Image Classification in Remote Sensing

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Abstract
One of the most important functions of remote sensing data is the production of Land Use and Land Cover maps and thus can be managed through a process called image classification. This paper looks into the following components related to the image classification process and procedures and image classification techniques and explains two common techniques K-means Classifier and Support Vector Machine (SVM).
**Keywords:** Remote Sensing, Image Classification, K-means Classifier, Support Vector Machine

1. Image Classification

Based on the idea that different feature types on the earth's surface have a different spectral reflectance and remittance properties, their recognition is carried out through the classification process. In a broad sense, image classification is defined as the process of categorizing all pixels in an image or raw remotely sensed satellite data to obtain a given set of labels or land cover themes (Lillesand, Keifer 1994). As can see in figure1.

SPOT multispectral image of the test area
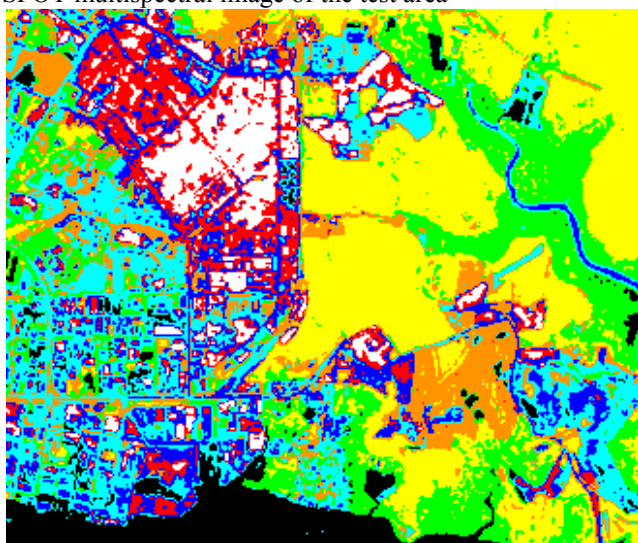
Thematic map derived from the SPOT image using an unsupervised classification algorithm.
Figure1. Example of Image Classification

2. Image Classification Procedures

General image classification procedures include:

- Design image classification scheme: they are usually information classes such as urban, agriculture, forest areas, etc. Conduct field surveys and collect ground information and other ancillary data of the study area.
- Preprocessing of the image, including radiometric, atmospheric, geometric and topographic corrections, image enhancement, and initial image clustering.
- Select representative areas of the image and analyze the initial clustering results or generate training signatures.
- Image classification algorithms running.
- Post-processing: complete geometric correction & filtering and classification decorating.
- Accuracy assessment: compare classification results with field studies.
     (Gong and Howarth 1990):

3. Image Classification Techniques

There are various classification approaches that have been developed and widely used to produce land cover maps (Aplin, Atkinson 2004). They range in logic, from supervised to unsupervised; parametric to non-parametric to non-metric, or hard and soft (fuzzy) classification, or per-pixel, sub-pixel, and prefield (Keuchel et al. 2003a, Jensen 2005) as can be seen from the brief descriptions of these categories in Table 1. However, there are two broad types of classification procedure and each finds application in the processing of remote sensing images: one is referred to as supervised classification and the other one is unsupervised classification. These can be used as alternative approaches, but are often combined into hybrid methodologies using more than one method (Richards, Jia 2006).

Table1.Summary of Remote Sensing Classification Techniques

Methods	Examples	Characteristics
Parametric	Maximum Likelihood classification and Unsupervised classification etc.	Assumptions: Data area normally distributed Prior Knowledge of class density functions
Non-Parametric	Nearest-neighbor classification, Fuzzy classification , Neural networks and support Vector machines etc.	No prior assumptions are made
Non-metric	Rule-based Decision tree classification	Can operate on both real-valued data and nominal scaled data statistical analysis
Supervised	Maximum Likelihood, Minimum Distance , and Parallelepiped classification etc.	Analyst Identifies training sites to represent in classes and each pixel is classified based on statistical analysis
Unsupervised	ISODATA and K-means etc.	Prior ground information not known. Pixels with similar spectral characteristics are grouped according to specific statistical criteria
Hard (parametric)	Supervised and Unsupervised classifications	Classification using discrete categories
Soft (non-Parametric)	Fuzzy Set Classification logic	Considers the heterogeneous nature of real world Each pixel is assigned a proportion of the in land cover type found within the pixel
Pre-Pixel		Classification of the image pixel by pixel
Object-oriented		Image regenerated into homogenous objects Classification preformed on each object and pixel
Hybrid Approaches		Includes expert systems and artificial intelligence

(Source Jensen, 2005: pp337-338)

Unsupervised image classification is a method in which the image interpreting software separates a large number of unknown pixels in an image based on their reflectance values into classes or clusters with no direction from the analyst (Tou, Gonzalez 1974). There are two most frequent clustering methods used for unsupervised classification: K-means and Iterative Self-Organizing Data Analysis Technique (ISODATA). These two methods rely purely on spectrally pixel-based statistics and incorporate no prior knowledge of the characteristics of the themes being studied. On the other hand, supervised classification is a method in which the analyst defines small

areas called training sites on the image, which contain the predictor variables measured in each sampling unit, and assigns prior classes to the sampling units (Černá, Chytrý 2005). The delineation of training areas representative of a cover type is most effective when an image analyst has knowledge of the geography of a region and experience with the spectral properties of the cover classes (Skidmore 1989).

The following diagrams show the major steps in the two common types of image classification:

Unsupervised

Supervised

The supervised technique has some advantage over the unsupervised one. In the supervised approach, useful information categories are distinct first, and then their spectral separability is examined while in the unsupervised approach, the computer determines spectrally separable class, and then defines their information value (Lillesand, Keifer 1994). Besides, unsupervised classification is easy to apply, does not require analyst-specified training data and is widely available in image processing and statistical software packages; moreover it automatically converts raw image data into useful information so long as there is higher classification accuracy (Langley, Cheshire & Humes 2001), but one disadvantage of this classification is that the classification process has to be repeated if new data (samples) are added.

Nevertheless; there are many limitations of both major classification methods (supervised and unsupervised) that were realized by Castellana, d'Addabbo & Pasquariello (2007) during independent utility and this led them to develop a new classification approach called "hybrid classification method". On the other hand, when using new generation images, characterized by a higher spatial and spectral resolution, it is still difficult to obtain satisfactory results by using supervised and unsupervised methods alone (Lewiński, Zaremski 2004) therefore, scientists have made great effor to develop advanced classification procedures which has resulted in the Automated Classification Approach used by (Ratanopad, Kainz 2006), Rx Classification Method (Zhang et al. 2007), Object-based Classification (Gamanya, De Maeyer & De Dapper 2009), SVM (Walter 2004), Standardized Object Oriented Automatic Classification (SOOAC) method based on fuzzy Logic, Knowledge-based Stratified Classification, Artificial Neural Networks(ANN) (Chen et al. 2002), Decision Tree Classification Method (DT) (Su et al. 2011), Bayesian and Hybrid Classifier (Pradhan, Ghose & Jeyaram 2010).

3.1 K-means Classifier

In this approach, classes are determined statistically by assigning pixels to the nearest cluster mean based on all available bands. In K-Means, a sequence of iteration starts with an initial set $C^{-(0)}$ (Tou, Gonzalez 1974). At each iteration t all $c \in C$ pixels are assigned to one of the clusters $S_k^{-(t)}$ as defined by the nearest neighbor principle. A new center $C_k^{-(t)}$ For a cluster is computed as follows:

$$C_j^{(t+1)} = \frac{1}{N_j} \sum (c_i | c_i \in S_j^{(t)})$$

However, the result of the K-Means clustering or the output of this technique could be influenced by the number of cluster centers specified, the choice of the initial cluster center, the sampling nature, the geometrical properties of the data, and clustering parameters (Vanderzee, Ehrlich 1995). It is relatively straightforward and has considerable intuitive appeal.

3.2 Support Vector Machine (SVM)

Recently, Support Vector Machine (SVM) classification algorithm has been used to classify imagery obtained from remote-sensing satellites (Keuchel et al. 2003b). SVM, the work of Vapnik and colleagues in the 1990's, was previously utilized in a remote sensing context by Gualtieri and Cromp in 1998 and Pal and Mather, 2005. This classification algorithm had been shown to be effective for face recognition in photos, handwriting and object recognition before it was adopted for use in remote sensing (Pal, Mather 2005, Hermes et al. 1999) and has proved popular for hyperspectral remote-sensing data (Camps-Valls et al. 2004, Melgani, Bruzzone 2004, Fauvel, Chanussot & Benediktsson 2006). Besides these successful applications of hyperspectral data, SVM is being used for various data types such as Landsat multispectral data. It is a non-parametric classifier that differentiates and divides the classes by determining the boundaries in feature space and maximizes the margin between the classes (Keuchel et al. 2003b). The surface is often called the optimal hyper plane, and the data points closest to the hyper plane are called support vectors. Classes are not separated by statistical learning theory means as in the maximum likelihood classifier, but by geometric criteria (Fauvel, Chanussot &

Benediktsson 2006).

The support vectors consider the critical elements of the training set. Implementation of SVM by the ENVI 4.8 software uses the pairwise classification strategy for multiclass classification. SVM classification output is the decision values of each pixel for each class, which are used for probability estimates. The ENVI4.8 software performs classification by selecting the highest probability. An optional threshold allows reporting pixels with all probability values less than the threshold as unclassified. SVM includes a penalty parameter that allows a certain degree of misclassification, which is particularly important for non-separable training sets. The penalty parameter controls the tradeoff between allowing training errors and forcing rigid margins. For example, assume that two classes are spectrally separable in feature space. If the two classes are separated by a line drawn in the feature space, to separate these two classes, the space between the two classes identifying a central hyperplane should be maximized (Pal, Mather 2005). To identify the hyperplane, the central distance between the closest points of each of the two classes is measured. These points are referred to as support vectors (Pal, Mather 2005). An SVM, simply demonstrated, is a binary example in a two dimensional feature space, as shown in Figure 2.

It is assumed that N training samples exist in the feature space with corresponding labels $y_i = +1$ or $y_j = -1$ respectively (Fauvel, Chanussot & Benediktsson 2006). To define the optimal hyperplane, w represents the vector normal to the hyperplane and b represents the bias so the hyperplane and is defined as:

$$w * x + b = 0$$

Where

x= a point lying on the hyperplane

w = is normal to the hyperplane

b = bias

$\frac{(|b|)}{(\|w\|)}$ = the perpendicular distance from the hyperplane to the origin with the Euclidean norm of w

(Foody, Mathur 2004)

For any training pixel x, the distance from the hyperplane can be calculated by:

$$f(x) = w * x + b$$

For a training pixel x to be classified in either class, it must satisfy one of the two following conditions:

$Y_i (w. X_i + b) \geq +1$ or $Y_i (w. X_i + b) \leq -1$

Linearly separable data are ideal but rarely occur in a real world data set. For non-linearly separable, there is a need to introduce lack variables ξ so that misclassified pixels transferred back to their original class in feature space (Fauvel, Chanussot & Benediktsson 2006). Therefore the conditions are:

$Y_i (w. X_i + b) > 1 - \zeta_i, \zeta_i \geq 0$ or $Y_i (w. X_i + b) < -1 - \zeta_i, \zeta_i \geq 0$

Final optimization of the margin is defined as:

$$min \left[\frac{\|w\|^2}{2} + c \sum_{i=1}^{N} \zeta_i \right]$$

Where; C represents the penalty parameter (Fauvel et al., 2006).
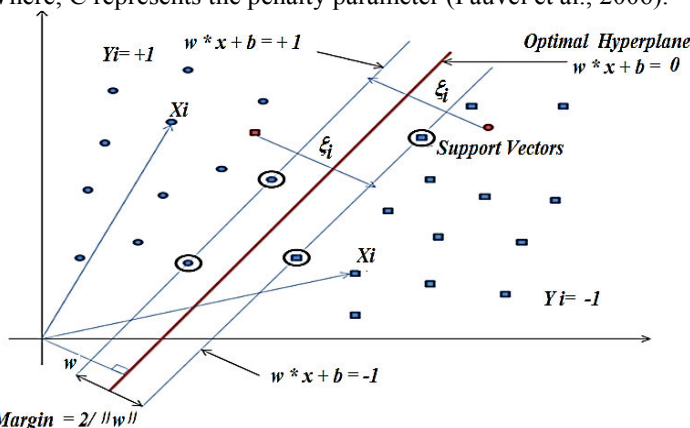
(Adapted from Fauvel, Chanussot & Benediktsson 2006)

Figure2.Example of a Non-Linearly Separable Case by SVM

This penalty parameter entered by the analyst in the ENVI 4.8 software, allows for a certain level of misclassifications. Larger assigned C value assigned means higher penalty for misclassified pixels (Pal, Mather 2005). Initially, SVM was a binary classification but a multiclass classification problem can be analyzed in order to examine a combination of several binary classifications, or basically, each pair of classes is measured

separately (Pal & Mather, 2005; ITT Visual Information Solutions, 2008b) and others indicated that this strategy gave the optimum results in the case of a multi-class scenario (Pal, Mather 2005, Melgani, Bruzzone 2004).
In fact, Mprovidesand Bruzzone (2004) state that SVMs provides higher accuracy than traditional methods such as the MLC, a theory that was tested by Melgani and Bruzzone (2004) for land cover classification mapping. Likewise, in remote-sensing, it is not common to create linearly separable sets of training classes, but by using kernels, nonlinear SVMs can be developed (Fauvel, Chanussot & Benediktsson 2006). Kernel methods can generalize remote sensing data through sorting and projection of data into a higher dimension (Fauvel, Chanussot & Benediktsson 2006). There are several kernels to choose from. The ENVI 4.8 software provides four different types: linear, polynomial, sigmoid, and radial basis function (RBF). This study chose RBF as it provides optimum results and has been proven to be the most popular from the literature (Pal, Mather 2005, Hermes et al. 1999, Melgani, Bruzzone 2004, Fauvel, Chanussot & Benediktsson 2006). The RBF kernel is defined as follows:

$$(x_i, x_j) = exp\left[-\gamma \|x_i - x_j\|^2\right]$$

In which the gamma γ parameter is entered by the analyst and controls the width of the kernel (Foody, Mathur 2004). In order to use the RBF kernel in the ENVI 4.8 software, the gamma γ and C parameters need to be wisely selected to avoid the SVM over fitting the training data, a common result of using high values for the two parameters (Foody, Mathur 2004). There is little information in the literature on ways to identify these parameters; as such, there is a necessity to resort to trial and error to select the optimal values for γ and C (Pal, Mather 2005).

4. Over View of Image classification

Until today, there is still need to produce regional land use land cover maps for the variety of purposes of government, public, private, and national security applications besides to support regional landscape planning and resource management (Aplin, Atkinson 2004, Jensen 2005). Many new classifications have been introduced and have become more popular compared to supervised classification and unsupervised classification (traditional classification algorithms) for land use and land cover mapping , change detection and improve the accuracy of maps and classified images. Dewan, Yamaguchi (2009) used the (ISODATA) clustering algorithm with the maximum likelihood method to produce classification maps as well as the same classification algorithms used by Binh et al. (2005) to create land cover maps and detect land cover changes in Vietnam. Müllerová in (2005) utilized (ISODATA) clustering algorithm, the Parallelepiped and Maximum Likelihood classification to land cover mapping.

For a particular study, it is often difficult to identify the best classifier due to the lack of a guideline for selection and the availability of suitable classification algorithms to hand. With the availability of various classification methods, the popular approach is a comparative analysis to try and decide what is best for a specific dataset. Moreover, the combination of different classification approaches has shown to be helpful for the improvement of classification accuracy. Many of classification algorithms are compared such as the study conducted by Guo et al. (2008), in which four broad classification methods were employed, which are Maximum Likelihood Classification (MLC), Self-Organized Neural Network (SONN), Support Vector Machine (SVM), and Decision Tree Classification (DTC). In conclusion, DTC determined as the best and MLC as one of the classical methods as it is more stable than the other three methods. While in another study conducted by (Pal, Mather 2005)Pal and Mather (2005), there was a comparison of Support Vector Machines (SVM), Maximum Likelihood, and Neural Network (ANN) classifiers to identify land cover types using Landsat 7 ETM+ and hyper spectral data. Both Neural Network (ANN) and SVM classifiers are dependent on user-defined parameters to achieve proper functionality. Results for the classifications showed SVM produced the most accurate results for both types of data.

In a another study presented by Foody and Mathur (2004), SVM was tested against other classifiers, Decision Trees and Neural Network data in an agricultural area in England to produce land use / land cover maps and determine the highest overall accuracy. The SVM classification resulted in 93.8% accuracy despite the ability of the SVM to function with minimum training data, training set size and overall accuracy are positively related (Foody, Mathur 2004). The classification process and results are influenced by a variety of factors, including availability of remotely sensed data, landscape complexity, image band selection, the classification algorithm used, analyst's knowledge about the study area, and analyst's experience with the classifiers used

Due to lack of reference and raw data in order to produce high accuracy classified images and maps, some researchers tried to combine most of the classification methods together as Hybrid classification. Hybrid classification takes advantage of both the supervised classification and unsupervised classification. In this method, multi-spectral images, firstly, an unsupervised one is preformed, then the result is interpreted using ground truth knowledge and, finally the original images are reclassified using a supervised classification with the aid of the statistics of the unsupervised classification as training knowledge. For example, Zaki, Abotalib Zaki

(2011) have obtained high results by using hybrid classification in a combination of unsupervised classifications (ISODATA) and Maximum likelihood as supervised to produce land cover maps by using multi-temporal Landsat images (TM) in Northeast Cairo, Egypt. Then, the post classification change detection technique and field investigation were applied and this method has proved beneficial for understanding human activity impacts on the urban environment. In a similar study, Alphan, Doygun and Unlukaplan (2009) used the same hybrid combination of multi-temporal Landsat and ASTER imagery to assess land cover (LC) changes in Turkey. Both studies concluded that this combination was useful to increase classification accuracy.

5. Conclusion

One of the most important uses of remote sensing is the production of Land Use / Land Cover maps and thus can be done through a process called "Image Classification". Image Classification had made great progress over the past decades in the following four areas: (1) producing land cover map at regional and global scale; (2) development and use of advanced classification algorithms, such as subpixel, pre-field, and knowledge-based classification algorithms; (3) use of multiple remote-sensing features, including spectral, spatial, multitemporal, and Multisensor information; and (4) incorporation of ancillary data into classification procedures, including such data as topography, soil, road, and census data. Accuracy assessment is an integral part in an image classification procedure.The success of an image classification in remote sensing depends on many factors, the availability of high-quality remotely sensed imagery and ancillary data, the design of a proper classification procedure, and the analyst's skills and experiences.

Reference

Alphan, H., Doygun, H. & Unlukaplan, Y.I. 2009, "Post-classification comparison of land cover using multitemporal Landsat and ASTER imagery: the case of Kahramanmaraş, Turkey", Environmental monitoring and assessment, vol. 151, no. 1, pp. 327-336.

Aplin, P. & Atkinson, P.M. 2004, "Predicting missing field boundaries to increase per-field classification accuracy", Photogrammetric Engineering and Remote Sensing, vol. 70, no. 1, pp. 141-149.

Binh, T.N.K.D., Vromant, N., Hung, N.T., Hens, L. & Boon, E. 2005, "Land cover changes between 1968 and 2003 in Cai Nuoc, Ca Mau peninsula, Vietnam", Environment, Development and Sustainability, vol. 7, no. 4, pp. 519-536.

Camps-Valls, G., Gómez-Chova, L., Calpe-Maravilla, J., Martín-Guerrero, J.D., Soria-Olivas, E., Alonso-Chordá, L. & Moreno, J. 2004, "Robust support vector method for hyperspectral data classification and knowledge discovery", Geoscience and Remote Sensing, IEEE Transactions on, vol. 42, no. 7, pp. 1530-1542.

Castellana, L., d'Addabbo, A. & Pasquariello, G. 2007, "A composed supervised/unsupervised approach to improve change detection from remote sensing", Pattern Recognition Letters, vol. 28, no. 4, pp. 405-413.

Černá, L. & Chytrý, M. 2005, "Supervised classification of plant communities with artificial neural networks", Journal of Vegetation Science, vol. 16, no. 4, pp. 407-414.

Chen, P., Lu, X., Liew, S. & Kwoh, L. 2002, "Quantification of land cover change and its impact on hydro-geomorphic processes in the upper yangtze using multi-temporal Landsat imagery: An example of the Minjiang area", Geoscience and Remote Sensing Symposium, 2002. IGARSS'02. 2002 IEEE InternationalIEEE, , pp. 1216.

Dewan, A.M. & Yamaguchi, Y. 2009, "Using remote sensing and GIS to detect and monitor land use and land cover change in Dhaka Metropolitan of Bangladesh during 1960-2005", Environmental monitoring and assessment, vol. 150, no. 1-4, pp. 237-249.

Fauvel, M., Chanussot, J. & Benediktsson, J.A. 2006, "Evaluation of kernels for multiclass classification of hyperspectral remote sensing data", Acoustics, Speech and Signal Processing, 2006. ICASSP 2006 Proceedings. 2006 IEEE International Conference onIEEE, , pp. II.

Foody, G.M. & Mathur, A. 2004, "A relative evaluation of multiclass image classification by support vector machines", Geoscience and Remote Sensing, IEEE Transactions on, vol. 42, no. 6, pp. 1335-1343.

Gamanya, R., De Maeyer, P. & De Dapper, M. 2009, "Object-oriented change detection for the city of Harare, Zimbabwe", Expert Systems with Applications, vol. 36, no. 1, pp. 571-588.

Gong P. and P.J. Howarth, 1990. An assessment of some factors influencing multispectral land-cover classification, Photogrammetric Engineering and Remote Sensing, 56(5):597-603.

Gualtieri, J.A. & Cromp, R.F. 1999, "Support vector machines for hyperspectral remote sensing classification", The 27th AIPR Workshop: Advances in Computer-Assisted RecognitionInternational Society for Optics and Photonics, , pp. 221.

Guo, J., Zhang, J., Zhang, Y. & Cao, Y. 2008, "Study on the comparison of the land cover classification for multitemporal MODIS images", Earth Observation and Remote Sensing Applications, 2008. EORSA

2008. International Workshop onIEEE, , pp. 1.

Hermes, L., Frieauff, D., Puzicha, J. & Buhmann, J.M. 1999, "Support vector machines for land usage classification in Landsat TM imagery", Geoscience and Remote Sensing Symposium, 1999. IGARSS'99 Proceedings. IEEE 1999 InternationalIEEE, , pp. 348.

Jensen, J. 2005, "Introductory Digital Image Processing, 3rd", .

Keuchel, J., Naumann, S., Heiler, M. & Siegmund, A. 2003a, "Automatic land cover analysis for Tenerife by supervised classification using remotely sensed data", Remote Sensing of Environment, vol. 86, no. 4, pp. 530-541.

Keuchel, J., Naumann, S., Heiler, M. & Siegmund, A. 2003b, "Automatic land cover analysis for Tenerife by supervised classification using remotely sensed data", Remote Sensing of Environment, vol. 86, no. 4, pp. 530-541.

Langley, S.K., Cheshire, H.M. & Humes, K.S. 2001, "A comparison of single date and multitemporal satellite image classifications in a semi-arid grassland", Journal of Arid Environments, vol. 49, no. 2, pp. 401-411.

Lewiński, S. & Zaremski, K. 2004, "Examples of object-oriented classification performed on high-resolution satellite images", Warszawa, vol. 11, pp. 349-358.

Lillesand, T.M. & Keifer, R.W. 1994, Remote Sensing and Image Interpretation, .

Melgani, F. & Bruzzone, L. 2004, "Classification of hyperspectral remote sensing images with support vector machines", Geoscience and Remote Sensing, IEEE Transactions on, vol. 42, no. 8, pp. 1778-1790.

Müllerová, J. 2005, "Use of digital aerial photography for sub-alpine vegetation mapping: A case study from the Krkonoše Mts., Czech Republic", Plant Ecology, vol. 175, no. 2, pp. 259-272.

Pal, M. & Mather, P. 2005, "Support vector machines for classification in remote sensing", International Journal of Remote Sensing, vol. 26, no. 5, pp. 1007-1011.

Pradhan, R., Ghose, M. & Jeyaram, A. 2010, "Land Cover Classification of Remotely Sensed Satellite Data using Bayesian and Hybrid classifier", International Journal of Computer Applications IJCA, vol. 7, no. 11, pp. 1-4.

Ratanopad, S. & Kainz, W. 2006, "Land cover classification and monitoring in northeast thailand using landsat5 TM data", ISPRS Technical Commission II Symposium, Vienna.

Richards, J.A. & Jia, X. 2006, Remote sensing digital image analysis: an introduction, Springer Verlag.

Skidmore, A. 1989, "Unsupervised training area selection in forests using a nonparametric distance measure and spatial information", Remote Sensing, vol. 10, no. 1, pp. 133-146.

Su, X., Wu, W., Li, H. & Han, Y. 2011, "Land-Use and Land-Cover Change Detection Based on Object-Oriented Theory", Image and Data Fusion (ISIDF), 2011 International Symposium on, pp. 1.

Tou, J.T. & Gonzalez, R.C. 1974, "Pattern recognition principles", Image Rochester NY, vol. 7.

Vanderzee, D. & Ehrlich, D. 1995, "Sensitivity of ISODATA to changes in sampling procedures and processing parameters when applied to AVHRR time-series NDV1 data", Remote Sensing, vol. 16, no. 4, pp. 673-686.

Walter, V. 2004, "Object-based classification of remote sensing data for change detection", ISPRS Journal of Photogrammetry and Remote Sensing, vol. 58, no. 3, pp. 225-238.

Zaki, R. & Abotalib Zaki, S.A. 2011, "Land Use and Land Cover Changes in Arid Region: The Case New Urbanized Zone, Northeast Cairo, Egypt", Journal of Geographic Information System, vol. 3, no. 3, pp. 173-194.

Zhang, Z.M., Verbeke, L., De Clercq, E., Ou, X.K. & De Wulf, R. 2007, "Vegetation change detection using artificial neural networks with ancillary data in Xishuangbanna, Yunnan Province, China", Chinese Science Bulletin, vol. 52, pp. 232-243.

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