ISSN (ONLINE): 2395-695X
ISSN (PRINT): 2395-695X

International Journal of Advanced Research in Basic Engineering Sciences and Technology (IJARBEST)
Volume 2, Special Issue 19, October 2016

Land Cover Classification in Remote Sensing Images: A Survey

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***Abstract*— Land cover classification is an integral part of remote sensing image analysis. This paper provides a survey of different land cover image classification approaches. It provides an overview of various steps involved in land cover classification and recent work carried out in this area. Experiments are conducted to perform land cover classification of LANDSAT images and the results are given.**

***Keywords*— Remote sensing, Land cover classification,; Supervised, Unsupervised, Extraction.**

I. INTRODUCTION

Land use/cover is the most excellent characteristic of landscapes on the earth's surface, and so it has become an integrated part of studies of global change [3]. At present, remote sensing technology is one of the most important techniques for the procurement of land use/cover data. Previously, visual judgment was the main method used for the extraction of instruction from remote sensing images. This method has a relatively high accuracy but its efficiency is relatively low. The essential methods for the automatic extraction of remote sensing information are supervised and unsupervised classification. However, in the occupancy of spectral confusion generated by ground objects, it is hard to acquire classification results with high accuracy. In the past few decades, a many of classification algorithms and theories of images have been proposed, but the precision of the classification of remote sensing images was not ideal. Many studies have shown that the precision of classification of remote sensing images cannot be effectively increased by improving the recognition algorithms previously used [3]. This paper intends to provide a survey of various techniques available for land cover classification of remote sensing images. The paper is organized as follows. Section II describes the steps involved in land cover classification of satellite images. Section III provides a survey of work carried out in the area of land cover classification of satellite images. Section IV gives the experimental results obtained for land cover classification using popular methods. Section V provides the conclusion.

II. LAND COVER CLASSIFICATION

Classification among the objects is easy task for humans but it has proved to be a confused problem for machines. The growth of high-capacity computers, the availability of high quality and low-priced video cameras, and the increasing need for automatic video analysis has produced an interest in object classification algorithms. A satellite image is the part of the earth taken using artificial satellites. These images have a variety of uses, like: cartography, military intelligence and meteorology. Satellite images are visible light images, water vapor images or infrared images Land cover classification process of satellite images consists of various steps including data pre-processing, feature extraction, trained data selection, judgment and classification and post-processing as depicted in Figure 1.

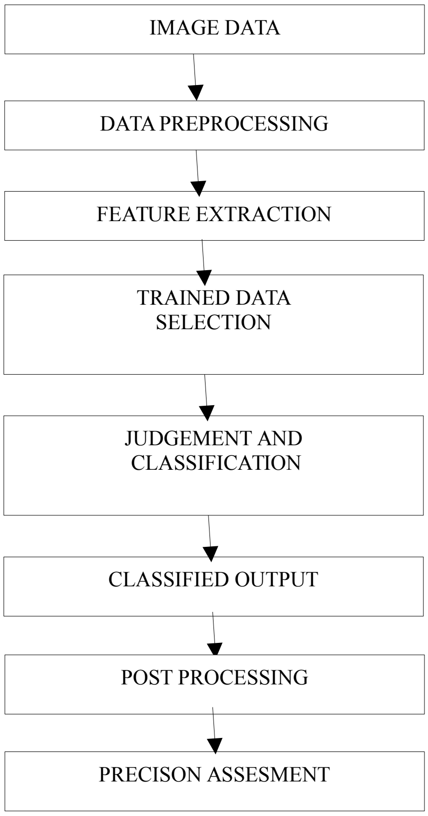

Fig 1. Steps for land cover classification

A. Pre-processing

It is necessary to preprocess the remote sensing data and terrain factor before forest vegetation classification with remote sensing. The main aggregation of remote sensing data preprocessing are as follows: geometric correction, topographic retribution, atmospheric correction, tasseled cap transform and so on. The terrain factor preprocessing is mainly acquisition of terrain factor using topographic map.

B. Feature Extraction

Texture is defined as the spatial variation in gray value, and is independent of color or luminance [1]. Texture is described mainly by histograms, the gray-level co-occurrence matrix, local statistics and characteristics of the frequency spectrum. At present, the gray-level co-occurrence matrix is most often used. Shape information about ground objects, which is one of the main features of remote sensing images, is an important aid for the extraction of information about ground objects [2]. The methods for discovering shape information about ground objects include methods based on perimeter and area, on area alone, and on perimeter-area ratio [5]. Nonstandard water bodies and shadows can be differentiated based on the area or by establishing a shape index based on area and perimeter [3].

C. Feature Selection

The collected data consists of several variables, but not all variables have the same influence on classification. Indeed, if we have insufficient training data, using too many features may damage classification performance. Many classification algorithms including ANNs do not generally perform well with data containing a wealth of attributes that are not predictive of class membership [6]. With these classifiers, feature selection has to take place before the data mining process starts.

III. LITERATURE REVIEW

The fusion methods used for the panchromatic and multispectral data can add hue, intensity and saturation (HIS) transformation, Principal Component Analysis, color standardization, and a wavelet transform [3] Typical features such as shadows can be used as a type of ground object in various studies [3, 4]. Texture analysis makes use of a single band, principal component analysis of the multispectral images was conducted [3]. Spectral separability analysis, incorporating mean and standard deviation values of extreme classes in each scene, was applied to all indices in order to assess the most suitable index for differentiating between degraded and non-degraded land [7][8]. This analysis revealed that the brightness index (BI) produced the best separability value and consequently was selected for further analysis [9]. Compared to the single dates, the usage of multi-temporal imagery for classification of land cover has increased both the average and the minimum separability of classes by the combination of spring and summer images [28]. Image fusion (or pan-sharpening) techniques have proven to be effective tools for providing better image information [10[11]. Four temporal features included the maximum, the minimum, the mean and the standard deviation value of the fused time series NDVI data were extracted for further land cover classification [12]. These temporal features could represent the vegetation growth characteristics and provided phonological information for improving vegetation type identification. The fou1r temporal features were composited with Landsat spectral data for further land cover classification. A new region-merging segmentation technique which incorporates the spectral and textural elements of the objects to be detected and also their different size and different behavior on various stages of scale, respectively [13].

The concept of scale is important in image analysis as most environmental dimensions carry one or more domain ns of scale [14] at which the individual spatial or temporal patches can be treated as functionally homogeneous. A Support Vector Machine (SVM) is used to classify vegetation and shadow objects related on spectral features at this segmentation level [15]. For precedent, [50] made a system for satellite image classification based on expert knowledge. More recently,[16] made a knowledge-base of urban objects, allowing the interpretation of high spatial resolution images in form to assist urban planner with mapping tasks. Re- cent studies devoted to trained knowledge formalization for auto-matic image interpretation have been directed towards ontologies. [17] proposed an ontology of spatial relations to teach medical image interpretation, which is the nenriched by fuzzy representations of concepts. Within the remote sensing scheme, both [18] and [19] propose ontology-based automatic procedures for image processing [20]. Supervised classification was done using ground checkpoints and digital topographic maps of the research area [21]. The area was classified into eight main classes: seawater, salt marshes, Sabkha, cropland, grassland, bare land, urban and quires.

Many researchers have mentioned that a meaningful correlation exists between spectral data and different vegetation buildup parameters [29] suggested that, when possible, three images (spring, early-summer, late-summer) be used in the identification of summer crops, winter crops and rangelands. The digital classification techniques add the unsupervised (K-means and ISODATA), supervised and object-based classification; out of which the most widely used classification technique is the supervised classification technique; however, object-related classification has shown better accuracy [30]. Furthermore, object-based classification is attainable with the use of high spatial resolution of the satellite imagery. Often, in cases of spectral mixtures, a hybrid classification is used for analyzing land features [31].

Newly many efforts aimed at it have become popular [32,33]. Moreover, the multiple classifier systems (MCSs) are construct to be successful with the combination of diverse classifiers. i.e., the classifiers should not commit the same faults. Further, the work of an MCS is highly dependent on the combination scheme. Many studies have been published in this area of research, e.g., if only class markers are available a majority voting [34,35] or label ranking [36,37] is used. If uninterrupted outputs like posteriori probabilities are applicable, an average or some other linear mixture can be used [38,39]. If the classifier outputs are explained as fuzzy membership values then fuzzy standards, acceptance functions and Dempster-Shafer techniques [40,8] can be used for mixture.

SNo	Author Name	Proposed Method	Year
1	XU Junyi et al	A new approach to dual-band polar metric radar remote sensing image classification	2005
2	AnFei Liu et al	A New ART Neural Networks for Remote Sensing Image Classification	2005
3	B. Uma Shankar et al	Remote Sensing Image Classification: A Neuro-fuzzy MCS Approach	2006
4	Ming-Hseng Tseng et al	A genetic algorithm rule-based approach for land-cover classification	2007
5	Ruvimbo Gamanya et al	An automated satellite image classification design using object-oriented segmentation algorithm	2007
6	YU Jie et al	Remote Sensing Image Classification Based on Improved Fuzzy *c*-Means	2008
7	Devis Tuia et al	Structured Output SVM for Remote Sensing Image Classification	2011
8	LIU Chuang et al	Research on Remote Sensing Image of Land Cover Classification Based on Multiple Classifier Combination	2011
9	Ying Liu et al	A self-trained semi supervised SVM approach to the remote sensing land cover classification	2013
10	Xiaoyong Bian et al	Clustering-Based Extraction of Near Border Data Samples for Remote Sensing Image Classification	2013
11	Chengjie Zhu et	Robust Semi-supervised Kernel-FCM Algorithm Incorporating Local Spatial Information for Remote Sensing Image Classification	2014
12	Mengmeng Li et al	Binary Partition Tree and energy minimization for object-based classification of urban land cover	2015
13	Jiaojiao Li et al	An efficient radial basis function neural network for hyper spectral remote sensing image classification	2015
14	Jianqiang Gao	A Novel Spatial Analysis Method for Remote Sensing Image Classification	2015
15	1 Pankaj Pratap Singh	Fixed Point ICA Based Approach for Maximizing the Non-gaussianity in Remote Sensing Image Classification	2015

The maximum likelihood classifier (MLC) was preferred for the land cover classification of Landsat data integrating temporal features extracted from time series data. The MLC was the traditional parametric classifier used for remote sensing data classification. The maximum likelihood classifier (MLC) was preferred for the land cover classification of Landsat data integrating temporal features extracted from time series data. The MLC was the traditional parametric classifier used for remote sensing data classification, which pretended that a hyper-ellipsoid decision volume could be used to approximate the shape of the information clusters [22].

TABLE I
RECENT WORK CARRIED OUT IN REMOTE SENSING IMAGE CLASSIFICATION

Pixel-based classification plays an important role in several remote sensing applications, such as land cover and target recognition. Remote sensing image classification is often performed by support vector machines—SVMs [23,24,25],artificial neural networks—ANNs[26,25], and optimum-path forest—OPF, but without taking in to account the spatial and temporal dependencies among pixels. [27] employed a linkage-based clustering algorithm for land cover classification using contextual information. Table 1 summarizes the recent work carried out in remote sensing image classification.

IV. EXPERIMENTS ON LAND COVER CLASSIFICATION

A 7-band LandSat Thematic Mapper (TM) image to create a land cover map of Pune and its surrounding region is considered in this experiment. The LandSat TM bands with their wavelengths and names are given in Figure 2 and Table II.

Fig 2. 7-band LandSat Thematic Mapper (TM) image of Pune

TABLE II.
BAND INFORMATION

Bands	Range	Names
Band 1	0.45 – 0.52	Red

Band 2	0.52 – 0.60	Green
Band 3	0.63 – 0.69	Blue
Band 4	0.76 – 0.90	NIR
Band 5	1.55 – 1.75	SWIR
Band 6	10.40 – 12.50	TIR
Band 7	2.08 – 2.95	MIR

The number of clusters is set as 50 and the resultant classified image with the land cover segments is shown in Figure 3.

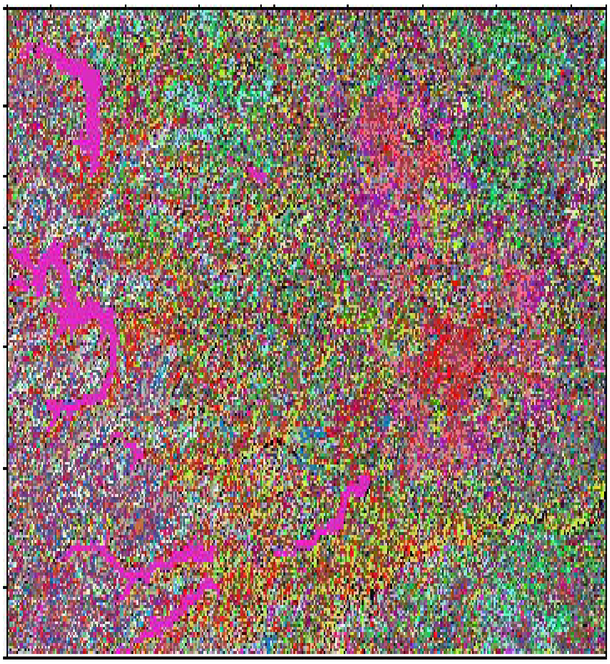

Fig 3. Cluster Image

By means of the cluster listed in Figure 4, information about all of the typical ground objects in the research area could be extracted. When cluster based image classification is adopted, the data after classification shown in Figure 5.

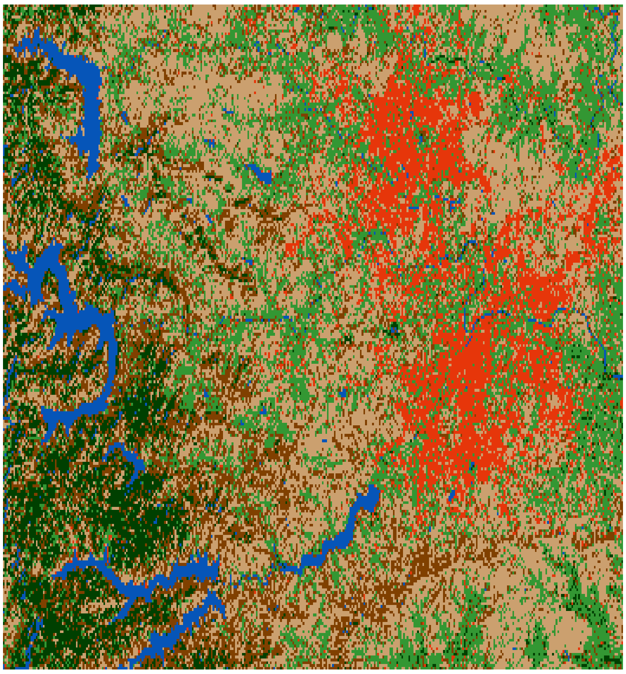

Fig 5. Classified Land Cover

	COLOR	NAME	DESCRIPTION	MINIMUM	MAXIMUM
1		Class 1	Class 1	0.000000	0.00000
2		Class 2	Class 2	1.000000	1.00000
3		Class 3	Class 3	2.000000	2.00000
4		Class 4	Class 4	3.000000	3.00000
5		Class 5	Class 5	4.000000	4.00000
6		Class 6	Class 6	5.000000	5.00000
7		Class 7	Class 7	6.000000	6.00000
8		Class 8	Class 8	7.000000	7.00000
9		Class 9	Class 9	8.000000	8.00000
10		Class 10	Class 10	9.000000	9.00000
11		Class 11	Class 11	10.000000	10.00000
12		Class 12	Class 12	11.000000	11.00000
13		Class 13	Class 13	12.000000	12.00000
14		Class 14	Class 14	13.000000	13.00000
15		Class 15	Class 15	14.000000	14.00000
16		Class 16	Class 16	15.000000	15.00000
17		Class 17	Class 17	16.000000	16.00000
18		Class 18	Class 18	17.000000	17.00000
19		Class 19	Class 19	18.000000	18.00000
20		Class 20	Class 20	19.000000	19.00000
21		Class 21	Class 21	20.000000	20.00000
22		Class 22	Class 22	21.000000	21.00000
23		Class 23	Class 23	22.000000	22.00000
24		Class 24	Class 24	23.000000	23.00000
25		Class 25	Class 25	24.000000	24.00000
26		Class 26	Class 26	25.000000	25.00000

Fig 4. Class Information

V. CONCLUSIONS

T This paper provided a study and brief knowledge about the different land cover image classification approaches It provided an overview of various steps involved in land cover classification and recent work carried out in this area. Classification of land cover of remote sensing images had been carried out for LANDSAT images and the results were also given. Most widely used approaches for image classification can be categorized as supervised and unsupervised, or parametric and nonparametric or object-oriented, sub pixel, per-pixel and per field or spectral classifiers, contextual classifiers and spectral-contextual classifiers or hard and soft classification.

REFERENCES

[1] Mäenpää .T and Pietikäinen .M, "Classification with color and texture: Jointly or separately?," Pattern Recognit., vol. 37, no. 8, pp. 1629–1640, 2004.

[2] Blaschke .T, "Object based image analysis for remote sensing," ISPRS Journal of Photogrammetry and Remote Sensing, vol. 65, no. 1. pp. 2–16, 2010.

[3] Zhang .R and Zhu .D, "Study of land cover classification based on knowledge rules using high-resolution remote sensing images," Expert Syst. Appl., vol. 38, pp. 3647–3652, 2011.

[4] Wang, T., Zhou, T., & Wu, Z, "Land use classification of remote sensing image based on knowledge rules," Chinese Geography and Geo-Information Science., vol. 24, no. 8, pp. 32–35, 2008.

[5] Li, X,"A new method to improve classification accuracy with shape information," Remote Sensing of Environment China, 10(4), 151–160, 1995.

[6] Roiger, R.J., Geatz, M.W, "Data Mining: A Tutorial-Based Primer," Addison Wesley, Boston, 2003.

[7] Kaufman, Y.J., Remer, L.A. "Detection of forests using MID-IR reflectance—an application for aerosol studies," IEEE Transactions on Geoscience and Remote Sensing., vol. 32, pp. 672–683, 1994.

[8] Lasaponara, R."Estimating spectral separability of satellite derived parameters for burned areas mapping in the Calabria region by using SPOTVegetation data," Ecological Modelling., vol. 196, pp. 265–270, 2006.

[9] Karnieli .A, Gilad . U, Ponzet .M, Svoray .T, Mirzadinov .R, and Fedorina .O, "Assessing land-cover change and degradation in the Central Asian deserts using satellite image processing and geostatistical methods," J. Arid Environ., vol. 72, no. 11, pp. 2093–2105, 2008.

[10] Pohl, C., Van Genderen, J.L,"Multi-sensor image fusion in remote sensing: concepts, methods and applications," International Journal of Remote Sensing., vol. 19, no. 5,pp. 823–854, 1998.

[11] Zhang, Y,"Understanding image fusion Photogrammetric Engineering and Remote Sensing," vol. 70, no . 6, pp. 657–661, 2004.

[12] Rouse, J. W., Jr., Haas, R. H., Schell, J. A., & Deering, D. W., "Monitoring vegetation systems in the Great Plains with ERTS. In S. C. Freden," Mercanti E.P., & Becker .M (Eds.), Third earth resources technology satellite-1 symposium technical presentations, section A (vol.I, pp. 309–317). Washington, DC: National Aeronautics and Space Administration, NASA SP-351, 1973.

[13] Baatz, M., & Scha¨pe, A. "Multiresolution segmentation—an optimization approach for high quality multi-scale image segmentation," In J. Strobl et al. (Eds.), Angewandte Geographische Informationsverarbeitung XII. Beita¨ ge zum AGIT-symposium Salzburg (pp. 12–23), 2000.

[14] Wiens, J. "Spatial scaling in ecology," Functional ecology., vol. 3, no. 8, pp. 120–129, 1989.

[15] Hsu, C.-W., Chang, C.-C., Lin, C.-J. "A practical guide to support vector classification," 2003,

[16] Forestier,G.,Puissant,A.,Wemmert,C.,Gançarski,P."Knowledge-based region labeling for remote sensing image interpretation," Comput . Environ .Urban Syst., vol. 36, pp. 470–480, 2012.

[17] Hudelot,C.,Atif,J.,Bloch,I."Fuzzy spatial relation ontology for image inter-pretation," Fuzzy Sets Syst., vol. 159, pp. 1929–1951, 2008.

[18] Durand,N.,Derivaux,S.,Forestier,G.,Wemmert,C.,Gançarski,P.,Boussai d,O., Puissant, A."Ontology-based object recognition for remote sensing image interpretation," In: Proceedings of the 19th IEEE Intelligence,vol.01.IEEEComputerSociety,Washington, DC, USA,pp.472–479, 2007.

[19] Andres,S.,Arvor,D.,Pierkot,C."Towards an ontological approach for classifying remote sensing images,".In:2012 International Conference on Signal Image Technology and Internet Based Systems (SITIS),pp.825–832, 2012.

[20] Bayoudh .M, Roux .E, Richard .G, and Nock .R, "Structural knowledge learning from maps for supervised land cover/classification: Application to the monitoring of land cover/use maps in French Guiana," Comput. Geosci., vol. 76, pp. 31–40, 2015.

[21] Shalaby .A and Tateishi .R, “Remote sensing and GIS for mapping and monitoring land cover and land-use changes in Northwestern coastal zone of Egypt,” Appl. Geogr., vol. 27, no. 1, pp. 28–41, 2007.

[22] Foody, G.M., Campbell, N.A., Trodd, N.M., Wood, T.F."Derivation and applications of probabilistic measures of class membership from the maximum-likelihood classification," Photogram. Eng. Remote Sens., vol. 58, pp. 1335–1341, 1992.

[23] N.Alajlan, Y.Bazi, F.Melgani, R.R.Yager, "Fusion of supervised and unsupervised learning for improved classification of hyper spectral images," Inf. Sci., vol. 217, no. 0, pp. 39–55, 2012.

[24] Keuchel .J, Naumann .S, Heiler .M, Siegmund .A. "Automatic landcover analysis for Tenerife by supervised classification using remotely sensed data," Remote Sens. Environ., vol. 86, no. 4, pp. 530–541, 2003.

[25] Knorn .J, Rabe .A, Radeloff .V.V, Kuemmerle .T, Kozak .J, Hostert .P, "Landcover mapping of large areas using chains classification of neighboring Land sat satellite images," RemoteSens. Environ., vol. 13, no. 5, pp. 957–964, 2009.

[26] Ji .C.Y, "Land-use classification of remotely sensed data using Kohonen self-organizing feature map neural networks," Photogrammetric Eng.RemoteSens., vol. 66, no. 12, pp.1451–1460, 2000.

[27] Stuckens .J, Coppin .P, Bauer .M, "Integrating contextual information with per-pixel classification for improved landcover classification," RemoteSens. Environ., vol. 71, no. 3, pp. 282–296, 2000.

[28] Yuan .F, Sawaya .K.E, Loeffelholz .B.C, and Bauer .M.E, “Land cover classification and change analysis of the Twin Cities (Minnesota) metropolitan area by multitemporal Landsat remote sensing,” Remote Sens. Environ., vol. 98, no. 2–3, pp. 317–328, 2005.Jensen, J.R., 1986. Introductory Digital Image Processing, A Remote Sensing Perspective. Prentice-Hall, New Jersey, 379pp.

[29] Houborg, R., Boegh, E., "Mapping leaf chlorophyll and leaf area index using inverse and forward canopy reflectance modeling and SPOT reflectance data," Remote Sensing of Environment vol. 112, no. 1, pp. 186–202, 2008.

[30] Kumar, P., Singh, B.K., Rani, M.,"An efficient hybrid classification approach for land use/land cover analysis in a semidesert area using ETM+ and LISS-III sensor," IEEE Sens. J., vol. 13, no. 6, pp. 2161–2165, 2013.

[31] Nizalapur, V., 2008. Land cover classification using multi-source data fusion of ENVISAT-ASAR and IRS P6 LISS-III satellite data – a case study over tropical moist deciduous forested regions of Karnataka, India. Int. Arch. Photogram. Rem. Sens. Spatial Inform. Sci. XXXVII (Part B6b), Beijing, China.

[32] Drucker, H., Cortes, C., Jackel, L.D., LeCun, Y., Vapnik, V."Boosting and other ensamble methods," Neural Computation., vol. 6, pp. 1289–1301, 1994.

[33] Bertolami, R., Bunke, H.: Ensemble methods for handwritten text line recognition systems. In: Proceedings of the IEEE International Conference on Systems, Man and Cybernetics. pp. 2334–2339, 2005.

[34] Kimura, F., Shridhar, M, "Handwritten numerical recognition based on multiple algorithms. Pattern Recognition," vol. 24, pp. 969–983, 1991.

[35] Franke, J., Mandler, E,"A comparison of two approaches for combining the votes of cooperating classifiers. In: Proceedings of 11th IAPR International Conference on Pattern Recognition systems," pp. 611–614, 1992.

[36] Ho, T.K., Hull, J.J., Srihari, S.N,"Decision combination in multiple classifier systems," IEEE Transactions on Pattern Analysis and Machine Intelligence., vol. 16, pp. 66–75,1994.

[37] Bagui, S.C., Pal, N.R,"A multistage generalization of the rank nearest neighbor classification rule. Pattern Recognition Letters," vol. 16, pp. 601–614, 1995.

[38] Xu, L., Krzyzak, A., Suen, C.Y.: Methods of combining multiple classifiers and their applications to h andwriting recognition. IEEE Transactions on Systems, Man, and Cybernetics., vol. 22, pp. 418–435, 1992.

[39] Hashem, Schmeiser, B,"Improving model accuracy using optimal linear combinations of trained neural networks," IEEE Transactions on Neural Networks., vol. **6, pp.** 792–794, 1995.

[40] Qi, J., Chehbouni, A., Huete, A.R., Kerr, Y.H., Sorooshian, S,"A modified soil adjusted vegetation index. Remote Sensing of Environments," vol. 48, pp. 119–126, 1994.