Global Journal of Researches in Engineering: F
Electrical and Electronics Engineering
Volume 15 Issue 6 Version 1.0 Year 2015
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals Inc. (USA)
Online ISSN: 2249-4596 & Print ISSN: 0975-5861

Techniques in Image Classification; A Survey

By Mr. S.V.S.Prasad , Dr. T. Satya Savithri & Dr. Iyyanki V. Murali Krishna

MLRIT, India

Abstract- This paper reviews on the current trends, problems and prospects of image classification including the factors affecting it. By the end of the session we will be summarizing the popular advanced classification approaches and methods that are used to improve classification accuracy. The main motive of this review is to suggest a suitable image processing procedure in order to have a successful classification of remotely sensed data into a thematic map.

Keywords: image classification, remote sensed data (rs), training samples (ts), isodata.

GJRE-F Classification : FOR Code: 280203

TECHNIQUESINIMAGECLASSIFICATIONASURVEY

Strictly as per the compliance and regulations of :

Techniques in Image Classification; A Survey

Mr. S.V.S.Prasad [α], Dr. T. Satya Savithri [σ] & Dr. Iyyanki V. Murali Krishna [ρ]

Abstract- This paper reviews on the current trends, problems and prospects of image classification including the factors affecting it. By the end of the session we will be summarizing the popular advanced classification approaches and methods that are used to improve classification accuracy. The main motive of this review is to suggest a suitable image processing procedure in order to have a successful classification of remotely sensed data into a thematic map.

Keywords: image classification, remote sensed data (rs), training samples (ts), isodata.

I. Introduction

The image classification plays an important role in environmental and socioeconomic applications. In order to improve the classification accuracy, scientists have laid path in developing the advanced classification techniques. [1-9] However, classifying a remotely sensed data into a thematic map is still a nightmare because of the following factors such as landscape complexity, image sensing and processing and classification approaches. The review concentrates on recent classification approaches and techniques which are often not available.

a) Remote sensing classification process

RS classification is generally a complex procedure which needs many factors to be considered. This procedure includes following steps that begins with the identification of suitable classification system, choosing appropriate training samples, processing of an image and extracting its features, applying a right and indeed classification method, post classification and accuracy assessments.

b) Selection of remotely sensed data

Airborne and space borne sensor data comes under RS data stream, which varies in spatial, radiometric, spectral and temporal resolutions. In order to have better image classification a suitable RS data needs to be collected, which depends upon strength and weakness of sensor data. In literature the characteristics of remotely sensed data is summarized by [10], [11] in spectral, radio metric, spatial and temporal resolutions with polarization and angularity. It is preferred to consider the factors while selecting suitable sensor data as per the user's need, which includes scaling, study area characteristics, availability of various image data and their characteristics, cost, time constraints and analyst's experience in using selected images. Scaling determines the study area; earlier research encountered a problem of image resolution of remotely sensed data in classification. In regular practice, a fine-scale classification system is adopted in order to achieve high spatial resolution data. For example, IKONS and SPOT 5 HRG are at regional level medium spatial resolution data. However, the influence of atmospheric conditions in moist and tropical regions cannot be neglected and they are often an obstacle for capturing the high quality sensor data. Therefore, it always proves to be beneficiary to have multiple sources of sensor data.

c) Selection of classification system and training samples

A better classification can be achieved only when we consider a suitable classification system with sufficient number of training samples. Generally, in a wide variety of applications we adopt hierarchy classification systems because different conditions are taken into account. A classification system should consider spatial resolution of selected RS data, compatibility with its previous work, image processing and classification algorithm availability and time constraints. The ultimate goal of choosing any classification system is to satisfy the need of an end user.

The image classification broadly depends on number of training samples and their representativeness. Training samples can be prepared by fieldwork or it can also be obtained from other means such as aerial photographs of fine spatial resolution and satellite images. The results of the classification are affected by the selection of training data, which generally may be based on single pixel, seed or polygon, also affected by fine spatial resolution image data if proper care is not taken. If coarse resolution data is used for classification data then the selection of TS becomes tedious under complex and heterogeneous case studies as it contains large volumes of mixed pixels.

d) Data Preprocessing

The image preprocessing is a technique which includes detection, restoration of bad lines, geometric rectification, radio metric calibration, atmospheric and

Author α: Assoc. Professor Dept. of ECE, MLRIT, Hyderabad.
e-mail: prasad.sista@gmail.com
Author σ: Professor, Dept. of ECE, JNTU, Hyderabad.
e-mail: tirumalasatya@gmail.com
Author ρ: Retd. Professor, CSIT and Director (R&D), JNTU, Hyderabad.
e-mail: ivm@ieee.org

topographic correction. If data is collected from different sources, it is necessary to check the quality before stepping into classification. If the single data image is utilized in classification atmospheric corrections may not be required but on the other hand it becomes mandatory for a multi-sensor data. A variety of correction techniques are presented [12-23].If the study area includes rugged or mountainous regions a topographic correction is needed, which is detailed [24-30].

e) Feature Extraction and Selection

The quality of an image classification depends on the selection of suitable variables. A variety of variables used in classification includes spectrum signature, vegetation indices, transformed images, textual information, multi temporal images, multi sensor images and ancillary data. The process of feature extraction is needed in order to minimize data redundancy in remotely sensed data or to excavate specific land cover information, that includes principle component analysis, minimum noise fraction transform discriminant analysis, decision boundary, feature extraction, non parametric weighted feature extraction, wavelet transform and spectral mixture analysis.

f) Selection of suitable classification method

The question of choosing a classification method is ambiguous because many factors such as spatial resolution of RD, multi-sensor data, availability of different classification software are involved. Each classification method has its own merits and demerits.

g) Post classification processing

Classification confusions arise in the regions such as urban areas, for example, consider between commercial and high intensity residential areas or between recreational grass and crops. In present example to reduce classification confusions we need to consider the property of spectral signature because it is similar to commercial and high intensity residential areas but on the other hand their population densities are different. Pasture and crops are largely located away from residential areas with sparse houses and low population densities, at this stage expert knowledge can be developed based on the relationship between housing or population densities and urban land use classes to help separate recreational grass from pasture and crops.

II. Evaluation of Classification Performance

Evaluating the classified results is an important step in classification procedure. The evaluation process may include qualitative evaluation based on expert knowledge to quantitative accuracy based on sampling strategies. The classification accuracy assessment is the most common approach for the evaluation of classification performance [31-32].

a) Classification of accuracy assessment

By the knowledge of sources of errors, classification accuracy assessment can be implemented in addition to classification error, position error, which resulting from registration, interpolating error and poor quality of training which may affect the classification accuracy. The classification accuracy assessment includes three basic steps 1.Sampling design, 2.Response design,3. Estimation and Analysis procedures

b) Advanced classification procedures

The advanced classification procedures such as neural networks, fuzzy sets and expert systems are highly applied for image classification. In general image classification approaches it can be grouped as supervised or unsupervised, parametric and nonparametric or hard and soft classifiers or per pixel, sub pixel, per field. Table provides brief description of these categories.

c) Use of multiple features of remote sensed data

Any remote sensed data generally contains many unique and special spectral radio metric temporal and polarization characteristics; the effective use of these features can improve the classification accuracy. The summary of table 3 presents the research efforts in order to improve the classification accuracy by considering the features of remote sensed data.

III. Discussions

a) Uncertainties in image classification

Uncertainties in image classification occur at different stages, influence classification accuracy. Improving and understanding the stages those contribute to uncertainty results in quality image classification.

b) Impact of spatial resolution

Spatial resolution is an important factor that affects classification details and accuracy, which influences the selection of a classification approach. Various reduction techniques have been developed and presented by different authors in their literature.

c) Selection of suitable variables

In practice, making a complete use of multiple features of different sensor data, implementing feature extraction and selecting variables as input for a classification procedure becomes important.

IV. Conclusion

This study helps upcoming scientists and researchers for opting a suitable classification procedure in their specific study. In our presentation we have concentrated extensively on the work done from the past decade that includes 1. Development and advanced classification algorithms such as sub pixel, per field and acknowledged based classification algorithms; 2. We have considered various remote sensing features including spectral, spatial, multi temporal and multi sensor information; 3. Incorporating an ancillary data into classification procedures that includes topography, soil, road and census data.

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 is 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 labeling 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.
	Sub pixel classifiers	The spectral value of each pixel is assumed to be a linear or non-linear combination of defined pure materials (or end members), providing proportional membership of each pixel to each end member.	Fuzzy-set classifiers, sub pixel classifier, spectral mixture analysis.
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.	E Cognition
	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	Hard	Making a definitive decision about the land	Most of the classifiers,

Global Journal of Researches in Engineering (F) Volume XV Issue VI Version I Year 2015

output is a definitive decision about land cover class or not	classification	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.	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, sub pixel 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 neighboring pixel information is used in image classification.	Iterated conditional modes, point-to-point contextual correction, and 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 parametric or non-parametric and contextual algorithms

Table 2 : A summary of classification methods

Category	Advanced classifiers	References
Per-pixel algorithms	Neural network	[33], [34], [35],[36], [37], [38], [39], [40], [41], [42], [43]
	Decision tree classifier, Spectral angle classifier, Supervised iterative classification (multistage classification)	[44], [45], [46],[47], [32],[8],[48],[49],[50], [51],[4]
	Enhancement-classification approach,MFM-5-Scale (Multiple-Forward-Mode approach to running the 5-Scale geometric-optical reflectance model)	[52],[53]
	Iterative partially supervised classification based on a combined use of a Radial Basis Function network and a Markov Random Field approach	[54]
	Classification by progressive generalization Support vector machine	[31],[55], [56], [57], [58],[59],[60], [61], [62], [63]
	Unsupervised classification based on independent component analysis mixture model, Optimal iterative unsupervised	[64],[65], [66]
	Model-based unsupervised classification, Linear constrained discriminant analysis	[67], [68] ,[69], [70]
	Multispectral classification based on probability density functions, Layered classification, Nearest-neighbor classification, Selected pixel classification	[71],[72],[73][74],[75],[76], [77]
Sub pixel algorithms	Imagine sub pixel classifier, Fuzzy classifier, Fuzzy expert system	[78], [3],[79],[80],[81], [82]
	Fuzzy neural network, Fuzzy-based multi sensor data fusion classifier, Rule-based machine-version approach	[3], [83],[84], [80], [85], [86], [87]
	Linear regression or linear least squares inversion	[88],[89]

Per-field algorithms	Per-field or per-parcel classification	[90],[5],[91]
	Per-field classification based on per-pixel or sub pixel classified image	[92]
	Parcel-based approach with two stages: per-parcel classification using conventional statistical classifier and then knowledge-based correction using contextual information	[93]
	Map-guided classification, Object-oriented classification, Graph-based, structural pattern recognition system, Spectral shape classifier	[94], [95],[96],[97], [98],[99],[100], [101], [102], [103]
Contextual-based approaches	ECHO (Extraction and Classification of Homogeneous Objects)	[104],[105], [106]
	Supervised relaxation classifier, Frequency-based contextual classifier	[107], [108], [109]
	Contextual classification approaches for high and low resolution data, respectively and a combination of both approaches	[110],[111]
	Contextual classifier based on region-growth algorithm, Fuzzy contextual classification, Iterated conditional modes	[112], [113]
	Fuzzy contextual classification, Iterated conditional modes, Sequential maximum a posteriori classification	[113], [59],[114], [115]
	Point-to-point contextual correction, Hierarchical maximum a posteriori classifier, Variogram texture classification	[116], [117], [118]
	Hybrid approach incorporating contextual information with per-pixel classification	[6]
	Two stage segmentation procedure	[119]
Knowledge-based algorithms	Evidential reasoning classification, Knowledge-based classification,Rule-based syntactical approach	[120],[121],[122], [123],[7],[124],[125] [107],[126], [97], [127],[128]
	Visual fuzzy classification based on use of exploratory and interactive visualization techniques	[129]
	Multi temporal classification based on decision fusion	[130]
	Supervised classification with ongoing learning capability based on nearest neighbor rule	[131]
Combinative approaches of multiple classifiers	Multiple classifier system (BAGFS: combines bootstrap aggregating with multiple feature subsets)	[132]
	A consensus builder to adjust classification output (MLC, expert system, and neural network)	[133]
	Integrated expert system and neural network classifier	[133]
	Improved neuro-fuzzy image classification system, Spectral and contextual classifiers, Mixed contextual and per-pixel classification, Combination of iterated contextual probability classifier and MLC	[134],[116],[135],[136]
	Combination of neural network and statistical consensus theoretic classifiers	[137]
	Combination of MLC and neural network using Bayesian techniques	[138]
	Combining multiple classifiers based on product rule, staked Regression, Combined spectral classifiers and GIS rule-based classification, Combination of MLC and decision tree classifier, Combination of non-parametric classifiers (neural network, decision tree classifier, and evidential reasoning),Combined supervised and unsupervised classification	[139],[140],[141][142],[97],[143]

Table 3 : Approaches for improving classification accuracy using multiple features of RS data

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	[144]
	Grey-level co-occurrence matrices(GLCM)	[145],[146],[147],[148], [149]
	Co-occurrence matrices, grey-level difference, texture-tone analysis ,features derived from Fourier spectrum, and Gabor filters	[150]
	GLCM, grey level difference histogram, sum and different histogram	[151], [152]
	Fractal information	[153],[154]
	Triangulated primitive neighborhood method, Semi variogram, Geo statistical analysis, Gabor filtering	[155], [156], [157], [158], [159]
Fusion of Multi sensor or multi resolution data	AIRSAR and TOPSAR, SPOT MS and PAN data, TM and aerial photographs, TM and radar, TM and IRS-1C-PAN data, TM and SPOT PAN data, SPOT and radar	[160], [161], [162], [163], [164], [165], [166], [167], [168]
	Hyper spectral and radar, IRS LISS III and PAN	[169], [170]
Use of multi temporaldata	Using multi temporal optical Images, Using multi temporal SAR images, Using multi temporal optical and SAR images	[171], [172], [173],[174],[175], [176], [177], [178], [179]
Image transforms	Fuzzy partition method, Stepwise regression analysis	[180], [180]
	Principal component analysis, Tasseled cap	[180] [173]
	Rotational transformation, Wavelet transform	[181] [182]
	Spectral mixture analysis, Gaussian mixture discriminant Analysis, Normalized difference built-up Index	[183], [184],[185], [186], [187], [188],[189], [190], [191]
Fine spatial resolution data	IKONOS or Quick Bird, ADAR digital multispectral image, Aerial photography and lidar data, Color infrared aerial images	[192], [193], [95], [194], [195], [109], [196],[197], [97], [198], [199]
Hyper –spectral data	AVIRIS	[200], [201], [202], [203], [204], [205]
	HyMap hyper spectral digital data, DAIS hyper spectral data, EO-1 Hyperion, Data obtained from Field Spec Pro FR spectro radiometer	[127] [206] [207], [208]

Table 4 : Techniques to improve classification accuracy for ancillary data; A summary

Method	Features	References
Use of ancillary data	DEM Topography, land use, and soil Maps	[209] [210]
	Road density, Road coverage, Census data	[211] [212] [213], [214] [173]
Stratification	Based on topography, Based on census data, Based on illumination and ecological zone, Based on shape index of the Patches	[215], [210], [216], [217]
Post classification processing	Kernel-based spatial reclassification	[218]
	Using zoning and housing density data to modify the initial classification result, Using contextual correction,	[213], [219]
	Using filtering based on co occurrence Matrix, Using polygon and rectangular mode filters, Using expert system to perform post classification sorting, Using knowledge-based system to correct misclassification	[220], [221], [222], [223]
Use of multisource data	Spectral, texture, and ancillary data (such as DEM, soil, existing GIS-based maps)	[123], [224],[225],[137],[226], [227],[7],[228]

References Références Referencias

1. 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.
2. 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.

3. 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.
4. 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.
5. 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).
6. 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.
7. 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.
8. 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.
9. GALLEGO, F.J., 2004, Remote sensing and land cover area estimation. International Journal of Remote Sensing, 25, pp. 3019–3047.
10. 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 (NewYork: John Wiley and Sons).
11. 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).
12. MARKHAM, B.L. and BARKER, J.L.,1987, Thematic Mapper bandpass solar exoatmospheric irradiances. International Journal of Remote Sensing, 8, pp. 517–523.
13. 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 N of Remote Sensing, 15, pp. 2065–2086.
14. CHAVEZ, P.S. JR, 1996, Image-based atmospheric corrections—revisited and improved. Photogrammetric Engineering and Remote Sensing, 62, pp. 1025–1036.
15. 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.
16. 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.\
17. TOKOLA, T., LO¨ FMAN, S. and ERKKILA¨, A., 1999, Relative calibration of multitemporal Landsat data for forest cover change detection. Remote Sensing of Environment, 68, pp. 1–11.
18. 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.
19. 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.
20. 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.
21. 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.
22. 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.
23. 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.
24. 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.
25. CIVCO, D.L., 1989, Topographicssa normalization of Landsat Thematic Mapper digital imagery. Photogrammetric Engineering and Remote Sensing, 55, pp. 1303–1309.
26. COLBY, J.D., 1991, Topographic normalization in rugged terrain. Photogrammetric Engineering and Remote Sensing, 57, pp. 531–537.

27. 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.
28. RICHTER, R., 1997, Correction of atmospheric and topographic effects for high spatial resolution satellite imagery. International Journal of Remote Sensing, 18, pp. 1099–1111.
29. 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.
30. 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.
31. 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.
32. 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.
33. 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.
34. 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.
35. ATKINSON, P.M. and TATNALL, A.R.L., 1997, Neural networks in remote sensing. International Journal of Remote Sensing, 18, pp. 699–709.
36. 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.
37. PAOLA, J.D. and SCHOWENGERDT, R.A., 1997, The effect of neural-network structure on amultispectral land-use/land-cover classification. Photogrammetric Engineering and Remote Sensing, 63, pp. 535–544.
38. FOODY, G.M., 2002a, Hard and soft classifications by a neural network with a nonexhaustively defined set of classes. International Journal of Remote Sensing, 23, pp.3853–3864.
39. 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.
40. 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. 091–3104.
41. 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.
42. 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.
43. 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.
44. 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.
45. 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.
46. 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.
47. 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.
48. 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.
49. 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.
50. SOHN, Y. and REBELLO, N.S., 2002, Supervised and unsupervised spectral angle classifiers. Photogrammetric Engineering and Remote Sensing, 68, pp. 1271–1281.

51. 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.
52. 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.
53. 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.
54. FERNA´ NDEZ-PRIETO, D., 2002, An iterative approach to partially supervised classification problems. International Journal of Remote Sensing, 23, pp. 3887–3892.
55. 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.
56. 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.
57. 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.
58. 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.
59. 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.
60. KIM, H., PANG, S., JE, H., KIM, D. and BANG, S.Y., 2003, Constructing support vector machine ensemble. Pattern Recognition, 36, pp. 2757–2767.
61. 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.
62. 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.
63. 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.
64. 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.
65. 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.
66. 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.
67. 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.
68. 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.
69. DU, Q. and CHANG, C., 2001, A linear constrained distance-based discriminant analysis for hyperspectral image classification. Pattern Recognition, 34, pp. 361–373.
70. 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.
71. 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.
72. 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.
73. JENSEN, J.R., 1996, Introduction to Digital Image Processing: A remote sensing perspective, 2nd edn (Piscataway, NJ: Prentice Hall).
74. 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.
75. 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.
76. 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.
77. 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.
78. 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.
79. 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.
80. 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.
81. 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.
82. 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.
83. 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).
84. KULKARNI, A.D. and LULLA, K., 1999, Fuzzy neural network models for supervised classification: multispectral image analysis. Geocarto International, 14, pp. 42–50.
85. 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.
86. 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.
87. 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.
88. 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.
89. 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.
90. 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.
91. 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.
92. 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.
93. 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.
94. 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.
95. 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.
96. 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.
97. 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.
98. 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.
99. BENZ, U.C., HOFMANN, P., ILLHAUCK, 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.

100. 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.
101. WALTER, V., 2004, Object-based classification of remote sensing data for change detection. ISPRS Journal of Photogrammetry & Remote Sensing, 58, pp. 225–238.
102. BARNSLEY,MJ,andBARR,SL,1997recognitionsyste m.Computers, Distinguishing Urban Land Use Categories Environments and Urban Systems, 21, pp. 209–225.
103. CARLOTTO, M.J., 1998, Spectral shape classification of Lands at Thematic Mapper imagery. Photogrammetric Engineering and Remote Sensing, 64, pp. 905–913.
104. BIEHL, L. and LANDGREBE, D., 2002, MultiSpec—a tool for multispectral-hyperspectral image data analysis. Computers and Geosciences, 28, pp. 1153–1159.
105. LANDGREBE, D.A., 2003, Signal Theory Methods in Multispectral Remote Sensing (Hoboken,NJ: John Wiley and Sons).
106. 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.
107. 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.
108. GONG, P. and HOWARTH, P.J., 1992, Frequency-based contextual classification and gray-levelvector reduction for land-use identification. Photogrammetric Engineering and Remote Sensing, 58, pp. 423–437.
109. 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.
110. 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.
111. 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.
112. LIRA, J. and MALETTI, G., 2002, A supervised contextual classifier based on a region-growth algorithm. Computers and Geosciences, 28, pp. 951–959.
113. 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.
114. MAGNUSSEN, S., BOUDEWYN, P. and WULDER, M., 2004, Contextual classification of LandsatTM images to forest inventory cover types. International Journal of Remote Sensing,25, pp. 2421–2440.
115. 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.
116. CORTIJO, F.J. and DE LA BLANCA, N.P., 1998, Improving classical contextual classification. International Journal of Remote Sensing, 19, pp. 1591–1613.
117. 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.
118. 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).
119. 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.
120. 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.
121. 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.
122. PEDDLE, D.R., 1995, Knowledge formulation for supervised evidential classification. Photogrammetric Engineering and Remote Sensing, 61, pp. 409–417.
123. 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.

124. 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.
125. LEIN, J.K., 2003, Applying evidential reasoning methods to agricultural land cover classification. International Journal of Remote Sensing, 24, pp. 4161–4180.
126. 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.
127. 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.
128. ONSI, H.M., 2003, Designing a rule- based classifier using syntactical approach. International Journal of Remote Sensing, 24, pp. 637–647.
129. 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.
130. JEON, B. and LANDGREBE, D.A., 1999, Decision fusion approaches for multitemporal classification. IEEE Transactions on Geoscience and Remote Sensing, 37, pp. 1227–1233.
131. 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.
132. 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.
133. 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.
134. 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.
135. 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.
136. TANSEY, K.J., LUCKMAN, A.J., SKINNER, L., BALTZTER, 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.
137. 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.
138. 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.
139. 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.
140. 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 rulebased land-cover classification in the Neuse river basin of North Carolina.Photogrammetric Engineering and Remote Sensing, 69, pp. 299–310.
141. 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.
142. 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.
143. 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.
144. 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.
145. 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.
146. 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.
147. 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.
148. 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.
149. BUTUSOV, O.B., 2003, Textural classification of forest types from Land sat 7 imagery. Mapping Sciences and Remote Sensing, 40, pp. 91–104.
150. 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 Geo science and Remote Sensing, 33, pp. 616–625.
151. 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 SARimagery. Remote Sensing of Environment, 59, pp. 234–247.
152. 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.
153. 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.
154. 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.
155. 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.
156. 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.
157. LLOYD, C.D., BERBEROGLU, S., CURRAN, P.J. and ATKINSON, P.M., 2004, A comparison oftexture measures for the per-field classification of Mediterranean land cover. International Journal of Remote Sensing, 25, pp. 3943–3965.
158. 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.
159. ANGELO, N.P. and HAERTEL, V., 2003, On the application of Gabor filtering in supervisedimage classification. International Journal of Remote Sensing, 24, pp. 2167–2189.
160. 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.
161. 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.
162. 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.
163. 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.
164. 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.
165. HAACK, B.N., SOLOMON, E.K., BECHDOL, M.A. and HEROLD, N.D., 2002, Radar and optical data omparison/integration for urban delineation: a case study. Photogrammetric Engineering and Remote Sensing, 68, pp. 1289–1296.
166. TEGGI, S., CECCHI, R. and SERAFINI, F., 2003, TM and IRS- 1C-PAN data fusion using multiresolution decomposition methods based on the ‘a` trous’ algorithm. International Journal of Remote Sensing, 24, pp. 1287–1301.
167. 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.
168. 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.
169. 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.
170. 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.
171. 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.

172. LUNETTA, R.S. and BALOGH, M.E., 1999, Application of multi-temporal Land sat 5 TM imagery for wetland identification. Photogrammetric Engineering and Remote Sensing,65, pp. 1303–1310.
173. 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.
174. 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.
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.
176. TOTTRUP, C., 2004, Improving tropical forest mapping using multi-date Landsat TM dataand pre-classification image smoothing. International Journal of Remote Sensing, 25,pp. 717–730.
177. PIERCE, L.E., BERGEN, K.M., DOBSON, M.C. and ULABY, F.T., 1998, Multi temporal land cover classification using SIR-C/X-SAR imagery. Remote Sensing of Environment, 64,pp. 20–33.
178. 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.
179. 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.
180. 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.
181. 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.
182. 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.
183. 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.
184. 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).
185. 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 end member spectral mixture models. Remote Sensing of Environment, 65, pp. 267–279.
186. 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.
187. 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.
188. 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.
189. 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.
190. 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.
191. 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.
192. 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.
193. GOETZ, S.J., WRIGHT, R.K., SMITH, A.J., ZINECKER, E. and SCHAUB, E., 2003, IKONOSimagery for resource management: tree cover, impervious surfaces, and riparian buffer analyses in the mid-Atlantic region. Remote Sensing of Environment, 88, pp.195–208.

194. 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.,858 D. Lu and Q. Weng 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 ScaleBiosphere–Atmosphere Experiment in Amazonia (LBA). Remote Sensing of Environment, 88, pp. 111–127.
195. 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 Geo information, 4, pp. 217–229.
196. 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.
197. WANG, L., SOUSA, W.P., GONG, P. and BIGING, G.S., 2004, Comparison of IKONOS and Quick Bird images for mapping mangrove species on the Caribbean coast of panama. remote Sensing of Environment, 91, pp. 432–440.
198. 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.
199. 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.
200. BENEDIKTSSON, J.A., SVEINSSON, J.R. and ARNASON, K., 1995, Classification and feature extraction of AVIRIS data. IEEE Transactions on Geo science and Remote Sensing, 33,pp. 1194–1205.
201. JIMENEZ, L.O., MORALES-MORELL, A. and CREUS, A., 1999, Classification of hyper dimensional data based on feature and decision fusion approaches using projection pursuit, majority voting, and neural networks. IEEE Transactions on Geo science and Remote Sensing, 37, pp. 1360–1366.
202. 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.
203. 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.
204. SEGL, K., ROESSNER, S., HEIDEN, U. and KAUFMANN, H., 2003, Fusion of spectral and shapefeatures for identification of urban surface cover types using reflective and thermalhyperspectral data. ISPRS Journal of Photogrammetry and Remote Sensing, 58,pp. 99–112.
205. PLATT, R.V. and GOETZ, A.F.H., 2004, A comparison of AVIRIS and Land sat for land use classification at the urban fringe. Photogrammetric Engineering and Remote Sensing,70, pp. 813–819.
206. PAL, M. and MATHER, P.M., 2004, Assessment of the effectiveness of support vector machines for hyper spectral data. Future Generation Computer System, 20, pp. 1215–1225.
207. 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.
208. 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.
209. 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.
210. BABAN, S.M.J. and YUSOF, K.W., 2001, Mapping land use/cover distribution on amountainous tropical island using remote sensing and GIS. International Journal of Remote Sensing, 22, pp. 1909–1918.
211. 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 LandsatTM data. International Journal of Remote Sensing, 23, pp. 3057–3078.
212. EPSTEIN, J., PAYNE, K. and KRAMER, E., 2002, Techniques for mapping suburban sprawl. Photogrammetric Engineering and Remote Sensing, 68, pp. 913–918.
213. HARRIS, P.M. and VENTURA, S.J., 1995, The integration of geographic data with remotelysensed imagery to improve classification in an urban area. Photogrammetric Engineering and Remote Sensing, 61, pp. 993–998.
214. MESEV, V., 1998, The use of census data in urban image classification. Photogrammetric Engineering and Remote Sensing, 64, pp. 431–438.
215. BRONGE, L.B., 1999, Mapping boreal vegetation using Landsat TM and topographic mapdata in a

stratified approach. Canadian Journal of Remote Sensing, 25, pp. 460–474.
216. 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.
217. NARUMALANI, S., ZHOU, Y. and JELINSKI, D.E., 1998, Utilizing geometric attributes of spatial linformation to improve digital image classification. Remote Sensing Reviews, 16,pp. 233–253.
218. BARNSLEY, M.J. and BARR, S.L., 1996, Inferring urban land use from satellite sensor imagesusing kernel-based spatial reclassification. Photogrammetric Engineering and Remote Sensing, 62, pp. 949–958.
219. 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.
220. 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.
221. STALLINGS, C., KHORRAM, S. and HUFFMAN, R.L., 1999, Incorporating ancillary data into alogical filter for classified satellite imagery. Geocarto International, 14, pp. 42–51.
222. STEFANOV, W.L., RAMSEY, M.S. and CHRISTENSEN, P.R., 2001, Monitoring urban land coverchange: an expert system approach to land cover classification of semiarid to aridurban centers. Remote Sensing of Environment, 77, pp. 173–185.
223. 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.
224. 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 andRemote Sensing, 34, pp. 100–112.
225. 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.
226. 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.
227. 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.
228. AMARSAIKHAN, D. and DOUGLAS, T., 2004, Data fusion and multisource image classification. International Journal of Remote Sensing, 25, pp. 3529–3539.