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# CLASSIFICATION OF LANDSAT 8 OPERATIONAL LAND IMAGER DATA USING SUPPORT VECTOR MACHINE

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**Abstract:** Developments in remote sensing techniques offer a powerful and cost effective means for land use/land cover mapping. LULC mapping information has been identified as one of the crucial data components for many aspects of global change studies and environmental applications. Support Vector Machines (SVM) is a relatively new supervised classification technique for land cover mapping. In this paper, support vector machine is used to classify Landsat 8 operational land Imager data into six major land cover classes. The training area is determined carefully by visual interpretation of false colour composite (FCC) and with the aid of ground control points which are collected using Juno Global Positioning system (GPS). Overall the study shows that SVM is able to classify satellite imagery of Landsat 8 with high overall accuracy and kappa coefficient of 79.45% and 0.78 respectively.

**Keywords:** Satellite Images, Support vector machine, Classification, GPS

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## INTRODUCTION

Land mapping is one of the most important application of remote sensing. It has been widely used in many fields such as land resource planning, geological mapping, town planning and studies of environmental change. Remote sensing measures land surfaces at various spatial and temporal scales. One of the widely used approaches for deriving land cover information from satellite images is classification. Various classification algorithms have been developed since first Landsat image was acquired in early 1970 [1] [2]. Among the most popular are the MLC, artificial neural network and Decision tree classification. The MLC is a parametric classifier based on statistical theory which is most widely used classifier [3] [4]. MLC needs large training area and assumption that the data are normally distributed [5]. Artificial Neural networks avoid some of the problems of the MLC by adopting a non-parametric approach. The most widely used classification of RS images is a group of networks called a multi-layer perceptron (MLP) [6] [7]. A decision tree classifier breaks an often very complex classification problem into multiple stages of simpler decision-making processes [8]. Depending on the number of variables used at each stage, there are univariate and multivariate decision trees [9]. Multivariate decision trees are often more accurate and can be more compact than univariate decision trees [10]. In recent years, support vector machine have been developed for better and reliable classification methods for land cover mapping.

## II. STUDY AREA

Muaffarnagar district of Uttar Pradesh has been taken for this work which lies between 29° 14' 28.35"N - 29° 42' 36.68"N Latitude and 77° 03' 45.26"E - 78° 11' 35.04"E Longitude. The study area is shown in Figure 1.

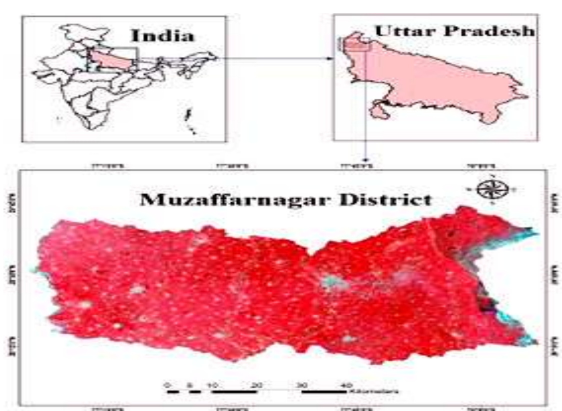



**Figure 1. Location map of study area**

## III. MATERIALS AND METHODS

**Software:** Three software have been used for this work. ERDAS IMAGINE 2014 is used for geometric correction. ENVI 5.1 is used for atmospheric correction, radiometric correction, ROI (region of interest) generation and then classification. ARC GIS 10.2 is used for map preparation.

**Satellite Data:** U.S. Geological Survey (USGS) Landsat 8, operational land Imager (OLI) sensor data (Entity ID LC81460402014312LGN00, Path 146, Row 40) of November 08, 2014 has been taken for the research work. This is 16-bit unsigned integer data. The OLI sensor has eleven band in different region of EMR in which we used only six bands (Blue, Green, Red, NIR, SWIR1 and SWIR2). The details of OLI sensor data are given below in Table1.

| Band Name | Bandwidth (µm) | Resolution |
|---|---|---|
| Band 2 Blue | 0.45 - 0.51 | 30 Meter |
| Band 3 Green | 0.53 - 0.59 | 30 Meter |
| Band 4 Red | 0.63 - 0.67 | 30 Meter |
| Band 5 NIR | 0.85 - 0.88 | 30 Meter |
| Band 6 SWIR 1 | 1.57 - 1.65 | 30 Meter |
| Band 7 SWIR 2 | 2.11 - 2.29 | 30 Meter |

**Table 1. Specification of OLI Sensor data**

**Support Vector Machine:** SVM is a supervised classification technique which is characterised by an efficient hyperplane searching technique which uses minimal training area and therefore consumes less processing time. This method is able to avoid over fitting problem and requires no assumption on data type. In case of non-parametric, SVM is capable for developing efficient decision boundaries and therefore can minimise misclassification. This is done through finding of optimal separating hyperplanes between classes by focusing on the training cases (support vectors) that lie at the edge of the class distributions, with the other training cases being excluded [11].

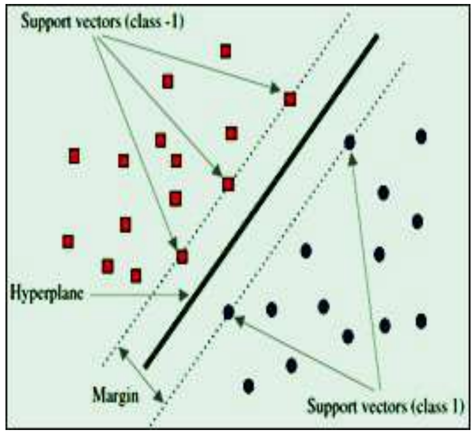



**Figure 2. Linear support vector machine**

**Methodology used for classification:**

The Landsat 8 OLI six bands were stacked and geometrically registered using second order polynomial transformation in ERDAS IMAGINE. The uniform distributed GCPs were used in such a way that the RMSE error is less than 0.33 pixel. The Nearest Neighbourhood algorithm is used for resampling. The study area is extracted using district boundary of Muzaffarnagar which is extracted from Survey of India (SOI) toposheet 53/G and 53/K scale of 1,250,000. The Dark object subtraction have been done in ENVI then region of Interest (ROI) files (water body, fallow land, built up, agriculture, orchard and dense vegetation) are generated for support vector machine classification. The gamma kernel function, penalty parameter and classification probability threshold values are set 0.010, 120 and 0.05 respectively.

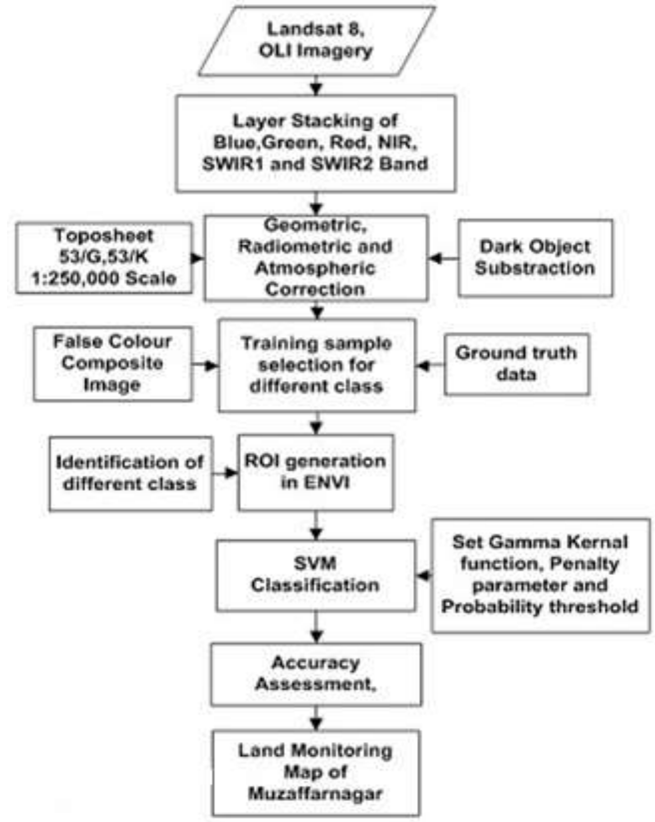
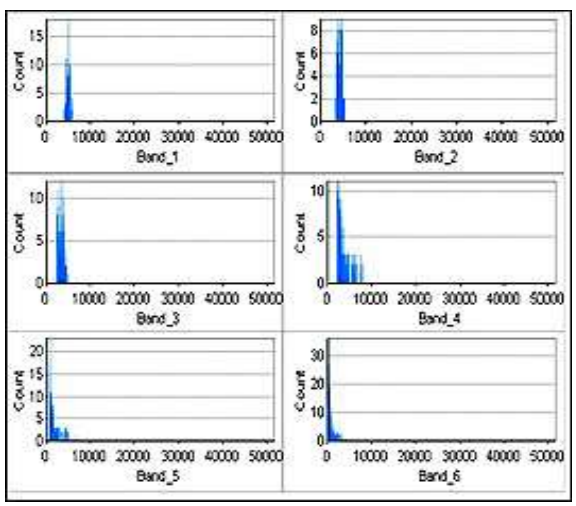
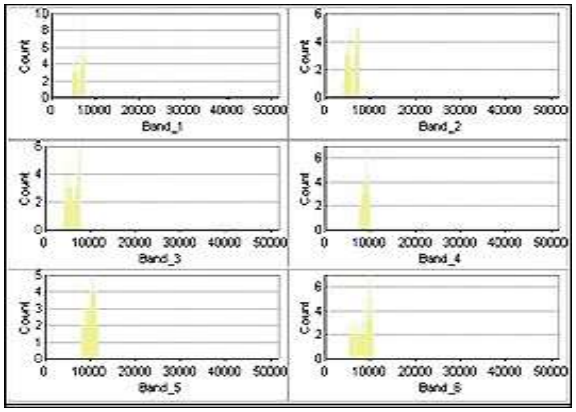



**Figure 3. Methodology flow diagram**

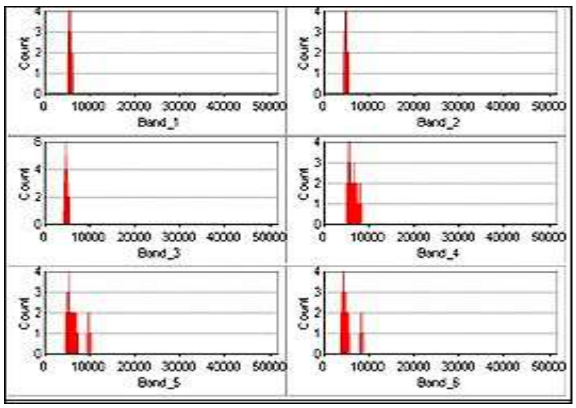
**Histogram for each class:**



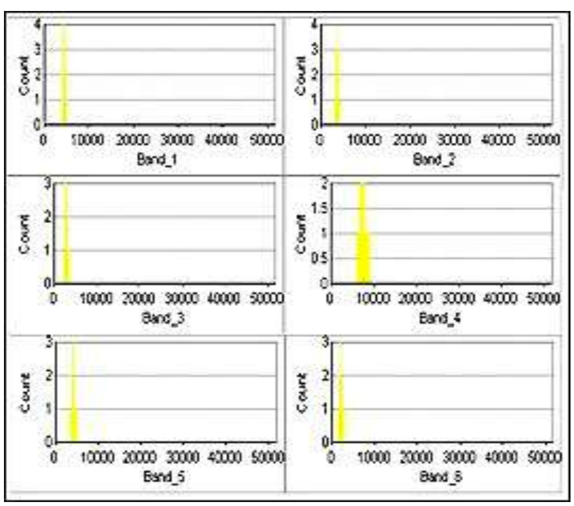

**(a) Water Body**



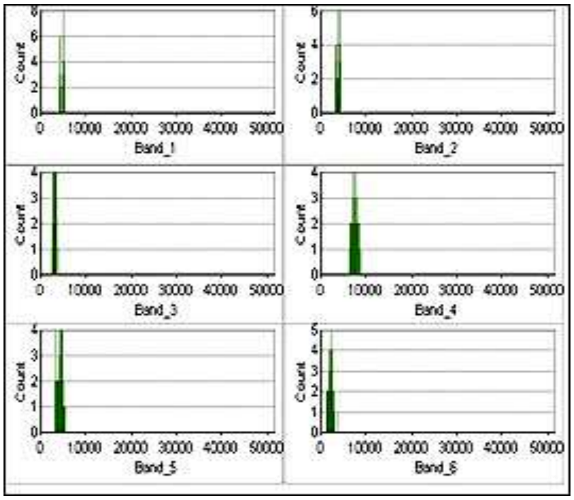

**(b) Fallow Land**



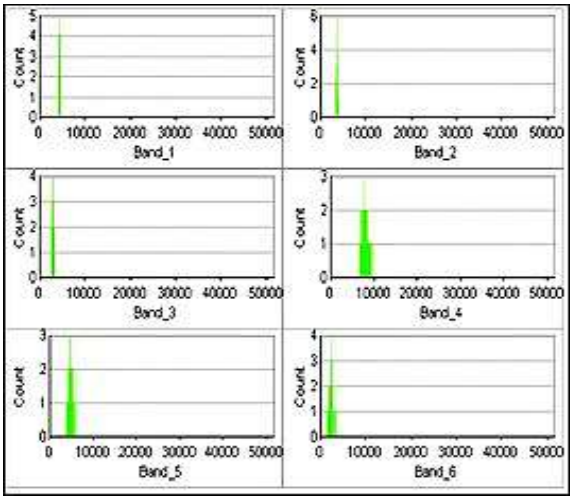

**(c) Built up**




**(d) Orchard**




**(e) Dense Vegetation**




**(f) Agriculture**

**Accuracy Assessment:** Accuracy assessment is used to compare the classification results with reference data, which is assumed to be true for determining the classification results. There are many methods to analyse the accuracy of remotely sensed data [12] [13]. In this study, confusion matrix or error matrix is used [14]. Reference data has been taken during the field visit on November 8, 2014.

The accuracy assessment has been done in ERDAS Imagine software. The accuracy of the classified images was assessed using producer's accuracy, user's accuracy, overall accuracy and kappa coefficient. The confusion matrix is shown in Table 2.

| Class | Reference | | | | | | |
|---|---|---|---|---|---|---|---|
| | WB | FL | BU | OR | DV | AG | Total |
| WB | 80 | 3 | 1 | 2 | 7 | 9 | 102 |
| FL | 0 | 241 | 10 | 8 | 2 | 13 | 274 |
| BU | 0 | 22 | 290 | 4 | 3 | 7 | 326 |
| OR | 0 | 5 | 8 | 178 | 17 | 23 | 231 |
| DV | 0 | 3 | 1 | 7 | 373 | 105 | 489 |
| AG | 8 | 6 | 3 | 14 | 116 | 412 | 559 |
| Total | 88 | 280 | 313 | 213 | 518 | 569 | |

*Overall Accuracy = 1574/1981=79.45*

*Kappa Coefficient (k)= 0.78*

*Where WB= Water body, FL=Fallow land, BU=Built up, OR= Orchard, DV= Dense Vegetation, AG=Agriculture.*

**Table 2. Confusion matrix**

## IV. RESULTS AND DISCUSSION

All pixels are classified into five groups (water body, fallow land, orchard, built up, dense vegetation and agriculture). Final classified images are depicted in Figure 4a and Figure 4b.

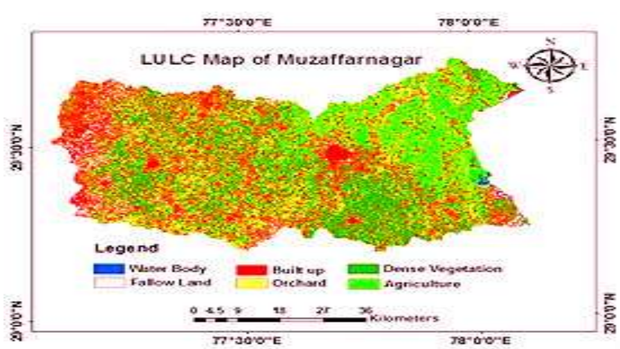



**Figure 4a. Classified Muzaffarnagar Map**

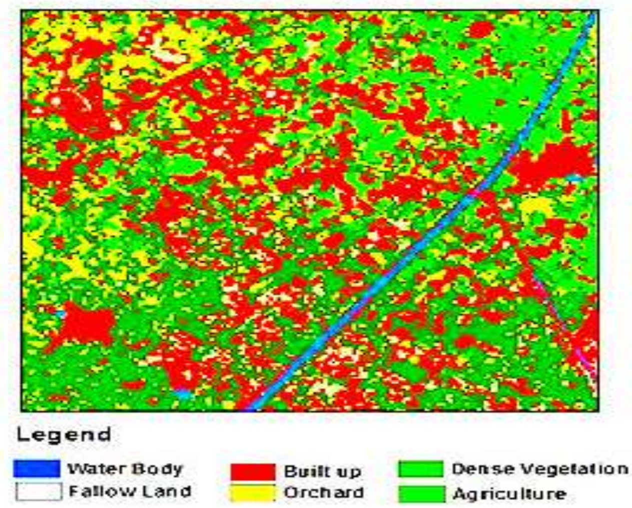



**Figure 4b. Classified Image using SVM**

## V.CONCLUSION

In this paper, we have studied the SVM classification for Muzaffarnagar district on Landsat 8 OLI data. The satellite image having six major land cover classes, have been classified successfully without any pixel being unclassified. SVM appear to be especially advantageous if dealing with heterogeneous classes for which only a small number of training samples are available. The overall accuracy and kappa coefficient of 79.45% and 0.78 respectively shows that this classifier can give high classification accuracy and has high agreement between ground truth and classified data.

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