British Journal of Applied Science & Technology
13(4): 1-11, 2016, Article no.BJAST.22037
ISSN: 2231-0843, NLM ID: 101664541

SCIENCEDOMAIN *international*
www.sciencedomain.org

Land Cover Classification Schemes Using Remote Sensing Images: A Recent Survey

S. Natya[1] and V. J. Rehna[2*]

[1]Research Scholar, Department of Electronics and Communication Engineering, Visvesvaraya Technological University, Jnana Sangama, Belagavi, Karnataka 590018, India.
[2]Department of Electronics and Communication Engineering, M.S Engineering College, Off Airport Road, Navaratna Agrahara, Sadahalli Post, Bangalore, Karnataka 562110, India.

Authors' contributions

This work was carried out in collaboration between both authors. Author SN designed the study, performed the analyses of the study, literature searches and wrote the first draft of the manuscript. Author VJR supervised the research work. Both authors read and approved the final manuscript.

Article Information

DOI: 10.9734/BJAST/2016/22037
Editor(s):
(1) Xu Jianhua, Department of Geography, East China Normal University, China.
Reviewers:
(1) Bintoora K. K. Adonia, Nkumba University, Uganda.
(2) Nilay Kanti Barman, Hijli College, West Bengal, India.
Complete Peer review History: http://sciencedomain.org/review-history/12511

Review Article

Received 14th September 2015
Accepted 31st October 2015
Published 2nd December 2015

ABSTRACT

Economic development and growth in population have prompted rapid changes to earth's land cover over the last few decades, and there is every indication that the pace of these changes will accelerate in the future. Therefore, systematic evaluations of Earth's land cover must be repeated at a frequency that allows monitoring of both long term trends as well as inter-annual variability, and at a level of spatial detail to allow study of land use patterns. Land cover analysis can be done most effectively through remote sensing images of various spatial, spectral and temporal resolutions to improve the selection of areas designed for agricultural, urban and/or industrial areas of a region. Astute efforts have been made in developing advanced classification algorithms and techniques for improving the accuracy of land cover classification. Recent image classification approaches for land cover pattern analysis have been brought together with their pros and cones by reviewing literatures, books, manuals and other related documents. Suitable classification algorithms may be chosen based on their performance, type of image and application area. Through this survey, various aspects regarding, preprocessing, classification

**Corresponding author: E-mail: rehnavj09@gmail.com;*

and accuracy assessment, new and unique land cover products may be generated which could not be produced by earlier techniques.

Keywords: Land use planning; land cover classification; remote sensing; image classification; geographical information systems.

1. INTRODUCTION

Land is one of the most important natural resources on which human life and their developmental activities are centered on [1]. Land cover refers to the physical material at the surface of the earth it can be a region covered by snow, forests, wetlands, dry land, grass land, open water, impervious surfaces and agriculture land. Land use refers to how people use the landscape whether for development, conservation, or mixed uses [2].

Knowledge about land use and land cover is important for many planning and management activities and is considered an essential element for modeling and understanding the earth as a system [3]. Information on land use and land cover also helps to overcome the problems of haphazard, uncontrolled development, deteriorating environmental quality, loss of prime agricultural lands, destruction of important wetlands, predict and assess impacts from floods and storm surges, loss of fish and wildlife habitat.

Remote sensing image classification techniques are essential in deriving land use land cover information for socio-economic planning and environmental applications [4]. The technological innovation in the field of Remote Sensing (RS) and Geographic Information System (GIS) have opened a new dimension to address a wide range of scientific problems of land use land cover classification as they provide timely, precise, and quality information inputs to decision making, while making sustainable use of natural resources and improving conservation practices. A satellite image provides qualitative information of a large geographic area that reduces the intricacy of field work. A suitable remotely sensed data for image classification is chosen by analyzing the strength and limitation of different type of sensor data available.

Land Use/ Land cover classification can be determined by measuring, analyzing and interpreting the satellite images collected from satellite sensors. The five main resolution characteristics of a satellite's sensor system can be summarised into:

- Spectral coverage/resolution i.e., band locations/width
- Spectral dimensionality: number of bands
- Radiometric resolution: quantization
- Spatial resolution/instantaneous field of view
- Temporal resolution

Once the raw remote sensing digital data has been acquired, it is then processed into usable information. The changes made to remote sensing data involve two major operations which are preprocessing and post-processing.

- Preprocessing of image includes radiometric correction and geometric correction.
- Digital image post-processing include image enhancement, image classification, and change detection.

Fig. 1 shows analysing satellite image for land cover feature identification which includes selection of remotely sensed image, finding a suitable classification system, selection of training samples, image pre-processing, feature selection/ extraction, selection of suitable classification approaches, post-classification processing and accuracy assessment.

These computerized process routines improve the image scene quality and aid in the data interpretation. Some of the major satellites which deliver images for precision agriculture are Indian Remote Sensing Satellite (IRS-1A, IRS-1C, IRS-1D), French SPOT, MODIS, ASTER, NOAA-AVHRR, LANDSAT TM/ETM, RADARSAT, ERS, RAPIDEYE, QUICKBIRD, IKONOS, ADEOS-II, CBERS-CCD and HJ-1 CCD etc.,

2. METHODS AND METHODOLOGY

The paper reviews recent technologies of land cover classification scheme using remotely sensing images to support precision farming. The review is prepared by referring to journals, conference papers, books, manuals/reports and other related documents. Over eight robust image classification schemes are discussed in this paper which are,

(i) Based on pixel information and are classified as pre-pixel classification, sub-pixel classification, pre-field classification, contextual classification, knowledge based classification and combination of multiple classifications.
(ii) Based on use of training samples and are classified as supervised classification and unsupervised classification.

About 53 documents including papers from national and international journals/conferences, 2 books and 3 manuals/reports have been referred in this survey. Stress has been given for recent land cover classification techniques using remotely sensing images to support precision farming by referring to published international journals in 2014-2015. Their commercial viability, application, potential and future scope of the algorithm has been analyzed in detail. A clear representation showing a particular method, its advantages/benefits and limitation/short comings are given.

3. RESULTS AND DISCUSSION

Remote sensing image classification is a commonly adopted method to obtain land cover information from Satellite images [5]. Digital image classification is the process of assigning pixels to meaningful classes. A pixel is assumed to be an individual unit which carries several spectral band values. The pixels of an image having comparable spectral values are assigned to one class. Classes are homogenous thus pixels of one class differ spectrally with the pixels of another class of the same image. These classes form regions on a map or an image, so that after classification digital image can be presented as a mosaic of consistent classes, each identified by a colour or symbol [6]. Land cover Image classification approaches can be done by either based on pixel information or based on use of training samples as shown in Fig. 2.

3.1 Based on Pixel Information

Image can be classified based on pixel information into following classification approaches pre-pixel classification, sub-pixel classification, pre-field classification, contextual classification, knowledge based classification and combination of multiple classifications.

3.1.1 Per-pixel classification approach

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 [7]. Commonly used Parametric Classifiers are Maximum likelihood classifier. Commonly used non-parametric classifiers are neural networks, Decision tree and Support Vector Machine. To improve performance in a non-parametric classification procedure, boosting, bagging or a hybrid of both techniques can be used [8]. Some of the per-pixel classifiers methods is described in Table 1.

3.1.2 Sub-pixel classification approach

Sub-pixel classification approaches have been developed to provide a more appropriate representation and accurate area estimation of land cover than per-pixel approaches, especially when coarse spatial resolution data are used [9]. In sub-pixel classification each pixel is considered mixed, and the real proportion of each class is estimated. Some of the Sub-pixel classifiers are described in Table 2.

Table 1. Per-pixel classifiers methods

Category	Advanced classifiers	Authors
Per-pixel classifiers	Two unsupervised classifications, algorithms based on RBF Neural Network and K-means	Rollet R, et al. 1998 [10]
	Minimum Distance-to-Means Classifier	Atkinson PM, et al. 2000 [11]
	Spectral angle Classifier	Sohn Y, et al. 2002 [12]
	Decision tree classifier	Lawrence R et al. 2004 [13]
	Supervised classification was performed using the maximum likelihood algorithm and 25 classes.	David Barry Hester, et al. 2008 [14]
	Support Vector Machine	Marconcini M, et al. 2009 [15]

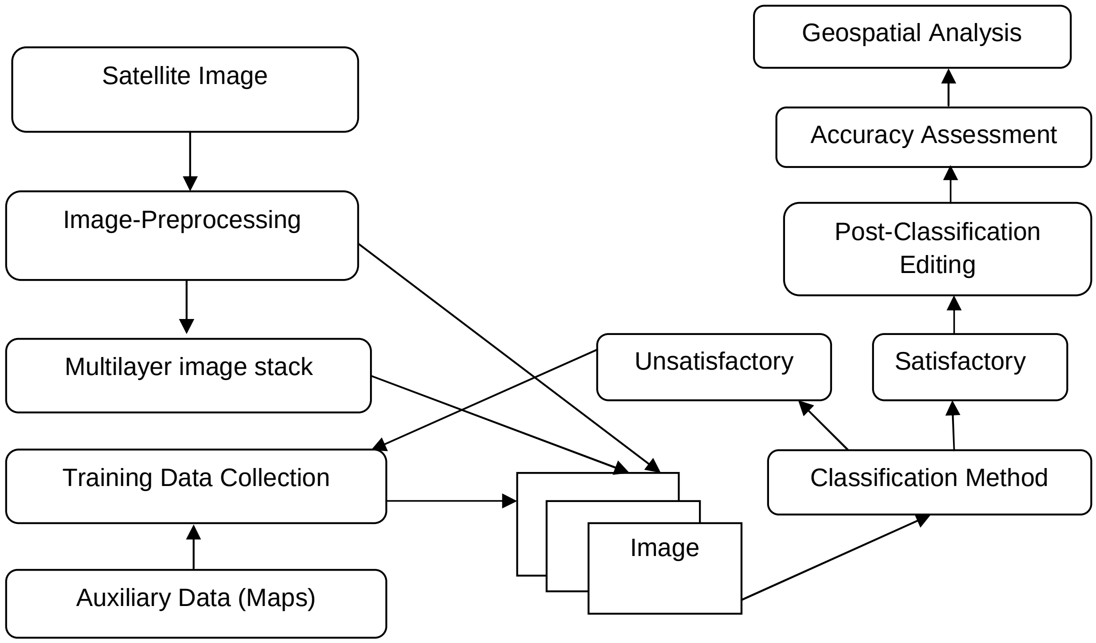

Fig. 1. Satellite image analysis [16]

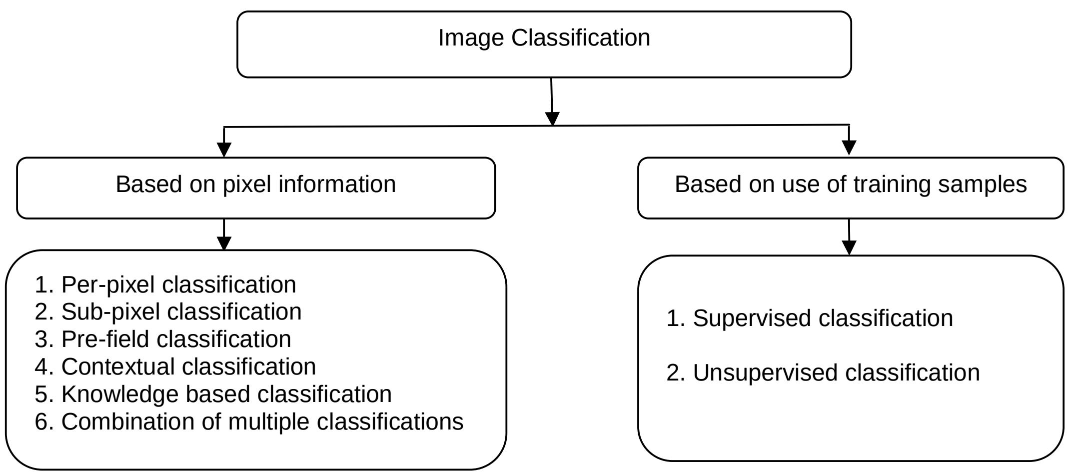

Fig. 2. Land cover image classification approaches [17]

3.1.3 Per-field classification approach

The Per-field classifier is designed to deal with the problem of environmental heterogeneity. The Per-field classifier averages out the noise by using land parcels (called ‘fields’) as individual units. The 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 [18]. Some of the pre-field classifiers are described in Table 3.

3.1.4 Contextual classification approach

Contextual classifieris an approach of classification based on contextual information in images. "Contextual" means this approach is focusing on the relationship of the nearby pixels, which is also called neighborhood. The goal of this approach is to classify the images by using the contextual information. Contextual classifiers were developed to overcome with the problem of intra-class spectral variations. Some of the contextual classifiers are described in Table 4.

3.1.5 Knowledge- based classification approach

Knowledge based classifier is more suited to handle complex data. Different kinds of ancillary data, such as digital elevation model, housing, soil map and temperature are easily available; they may be integrated into a classification procedure in different ways [8]. Some of the knowledge based classifier is described in Table 5.

3.1.6 Combination of multiple classification approach

Research have explored different techniques such as a production rule, a sum rule, stacked regression methods majority voting and thresholds to combine multiple classification results to provides improved classification accuracy compared to the use of a single classifier. Some of the Combination of multiple classifiers is described in Table 6.

3.2 Based on Use of Training Samples

3.2.1 Supervised classification

Supervised classification methods require input from an analyst. The input from analyst is known as training set. All the supervised classifications usually have a sequence of operations that must be followed [41].

- Defining of the Training Sites.
- Extraction of Signatures.
- Classification of the Image.

Table 2. Sub-pixel classifiers methods

Category	Advanced classifiers	Authors
Sub-pixel classifiers	Rule-based machine-version approach	Foschi, et al. 1997 [19]
	Image Sub-pixel classifier	Huguenin RL, et al. 1997 [20]
	Neural Networks	Mannan B, et al. 2003 [21]
	Regression modelling	Yang X, et al. 2005 [22]
	Fuzzy-spectral mixture analysis	Tang J, et al. 2007 [23]

Table 3. Per-field classifiers methods

Category	Advanced classifiers	Authors
Per-field classifiers	Per-field classification based on per-pixel or sub-pixel classified image	Aplin, et al. 2001 [24]
	Per-field or per-parcel classification	Wu S, et al. 2007 [25]
	Object-based classification	Volker Walter, 2003 [26]
		Mengistie Kindu et al. 2013 [27]
		Thunig H, et al. 2011 [28]

Table 4. Contextual classification methods

Category	Advanced classifiers	Authors
Contextual classifiers	Fuzzy contextual classifier	Binaghi E, et al. 1997 [29]
	Point-to-point contextual correction	Cortijo, et al.1998 [30]
	Contextual classifier based on region-growth algorithm	Lira, et al. 2002 [31]
	Frequency-based contextual classifier	Xu B, et al. 2003 [32]
	Extraction and Classification of homogeneous objects	Lu D, et al. 2004 [33]

Table 5. Knowledge based classifier methods

Category	Advanced classifiers	Authors
Knowledge based classifier	Knowledge-based classification	Dobson MC, et al. 1996 [34]
		Schmidt KS, et al. 2004 [35]
		Hashimoto S, et al. 2012 [36]
	Rule-based syntactical approach	Onsi 2003 [37]

Table 6. Combination of multiple classifiers methods

Category	Advanced classifiers	Authors
Combination of multiple classifiers	Neural network, decision tree classifier and evidential reasoning	Huang, et al. 2004 [38]
	Maximum Likelihood Classifier (ML), Support Vector Machine (SVM), Artificial Neural Networks (ANN), Spectral Angle Mapper (SAM), Minimum Distance Classifier (MD) And Decision Tree Classifier (DTC)	Lijun Dai, et al. 2010 [39]
	Multiple Support Vector Machine (SVM) with the core of the Radial Based Function (RBF), SVM with the core of linear function, Neural Network (BP), decision tree of rough set, random forest, and K nearest neighbor	Jiahui Xu, et al. 2012 [40]

Training sample is the most important factor in the supervised satellite image classification methods. Accuracy of the methods highly depends on the samples taken for training. Training samples are two types, one used for classification and another for supervising classification accuracy. Most commonly used supervised classification approaches are:

3.2.1.1 Maximum likelihood

Maximum likelihood decision rule is based on Gaussian estimate of the probability density function of each class. Maximum likelihood classifier evaluates both the variance and covariance of the spectral response patterns in classifying an unknown pixel. It assumes the distribution of the cloud of points forming the category training data to be normally distributed. Under this assumption, distribution of response pattern can be described by mean vector and the covariance matrix. From the given parameters the statistical probability of a given pixel value can be computed. By computing the probability of the pixel value, an undefined pixel can be classified. After evaluating the probability the pixel would be assigned to the one with highest probability value. One of the drawbacks in maximum likelihood classifier is large number of computation required to classify each pixel [17].

3.2.1.2 Artificial Neural Network (ANN)

ANN has become increasingly popular for classification of remote sensing data. ANN is a simple structure consisting a set of processing units, interconnected with each other by weighted channels similar to a biological neuron [42]. The major appeal of ANN lies in its higher tolerance to any noise in the data, distribution free assumption, its ability to weight the importance of variables in the analysis and its capability to perform adequately in the presence of small training data set [43]. The feed forward BPNN learning algorithm is the most common algorithm used for remote sensing image classification [44].

3.2.1.3 Bayesian Network (BN)

Bayesian Network provide a very general and yet effective graphical language for factoring joint probability distributions which in turn make them very popular for classification. A BN is a graphical model represents variables (as nodes) and cause-effect relationships (as directed links) between variables. All geographical data has uncertainty associated with its attributes, a BN uses belief probabilities to represent these uncertainties in a mathematically sound way. The two major tasks in learning a BN are learning the graphical structure and then learning the parameters for that structure [45].

3.2.1.4 Decision tree

Decision tree approach is a non-parametric classifier and an example of machine learning algorithm. It involves a recursive partitioning of the feature space, based on a set of rules that are learned by an analysis of the training set. A tree structure is developed where at each branching a specific decision rule is implemented, which may involve one or more combinations of the attribute inputs. A new input vector then “travels” from the root node down through successive branches until it is placed in a specific class. Decision tree has ability to handle missing and noisy data, and non-parametric nature. Decision trees are not constrained by any lack of knowledge of the class distributions. It can be trained quickly, takes less computational time [46]. C5.0 is flexible and is based on decision tree algorithm that is one of the most effective form of inductive learning [47]. Combining Bayes method with inductive learning not only improves classification accuracy greatly, but also extends the classification by subdivide some classes with the discovered knowledge [48].

3.2.1.5 Minimum distance

Minimum distance classifies image data on a database file using a set of 256 possible class signature segments as specified by signature parameter. Each segment specified in signature, for example, stores signature data pertaining to a particular class. Only the mean vector in each class signature segment is used. Other data, such as standard deviations and covariance matrices, are ignored (though the maximum likelihood classifier uses this). The result of the classification is a theme map directed to a specified database image channel. A theme map encodes each class with a unique gray level. The gray-level value used to encode a class is specified when the class signature is created. If the theme map is later transferred to the display, then pseudo-colour table should be loaded so that each class is represented by a different colour [49].

3.2.1.6 Parallel piped

In the parallelepiped decision rule, the data file values of the candidate pixel are compared to upper and lower limits. These limits can be either the minimum and maximum data file values of each band in the signature or the mean of each band, plus and minus a number of standard deviations, or any limits that you specify, based on your knowledge of the data and signatures. There are high and low limits for every signature in every band. When a pixel's data file values are between the limits for every band in a signature, then the pixel is assigned to that signature's class. Limitation of this approach is that since parallelepipeds have "corners", pixels may be classified which are actually quite far, spectrally, from the mean of the signature [50].

3.2.1.7 K-nearest Neighbor (KNN)

Nearest neighbor based algorithms are simple but effective methods used in statistical classification. Categorizing unlabeled samples is based on their distance from the samples in training dataset. KNN classification a set of k nearest neighbors is computed for an unlabeled sample instead of a single nearest neighbor. Then, the test sample is assigned to the class that occurs most frequently among the k-nearest training samples. If the ranges of the data in each dimension vary considerably, this can affect the accuracy of the nearest neighbour based classifications. Thus, both the training and testing data need be normalized [51].

3.2.1.8 Mahalanobis classification

It is based on correlations between variables by which different patterns can be identified and analyzed. It gauges similarity of an unknown sample set to a known one. It differs from Euclidean distance. It takes into account the correlations of the data set and is scale-invariant. The author [52] illustrate Mahalanobis classification algorithm that uses spatial thresholds defined from the local knowledge to extract the reliable urban land cover information from the selected optical and microwave data sets.

3.2.1.9 Object base classification

Object-oriented classification pattern deals with image objects which share the similar attributes, such as Digital Number (DN) value, spectral characteristics, texture, size, shape, compactness, context information with adjacent image objects, etc [53,54]. Hence in object-oriented classification pattern, image object is the aggregation of similar pixels by image segmentation method, so the formation of image objects is a weighed mean process and can reduce the influence of random noise point which decreases the limitations exist in the feature analysis in other classifiers [55].

<u>3.2.2 Unsupervised classification</u>

Unsupervised Classification technique uses clustering mechanisms to group satellite image pixels into unlabelled classes/clusters. Later analyst assigns meaningful labels to the clusters and produces well classified satellite image. Unsupervised methods are usually very fast and computationally efficient. Most common unsupervised satellite image classifications are:

3.2.2.1 ISODATA (Iterative Self-Organizing Data Analysis Technique)

The ISODATA clustering method uses the minimum spectral distance formula to form clusters. It begins with either arbitrary cluster means or means of an existing signature set and each time the clustering repeats, the means of these clusters are shifted. The new cluster means are used for the next iteration. The ISODATA utility repeats the clustering of the image until either a maximum number of iterations has been performed or a maximum percentage of unchanged pixels have been reached between two iterations [56]

3.2.2.2 Support Vector Machine (SVM)

The SVM formulation is based on the Structural Risk Minimization principle, which is an inductive principle for model selection that aims at providing a trade-off between hypothesis space complexity and quality of fitting the training data. The SVM approach has excellent properties like, good generalization ability, high effectiveness in hyper dimensional feature space, learning phase associated with the minimization of a convex cost function that guarantees the uniqueness of the solution and the possibility to be implemented in a parallel architecture thus reducing the overall computational time by an adequate parallel processing [57].

3.2.2.3 K-Means

It is a popular statistics and data mining technique. It partitions n observations into k clusters based on Euclidean mean value. Advantages with the K-Means technique are simple to process and fast execution. Limitation with this method is analyst should know priori number of classes [58].

4. CONCLUSION

Selection of a suitable classifier requires consideration of many factors, such as classification accuracy, algorithm performance, and computational resources. Classification algorithms can be per pixel, sub pixel, per field, contextual, knowledge based and combination of multiple classifiers. Classification approaches may vary with different types of remote-sensing data. Pixel-based image analysis is limited because the image pixels are not true geographical objects and the pixel topology is limited. Pixel based image analysis largely neglects the spatial photo-interpretive elements such as texture, context, and shape; the increased variability implicit within high spatial resolution imagery confuses traditional pixel-based classifiers resulting in lower classification accuracies. A per-field or object-oriented classification approach is most favorable for fine spatial resolution data as the impact of the shadow problem and the wide spectral variation within the land-cover classes is isolated. Sub-pixel classification methods can overcome the problem associated with mixed pixels in medium and coarse spatial resolution data. Contextual classification is developed to overcome the problem of intraclass spectral variation. Knowledge based classification approach is most suitable when dealing with multisource data such as combination of spectral signatures, texture and context information and ancillary data. Hybrid approaches of combining multiple classification schemes has been found to be helpful for improvement of classification accuracy which is based on the type of image obtained from remote sensors (multispectral image, superspectral image or hyperspectral image) and the application area.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

1. Muthukrishnan A, Aruchamy S, Jose Ravindraraj B. Land use facet is indicator of coastal land management: A case study of tuticorin coast using geospatial techniques. International Journal of Advances in Remote Sensing and GIS, 2013;1(3):244-263.
2. Bergmann Associates. Mohawk River Watershed Regulatory Review & Analysis; 2014.
3. Thomas Lillesand, Ralph W Kiefer, Jonathan Chipman. Remote sensing and image interpretation. 7th ed. John Wiley & Sons; 2015.
4. Miao Li, Shuying Zang, Bing Zhang, Shanshan Li, Changshan Wu. A review of remote sensing image classification techniques: The role of spatio-contextual information. European Journal of Remote Sensing. 2014;47:389-411.
5. Gao Y, Mas JF. A comparison of the performance of pixel based and object based classifications over images with various spatial resolutions. Online Journal of Earth Sciences. 2008;2:27-35.
6. Jawak SD, Devliyal P, Luis AJ. A comprehensive review on pixel oriented and object oriented methods for information extraction from remotely sensed satellite images with a special emphasis on cryospheric applications.

Advances in Remote Sensing. 2015;4:177-195.
7. Lu D, Weng Q. A survey of image classification methods and techniques for improving classification performance. International Journal of Remote Sensing. 2007;28(5):823-870.
8. Geeta R Gupta, Kamalapur SM. Study of classification of remote sensing images using particle swarm optimization based approach. International Journal of Application or Innovation in Engineering & Management. 2014;3(10):165-169.
9. Foody GM, Cox DP. Subpixel land cover composition estimation using a linear mixture model and fuzzy membership functions. International Remote Sensing. 1994;15:619-631.
10. Rollet R, Benie GB, Li W, Wang S, Boucher JM. Image classification algorithm based on the RBF neural network and K-means. International Journal of Remote Sensing. 1998;19:3003-3009. DOI:http://dx.doi.org/10.1080/014311698214398
11. Atkinson PM, Lewis P. Geostatistical classification for remote sensing: An introduction. Computers & Geosciences. 2000;26:361-371. DOI:http://dx.doi.org/10.1016/S0098-3004(99)00117-X
12. Sohn Y, Rebello NS. Supervised and unsupervised spectral angle classifiers. Photogrammetric Engineering and Remote Sensing. 2002;68:1271–1281.
13. Lawrenc ER, Bunn A, Powell S, Zmabon M. Classification of remotely sensed imagery using stochastic gradient boosting as a refinement of classification tree analysis. Remote Sensing of Environment. 2004;90:331–336.
14. David Barry Hester, Halil I Cakir, Stacy AC Nelson, Siamak Khorram. Per-pixel classification of high spatial resolution satellite imagery for urban land-cover mapping. Photogrammetric Engineering & Remote Sensing. 2008;74(4):463–471.
15. Marconcini M, Camps Valls G, Bruzzone L. A composite semisupervised SVM for classification of hyperspectral images. IEEE Geoscience and Remote Sensing Letters. 2009;6:234-238. DOI:http://dx.doi.org/10.1109/LGRS.2008.2009324
16. Chandra Giri, Jordan Long. Land cover characterization and mapping of South America for the Year 2010 Using Landsat 30 m satellite data. Remote Sensing. 2014;6:9494-9510.
17. Ablin R, Helen Sulochana C. A survey of hyperspectral image classification in remote sensing. International Journal of Advanced Research in Computer and Communication Engineering. 2013;2(8): 2986-3000
18. Janssen LF, Molenaar M. Terrain object, their dynamics and their monitoring by integration of GIS and remote sensing. IEEE Transactions on Geoscience and Remote Sensing. 1995;33:749–758.
19. Foschi PG, Smith DK. Detecting subpixel woody vegetation in digital imagery using two artificial intelligence approaches. Photogrammetric Engineering and Remote Sensing. 1997;63:493–500.
20. Huguenin RL, Karaska MA, Blaricom DV, Jensen JR. Subpixel classification of bald cypress and tupelo gum trees in thematic mapper imagery. Photogrammetric Engineering and Remote Sensing. 1997; 63:717–725.
21. Mannan B, Ray AK. Crisp and fuzzy competitive learning networks for supervised classification of multispectral IRS scenes. International Journal of Remote Sensing. 2003;24:3491-3502. DOI:http://dx.doi.org/10.1080/0143116021000053805
22. Yang X, Liu Z. Use of satellite-derived landscape imperviousness index to characterize urban spatial growth. Computers, Environment and Urban Systems. 2005;29:524-540. DOI:http://dx.doi.org/10.1016/j.compenvurbsys.2005.01.005
23. Tang J, Wang L, Myint SW. Improving urban classification through fuzzy supervised classification and spectral mixture analysis. International Journal of Remote Sensing. 2007;28:4047-4063. DOI:http://dx.doi.org/10.1080/01431160701227687
24. Aplin P, Atkinson PM. Sub-pixel land cover mapping for per-field classification. International Journal of Remote Sensing. 2001;22:2853–2858.
25. Wu S, Silvan Cardenas J, Wang L. Per-field urban land use classification based on tax parcel boundaries. International Journal of Remote Sensing. 2007;28(12): 2777–2800
26. Volker Walter. Object-based classification of remote sensing data for change detection. ISPRS Journal of

Photogrammetry & Remote Sensing. 2004;58:225–238.

27. Mengistie Kindu, Thomas Schneider, Demel Teketay, Thomas Knoke. Land use/land cover change analysis using object-based classification approach in Munessa-Shashemene Landscape of the Ethiopian Highlands Remote Sensing. 2013;5(5):2411-2435.
DOI: 10.3390/rs5052411
28. Thunig H, Wolf N, Naumann S, Siegmund A, Jurgens C, Uysal C, Maktav D. Land use/land cover classification for applied urban planning - The challenge of automation. Urban Remote Sensing Event. 2011;229–232.
DOI: 10.1109/JURSE.2011.5764762
29. Binaghi E, Madella P, Montesano MG, RampinI A. Fuzzy contextual classification of multisource remote sensing images. IEEE Transactions on Geoscience and Remote Sensing. 1997;35:326–339.
30. Cortijo FJ, De La Blanca NP. Improving classical contextual classification. International Journal of Remote Sensing. 1998;19:1591–1613.
31. Lira J, Maletti G. A supervised contextual classifier based on a region-growth algorithm. Computers and Geosciences. 2002;28:951–959.
32. Xu B, Gong P, Seto E, Spear R. 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. 2003;69:529–536.
33. Lu D, Weng Q. Spectral mixture analysis of the urban landscapes in Indianapolis with Landsat ETM+ imagery. Photogrammetric Engineering and Remote Sensing. 2004; 70:1053–1062.
34. Dobson MC, Pierce LE, Ulaby FT. Knowledge-based land-cover classification using ERS-1/JERS-1 SAR composites. Geoscience and Remote Sensing. IEEE Transactions. 1996;34(1):83–99.
DOI: 10.1109/36.481896
35. Schmidt KS, Skidmore AK, Kloosterman EH, Van Oosten H, Kumar L. Janssen JAM. Mapping coastal vegetation using an expert system and hyperspectral imagery. Photogrammetric Engineering and Remote Sensing. 2004;70:703–715.
36. Hashimoto S, Tadono T, Onosato M, Hori M. Probabilistic land cover classification approach toward knowledge-based satellite data interpretations. Geoscience and Remote Sensing Symposium (IGARSS). IEEE International. 2012;1513–1516.
DOI: 10.1109/IGARSS.2012.6351247
37. Onsi HM. Designing a rule-based classifier using syntactical approach. International Journal of Remote Sensing. 2003;24:637–647.
38. Huang Z, Lees BG. Combining non-parametric models for multisource predictive forest mapping. Photo-grammetric Engineering and Remote Sensing. 2004;70:415–425.
39. Lijun Dai, Chuang Liu. Multiple classifier combination for land cover classification of remote sensing image. Information Science and Engineering (ICISE). 2nd International Conference. 2010;3835–3839.
DOI: 10.1109/ICISE.2010.5691420
40. Jiahui Xu, Weimin Ju, Zhongwen Hu. Object-oriented land cover classification of HJ-1B CCD image through multiple classifier fusion. Geoinformatics (GEOINFORMATICS). 20th International Conference. 2012;1–6.
DOI:10.1109/Geoinformatics.2012.6270346
41. Perumal K, Bhaskaran R. Supervised classification performance of multispectral images. Journal of Computing. 2010;2(2): 124-129.
42. Aleksander I, Morton H. An introduction to neural computing. Chapman and Hall. London; 1990.
43. Benediktsson JA, Swain PH, Ersoy OK. Neural network approaches versus statistical methods in classification of multiscore remote sensing data. IEEE Transaction on Geosciences and Remote Sensing. 1990;28:540-551.
44. Ibrahim MA, Arora MK, Ghosh SK, Hua-mei Chen. Approaches to improve accuracy of neural network classification of images dominated by mixed pixels. Geoscience and Remote Sensing Symposium; 2004.
DOI: 10.1109/IGARSS.2004.1369090
45. Khanteymoori AR, Homayounpour MM, Menhaj MB. A Bayesian network based approach for data classification using structural learning. Springer-Verlag Berlin Heidelberg. 2008;6:25-32.
46. Uttam Kumar, Ramachandra TV. Evaluation of algorithms for land covers

analysis using hyperspectral data. Technical Report 111. 2002;1-120.
47. Debasish Chaudhuri. Hybrid Image Classification Technique for Land-cover Mapping in the Arctic, tundra north slope, Alaska. UMI microform 3316328.2008
48. Deren LI, Kaichang DI, Deyi LI. Land use classification of remote sensing image with GIS data based on spatial data mining techniques. International Archives of Photogrammetry and Remote Sensing. Amsterdam. 2000;33(Part B3):238-245.
49. Sarath T, Nagalakshmi G, Jyothi S. A study on hyperspectral remote sensing classifications. International Conference on Information and Communication Technologies (ICICT). 2014;5-8.
50. Yousif Ali Hussin. Remotely sensed image classification. UNEP-ITC RS/GIS for Monitoring and Assessment of Iraqi Marshland. 2005;6-10.
51. Debabrata Ghosh, Naima Kaabouch. A survey on remote sensing scene classification algorithms. WSEAS Transactions on Signal Processing. 2014; 10:504-519.
52. Battsengel V, Amarsaikhan D, Bat-Erdene Ts, Egshiglen E, Munkh-Erdene A, Ganzorig M. Advanced classification of lands at TM and Envisat images of Mongolia. Advances in Remote Sensing. 2013;2(2):102-110.
DOI: 10.4236/ars.2013.22014
53. Blaschke T, Hay GJ. Object-oriented image analysis and scale-space: Theory and methods for modeling and evaluating multi-scale landscape structures. International Archives of Photogrammetry & Remote Sensing. 2001;34(4/W5):22–29.
54. Blaschke T, Strobl J. What's wrong with Pixels? Some recent developments interfacing remote sensing and GIS. Geo-BIT/GIS. 2001;6:12–17.
55. Yongxue LIU, Manchun LI, Liang MAO, Feifei XU, Shuo HUANG. Review of remotely sensed imagery classification patterns based on object-oriented image analysis. Chinese Geographical Science. 2006;16(3):282–288.
56. Mohammed Karemuddin, Shaik Rusthum. Producing land use land cover using satellite image and image processing techniques a case study of the Somajiguda GHMC Ward. International Journal of Innovative Technology and Research. 2015;3(4):2269-2275.
57. Francesca Bovolo, Lorenzo Bruzzone, Lorenzo Carlin. A novel technique for sub-pixel image classification based on support vector machine. IEEE Transactions on Image Processing. 2010;19:2983-2999.
58. Sunitha Abburu, Suresh Babu Golla. Satellite image classification methods and techniques: A review. International Journal of Computer Applications (0975 – 8887). 2015;119(8):20-25.

Peer-review history:
The peer review history for this paper can be accessed here:
http://sciencedomain.org/review-history/12511