CHAPTER 2

STATISTICAL SIGNIFICANCE IN THE CROP CLASSIFICATION ACCURACY USING DIFFERENT ALGORITHMS

2.1 INTRODUCTION

The advent of high resolution satellite imagery is now offering new possibilities in accurate crop classification than the traditional satellite imagery (Yang et al., 2011). Crop classification maps are very useful for the estimation of crop diversity as well as for making agricultural disaster compensation. These maps are also helpful in the management of agricultural fields in order to get a better crop yield production. However, because of high spectral variability or heterogeneity in the agricultural fields, crop monitoring is not always possible through coarse resolution images. The high spatial resolution multi-spectral satellite sensors such as LISS-IV in optical and NIR bands emerged as a possible approach for crop type monitoring. The LISS-IV sensor has the potential to capture the intrafield variability within the crop fields (Sesha Sai and Narasimha Rao, 2008).

Single date multispectral satellite imagery is often used for the crop identification and classification. Whereas, numerous researchers have recognized the benefits of using multi-date imagery to map agricultural crops (Panigrahy and Sharma, 1997; Simonneaux et al., 2008). The use of single-date or multi-date imagery depends on different factors such as type of the imagery and the number of bands contained in the imagery (Singh et al., 2015), weather constraints, types of crops grown in the region and their growing periods. Crop calendars can be used to determine whether all the major crops can be covered on a single date image in a region otherwise multi-date images need to be used. Many times only a single date cloud free satellite scene can be taken during the optimum crop identification and classification period for a given region. Thus, different types of classification algorithms and large number of training samples were usually employed for accurately identifying the crops from the single date imagery (Yang et al., 2011).

In the field of remote sensing, several classification algorithms have been developed to undertake the problems related to the multispectral satellite data classification (Banerjee and Srivastava, 2013; 2014). In this study, kernel based SVMs, ML classification and NDVI algorithms were used for the different crop classification. SVMs algorithm was selected among the others due to its increasingly far-reaching demands with the remote sensing data for the classification (Islam et al., 2012; Singh et al., 2014; Srivastava et al., 2014). Kernel based SVM algorithm has been extensively used with remote-sensing data for the classification during the last decades (Huang et al., 2002; Foody and Mathur, 2004; Pal and Mather, 2004; Mountrakis et al., 2011; Pal et al., 2013; Islam et al., 2014; Singh et al., 2014). Huang et al. (2002) compared the accuracy achieved by SVM, ANN, ML and DT algorithms for classifying land cover from Landsat TM and MODIS data-sets and found satisfactory results using SVMs with polynomial and radial basis function kernels.

Furthermore, SVMs have been demonstrated to achieve high classification accuracy in comparison to several other classification algorithms. The output of SVMs depends on the input pixels, pointing out that training is potentially a significant stage for optimizing classification accuracy (Pouteau and Collin, 2013). Out of several forms of kernel methods, the polynomial and radial basis functions have shown good results for land use/land cover classification with remotely sensed data (Pal and Mather, 2005). SVMs algorithm does not depend only on the type of kernel function. There are some major concerns in the design of SVMs. The choice of specific kernel parameters, suitable kernel function, regularization parameter and strategies for multiclass classification can affect the classification accuracy (Vapnik, 1998; Pal, 2009; Mountrakis et al., 2011; Srivastava et al., 2012).

Several other classification algorithms such as ML and NDVI classification have been developed. Despite limitations due to its assumption of normal distribution of class signature (Swain and Davis, 1978), ML algorithm is perhaps one of the most widely used algorithms (Wang, 1990; Hansen et al., 1996). ML classification algorithm quantitatively evaluates the variance and covariance of the category spectral response patterns during classification of an unknown pixel (Lillesand and Kiefer, 2002). The potential of NDVI has created great interest to study the global biosphere dynamics (Goward et al., 1990). Numerous investigators have related the NDVI with several vegetation phenomena such as vegetation seasonal dynamics, percentage ground cover determination, LAI measurement, biomass estimation, and FPAR (Fraction of Absorbed Photosynthetically Active Radiation) at global and continental scales (Lillesand and Kiefer, 2002). NDVI values do not provide land cover type directly; it generally quantifies the biophysical activity of the land surface. However, a time series of NDVI values can separate various land cover types based on their phenology or seasonal signals (Lenney et al., 1996). The multi-temporal phenological metrics have been developed and used by Reed *et al.* (1994) and DeFries *et al.* (1998) to derive land cover classifications from AVHRR data. In this study, the ranges of NDVI value for different crop types were defined with the help of ground truth information and performed classification.

In the previous studies, several researches indicated the radial basis function kernel to work well with the remote sensing data-sets (Foody and Mathur, 2004; Pal and Mather, 2004). Paneque-Gálvez et al. (2013) have shown better performance of SVM radial basis function and SVM sigmoid classifiers in comparison to SVM linear and SVM polynomial classifiers. In few studies, the performance of second-order polynomial kernel was found better in comparison to radial basis kernel for the classification using hyperspectral data (Bahria et al., 2011). Schwert et al. (2013) used the third-order polynomial function kernel with gamma parameter 1 for the change detection classification which yielded the most accurate results in comparison to linear, radial basis and sigmoid function kernels. Limited research has been conducted on LISS-IV data using SVMs, ML and NDVI algorithm for the crop classification in Varanasi, India.

Rigorous assessment of SVMs with respect to different kernel functions and degrees of polynomial were attempted along with the ML and NDVI based classification. Sophisticated statistical analysis such as Z-test and χ^2-test were attempted to estimate the significance of differences in the classification accuracies achieved by different algorithms. This study offers significant information of crop type in the area dominated by agricultural practices.

2.2 STUDY AREA AND MATERIALS

The ground truth information of 16 different crop and non-crop classes were collected from the study area carried out in Varanasi district of Uttar Pradesh, India. It is situated at the bank of holy river Ganga. This ground truth information was collected with the help of Global Positioning System (GPS) during field visit on 6 April 2013. Wheat is the most significant crop of Rabi season in Varanasi. The study area, located between 25° 12′ 09″ to 25° 17′ 09″ N and from 82° 55′ 07″ to 83° 03′ 14″ E, is about 12576 ha. The specification of LISS-IV sensor data, acquired on 6 April 2013, is given in the Table 2.1.

Table 2.1 Specification of LISS-IV sensor

Specification	LISS-IV sensor
Sensor type	Multispectral
No of bands	3
Spectral bands (µm)	B2 0.52-0.59, B3 0.62-0.68, B4 0.77-0.86
Spatial resolution (m)	5.8
Swath (km)	70
Temporal resolution (days)	24
Radiometric resolution	10-bit

The crop classification study was done using different algorithms as implemented in the Environment for Visualizing Images (ENVI) software version 5.1. Figure 2.1 shows the study area used in the classification.

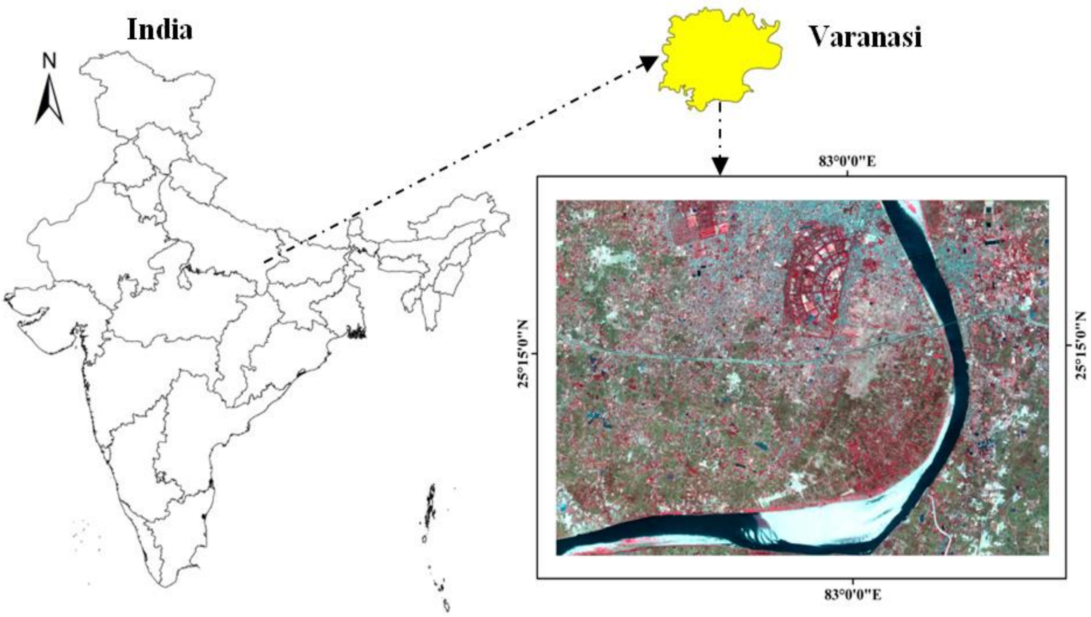

Figure 2.1 The location map of study area with false colour composite (FCC) image of LISS-IV sensor

2.3 METHODOLOGY

2.3.1 Image pre-processing and data preparation

The atmospheric correction for a single date image is often equivalent to subtracting a constant from all pixels in a spectral band. Thus, the atmospheric correction is not required for remote sensing applications such as image classification for the same calendar date image (Song et al., 2001). The 3 bands such as B2 (green, 0.52-0.59 μm), B3 (red, 0.62-0.68 μm) and B4 (NIR, 0.77-0.86 μm) were taken for the layer stacking to generate the FCC image. After the generation of FCC image, the geometrical correction was done. The subset selection was done to extract the data covering the study area for crop and non-crop classification. After selecting the subset, training areas were selected and region of interest (ROI) files were generated. The training and testing samples were collected from the different fields within and outside Banaras Hindu University (BHU) agriculture farm house located in the Varanasi district. The training and validation data-sets used for the classification are presented in Table 2.2.

Table 2.2 Training and validation data-sets used for the classification

Class name	Training data-set	Validation data-set	Class name	Training data-set	Validation data-set
Barley	249	127	Sugarcane	208	107
Wheat	411	199	Other crops	493	248
Lentil	252	126	Water	412	208
Mustard	237	121	Sand	457	221
Pigeon pea	230	112	Built up	306	153
Linseed	229	113	Fallow land	289	143
Corn	346	163	Sparse vegetation	498	268
Pea	263	129	Dense vegetation	499	245

A random sampling was done to collect the training and testing samples. One of the ROI files was used as training data-set. These training samples were used to train the classification algorithms for the crop classification. Other ROI file was used for the ground validation. An independent data-set consisting of total 2683 pixels were used to test the classification accuracy and more than two times of the test pixels were used to train the algorithms.

2.3.2 Spectral separability

To determine the spectral separability among crop types, the *M*-statistic (Kaufman and Remer, 1994) and *J-M* distance method (Richards, 1999) were used. The *M*-statistic determines class separability between two bands of LISS-IV sensor from two sample class distributions characterized by mean and standard deviation values. *M*-statistic used in the present study is given by the equation 2.1.

$$M = (\mu_1-\mu_2)/(\sigma_1+\sigma_2) \tag{2.1}$$

where μ_1 is the mean reflectance value of crop type 1, μ_2 is the mean reflectance value of crop type 2, σ_1 is the standard deviation value of crop type 1 and σ_2 is the standard deviation value of crop type 2. The value of $M < 1$ indicates that the classes are significantly overlapping and the ability to separate the regions is poor. On other hand, the value of $M > 1$ indicates that the histogram means are well separated and the regions are relatively easy to discriminate. *M*-statistics were compared for each pair of crop types for given spectral bands of LISS-IV image.

The *J-M* measurement is based on Bhattacharya distance. It allows to indicate how well a selected spectral class pair is statistically separated. *J-M* distance for two classes' *a* and *b* is given by the equations 2.2 and 2.3.

$$JM_{ab} = \sqrt{2(1 - exp(-\alpha)} \tag{2.2}$$

$$\alpha = \frac{1}{8}(\mu_a - \mu_b)^T \left(\frac{C_a+C_b}{2}\right)^{-1}(\mu_a - \mu_b) + \frac{1}{2}\ln\left[\frac{\frac{1}{2}|C_a+C_b|}{\sqrt{|C_a||C_b|}}\right] \tag{2.3}$$

where μ_a and μ_b are mean values for classes *a* and *b*, C_a and C_b are the covariance matrices for classes *a* and *b*, and *T* denotes the transpose of a vector. *J-M* distance provides an index between 0.0 and 2.0. Its values > 1.7 demonstrates that the classes are well separated (ITT Industries Inc., 2006). A *J-M* distance value < 1.0 indicates poor separability between the pair of classes.

2.3.3 Support vector machines based classification

SVM is a non-parametric classification algorithm, originating from statistical learning theory (Vapnik, 1998; Mountrakis et al., 2011). It is initially projected to construct an optimal separating hyperplane when the training data are linearly separable. The algorithm maximizes the margin between the optimal linear separating hyperplane and the closest training samples. The training samples closest to the hyperplane used to measure the margin are termed as support vectors (Vapnik, 1998; Huang et al., 2002). In the case of two class classification problem, algorithm selects the one that provides the maximum margin between the two classes, among the infinite number of linear decision boundaries. The margin is defined as the sum of the distances to the hyperplane from the closest points of the two classes (Vapnik, 1998). At the same time SVMs identify the optimal decision boundary between the classes to minimize the misclassification (Mountrakis et al., 2011). When it is not possible to avoid misclassification between some training samples then penalty parameter is introduced to indicate the trade-off between penalty of misclassification against simplicity of the hyperplane. A smaller value of penalty parameter indicates more tolerance of misclassification. The SVMs has the capability to grip the extremely non-linear problems even with noisy training data-set. It transforms essentially the non-linear problems into a linear one by using kernel functions to map the original input space into a new feature space with higher dimensions (Vapnik, 1998). The function $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$ is called the kernel function and C > 0 is the penalty parameter of the error term. Here, the training vectors x_i are mapped into a higher dimensional space by the function ϕ. The four SVM kernels used in this study (linear, polynomial, radial basis and sigmoid) are given in the equations 2.4, 2.5, 2.6 and 2.7.

$$Linear: K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \boldsymbol{x}_i^T \boldsymbol{x}_j \tag{2.4}$$

$$Polynomial: K(\mathbf{x}_i, \mathbf{x}_j) = (\gamma\, \mathbf{x}_i^T \mathbf{x}_j + r)^d,\ \gamma > 0 \tag{2.5}$$

$$Radial\ basis\ function: K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\gamma \left\| (\mathbf{x}_i, \mathbf{x}_j) \right\|^2\right),\ \gamma > 0 \tag{2.6}$$

$$Sigmoid: K(\mathbf{x}_i, \mathbf{x}_j) = \tan H(\gamma\, \mathbf{x}_i^T \mathbf{x}_j + r) \tag{2.7}$$

where γ, r and d are the gamma term in the kernel function, bias term in the kernel function and polynomial degree term, respectively. The values of gamma and penalty parameters were taken 0.33 and 100 respectively. The penalty parameter controls the trade-off between margin and misclassification error, whereas the gamma parameter controls the width of the kernel function (Cortes and Vapnik, 1995).

A number of SVM algorithms have been designed, each employing a different type of kernel. However, a linear, polynomial with degrees 2 to 6, radial basis function and sigmoid function kernels were evaluated in this study. Prior to the image classification, a kernel is applied to the input feature space to increase the separability between the classes. Details were given, regarding the commonly used SVM kernels in remote sensing for the classification (Kavzoglu and Colkensen, 2009). A major reason for the popularity of SVM to classify remotely sensed data is due to its potential to produce a higher classification accuracy than the ANN algorithms (Foody and Mathur, 2004; Waske and Benediktsson, 2007).

2.3.4 Maximum likelihood based classification

The ML classification is a well-known parametric classification algorithm based on statistical theory. It relies on the second-order statistics of a Gaussian probability density function model for each class. This algorithm is based on the probability that a pixel belongs to a particular class. The basic equation assumes that these probabilities are equal for all classes in each band, and the input bands have normal distributions. Each pixel is assigned to the class that has the highest probability (Richards, 1999). If there is a prior knowledge that the probabilities are not equal for all classes, then the weight factors can be specified for particular classes. Unless there is a prior knowledge of the probability, it is recommended that the weight factors should not be specified

(Hord, 1982). In this case, by default, the weight factor is assigned 1.0 in the equation 2.8. The equation for the ML classifier is given as:

$$D = \ln(a_c) - [0.5 \ln(|Cov_c|)] - [0.5\ (X - M_c)]\ T\ (Cov_c^{-1})\ (X - M_c)] \quad (2.8)$$

where D = weighted distance, c = particular class, X = measurement vector of the candidate pixel, M_c = mean vector of the sample of class c, a_c = percent probability that any candidate pixel is a member of class c, Cov_c = covariance matrix of the pixels in the sample of class c, $|Cov_c|$ = determinant of Cov_c, Cov_c^{-1} = inverse of Cov_c, ln = natural logarithm function and T = transposition function.

2.3.5 Normalized difference vegetation index based classification

The vegetation covered areas have a relatively high NIR reflectance and low visible reflectance. Due to this type of property of vegetation, the different mathematical quantities of the NIR and red band have been found to be sensitive indicators for the condition of green vegetation (Lillesand and Kiefer, 2002). The most commonly used mathematical combination is the NDVI classification. The NDVI classification is based on the NDVI values generated from Red and NIR bands of LISS-IV image and is given in the equation 2.9.

$$NDVI = \frac{(NIR-Red)}{(NIR+Red)} \quad (2.9)$$

The NDVI separates green vegetation from its background soil brightness and retains the ability to minimize topographic effects. The range of NDVI values are from -1 to +1, which are scaled from 0 to 255 for display purposes. Zero NDVI values represent no vegetation available on that region. The NDVI values are sensitive to the presence of vegetation. Since the presence of green vegetation usually decreases the signal in the red band due to chlorophyll absorption and increases the signal in the NIR band wavelength due to light scattering by leaves (Tucker et al., 1985). The higher NDVI value indicates high green leaf area or higher biomass content of vegetation.

2.3.6 Classification accuracy

The accuracy of the different thematic maps produced from the classifiers was assessed from the computation of the error matrix statistics (Congalton and Green, 1999). As a result, the overall accuracy (*OA*), producer's accuracy (*PA*), user's accuracy (*UA*) and the kappa coefficient (κ) are computed by the equations 2.10, 2.11, 2.12 and 2.13.

$$OA = \frac{1}{N}\sum_{t=1}^{r} n_{ii} \qquad (2.10)$$

$$PA = \frac{n_{ii}}{n_{icol}}, \qquad (2.11)$$

$$UA = \frac{n_{ii}}{n_{irow}}, \qquad (2.12)$$

$$\kappa = N\sum_{t=1}^{r} n_{ii} - \sum_{t=1}^{r} \frac{n_{i\,col}\, n_{irow}}{N^2} - \sum_{t=1}^{r} n_{icol} n_{irow} \qquad (2.13)$$

where n_{ii} is the number of pixels correctly classified in a category; N is the total number of pixels in the confusion matrix; r is the number of rows; and n_{icol} and n_{irow} are the column (reference data) and row (predicted classes) total, respectively.

The *OA* can be assessed by dividing the sum of correctly classified pixels to the total number of testing pixels used in the classification. The *UA*, which is a measure of commission error and indicative of the probability that a category classified on the map actually represents that category on the ground. Similarly, *PA* is a measure of omission error and indicative of the probability that the actual areas being correctly classified (Lillesand and Kiefer, 2002). κ is computed to compare the true agreement between the classes actually occurred on the ground *vs.* classified by the classifiers which occur by chance (Cohen, 1960). κ analysis was also performed to test whether each classification was significantly better than a random classification. A κ value of 0 corresponds to a total random classification, while κ value of 1 represents a perfect agreement between the classification and reference data (Congalton and Green, 1999). Validation points were generally selected based on randomly distributed inhomogeneous regions and away from the locations where the training points had been collected, ensuring non-overlap of pixels between the training data and validation data. This information was obtained from field visits and previous studies which were conducted in the area.

2.3.7 Statistical significance of classifiers performance

The statistical significance of differences between two proportions may be evaluated using McNemar's test (Agresti, 1996).

2.3.7.1 *Z*-test

The *Z*-test is generally performed to test the hypothesis whether two classification algorithms provided similar accuracy results. The test is based on the standardized normal test given by the equation 2.14.

$$Z = \frac{f_{12} - f_{21}}{\sqrt{f_{12} + f_{21}}} \tag{2.14}$$

where f_{12} denotes the number of samples that were correctly classified by the first classification algorithm but misclassified by the second classification algorithm. Similarly, f_{21} denotes the number of samples that were misclassified by first classification algorithm and correctly classified by the second classification algorithm (Foody, 2004; Leeuw et al., 2006). A difference in the classification accuracy between the confusion matrices is statistically significant ($p \leq 0.05$) if the Z value is more than 1.96 (Congalton et al., 1983).

2.3.7.2 χ^2- test

χ^2-test is a nonparametric statistical test to determine whether the two or more classifications are independent or not. The properly applied test may give us the answer by rejecting the null hypothesis or failing to reject it. The value of χ^2 found less than that of the value corresponding to our level of confidence indicates that our null hypothesis is probably true. On other hand, if value of χ^2 lies over the level of confidence, then our χ^2-test rejects the null hypothesis. Therefore, we conclude that the two classifications are dependent on each other. For the critical value defined as $\chi^2_{0:05(1)}$ = 3.841, the null hypothesis is not rejected if $\chi^2 < \chi^2_{0:05(1)}$. The McNemar's (1947) test is based on the test given by the equation 2.15.

$$\chi^2 = (f_{12}-f_{21})^2 / (f_{12}+f_{21}) \quad (2.15)$$

This test works well when $(f_{12}+f_{21})/2 > 10$. For other cases, a binomial test has been used as recommended by Agresti (1996).

The Z-test and χ^2- test are based on 2×2 dimension confusion matrices. These tests were performed to test independency between the two classification algorithms. The number of correctly and wrongly classified data pixels for two algorithms was tabulated as in Table 2.3.

Table 2.3 Cross tabulation of number of correctly and wrongly classified pixels for two algorithms

Allocation	Classification 2		
Classification 1	Correct	Incorrect	Sum
Correct	f_{11}	f_{12}	$f_{11}+f_{12}$
Incorrect	f_{21}	f_{22}	$f_{21}+f_{22}$
Sum	$f_{11}+f_{21}$	$f_{12}+f_{22}$	

2.4 RESULTS AND DISCUSSION

2.4.1 Assessment of classification accuracies using different algorithms

Several crops such as barley, wheat, lentil, mustard, pigeon pea, linseed, corn, pea, sugarcane and other crops grown in Varanasi district were classified. Other non-crop classes such as water, sand, built up, fallow land, sparse vegetation and dense vegetation were also classified. Before the classification, M-statistic and J-M distance methods were applied to find the separability between the crop and non-crop classes. The combination of band 3 and band 4 provided the overall best separation between the classes in all three types of band combinations using M-test. The overall best separation observed between band 3 *vs.* band 4 may be due to unique and high spectral reflectance values of the crops in these bands. The overall low separation between the classes was found using combination of band 2 and 3 due to mix and poor reflectance of the crops in the green and red bands. The moderate separation between classes was found using combination of band 2 and 4. The values of $M > 1$ were found for the 95% pair of classes which means that the classes were found well separated and the values of $M < 1$ were found for remaining pairs means that the classes were poorly separable. The separability analysis using *J-M* method also showed the better separation between almost all the classes. The separability analysis using *J-M* method is given in Table 2.4.

Table 2.4 Separability analysis between different crop and non-crop classes using *J-M* distance method

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1		1.96	1.14	1.87	2.00	1.94	2.00	2.00	2.00	1.98	2.00	2.00	2.00	2.00	1.90	2.00
2	1.96		1.91	1.86	2.00	1.94	2.00	2.00	2.00	1.66	2.00	2.00	2.00	2.00	1.94	2.00
3	1.14	1.91		1.92	2.00	1.86	2.00	2.00	2.00	1.99	2.00	2.00	2.00	2.00	1.93	2.00
4	1.87	1.86	1.92		2.00	1.11	1.97	1.88	2.00	1.71	2.00	2.00	2.00	2.00	1.49	2.00
5	2.00	1.99	2.00	2.00		1.95	1.95	1.93	1.10	1.93	2.00	2.00	2.00	2.00	1.99	1.31
6	1.94	1.94	1.86	1.11	1.95		1.93	1.83	1.98	1.60	2.00	2.00	2.00	1.85	1.35	2.00
7	2.00	2.00	2.00	1.97	1.95	1.93		1.12	1.95	1.95	2.00	2.00	2.00	2.00	1.79	1.80
8	2.00	2.00	2.00	1.88	1.93	1.83	1.12		1.97	1.92	2.00	2.00	2.00	2.00	1.16	2.00
9	2.00	2.00	2.00	2.00	1.10	1.98	1.95	1.97		1.98	2.00	2.00	2.00	2.00	2.00	1.50
10	1.98	1.66	1.99	1.71	1.93	1.60	1.95	1.92	1.98		2.00	2.00	1.99	2.00	1.76	1.99
11	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00		2.00	1.96	2.00	2.00	2.00
12	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00		1.78	2.00	2.00	2.00
13	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.99	1.96	1.78		2.00	2.00	2.00
14	2.00	2.00	2.00	2.00	2.00	1.85	2.00	2.00	2.00	2.00	2.00	2.00	2.00		1.97	2.00
15	1.90	1.94	1.93	1.49	2.00	1.35	1.79	1.16	2.00	1.76	2.00	2.00	2.00	1.97		2.00
16	2.00	2.00	2.00	2.00	1.31	2.00	1.80	1.99	1.50	1.99	2.00	2.00	2.00	2.00	2.00	

1 – Barley, 2 – Wheat, 3 – lentil, 4 – Mustard, 5 – Pigeon pea, 6 – linseed, 7 – corn, 8 – Pea, 9 – Sugarcane, 10 – other crops, 11 – Water, 12 – Sand, 13 – Built up, 14 – Fallow land, 15 – Sparse vegetation, and 16 – Dense vegetation

Especially in the case of non-crop classes, the separability was found better than the crop classes due to its unique and high spectral reflectance. Visual comparison between kernel based SVMs classification maps indicated well separation between the crop and non-crop classes and provided the accurate results. The classification maps produced using SVMs with linear kernel and polynomial of degrees 2 to 6 algorithms are shown in Figure 2.2.

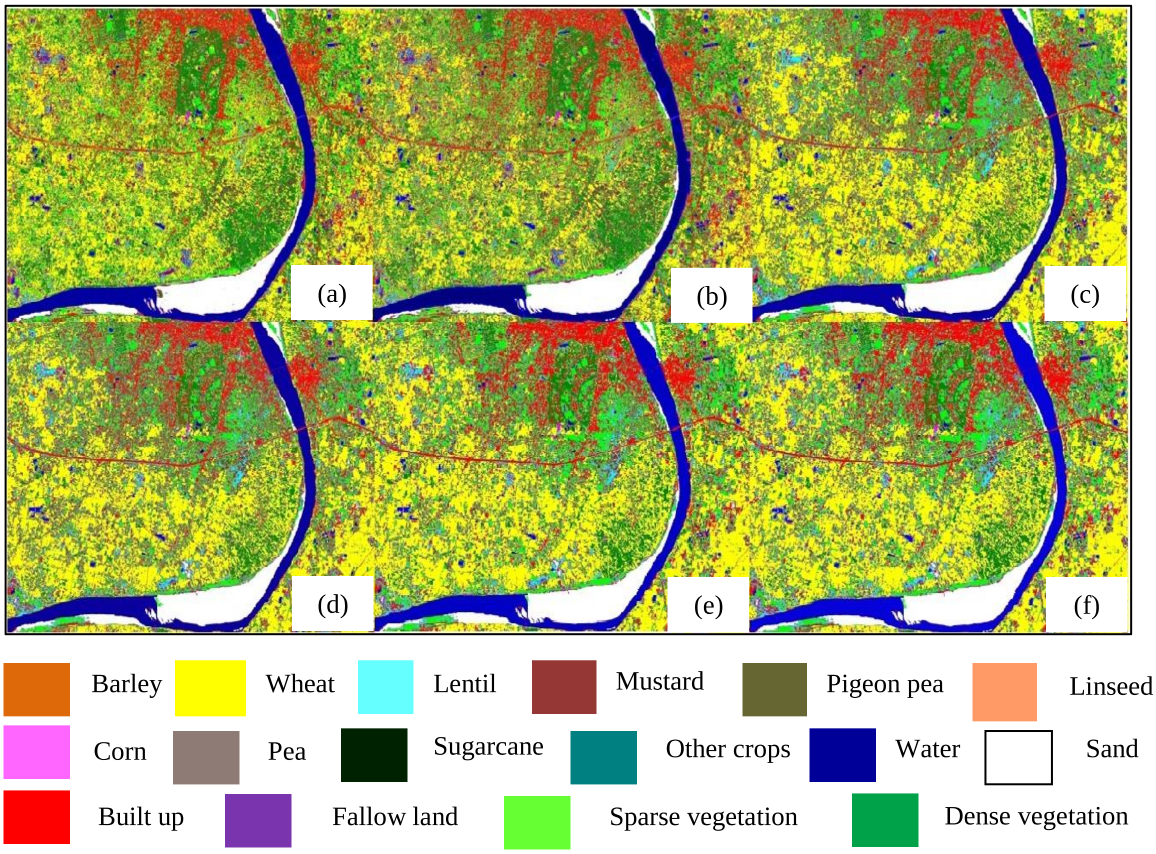

Figure 2.2 (a) SVMs with linear kernel (b) SVMs with polynomial of degree 2 (c) SVMs with polynomial of degree 3 (d) SVMs with polynomial of degree 4 (e) SVMs with polynomial of degree 5 (f) SVMs with polynomial of degree 6 classification maps

The classification maps produced by the SVMs with radial basis function kernel and ML classification algorithms were also found visually very good. Good visualization of SVMs with sigmoid kernel but fair visualization of NDVI classification map was found. The classification maps produced from the SVMs with radial basis, sigmoid kernel, ML and NDVI algorithms are shown in Figure 2.3.

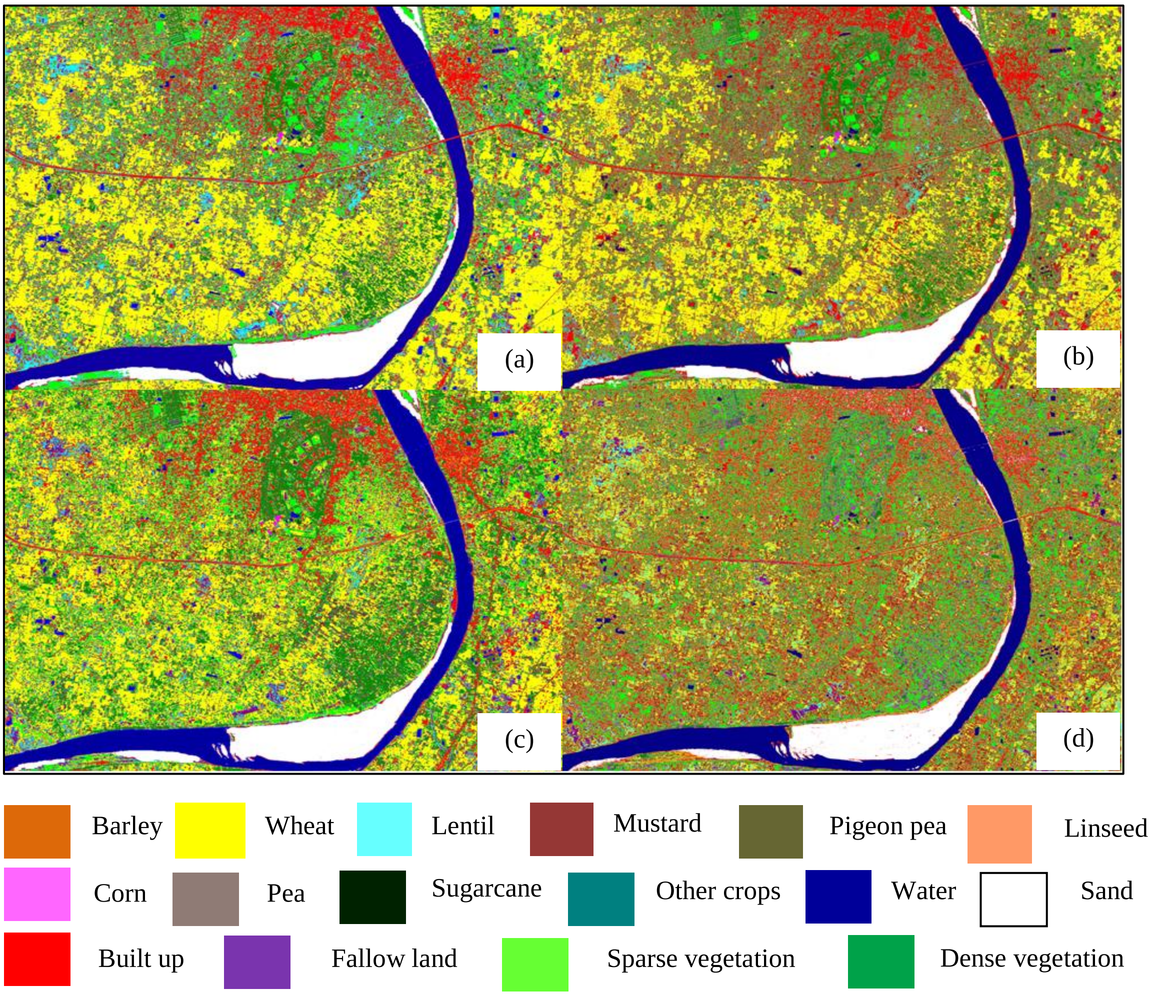

Figure 2.3 (a) SVMs with radial basis kernel (b) SVMs with sigmoid kernel (c) ML classification (d) NDVI classification maps

These classification maps were evaluated in terms of their *OA*, *UA*, *PA* and *κ*. The accuracy assessed by SVMs with linear kernel and polynomial kernel of degrees 2 to 6 is presented in Table 2.5. The accuracy results were also assessed using SVMs with radial basis and sigmoid kernels, ML and NDVI classification algorithms and compared. The comparative study is given in Table 2.6. On comparing the results obtained from the SVMs, ML and NDVI classification, the highest 87.33% *OA* was achieved by the SVMs with polynomial function kernel of degree 6. Similar accuracy results were found using SVMs with linear function kernel having *OA* 85.05%, and polynomial with degrees of 2, 3, 4, and 5 having *OA* 85.69%, 86.47%, 86.54%, and 87.10%, respectively.

Table 2.5 Accuracy measures by SVMs with linear kernel and polynomial kernel of degrees 2 to 6

	Linear kernel		Polynomial kernel									
			Degree 2		Degree 3		Degree 4		Degree 5		Degree 6	
Class name	*PA* (%)	*UA* (%)	*PA* (%)	*UA* (%)	*PA* (%)	*UA* (%)	*PA* (%)	*UA* (%)	*PA* (%)	*UA* (%)	*PA* (%)	*UA* (%)
Barley	74.80	75.40	74.80	75.40	82.13	81.78	81.89	77.04	79.53	80.80	82.68	80.15
Wheat	95.98	95.02	93.97	96.89	97.49	96.52	94.97	97.42	94.47	96.91	94.47	96.91
Lentil	77.78	74.24	76.98	74.05	82.54	81.23	77.78	79.67	82.54	79.39	80.95	81.60
Mustard	79.34	73.28	79.34	76.80	81.74	77.68	80.17	77.60	80.99	77.78	80.99	78.40
Pigeon pea	62.50	71.43	68.75	74.04	79.36	78.26	67.86	78.35	71.43	77.67	70.54	79.00
Linseed	52.21	60.20	52.21	63.44	61.26	64.97	49.56	69.14	52.21	69.41	52.21	69.41
Corn	84.66	83.13	84.66	83.64	81.53	86.51	84.05	83.03	84.66	84.66	86.50	84.43
Pea	73.64	79.83	73.64	79.17	81.05	73.51	73.64	78.51	74.42	79.34	73.64	81.20
Sugarcane	75.70	68.64	75.70	72.97	81.31	71.90	80.37	72.88	81.31	71.31	82.24	75.86
Other crops	84.27	86.36	87.50	85.43	87.50	87.13	89.92	87.11	91.13	87.94	91.94	88.03
Water	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Sand	99.10	92.63	99.10	91.63	98.19	93.53	98.64	91.60	99.10	91.63	99.10	91.63
Built up	86.93	98.52	86.93	98.52	90.20	98.00	86.93	97.79	86.93	98.52	86.93	98.52
Fallow land	99.30	98.60	99.30	99.30	98.60	98.60	99.30	99.30	99.30	99.30	99.30	99.30
Sparse vegetation	86.94	80.34	89.18	80.47	90.04	84.31	91.42	80.07	90.67	80.46	90.30	80.40
Dense vegetation	87.76	90.72	88.16	90.38	87.53	91.53	87.76	90.72	87.76	93.89	88.16	90.76

Linear kernel: *OA* = (2282/2683) = 85.05%, κ = 0.8394
Polynomial kernel of degree 2: *OA* = (2299/2683) = 85.69%, κ = 0.8462
Polynomial kernel of degree 3: *OA* = (2320/2683) = 86.47%, κ = 0.8551
Polynomial kernel of degree 4: *OA* = (2322/2683) = 86.54%, κ = 0.8554
Polynomial kernel of degree 5: *OA* = (2337/2683) = 87.10%, κ = 0.8614
Polynomial kernel of degree 6: *OA* = (2343/2683) = 87.33%, κ = 0.8638

The data acquired especially at the high chlorophyll stage may provide further discrimination and increase in the classification accuracy. The classification accuracies using SVMs with radial basis, sigmoid function and ML algorithms were found 86.06%, 81.92% and 85.13%, respectively. The low *OA* (74.32%) was achieved by the NDVI classification algorithm. Wheat crop was found to be the most dominant crop and corn crop was identified as the least dominant crop. This was due to the fact that the corn crop is not the seasonal crop and was grown for research purposes in the BHU agricultural farm house and a few other places in Varanasi district. Among all the algorithms, SVMs and ML provided the good *PA* and *UA* for almost all the sixteen classes. The *PA* and *UA* were found to be excellent for wheat, other crops and corn categories in crop classes. Other crop categories also showed very good *PA* and *UA* for all the classification algorithms except for the linseed crop which provided the fair results. The *OA*, *PA* and *UA* of linseed crop were found to be less in the comparison to the other categories of crop and non-crop because of some spectral mixing or similar spectral reflectance of linseed with the other crop classes and some non-crop classes.

Table 2.6 Accuracy achieved by SVMs with radial basis and sigmoid kernels, ML and NDVI classification algorithms

	Radial basis kernel		Sigmoid kernel		ML classification		NDVI classification	
Class name	*PA* (%)	*UA* (%)	*PA* (%)	*UA* (%)	*PA* (%)	*UA* (%)	*PA* (%)	*UA* (%)
Barley	76.38	75.78	88.98	63.48	74.80	75.40	81.89	69.80
Wheat	93.47	97.38	93.97	89.05	95.98	95.50	58.29	62.70
Lentil	77.78	75.38	50.00	75.00	77.78	74.24	67.46	64.89
Mustard	79.34	74.42	87.60	65.84	78.51	73.64	85.87	51.43
Pigeon pea	75.00	75.68	62.50	72.92	62.50	71.43	70.54	71.82
Linseed	51.33	66.67	42.48	59.26	52.21	59.60	45.13	49.04
Corn	84.66	82.63	72.39	82.52	84.05	84.57	69.94	77.55
Pea	73.64	79.17	77.52	66.67	75.97	79.67	78.29	66.01
Sugarcane	75.70	71.68	75.70	59.56	75.70	68.64	75.70	55.10
Other crops	87.90	85.49	75.00	81.58	85.08	86.12	63.71	68.10
Water	100.0	100.0	100.0	100.0	100.0	100.0	96.63	100.0
Sand	99.10	91.63	99.10	91.25	99.10	91.63	97.03	86.64
Built up	86.93	98.52	86.27	98.51	86.93	98.52	56.61	98.02
Fallow land	99.30	99.30	98.60	99.30	99.30	99.30	95.10	95.77
Sparse vegetation	89.93	80.60	81.72	79.93	86.57	80.28	63.06	94.94
Dense vegetation	87.76	94.30	84.08	94.93	87.76	90.72	74.69	96.32

Radial basis kernel: *OA* = (2309/2683) = 86.06%, κ = 0.8502
Sigmoid kernel: *OA* = (2198/2683) = 81.92%, κ = 0.8060
ML classification: *OA* = (2284/2683) = 85.13%, κ = 0.8402
NDVI classification: *OA* = (1994/2683) = 74.32%, κ = 0.7252

Almost all the non-crop classes showed excellent *PA* and *UA* for all the algorithms. The *OA* of non-crop classes was found to be higher in comparison to almost all crop classes due to having unique spectral response of non-crop classes. The highest *OA* achieved was 100% for water by almost all the classification algorithms. The 100% *OA* indicates that there was no mixing or unmixing of the other classes with the water. A little bit less accuracy was found for fallow land due to less mixing with linseed. Some pixels of sand were misclassified as built up and some pixels of built up were misclassified as sand. This type of mixing occurred only due to the similar spectral response of built up and sand. In the crop classes, the highest *OA* obtained for the wheat crop indicates that there was very less mixing with the other crops and barley classes.

Linseed crop showed lowest *UA* and *PA* and presented the maximum confusion with sparse vegetation, mustard, other crops and lentil crop classes. The confusion with linseed crop was caused mainly due to having similar spectral features of these class types. Wheat was found to be the easiest crop to identify within the crop classes, whereas linseed was found very difficult to identify. SVMs with polynomial of degree 2 provided 52.21% *PA* and 63.44% *UA* for the linseed crop indicates that 52.21% of the linseed areas were correctly identified as linseed, whereas 63.44% of the linseed areas were actually linseed. As another example, the *PA* and *UA* for sugarcane using SVMs with polynomial of degree 6 were found to be 82.24% and 75.86% respectively. These values indicate that 82.24% of the sugarcane areas on the ground were correctly identified as sugarcane, but only 75.86% of the areas called sugarcane on the classification map were actually sugarcane.

Some small portions of the wheat, mustard, linseed, pigeon pea, corn and sparse vegetation were misclassified as other crops class. Similarly, some portions of mustard, linseed, corn, pea and other crops classes were misclassified as sparse vegetation. This type of misclassification was partially due to spectral similarities among the classes and partially due to variability within the field. A very high spectral similarity was found among sugarcane, pigeon pea and dense vegetation classes. The high spectral similarity observed between barley and lentil also created confusion and showed misclassification with each other. A large variation between *PA* and small variation between *UA* was found in pigeon pea crop, whereas small variation between *PA* and large variation between *UA* was found in sugarcane within the crop classes by almost all the algorithms. This type of large variation was due to spectral similarity and within the intrafield variability. A very small variation between *PA* and *UA* was found for wheat, corn and fallow land classes, whereas a large difference between *PA* and *UA* was found for linseed and pea crop using almost all the algorithms. The values of κ using SVMs with linear, polynomial with degrees of 2, 3, 4, 5, 6, radial basis and sigmoid function kernels were found to be 0.8394, 0.8462, 0.8551, 0.8554, 0.8614, 0.8638, 0.8502 and 0.8060, respectively. Other κ values using ML and NDVI classification were found to be 0.8402 and 0.7252, respectively. As an example, the value of κ equals to 0.8502 indicates that the achieved classification accuracy was 85% better than the random assignment of pixels to classes.

2.4.2 Test for statistical significance in the classification accuracy

The statistical significance of differences in the accuracy of the classifications was assessed using a McNemar's test for the independent samples. The *Z*-test and χ^2-test were utilized to test whether the two classification results were significantly different or not. Interpretation of the test results was based on the *Z*-test for example, a value $Z > |1.96|$ indicates a statistically significant difference in classification accuracy at the 95% confidence level. The classification results were statistically signified that all the combinations were given *Z* values more than 1.96 except SVMs with polynomial of degree 6 *vs.* SVMs with polynomial of degree 5. It means that all the combinations were found to be significantly different, but insignificantly different combination was observed by SVMs with polynomial of degree 6 *vs.* SVMs with polynomial of degree 5 ($Z = 1.34$, $p = 0.1802$). The combination using SVMs with polynomial of degree 6 *vs.* SVMs with polynomial of degree 5 was significantly more accurate than the other combinations. Critically, SVM with polynomial of degree 6 resulted 0.23% increase in the classification accuracy than the SVMs with polynomial of degree 5 which was statistically insignificant. The increase in κ using SVMs with polynomial of degree 6 with respect to SVMs with polynomial of degree 5 was found not to be statistically significant with *Z* value 1.34 and *p*-value 0.1802. The *Z* value was found less than 1.96

at the 95% confidence level. Notably, significant increases in the classification accuracy were obtained for barley, lentil, mustard, pigeon pea, linseed, pea and sugarcane.

Due to different growing stages of crops and management conditions of the crop fields, it was not very clear visually that how well the crops were separated. Most of the fields on the classification maps had only one dominant class whereas all fields contained small inclusions of some other classes due to the within-field variability and the spectral similarities among some of the classes. κ analysis was done for comparing the classifications with a random classification which provided all the *Z*-test values greater than 1.96, except SVMs with polynomial of degree 6 and 5 having critical value of 0.05 significant level. Therefore, all the classifications were found significantly better than a random classification at the 95% confidence level except SVMs with polynomial of degree 6 and 5. *Z*-test and χ^2-test values for making pairwise comparisons among the classification algorithms are presented in Table 2.7.

Table 2.7 Statistical significance of differences in classification accuracy between two different algorithms

Classification1	Classification 2	*Z*-test	$\chi 2$-test	*p* value
SVMs with polynomial of degree 6	SVMs with linear function	6.06	36.72	<0.0001
SVMs with polynomial of degree 6	SVMs with polynomial of degree 2	4.78	22.85	<0.0001
SVMs with polynomial of degree 6	SVMs with polynomial of degree 3	3.48	12.11	=0.0005
SVMs with polynomial of degree 6	SVMs with polynomial of degree 4	3.37	11.36	=0.0008
SVMs with polynomial of degree 6	SVMs with polynomial of degree 5	1.34	1.80	=0.1802
SVMs with polynomial of degree 6	SVMs with radial basis function	4.19	17.56	<0.0001
SVMs with polynomial of degree 6	SVMs with sigmoid function	8.76	76.74	<0.0001
SVMs with polynomial of degree 6	ML classification algorithm	5.99	35.88	<0.0001
SVMs with polynomial of degree 6	NDVI classification	15.06	226.8	< 0.0001

The classification results using SVMs with polynomial of degree 6 and degree 5 were found significantly better than the other algorithms, but there was no significant difference between these two algorithms in the *OA* (87.33% *vs.* 87.10%). Other classification algorithms showed significant differences with the SVMs with polynomial of degree 6 having different *p* values. The value of χ^2 was found 1.80 using SVMs with polynomial of degree 6 *vs.* 5 which was lower than the critical value of 3.841. It means that the χ^2-test accepted the null hypothesis and indicated that they were not statistically different. In all other combinations, the χ^2-test rejected the null hypothesis because all the χ^2 values were found more than the critical value. It was concluded that, except the combination of SVMs with polynomial of degree 6 *vs.* 5, the other combinations of classification accuracy results found statistically different.

2.5 CONCLUSION

The classification of agricultural crops using LISS-IV data was found effective in identifying the different crop types. The performance of SVMs with polynomial of degree 6 showed better results with respect to other classification algorithms. The classification maps provided fairly good crop classification indicated by the good separation observed between the classes by the separability analysis performed before the classification. The results in terms of *OA*, κ and McNemar's test suggest that the SVMs with polynomial function kernel can provide better classification accuracy in comparison to other kernel based SVMs, ML and NDVI classification algorithms using LISS-IV data.