IDENTIFICATION OF GROWTH STAGE OF SUGARCANE CROP USING DECISION TREE FOR LANDSAT-8 DATA

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KEY WORDS: DECISION TREE CLASSIFIER, VEGETATION INDICES, CROP IDENTIFICATION, LANDSAT-8

ABSTRACT: Remote sensing images are useful for identifying crops. Freely available medium resolution Landsat-8 data is used in this study to identify sugarcane crop area from the study scene. Many authors have proved usefulness of Landsat-8 for crop identification and mapping. However, for fields having size less than one acre, Landsat-8 data of 30 m resolution may produce inaccurate results. In this investigation, decision trees have been constructed using only spectral reflectance response of bands, only principal components, combined use of spectral reflectance and texture images and combined use of spectral reflectance and Normalized Difference Vegetation Index (NDVI). Ten images acquired over a year, of the study area have been observed to prepare crop growth profile. NDVI, Leaf Area Index (LAI), Green-Red Vegetation Index (GRVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI), VI-Green, Normalized Red (NR), Normalized Near Infra-Red (NNIR), Difference Vegetation Index (DVI) and Urban Index (UI) images have been prepared. It has been observed that NDVI, LAI, GRVI, EVI, SAVI and DVI show similar spectral response curve and confirm the prepared crop growth profile. Decision tree identifies area other than crop at level one and further crop area is classified into ripening/ growing and harvest/senescence stage. It has been observed that low spectral reflectance of red band can support demarcation of sugarcane crop area effectively. Classified image is validated using ground truth data collected from 58 fields having sugarcane crop at senescence and 23 fields with crop at ripening stage. Results are compared with widely used Maximum Likelihood Classifier (MLC) method. Overall accuracy of MLC is higher but user's and producer's accuracy of decision tree increases by more than 5%. Accuracy assessment also shows that combined use of spectral reflectance and NDVI resulted in higher user's and producer's accuracy for identification of growth stage of sugarcane crop.

1. INTRODUCTION

Remote sensing images are useful for identification of crop types as larges area can be covered. Many sensors are available which can provide temporal profile of the same area. Selection of images and their time of capture is an important factor to consider for crop identification. This selection depends on spatial, spectral and temporal resolution of the sensors available. High spatial resolution images are more expensive and temporally limited to some extent.

The size of pixel in the image plays an important role in classifier accuracies. The number of pixels contained in one field will affect the classification accuracy. The spectral reflectance value of the crop is directly related to its phenological growth stage. Life cycle of a crop is sowing time, sprouting, maturing and harvesting. This varies with type of crop and can be recorded as spectral profiles. Spectral profiles generated for different crops can be used to identify type of the crop present in the field and also growth stage of a crop.

Transforming remote sensed images into thematic maps is usually done as multispectral image classification. (Jensen, 2006) Algorithms used for classification can be grouped into 2 categories: parametric (Maximum Likelihood classifier) and non-parametric (Decision Tree classifier). This depends on, whether each class is normally distributed or not.

A large number of authors have conducted comparisons of decision tree with other classifiers such as MLC, neural network and found that decision trees performed better (German et al.; Pal et al. 2001). In comparison to neural networks, decision trees are faster trained. The execution time required by a DT is less and is not a "black box" like a neural network, (Gahegan et al., 1998).

(Amit Verma et. al. 2016), Illustrated the use of decision tree method to classify the land into crop land and non-crop land and also classified different crops. Authors carried out classification using an integrated approach based on texture measures and vegetation indices as input to a decision tree. They found that inclusion of texture improved classification accuracy of 89.42%.

(Vladimir et. al., 2014), performed pixel-based cropland classification and used the fusion of data from satellite images with different resolutions. Authors used temporal multispectral images acquired at different resolutions from Landsat-8 and RapidEye. A new fusion method was utilized in combination with a robust random forest classifier in improving the overall classification performance. (Tassetti et. al., 2010) used vegetation index (NDVI & TDVI masks) and texture measures along with edge-density features to measure its impact on LULC classification on IKONOS imagery. Authors concluded that NDVI band combined with six texture features achieved an accuracy of 80.01% compared to 63.44% of accuracy achieved by input from few spectral bands only.

(Yacouba et. al., 2014) performed classification using expert system decision tree and Ctree model to assess the land use land cover change (LULC). Authors attained classification overall accuracies of 94, 97 and 92% for three date images of Landsat-7. They have not compared these results with any other classification method. (Karakus et. al., 2016) used SPOT 5 image to compare the potential classification accuracy provided by pan sharpened image (Gram-Schmidt). Four different classification methods were investigated: maximum likelihood, decision tree, support vector machine at the pixel level and object based classification methods. Authors concluded that 95% classification is achieved for object based classification.

(Peña et. al., 2014) used C4.5 decision tree, logistic regression (LR), support vector machine (SVM) and multilayer perceptron (MLP) neural network methods, both as single classifiers and combined in a hierarchical classification. Authors used ASTER satellite images for mapping crops and concluded that SVM+SVM classifier improved these results to 89%.

(Srikrishna Shastri et. al., 2016) used LISS-IV dataset and applied Brovey Transform, Principal Component Analysis, Multiplicative Technique (MT), Intensity Hue Saturation and High Pass Filtering (HPF) methods for image fusion. (Uttam Kumar et. al., 2015) used dataset of Landsat-5 TM bands with spatial resolution of 30m and World View-2 (WV-2) with spatial resolution of 2m. Authors observed that fusing bands of 2 m spatial resolution can attain higher producer’s, user’s and overall accuracies as compared to the classification of medium- resolution Landsat and WV-2 data.

The main objective of this research is to improve the accuracy of the classification process by designing rules for the extracted features. Knowledge in the form of classification rules is extracted from the spatial data by using the Decision Tree approach. Classification rules are applied to classify the satellite image and then the accuracy assessment of the whole process is carried out to check, whether there is any change in the classification accuracy. Another sub-objective is to assess the impact of selection features i.e. spectral reflectance values, derived indices like NDVI, LAI, GRVI, EVI, SAVI and DVI for the decision tree classifier on the accuracy of the classification process

2. IMAGE DATASET DETAILS

Multispectral medium-resolution images from Landsat-8 are used to conduct this study. Ten images are acquired for a period of one year, 19th April, 2016 to 24th May 2017 downloaded from the USGS Earth Explorer database (United States Geological Survey) (http://earthexplorer.usgs.gov/). Images considered for study have cloud cover less than 10%. Landsat-8 has 16 days repeat cycle, providing data at swath of 185kms. Images are Level 1T (terrain corrected) scene of the OLI/TIRS sensor, of path & row: 146 & 46. Landsat-8 provide images in 11 bands with spatial resolution of 30 m for seven multispectral bands, 15m for PAN band and 2 thermal bands acquired at 100m, resampled to 30m.

3. STUDY AREA

The study site is Navin Kaigaon village in Maharashtra, India. The study area lies between 19° 10' 1.6" to 21° 16' 29.75" North Latitude and 74° 43' 44.83" to 76° 53' 42.79" East Longitude. It has mixture of land covers i.e. road, water body, buildings, bare farms and largest area has sugarcane crop and few farms with mango trees. This region has majorly agricultural land and a large number of fields have sugarcane crop at various growth stages. So, the focus of this study is to identify sugarcane crop at ripening/ growing and harvest/senescence stage.

For small field sizes, high resolution imagery from commercial satellites would be appropriate choice. However, the spectral characteristics of Landsat-8 are found to be suitable for classification of cropland, (F. Löw et. al., 2013). In this study area, minimum field size is 1 Acre ≈ 66 m, so the pixel size of Landsat-8 is adequate.

The study area has sugarcane crop at various growth stages. Crop fields of the study area are irregular in shape and size. Fields vary from one acre to twenty acres and even larger. The satellite data from Landsat-8 is used, considering size of the crop fields. As the spatial resolution is 30m for the bands used for study, fields have minimum 4 pixels (1Acre = 4400 sq.m). The blue, green, red, near infrared (NIR), and two short wave infrared (SWIR 1 and 2) bands are most commonly used for identification of crops. The red band has major chlorophyll absorption spectral range. Reflectance values of red band are very low, as sugarcane crop grows to its peak growth stage. Also, blue band shows higher spectral reflectance values when sugarcane reaches senescence stage. Figure 1 shows the subset of the image used in this study.

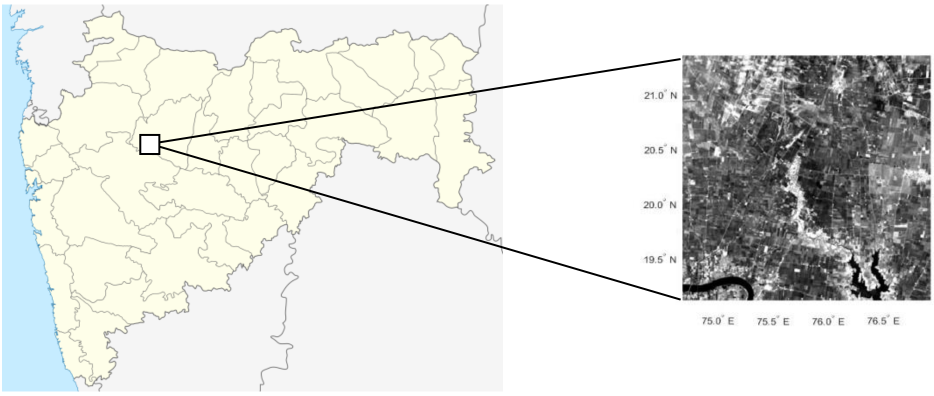

Figure 1. The study area is in the center of Maharashtra, India. Left hand-side is map of the Maharashtra state and right-hand side is image subset obtained from Landsat8.

4. Methodology used and Experimentation

After obtaining Landsat8 data, images are preprocessed/ corrected. Corrected image is taken as input and various classification algorithms are applied to check which classification techniques generates accurately classified data. Layer stacked images were also created using spectral features and texture features of reflectance image to apply classification algorithms.

4.1 Image Preprocess/Correction

Landsat8, L1T products are radiometrically & geometrically corrected. It uses GCPs and DEMs to perform geometric corrections. L1T image is presented in units of Digital Numbers (DNs), which can be rescaled to spectral radiance/ Top-Of-Atmosphere (TOA) reflectance. Landsat8 images (MS bands and PAN band) were converted to Top-of-Atmosphere reflectance values by applying radiometric calibration. (Information courtesy: usgs.gov/Landsat8DataUserhandbook.pdf). Accuracy of corrected image was verified with the Landsat8 surface reflectance higher level image obtained from USGS.

4.2 Classification methods used in the experiments

Supervised classification methods are based on the prior knowledge of the area to be classified. In this study methods used are Maximum Likelihood Classifier (MLC) and decision tree classifier. Major land cover classes namely road, water body, buildings, bare farms and largest area having sugarcane crop and few farms with mango trees are found to be present in the study area.

Maximum likelihood classifier: This is a supervised method to classify pixels into classes. The probability of pixels belonging to the identified set of classes is computed and then they are assigned to the class for which their probability is highest. Maximum Likelihood follows Bayesian probability (Paul 2009).

Decision Tree Classifier: Decision tree is non parametric classifier. Decision trees can be used to identify objects and classify them into various classes was introduced by (Hunt et.al.,1996). In decision tree, the root and internal nodes contain attribute test conditions and it works as a binary classifier at each level. At every level according to the result of the condition tested, records are separated having different characteristics. 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 branch 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. Building an optimal decision tree is key problem in decision tree classifier. Using given set of attributes, many decision trees can be built. Different trees will have different time complexities as some of the trees are more accurate than others. Constructing the optimal decision tree is compute intensive task.

4.3 Vegetation Indices used in this study

Annual NDVI profile of sugarcane crop is generated to characterize growth/ phenology spectral changes. This profile is created using multi-temporal L-8 dataset. Ten images with less than 10% cloud cover have been preprocessed and calibrated to create spectral growth profile.

NDVI, Leaf Area Index (LAI), Green-Red Vegetation Index (GRVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI) and Difference Vegetation Index (DVI) images have been prepared. It has been observed that NDVI, LAI, GRVI, EVI, SAVI and DVI show similar spectral response curve and confirm the prepared crop growth profile. Since all six indices calculated are found to be strongly correlated, correlation coefficient > 0.98, so only NDVI amongst all indices can be used to construct decision rules. Figure 2 shows the spectral response curve for the computed vegetation indices.

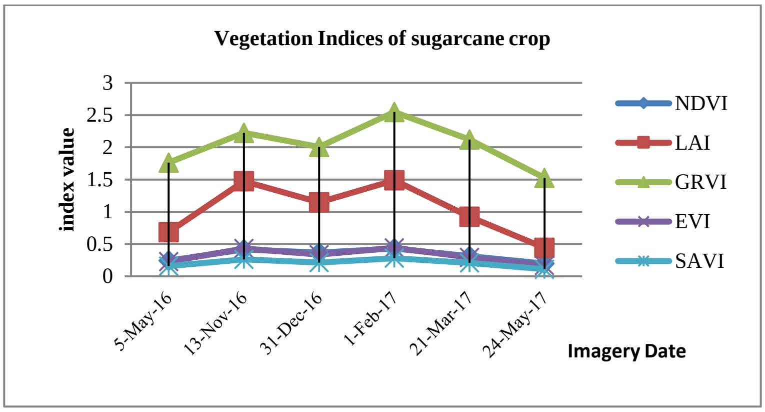

Figure 2. The spectral response curve for the vegetation indices (NDVI, LAI, GRVI, EVI, SAVI).

4.4. Ground truth data

To collect in-situ (ground truth) data, a team visited the study area in first week of June 2017. A total of 144 fields were selected from all over the study area to capture the spatial variability of spectral signatures of the same crop types. During the visit, 58 fields having sugarcane crop at senescence and 23 fields with crop at ripening stage were annotated. Other land cover classes i.e. water body, road, bare farm and urban area was also annotated. Training and testing set has been prepared by selecting pixels from different locations representing identified land cover features of the study area. Two different set of training and test samples were created for classification. Training set contained 423points as training samples. Using the training samples, the whole image area is classified into desired land cover types. Different set of 435points were created for testing the classification accuracies.

To select decision criteria for constructing decision tree, separability of training dataset has been computed using Jeffries-Matusita (J-M) and Transformed Divergence(T-D) values. A J-M distance of 2.0 indicates spectral classes can be classified with 100% accuracy (John, 2006). J-M and T-D values are recorded for different land covers which are marked using ground truth data collected. The training dataset shows required separation if J-M and T-D values are more than 1.9 and values below this have mixed pixels showing lower separation. While constructing decision tree, bands are considered having maximum separation values. Table 1 shows the J-M and T-D values for the annotated classes training dataset. J-M separability amongst identified classes is considered while constructing various decision trees and it has been observed low J-M values (less than 1.8) lowers accuracy of the classified image.

Table 1 : J-M and T-D values computed from training dataset for 24 May 2017 Landsat-8 image

Class Label	SC-HRVST	SC-GROWN	WATERBODY	OTHERS
SC-HRVST	0	1.90,1.99	2.0,2.0	1.45,1.90
SC-GROWN		0	2.0,2.0	1.99,2.0
WATERBODY			0	1.99,2.0
OTHERS				0

4.5 Decision tree

Decision tree works as a binary classifier at every level. A decision tree classifier is constructed by using training set and forming decision rules using multispectral bands. At level one, decision tree identifies water-body using spectral reflectance values of band 7 (SWIR 2) and at next level uses band 4 (red) or 3(green) to classify settlement/road/bare-farm labeled as class, others from the image. Further crop area is classified into ripening/ growing and harvest/senescence stage using NDVI values. NDVI values greater than 0.468 clearly identifies sugarcane crop at ripening/ growing stage.

It has been observed that low spectral reflectance of red band (L8: 0.64 µm to 0.67 µm) can support demarcation of sugarcane crop area effectively. Various decision trees were constructed by considering separability amongst the classes. The decision trees constructed uses spectral reflectance values of bands with highest separability and it has been observed that sugarcane crop at two growth stages, growing/harvest is best separable using vegetation indices. Figure 3 shows the optimal decision tree, producing best overall accuracy. This decision tree optimal as number of comparison operation required is less and using derived features, number of levels for decision making is only 3 as compared to seven levels, in case if only spectral reflectance values are used. Also accuracy is better.

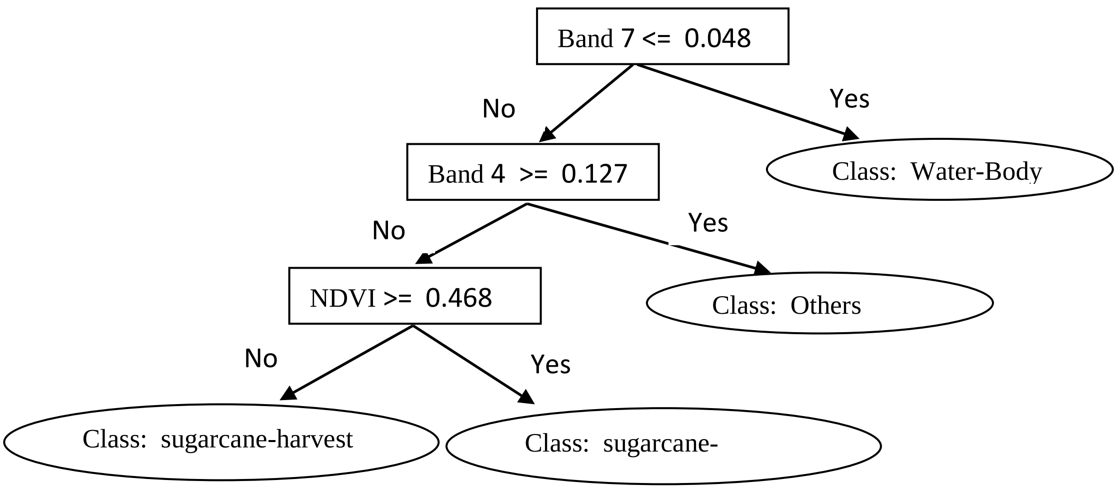

Figure 3 Decision tree for classifying four classes for Landsat-8 images dated 24th and 8th May 2017.

5. RESULT: CLASSIFICATION ACCURACIES AND KAPPA COEFFICIENTS

The result is validated by comparing the four classes identified as water-body, others and sugarcane crop fields at two stages (ripening/ growing and harvest/ senescence) with the ground truth region of interests marked. To compare results of the designed decision tree, both the images were also classified using MLC.

Classified image is validated using ground truth data collected from 58 fields having sugarcane crop at senescence and 23 fields with crop at ripening stage. Results are compared with widely used Maximum Likelihood Classifier

(MLC) method. Overall accuracy of MLC is higher but user's and producer's accuracy of decision tree increases by more than 5% for sugarcane crop at senescence and ripening stage. Accuracy assessment also shows that combined use of spectral reflectance and NDVI resulted in higher user's and producer's accuracy for identification of growth stage of sugarcane crop. The observations are recorded as shown in table 2 and 3.

Table 2 : Classification results for 24th May and 8th May 2017 Landsat-8 image

Sensor	Imagery Date	*DT OA (%)	DT Kappa	MLC OA (%)	MLC Kappa
Landsat - 8	24 May 2017	88.97%	0.86	89.88%	0.86
	8 May 2017	83.67%	0.79	87.12%	0.82

*DT: Decision Tree OA : Overall Accuracy MLC: Maximum Likelihood Classifier

Table 3 : User's accuracy (UA) & Producer's accuracy(PA) for 24th May and 8th May 2017 Landsat-8 image

Imagery Date: 24 May 2017					Imagery Date: 8 May 2017				
Class	Decision Tree		Maximum Likelihood Classifier		Class	Decision Tree		Maximum Likelihood Classifier	
	UA%	PA%	UA%	PA%		UA%	PA%	UA%	PA%
SC-Harvest	96.08	70	79.41	79.41	SC-Harvest	78.43	62.99	80.39	73.21
SC-Grown	97.22	97.22	93.06	97.00	SC-Grown	95.83	94.52	88.39	95.52
Water-Body	100	100	100	100	Water-Body	98.15	100	98.15	100
Others	72.55	96.52	88.24	86.54	Others	71.25	85.5	83.01	84.67

Following figures show the input images dated 24th May and 8th May 2017 and the classified images produced using decision tree classifier constructed and maximum likelihood classifier.

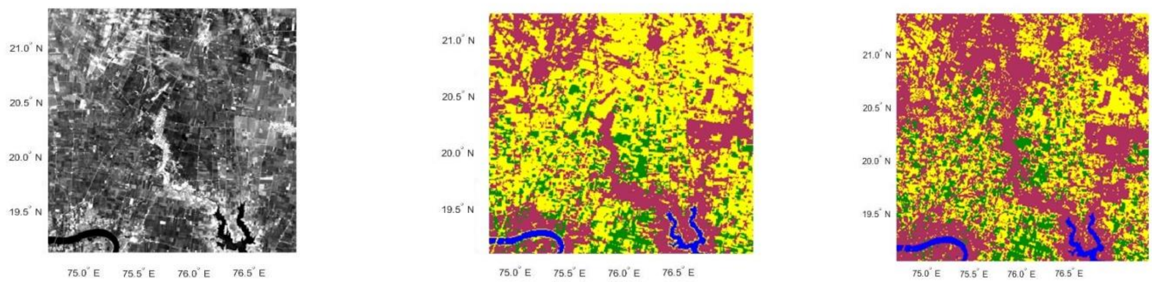

Figure 4. a) Input Landsat8 image of date 24th May'17 b) DT classified image c) MLC classified image

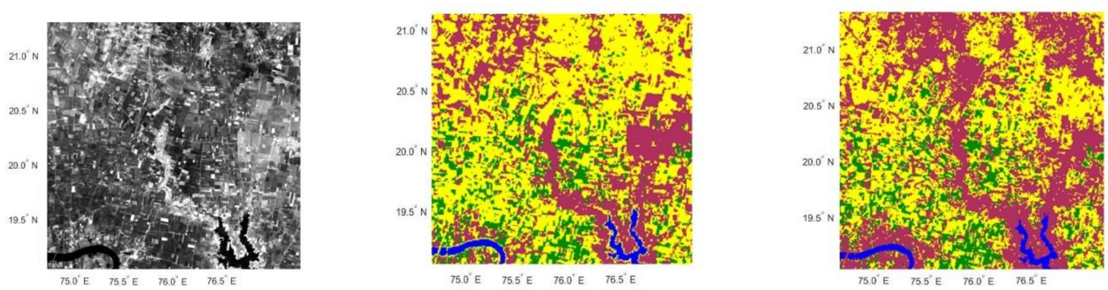

Figure 5. a) Input Landsat8 image of date 8th May'17 b) DT classified image c) MLC classified image

6. CONCLUSIONS AND FUTURE SCOPE

Coarse resolution Landsat-8 data has been classified using decision tree. Decision tree constructed using spectral reflectance values and vegetation indices generate classified image with better accuracy. Classified image results are compared with the result produced by (Amit Kumar et.al., 2016) on LISS-IV image. Authors have constructed two decision tress, using vegetation indices and combined use of vegetation indices and texture features. They found overall accuracy and kappa coefficient to be 81.08 % and 0.79 for decision tree using vegetation indices and improved accuracy of for combined textural feature with vegetation indices decision tree, 89.42 % and 0.87 respectively.

In our experiments decision tree constructed using spectral reflectance values and vegetation indices have overall accuracy and kappa coefficient of 88.97% and 0.86. The tree constructed has very less decision rules as compared to the decision rules used by (Amit Kumar et.al. , 2016), so computational complexity is less. The results are motivating since images used are taken from freely available satellite and resolution is 30m as compared to high-resolution of LISS-IV, 5.8m. Results are also compared with MLC and found to have similar accuracy i.e. 89.88% and 0.86 whereas User's and producer's accuracy is found to be better.

This work can be further extended on LISS-IV images using similar decision tree and also fusion of Landsat-8 with LISS-IV. LISS-IV doesn't have blue band and Landsat-8 image having blue band shows that sugarcane crop in senescence/ harvesting stage can be accurately identified from higher spectral reflectance values of blue band. Fusion of coarse-resolution bands with high-resolution bands can be done to classify.

REFERENCES

[1] Amit Kumar Verma, P.K Garg, K.S Hari Prasad, V.K Dadhwal, 2016. Classification of LISS-IV imagery using decision tree methods, The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLI-B8, 2016 XXIII ISPRS Congress, 12–19 July 2016, Prague, Czech Republic.

[2] A.N. Tassetti, E.S. Malinverni, M. Hahn , 2010. Texture analysis to improve supervised classification in IKONOS imagery ISPRS TC VII Symposium – 100 Years ISPRS, Vienna, IAPRS, Vol. XXXVIII, Part 7A.

[3] Brandt Tso and Paul Mather, Classification methods for remotely sensed data, Second edition, 2009, pp. 57-60.

[4] Diallo Yacouba, Xu Yuanjin, Hu Guangdao, Bokhari AA, Wen Xingping, 2014. Change Detection Using Data Stacking and Decision Tree Techniques in Puer-Simao Counties of Yunnan Province, China, Sci-Afric Journal of Scientific Issues, Research and Essays Vol. 2 (11), pp. 491-502, (ISSN 2311-6188)

[5] John A. Richards , Xiuping Jia, 2006. Remote Sensing Digital Image Analysis An Introduction 4th Edition, Springer-Verlag Berlin Heidelberg, pp. 273-275.

[6] José M. Peña, Pedro A. Gutiérrez, César Hervás- Martínez, Johan Six, Richard E. Plant and Francisca López-Granados, 2014. Object-Based Image Classification of Summer Crops with Machine Learning Methods, Remote Sensing, 6, 5019-5041; [doi:10.3390/rs6065019]

[7] F. Löw and G. Duveillerb, 2013. Determining suitable image resolutions for accurate supervised crop classification using remote sensing data, Proc. SPIE 8893, 88930I1.

[8] P. Karakus, H. Karabork,2016. Effect of pansharpened image on some of pixel based and object based classification accuracy, The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLI-B7, 2016 XXIII ISPRS Congress, 12–19 July 2016, Prague, Czech Republic.

[9] Srikrishna Shastri C., Ashok Kumar T., and Shiva Prakash Koliwad, 2016. Advances in classification techniques for semi urban land features using high resolution satellite data, International Journal of Advanced Remote Sensing and GIS 2016, Volume 5, Issue 3, pp. 1639-1648.

[10] Uttam Kumar, Cristina Milesi, Ramakrishna R. Nemani, Saikat Basu , 2015. Multi sensor multi resolution image fusion for improved vegetation & urban area classification, The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XL-7/W4.

[11] Vladimir Crnojevic, Predrag Lugonja,Branko Brkljač, and Borislav Brunet, 2014. Classification of small agricultural fields using combined Landsat-8 and RapidEye imagery:case study of northern Serbia, Journal of Applied Remote Sensing, Vol. 8.

[12] http://earthexplorer.usgs.gov , last accessed on 30th May 2017.

[13] http://usgs.gov/Landsat8DataUserhandbook.pdf, last accessed on 30th May 2017.