online: 17 Mar 2007.

International Journal of Remote Sensing
Vol. 28, No. 5, 10 March 2007, 823–870

Taylor & Francis
Taylor & Francis Group

Review article

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

D. LU*† and Q. WENG‡

†Center for the Study of Institutions, Population, and Environmental Change, Indiana University, Bloomington, IN 47408, USA

‡Department of Geography, Geology, and Anthropology, Indiana State University, Terre Haute, IN 47809, USA

(*Received 23 November 2005; in final form 31 March 2006*)

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

*Corresponding author. Email: dlu@indiana.edu

International Journal of Remote Sensing
ISSN 0143-1161 print/ISSN 1366-5901 online © 2007 Taylor & Francis
http://www.tandf.co.uk/journals
DOI: 10.1080/01431160600746456

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.

Acknowledgments

The authors wish to acknowledge the support from the Center for the Study of Institutions, Population, and Environmental Change (CIPEC) at Indiana University, through funding from the National Science Foundation (grant NSF SBR no. 9906826).

References

ADAMS, J.B., SMITH, M.O. and GILLESPIE, A.R., 1993, Imaging spectroscopy: interpretation based on spectral mixture analysis. In C.M. Pieters and P..A.J. Englert (Eds), *Remote Geochemical Analysis: Elemental and mineralogical composition*, pp. 145–166 (New York: Cambridge University Press).

ADAMS, J.B., SABOL, D.E., KAPOS, V., FILHO, R.A., ROBERTS, D.A., SMITH, M.O. and GILLESPIE, A.R., 1995, Classification of multispectral images based on fractions of endmembers: application to land cover change in the Brazilian Amazon. *Remote Sensing of Environment*, **52**, pp. 137–154.

ALTHAUSEN, J.D., 2002, What remote sensing system should be used to collect the data? In J.D. Bossler, J.R. Jensen, R.B. McMaster and C. Rizos (Eds), *Manual of Geospatial Science and Technology*, pp. 276–297 (New York: Taylor and Francis).

AMARSAIKHAN, D. and DOUGLAS, T., 2004, Data fusion and multisource image classification. *International Journal of Remote Sensing*, **25**, pp. 3529–3539.

ANGELO, N.P. and HAERTEL, V., 2003, On the application of Gabor filtering in supervised image classification. *International Journal of Remote Sensing*, **24**, pp. 2167–2189.

APAN, A., HELD, A., PHINN, S. and MARKLEY, J., 2004, Detecting sugarcane 'orange rust' disease using EO-1 Hyperion hyperspectral imagery. *International Journal of Remote Sensing*, **25**, pp. 489–498.

APLIN, P. and ATKINSON, P.M., 2001, sub-pixel land cover mapping for per-field classification. *International Journal of Remote Sensing*, **22**, pp. 2853–2858.

APLIN, P., ATKINSON, P.M. and CURRAN, P.J., 1999a, Per-field classification of land use using the forthcoming very fine spatial resolution satellite sensors: problems and potential solutions. In P.M. Atkinson and N.J. Tate (Eds), *Advances in Remote Sensing and GIS Analysis*, pp. 219–239 (New York: John Wiley and Sons).

APLIN, P., ATKINSON, P.M. and CURRAN, P.J., 1999b, Fine spatial resolution simulated satellite sensor imagery for land cover mapping in the United Kingdom. *Remote Sensing of Environment*, **68**, pp. 206–216.

ASNER, G.P. and HEIDEBRECHT, K.B., 2002, Spectral unmixing of vegetation, soil and dry carbon cover in arid regions: comparing multispectral and hyperspectral observations. *International Journal of Remote Sensing*, **23**, pp. 3939–3958.

ATKINSON, P.M. and APLIN, P., 2004, Spatial variation in land cover and choice of spatial resolution for remote sensing. *International Journal of Remote Sensing*, **25**, pp. 3687–3702.

ATKINSON, P.M. and CURRAN, P.J., 1997, Choosing an appropriate spatial resolution for remote sensing investigations. *Photogrammetric Engineering and Remote Sensing*, **63**, pp. 1345–1351.

ATKINSON, P.M. and TATNALL, A.R.L., 1997, Neural networks in remote sensing. *International Journal of Remote Sensing*, **18**, pp. 699–709.

ATKINSON, P.M., CUTLER, M.E.J. and LEWIS, H., 1997, Mapping sub-pixel proportional land cover with AVHRR imagery. *International Journal of Remote Sensing*, **18**, pp. 917–935.

AUGUSTEIJN, M.F., CLEMENS, L.E. and SHAW, K.A., 1995, Performance evaluation of texture measures for ground cover identification in satellite images by means of a neural network classifier. *IEEE Transactions on Geoscience and Remote Sensing*, **33**, pp. 616–625.

BABAN, S.M.J. and YUSOF, K.W., 2001, Mapping land use/cover distribution on a mountainous tropical island using remote sensing and GIS. *International Journal of Remote Sensing*, **22**, pp. 1909–1918.

BAN, Y., 2003, Synergy of multitemporal ERS-1 SAR and Landsat TM data for classification of agricultural crops. *Canadian Journal of Remote Sensing*, **29**, pp. 518–526.

BARALDI, A. and PARMIGGIANI, F., 1995, An investigation of the textural characteristics associated with gray level cooccurrence matrix statistical parameters. *IEEE Transactions on Geoscience and Remote Sensing*, **33**, pp. 293–304.

BARANDELA, R. and JUAREZ, M., 2002, Supervised classification of remotely sensed data with ongoing learning capability. *International Journal of Remote Sensing*, **23**, pp. 4965–4970.

BARNSLEY, M.J., 1999, Digital remote sensing data and their characteristics. In P. Longley, M. Goodchild, D.J. Maguire and D.W. Rhind (Eds), *Geographical Information Systems: Principles, techniques, applications, and management*, 2nd edn, pp. 451–466 (New York: John Wiley and Sons).

BARNSLEY, M.J. and BARR, S.L., 1996, Inferring urban land use from satellite sensor images using kernel-based spatial reclassification. *Photogrammetric Engineering and Remote Sensing*, **62**, pp. 949–958.

BARNSLEY, M.J. and BARR, S.L., 1997, Distinguishing urban land-use categories in fine spatial resolution land-cover data using a graph-based, structural pattern recognition system. *Computers, Environments and Urban Systems*, **21**, pp. 209–225.

BASTIN, L., FISHER, P. and WOOD, J., 2002, Visualizing uncertainty in multispectral remotely sensed imagery. *Computers & Geosciences*, **28**, pp. 337–350.

BATESON, A. and CURTISS, B., 1996, A method for manual endmember selection and spectral unmixing. *Remote Sensing of Environment*, **55**, pp. 229–243.

BEAUBIEN, J., CIHLAR, J., SIMARD, G. and LATIFOVIC, R., 1999, Land cover from multiple Thematic Mapper scenes using a new enhancement-classification methodology. *Journal of Geophysical Research*, **104**, pp. 27909–27920.

BENEDIKTSSON, J.A. and KANELLOPOULOS, I., 1999, Classification of multisource and hyperspectral data based on decision fusion. *IEEE Transactions on Geoscience and Remote Sensing*, **37**, pp. 1367–1377.

BENEDIKTSSON, J.A., SVEINSSON, J.R. and ARNASON, K., 1995, Classification and feature extraction of AVIRIS data. *IEEE Transactions on Geoscience and Remote Sensing*, **33**, pp. 1194–1205.

BENZ, U.C., HOFMANN, P., WILLHAUCK, G., LINGENFELDER, I. and HEYNEN, M., 2004, Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry & Remote Sensing*, **58**, pp. 239–258.

BERBEROGLU, S., LLOYD, C.D., ATKINSON, P.M. and CURRAN, P.J., 2000, The integration of spectral and textural information using neural networks for land cover mapping in the Mediterranean. *Computers and Geosciences*, **26**, pp. 385–396.

BIEHL, L. and LANDGREBE, D., 2002, MultiSpec—a tool for multispectral-hyperspectral image data analysis. *Computers and Geosciences*, **28**, pp. 1153–1159.

BINAGHI, E., MADELLA, P., MONTESANO, M.G. and RAMPINI, A., 1997, Fuzzy contextual classification of multisource remote sensing images. *IEEE Transactions on Geoscience and Remote Sensing*, **35**, pp. 326–339.

BINAGHI, E., BRIVIO, P.A., GHEZZI, P. and RAMPINI, A., 1999, A fuzzy set accuracy assessment of soft classification. *Pattern Recognition Letters*, **20**, pp. 935–948.

BLOCH, I., 1996, Information combination operators for data fusion: a comparative review with classification. *IEEE Transactions on Systems, Man, and Cybernetics*, **26**, pp. 52–67.

BOLSTAD, P.V. and LILLESAND, T.M., 1992, Rule-based classification models: flexible integration of satellite imagery and thematic spatial data. *Photogrammetric Engineering and Remote Sensing*, **58**, pp. 965–971.

BRISCO, B. and BROWN, R.J., 1995, Multidate SAR/TM synergism for crop classification in western Canada. *Photogrammetric Engineering and Remote Sensing*, **61**, pp. 1009–1014.

BRONGE, L.B., 1999, Mapping boreal vegetation using Landsat TM and topographic map data in a stratified approach. *Canadian Journal of Remote Sensing*, **25**, pp. 460–474.

BROWN, M., GUNN, S.R. and LEWIS, H.G., 1999, Support vector machines for optimal classification and spectral unmixing. *Ecological Modeling*, **120**, pp. 167–179.

BRUZZONE, L., CONESE, C., MASELLI, F. and ROLI, F., 1997, Multisource classification of complex rural areas by statistical and neural-network approaches. *Photogrammetric Engineering and Remote Sensing*, **63**, pp. 523–533.

BRUZZONE, L., PRIETO, D.F. and SERPICO, S.B., 1999, A neural-statistical approach to multitemporal and multisource remote-sensing image classification. *IEEE Transactions on Geoscience and Remote Sensing*, **37**, pp. 1350–1359.

BUTUSOV, O.B., 2003, Textural classification of forest types from Landsat 7 imagery. *Mapping Sciences and Remote Sensing*, **40**, pp. 91–104.

CANTERS, F., 1997, Evaluating the uncertainty of area estimates derived from fuzzy land-cover classification. *Photogrammetric Engineering and Remote Sensing*, **63**, pp. 403–414.

CANTY, M.J., NIELSEN, A.A. and SCHMIDT, M., 2004, Automatic radiometric normalization of multitemporal satellite imagery. *Remote Sensing of Environment*, **91**, pp. 441–451.

CARLOTTO, M.J., 1998, Spectral shape classification of Landsat Thematic Mapper imagery. *Photogrammetric Engineering and Remote Sensing*, **64**, pp. 905–913.

CARR, J.R., 1999, Classification of digital image texture using variograms. In P.M. Atkinson and N.J. Tate (Eds), *Advances in Remote Sensing and GIS Analysis*, pp. 135–146 (New York: John Wiley and Sons).

CARR, J.R. and MIRANDA, F.P., 1998, The semivariogram in comparison to the co-occurrence matrix for classification of image texture. *IEEE Transactions on Geoscience and Remote Sensing*, **36**, pp. 1945–1952.

CHALIFOUX, S., CAVAYAS, F. and GRAY, J.T., 1998, Mapping-guided approach for the automatic detection on Landsat TM images of forest stands damaged by the spruce budworm. *Photogrammetric Engineering and Remote Sensing*, **64**, pp. 629–635.

CHAVEZ, P.S. JR, 1996, Image-based atmospheric corrections—revisited and improved. *Photogrammetric Engineering and Remote Sensing*, **62**, pp. 1025–1036.

CHEN, C.-M., HEPNER, G.F. and FORSTER, R.R., 2003, Fusion of hyperspectral and radar data using the IHS transformation to enhance urban surface features. *ISPRS Journal of Photogrammetry and Remote Sensing*, **58**, pp. 19–30.

CHEN, D. and STOW, D.A., 2002, The effect of training strategies on supervised classification at different spatial resolution. *Photogrammetric Engineering and Remote Sensing*, **68**, pp. 1155–1162.

CHEN, D. and STOW, D.A., 2003, Strategies for integrating information from multiple spatial resolutions into land-use/land-cover classification routines. *Photogrammetric Engineering and Remote Sensing*, **69**, pp. 1279–1287.

CHEN, D., STOW, D.A. and GONG, P., 2004, Examining the effect of spatial resolution and texture window size on classification accuracy: an urban environment case. *International Journal of Remote Sensing*, **25**, pp. 2177–2192.

CHEN, K.S., TZENG, Y.C., CHEN, C.F. and KAO, W.L., 1995, Land-cover classification of multispectral imagery using a dynamic learning neural network. *Photogrammetric Engineering and Remote Sensing*, **61**, pp. 403–408.

CHEN, K.S., YEN, S.K. and TSAY, D.W., 1997, Neural classification of SPOT imagery through integration of intensity and fractal information. *International Journal of Remote Sensing*, **18**, pp. 763–783.

CHUST, G., DUCROT, D. and PRETUS, J.L., 2004, Land cover discrimination potential of radar multitemporal series and optical multispectral images in a Mediterranean cultural landscape. *International Journal of Remote Sensing*, **25**, pp. 3513–3528.

CIHLAR, J., 2000, Land cover mapping of large areas from satellites: status and research priorities. *International Journal of Remote Sensing*, **21**, pp. 1093–1114.

CIHLAR, J., XIAO, Q., CHEN, J., BEAUBIEN, J., FUNG, K. and LATIFOVIC, R., 1998, Classification by progressive generalization: a new automated methodology for remote sensing multispectral data. *International Journal of Remote Sensing*, **19**, pp. 2685–2704.

CINGOLANI, A.M., RENISON, D., ZAK, M.R. and CABIDO, M.R., 2004, Mapping vegetation in a heterogeneous mountain rangeland using Landsat data: an alternative method to define and classify land-cover units. *Remote Sensing of Environment*, **92**, pp. 84–97.

CIVCO, D.L., 1989, Topographic normalization of Landsat Thematic Mapper digital imagery. *Photogrammetric Engineering and Remote Sensing*, **55**, pp. 1303–1309.

COLBY, J.D., 1991, Topographic normalization in rugged terrain. *Photogrammetric Engineering and Remote Sensing*, **57**, pp. 531–537.

COLLINS, M.J., DYMOND, C. and JOHNSON, E.A., 2004, Mapping subalpine forest types using networks of nearest neighbor classifiers. *International Journal of Remote Sensing*, **25**, pp. 1701–1721.

CONESE, C. and MASELLI, F., 1994, Evaluation of contextual, per-pixel and mixed classification procedures applied to a subtropical landscape. *Remote Sensing Reviews*, **9**, pp. 175–186.

CONGALTON, R.G., 1991, A review of assessing the accuracy of classification of remotely sensed data. *Remote Sensing of Environment*, **37**, pp. 35–46.

CONGALTON, R.G. and GREEN, K., 1993, A practical look at the sources of confusion in error matrix generation. *Photogrammetric Engineering and Remote Sensing*, **59**, pp. 641–644.

CONGALTON, R.G. and GREEN, K., 1999, *Assessing the Accuracy of Remotely Sensed Data: Principles and practices* (Boca Raton, London, New York: Lewis Publishers).

CONGALTON, R.G. and MEAD, R.A., 1983, A quantitative method to test for consistency and correctness in photo interpretation. *Photogrammetric Engineering and Remote Sensing*, **49**, pp. 69–74.

CONGALTON, R.G. and PLOURDE, L., 2002, Quality assurance and accuracy assessment of information derived from remotely sensed data. In J. Bossler (Ed.), *Manual of Geospatial Science and Technology* (London: Taylor & Francis), pp. 349–361.

CORTIJO, F.J. and DE LA BLANCA, N.P., 1997, A comparative study of some non-parametric spectral classifiers: application to problems with high-overlapping training sets. *International Journal of Remote Sensing*, **18**, pp. 1259–1275.

CORTIJO, F.J. and DE LA BLANCA, N.P., 1998, Improving classical contextual classification. *International Journal of Remote Sensing*, **19**, pp. 1591–1613.

CRACKNELL, A.P., 1998, Synergy in remote sensing—what's in a pixel? *International Journal of Remote Sensing*, **19**, pp. 2025–2047.

CRAWFORD, M.M., KUMAR, S., RICARD, M.R., GIBEAUT, J.C. and NEUENSCHWANDER, A.L., 1999, Fusion of airborne polarimetric and interfermetric SAR data for classification of coastal environments. *IEEE Transactions on Geoscience and Remote Sensing*, **37**, pp. 1306–1315.

CROSETTO, M., RUIZ, J.A.M. and CRIPPA, B., 2001, Uncertainty propagation in models driven by remotely sensed data. *Remote Sensing of Environment*, **76**, pp. 373–385.

CUSHNIE, J.L., 1987, The interactive effect of spatial resolution and degree of internal variability within land-cover types on classification accuracies. *International Journal of Remote Sensing*, **8**, pp. 15–29.

DAI, X. and KHORRAM, S., 1998, A hierarchical methodology framework for multisource data fusion in vegetation classification. *International Journal of Remote Sensing*, **19**, pp. 3697–3701.

DEAN, A.M. and SMITH, G.M., 2003, An evaluation of per-parcel land cover mapping using maximum likelihood class probabilities. *International Journal of Remote Sensing*, **24**, pp. 2905–2920.

DEBEIR, O., VAN DEN STEEN, I., LATINNE, P., VAN HAM, P. and WOLFF, E., 2002, Textural and contextual land-cover classification using single and multiple classifier systems. *Photogrammetric Engineering and Remote Sensing*, **68**, pp. 597–605.

DEFRIES, R.S. and CHAN, J.C., 2000, Multiple criteria for evaluating machine learning algorithms for land cover classification from satellite data. *Remote Sensing of Environment*, **74**, pp. 503–515.

DEFRIES, R.S., HANSEN, M., TOWNSHEND, J.R.G. and SOHLBERG, R., 1998, Global land cover classification at 8 km spatial resolution: the use of training data derived from Landsat imagery in decision tree classifiers. *International Journal of Remote Sensing*, **19**, pp. 3141–3168.

DENNISON, P.E. and ROBERTS, D.A., 2003, Endmember selection for multiple endmember spectral mixture analysis using endmember average RMSE. *Remote Sensing of Environment*, **87**, pp. 123–135.

DU, Q. and CHANG, C., 2001, A linear constrained distance-based discriminant analysis for hyperspectral image classification. *Pattern Recognition*, **34**, pp. 361–373.

DU, Q. and REN, H., 2003, Real-time constrained linear discriminant analysis to target detection and classification in hyperspectral imagery. *Pattern Recognition*, **36**, pp. 1–12.

DU, Y., TEILLET, P.M. and CIHLAR, J., 2002, Radiometric normalization of multitemporal high-resolution satellite images with quality control for land cover change detection. *Remote Sensing of Environment*, **82**, pp. 123–134.

DUNGAN, J.L., 2002, Toward a comprehensive view of uncertainty in remote sensing analysis. In G.M. Foody and P.M. Atkinson (Eds), *Uncertainty in Remote Sensing and GIS*, pp. 25–35 (Chichester: John Wiley & Sons).

DYMOND, J.R. and SHEPHERD, J.D., 1999, Correction of the topographic effect in remote sensing. *IEEE Transactions on Geoscience and Remote Sensing*, **37**, pp. 2618–2620.

EHLERS, M., 1990, Remote sensing and geographic information systems: towards integrated spatial information processing. *IEEE Transactions on Geoscience and Remote Sensing*, **28**, pp. 763–766.

EHLERS, M., EDWARDS, G. and BEDARD, Y., 1989, Integration of remote sensing with geographic information systems: a necessary evolution. *Photogrammetric Engineering and Remote Sensing*, **55**, pp. 1619–1627.

EKSTRAND, S., 1996, Landsat TM-based forest damage assessment: correction for topographic effects. *Photogrammetric Engineering and Remote Sensing*, **62**, pp. 151–161.

EMERSON, C.W., LAM, N.S. and QUATTROCHI, D.A., 1999, Multi-scale fractal analysis of image texture and pattern. *Photogrammetric Engineering and Remote Sensing*, **65**, pp. 51–61.

EMRAHOGLU, N., YEGINGIL, I., PESTEMALCI, V., SENKAL, O. and KANDIRMAZ, H.M., 2003, Comparison of a new algorithm with the supervised classifications. *International Journal of Remote Sensing*, **24**, pp. 649–655.

EPSTEIN, J., PAYNE, K. and KRAMER, E., 2002, Techniques for mapping suburban sprawl. *Photogrammetric Engineering and Remote Sensing*, **68**, pp. 913–918.

ERBEK, F.S., OZKAN, C. and TABERNER, M., 2004, Comparison of maximum likelihood classification method with supervised artificial neural network algorithms for land use activities. *International Journal of Remote Sensing*, **25**, pp. 1733–1748.

ERIKSON, M., 2004, Species classification of individually segmented tree crowns in high-resolution aerial images using radiometric and morphologic image measures. *Remote Sensing of Environment*, **91**, pp. 469–477.

EROL, H. and AKDENIZ, F., 1996, A multi-spectral classification algorithm for classifying parcels in an agricultural region. *International Journal of Remote Sensing*, **17**, pp. 3357–3371.

EROL, H. and AKDENIZ, F., 1998, A new supervised classification method for quantitative analysis of remotely sensed multi-spectral data. *International Journal of Remote Sensing*, **19**, pp. 775–782.

ESTES, J.E. and LOVELAND, T.R., 1999, Characteristics, sources, and management of remotely-sensed data. In P. Longley, M. Goodchild, D.J. Maguire and D.W. Rhind (Eds), *Geographical Information Systems: Principles, Techniques, Applications, and Management*, 2nd edn, pp. 667–675 (New York: John Wiley and Sons).

FERNANDES, R., FRASER, R., LATIFOVIC, R., CIHLAR, J., BEAUBIEN, J. and DU, Y., 2004, Approaches to fractional land cover and continuous field mapping: a comparative assessment over the BOREAS study region. *Remote Sensing of Environment*, **89**, pp. 234–251.

FERNÁNDEZ-PRIETO, D., 2002, An iterative approach to partially supervised classification problems. *International Journal of Remote Sensing*, **23**, pp. 3887–3892.

FINN, J.T., 1993, Use of the average mutual information index in evaluating classification error and consistency. *International Journal of Geographical Information Systems*, **7**, pp. 349–366.

FISHER, P., 1997, The pixel: a snare and a delusion. *International Journal of Remote Sensing*, **18**, pp. 679–685.

FLYGARE, A-M., 1997, A comparison of contextual classification methods using Landsat TM. *International Journal of Remote Sensing*, **18**, pp. 3835–3842.

FOODY, G.M., 1992, On the compensation for chance agreement in image classification accuracy assessment. *Photogrammetric Engineering and Remote Sensing*, **58**, pp. 1459–1460.

FOODY, G.M., 1996, Approaches for the production and evaluation of fuzzy land cover classification from remotely-sensed data. *International Journal of Remote Sensing*, **17**, pp. 1317–1340.

FOODY, G.M., 1998, Sharpening fuzzy classification output to refine the representation of sub-pixel land cover distribution. *International Journal of Remote Sensing*, **19**, pp. 2593–2599.

FOODY, G.M., 1999, Image classification with a neural network: from completely-crisp to fully-fuzzy situation. In P.M. Atkinson and N.J. Tate (Eds), *Advances in Remote Sensing and GIS Analysis*, pp. 17–37 (New York: John Wiley and Sons).

FOODY, G.M., 2002a, Hard and soft classifications by a neural network with a non-exhaustively defined set of classes. *International Journal of Remote Sensing*, **23**, pp. 3853–3864.

FOODY, G.M., 2002b, Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, **80**, pp. 185–201.

FOODY, G.M., 2004a, Thematic map comparison: evaluating the statistical significance of differences in classification accuracy. *Photogrammetric Engineering and Remote Sensing*, **70**, pp. 627–633.

FOODY, G.M., 2004b, Supervised image classification by MLP and RBF neural networks with and without an exhaustively defined set of classes. *International Journal of Remote Sensing*, **25**, pp. 3091–3104.

FOODY, G.M. and ARORA, M.K., 1997, An evaluation of some factors affecting the accuracy of classification by an artificial neural network. *International Journal of Remote Sensing*, **18**, pp. 799–810.

FOODY, G.M. and ATKINSON, P.M. (Eds), 2002, *Uncertainty in Remote Sensing and GIS* (Hoboken, NJ: John Wiley & Sons).

FOODY, G.M. and COX, D.P., 1994, Sub-pixel land cover composition estimation using a linear mixture model and fuzzy membership functions. *International Journal of Remote Sensing*, **15**, pp. 619–631.

FOODY, G.M. and MATHUR, A., 2004a, A relative evaluation of multiclass image classification by support vector machines. *IEEE Transactions on Geoscience and Remote Sensing*, **42**, pp. 1336–1343.

FOODY, G.M. and MATHUR, A., 2004b, Toward intelligent training of supervised image classifications: directing training data acquisition for SVM classification. *Remote Sensing of Environment*, **93**, pp. 107–117.

FOODY, G.M., MCCULLOCH, M.B. and YATES, W.B., 1995, Classification of remotely sensed data by an artificial neural network: issues related to training data characteristics. *Photogrammetric Engineering and Remote Sensing*, **61**, pp. 391–401.

FOSCHI, P.G. and SMITH, D.K., 1997, Detecting subpixel woody vegetation in digital imagery using two artificial intelligence approaches. *Photogrammetric Engineering and Remote Sensing*, **63**, pp. 493–500.

FRANKLIN, J., PHINN, S.R., WOODCOCK, C.E. and ROGAN, J., 2003, Rationale and conceptual framework for classification approaches to assess forest resources and properties. In M.A. Wulder and S.E. Franklin (Eds), *Remote Sensing of Forest Environments: Concepts and case studies*, pp. 279–300 (Boston: Kluwer Academic Publishers).

FRANKLIN, S.E., 2001, *Remote Sensing for Sustainable Forest Management* (New York: Lewis Publishers).

FRANKLIN, S.E. and PEDDLE, D.R., 1989, Spectral texture for improved class discrimination in complex terrain. *International Journal of Remote Sensing*, **10**, pp. 1437–1443.

FRANKLIN, S.E. and PEDDLE, D.R., 1990, Classification of SPOT HRV imagery and texture features. *International Journal of Remote Sensing*, **11**, pp. 551–556.

FRANKLIN, S.E. and WULDER, M.A., 2002, Remote sensing methods in medium spatial resolution satellite data land cover classification of large areas. *Progress in Physical Geography*, **26**, pp. 173–205.

FRANKLIN, S.E., CONNERY, D.R. and WILLIAMS, J.A., 1994, Classification of alpine vegetation using Landsat Thematic Mapper, SPOT HRV and DEM data. *Canadian Journal of Remote Sensing*, **20**, pp. 49–56.

FRANKLIN, S.E., WULDER, M.A. and LAVIGNE, M.B., 1996, Automated derivation of geographic window sizes for remote sensing digital image texture analysis. *Computers and Geosciences*, **22**, pp. 665–673.

FRANKLIN, S.E., PEDDLE, D.R., DECHKA, J.A. and STENHOUSE, G.B., 2002, Evidential reasoning with Landsat TM, DEM and GIS data for land cover classification in support of grizzly bear habitat mapping. *International Journal of Remote Sensing*, **23**, pp. 4633–4652.

FRIEDL, M.A. and BRODLEY, C.E., 1997, Decision tree classification of land cover from remotely sensed data. *Remote Sensing of Environment*, **61**, pp. 399–409.

FRIEDL, M.A., BRODLEY, C.E. and STRAHLER, A.H., 1999, Maximizing land cover classification accuracies produced by decision trees at continental to global scales. *IEEE Transactions on Geoscience and Remote Sensing*, **37**, pp. 969–977.

FRIEDL, M.A., MCGWIRE, K.C. and MCIVER, D.K., 2001, An overview of uncertainty in optical remotely sensed data for ecological applications. In C.T. Hunsaker, M.F. Goodchild, M.A. Friedl and T.J. Case (Eds), *Spatial Uncertainty in Ecology: Implications for remote sensing and GIS applications*, pp. 258–283 (New York: Springer-Verlag).

GAHEGAN, M. and EHLERS, M., 2000, A framework for the modeling of uncertainty between remote sensing and geographic information systems. *ISPRS Journal of Photogrammetry and Remote Sensing*, **55**, pp. 176–188.

GALLEGO, F.J., 2004, Remote sensing and land cover area estimation. *International Journal of Remote Sensing*, **25**, pp. 3019–3047.

GARCIA-HARO, F.J., GILABERT, M.A. and MELIA, J., 1999, Extraction of endmembers from spectral mixtures. *Remote Sensing of Environment*, **68**, pp. 237–253.

GARGUET-DUPORT, B., GIREL, J., CHASSERY, J. and PAUTOU, G., 1996, The use of multiresolution analysis and wavelet transform for merging SPOT panchromatic and multispectral image data. *Photogrammetric Engineering and Remote Sensing*, **62**, pp. 1057–1066.

GENELETTI, D. and GORTE, B.G.H., 2003, A method for object-oriented land cover classification combining Landsat TM data and aerial photographs. *International Journal of Remote Sensing*, **24**, pp. 1273–1286.

GILABERT, M.A., CONESE, C. and MASELLI, F., 1994, An atmospheric correction method for the automatic retrieval of surface reflectance from TM images. *International Journal of Remote Sensing*, **15**, pp. 2065–2086.

GITAS, I.Z., MITRI, G.H. and VENTURA, G., 2004, Object-based image classification for burned area mapping of Creus Cape Spain, using NOAA-AVHRR imagery. *Remote Sensing of Environment*, **92**, pp. 409–413.

GOETZ, S.J., WRIGHT, R.K., SMITH, A.J., ZINECKER, E. and SCHAUB, E., 2003, IKONOS imagery for resource management: tree cover, impervious surfaces, and riparian buffer analyses in the mid-Atlantic region. *Remote Sensing of Environment*, **88**, pp. 195–208.

GONG, P., 1994, Integrated analysis of spatial data from multiple sources: an overview. *Canadian Journal of Remote Sensing*, **20**, pp. 349–359.

GONG, P., 1996, Integrated analysis of spatial data from multiple sources: using evidential reasoning and artificial neural network techniques for geological mapping. *Photogrammetric Engineering and Remote Sensing*, **62**, pp. 513–523.

GONG, P. and HOWARTH, P.J., 1992, Frequency-based contextual classification and gray-level vector reduction for land-use identification. *Photogrammetric Engineering and Remote Sensing*, **58**, pp. 423–437.

GONG, P., MARCEAU, D.J. and HOWARTH, P.J., 1992, A comparison of spatial feature extraction algorithms for land-use classification with SPOT HRV data. *Remote Sensing of Environment*, **40**, pp. 137–151.

GOPAL, S. and WOODCOCK, C., 1994, Theory and methods for accuracy assessment of thematic maps using fuzzy sets. *Photogrammetric Engineering and Remote Sensing*, **60**, pp. 181–188.

GORDON, D.K. and PHILLIPSON, W.R., 1986, A texture enhancement procedure for separating orchard from forest in Thematic Mapper imagery. *International Journal of Remote Sensing*, **8**, pp. 301–304.

GROOM, G.B., FULLER, R.M. and JONES, A.R., 1996, Contextual correction: techniques for improving land cover mapping from remotely sensed images. *International Journal of Remote Sensing*, **17**, pp. 69–89.

GU, D. and GILLESPIE, A., 1998, Topographic normalization of Landsat TM images of forest based on subpixel sun-canopy-sensor geometry. *Remote Sensing of Environment*, **64**, pp. 166–175.

GUERSCHMAN, J.P., PARUELO, J.M., DI, BELLA, C., GIALLORENZI, M.C. and PACIN, F., 2003, Land cover classification in the Argentine Pampas using multitemporal Landsat TM data. *International Journal of Remote Sensing*, **24**, pp. 3381–3402.

HAACK, B.N., SOLOMON, E.K., BECHDOL, M.A. and HEROLD, N.D., 2002, Radar and optical data comparison/integration for urban delineation: a case study. *Photogrammetric Engineering and Remote Sensing*, **68**, pp. 1289–1296.

HAAPANEN, R., EK, A.R., BAUER, M.E. and FINLEY, A.O., 2004, Delineation of forest/ nonforest land use classes using nearest neighbor methods. *Remote Sensing of Environment*, **89**, pp. 265–271.

HADJIMITSIS, D.G., CLAYTON, C.R.I. and HOPE, V.S., 2004, An assessment of the effectiveness of atmospheric correction algorithms through the remote sensing of some reservoirs. *International Journal of Remote Sensing*, **25**, pp. 3651–3674.

HALE, S.R. and ROCK, B.N., 2003, Impacts of topographic normalization on land-cover classification accuracy. *Photogrammetric Engineering and Remote Sensing*, **69**, pp. 785–792.

HANSEN, M., DUBAYAH, R. and DEFRIES, R., 1996, Classification trees: an alternative to traditional land cover classifiers. *International Journal of Remote Sensing*, **17**, pp. 1075–1081.

HARALICK, R.M., SHANMUGAM, K. and DINSTEIN, I., 1973, Textural features for image classification. *IEEE Transactions on Systems, Man and Cybernetics*, **3**, pp. 610–620.

HARDIN, P.J., 1994, Parametric and nearest-neighbor methods for hybrid classification: a comparison of pixel assignment accuracy. *Photogrammetric Engineering and Remote Sensing*, **60**, pp. 1439–1448.

HARDIN, P.J. and SHUMWAY, J.M., 1997, Statistical significance and normalized confusion matrices. *Photogrammetric Engineering and Remote Sensing*, **63**, pp. 735–740.

HARRIS, P.M. and VENTURA, S.J., 1995, The integration of geographic data with remotely sensed imagery to improve classification in an urban area. *Photogrammetric Engineering and Remote Sensing*, **61**, pp. 993–998.

HAY, G.J., NIEMANN, K.O. and MCLEAN, G.F., 1996, An object-specific image-texture analysis of H-resolution forest imagery. *Remote Sensing of Environment*, **55**, pp. 108–122.

HE, D.C. and WANG, L., 1990, Texture unit, textural spectrum and texture analysis. *IEEE Transactions on Geoscience and Remote Sensing*, **28**, pp. 509–512.

HELMER, E.H., BROWN, S. and COHEN, W.B., 2000, Mapping montane tropical forest successional stage and land use with multi-date Landsat imagery. *International Journal of Remote Sensing*, **21**, pp. 2163–2183.

HEO, J. and FITZHUGH, T.W., 2000, A standardized radiometric normalization method for change detection using remotely sensed imagery. *Photogrammetric Engineering and Remote Sensing*, **66**, pp. 173–182.

HEROLD, M., LIU, X. and CLARKE, K.C., 2003, Spatial metrics and image texture for mapping urban land use. *Photogrammetric Engineering and Remote Sensing*, **69**, pp. 991–1001.

HINTON, J.C., 1996, GIS and remote sensing integration for environmental applications. *International Journal of Geographical Information Systems*, **10**, pp. 877–890.

HINTON, J.C., 1999, Image classification and analysis using integrated GIS. In P.M. Atkinson and N.J. Tate (Eds), *Advances in Remote Sensing and GIS Analysis*, pp. 207–218 (New York: John Wiley and Sons).

HODGSON, M.E., JENSEN, J.R., TULLIS, J.A., RIORDAN, K.D. and ARCHER, C.M., 2003, Synergistic use lidar and color aerial photography for mapping urban parcel imperviousness. *Photogrammetric Engineering and Remote Sensing*, **69**, pp. 973–980.

HOFFBECK, J.P. and LANDGREBE, D.A., 1996, Classification of remote sensing having high spectral resolution images. *Remote Sensing of Environment*, **57**, pp. 119–126.

HSU, C. and LIN, C., 2002, A comparison of methods for multi-class support vector machines. *IEEE Transactions on Neural Networks*, **13**, pp. 415–425.

HUANG, C., DAVIS, L.S. and TOWNSHEND, J.R.G., 2002, An assessment of support vector machines for land cover classification. *International Journal of Remote Sensing*, **23**, pp. 725–749.

HUANG, Z. and LEES, B.G., 2004, Combining non-parametric models for multisource predictive forest mapping. *Photogrammetric Engineering and Remote Sensing*, **70**, pp. 415–425.

HUBERT-MOY, L., COTONNEC, A., LE DU, L., CHARDIN, A. and PEREZ, P., 2001, A comparison of parametric classification procedures of remotely sensed data applied on different landscape units. *Remote Sensing of Environment*, **75**, pp. 174–187.

HUDSON, W.D. and RAMM, C.W., 1987, Correct formulation of the Kappa coefficient of agreement. *Photogrammetric Engineering and Remote Sensing*, **53**, pp. 421–422.

HUGHES, G.F., 1968, On the mean accuracy of statistical pattern recognizers. *IEEE Transactions on Information Theory*, **14**, pp. 55–63.

HUGUENIN, R.L., KARASKA, M.A., BLARICOM, D.V. and JENSEN, J.R., 1997, Subpixel classification of Bald Cypress and Tupelo Gum trees in Thematic Mapper imagery. *Photogrammetric Engineering and Remote Sensing*, **63**, pp. 717–725.

HUNG, M. and RIDD, M.K., 2002, A subpixel classifier for urban land-cover mapping based on a maximum-likelihood approach and expert system rules. *Photogrammetric Engineering and Remote Sensing*, **68**, pp. 1173–1180.

HUNSAKER, C.T., GOODCHILD, M.F., FRIEDL, M.A. and CASE, T.J. (Eds), 2001, *Spatial Uncertainty in Ecology: Implications for remote sensing and GIS applications* (New York: Springer-Verlag).

HURTT, G., XIAO, X., KELLER, M., PALACE, M., ASNER, G.P., BRASWELL, R., BRONDIZIO, E.S., CARDOSO, M., CARVALHO, C.J.R., FEARON, M.G., GUILD, L.,

HAGEN, S., HETRICK, S., MOORE III, B., NOBRE, C., READ, J.M., SA, T., SCHLOSS, A., VOURLITIS, G. and WICKEL, A.J., 2003, IKONOS imagery for the Large Scale Biosphere–Atmosphere Experiment in Amazonia (LBA). *Remote Sensing of Environment*, **88**, pp. 111–127.

HUTCHINSON, C.F., 1982, Techniques for combining Landsat and ancillary data for digital classification improvement. *Photogrammetric Engineering and Remote Sensing*, **48**, pp. 123–130.

IRONS, J.R., MARKHAM, B.L., NELSON, R.F., TOLL, D.L., WILLIAMS, D.L., LATTY, R.S. and STAUFFER, M.L., 1985, The effects of spatial resolution on the classification of Thematic Mapper data. *International Journal of Remote Sensing*, **6**, pp. 1385–1403.

JAKUBAUKAS, M.E., 1997, Effects of forest succession on texture in Landsat Thematic Mapper imagery. *Canadian Journal of Remote Sensing*, **23**, pp. 257–263.

JANSSEN, L.F. and MOLENAAR, M., 1995, Terrain objects, their dynamics and their monitoring by integration of GIS and remote sensing. *IEEE Transactions on Geoscience and Remote Sensing*, **33**, pp. 749–758.

JANSSEN, L.F.J. and VAN DER WEL, F.J.M., 1994, Accuracy assessment of satellite derived land-cover data: a review. *Photogrammetric Engineering and Remote Sensing*, **60**, pp. 419–426.

JANSSEN, L.F., JAARSMA, M.N. and VAN DER LINDEN, E.T.M., 1990, Integrating topographic data with remote sensing for land-cover classification. *Photogrammetric Engineering and Remote Sensing*, **56**, pp. 1503–1506.

JENSEN, J.R., 1996, *Introduction to Digital Image Processing: A remote sensing perspective*, 2nd edn (Piscataway, NJ: Prentice Hall).

JENSEN, J.R. and COWEN, D.C., 1999, Remote sensing of urban/suburban infrastructure and socioeconomic attributes. *Photogrammetric Engineering and Remote Sensing*, **65**, pp. 611–622.

JEON, B. and LANDGREBE, D.A., 1999, Decision fusion approaches for multitemporal classification. *IEEE Transactions on Geoscience and Remote Sensing*, **37**, pp. 1227–1233.

JIANG, H., STRITTHOLT, J.R., FROST, P.A. and SLOSSER, N.C., 2004, The classification of late seral forests in the Pacific Northwest USA using Landsat ETM+ imagery. *Remote Sensing of Environment*, **91**, pp. 320–331.

JIMENEZ, L.O., MORALES-MORELL, A. and CREUS, A., 1999, Classification of hyperdimensional data based on feature and decision fusion approaches using projection pursuit, majority voting, and neural networks. *IEEE Transactions on Geoscience and Remote Sensing*, **37**, pp. 1360–1366.

JU, J., KOLACZYK, E.D. and GOPAL, S., 2003, Gaussian mixture discriminant analysis and sub-pixel land cover characterization in remote sensing. *Remote Sensing of Environment*, **84**, pp. 550–560.

KALKHAN, M.A., REICH, R.M. and CZAPLEWSKI, R.L., 1997, Variance estimates and confidence intervals for the Kappa measure of classification accuracy. *Canadian Journal of Remote Sensing*, **23**, pp. 210–216.

KARTIKEYAN, B., GOPALAKRISHNA, B., KALUBARME, M.H. and MAJUMDER, K.L., 1994, Contextual techniques for classification of high and low resolution remote sensing data. *International Journal of Remote Sensing*, **15**, pp. 1037–1051.

KARTIKEYAN, B., SARKAR, A. and MAJUMDER, K.L., 1998, A segmentation approach to classification of remote sensing imagery. *International Journal of Remote Sensing*, **19**, pp. 1695–1709.

KASHYAP, R.L., CHELLAPPA, R. and KHOTANZAD, A., 1982, Texture classification using features derived from random field models. *Pattern Recognition Letters*, **1**, pp. 43–50.

KAVZOGLU, T. and MATHER, P.M., 2004, The use of backpropagating artificial neural networks in land cover classification. *International Journal of Remote Sensing*, **24**, pp. 4907–4938.

KEUCHEL, J., NAUMANN, S., HEILER, M. and SIEGMUND, A., 2003, Automatic land cover analysis for Tenerife by supervised classification using remotely sensed data. *Remote Sensing of Environment*, **86**, pp. 530–541.

KIM, H., PANG, S., JE, H., KIM, D. and BANG, S.Y., 2003, Constructing support vector machine ensemble. *Pattern Recognition*, **36**, pp. 2757–2767.

KOKALYA, R.F., DESPAIN, D.G., CLARK, R.N. and LIVO, K.E., 2003, Mapping vegetation in Yellowstone National Park using spectral feature analysis of AVIRIS data. *Remote Sensing of Environment*, **84**, pp. 437–456.

KOLTUNOV, A. and BEN-DOR, E., 2001, A new approach for spectral feature extraction and for unsupervised classification of hyperspectral data based on the Gaussian mixture model. *Remote Sensing Reviews*, **20**, pp. 123–167.

KOLTUNOV, A. and BEN-DOR, E., 2004, Mixture density separation as a tool for high-quality interpretation of multi-source remote sensing data and related issues. *International Journal of Remote Sensing*, **25**, pp. 3275–3299.

KONTOES, C.C. and ROKOS, D., 1996, The integration of spatial context information in an experimental knowledge based system and the supervised relaxation algorithm: two successful approaches to improving SPOT-XS classification. *International Journal of Remote Sensing*, **17**, pp. 3093–3106.

KONTOES, C., WILKINSON, G.G., BURRILL, A., GOFFREDO, S. and MEGIER, J., 1993, An experimental system for the integration of GIS data in knowledge-based image analysis for remote sensing of agriculture. *International Journal of Geographical Information Systems*, **7**, pp. 247–262.

KULKARNI, A.D. and LULLA, K., 1999, Fuzzy neural network models for supervised classification: multispectral image analysis. *Geocarto International*, **14**, pp. 42–50.

KUROSU, T., YOKOYAMA, S. and CHIBA, K., 2001, Land use classification with textural analysis and the aggregation technique using multi-temporal JERS-1 L-band SAR images. *International Journal of Remote Sensing*, **22**, pp. 595–613.

LANDGREBE, D.A., 2003, *Signal Theory Methods in Multispectral Remote Sensing* (Hoboken, NJ: John Wiley and Sons).

LAWRENCE, R., BUNN, A., POWELL, S. and ZMABON, M., 2004, Classification of remotely sensed imagery using stochastic gradient boosting as a refinement of classification tree analysis. *Remote Sensing of Environment*, **90**, pp. 331–336.

LECKIE, D.G., 1998, Forestry applications using imaging radar. In F.M. Henderson and A.J. Lewis (Eds), *Principles and Applications of Imaging Radar, Manual of Remote Sensing*, 3rd edn, vol. 2, pp. 437–509 (New York: John Wiley and Sons).

LEE, T.W., LEWICKI, M.S. and SEJNOWSKI, T.J., 2000, ICA mixture models for unsupervised classification of non-gaussian classes and automatic context switching in blind signal separation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **22**, pp. 1078–1089.

LEFSKY, M.A. and COHEN, W.B., 2003, Selection of remotely sensed data. In M.A. Wulder and S.E. Franklin (Eds), *Remote Sensing of Forest Environments: Concepts and case studies*, pp. 13–46 (Boston: Kluwer Academic Publishers).

LEIN, J.K., 2003, Applying evidential reasoning methods to agricultural land cover classification. *International Journal of Remote Sensing*, **24**, pp. 4161–4180.

LEPRIEUR, C.E., DURAND, J.M. and PEYRON, J.L., 1988, Influence of topography on forest reflectance using Landsat Thematic Mapper and digital terrain data. *Photogrammetric Engineering and Remote Sensing*, **54**, pp. 491–496.

LI, S., KWOK, J.T. and WANG, Y., 2002, Using the discrete wavelet frame transform to merge Landsat TM and SPOT panchromatic images. *Information Fusion*, **3**, pp. 17–23.

LIRA, J. and MALETTI, G., 2002, A supervised contextual classifier based on a region-growth algorithm. *Computers and Geosciences*, **28**, pp. 951–959.

LIU, Q.J., TAKAMURA, T. and TAKEUCHI, N., 2002a, Mapping of boreal vegetation of a temperate mountain in China by multitemporal Landsat TM imagery. *International Journal of Remote Sensing*, **23**, pp. 3385–3405.

LIU, W., GOPAL, S. and WOODCOCK, C.E., 2004, Uncertainty and confidence in land cover classification using a hybrid classifier approach. *Photogrammetric Engineering and Remote Sensing*, **70**, pp. 963–972.

LIU, X., SKIDMORE, A.K. and OOSTEN, H.V., 2002b, Integration of classification methods for improvement of land-cover map accuracy. *ISPRS Journal of Photogrammetry and Remote Sensing*, **56**, pp. 257–268.

LLOYD, C.D., BERBEROGLU, S., CURRAN, P.J. and ATKINSON, P.M., 2004, A comparison of texture measures for the per-field classification of Mediterranean land cover. *International Journal of Remote Sensing*, **25**, pp. 3943–3965.

LLOYD, R.E., HODGSON, M.E. and STOKES, A., 2002, Visual categorization with aerial photography. *Annals of the Association American Geographers*, **92**, pp. 241–266.

LO, C.P. and CHOI, J., 2004, A hybrid approach to urban land use/cover mapping using Landsat 7 Enhanced Thematic Mapper Plus (ETM+) images. *International Journal of Remote Sensing*, **25**, pp. 2687–2700.

LOBELL, D.B., ASNER, G.P., LAW, B.E. and TREUHAFT, R.N., 2002, View angle effects on canopy reflectance and spectral mixture analysis of coniferous forests using AVIRIS. *International Journal of Remote Sensing*, **23**, pp. 2247–2262.

LOBO, A., CHIC, O. and CASTERAD, A., 1996, Classification of Mediterranean crops with multisensor data: per-pixel versus per-object statistics and image segmentation. *International Journal of Remote Sensing*, **17**, pp. 2385–2400.

LOW, H.K., CHUAH, H.T. and EWE, H.T., 1999, A neural network land use classifier for SAR images using textural and fractal information. *Geocarto International*, **14**, pp. 66–73.

LU, D. and WENG, Q., 2004, Spectral mixture analysis of the urban landscapes in Indianapolis with Landsat ETM+ imagery. *Photogrammetric Engineering and Remote Sensing*, **70**, pp. 1053–1062.

LU, D., MORAN, E. and BATISTELLA, M., 2003, Linear mixture model applied to Amazonian vegetation classification. *Remote Sensing of Environment*, **87**, pp. 456–469.

LU, D., MAUSEL, P., BATISTELLA, M. and MORAN, E., 2004, Comparison of land-cover classification methods in the Brazilian Amazon Basin. *Photogrammetric Engineering and Remote Sensing*, **70**, pp. 723–731.

LUCIEER, A. and KRAAK, M., 2004, Interactive and visual fuzzy classification of remotely sensed imagery for exploration of uncertainty. *International Journal of Geographic Information Science*, **18**, pp. 491–512.

LUNETTA, R.S. and BALOGH, M.E., 1999, Application of multi-temporal Landsat 5 TM imagery for wetland identification. *Photogrammetric Engineering and Remote Sensing*, **65**, pp. 1303–1310.

LUNETTA, R.S., EDIRIWCKREMA, J., IIAMES, J., JOHNSON, D.M., LYON, J.G., MCKERROW, A. and PILANT, A., 2003, A quantitative assessment of a combined spectral and GIS rule-based land-cover classification in the Neuse river basin of North Carolina. *Photogrammetric Engineering and Remote Sensing*, **69**, pp. 299–310.

LUO, R.C. and KAY, M.G., 1989, Multisensor integration and fusion for intelligent systems. *IEEE Transactions on Systems, Man, and Cybernetics*, **19**, pp. 901–931.

MA, Z. and REDMOND, R.L., 1995, Tau coefficients for accuracy assessment of classification of remote sensing data. *Photogrammetric Engineering and Remote Sensing*, **61**, pp. 435–439.

MACEACHREN, A.M. and KRAAK, M., 2001, Research challenges in geovisualization. *Cartography and Geographic Information Systems*, **28**, pp. 3–12.

MCGOVERN, E.A., HOLDEN, N.M., WARD, S.M. and COLLINS, J.F., 2002, The radiometric normalization of multitemporal Thematic Mapper imagery of the midlands of Ireland—a case study. *International Journal of Remote Sensing*, **23**, pp. 751–766.

MCGWIRE, K., MINOR, T. and FENSTERMAKER, L., 2000, Hyperspectral mixture modeling for quantifying sparse vegetation cover in arid environments. *Remote Sensing of Environment*, **72**, pp. 360–374.

McIver, D.K. and Friedl, M.A., 2001, Estimating pixel-scale land cover classification confidence using nonparametric machine learning methods. *IEEE Transactions on Geoscience and Remote Sensing*, **39**, pp. 1959–1968.

Magnussen, S., Boudewyn, P. and Wulder, M., 2004, Contextual classification of Landsat TM images to forest inventory cover types. *International Journal of Remote Sensing*, **25**, pp. 2421–2440.

Mannan, B. and Ray, A.K., 2003, Crisp and fuzzy competitive learning networks for supervised classification of multispectral IRS scenes. *International Journal of Remote Sensing*, **24**, pp. 3491–3502.

Mannan, B., Roy, J. and Ray, A.K., 1998, Fuzzy ARTMAP supervised classification of multi-spectral remotely-sensed images. *International Journal of Remote Sensing*, **19**, pp. 767–774.

Marceau, D.J., Howarth, P.J., Dubois, J.M. and Gratton, D.J., 1990, Evaluation of the grey-level co-occurrence matrix method for land-cover classification using SPOT imagery. *IEEE Transactions on Geoscience and Remote Sensing*, **28**, pp. 513–519.

Markham, B.L. and Barker, J.L., 1987, Thematic Mapper bandpass solar exoatmospheric irradiances. *International Journal of Remote Sensing*, **8**, pp. 517–523.

Maselli, F., 2001, Definition of spatially variable spectral endmembers by locally calibrated multivariate regression analysis. *Remote Sensing of Environment*, **75**, pp. 29–38.

Maselli, F., Conese, C. and Petkov, L., 1994, Use of probability entropy for the estimation and graphical representation of the accuracy of maximum likelihood classifications. *ISPRS Journal of Photogrammetry and Remote Sensing*, **49**, pp. 13–20.

Maselli, F., Rodolfi, A. and Conese, C., 1996, Fuzzy classification of spatially degraded Thematic Mapper data for the estimation of sub-pixel components. *International Journal of Remote Sensing*, **17**, pp. 537–551.

Maselli, F., Rodolfi, A., Bottai, L., Romanelli, S. and Conese, C., 2000, Classification of Mediterranean vegetation by TM and ancillary data for the evaluation of fire risk. *International Journal of Remote Sensing*, **21**, pp. 3303–3313.

Mather, P.M., 2004, *Computer Processing of Remotely-Sensed Images: An introduction*, 3rd edn (Chichester: John Wiley & Sons).

Mausel, P.W., Kramber, W.J. and Lee, J.K., 1990, Optimum band selection for supervised classification of multispectral data. *Photogrammetric Engineering and Remote Sensing*, **56**, pp. 55–60.

Mesev, V., 1998, The use of census data in urban image classification. *Photogrammetric Engineering and Remote Sensing*, **64**, pp. 431–438.

Meyer, P., Itten, K.I., Kellenberger, T., Sandmeier, S. and Sandmeier, R., 1993, Radiometric corrections of topographically induced effects on Landsat TM data in alpine environment. *ISPRS Journal of Photogrammetry and Remote Sensing*, **48**, pp. 17–28.

Michelson, D.B., Liljeberg, B.M. and Pilesjo, P., 2000, Comparison of algorithms for classifying Swedish land cover using Landsat TM and ERS-1 SAR data. *Remote Sensing of Environment*, **71**, pp. 1–15.

Mitra, P., Shankar, B.U. and Pal, S.K., 2004, Segmentation of multispectral remote sensing images using active support vector machines. *Pattern Recognition Letters*, **25**, pp. 1067–1074.

Moody, A., 1998, Using Landsat spatial relationships to improve estimates of land-cover area from coarse resolution remote sensing. *Remote Sensing of Environment*, **64**, pp. 202–220.

Mowrer, H.T. and Congalton, R.G. (Eds), 2000, *Quantifying Spatial Uncertainty in Natural Resources: Theory and applications for GIS and remote sensing* (Chelsea, MI: Ann Arbor Press).

Muller, S.V., Walker, D.A., Nelson, F.E., Auerbach, N.A., Bockheim, J.G., Guyer, S. and Sherba, D., 1998, Accuracy assessment of a land-cover map of the Kuparuk river basin, Alaska: considerations for remote regions. *Photogrammetric Engineering and Remote Sensing*, **64**, pp. 619–628.

MUNECHIKA, C.K., WARNICK, J.S., SALVAGGIO, C. and SCHOTT, J.R., 1993, Resolution enhancement of multispectral image data to improve classification accuracy. *Photogrammetric Engineering and Remote Sensing*, **59**, pp. 67–72.

MURAI, H. and OMATU, S., 1997, Remote sensing image analysis using a neural network and knowledge-based processing. *International Journal of Remote Sensing*, **18**, pp. 811–828.

MUSTARD, J.F. and SUNSHINE, J.M., 1999, Spectral analysis for earth science: investigations using remote sensing data. In A.N. Rencz (Ed.), *Remote Sensing for the Earth Sciences: Manual of remote sensing*, 3rd edn, vol. 3, pp. 251–307 (New York: John Wiley & Sons).

MYINT, S.W., 2001, A robust texture analysis and classification approach for urban land-use and land-cover feature discrimination. *Geocarto International*, **16**, pp. 27–38.

NARASIMHA RAO, P.V., SESHA SAI, M.V.R., SREENIVAS, K., KRISHNA RAO, M.V., RAO, B.R.M., DWIVEDI, R.S. and VENKATARATNAM, L., 2002, Textural analysis of IRS-1D panchromatic data for land cover classification. *International Journal of Remote Sensing*, **23**, pp. 3327–3345.

NARUMALANI, S., ZHOU, Y. and JELINSKI, D.E., 1998, Utilizing geometric attributes of spatial information to improve digital image classification. *Remote Sensing Reviews*, **16**, pp. 233–253.

NEVILLE, R.A., LEVESQUE, J., STAENE, K., NADEAU, C., HAUFF, P. and BORSTAD, G.A., 2003, Spectral unmixing of hyperspectral imagery for mineral exploration: comparison of results from SFSI and AVIRIS. *Canadian Journal of Remote Sensing*, **29**, pp. 99–110.

NIRALA, M.L. and VENKATACHALAM, G., 2000, Rotational transformation of remotely sensed data for land use classification. *International Journal of Remote Sensing*, **21**, pp. 2185–2202.

NYOUNGUI, A., TONYE, E. and AKONO, A., 2002, Evaluation of speckle filtering and texture analysis methods for land cover classification from SAR images. *International Journal of Remote Sensing*, **23**, pp. 1895–1925.

OETTER, D.R., COHEN, W.B., BERTERRETCHE, M., MAIERSPERGER, T.K. and KENNEDY, R.E., 2000, Land cover mapping in an agricultural setting using multiseasonal Thematic Mapper data. *Remote Sensing of Environment*, **76**, pp. 139–155.

OKIN, G.S., ROBERTS, D.A., MURRAY, B. and OKIN, W.J., 2001, Practical limits on hyperspectral vegetation discrimination in arid and semiarid environments. *Remote Sensing of Environment*, **77**, pp. 212–225.

OLTHOF, I., KING, D.J. and LAUTENSCHLAGER, R.A., 2004, Mapping deciduous forest ice storm damage using Landsat and environmental data. *Remote Sensing of Environment*, **89**, pp. 484–496.

ONSI, H.M., 2003, Designing a rule-based classifier using syntactical approach. *International Journal of Remote Sensing*, **24**, pp. 637–647.

OZKAN, C. and ERBEK, F.S., 2003, The comparison of activation functions for multispectral Landsat TM image classification. *Photogrammetric Engineering and Remote Sensing*, **69**, pp. 1225–1234.

PAL, M. and MATHER, P.M., 2003, An assessment of the effectiveness of decision tree methods for land cover classification. *Remote Sensing of Environment*, **86**, pp. 554–565.

PAL, M. and MATHER, P.M., 2004, Assessment of the effectiveness of support vector machines for hyperspectral data. *Future Generation Computer System*, **20**, pp. 1215–1225.

PAOLA, J.D. and SCHOWENGERDT, R.A., 1995, A review and analysis of back propagation neural networks for classification of remotely sensed multispectral imagery. *International Journal of Remote Sensing*, **16**, pp. 3033–3058.

Paola, J.D. and Schowengerdt, R.A., 1997, The effect of neural-network structure on a multispectral land-use/land-cover classification. *Photogrammetric Engineering and Remote Sensing*, **63**, pp. 535–544.

Peddle, D.R., 1995, Knowledge formulation for supervised evidential classification. *Photogrammetric Engineering and Remote Sensing*, **61**, pp. 409–417.

Peddle, D.R. and Ferguson, D.T., 2002, Optimization of multisource data analysis: an example using evidential reasoning for GIS data classification. *Computers & Geosciences*, **28**, pp. 45–52.

Peddle, D.R., Foody, G.M., Zhang, A., Franklin, S.E. and Ledrew, E.F., 1994, Multisource image classification II: an empirical comparison of evidential reasoning and neural network approaches. *Canadian Journal of Remote Sensing*, **20**, pp. 396–407.

Peddle, D.R., Johnson, R.L., Cihlar, J. and Latifovic, R., 2004, Large area forest classification and biophysical parameter estimation using the 5-Scale canopy reflectance model in Multiple-Forward-Mode. *Remote Sensing of Environment*, **89**, pp. 252–263.

Pedley, M.I. and Curran, P.J., 1991, Per-field classification: an example using SPOT HRV imagery. *International Journal of Remote Sensing*, **12**, pp. 2181–2192.

Penaloza, M.A. and Welch, R.M., 1996, Feature selection for classification of polar regions using a fuzzy expert system. *Remote Sensing of Environment*, **58**, pp. 81–100.

Phinn, S.R., 1998, A framework for selecting appropriate remotely sensed data dimensions for environmental monitoring and management. *International Journal of Remote Sensing*, **19**, pp. 3457–3463.

Phinn, S.R., Menges, C., Hill, G.J.E. and Stanford, M., 2000, Optimizing remotely sensed solutions for monitoring, modeling, and managing coastal environments. *Remote Sensing of Environment*, **73**, pp. 117–132.

Phinn, S., Stanford, M., Scarth, P., Murray, A.T. and Shyy, P.T., 2002, Monitoring the composition of urban environments based on the vegetation-impervious surface-soil (VIS) model by subpixel analysis techniques. *International Journal of Remote Sensing*, **23**, pp. 4131–4153.

Pierce, L.E., Bergen, K.M., Dobson, M.C. and Ulaby, F.T., 1998, Multitemporal land-cover classification using SIR-C/X-SAR imagery. *Remote Sensing of Environment*, **64**, pp. 20–33.

Platt, R.V. and Goetz, A.F.H., 2004, A comparison of AVIRIS and Landsat for land use classification at the urban fringe. *Photogrammetric Engineering and Remote Sensing*, **70**, pp. 813–819.

Podest, E. and Saatchi, S., 2002, Application of multiscale texture in classifying JERS-1 radar data over tropical vegetation. *International Journal of Remote Sensing*, **23**, pp. 1487–1506.

Pohl, C. and van Genderen, J.L., 1998, Multisensor image fusion in remote sensing: concepts, methods, and applications. *International Journal of Remote Sensing*, **19**, pp. 823–854.

Powell, R.L., Matzke, N., de Souza Jr, C., Clark, M., Numata, I., Hess, L.L. and Roberts, D.A., 2004, Sources of error in accuracy assessment of thematic land-cover maps in the Brazilian Amazon. *Remote Sensing of Environment*, **90**, pp. 221–234.

Price, J.C., 2003, Comparing MODIS and ETM+ data for regional and global land classification. *Remote Sensing of Environment*, **86**, pp. 491–499.

Price, K.P., Guo, X. and Stiles, J.M., 2002, Optimal Landsat TM band combinations and vegetation indices for discrimination of six grassland types in eastern Kansas. *International Journal of Remote Sensing*, **23**, pp. 5031–5042.

Qiu, F. and Jensen, J.R., 2004, Opening the black box of neural networks for remote sensing image classification. *International Journal of Remote Sensing*, **25**, pp. 1749–1768.

Quattrochi, D.A. and Goodchild, M.F. (Eds), 1997, *Scale in Remote Sensing and GIS* (New York: Lewis Publishers).

RASHED, T., WEEKS, J.R., GADALLA, M.S. and HILL, A.G., 2001, Revealing the anatomy of cities through spectral mixture analysis of multispectral satellite imagery: a case study of the Greater Cairo region, Egypt. *Geocarto International*, **16**, pp. 5–15.

RASHED, T., WEEKS, J.R., ROBERTS, D., ROGAN, J. and POWELL, R., 2003, Measuring the physical composition of urban morphology using multiple endmember spectral mixture analysis. *Photogrammetric Engineering and Remote Sensing*, **69**, pp. 1011–1020.

RAY, S.S., 2004, Merging of IRS LISS III and PAN data—evaluation of various methods for a predominantly agricultural area. *International Journal of Remote Sensing*, **25**, pp. 2657–2664.

RICHTER, R., 1997, Correction of atmospheric and topographic effects for high spatial resolution satellite imagery. *International Journal of Remote Sensing*, **18**, pp. 1099–1111.

RICOTTA, C., 2004, Evaluating the classification accuracy of fuzzy thematic maps with a simple parametric measure. *International Journal of Remote Sensing*, **25**, pp. 2169–2176.

RICOTTA, C. and AVENA, G.C., 1999, The influence of fuzzy set theory on the areal extent of thematic map classes. *International Journal of Remote Sensing*, **20**, pp. 201–205.

RICOTTA, C. and AVENA, G.C., 2002, Evaluating the degree of fuzziness of thematic maps with a generalized entropy function: a methodological outlook. *International Journal of Remote Sensing*, **23**, pp. 4519–4523.

ROBERTS, D.A., BATISTA, G.T., PEREIRA, J.L.G., WALLER, E.K. and NELSON, B.W., 1998a, Change identification using multitemporal spectral mixture analysis: applications in eastern Amazonia. In R.S. Lunetta and C.D. Elvidge (Eds), *Remote Sensing Change Detection: Environmental Monitoring Methods and Applications*, pp. 137–161 (Chelsea, MI: Ann Arbor Press).

ROBERTS, D.A., GARDNER, M., CHURCH, R., USTIN, S., SCHEER, G. and GREEN, R.O., 1998b, Mapping chaparral in the Santa Monica mountains using multiple endmember spectral mixture models. *Remote Sensing of Environment*, **65**, pp. 267–279.

ROBERTS, D.A., SMITH, M.O. and ADAMS, J.B., 1993, Discriminating green vegetation, non-photosynthetic vegetation, and soils in AVIRIS data. *Remote Sensing of Environment*, **44**, pp. 255–269.

SAN MIGUEL-AYANZ, J. and BIGING, G.S., 1996, An iterative classification approach for mapping natural resources from satellite imagery. *International Journal of Remote Sensing*, **17**, pp. 957–982.

SAN MIGUEL-AYANZ, J. and BIGING, G.S., 1997, Comparison of single-stage and multi-stage classification approaches for cover type mapping with TM and SPOT data. *Remote Sensing of Environment*, **59**, pp. 92–104.

SANTOS, J.R., FREITAS, C.C., ARAUJO, L.S., DUTRA, L.V., MURA, J.C., GAMA, F.F., SOLER, L.S. and SANT' ANNA, S.J.S., 2003, Airborne P-band SAR applied to the aboveground biomass studies in the Brazilian tropical rainforest. *Remote Sensing of Environment*, **87**, pp. 482–493.

SCHMIDT, K.S., SKIDMORE, A.K., KLOOSTERMAN, E.H., VAN OOSTEN, H., KUMAR, L. and JANSSEN, J.A.M., 2004, Mapping coastal vegetation using an expert system and hyperspectral imagery. *Photogrammetric Engineering and Remote Sensing*, **70**, pp. 703–715.

SCHOWENGERDT, R.A., 1996, On the estimation of spatial-spectral mixing with classifier likelihood functions. *Pattern Recognition Letters*, **17**, pp. 1379–1387.

SEGL, K., ROESSNER, S., HEIDEN, U. and KAUFMANN, H., 2003, Fusion of spectral and shape features for identification of urban surface cover types using reflective and thermal hyperspectral data. *ISPRS Journal of Photogrammetry and Remote Sensing*, **58**, pp. 99–112.

SENOO, T., KOBAYASHI, F., TANAKA, S. and SUGIMURA, T., 1990, Improvement of forest type classification by SPOT HRV with 20 m mesh DTM. *International Journal of Remote Sensing*, **11**, pp. 1011–1022.

SETTLE, J. and CAMPBELL, N., 1998, On the errors of two estimators of subpixel fractional cover when mixing is linear. *IEEE Transactions on Geosciences and Remote Sensing*, **36**, pp. 163–169.

SETTLE, J.J. and DRAKE, N.A., 1993, Linear mixing and the estimation of ground cover proportions. *International Journal of Remote Sensing*, **14**, pp. 1159–1177.

SHABAN, M.A. and DIKSHIT, O., 2001, Improvement of classification in urban areas by the use of textural features: the case study of Lucknow city, Uttar Pradesh. *International Journal of Remote Sensing*, **22**, pp. 565–593.

SHABAN, M.A. and DIKSHIT, O., 2002, Evaluation of the merging of SPOT multispectral and panchromatic data for classification of an urban environment. *International Journal of Remote Sensing*, **23**, pp. 249–262.

SHAH, C.A., ARORA, M.K. and VARSHNEY, P.K., 2004, Unsupervised classification of hyperspectral data: an ICA mixture model based approach. *International Journal of Remote Sensing*, **25**, pp. 481–487.

SHALAN, M.A., ARORA, M.K. and GHOSH, S.K., 2003, An evaluation of fuzzy classifications from IRS 1C LISS III imagery: a case study. *International Journal of Remote Sensing*, **24**, pp. 3179–3186.

SHARMA, K.M.S. and SARKAR, A., 1998, A modified contextual classification technique for remote sensing data. *Photogrammetric Engineering and Remote Sensing*, **64**, pp. 273–280.

SHI, W., ZHU, C.Q., ZHU, C. and YANG, X., 2003, Multi-band wavelet for fusing SPOT panchromatic and multispectral images. *Photogrammetric Engineering and Remote Sensing*, **69**, pp. 513–520.

SHIMABUKURO, Y.E., BATISTA, G.T., MELIO, E.M.K., MOREIRA, J.C. and DUARTE, V., 1998, Using shade fraction image segmentation to evaluate deforestation in Landsat Thematic Mapper images of the Amazon region. *International Journal of Remote Sensing*, **19**, pp. 535–541.

SIMONE, G., FARINA, A., MORABITO, F.C., SERPICO, S.B. and BRUZZONE, L., 2002, Image fusion techniques for remote sensing applications. *Information Fusion*, **3**, pp. 3–15.

SMALL, C., 2004, The Landsat ETM+ spectral mixing space. *Remote Sensing of Environment*, **93**, pp. 1–17.

SMITH, G.M. and FULLER, R.M., 2001, An integrated approach to land cover classification: an example in the Island of Jersey. *International Journal of Remote Sensing*, **22**, pp. 3123–3142.

SMITH, M.O., USTIN, S.L., ADAMS, J.B. and GILLESPIE, A.R., 1990, Vegetation in Deserts: I. A regional measure of abundance from multispectral images. *Remote Sensing of Environment*, **31**, pp. 1–26.

SMITS, P.C., DELLEPIANE, S.G. and SCHOWENGERDT, R.A., 1999, Quality assessment of image classification algorithms for land-cover mapping: a review and a proposal for a cost-based approach. *International Journal of Remote Sensing*, **20**, pp. 1461–1486.

SOARES, J.V., RENNO, C.D., FORMAGGIO, A.R., YANASSE, C.C.F. and FRERY, A.C., 1997, An investigation of the selection of texture features for crop discrimination using SAR imagery. *Remote Sensing of Environment*, **59**, pp. 234–247.

SOHN, Y. and REBELLO, N.S., 2002, Supervised and unsupervised spectral angle classifiers. *Photogrammetric Engineering and Remote Sensing*, **68**, pp. 1271–1281.

SOHN, Y., MORAN, E. and GURRI, F., 1999, Deforestation in north-central Yucatan (1985–1995): mapping secondary succession of forest and agricultural land use in Sotuta using the cosine of the angle concept. *Photogrammetric Engineering and Remote Sensing*, **65**, pp. 947–958.

SOLAIMAN, B., PIERCE, L.E. and ULABY, F.T., 1999, Multisensor data fusion using fuzzy concepts: application to land-cover classification using ERS-1/JERS-1 SAR composites. *IEEE Transactions on Geoscience and Remote Sensing*, **37**, pp. 1316–1326.

SOLBERG, A.H.S., TAXT, T. and JAIN, A.K., 1996, A Markov random field model for classification of multisource satellite imagery. *IEEE Transactions on Geoscience and Remote Sensing*, **34**, pp. 100–112.

SONG, C., WOODCOCK, C.E., SETO, K.C., LENNEY, M.P. and MACOMBER, S.A., 2001, Classification and change detection using Landsat TM data: when and how to correct atmospheric effect. *Remote Sensing of Environment*, **75**, pp. 230–244.

SOUTH, S., QI, J. and LUSCH, D.P., 2004, Optimal classification methods for mapping agricultural tillage practices. *Remote Sensing of Environment*, **91**, pp. 90–97.

SRINIVASAN, A. and RICHARDS, J.A., 1990, Knowledge-based techniques for multisource classification. *International Journal of Remote Sensing*, **11**, pp. 505–525.

STALLINGS, C., KHORRAM, S. and HUFFMAN, R.L., 1999, Incorporating ancillary data into a logical filter for classified satellite imagery. *Geocarto International*, **14**, pp. 42–51.

STEELE, B.M., 2000, Combining multiple classifiers: an application using spatial and remotely sensed information for land cover type mapping. *Remote Sensing of Environment*, **74**, pp. 545–556.

STEFAN, S. and ITTEN, K.I., 1997, A physically-based model to correct atmospheric and illumination effects in optical satellite data of rugged terrain. *IEEE Transactions on Geoscience and Remote Sensing*, **35**, pp. 708–717.

STEFANOV, W.L., RAMSEY, M.S. and CHRISTENSEN, P.R., 2001, Monitoring urban land cover change: an expert system approach to land cover classification of semiarid to arid urban centers. *Remote Sensing of Environment*, **77**, pp. 173–185.

STEHMAN, S.V., 1996, Estimating the Kappa coefficient and its variance under stratified random sampling. *Photogrammetric Engineering and Remote Sensing*, **62**, pp. 401–407.

STEHMAN, S.V., 1997, Selecting and interpreting measures of thematic classification accuracy. *Remote Sensing of Environment*, **62**, pp. 77–89.

STEHMAN, S.V., 2004, A critical evaluation of the normalized error matrix in map accuracy assessment. *Photogrammetric Engineering and Remote Sensing*, **70**, pp. 743–751.

STEHMAN, S.V. and CZAPLEWSKI, R.L., 1998, Design and analysis for thematic map accuracy assessment: fundamental principles. *Remote Sensing of Environment*, **64**, pp. 331–344.

STEININGER, M.K., 2000, Satellite estimation of tropical secondary forest aboveground biomass data from Brazil and Bolivia. *International Journal of Remote Sensing*, **21**, pp. 1139–1157.

STRAHLER, A., WOODCOCK, C. and SMITH, J., 1986, On the nature of models in remote sensing. *Remote Sensing of Environment*, **20**, pp. 121–139.

STUCKENS, J., COPPIN, P.R. and BAUER, M.E., 2000, Integrating contextual information with per-pixel classification for improved land cover classification. *Remote Sensing of Environment*, **71**, pp. 282–296.

SUGUMARAN, R., ZERR, D. and PRATO, T., 2002, Improved urban land cover mapping using multitemporal IKONOS images for local government planning. *Canadian Journal of Remote Sensing*, **28**, pp. 90–95.

TANSEY, K.J., LUCKMAN, A.J., SKINNER, L., BALZTER, H., STROZZI, T. and WAGNER, W., 2004, Classification of forest volume resources using ERS tandem coherence and JERS backscatter data. *International Journal of Remote Sensing*, **25**, pp. 751–768.

TEGGI, S., CECCHI, R. and SERAFINI, F., 2003, TM and IRS-1C-PAN data fusion using multiresolution decomposition methods based on the 'à trous' algorithm. *International Journal of Remote Sensing*, **24**, pp. 1287–1301.

TEILLET, P.M., GUINDON, B. and GOODENOUGH, D.G., 1982, On the slope-aspect correction of multispectral scanner data. *Canadian Journal of Remote Sensing*, **8**, pp. 84–106.

THENKABAIL, P.S., ENCLONA, E.A., ASHTON, M.S. and VAN DER MEER, B., 2004a, Accuracy assessments of hyperspectral waveband performance for vegetation analysis applications. *Remote Sensing of Environment*, **91**, pp. 354–376.

THENKABAIL, P.S., ENCLONA, E.A., ASHTON, M.S., LEGG, C. and DE DIEU, M.J., 2004b, Hyperion, IKONOS, ALI, and ETM+ sensors in the study of African rainforests. *Remote Sensing of Environment*, **90**, pp. 23–43.

THESEIRA, M.A., THOMAS, G., TAYLOR, J.C., GEMMELL, F. and VARJO, J., 2003, Sensitivity of mixture modeling to endmember selection. *International Journal of Remote Sensing*, **24**, pp. 1559–1575.

THOMAS, N., HENDRIX, C. and CONGALTON, R.G., 2003, A comparison of urban mapping methods using high-resolution digital imagery. *Photogrammetric Engineering and Remote Sensing*, **69**, pp. 963–972.

TOKOLA, T., LÖFMAN, S. and ERKKILÄ, A., 1999, Relative calibration of multitemporal Landsat data for forest cover change detection. *Remote Sensing of Environment*, **68**, pp. 1–11.

TOKOLA, T., SARKEALA, J. and VAN DER LINDEN, M., 2001, Use of topographic correction in Landsat TM-based forest interpretation in Nepal. *International Journal of Remote Sensing*, **22**, pp. 551–563.

TOMPKINS, S., MUSTARD, J.F., PIETERS, C.M. and FORSYTH, D.W., 1997, Optimization of endmembers for spectral mixture analysis. *Remote Sensing of Environment*, **59**, pp. 472–489.

TOTTRUP, C., 2004, Improving tropical forest mapping using multi-date Landsat TM data and pre-classification image smoothing. *International Journal of Remote Sensing*, **25**, pp. 717–730.

TOUTIN, T., 2004, Geometric processing of remote sensing images: models, algorithms and methods. *International Journal of Remote Sensing*, **25**, pp. 1893–1924.

TROTTER, C.M., 1991, Remotely sensed data as an information source for geographical information systems in natural resource management: a review. *International Journal of Geographical Information Systems*, **5**, pp. 225–239.

TSO, B.C.K. and MATHER, P.M., 1999, Classification of multisource remote sensing imagery using a genetic algorithm and Markov random fields. *IEEE Transactions on Geoscience and Remote Sensing*, **37**, pp. 1255–1260.

TSO, B. and MATHER, P.M., 2001, *Classification Methods for Remotely Sensed Data* (New York: Taylor and Francis Inc).

ULFARSSON, M.O., BENEDIKTSSON, J.A. and SVEINSSON, J.R., 2003, Data fusion and feature extraction in the wavelet domain. *International Journal of Remote Sensing*, **24**, pp. 3933–3945.

UNSER, M., 1995, Texture classification and segmentation using wavelet frames. *IEEE Transactions on Image Processing*, **4**, pp. 1549–1560.

VAN DER MEER, F., 1999, Iterative spectral unmixing (ISU). *International Journal of Remote Sensing*, **20**, pp. 3431–3436.

VAN DER SANDE, C.J., DE JONG, S.M. and DE ROO, A.P.J., 2003, A segmentation and classification approach of IKONOS-2 imagery for land cover mapping to assist flood risk and flood damage assessment. *International Journal of Applied Earth Observation and Geoinformation*, **4**, pp. 217–229.

VAN DER WEL, F., VAN DER GAAG, L. and GORTE, B., 1997, Visual exploration of uncertainty in remote sensing classification. *Computers & Geosciences*, **24**, pp. 335–343.

VERBEKE, L.P.C., VABCOILLIE, F.M.B. and DE WULF, R.R., 2004, Reusing back-propagating artificial neural network for land cover classification in tropical savannahs. *International Journal of Remote Sensing*, **25**, pp. 2747–2771.

VERMOTE, E., TANRE, D., DEUZE, J.L., HERMAN, M. and MORCRETTE, J.J., 1997, Second simulation of the satellite signal in the solar spectrum, 6S: an overview. *IEEE Transactions on Geoscience and Remote Sensing*, **35**, pp. 675–686.

WALTER, V., 2004, Object-based classification of remote sensing data for change detection. *ISPRS Journal of Photogrammetry & Remote Sensing*, **58**, pp. 225–238.

WANG, L., SOUSA, W.P., GONG, P. and BIGING, G.S., 2004, Comparison of IKONOS and QuickBird images for mapping mangrove species on the Caribbean coast of panama. *Remote Sensing of Environment*, **91**, pp. 432–440.

WANG, M. and HOWARTH, P.J., 1994, Multisource spatial data integration: problems and some solutions. *Canadian Journal of Remote Sensing*, **20**, pp. 360–367.

WANG, Y. and CIVCO, D.L., 1994, Evidential reasoning-based classification of multi-source spatial data for improved land cover mapping. *Canadian Journal of Remote Sensing*, **20**, pp. 380–395.

WARRENDER, C.E. and AUGUSTEIHN, M.F., 1999, Fusion of image classification using Bayesian techniques with Markov random fields. *International Journal of Remote Sensing*, **20**, pp. 1987–2002.

WELCH, R. and EHLERS, M., 1987, Merging multi-resolution SPOT HRV and Landsat TM data. *Photogrammetric Engineering and Remote Sensing*, **53**, pp. 301–303.

WILKINSON, G.G., 1996, A review of current issues in the integration of GIS and remote sensing data. *International Journal of Geographical Information Systems*, **10**, pp. 85–101.

WILLIAMS, J., 2001, *GIS Processing of Geocoded Satellite Data* (Chichester: Springer and Praxis Publishing).

WOLTER, P.T., MLADENOFF, D.J., HOST, G.E. and CROW, T.R., 1995, Improved forest classification in the northern lake states using multi-temporal Landsat imagery. *Photogrammetric Engineering and Remote Sensing*, **61**, pp. 1129–1143.

WOODCOCK, C.E. and GOPAL, S., 2000, Fuzzy set theory and thematic maps: accuracy assessment and area estimation. *International Journal of Geographic Information Science*, **14**, pp. 153–172.

WOODCOCK, C.E. and STRAHLER, A., 1987, The factor of scale in remote sensing. *Remote Sensing of Environment*, **21**, pp. 311–332.

WU, D. and LINDERS, J., 2000, Comparison of three different methods to select features for discriminating forest cover types using SAR imagery. *International Journal of Remote Sensing*, **21**, pp. 2089–2099.

XU, B., GONG, P., SETO, E. and SPEAR, R., 2003, Comparison of gray-level reduction and different texture spectrum encoding methods for land-use classification using a panchromatic IKONOS image. *Photogrammetric Engineering and Remote Sensing*, **69**, pp. 529–536.

YOCKY, D.A., 1996, Multiresolution wavelet decomposition image merger of Landsat Thematic Mapper and SPOT panchromatic data. *Photogrammetric Engineering and Remote Sensing*, **62**, pp. 1067–1074.

ZHA, Y., GAO, J. and NI, S., 2003, Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. *International Journal of Remote Sensing*, **24**, pp. 583–594.

ZHANG, C., FRANKLIN, S.E. and WULDER, M.A., 2004, Geostatistical and texture analysis of airborne-acquired images used in forest classification. *International Journal of Remote Sensing*, **25**, pp. 859–865.

ZHANG, J. and FOODY, G.M., 2001, Fully-fuzzy supervised classification of sub-urban land cover from remotely sensed imagery: statistical neural network approaches. *International Journal of Remote Sensing*, **22**, pp. 615–628.

ZHANG, J. and KIRBY, R.P., 1999, Alternative criteria for defining fuzzy boundaries based on fuzzy classification of aerial photographs and satellite images. *Photogrammetric Engineering and Remote Sensing*, **65**, pp. 1379–1387.

ZHANG, Q. and WANG, J., 2003, A rule-based urban land use inferring method for fine-resolution multispectral imagery. *Canadian Journal of Remote Sensing*, **29**, pp. 1–13.

ZHANG, Q., WANG, J., PENG, X., GONG, P. and SHI, P., 2002, Urban built-up land change detection with road density and spectral information from multitemporal Landsat TM data. *International Journal of Remote Sensing*, **23**, pp. 3057–3078.

ZHANG, Y., 1999, Optimisation of building detection in satellite images by combining multispectral classification and texture filtering. *ISPRS Journal of Photogrammetry and Remote Sensing*, **54**, pp. 50–60.

ZHU, G. and BLUMBERG, D.G., 2002, Classification using ASTER data and SVM algorithms: the case study of Beer Sheva, Israel. *Remote Sensing of Environment*, **80**, pp. 233–240.

ZHUANG, X., ENGEL, B.A., XIONG, X. and JOHANNSEN, C.J., 1995, Analysis of classification results of remotely sensed data and evaluation of classification algorithms. *Photogrammetric Engineering and Remote Sensing*, **61**, pp. 427–433.