IDENTIFYING THE MOST IMPORTANT SPECTRAL AND TEXTURAL FEATURES TO MAP SPECIFIC CROPS WITH VERY HIGH RESOLUTION IMAGES

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ABSTRACT

Automated specific crop mapping for small holder farming from remote sensing images is highly desirable for timely information about the cultivated crop to manage agricultural practices and to ensure food security. The land parcels in smallholder farming are often small and also there is a common practice to cultivate more than one crops within single agricultural field. For mapping crops in such smallholder farming, very high resolution satellite images are desired in order to avoid mixed pixel problem which often occurs in lower resolution images. The potential of these very high resolution images has been demonstrated for crop mapping in smallholder farming by many studies. Also, these images have been acknowledged for its spectral and temporal characteristics where the information from multi-spectral and multi-date image bands have been demonstrated as useful for crop classification by several studies. However, the reported studies are largely focusing on multi-crop classification problem where the classifier is built to classify between two or more crops. This kind of classifiers require balanced and significant number of samples from each class. In our application of specific crop mapping, we are interested in mapping single crop where the ground truth samples are largely available for that specific crop. This kind of problem is referred as one-class classification. Several classifiers have been reported in the literature for one-class classification and demonstrated as effective for various remote sensing applications. However, the exploration of these one-class classifiers for specific crop mapping using very high resolution satellite imagery is limited and thus this study aims to explore it. Features derived from images which represent the unique characteristics of the objects in the images are the fundamental input to the classifier. The choice of features plays a key role in classification accuracy. Numerous spectral and textural features have been reported as effective for crop classification using satellite images. Each feature represents the content of the image in a unique way and it is challenging to decide which features are suitable for our application. Moreover, extracting all the reported features for number of bands of multi-temporal images will lead to high dimensionality of features. This makes the classification process complex and poses the curse of dimensionality issue. Moreover, the presence of irrelevant and redundant features may severely affect the performance of the classifier. Hence, it is important to reduce the feature dimensionality by identifying the most important features before performing classification. In remote sensing applications, feature reduction is commonly achieved by adopting a feature selection algorithm. To this end, in this study, a framework has been developed for mapping specific crop using multi-temporal satellite images. This framework includes three pipelining processes: 1) extraction of various spectral and textural features that are anticipated to be effective for crop classification; 2) identification of most important features among the extracted ones for our application using a feature selection algorithm; 3) identifying specific crop using one-class classification based on the selected important features in step2. In literature, several methods have been reported as effective for feature selection and one-class classification. It is critical to choose one among them for our application as the performance of these methods are often varying for different study areas and data sets. Hence in this study, four feature selection algorithms such as Fisher's method, Infinite Feature Selection (InfFS), Forward Feature Selection (FFS) and Multiple-Kernel-Learning (MKL) are considered for identifying the most important features. Likewise, two supervised one-class classifiers based on Support Vector Machine (SVM) and three unsupervised classifiers based on Gaussian, Principal Component Analysis (PCA) and

K-means are considered for one-class classification. These methods are evaluated and compared by considering five crops for specific crop mapping using three world-view images of different dates. From the results, it is inferred that features selected by Fisher or MKL used with One-class SVM consistently produced superior classification accuracy for identification of all five crops. However, the maximum overall accuracy obtained for different crops is inconsistent which is in the range of 77% to 90%. Several specific inferences made in this study are provided in results section (chapter 4).
Index Terms - Specific crop mapping, spectral and textural features, one-class classification, feature selection, multi-temporal.

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1. INTRODUCTION

1.1. Motivation and problem statement

Agriculture is a key factor that influences social and economic growth of a country. Hence, an effective agricultural management system is vital for any country practicing agriculture. This system includes: i) planning and accomplishment of food production for meeting the demands of an increasingly growing population and domestic animals; ii) increasing the yield for export according to the global market demand to increase the revenue of the country; iii) management of water resources for irrigation and other purposes. Moreover, the government needs to estimate the yield of a specific crop (e.g. major food crop of the country) to ensure the food security of the country. For effective management of all the aforementioned activities, accurate and timely information about the cultivation of specific crop and its spatial distribution are crucial (Doraiswamy et al. 2004; Thenkabail et al. 2009; De Wit et al. 2004). This information can be collected by manual crop mapping through field survey. However, it is practically infeasible as this information needs to be collected repeatedly over large areas which is a time-, cost- and labor-intensive process. Hence, an automated and low-cost approach for accurate and timely mapping of specific crop over large area is highly desirable.

Remote sensing technology with various kinds of platforms and sensors provides images with varying scale, spectral and temporal resolutions. The features that can be derived from the images with aforementioned characteristics have been demonstrated as an effective tool for capturing the physical and chemical properties of vegetation (Adam et al. 2010; Moran et al. 1997). Thus remote sensing images have been recognized as a potential source for vegetation related studies at local, regional and global scales (Lawley et al. 2016; Adam et al. 2010; Xie et al. 2008). In particular, the usefulness of satellite images for crop mapping has been demonstrated by numerous studies (Chellasamy et al. 2014; Ozdarici-Ok et al. 2015). However, the choice of satellite image depends on the characteristics of the designated application and the nature of agricultural pattern in the study area. For example, in most developing countries, smallholder subsistence agriculture is prevalent (Debats et al. 2016). In this type of agriculture, cultivation of two to three types of crop in the same agricultural field is common (Valbuena et al. 2015). Moreover, in small-holder farming, the land parcels are often smaller. In such cases, it is possible that more than one land parcel cultivated with different crops can be covered by single pixel if the spatial resolution of the chosen image is lower. This leads to mixed pixel problem and increases the classification complexity (Lobell et al. 2004; De Wit et al. 2004). Moreover, in application of crop classification, the crops can be differentiated based on their spectral and textural (i.e. spatial pattern) variations as described later in Chapter 3 (Chellasamy et al. 2014; Qayyum et al. 2013; Kim et al. 2014). The spatial pattern of the crops could be captured more precisely in very high resolution images compared to low resolution images (Puissant et al. 2005). For capturing rich spectral information, multi-spectral images are desired (Chellasamy et al. 2014). Also, the images of different crop growth stages help to capture the crop phenology which can further contribute for better crop discrimination (Yusoff et al. 2015). Thus, very high spatial resolution, multi-spectral and multi-temporal images are desired for the application of crop mapping which has been already demonstrated by several studies. Currently, there are several satellites in operation which provide the multi-spectral images periodically with very high spatial resolution. This makes rapid and timely mapping of crops for larger areas feasible.

Though the satellite images with desired characteristics are available for crop mapping, it is still challenging to map the crops in an automated way. Several studies have already attempted to automate crop mapping from satellite images (Chellasamy et al. 2014; Ozdarici-Ok et al. 2015; Wang et al. 2004). However, the accuracies reported by them are highly variable (e.g. accuracies in the range of 60% to 90%). There can be many reasons for this variability such as characteristics of crops considered for mapping, complexity of the study area and climatic conditions. Besides these physical characteristics, the choice of image features and the choice of classifiers for automatic mapping of crops play a vital role in the classification accuracy (Peña et al. 2014; Chellasamy et al. 2014). Concerning the image features, numerous spectral (e.g., vegetation indices) and textural (e.g., features derived from Gray Level Co-occurrence Matrix (GLCM), Local Binary Pattern (LBP) etc.) features have been reported as effective for vegetation related studies including crop classification (Peña-Barragán et al. 2011; Niemi et al. 2016). However, extracting these features for satellite image with considerable number of spectral bands will lead to sharp increase in the dimensionality of the feature space. Furthermore, in the scenario of using multi-temporal images, the dimensionality of features will increase abruptly. For example, in this study, dimensionality of features that are extracted for three multi-temporal WorldView-2 images is 4848 (cf. Tables 4-1 & 4-2 in chapter 4). Thus, the classification becomes computationally complex in a high-dimensional feature space and also it may lead to curse of dimensionality issue, particularly model overfitting problem (Roffo 2016; Tang et al. 2014; Liu et al. 2016). For instance, it is a well-known fact that if the dimensionality of the features is greater than the number of samples available for training the classification model, then there would be a high probability for model overfitting (Han et al. 2014) . Also, the presence of irrelevant and redundant features may decline the performance of the classifier (Cutler et al. 2012; Guo et al. 2008). Hence, it is important to reduce the dimensionality of the features to build a robust and reliable classifier. It is a common practice in image classification applications to reduce the dimensionality of features by identifying the most important features that are significantly contributing for the discrimination of different classes considered for classification (Roffo 2016). This approach is commonly referred as feature selection. Several feature selection algorithms have been reported as effective in the literature (Kojadinovic et al. 2000; Roffo 2016; Wang et al. 2014). But choosing the suitable one for our application and dataset is critical, as each possesses its own advantages and disadvantages. Thus, one of the problems that will be addressed in this study is identifying the most promising combination of spectral- and textural- features from multi-temporal satellite images for mapping specific crops using an appropriate feature selection algorithm that is found by comparing several such algorithms.

Apart from features, the selection of classifier plays a key role in the classification. The choice of classifier depends on the nature of classification problem and availability of additional information required for constructing that particular classifier (e.g., significant number of ground truth samples are mandatory for training in order to choose supervised classifiers). In our application of specific crop mapping, we are interested in constructing classifier for identifying single crop based on the ground truth samples available for target class. This classification problem falls under the category of one-class classification (Mack et al. 2016). Here, a classification boundary or prototype is defined based on the target samples and the new unseen samples are classified as target or outliers based on their degree of membership to the defined boundary or prototype (Khan et al. 2014). Several one-class classifiers based on unsupervised, semi-supervised and supervised approaches have been reported in the literature (Khan et al. 2014; Tax 2001; Muñoz-Marí et al. 2010). The potential of these one-class classifiers have been demonstrated by several studies for various image classification problems including remote sensing applications such as cropland mapping, built-up area mapping and disaster damage mapping (Li, Xu, et al. 2010; Zhang et al. 2014; Shen et al. 2011) . However, the exploration of one-class classification for specific crop mapping, particularly using very high resolution multi-spectral images is limited. Thus, this study aims to explore the potential of one-class classification for specific crop mapping for the selected study area and remote sensing data by evaluating several one-class classifiers.

1.2. Research identification

1.2.1. Research objectives

The primary objective of this study is to identify spectral and textural image features that are best suited to map specific crops using multi-temporal very high resolution satellite images. The specific objectives in this study are:

a) To extract various kinds of spectral and textural features from multi-spectral and panchromatic (PAN) bands to evaluate their significance to map specific crop.
b) To evaluate the usefulness of multi-temporal over mono-temporal images for specific crop mapping
c) To evaluate the significance of incorporating feature selection in the classification process.
d) To identify the feature selection algorithm that best suits our application among the reported algorithms.
e) To evaluate different one-class classifiers to study the performance of the classifiers for specific crop mapping application.

1.2.2. Research questions

a.1) What kind of features are most significant for the application of specific crop mapping?

a.2) What is the significance of multi-spectral vs PAN bands of satellite imagery in specific crop mapping?

b.1) Are the multi-temporal images more significant than mono-temporal images for specific crop mapping?

b.2) Is there any impact in the choice of timing of image for mapping specific crop in mono-temporal image based classification?

c.1) Is there any impact in classification with and without feature selection?

d.1) Does the choice of feature selection algorithm have impact in the classification accuracy?

d.2) Are the features selected by a feature selection algorithm same or unique for different crops?

d.3) Are the features selected by different feature selection algorithms same for a specific crop?

d.4) Are the features selected by a specific feature selection algorithm for mapping a specific crop varies across months?

e.1) Does the choice of classifier have impact in the classification accuracy?

e.2) Are target class samples alone sufficient for building a robust one-class classifier or is the inclusion of outlier samples required to build a robust classifier that minimizes false positives?

1.3. Innovations and contributions

- Numerous features such as GLCM, LBP, spectral bands reflectance values, vegetation indices and GLCM features of vegetation indices and LBP image were evaluated in order to identify the crop specific importance features to map specific crop using high resolution satellite images. These combination of features are not collectively examined yet for this application.
- Multi-kernel learning approach is adopted for feature selection for specific crop mapping which has not been examined before for this specific application.
- Four feature selection algorithms are compared for the identification of most important features for specific crop mapping based on one-class classifiers. This kind of comparison for this application has not been reported yet.
- We have examined the potential of different one-class classifiers for specific crop mapping which is also not reported yet.
- We have implemented LBP algorithm in Python in such a way that it can run in Google Earth Engine (GEE) environment.
- We have written several MATLAB scripts to create a framework to evaluate four feature selection algorithms and five one-class classifiers.

1.4. Structure of the thesis

This thesis has five chapters. Chapter 1 provides the relevant background, overview of the research problems to be addressed, research objectives, research questions and the innovations and contributions made in this research. Chapter 2 provides the literature review. The description about the methodology is presented in chapter 3. The experimental setup, results and discussions are provided in chapter 4. Chapter 5 provides the overall discussion, conclusions and recommendations.

2. LITERATURE REVIEW

This chapter provides a discussion of relevant literature to establish the state-of-the-art and a justification for choice of data and of the various methods in this study.

2.1. Crop classification using remote sensing images

Numerous studies have been conducted for automated mapping of crops using various kinds of remote sensing images such as multispectral, hyperspectral and Synthetic Aperture Radar (SAR), captured from both air- and space-borne platforms (Kussul et al. 2014; Peralta et al. 2016; Zhang, Yang, et al. 2016; Zhang, Sun, et al. 2016). Each of these image types has unique characteristics, and each comes with advantages and limitations. The choice of image type for crop mapping depends on the availability of data for the specific site, and on other requirements such as scale (large or small), temporal (how often to be monitored), characteristics of the study area (weather conditions) and cost (Ozdarici-Ok et al. 2015). For example, hyperspectral images provide high spectral information, which is highly desirable for crop classification, but it is comparatively expensive and sensitive to weather conditions such as cloud cover and poor illumination condition which leads to weak reflectance (Löw et al. 2013). Using multispectral images is cheaper, but it is also sensitive to weather conditions (Lorenzi et al. 2013; Ozdarici-Ok et al. 2015). Alternatively, SAR is less affected by weather conditions, but it is prone to high noise e.g., speckle noise. As described in Chapter 1, an important requirement for the application of crop mapping in smallholder farms is the availability of images with high spatial resolution, and adequate spectral and temporal information, covering a large area to allow cost-effective solutions (Ozdarici-Ok et al. 2015).

Very high spatial resolution multispectral images from satellites such as Quickbird, WorldView and GeoEye have been reported as sufficiently satisfying the above requirements for crop mapping in smallholder farms (Dhumal et al. 2015; Castillejo-González et al. 2009). For example, Castillejo-González et al. (2009) used Quickbird images to perform land cover classification of 10 classes, among them 3 crop classes. They examined pan-sharpened and multispectral images independently for the classification process to determine whether spectral information (from multispectral images) represented in higher spatial resolution (from pan-sharpened images) improves the classification accuracy. They reported an increase of about 3% in accuracy with pan-sharpened image as compared to use of multispectral data only. Karakizi et al. (2016) used pan-sharpened and multispectral WorldView-2 images independently to classify six vine varieties. They reported no significant accuracy difference between pan-sharpened and multispectral imagery, which contrasts with the findings by Castillejo-González et al. (2009). Ozdarici-Ok et al. (2015) used three different multispectral very high resolution (VHR) images (Ikonos, Quickbird and Kompsat-2) for classification of six crops, and achieved a kappa index of 0.85 for the images from aforementioned satellites. They also reported that a single date VHR multispectral image alone is sufficient for crop mapping by choosing the right image acquisition data i.e., mid-crop growth stage (mid-season) rather than early-crop growth stage (early season). Chellasamy et al. (2014) examined multispectral WorldView2 images from early-season, mid-season and a combination of these two independently to classify 15 crops. An improvement in accuracy was achieved for the combined use of early- and mid-season images (92%) compared to the accuracy with mid-season image alone (86%) with accuracy significantly inferior when image of early-season alone was used for classification (64%). Overall, it is evident from previous studies that VHR images can suitably be applied to smallholder crop mapping over larger areas. However, it is still challenging to choose an optimal combination of images (i.e., mono- or multi-temporal with either panchromatic alone or panchromatic + multispectral) that is suitable as the conclusions drawn by different studies are inconsistent. Thus, in this study, we dedicate one of the research objectives to explore this matter.

2.2. Feature extraction for crop classification

Features are the information extracted from images by performing some mathematical functions to capture the unique characteristics of real world entities present in the image. These features are the fundamental input for any classifier. In our application of crop classification, features can be characterized by spectral variability, by variation in spatial pattern or by both (Peña-Barragán et al. 2011; Kim et al. 2014).

In literature, numerous spectral and textural features have been reported t as effective to capture the spectral and spatial pattern characteristics which can be used for crop classification (Conrad et al. 2010; Rodriguez-Galiano et al. 2012; Simonneaux et al. 2008).

2.2.1. Spectral features

Vegetation indices are a class of spectral features recognized as important in vegetation studies (Bannari et al. 1995). Many vegetation indices have been reported in literature for the crop classification process (Bannari et al. 1995; Peña-Barragán et al. 2011). Among them, NDVI proposed by Tucker (1979) is used widely and it has been proven as effective in crop classification using VHR multispectral images (Upadhyay et al. 2012). NDVI is derived by taking the normalized difference ratio of two bands, commonly NIR and red bands are used (Tucker 1979). However, the indices derived from combinations of other spectral bands are also reported to be useful for crop classification. For example, Chellasamy et al. (2014) classified 15 crops using five different NDVIs which were based on different band combinations of Worldview-2 data, and with which an accuracy around 85% was achieved. A number of studies reported that the standard NDVI based on red and NIR bands is sensitive to soil background and atmospheric conditions. It has been widely reported that distance-based vegetation indices such as SAVI minimize the effect of soil in the background of vegetation (Gilabert et al. 2002). In the same way, several vegetation indices have been reported in the literature with variable potential for crop classification. For example, Agapiou et al. (2012) explored 71 vegetation indices derived from hyperspectral and multispectral images to identify the archaeological crop marks. They reported that among multispectral vegetation indices NDVI, SAVI and simple band ratios are the most useful features for their application. However, it remains hard to choose the most appropriate vegetation index among the reported ones for our application of crop mapping. Hence, in this study several vegetation indices such as variants of NDVI, SAVI and other ratios are considered.

2.2.2. Textural features

Though spectral features such as vegetation indices have been demonstrated as effective for crop classification, they suffer from discriminating crops with similar spectral characteristics (Peña-Barragán et al. 2011). In such cases, textural features of the crops are reported to be more useful (Peña-Barragán et al. 2011). Various types of textural feature have been examined for crop classification (Taşdemir et al. 2011; Ghosh et al. 2014; Akar et al. 2015). Statistical textural features based on GLCM are classic features used for our purpose (Aguilar et al. 2015; Tsai et al. 2006; Yu et al. 2006). Several GLCM features have been reported in the literature. For example, (Haralick et al. 1973) initially proposed 14 GLCM features and in addition to these, other GLCM features were gradually defined (Albregtsen (2008). However, only few GLCM features are widely used in vegetation studies (Aguilar et al. 2015; Peña-Barragán et al. 2011). For example, Schmedtmann et al. (2015) used only eight GLCM features for crop classification from multispectral images. Peña-Barragán et al. (2011) examined the same eight GLCM features for crop classification using multispectral images and reported that among eight features, only homogeneity, dissimilarity and entropy are found to be useful for crop classification. Alternative to statistical textures such as GLCM, textural features based on a filtering approach are also widely reported to be effective for remote sensing studies including crop classification (Akar et al. 2015; Rabatel et al. 2008). For example, Qayyum et al. (2013) compared textural features with filtering techniques such as Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) with GLCM for crop classification. The authors concluded that the classification using DWT features provided better accuracy compared to other features. Chellasamy et al. (2014) reported that textural features based on Gabor filters alone effectively classified 15 different crops from WorldView-2 data with an overall accuracy of 88%, which was higher than the accuracy produced by vegetation indices (83%). Rabatel et al. (2008) demonstrated the potential of Gabor filters in identifying planted vineyards using aerial images. Reis et al. (2011) used Gabor features to map hazelnut vegetation from Quickbird panchromatic images and achieved a kappa index of 0.74, higher than the one using multi-band spectral reflectance values (0.68). Though filtering approaches are reported to be effective for textural analysis, it is challenging to adopt these methods for remote sensing images. This is because, in this approach, texture can be represented by a collection of values. For example, Chellasamy et al. (2014) used Gabor texture for crop classification. In general, Gabor texture is defined by a set of filters where each filter is tuned to capture the information in specific orientation and frequency. Chellasamy et al. (2014)used 40 filters to describe Gabor texture which led to the feature dimension of 40 for each band. Extracting these features for a number of bands in multispectral images will lead to very high feature dimensionality. Further, it brings the curse of dimensionality issue as discussed in Chapter 1. Moreover, these features cannot be reduced by a feature selection approach as these features collectively represent a single texture measure.. Therefore, it is not suitable for studies that do not have sufficient training samples to overcome the curse of dimensionality. Another type of textural feature, the Local Binary Pattern (LBP), has been widely used. It is computationally simple, and has been demonstrated as effective for several remote sensing applications including crop classification (Gevaert et al. 2016; Li, Liu, et al. 2010). Musci et al. (2012) examined LBP and GLCM features independently to classify Ikonos-2 images into three classes: grass, forest and urban. They reported that LBP produced a higher kappa index (0.93) compared to GLCM features (0.80). Chowdhury et al. (2015) demonstrated that extracting GLCM textures for LBP image is effective for mapping roadside vegetation. However, the studies that have reported LBP as an effective textural measure are mainly focused on discrimination between vegetation and other land cover types, whereas, the potential of LBP to discriminate between crops has not been largely explored. Thus, in this study, we intend to examine the LBP features and various GLCM features based on reflectance- and LBP- images for discrimination of crops.

2.2.3. Combination of spectral and textural features

Often it is reported that a combination of spectral and textural features produces greater accuracy than when they are used in isolation for crop classification (Ursani et al. 2012; Dhumal et al. 2015). Most of the above-mentioned studies that compared the spectral and textural features independently, also examined the combined use of both types of feature for crop classification. For example, Chellasamy et al. (2014) reported that the combined use of spectral and textural features produced higher accuracy than when they were used in isolation.

2.3. Feature selection

The extraction of various aforementioned textural and spectral features from different bands of multispectral images significantly increases the dimensionality of the final feature set for the classification that, in turn, increases the chances of overfitting (Guyon 2006; Pan et al. 2010). Moreover, not all textural and spectral features may be equally relevant (noise) and some of the features may be redundant (Roffo 2016). The presence of such features may affect the performance of the classifier and decrease classification accuracy (Kabir et al. 2010). Hence, the selection of features is an essential step before classification takes place (Puig et al. 2010). Many remote sensing application studies reported that classification based on selected features using a feature selection algorithm improved classification accuracy (Pan et al. 2010; Li et al. 2008). In general, two kinds of feature selection strategies are used: 1) a filtering approach, in which feature selection analyzes the intrinsic characteristics of the data without consideration of the final classifier (Tang et al. 2014); and 2) a wrapper approach, in which the relevance of the features is evaluated using the final classifier (Kabir et al. 2010; Kojadinovic et al. 2000). The former is computationally faster and is not biased to the classifier (Tang et al. 2014). The latter is biased to the final classifier but is often reported to be effective as the feature evaluation is carried with the classifier in mind (Kumar et al. 2014). In the wrapper approach, two strategies (sequential forward selection and sequential backward selection) are reported to be simple and widely used (Kumar et al. 2014; Guyon 2006; Guyon et al. 2003). In the filtering approach, Fisher's method is efficient and faster but it is a univariate approach and is known to be ineffective for handling feature redundancy (Tang et al. 2014). Roffo et al. (2015b) proposed a new feature selection algorithm, called Infinite Feature Selection (InfFS) based on a filtering approach and claimed it as effective and superior by comparing several feature selection algorithms on two benchmark data sets. The important drawback in the aforementioned feature selection algorithms is that they cannot concurrently evaluate all the features i.e. they either evaluate the features individually or specific subset of features rather than evaluating all the features at once. In such cases, the importance of co-occurrence of certain features cannot be captured (Tang et al. 2014). Many studies reported Multiple-Kernel-Learning (MKL) as an effective tool for feature selection, which can evaluate the importance of all features by concurrently estimating the contribution of each feature in the final classification accuracy (Dileep et al. 2009; Wang et al. 2014). However, it has been reported that the performance of MKL may degrade when the number of training samples is not proportionally much higher than the number of features (Bucak et al. 2014b; Gönen et al. 2011). In summary, each feature selection algorithm possesses its own advantages and disadvantages and hence, it is desired to find the algorithm that best suits for the application and characteristics of data at hand (e.g., available number of training samples).

2.4. Classifiers for crop classification

The crop classification process can be broadly categorized into three approaches: 1) supervised approach, 2) unsupervised approach and 3) semi-supervised. The supervised approach is the most commonly found approach in literature for remote sensing applications including crop classification (Mather et al. 2016; Castillejo-González et al. 2009). Several supervised approaches have been reported, but the ones based on machine learning are found to be more successful (Liu et al. 2015; Löw et al. 2013). Several studies have made a comparative study between different supervised learning algorithms for crop classification. For example, Ozdarici-Ok et al. (2015) compared four classifiers: Support Vector Machine (SVM), Random Forest (RF), Gaussian Mixture Model (GMM) and Maximum Likelihood Classifier (MLC) to classify six different crops from single date multispectral images of three different sensors and reported SVM as superior. Peña et al. (2014) evaluated four classifiers: C4.5 decision tree, logistic regression, SVM and Multi-Layer Perceptron (MLP) to classify nine crops in an ASTER satellite image and reported that MLP and SVM are performing better than others. In most vegetation related studies, SVM is used as the classifier and is reported to be effective (Liu et al. 2015; Löw et al. 2013). The above-mentioned supervised learning classifiers used in different studies are designed for multi-class classification, i.e., they require labelled samples for two or more classes to train the classifier. Moreover, these classifiers do not perform well when any of the classes is under-sampled or completely absent (Khan et al. 2014). However, as mentioned in Chapter 1, our application is specific crop mapping (i.e., single crop identification) with ground samples largely limited to single class. In such case, the aforementioned classifiers cannot be adopted. In literature, several classifiers have been reported to address the above described one-class classification problem (Tax 2001; Mather et al. 2016; Khan et al. 2014). The basic principle behind one-class classification is defining a classification boundary based on the target samples alone and all new unseen samples that lie outside this boundary are classified as outliers (Khan et al. 2014). Hence, several studies refer one-class classification as outlier detection or novelty detection (Gardner et al. 2006; Hodge et al. 2004). Some studies are also using the term concept learning or single class classification to refer the one-class classification (Japkowicz 2001; El-Yaniv et al. 2007) . The one-class classifiers reported in the literature can be broadly categorized based on two aspects:

1) Type of internal model used by the classifier to classify the samples: Based on the internal model, the classifiers can again be subcategorized into three categories: a) Density based e.g., one-class Gaussian model (Markou et al. 2003) b) Reconstruction based e.g., one-class Principal Component Analysis (one-class PCA) (Tax 2001) and c) Boundary based e.g., one-class SVM (OCSVM) () (Schölkopf et al. 1999).

2) Choice of learning strategy: a) Supervised: building a classifier based on labeled samples of either target class alone or both target and outlier classes (e.g., OCSVM) (Schölkopf et al. 1999); b) Semi-supervised: building a classifier based on both labeled and unlabeled samples (e.g., semi-supervised OCSVM) (Muñoz-Marí et al. 2010); c) Unsupervised: building a classifier based on unlabeled samples (e.g. one-class PCA) (Tax 2001).

Numerous studies have demonstrated the potential of these one-class classifiers for various applications including remote sensing (Khan et al. 2014; Zhang et al. 2014; Sanchez-Hernandez et al. 2007). Particularly, one-class SVMs based on supervised approach are widely reported for remote sensing applications (Banerjee et al. 2006; Zhang et al. 2014). The reported one-class SVMs are largely developed based on one of the two kinds of OCSVMs proposed by Schölkopf et al. (1999) and by Tax et al. (2004). The OCSVM proposed by Schölkopf et al. (1999) defines the classification boundary using hyperplane whereas the support vector domain description (SVDD) proposed by Tax et al. (2004) defines the classification boundary based on hypersphere. These two kinds of SVMs are the widely used one-class classifiers for remote sensing applications. For example, Zhang et al. (2014) used hyperplane-based OCSVM to differentiate the built-up (target class) areas from non-built-up areas (outliers) using Landsat ETM image. The classification was based on spectral and textural features and they achieved a maximum accuracy of 90%. Sanchez-Hernandez et al. (2007) used SVDD to map a specific land cover class 'fenland' and reported that SVDD produced superior results compared to other one-class classifiers such as mixture of Gaussians and Parzen density estimators. Clauss et al. (2016) used OCSVM to map paddy rice crop in China using MODIS images and achieved an overall accuracy of 90%. They reported that the choice of optimal outlier ratio (one of the hyper-parameters in OCSVM) is tricky in absence of outlier samples. Hence, they included outlier samples in addition to target class samples to identify the optimal outlier ratio. Besides the outlier ratio, the choice of kernel has also been reported to have significant impact on the performance of the SVM-based classifiers (Khan et al. 2014). Several studies reported that Gaussian kernel often performed better than other commonly used linear and polynomial kernels (Khan et al. 2014; Tax 2001).

Though supervised approaches are predominantly being used in remote sensing applications, few studies reported that semi-supervised and unsupervised approaches are performing better than supervised approaches (Muñoz-Marí et al. 2010). For example, Muñoz-Marí et al. (2010) presented two semi-supervised OCSVMs which were developed by modifying the OCSVM proposed by Schölkopf et al. (1999). They evaluated the proposed methods against the conventional supervised OCSVM and unsupervised Guassian_DD based on four remote sensing applications: Urban monitoring, crop mapping, cloud mapping and change detection. They found that the performance of these four methods are highly inconsistent for different applications and datasets. For example, in crop mapping application, unsupervised Guassian_DD outperformed other supervised and semi-supervised SVM based classifiers. Whereas, in change detection application, conventional OCSVM produced superior results and in other two applications, the proposed semi-supervised OCSVMs were found to be superior. This shows that the choice of classification strategy (e.g., supervised or unsupervised) depends on the application and dataset. The potential of both supervised and unsupervised one-class classifiers for mapping specific crops from very high resolution satellite images is not yet studied. Hence, one of the objectives in this study is to evaluate different one-class classifiers that are based on both supervised and unsupervised approaches. To this end, two supervised OCSVMs proposed by Schölkopf et al. (1999) and (Tax et al. 2004) and three unsupervised one-class classifiers such as classifiers based on Gaussian, k-means and PCA presented by Tax (2001) are considered in this study.

3. MATERIALS AND METHODS

This chapter focuses on developing a framework for mapping specific (target) crop using both single- and multi-date satellite images based on one-class classification. The framework consists of three segments: i) feature extraction for obtaining image features that represent the spectral and textural characteristics of the crops; ii) feature selection to identify the most important features among the extracted ones in order to overcome the issue of 'curse of dimensionality' as mentioned in Introduction (chapter 1); and iii) one-class classification to map specific crops using the selected features. Several methods have been reported as effective for performing each of the above mentioned tasks and hence it is still difficult to choose the suitable one for our application. Thus, in this study, several methods for feature section and classification are considered and evaluated. The background and description of these methods are described in the sections subsequent to the description of study area and data used.

3.1. Study Area and Data Used

This research is based on the research project STARS (http://www.stars-project.org/en/) and all used data have been collected as part of this project.

3.1.1. Study Area

The study area chosen for this research is situated in Sukumba, Koutiala district, Mali. The motive behind this research is to improve the cropping practices of smallholder farms in Sub-Saharan Africa. The area considered for this study is around 10 km x 10 km. There are five major crops grown in this area which are considered in this study of specific crop mapping: maize, millet, peanut, sorghum and cotton.

3.1.2. Data used

Satellite imagery:

This study uses very high spatial resolution images acquired using Worldview-2 satellite sensor which has a revisit period of 1-2 days. These images consist of eight multispectral bands and one panchromatic band with spatial resolutions of 1.84 m and 0.46 m respectively. The bands specification is shown in the **Table 3-1** below. –

Table 3-1 Bands specification

Band	Wavelength (µm)
1 – Coastal Blue	0.40 - 0.45
2 – Blue	0.45 - 0.51
3 – Green	0.51 - 0.58
4 – Yellow	0.585 - 0.625
5 – Red	0.63 - 0.69
6 – Red Edge	0.705 - 0.745
7 – Near Infrared (NIR1)	0.77 - 0.895
8 – NIR2	0.86 - 1.04
Panchromatic	0.45 - 0.80

Three images are considered for this study which were acquired in 2014 (from May to November) at different time intervals as mentioned below.

- 22 May, 2014
- 18 October, 2014
- 14 November, 2014

Radiometric and atmospheric corrections were already done for these images and also they were orthorectified and co-registered. More details of these pre-processing steps can be found in the link (http://web.natur.cuni.cz/gis/lucc/wp-content/uploads/2016/06/poster_2016_EARSeL_NASA_Prague_v3_printed.pdf).

Field data:
The ground truth samples (in total 3652) collected through filed survey were used for building and evaluating the feature selection methods and classifiers for one-crop classification. More details about the framing of training and testing sets from these samples for performing classification are provided in experimental design section (chapter 4).

3.2. Feature extraction

The fundamental step in any image-based classification is the feature extraction where the image is transformed into useful information by performing some mathematical operations and this information is generally referred as features. As described earlier in chapter 2, various spectral and textural features which are anticipated to be effective for crop classification based on literature are considered in this study. These features are described below and summarized in Section 3.2.3.

3.2.1. Spectral features

The features that represent the characteristics of an entity based on reflectance values of the satellite image bands are referred as spectral features. Two kinds of spectral features are considered in this study and they are briefly described below.

3.2.1.1. Reflectance values

The reflectance values of the spectral bands of satellite imagery are often considered as useful features particularly for crop classification (Shwetank et al. 2010). In this study, all 8 spectral bands' values of wordview-2 are considered as features which are represented as b1 to b8. For example, red, green and blue bands of Wordview-2 image for a portion of the study area is shown in Figure 3-1.

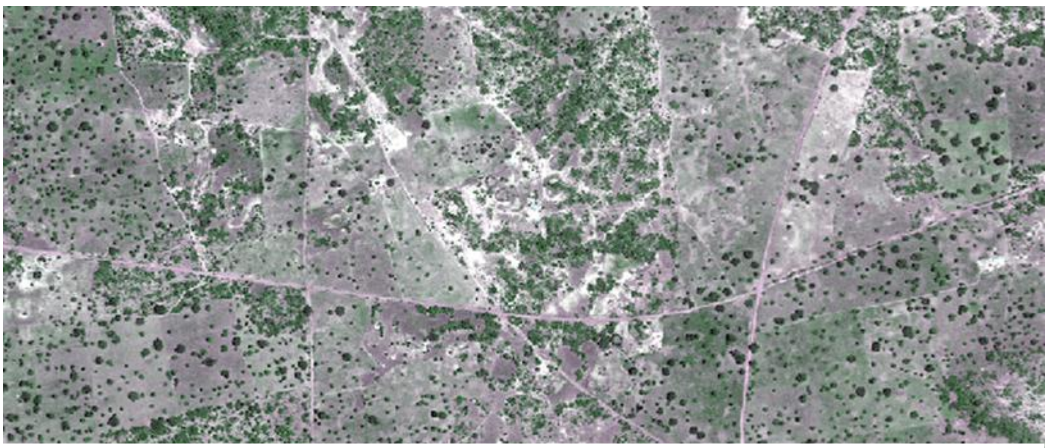

Figure 3-1 Red, green and blue bands of Worldview-2 image

3.2.1.2. Vegetation indices

As described earlier, vegetation indices are recognized as the most powerful and conventionally used features for any remote sensing based vegetation related studies. These are the ratios derived based on different combinations of spectral bands. Seven vegetation indices which are reported as effective are considered in this study and the formulations are given below.

i) The below three vegetation indices are derived for all two possible band combinations of bands 2 to 8.

- Normalized Vegetation Index (NVI)

  NVI = (band1 – band2) / (band1 + band2)

- Difference Vegetation Index (DVI)

  DVI = band1 – band2

- Ratio Vegetation Index (RVI)

  RVI = band1 / band2

ii) The formulations of other four vegetation indices are as follows:

- Enhanced Vegetation Index (EVI)

  $$\mathrm{EVI} = 2.5 * \frac{(\mathrm{NIR}-\mathrm{Red})}{(\mathrm{NIR}+6*\mathrm{Red}-7.5*\mathrm{Blue}+1)}$$

- Transformed Chlorophyll Absorption Ratio Index (TCARI)

  TCARI = 3[(Red Edge − Red) − 0.2(Red Edge − Green) (Red Edge / Red)]

- Soil-Adjusted Vegetation Index (SAVI)

  $$\mathrm{SAVI} = \frac{1.5 * (\mathrm{NIR}-\mathrm{Red})}{(\mathrm{NIR}+\mathrm{Red}+0.5)}$$

- Modified Soil-Adjusted Vegetation Index (MSAVI)

  $$\mathrm{MSAVI} = \frac{2*\mathrm{NIR}+1-\sqrt{(2*\mathrm{NIR}+1)^2-8*(\mathrm{NIR}-\mathrm{Red})}}{2}$$

For example, NVI image of bands 2 and 6 is shown in Figure 3-2.

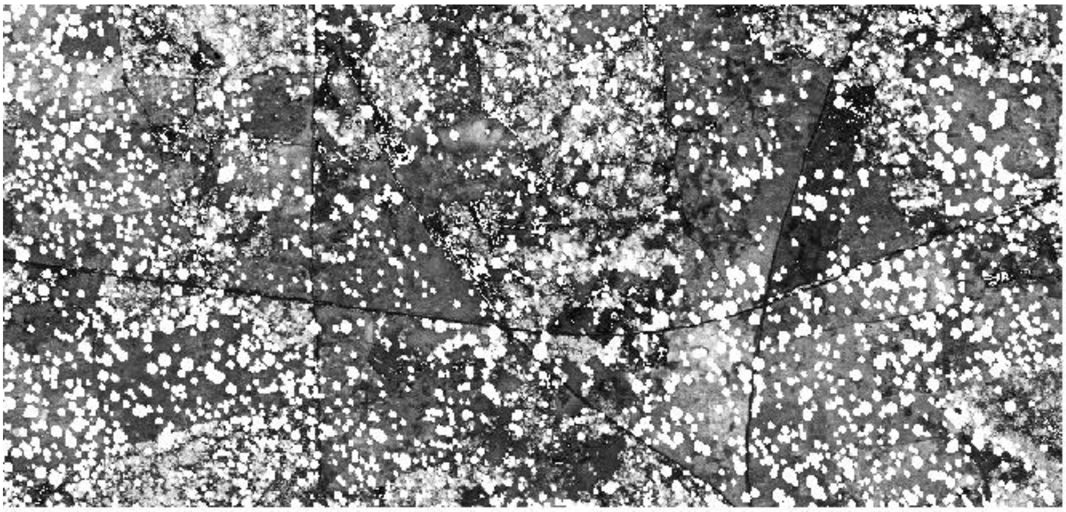

Figure 3-2 NVI image of bands 2 and 6

3.2.2. Textural features

Texture is an intrinsic property of the image which can be seen in all the images from remotely sensed data to microscopic photography. Texture describes the content of the image based on the spatial distribution pattern of image pixel values (e.g., reflectance value) (Pratt et al. 1978). Several methods are available for deriving the textural information from the image. Among them, the widely used two methods such as GLCM and LBP are considered in this study to extract the textural features for crop classification.

3.2.2.1. Gray-Level Co-occurrence Matrix (GLCM)

GLCM-based textural features were developed by (Haralick et al. 1973) which defines texture in terms of local grey–level statistics based on the spatial distribution of grey values which are constant or slowly varying within the band of the remotely sensed imagery. The first step in this method is the construction of co-occurrence matrix which is achieved by forming a relative displacement vector *(d, θ)*. This vector describes the relative frequencies of grey level pairs of pixels separated by a distance *d* in the direction θ. In this study, the GLCM matrix is constructed by averaging over four directions (0°, 45°, 90° and 135°) and restricted to a distance of one pixel (d=1) to obtain the textural features at reduced computational cost (Cutler et al. 2012). From this matrix, a number of statistical measurements can be derived as described by (Haralick et al. 1973). In this study, 18 textural measures that can be derived from this matrix are considered for the crop classification process. The considered features are: 1) Angular Second Moment (asm) 2) Contrast (contrast) 3) Correlation (corr) 4) Sum of Squares: Variance (svar) 5) Inverse Difference Moment (idm) 6) Sum Average (savg) 7) Sum Variance (var) 8) Sum Entropy (sent) 9) Entropy (ent) 10) Difference Variance (dvar) 11) Difference Entropy (dent) 12) Information Measures of Correlation1 (imcorr1) 13) Information Measures of Correlation2 (imcorr2) 14) Maximal Correlation Coefficient (maxcorr) 15) Dissimilarity (diss) 16) Inertia (inertia) 17) Prominence (prom) and 18) Shade (shade). The detailed procedure for GLCM matrix construction and a detailed description of each texture measure can be found in Albregtsen (2008) and (Haralick et al. 1973).

In this study, the GLCM features are extracted for three different types of images such as reflectance image, LPB image derived for each spectral band and vegetation index images. More details about the images used for GLCM features extraction are provided in Section 3.2.3. For example, SAVG texture derived for band 3 is depicted in Figure 3-3.

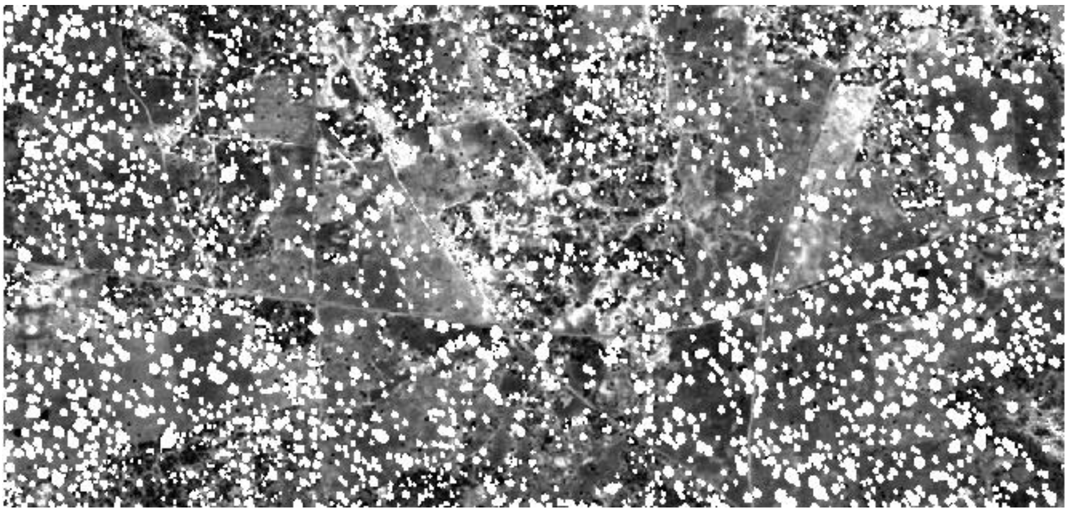

Figure 3-3 SAVG texture of band 3

3.2.2.2. Local Binary Pattern (LBP)

LBP is one of the widely used approaches to capture the textural information of an image. In this approach, a local representation of texture is computed by considering a local neighborhood for each pixel which results in an LBP image. The derived LBP image captures the patterns like edge and corner features. Several variants of LBP have been reported in the literature. In this study, the commonly used LBP algorithm as described in (Chowdhury et al. 2015) has been adopted and the procedure is described below:

Step 1: Select a pixel in the image and consider its 8 neighborhood pixels.

Step 2: Replace the neighborhood pixels with 1 if they are greater than center pixel value, otherwise with 0.

Step 3: Arrange the updated neighborhood pixel values in clockwise direction to form an 8-bit binary pattern.

Step 4: Convert the derived binary pattern into a decimal value and assign this value to the center pixel.

Step 5: Repeat step 1 to 4 for all the pixels in the image to derive the LBP image.

For example, the LBP texture derived for PAN band is shown in Figure 3-4.

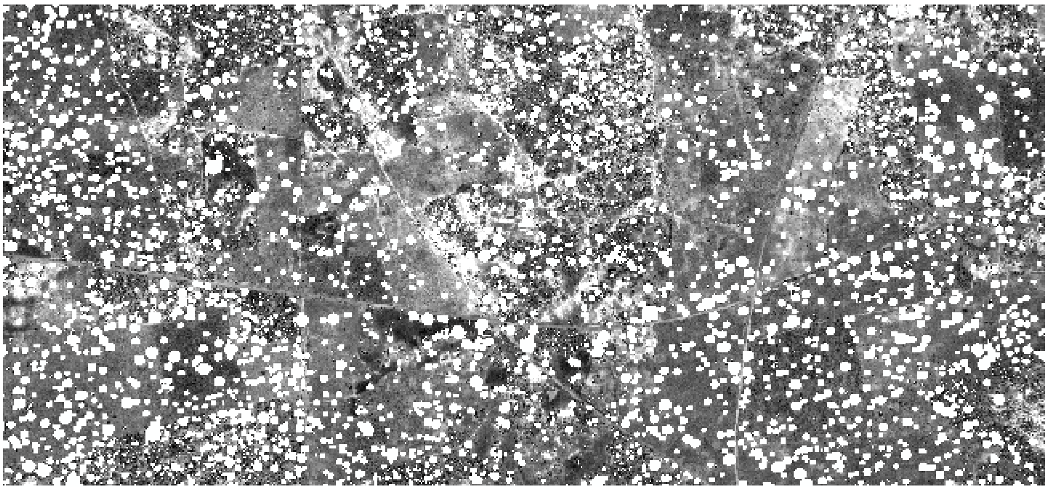

Figure 3-4 LBP texture of PAN band

3.2.3. Summary of features used in this study

Total number of features that were extracted from PAN and multi-spectral imageries and the naming convention followed for each feature throughout this thesis are provided in **Table 3-2 and Table 3-3.**

Table 3-2 Features extracted for Panchromatic image

Feature type	Naming convention	Features count	Description
Reflectance value	PAN band	1	This is the reflectance value of panchromatic image.
Entropy	entropy	1	Entropy value calculated for panchromatic band.
LBP	LBP	1	LBP texture calculated for panchromatic band.
GLCM-reflectance	GLCM texture (e.g., savg, prom, diss, etc.)	18	GLCM textural measures calculated for panchromatic band.
GLCM-LBP	LBP texture (e.g. LBP_savg, LBP_prom, LBP_diss etc.).	18	GLCM textural measures calculated for LBP image.
	Total	39	

Table 3-3 Features extracted for multispectral image

Feature type	Naming convention	Features count	Description
Reflectance values	b1 to b8	8	These are the reflectance values of multispectral image.
Vegetation indices	Name of the vegetation index (EVI, SAVI, TCARI, MSAVI)	4	Vegetation indices calculated based on the formulae mentioned in chapter 3.
Vegetation indices for all band combinations	Name of the vegetation index_band combination (e.g., NDI_b1_b2, DVI_b1_b2, RVI_b1_b2 etc.)	63	Vegetation indices calculated based on the formulae mentioned in chapter 3 for all band combinations.
LBP	LBP_band (e.g., LBP_b1, LBP_b2 etc.)	8	LBP texture calculated for multispectral bands.
GLCM-reflectance	Band_texture (e.g., b1_savg, b3_prom, b5_diss etc.)	144	GLCM textural measures calculated for multispectral bands.
GLCM-LBP	LBP_band _texture (e.g., LBP_b1_savg, LBP_b3_prom, LBP_b5_diss etc.)	144	GLCM textural measures calculated for LBP texture images.
GLCM-vegetation indices	Vegetation index_texture (e.g., SAVI_savg, TCARI_prom, NDI_b7_b8_diss etc.)	1206	GLCM textural measures calculated for vegetation indices.
	Total	1577	

3.3. Feature selection

Feature selection is the process of identifying the most contributing features for the designated application which helps to remove the irrelevant and redundant features thereby reducing the dimensionality of features (Tang et al. 2014). Feature selection is largely classified into two paradigms such as filtering and wrapper approach. In filtering approach, the feature selection is based on analyzing the intrinsic characteristics of the data without considering the final classifier used for the classification process (He et al. 2006). Whereas, in the wrapper approach, the relevance of features is evaluated using the final classifier used for the classification process (Kabir et al. 2010; Kojadinovic et al. 2000). In this study, four feature selection algorithms, each belongs to one of the aforementioned paradigms, are considered. These algorithms are described below.

3.3.1. Fisher's approach

Fisher's approach is one of the widely used filtering based feature selection approaches which derives a univariate metric for each feature based on the ratio of inter-class discrimination and intra-class variance as defined below:

$$F_i = \frac{\sum_{k=1}^{K} n_j\left(\mu_{ij} - \mu_i\right)^2}{\sum_{k=1}^{K} n_j\, \rho_{ij}^2}$$

Where μ_{ij} and ρ_{ij} are mean and variance of i-th feature in j-th class respectively, n_j is the number of instances in the j-th class and μ_i is the mean of the i-th feature.

Once the Fisher's score is derived for each feature, they are ranked based on it. In general, the desired number of top ranked features are clubbed together as the final feature subset that contains the important features for the classification process. In this study, after obtaining the rank for each feature, the top ranked features are incrementally added to the final feature subset and concurrently evaluated using the final classifier (e.g., one-class SVM) at every step i.e. after adding one new feature. The number of features in the selected list is controlled by the following criteria: the incremental addition of the top ranked features to the final feature subset continues as long as the newly added feature leads to an increase in classification accuracy.

3.3.2. Infinite feature selection (InfFS)

InfFS is a recently proposed filtering-based feature selection approach by Roffo et al. (2015b). They claimed it as the state-of-the-art as it outperforms several feature selection approaches including Fisher's method when evaluated using some benchmark datasets. In this approach, the features are represented as fully connected directed graphs where each node represents a feature. The edges connecting the nodes are assigned with weights computed based on pairwise measures (standard deviation and correlation) which models pairwise relations among feature distributions. A score for each node is estimated based on the number of times that node is visited when taking into account *all the possible feature subsets* as paths on a graph. Based on this score, the nodes (features) are ranked. After ranking the features, the final list of selected features is obtained using the same procedure as followed in Fisher's approach (section 3.3.1). Theoretically, this approach is more robust compared to above mentioned Fisher's approach as it is based on the multi-variate scheme where features are evaluated in a collective way which makes it capable of handling redundant features. Whereas, Fisher's approach is a univariate approach where the importance of features is evaluated independently and therefore it cannot handle the feature redundancy effectively. The detailed description of InfFS algorithm can be found in Roffo et al. (2015b).

3.3.3. Forward feature selection (FFS)

Forward feature selection belongs to the wrapper scheme where the importance of features is evaluated using the designated classifier (e.g., OCSVM) to be used for performing final classification. In this approach, the initial feature set starts with an empty list and the features are added iteratively one at a time to the list based on specific criteria. In this study, the commonly used classification accuracy is adopted as a criterion for incorporating a feature to the final feature subset. For example, in first step, a single feature which gives maximum classification accuracy will be added to the initial empty list. Subsequently, the new feature will be added to the list if it increases the classification accuracy when it is evaluated along with the existing features in the list.

3.3.4. Multiple kernel learning (MKL)

In general, MKL has been developed to address the problem of integrating features from multiple sources or representations (e.g., vegetation indices, spectral values, textures etc.) for performing classification based on kernel-based classifiers (Bucak et al. 2014a; Gu et al. 2015). The principle behind MKL is that the features from multiple sources are represented as individual feature subsets. Subsequently, kernel matrices are independently constructed for each feature subset. Finally, the kernel integration is achieved through the weighted sum of these kernel matrices:

$$k\left(x, x^{\prime}\right) = \sum_{m} \beta_m \, k_m(x, x^{\prime})$$

Where $k\left(x, x^{\prime}\right)$ is the integrated kernel, $k_m\left(x, x^{\prime}\right)$ is an independent kernel constructed for entities x and $x^{\prime}$, β_m is a nonnegative weighting parameter with $\sum_m \beta_m = 1$ and m is the number of feature subsets.

The weights for each kernel matrix β can be defined in several ways. For instance, one simple way is to assign equal weights to all kernel matrices or assigning weights based on grid search approach using cross-validation. Alternatively, in most of the MKL approaches, these kernel weights β_m are automatically learned together with other parameters of SVM by optimizing a single objective function (Rakotomamonjy et al. 2008). These learned weights associated with each kernel (i..e. each feature subset) portrays their contribution in the final classification process which can be used for feature selection (Cao et al. 2015; Gönen et al. 2011). For example, for selecting the important features, the kernel matrix is constructed independently for each feature and the corresponding weights β are estimated by MKL algorithm. Subsequently, the features contributing more than P% (1% is considered in this study) in the final classification accuracy i.e. features corresponding to β > threshold T_W (0.01) are selected as the important features for the crop classification. In this study, we adopted the widely used Simple-MKL algorithm developed by Rakotomamonjy et al. (2008) to estimate the amount of contribution of each feature for the classification accuracy by learning the weights β associated with each kernel (feature). Here, the number of kernels is equal to the number of features considered for feature selection. The overall process of MKL-based feature selection is depicted in Figure 3-5. The mathematical background of the adopted Simple-MKL algorithm can be found in Rakotomamonjy et al. (2008).

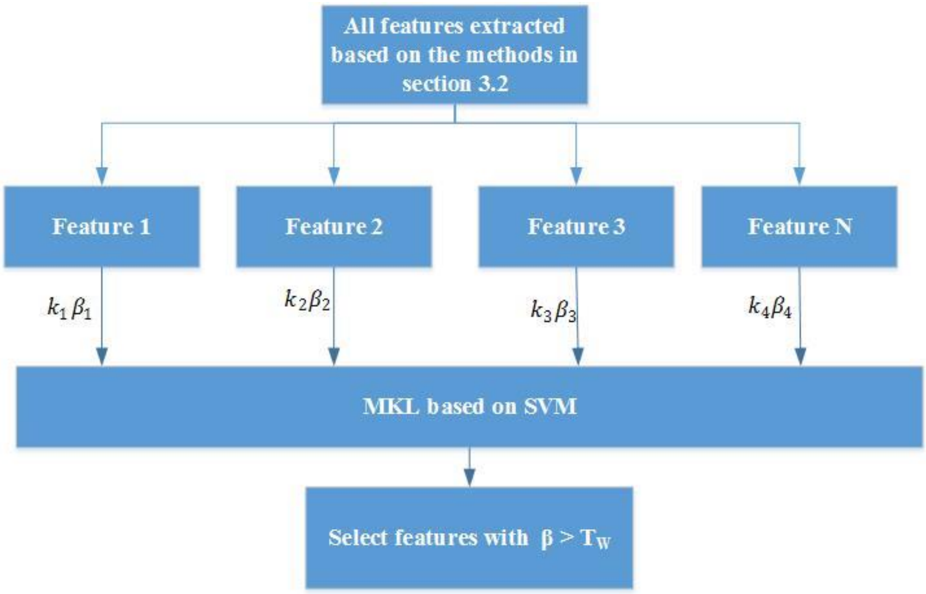

Figure 3-5 Overview of MKL-based feature selection

3.3.5. Composite feature selection approach (CFSA)

The aforementioned feature selection algorithms work in its own way to estimate the feature importance. Hence, in this study, the important features selected by these four algorithms are considered and evaluated together for crop classification. Furthermore, this approach is compared against the features selected independently by the above algorithms in terms of classification accuracy.

3.4. One-class classification

Conventionally, the classifiers are designed for addressing binary or multi-class classification problems. Conversely, one-class classification is adopted for a specific scenario where the samples of target class are available with either absence or unbalanced number of negative samples (Manevitz et al. 2001). In such case, the classification model is built largely based on the distribution of samples of target class. Subsequently, the model will be used to classify the new unseen samples where they are classified as outliers if they are too different from the built model according to certain metrics, otherwise, they are classified as samples of target class. Several one-class classifiers have been developed under both the categories of supervised and unsupervised approaches (Tax 2001). Most of them are readily available as software tools. In this study, different one-class classifiers are considered which are briefly described below.

3.4.1. Supervised approach

SVM is a canonical classifier based on supervised approach which is commonly used in many remote sensing image classification applications. Traditionally, SVM is a binary classifier where it defines a hyper-plane in feature space to separate two classes by largely holding the maximum margin property i.e. the closest points from each class to the hyper-plane is equidistant (Furey et al. 2000). The sample points used to define the hyper-plane are referred as support vectors. The most advantageous characteristic of SVM is that it is capable of handling non-linear classification problem i.e. SVM defines a non-linear boundary to classify the data points of different classes which are not linearly separable in original feature space. This is achieved by projecting the data into high dimensional space called feature space where the data is expected to be linearly separable (Schölkopf et al. 2002). Subsequently, the hyper-plane should be defined in the higher dimensional feature space to linearly separate the data between classes. However, to avoid learning the mapping function, kernel function is used to measure the similarity between the samples in feature space. The most common kernel function is the Radial Basis Function (RBF), also called Gaussian function. The detailed background of SVM can be found in (Schölkopf et al. 2002).

One-class SVM is a variant of binary-class SVM which is designed to handle the one-class classification problem. Two types of one-class SVMs are reported in the literature and they are described below.

a) **OCSVM_P:** This approach is proposed by Schölkopf et al. (1999). In this approach, a hyper-plane is constructed by separating all target samples in the feature space by maximizing the distance of the hyperplane from the origin. More information about this method can be found in Schölkopf et al. (1999).
b) **OCSVM_S:** This method is developed by Tax et al. (2004) and commonly referred as SVDD in literature. In contrast to the above method based on plane-based classification boundary, this approach constructs a spherical boundary i.e., fits a hyper-sphere around the target samples in feature space for classification. The hyper-sphere is fitted based on two parameters: 1) center ‘A’ of the sphere which is derived based on the linear combination of support vectors and 2) radius ‘R’ which is derived based on minimizing the distance of all target samples to the center with the objective of minimizing the hyper-sphere volume. After constructing the hyper-sphere, the new unseen samples that lie inside this sphere are classified as target class, otherwise they are classified as outliers. The readers are referred to Tax et al. (2004) for detailed description of this algorithm.

Another most important parameter associated with above classification methods is the outlier ratio. This helps the classifier to construct a tightened and regularized classification boundary by setting this outlier fraction as the upper bound on the number of training samples that can be considered as outliers (Schölkopf et al. 1999). The choice of optimal value for this outlier fraction is crucial as it has significant influence in the definition of classification boundary (e.g., radius R in OCSVM is defined based on this outlier ratio) and thereby determining the classification accuracy (Clauss et al. 2016). In case of presence of negative samples, it can also be used to tune the classification boundary which is reported to significantly reduce the impact of the choice of outlier fraction (Clauss et al. 2016).

3.4.2. Unsupervised approach

In this study, we used three commonly used unsupervised one-class classifiers and they are briefly described below.

a) **Gaussian method:** In this approach, the one-class classification model is constructed by defining the 'd' dimensional Gaussian distribution function based on the target training samples. The defined Gaussian space is divided into lower and higher density regions based on a specific threshold (derived based on given outlier ratio). The new unseen samples that lie inside the higher density region are classified as target samples, otherwise they are classified as outliers.
b) **k-means method:** This approach is based on k-means clustering method. The basic assumption behind this method is that the clusters of target training samples derived based on k-means algorithm could act as the prototypes for classifying the new unseen samples. That is, the training samples are clustered into k-clusters using k-means clustering (k-value is determined based on the outlier ratio). Then the new unseen samples are classified as target class if they lie within certain distance to any of the cluster centers, otherwise they are classified as outliers.
c) **PCA method:** In this approach, the target samples in original feature space are projected into another feature space which is defined based on the Eigen vectors computed from the covariance matrix constructed based on the features of the target samples available for training. For predicting the class of the new unseen samples, it is projected to the new feature space which is constructed based on the target samples and then they are reconstructed to the original feature space. If the reconstruction error i.e. the difference between the original and reconstructed sample is minimum, then it is classified as target class, otherwise it is classified as outlier. The threshold for accepting the reconstruction error is defined based on the outlier ratio.

More information about the above unsupervised one-class classification methods can be found in (Tax 2001).

In all the above methods, the classification criteria are highly influenced by the outlier ratio value and this value is tuned based on cross-validation approach as described in chapter 4.

3.5. Overall work flow for mono- and multi- temporal images based crop classification

In this study, crop classification is intended to perform using both mono- and multi-temporal images. In mono-temporal image based classification, the features listed in **Table 3-2** and **Table 3-3** are extracted from PAN and each band of multi-spectral image. Subsequently, the important features are identified by all four feature selection algorithms independently. Finally, the features selected by each feature selection algorithm are used for crop classification based on five one-class classifiers. The overall work flow is depicted in **Figure 3-6**. In multi-temporal images based classification, the features extracted for single date images are concatenated into single feature set and the same steps are followed for feature selection and classification as followed in case of mono-temporal image based classification.

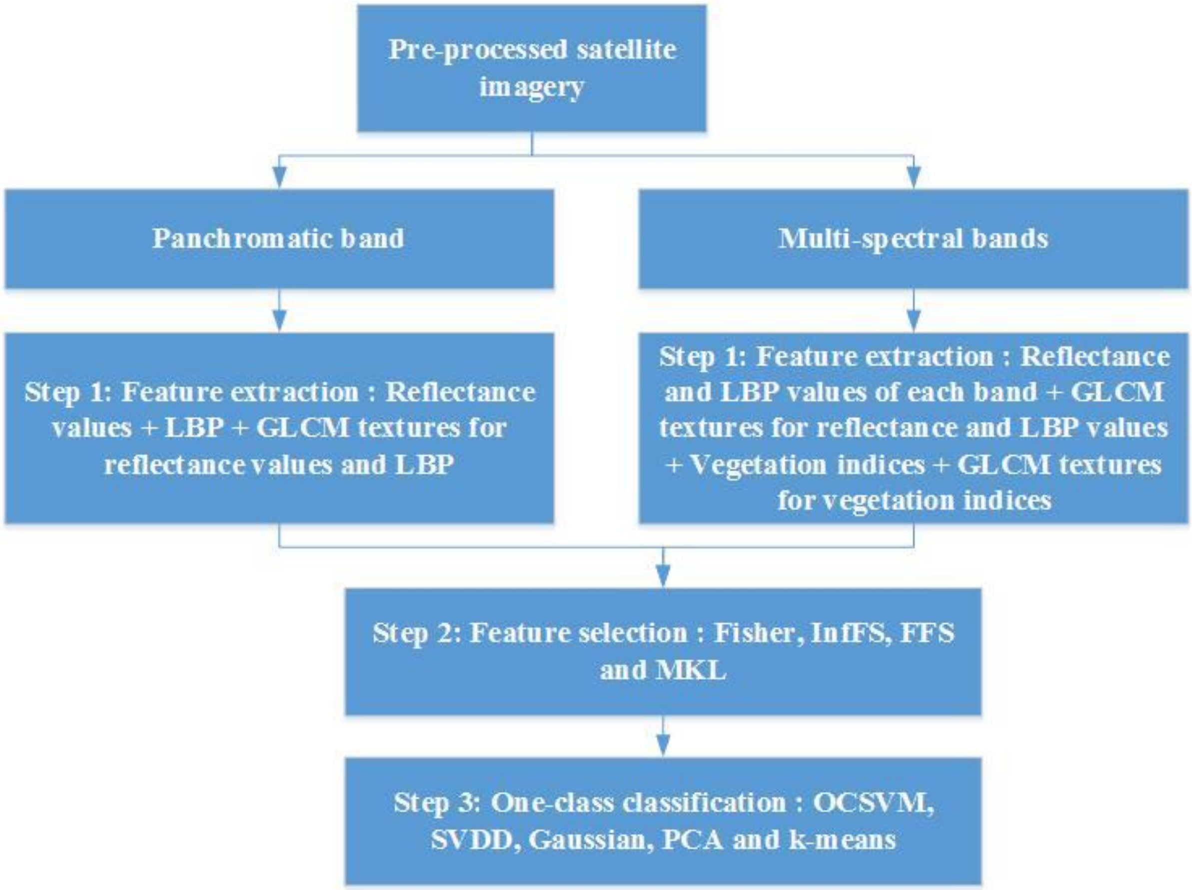

Figure 3-6 Overall workflow of the proposed research framework

In this chapter, the background and description about the various methods used for performing one-class crop classification are provided. The evaluation and analysis of these methods are reported in the subsequent chapter.

4. EXPERIMENTAL SETUP, RESULTS AND DISCUSSION

This chapter provides the experimental setup for evaluating the methods used in the proposed framework for identification of specific crop using one-class classifiers based on the most important features identified by the feature selection approaches. Four experiments were designed and evaluated using the data sets described in Chapter 3. In this chapter, the results and discussion of each experiment are presented together as an independent sub-section. This is because, the subsequent experiments were designed based on the inferences made in previous experiments. Solely for the convenience (in particular to reduce the number of reporting) the experiments and results of multi-temporal features based classification were presented first and subsequently the mono-temporal features-based classification was presented.

4.1. Experimental setup:

All methods in this study were evaluated based on the classification accuracy. The information about the ground truth samples used for constructing and evaluating the classifiers was provided in Table 4-1. Moreover, the classifiers used in this study have number of tunable parameters commonly referred as hyper-parameters. The definition of these hyper-parameters play a significant role in the classification accuracy. In this study, the hyper-parameters were tuned using a 5-fold cross validation based on grid search approach. The information about the grid-search space defined for tuning hyper-parameters are provided in Table 4-2.

Table 4-1 Ground truth samples used for constructing and evaluating the classifiers

Crop name (referred as)	Samples used for classifier construction	Samples used for classifier evaluation
Maize (Crop 1)	400	234
Millet (Crop 2)	540	312
Peanut (Crop 3)	360	208
Sorghum (Crop 4)	480	299
Cotton (Crop 5)	520	299
Total number of samples	2300	1352

Table 4-2. Grid-search space defined for tuning hyper-parameters

Hyper-parameter	Grid search space	Description
C	0.001 to 100, step size – multiples of 10	Regularization parameter used in SVM-based classifiers which has a significant effect on the generalization performance of the classifier.
gamma	0.0001 to 1.0, step size – multiples of 10	Gaussian kernel was used for both SVM-based classifiers. Gamma is used to define the width of the Gaussian kernel which is also a regularization parameter.
Outlier fraction	0.01 to 0.2, step size – 0.05	This parameter is used to control the classification boundary and to define the thresholds associated with the classifiers used as described in Chapter 3.

4.2. Experiment 1: Feature selection and classification for specific crop mapping based on multi-temporal images

The objective of this experiment was to examine the usefulness of multi-temporal images for specific crop mapping. To accomplish the objective, the features extracted from PAN and multi-spectral images corresponding to three months (May, Oct and Nov) were integrated into single feature set. The size of the feature set was 4848 (three times the number of features from single date imagery (cf. **Table 3-2** and **Table 3-3**). The most important features specific to each crop was identified using four feature selection algorithms (cf. Chapter 3) and subsequently, they were independently evaluated using five classifiers. The important features selected for each crop by different feature selection algorithms are briefly reported in the tables from Table 4-3 to Table 4-8 and the detailed descriptions are provided in Table A-1 to Table A-2 in Appendix. The overall accuracy achieved by the classifiers for each crop based on the selected features from each feature selection algorithm is depicted in Figure 4-1.

Table 4-3. **Selected features for Crop 1 based on multi-temporal features**

Feature selection method	Number of features selected (months)	Brief description of the largely selected features
Fisher	5 (all from Oct)	Savg texture of vegetation indices (NDI, DVI and RVI); savg of band 6
InfFS	7 (2 from May and 5 from Oct)	Prominence texture of LBP image of different bands
FFS	7 (all from Oct)	Savg texture of vegetation indices (NDI, RVI and DVI)
MKL	25 (2, 22 and 1 from May, Oct and Nov, respectively)	Savg, prominence and dissimilarity textures of vegetation indices (NDI, DVI and RVI)

Table 4-4. **Selected features for Crop 2 based on multi-temporal features**

Feature selection method	Number of features selected (months)	Brief description of the largely selected features
Fisher	10 (all from May)	Reflectance values of bands 1,4 and 6; Vegetation indices DVI based on bands 2,4 and 5; savg texture of vegetation indices (DVI) and savg of band 1
InfFS	5 (all from May)	Prominence texture of LBP image of different bands
FFS	11 (9 from May and 2 from Oct)	Vegetation indices (NDI, RVI and DVI); Savg texture of vegetation indices (DVI and SAVI); savg of band 4
MKL	11 (7 from May and 4 from Oct)	Savg and prominence textures of vegetation indices (DVI); vegetation indices of DVI; savg of band 6

Table 4-5. **Selected features for Crop 3 based on multi-temporal features**

Feature selection method	Number of features selected (months)	Brief description of the largely selected features
Fisher	8 (all from Oct)	Savg texture of vegetation indices (NDI and RVI);
InfFS	5 (all from Oct)	Prominence texture of LBP image of different bands
FFS	9 (1 from May and 8 from Oct)	Savg texture of vegetation indices (NDI and SAVI); savg of band 4 and LBP of band 4
MKL	41 (3 from May and 38 from Oct)	Savg of NDI,RVI, DVI and SAVI; Shade, prominence, inertia textures of vegetation indices; vegetation indices of DVI; savg of band 6

Table 4-6. **Selected features for Crop 4 based on multi-temporal features**

Feature selection method	Number of features selected (months)	Brief description of the largely selected features
Fisher	5 (all from Oct)	Savg texture of vegetation indices (NDI, DVI and RVI);
InfFS	5 (all from Oct)	Prominence texture of LBP image of different bands
FFS	7 (all from Oct)	Savg texture of vegetation indices (NDI, RVI and MSAVI); correlation and contrast of TCARI
MKL	36 (all from Oct)	Savg, prominence and dissimilarity textures of vegetation indices (NDI, DVI and RVI); correlation and contrast of TCARI

Table 4-7. **Selected features for Crop 5 based on multi-temporal features**

Feature selection method	**Number of features selected (months)**	**Brief description of the largely selected features**
Fisher	10 (all from Oct)	Savg texture of vegetation indices (NDI and DVI); Vegetation indices of DVI; savg of band 6 and band 7
InfFS	9 (5 from May and 4 from Oct)	Prominence texture of LBP image of different bands
FFS	8 (4 from May and 4 from Oct)	Savg texture of vegetation indices (NDI and DVI); Savg of band 4 and band 7
MKL	28 (10, 9 and 9 from May, Oct and Nov, respectively)	Savg of bands 3 to 8; Savg and variance of vegetation indices (NDI, RVI and DVI);

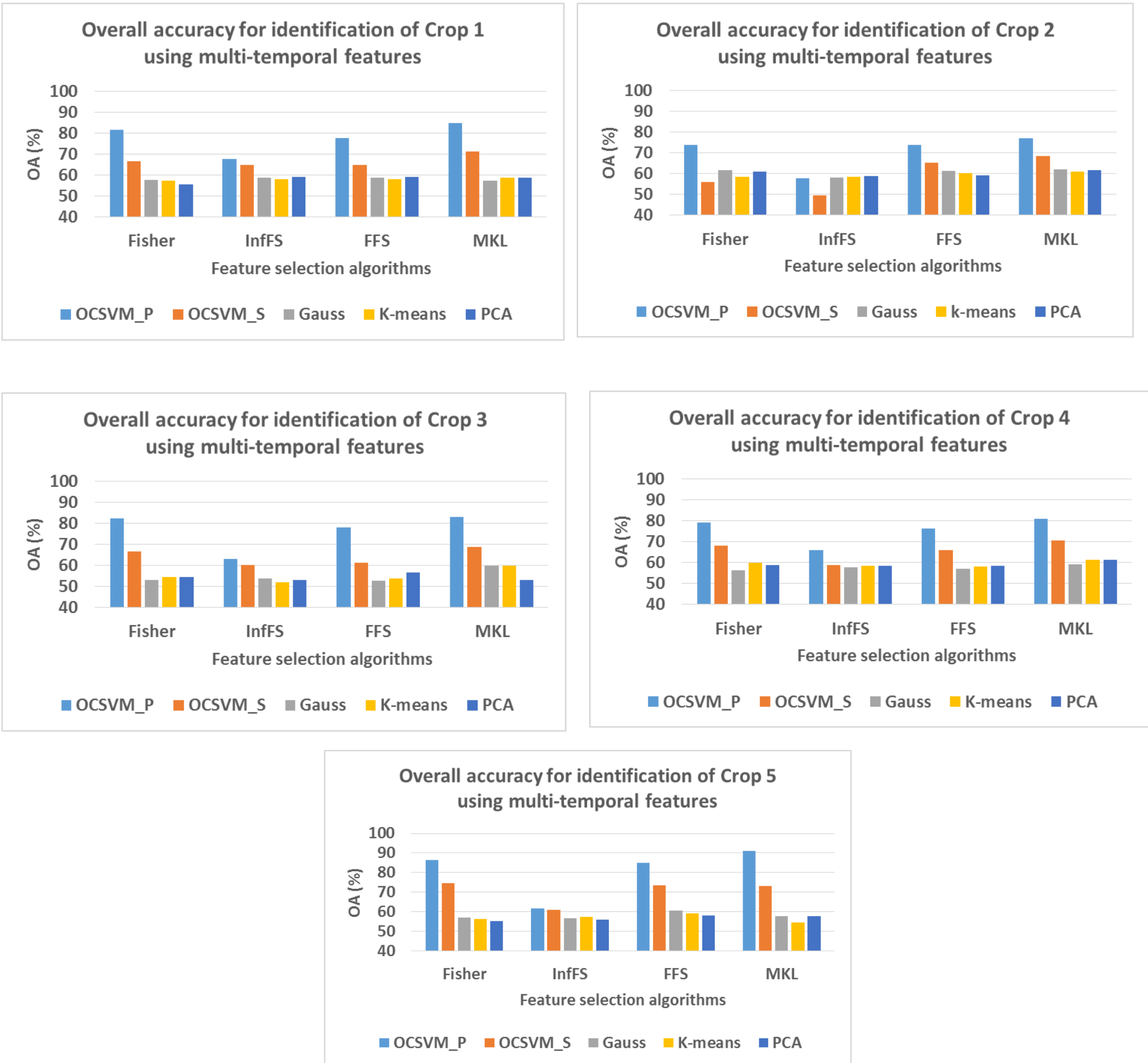

Figure 4-1. Overall accuracy achieved by the five classifiers for each crop based on the selected features from each feature selection algorithm

4.2.1. Inferences from Experiment 1:

The results of Experiment 1 were analyzed in several aspects as described below.

Usefulness of multi-temporal features: Though features were provided from three months (May, Oct and Nov), the feature selection algorithm mostly selects features from single date image alone as the most important features for crop classification. For example, Fisher's algorithm selected features of Oct alone for crops 1, 3, 4, &5 and features of May for Crop 2. All four feature selection algorithms selected features of Oct alone as the most important features for Crop 4. Though in some cases, the features from different months were selected the features from specific month were found to be dominating. For example, MKL algorithm selected 26 features as important for Crop 1, but among them 23 features belong to the month of Oct. Overall, the role of multi-temporal features is not significant except for feature selection by MKL for Crops 2 and 5. This implies that the features of single date image might alone be sufficient for specific crop mapping. Though, the results indicate that single date features might be sufficient for mapping some crops crop, the month of the selected features varies for different crops. For example, May month was found to be significant for crop 2, whereas the features of Oct were found to be significant for crops 1, 3 and 4. The features from all three seasons were found to be useful for crop 5. Thus, it is hard to make decision about the role of multi-temporal features from these results alone. In order to have a clear picture about the role of multi-temporal features, the classification based on multi-temporal features needs to be compared with classification from single date images. This was the major objective of Experiment 2.

Feature selection algorithms: Among four feature selection algorithms, the features selected by MKL often produced greater classification accuracy. Next to MKL, features selected by Fisher's method were found to be producing better classification accuracy than other algorithms. Sometimes, Fisher's method produced classification accuracy closer to MKL algorithm, however with lesser number of selected features compared to MKL. For example, Fisher's method selected five features for crop 1 and eight features for crop 3 and produced accuracies of 81% and 82% respectively. Whereas, MKL selected 26 features for Crop 1 and 41 features for Crop 3 and produced accuracies around 84% and 83% respectively. These accuracies are closer to the accuracies produced by Fisher's method but with relatively lesser number of features (~ five times lesser in case of crop 3). Amongst all, InfFS algorithm was the least performing approach and often the classification accuracy produced by this algorithm was 10-20% lower than other algorithms for specific classifier. For example, MKL, FFS and Fisher's method produced classification accuracy more than 85% for Crop 5, whereas InfFS produced only around 60% (cf. Figure 4-1). InfFS algorithm was anticipated to perform well as it has been reported as the state-of-the-art by Roffo et al. (2015a) after comparing several feature selection algorithms including Fisher's method and FFS based on evaluating two benchmark datasets. However, there is no specific reason for the inferior performance of this algorithm for our application and dataset. Overall, MKL was found to be the suitable algorithm for this specific application and dataset compared to other feature selection algorithms.

Important features: The number of features selected for each crop by specific feature selection algorithm varies. However, among the initially considered 4848 features, maximum number of features selected by a feature selection algorithm was always less than 45 which is 100 times lesser than the original feature size. Several types of features such as spectral band reflectance values, vegetation indices, LBP textures, GLCM textures of reflectance, LBP and vegetation indices were considered in this study. Among them mostly GLCM textures of vegetation indices were selected by three well performing feature selection algorithms (MKL, Fisher and FFS). Moreover, among 18 GLCM features, savg of vegetation indices (NDI, RVI, DVI and SAVI) were selected more often by the above mentioned three algorithms for all crops (cf. Table A-1 to Table A-5). Next to savg, prominence of vegetation indices was selected frequently as important feature. In few cases, the textures such as inertia, shade and contrast of vegetation indices were selected. However, the widely reported standard eight GLCM textures for vegetation related studies as mentioned in Chapter 2 were not selected as important features by any of the considered feature selection algorithms. In literature LBP texture has been reported to be more effective than GLCM features by several studies as mentioned in Chapter 2. However, in our case, LBP was not largely selected by the feature selection algorithms. However, GLCM textures of LBP images were always selected as the most important features by InfFS algorithm for all crops.As stated earlier, the accuracy produced by InfFS was always inferior than other algorithms which mostly select features by excluding LBP related features. Overall, in summary the GLCM textures, mostly savg and prominence derived for several vegetation indices were found to be the most significant features for identification of all five crop types.

Pan vs multi-spectral: The features based on reflectance values of PAN image were not selected by any of the considered feature selection algorithms for all crops. However, even in case of multi-spectral images, the features based on reflectance of spectral bands such as vegetation indices, LBP and GLCM textures were hardly selected as important features. Rather, the features based on textural-spectral combination such as GLCM textures of vegetation indices were predominantly selected as important features. This highlights the importance of multi-spectral image for the application of specific crop mapping.

Performance of the classifiers: The features selected by each feature selection algorithm were evaluated using five one-class classifiers. Among them, two classifiers OCSVM_P and OCSVM_S are based on supervised approach and the remaining classifiers K-means, Gaussian and PCA are based on unsupervised approach. The two supervised classifiers consistently outperformed the unsupervised classifiers with maximum accuracy difference of 30% for crop 5. This highlights the superiority of supervised approach. Among supervised approaches, OCSVM_P consistently outperformed OCSVM_S with maximum accuracy difference around 12% for Crop 5. Overall, after evaluating different one-class classifiers, OCSVM_P based on supervised approach was found to be the most suitable classifier for our application of specific crop mapping.

4.3. Experiment 2: Comparison of specific crop classification based on mono vs multi temporal image features

Based on the results of Experiment 1, it was hard to infer the significance of multi-temporal features because of the reasons stated earlier in Experiment 1. The objective of this experiment was to examine the potential of single date imagery against the multi-temporal images for specific crop mapping. Also, another objective is to examine whether the features selected by a specific feature selection algorithm are consistent across all months or it varies between the months. To this end, the important features of single date images were identified for each crop using the feature selection algorithms and independently evaluated using different one-class classifiers. The important features selected for each crop by various feature selection algorithms are provided in the Appendix A (see Table A-6 to table A-10). We inferred that the performance of the different one-class classifiers in Experiment 2 was similar to that of Experiment 1 where OCSVM_P consistently outperforms other classifiers. Moreover, the focus of this experiment is to compare the significance of mono vs multi-temporal features rather than the comparison of classifiers. Hence, the results of the best performing classifier OCSVM_P alone was presented in Figure 4-2 to compare the significance of mono and multi-temporal features for specific crop mapping.

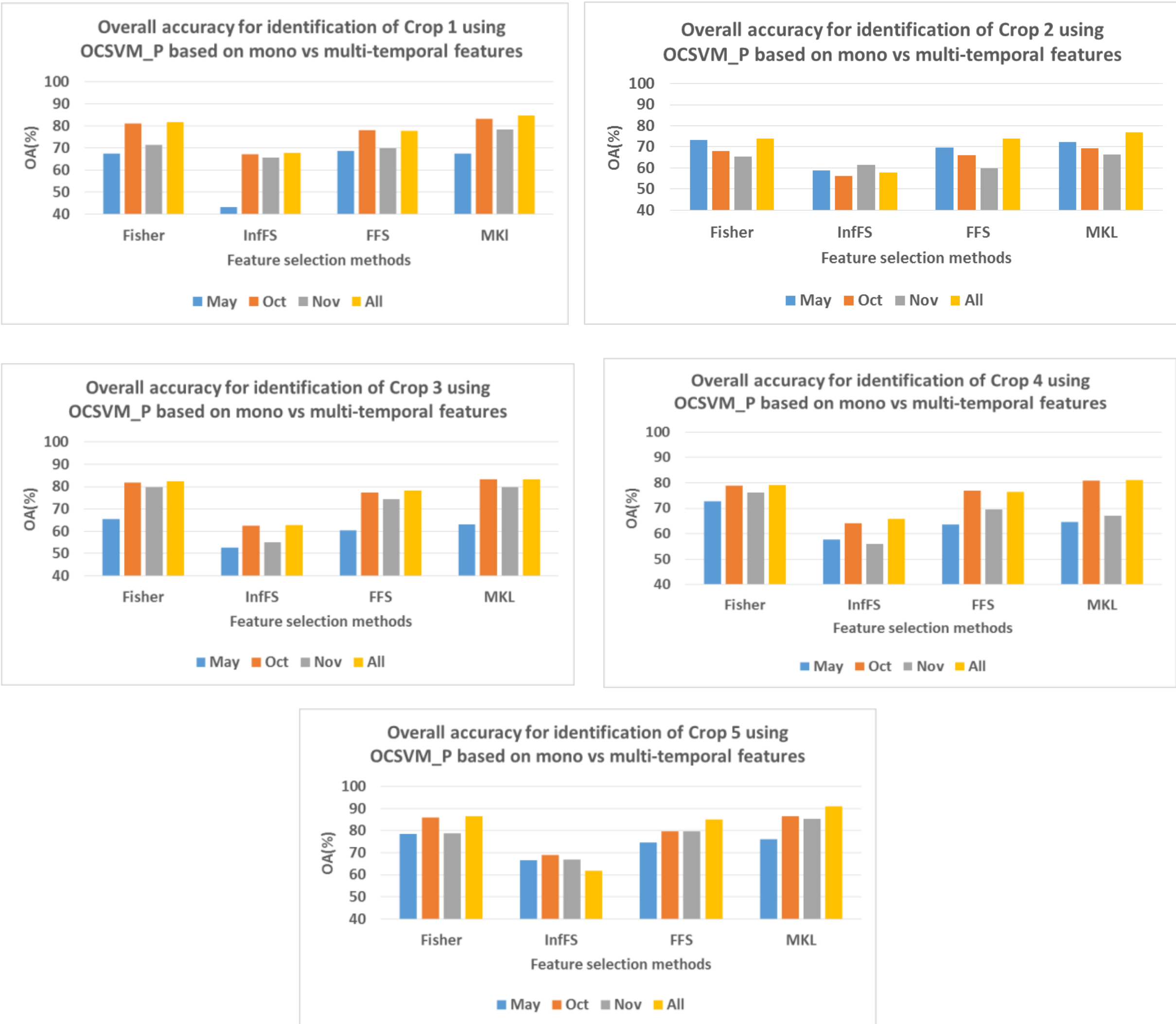

Figure 4-2. Overall accuracy achieved by OCSVM_P for mono and multi-temporal features for specific crop mapping.

4.3.1. Inferences from Experiment 2:

Single vs multi date features for crop classification: The classification accuracy produced for each crop based on single-date features significantly varies between months. For example, classification accuracy for Crop 1 was 67%, 83% and 78% for the features (selected by MKL) from May, Oct and Nov imagery, respectively. This shows that imagery of Oct is highly suitable for identification for Crop 1. Similarly, from the classification results as depicted in Figure 4-2, it was inferred that May imagery was suitable for Crop 2 alone, whereas Oct imagery was more suitable for Crops 3 & 4, and both Oct and Nov imageries were suitable for Crop 5. These results highlight the importance of choice of month of the image in the application of specific crop mapping. In order to analyze the significance of multi-date features over single-date features, the best results obtained for each crop based on single-date features were compared with the results of multi-temporal image features. The results show that only for Crops 2 and 5, there was an increase of 4% overall accuracy for multi-temporal features over single-date features. Otherwise, there was no significant accuracy difference (less than 1% accuracy difference) between single- and multi-date features for the classification of Crops 1, 3 and 4. This highlights that the need of multi-temporal images depends on the choice of crop to be identified.

Consistency of selected features across months: The type and number of features selected by a specific feature selection algorithm for a single crop largely varies across months (Cf. Table A-6 to Table A-10). For example, MKL algorithm selected five features from May imagery and 21 features from Oct imagery as important features for identification of crop 1. This shows that the significance of features for identification of specific crop varies between months. Therefore, it is essential to identify the month specific important features for specific crop mapping.

Other major inferences were similar to the inference made in Experiment 1. For example:

- The textures based on vegetation index were often selected as important features when compared to textures based on band reflectance values.
- The features from PAN image were not selected as important features.
- MKL and Fisher performs better than other two feature selection algorithms. InfFS algorithm always chose the same set of features (LBP) regardless of the choice of crop and month of the chosen image for classification. However, it was the least performing feature selection algorithm.

4.4. Experiment 3: Analyzing Composite feature selection approach (CFSA) described in Chapter 3

The features selected by different feature selection algorithms often vary. As described in Chapter 3, it was anticipated that combining features selected from different feature selection algorithms would improve the classification accuracy. To this end, the features selected by different feature selection algorithms were considered and evaluated using the best performing classifier OCSVM_P identified from previous experiments. For this experiment, the multi-temporal feature set was considered. The classification accuracy obtained from integrated features which were selected by all feature selection algorithms is presented in Figure 4-3. For comparison, the classification accuracy based on features selected by top performing MKL algorithm is also presented in Figure 4-3.

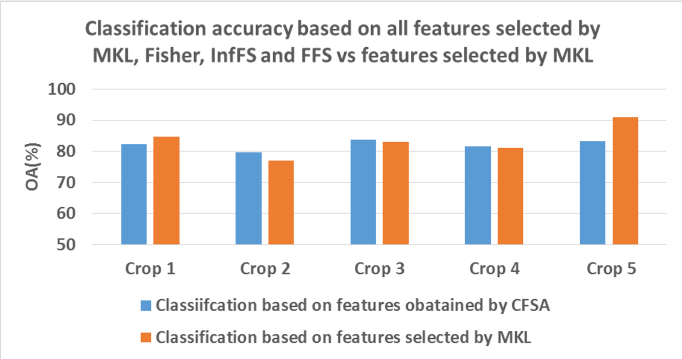

Figure 4-3 Classification accuracy achieved by OCSVM_P based on selected features from CFSA vs MKL

4.4.1. Inference from Experiment 3:

The classification accuracy was dropped for Crop 1 (from 84% to 82%) and Crop 5 (from 90% to 83%) and there was no change in the classification accuracy for Crops 3 & 4. The classification accuracy of Crop 2 was increased (from 77% to 79%) when features selected by other features selection algorithms were used along with the features selected by MKL for classification. The performance of CFSA was inconsistent between crops and moreover it is computationally intensive compared to individual algorithm as it required features from all feature selection algorithms. Hence, it would not be a wise approach to be adopted, particularly for our application.

4.5. Experiment 4: Training one-class classifier using outlier samples along with target samples

It has been reported in literature that using outlier samples along with target samples for training the one-class classifier will improve the classification accuracy. In order to examine this, the classifier OCSVM_P was trained using both target (specific crop) and outlier (other crops) samples and subsequently evaluated based on testing samples. This experiment was conducted using the features selected by MKL from multi-temporal features as these features were selected as the best features in experiment 1. The classification accuracies are depicted in Figure 4-4. For comparison, the classification accuracy of OCSVM_P trained using target samples alone based on the features selected by MKL from multi-temporal features is also depicted in Figure 4-4.

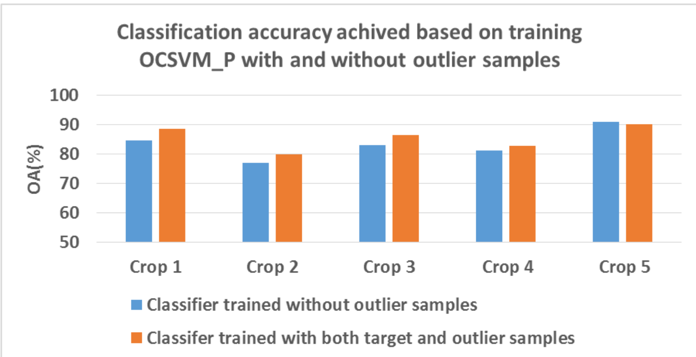

Figure 4-4 Classification results of OCSVM_P trained with and without outlier samples

4.5.1. Inference from Experiment 4:

From the results, it was inferred that the inclusion of outlier samples in training the one-class classifiers for specific crop mapping had significantly improved the classification accuracy. For example, there was an accuracy improvement for Crops 1 to 4 in the range 1% to 4% when outlier samples were used along with the target samples for training the one-class classifier. This highlights the significance of outlier samples in the construction of one-class classifiers.

4.6. Classification maps

The best peforming classifier (OCSVM_P based on MKL selected features) was used to classify a subset of satellite image as depcicted in **Figure 4-5**, in order to visually examine the generalization characterictics of the classifier. The image subset contains the ground truth samples which are hihlighted in **Figure 4-5** using the polygons. These ground truth samples (polygons) were used for visually comapre the classification results. The classification maps produced for each crop are shown in **Figure 4-6** to **Figure 4-10**.

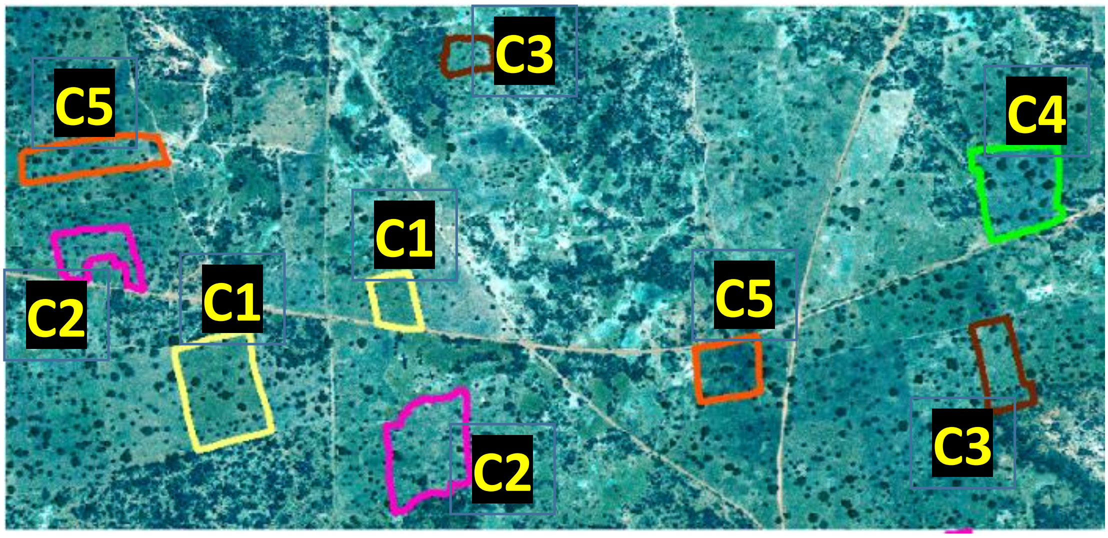

Figure 4-5 A subset of satellite image considered for specific crop mapping using the best performing classifeir. The polygons represnts the ground truth and the annotations C1- C5 indicates the name of the crop covered by the ploygons (C1- Maize, C2- Millet, C3- Peanut, C4-Sorghum and C5-Cotton).

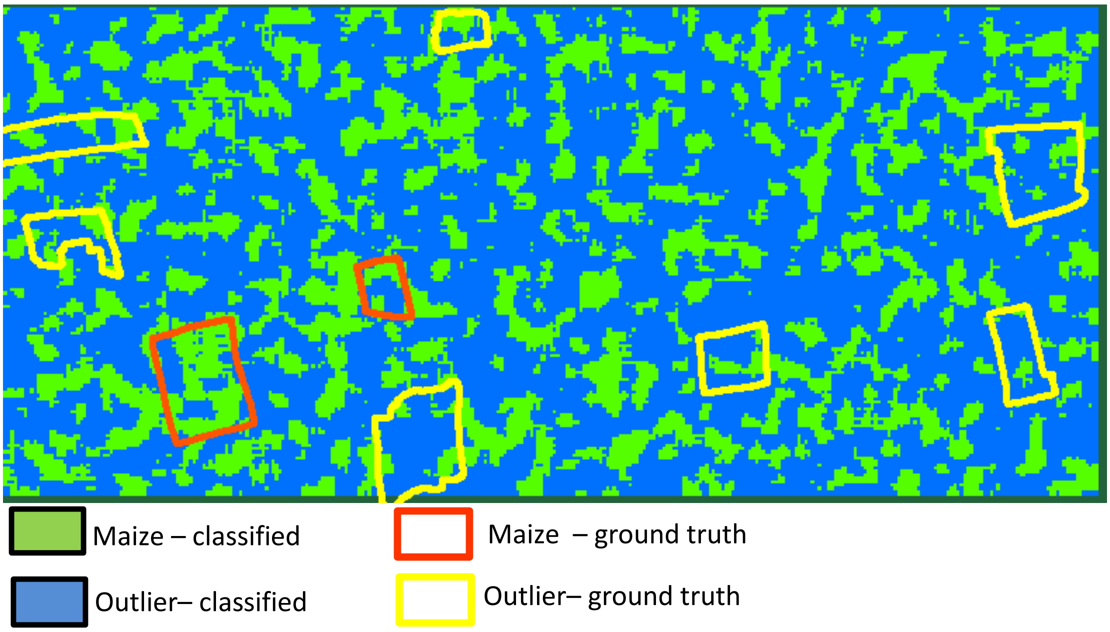

Figure 4-6 Classification map of Maize

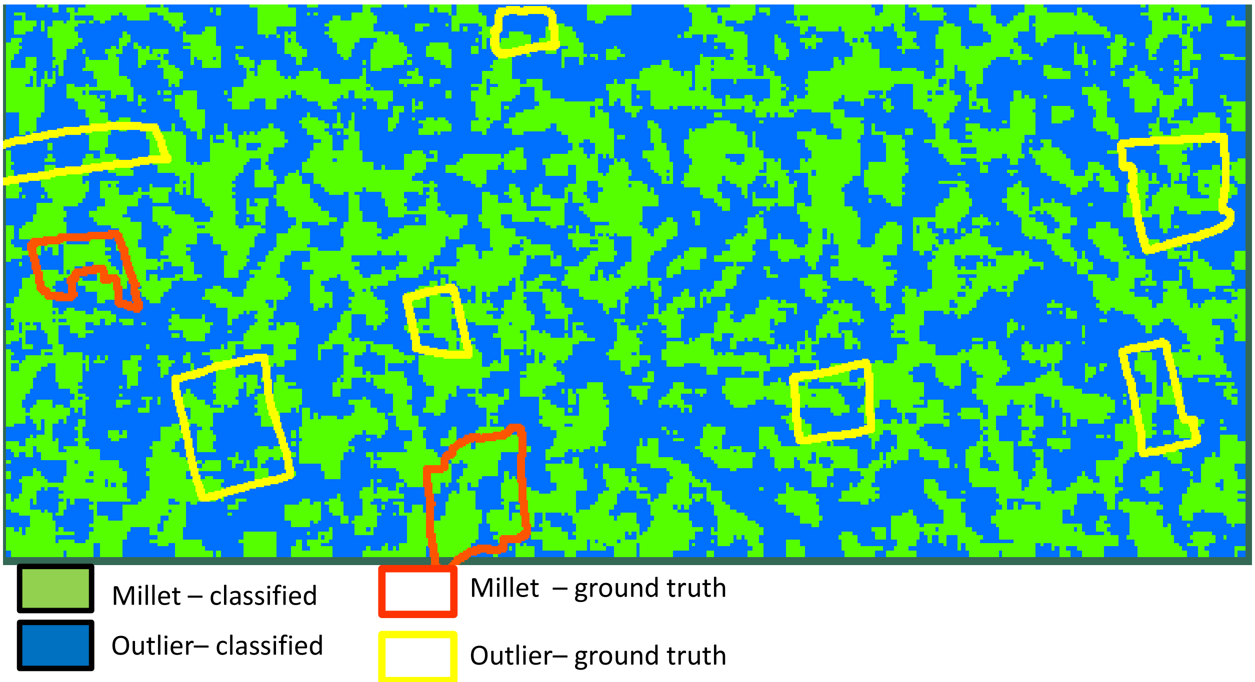

Figure 4-7 Classification map of Millet

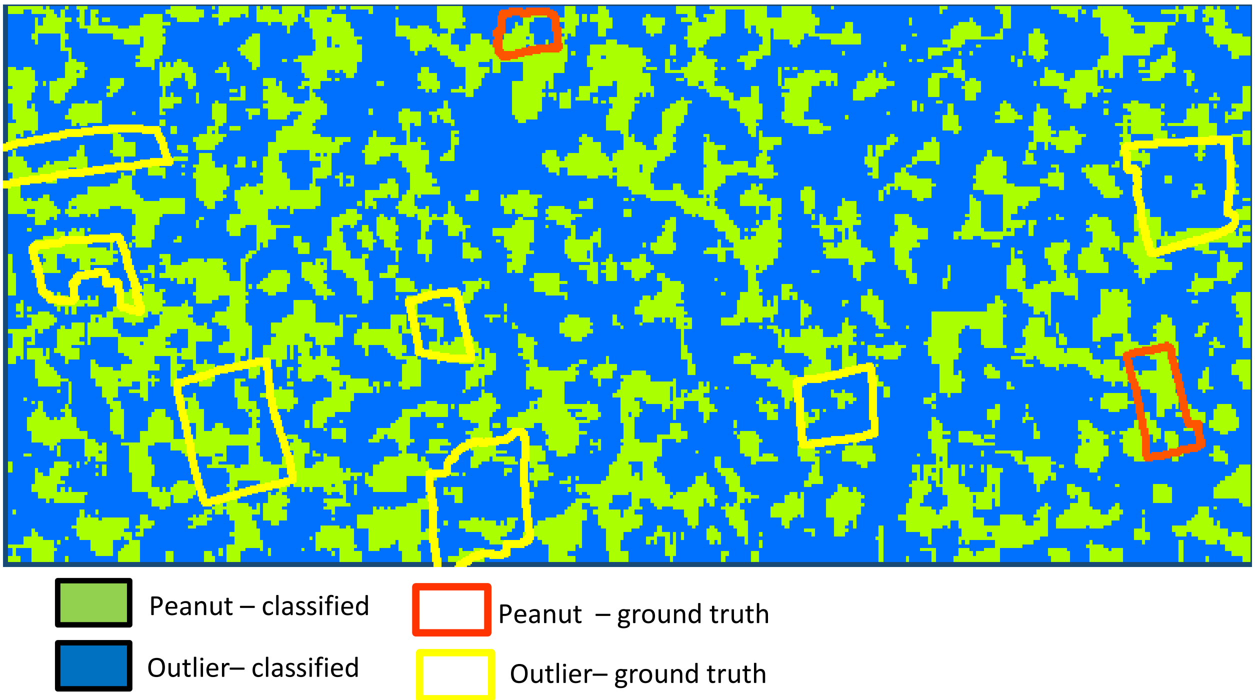

Figure 4-8 Classification map of Peanut

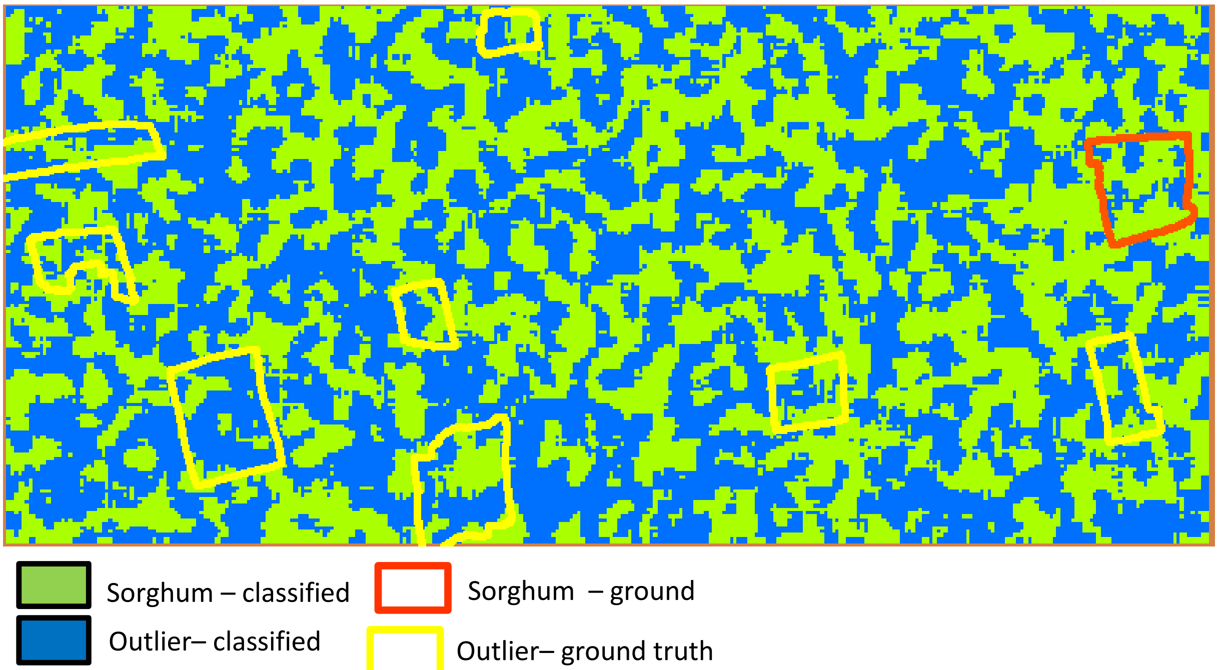

Figure 4-9 Classified map of Sorghum

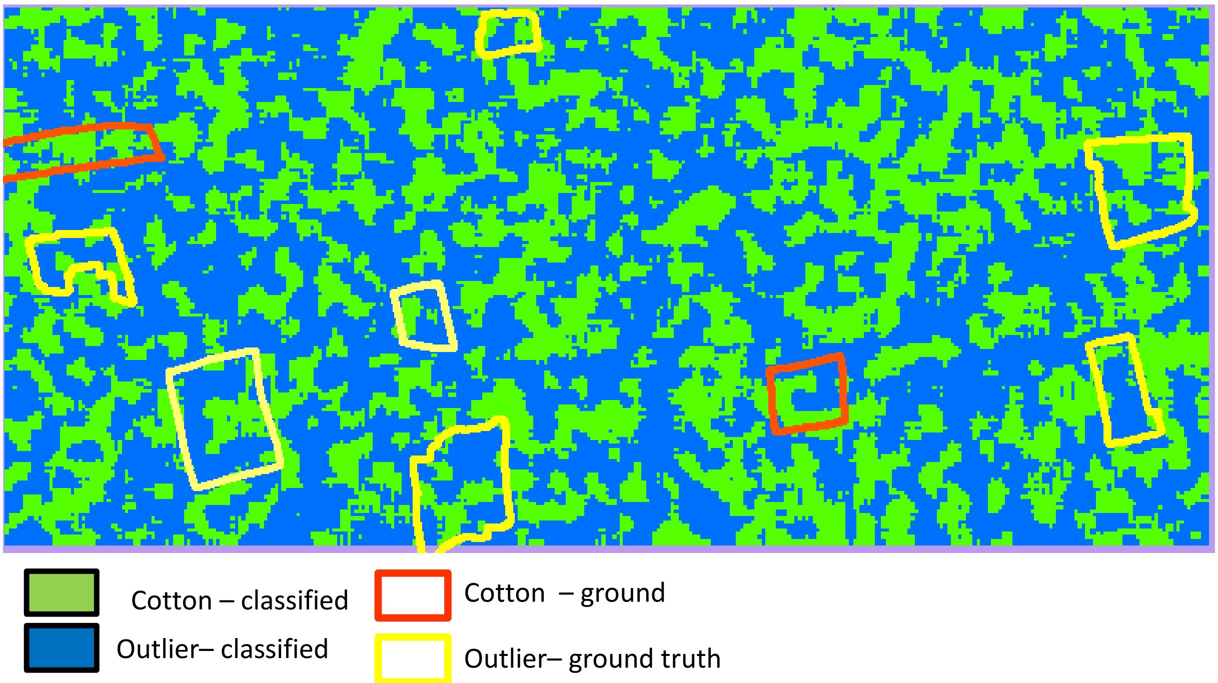

Figure 4-10 Classified map of Cotton

The classifier used to generate the above maps statistically produced an overall accuracy in the range of 77% to 90% when evaluated using the testing sets. However, it is not reflected well on the produced maps where significant number of mis-classifications are visible for all crops. This might be because of the poor representativeness of the used training and testing samples or limitations with the generalization capability of the classifier or limitations in the pixel-based classification approach as reported in literature by several studies (Castillejo-González et al. 2009; Peña et al. 2014). However, the reason for this issue needs to be examined.

In this chapter, the primary objective of identifying the most important features for specific crop mapping was accomplished by implementing and evaluating several methods in the proposed framework. This includes the evaluation of four feature selection algorithms and five one-class classifiers by conducting four experiments. The results and discussion of each experiment were provided in the corresponding experiment sections. The inferences made from the experiments are briefly discussed in next chapter by associating it with the research questions raised in chapter 1.

5. CONCLUSIONS AND RECOMMENDATIONS

This study focused on the identification of the most important features to map specific crops using very high resolution satellite images. A framework was designed to build a classifier based on both mono- and multi-temporal imageries of World-View 2. Three World-View imageries taken at May, October and November were considered in this study for mapping five crops independently. The designed framework comprises of three pipelining processes:

1) Feature extraction: In this study, numerous spectral and textural features that have been reported in literature or anticipated as effective for classification of crops based on remote sensing images were adopted. These features include reflectance values of multi-spectral image bands, various vegetation indices, LBP textures based on reflectance and GLCM textures based on reflectance, vegetation indices and LBP image . Extracting these features for a single world-view image led to 1616 features. In multi-temporal images based classification, (3 images were used in our study), the dimensionality of features increased to 4848.

2) Feature selection: The dimensionality (number) of features was reduced by selecting the most important ones. This was done to overcome the curse of dimensionality. Four feature selection algorithms were considered in this study: Fisher, InfFS, FFS and MKL. These algorithms were evaluated and compared based on their performance for crop classification.

3) Classification: The final step was to build a classifier based on the features selected by each of the feature selection algorithms. Five one-class classifiers were considered: OCSVM_P, OCSVM_S, Gaussian, PCA and K-means. The first two classifiers are based on supervised approach and the other three are based on unsupervised approach.

Several methods were considered for accomplishing each task, and they were evaluated by designing four experiments in order to address the research questions raised in chapter 1. The inferences made from the experiments related to each research question are briefly discussed below:

RQ-1: What kind of features are the most significant to map specific crops?

Generally, the combination of textural-spectral features (i.e. GLCM textures derived for vegetation indices) were selected as the most important features by the best performing feature selection algorithms (MKL and Fisher). Particularly, savg texture derived for several vegetation indices (NVI, RVI, DVI and SAVI) was largely selected as the most significant feature (cf. Table A-1 to Table A-10). Moreover, this was the only feature which was found to be selected as important for mapping all the crops.

RQ-2: What is the significance of multi-spectral vs PAN bands to map specific crops?

The multi-spectral images were found to be more useful for specific crop mapping as none of the well performing feature selection algorithms (MKL and Fisher) selected PAN image features as important for mapping all five crops (Table A-1 to Table A-10).

RQ-3: What is the significance of multi temporal images over mono temporal images to map specific crops?

The choice of multi- or mono- temporal images for specific crop mapping depends on the crop to be mapped. The results show that the use of multi-temporal images led to an increase of 4% in the overall accuracy for the crops millet and cotton. For the other crops (maize, peanut and sorghum), the information from mono-temporal image itself was found to be sufficient as there was no significant accuracy difference noticed (the accuracy difference was less than 1%) between single- and multi-date image features (cf. Figure 4-2).

RQ-4: Which is the best time period to map specific crops in mono-temporal image based classification?

The results show that a specific crop can be identified best by using the image captured in specific month. For example, classification accuracy for crop maize was 67%, 83% and 78% for the features (selected by MKL) from May, Oct and Nov imagery, respectively. However, the image captured in May produced higher accuracy than images of other months (Oct and Nov) for classification of crop millet. The image captured in Oct produced higher accuracy for classification of crops peanut and sorghum as well. For cotton crop, both Oct and Nov imagery provided similar accuracies, but higher than the accuracy obtained from May image (cf. Figure 4-2).

RQ-5 Is there any impact in classification with and without feature selection?

In this study, no experiment was conducted by fitting the classifier with all features to compare its accuracy with classification based on selected features. However, the impact of feature selection can be inferred implicitly from one of the conducted experiments. For example, the features selected by different feature selection algorithms were integrated and used for fitting the classifier. However, the classification accuracy was reduced to 2% and 7% for crops 1 and 5 respectively compared to the accuracy achieved by features selected by single feature selection algorithm (cf. Figure 4-3). This shows that increasing few features lead to an accuracy drop which again highlights the importance of feature selection.

RQ-6 Does the choice of feature selection algorithm have impact in the classification accuracy?

Yes, the choice of features has significant impact in the classification accuracy. For example, the features selected based on MKL consistently produced higher classification accuracy than other features from other algorithms. For instance, MKL method produced classification accuracy around 90% for Crop 5, whereas InfFS produced only around 60% (cf. Figure 4-1)

RQ-7 Do the feature importance varies for each crop and each season?

The features selected by the best performing algorithm (MKL) were not same for different crops. However, there were some features such as savg of vegetation index was commonly selected for all crops. Moreover, the importance (potential) of features to map a specific crop varies across seasons i.e., the features selected by an algorithm for a specific crop largely varies across months. For example, MKL algorithm selected five features from May imagery and 21 features from Oct imagery as important features for identification of crop 1 in mono-temporal based classification (cf. Table A-6 to Table A-10). This highlights the need of season-specific features for crop identification.

RQ-8 To which degree the choice of classifier (e.g., supervised vs unsupervised) affects the classification accuracy?

Yes, the choice of classifier has significant impact in the classification accuracy. When comparing the classifiers in terms of supervised and unsupervised category, both supervised classifiers based on SVM significantly outperformed the unsupervised approach with a maximum accuracy difference of 30%.

Among supervised classifiers, OCSVM_P consistently outperformed OCSVM_S with a maximum accuracy difference around 12%.

RQ-9 Are target class samples alone sufficient for building a robust one-class classifier or is the inclusion of outlier samples required to build a robust classifier that minimizes false positives?

A separate experiment was dedicated to analyze the significance of outlier samples in training the one-class classifier. The results show that the inclusion of outlier samples along with target samples while training the classifier makes it more robust. For example, there was an accuracy improvement for Crops 1 to 4 in the range 1% to 4% when outlier samples were used along with the target samples for training the one-class classifier (cf. Figure 4-4).

Overall, the proposed framework to map specific crops performed well. An accuracy of around 90% for crop 5, around 80% for crops 1, 3 and 4 and around 77% for crop 2 was achieved by the best performing classifier (OCSVM_P) when constructed with the features selected by the best performing feature selection algorithm (MKL). In this study, the classification process was carried out at pixel-level. However, several studies highlight that performing feature extraction and classification at segment level is more effective and accurate than pixel level classification (Castillejo-González et al. 2014; Ozdarici-Ok et al. 2015). Hence, the accuracy achieved in this study for crop identification might be improved by performing classification at segment level. But it is still uncertain whether the selected features at pixel-level hold for segment-level classification. Hence, exploring the proposed framework for segment-level crop classification would be one of the potential extensions of this work.

Although the selected spectral and textural features have potential to map specific crops, there still exists the problem of generalization. That is, the selected features are crop specific and it is hard to define the feature set that can be generalized for all crops. This generalization problem is the major challenge that generally subsists in the image classification applications regardless of the domain (Penatti et al. 2015). Recently, the features that can be directly learned from the images based on deep learning approaches such as Convolutional Neural Network (CNN) are reported to be more robust for generalization issues (Penatti et al. 2015). The potential of CNN features has been demonstrated for several remote sensing applications including land cover classification (Cheng et al. 2016; Hu et al. 2015). These CNN features are reported to be superior to conventional hand-crafted features (e.g., textures) especially for the applications of very high spatial resolution images (Hu et al. 2015; Cheng et al. 2016). Hence, exploring the CNN features for the application of specific crop mapping would be worthy.

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Appendix A

Table A-1 Selected features for crop 1 based on multi-temporal features

Fisher		InfFS		FFS		MKL	
Month	**Features**	**Month**	**Features**	**Month**	**Features**	**Month**	**Features**
OCT	b6_savg	OCT	LBP_b5_prom	OCT	NDI_b4_b2_savg	OCT	DVI_b3_b2_savg
OCT	DVI_b6_b2_savg	OCT	LBP_b8_prom	OCT	RVI_b4_b3_savg	OCT	DVI_b4_b2_savg
OCT	DVI_b6_b3_savg	MAY	LBP_b2_prom	OCT	NDI_b5_b3_savg	OCT	DVI_b6_b3_prom
OCT	NDI_b4_b2_savg	MAY	LBP_b3_prom	OCT	DVI_b6_b3_diss	OCT	DVI_b6_b3_savg
OCT	RVI_b4_b2_savg	MAY	LBP_b4_prom	OCT	NDI_b8_b3_savg	OCT	DVI_b6_b4_savg
		MAY	LBP_b5_prom	OCT	DVI_b7_b5_savg	OCT	DVI_b7_b3_prom
		MAY	LBP_b7_prom	OCT	DVI_b7_b6_savg	OCT	DVI_b7_b4_savg
						OCT	DVI_b7_b5_savg
						OCT	DVI_b7_b6_savg
						OCT	DVI_b8_b2_savg
						OCT	DVI_b8_b3_savg
						OCT	DVI_b8_b6_savg
						OCT	DVI_b8_b7_savg
						OCT	NDI_b4_b2_savg
						OCT	NDI_b5_b4_savg
						OCT	NDI_b6_b3_savg
						OCT	NDI_b8_b6_savg
						MAY	NDI_b5_b2_diss
						MAY	NDI_b5_b2_prom
						OCT	RVI_b4_b2_savg
						OCT	RVI_b6_b3_savg
						OCT	RVI_b8_b6_savg
						OCT	RVI_b8_b7_diss
						OCT	RVI_b8_b7_savg
						NOV	RVI_b5_b2_savg

Table A-2 Selected features for crop 2 based on multi-temporal features

Fisher		InfFS		FFS		MKL	
Month	**Features**	**Month**	**Features**	**Month**	**Features**	**Month**	**Features**
MAY	b1	MAY	LBP_b2_prom	OCT	SAVI_savg	OCT	DVI_b6_b3
MAY	b6	MAY	LBP_b5_prom	OCT	b4_savg	OCT	b6_savg
MAY	b1_savg	MAY	LBP_b7_prom	MAY	DVI_b4_b2_savg	MAY	b2
MAY	b1_savg_1	MAY	LBP_b8_prom	MAY	DVI_b5_b2_savg	MAY	b6_savg
MAY	DVI_b4_b2	MAY	LBP_b3_prom	MAY	DVI_b6_b3	OCT	DVI_b6_b2_savg
MAY	DVI_b5_b2			MAY	DVI_b4_b3_savg	OCT	DVI_b6_b3_savg
MAY	b4			MAY	DVI_b6_b2_savg	MAY	DVI_b4_b2_prom
MAY	b4_savg			MAY	NDI_b7_b6	MAY	DVI_b4_b2_savg
MAY	DVI_b4_b2_savg			MAY	NDI_b8_b6	MAY	DVI_b4_b3_prom
MAY	DVI_b5_b2_savg			MAY	RVI_b4_b2	MAY	DVI_b4_b3_savg
				MAY	RVI_b5_b3	MAY	DVI_b6_b2_savg

Table A-3 Selected features for crop 3 based on multi-temporal features

Fisher		InfFS		FFS		MKL	
Month	**Features**	**Month**	**Features**	**Month**	**Features**	**Month**	**Features**
OCT	NDI_b6_b2_savg	OCT	LBP_b2_prom	OCT	LBP_b4_savg	OCT	MSAVI2
OCT	NDI_b7_b2_savg	OCT	LBP_b5_prom	OCT	NDI_b6_b2_savg	OCT	NDI_b6_b4
OCT	NDI_b7_b3_savg	OCT	LBP_b7_prom	OCT	RVI_b4_b2_savg	OCT	NDI_b8_b2
OCT	NDI_b7_b4_savg	OCT	LBP_b8_prom	OCT	RVI_b8_b7_saavg	OCT	RVI_b7_b5
OCT	NDI_b7_b5_savg	OCT	LBP_b3_prom	OCT	b4_imcorr1	OCT	SAVI
OCT	NDI_b8_b2_savg			OCT	b8_diss	OCT	DVI_b5_b3_savg
OCT	NDI_b8_b5_savg			MAY	MSAVI2_diss	OCT	DVI_b5_b4_savg
OCT	SAVI_savg			OCT	SAVI_imcorr1	OCT	DVI_b5_b4_var
				OCT	MSAVI2_imcorr1	OCT	DVI_b6_b3_savg
						OCT	DVI_b6_b4_savg
						OCT	DVI_b7_b3_savg
						OCT	DVI_b7_b5_savg
						OCT	DVI_b8_b3_prom
						OCT	DVI_b8_b6_savg
						OCT	NDI_b4_b2_savg
						OCT	NDI_b4_b3_savg
						OCT	NDI_b5_b3_prom
						OCT	NDI_b5_b4_savg
						OCT	NDI_b6_b4_savg
						OCT	NDI_b7_b2_savg
						OCT	NDI_b7_b3_savg
						OCT	NDI_b7_b4_savg
						OCT	NDI_b8_b2_savg
						OCT	NDI_b8_b4_savg
						MAY	NDI_b8_b6_inerti
						OCT	RVI_b3_b2_inertia
						OCT	RVI_b3_b2_shade
						OCT	RVI_b4_b2_savg
						OCT	RVI_b4_b3_savg
						OCT	RVI_b5_b2_prom
						OCT	RVI_b5_b3_savg
						OCT	RVI_b5_b4_savg
						OCT	RVI_b6_b3_savg
						OCT	RVI_b6_b4_savg
						OCT	RVI_b6_b5_savg
						OCT	RVI_b8_b3_savg
						MAY	RVI_b8_b6_savg
						MAY	RVI_b5_b3_prom
						OCT	RVI_b8_b6_inertia
						OCT	MSAVI2_savg
						OCT	SAVI_savg

Table A-4 Selected features for crop 4 based on multi-temporal features

Fisher		InfFS		FFS		MKL	
Month	**Features**	**Month**	**Features**	**Month**	**Features**	**Month**	**Features**
OCT	DVI_b3_b2_savg	OCT	LBP_b2_prom	OCT	NDI_b8_b7_savg	OCT	DVI_b3_b2_savg
OCT	DVI_b5_b4_savg	OCT	LBP_b4_prom	OCT	RVI_b3_b2_savg	OCT	DVI_b5_b2_savg
OCT	NDI_b3_b2_savg	OCT	LBP_b5_prom	OCT	b1_imcorr2	OCT	DVI_b5_b4_savg
OCT	RVI_b5_b3_savg	OCT	LBP_b7_prom	OCT	b3_asm	OCT	DVI_b6_b2_savg
OCT	RVI_b5_b4_savg	OCT	LBP_b8_prom	OCT	TCARI_contrast	OCT	DVI_b6_b4_savg
				OCT	TCARI_corr	OCT	DVI_b7_b4_savg
				OCT	MSAVI2_savg	OCT	DVI_b7_b6_savg
						OCT	DVI_b8_b3_savg
						OCT	DVI_b8_b6_savg
						NOV	DVI_b7_b3_prom
						OCT	NDI_b4_b3_savg
						OCT	NDI_b6_b3_savg
						OCT	NDI_b7_b3_savg
						OCT	NDI_b7_b6_savg
						OCT	NDI_b8_b2_savg
						OCT	NDI_b8_b3_savg
						OCT	NDI_b8_b5_savg
						OCT	NDI_b8_b6_savg
						OCT	RVI_b4_b2_savg
						OCT	RVI_b4_b3_savg
						OCT	RVI_b5_b3_savg
						OCT	RVI_b6_b4_prom
						OCT	RVI_b6_b4_savg
						OCT	RVI_b6_b5_prom
						OCT	RVI_b6_b5_savg
						OCT	RVI_b7_b2_prom
						OCT	RVI_b7_b4_savg
						OCT	RVI_b7_b6_savg
						OCT	RVI_b8_b2_savg
						OCT	RVI_b8_b5_asm
						OCT	RVI_b8_b5_ent
						OCT	RVI_b8_b5_prom
						OCT	RVI_b8_b5_savg
						OCT	MSAVI2_savg
						OCT	TCARI_contrast
						OCT	TCARI_corr

Table A-5 Selected features for crop 5 based on multi-temporal features

Fisher		InfFS		FFS		MKL	
Month	**Features**	**Month**	**Features**	**Month**	**Features**	**Month**	**Features**
OCT	DVI_b6_b2	OCT	LBP_b2_prom	OCT	DVI_b6_b2_savg	OCT	NDI_b6_b3
OCT	DVI_b6_b3	OCT	LBP_b3_prom	OCT	DVI_b6_b3_savg	OCT	b6_savg
OCT	b6	OCT	LBP_b5_prom	OCT	DVI_b6_b4_savg	NOV	b5_savg
OCT	b6_savg	OCT	LBP_b8_prom	OCT	DVI_b7_b3_savg	MAY	b3_savg
OCT	b7_savg	MAY	LBP_b2_prom	MAY	b4_savg	MAY	b4_savg
OCT	DVI_b6_b2_savg	MAY	LBP_b3_prom	MAY	b7_savg	MAY	b7_savg
OCT	DVI_b6_b3_savg	MAY	LBP_b4_prom	MAY	NDI_b5_b2_savg	MAY	b8_savg
OCT	DVI_b6_b4_savg	MAY	LBP_b5_prom	MAY	NDI_b6_b2_var	OCT	DVI_b6_b3_savg
OCT	DVI_b7_b3_savg	MAY	LBP_b7_prom			OCT	DVI_b7_b2_savg
OCT	NDI_b6_b3_savg					NOV	DVI_b6_b5_savg
						NOV	DVI_b7_b4_savg
						MAY	DVI_b6_b2_savg
						MAY	DVI_b7_b3_shade
						MAY	DVI_b8_b4_svar
						OCT	NDI_b6_b3_savg
						NOV	NDI_b4_b2_savg
						NOV	NDI_b6_b5_savg
						MAY	NDI_b5_b2_savg
						MAY	NDI_b6_b2_var
						OCT	RVI_b6_b3_savg
						OCT	RVI_b6_b5_var
						OCT	RVI_b7_b3_savg
						OCT	RVI_b8_b6_savg
						NOV	RVI_b6_b2_savg
						NOV	RVI_b6_b5_savg
						NOV	RVI_b7_b2_savg
						NOV	RVI_b8_b4_savg
						MAY	RVI_b6_b3_prom

Table A-6 Selected features for crop 1 based on 2 based on mono-temporal features

	Fisher	**InfFS**	**FFS**	**MKL**
MAY	NDI_b4_b2_savg	LBP_b2_prom	LBP_b7_sent	RVI_b5_b2_savg
	RVI_b4_b2_savg	LBP_b5_prom	NDI_b7_b6_savg	RVI_b7_b2_savg
	RVI_b5_b2_savg	LBP_b4_prom	NDI_b8_b6_savg	NDI_b5_b2_diss
	NDI_b5_b2_prom		RVI_b4_b2_savg	NDI_b5_b2_prom
	b1_asm		RVI_b5_b3_savg	DVI_b6_b2_savg
	b1_imcorr1		RVI_b7_b6_savg	DVI_b6_b3_savg
			RVI_b8_b6	
			b1_asm	
			b1_imcorr1	
			MSAVI2_imcorr2	
			TCARI_dvar	
			TCARI_imcorr1	
OCT	b6_savg	LBP_b5_prom	NDI_b4_b2_savg	DVI_b3_b2_savg
	DVI_b6_b2_savg	LBP_b8_prom	RVI_b4_b3_savg	DVI_b4_b2_savg
	DVI_b6_b3_savg	LBP_b2_prom	NDI_b5_b3_savg	DVI_b6_b3_prom

	NDI_b4_b2_savg RVI_b4_b2_savg	LBP_b7_prom LBP_b4_prom LBP_b3_prom	DVI_b6_b3_diss NDI_b8_b3_savg DVI_b7_b5_savg DVI_b7_b6_savg	DVI_b6_b3_savg DVI_b6_b4_savg DVI_b7_b3_prom DVI_b7_b4_savg DVI_b7_b5_savg DVI_b7_b6_savg DVI_b8_b2_savg DVI_b8_b3_savg DVI_b8_b6_savg DVI_b8_b7_savg NDI_b4_b2_savg NDI_b5_b4_savg NDI_b6_b3_savg NDI_b8_b6_savg RVI_b4_b2_savg RVI_b6_b3_savg RVI_b8_b6_savg RVI_b8_b7_diss
NOV	DVI_b6_b3_savg RVI_b5_b3_savg RVI_b6_b3_savg NDI_b6_b3_savg NDI_b5_b3_savg DVI_b7_b3_savg b1_savg	LBP_b4_prom LBP_b7_prom LBP_b3_prom	LBP_b6_asm NDI_b8_b7_savg RVI_b5_b3_savg RVI_b7_b2_savg b8_imcorr2 SAVI_dent SAVI_dvar	NDI_b8_b7_savg RVI_b5_b3_savg RVI_b7_b2_savg RVI_b8_b7_diss DVI_b6_b3_savg DVI_b6_b4_savg DVI_b7_b3_prom

Table A-7 Selected features for crop 2 based on mono-temporal features

	Fisher	InfFS	FFS	MKL
MAY	b1 b1_2 b1_savg b1_savg_1 DVI_b4_b2 DVI_b5_b2 b4 b4_savg DVI_b4_b2_savg DVI_b5_b2_savg	LBP_b2_prom LBP_b5_prom LBP_b4_prom	DVI_b4_b2_savg DVI_b5_b2_savg DVI_b6_b3 DVI_b4_b3_savg DVI_b6_b2_savg NDI_b7_b6 NDI_b8_b6 RVI_b4_b2 RVI_b5_b3	RVI_b5_b2_savg RVI_b7_b2_savg NDI_b5_b2_diss NDI_b5_b2_prom DVI_b6_b2_savg DVI_b6_b3_savg DVI_b4_b2_prom DVI_b4_b2_savg DVI_b4_b3_prom DVI_b4_b3_savg b2 b6_savg
OCT	b6_savg DVI_b6_b2 b6 DVI_b6_b4 DVI_b6_b3	LBP_b5_prom LBP_b8_prom LBP_b2_prom	SAVI_savg b4_savg LBP_b6_idm NDI_b8_b7_savg b1_savg b6_savg b7_savg MSAVI2_dvar	b6_savg DVI_b6_b2_savg DVI_b6_b3_savg b7_savg
NOV	TCARI_prom RVI_b5_b3_savg NDI_b5_b3_savg DVI_b6_b5_savg b7_savg DVI_b7_b2_savg DVI_b7_b5_prom NDI_b3_b2_diss DVI_b6_b4_savg DVI_b6_b2_savg	LBP_b7_prom LBP_b4_prom LBP_b6_prom LBP_b3_prom LBP_b8_prom LBP_b5_prom	DVI_b6_b3_savg LBP_b2_diss LBP_b6_idm LBP_b6_savg TCARI_savg b1_contrast b1_savg b4_savg b5_savg b6 b6_savg b8_diss TCARI_prom	DVI_b6_b2_savg b5_savg b6_savg b8_savg TCARI_savg TCARI_prom

Table A-8 Selected features for crop 3 based on mono-temporal features

	Fisher	InfFS	FFS	MKL
MAY	b1_savg b8_imcorr2 b8_asm b8_ent DVI_b6_b4_savg NDI_b8_b7_savg	LBP_b2_prom LBP_b5_prom LBP_b4_prom LBP_b7_prom LBP_b6_prom LBP_b3_prom LBP_b8_prom	DVI_b6_b4_savg NDI_b8_b7_savg b1_idm b7_asm b8_imcorr2 EVI_dvar MSAVI2_asm MSAVI2_diss MSAVI2_imcorr1 TCARI_var	NDI_b8_b6_inerti RVI_b8_b6_savg RVI_b5_b3_prom DVI_b6_b4_savg NDI_b8_b7_savg MSAVI2_imcorr1 Pan_savg Pan_imcorr2
OCT	NDI_b6_b2_savg NDI_b7_b2_savg NDI_b7_b3_savg NDI_b7_b4_savg NDI_b7_b5_savg NDI_b8_b2_savg NDI_b8_b5_savg SAVI_savg	LBP_b5_prom LBP_b8_prom LBP_b2_prom LBP_b7_prom LBP_b4_prom	NDI_b6_b2_savg RVI_b4_b2_savg RVI_b8_b7_saavg b4_imcorr1 b8_diss SAVI_imcorr1 MSAVI2_imcorr1	MSAVI2 NDI_b6_b4 NDI_b8_b2 RVI_b7_b5 SAVI DVI_b5_b3_savg DVI_b5_b4_savg DVI_b5_b4_var DVI_b6_b3_savg DVI_b6_b4_savg DVI_b7_b3_savg DVI_b7_b5_savg DVI_b8_b3_prom DVI_b8_b6_savg NDI_b4_b2_savg NDI_b4_b3_savg NDI_b5_b3_prom NDI_b5_b4_savg NDI_b6_b4_savg NDI_b7_b2_savg NDI_b7_b3_savg NDI_b7_b4_savg NDI_b8_b2_savg NDI_b8_b4_savg RVI_b3_b2_inertia RVI_b3_b2_shade RVI_b4_b2_savg RVI_b4_b3_savg RVI_b5_b2_prom RVI_b5_b3_savg RVI_b5_b4_savg RVI_b6_b3_savg RVI_b6_b4_savg RVI_b6_b5_savg RVI_b8_b3_savg RVI_b8_b6_inertia MSAVI2_savg SAVI_savg

NOV	NDI_b8_b3_savg NDI_b7_b3_savg NDI_b8_b4_savg DVI_b8_b4_savg DVI_b8_b3_savg DVI_b8_b5_savg NDI_b8_b2_savg DVI_b6_b4_savg RVI_b8_b6_interia NDI_b7_b4	LBP_b7_prom LBP_b4_prom LBP_b6_prom LBP_b3_prom LBP_b8_prom LBP_b5_prom LBP_b2_prom b8_prom b7_prom	NDI_b5_b2_savg NDI_b6_b4_savg RVI_b8_b3_savg b2_diss b8_diss MSAVI2_svar MSAVI2_savg	DVI_b6_b3_savg DVI_b6_b4_savg DVI_b7_b3_savg DVI_b7_b5_savg DVI_b8_b3_prom NDI_b4_b3_savg NDI_b5_b3_prom NDI_b5_b4_savg NDI_b6_b4_savg NDI_b7_b2_savg NDI_b7_b3_savg RVI_b4_b3_savg RVI_b5_b2_prom RVI_b5_b3_savg RVI_b5_b4_savg RVI_b6_b3_savg RVI_b6_b4_savg RVI_b6_b5_savg MSAVI2_savg EVI

Table A-9 Selected features for crop 4 based on mono-temporal features

	Fisher	InfFS	FFS	MKL
MAY	b4_diss NDI_b7_b6_savg NDI_b8_b2_savg DVI_b5_b4_savg NDI_b3_b2_savg b1_savg b3_diss b5_diss	LBP_b2_prom LBP_b5_prom LBP_b7_prom LBP_b4_prom	LBP_b3_savg LBP_b8_corr b1_savg b2_ent b3_sent b5_diss b5_var EVI_var	DVI_b7_b4 b3_ent b4_diss NDI_b7_b6_savg NDI_b8_b2_savg MSAVI2_savg
OCT	DVI_b3_b2_savg DVI_b5_b4_savg NDI_b3_b2_savg RVI_b5_b3_savg RVI_b5_b4_savg	LBP_b5_prom LBP_b8_prom LBP_b2_prom LBP_b7_prom LBP_b4_prom	NDI_b8_b7_savg RVI_b3_b2_savg b1_imcorr2 b3_asm TCARI_contrast TCARI_corr MSAVI2_savg	DVI_b3_b2_savg DVI_b5_b2_savg DVI_b5_b4_savg DVI_b6_b2_savg DVI_b6_b4_savg DVI_b7_b4_savg DVI_b7_b6_savg DVI_b8_b3_savg DVI_b8_b6_savg NDI_b4_b3_savg NDI_b6_b3_savg NDI_b7_b3_savg NDI_b7_b6_savg NDI_b8_b2_savg NDI_b8_b3_savg NDI_b8_b5_savg NDI_b8_b6_savg RVI_b4_b2_savg RVI_b4_b3_savg RVI_b5_b3_savg RVI_b6_b4_prom RVI_b6_b4_savg RVI_b6_b5_prom RVI_b6_b5_savg RVI_b7_b2_prom RVI_b7_b4_savg RVI_b7_b6_savg RVI_b8_b2_savg RVI_b8_b5_asm RVI_b8_b5_ent RVI_b8_b5_prom RVI_b8_b5_savg MSAVI2_savg TCARI_contrast TCARI_corr
NOV	b8_savg	LBP_b4_prom	DVI_b6_b4_savg	DVI_b5_b2_savg

	b7_savg b6_savg DVI_b3_b2_savg DVI_b5_b4_savg NDI_b3_b2_savg RVI_b5_b3_savg b3_savg	LBP_b7_prom LBP_b3_prom LBP_b6_prom LBP_b5_prom LBP_b8_prom LBP_b2_prom b8_prom b7_prom b1_prom	LBP_b5_savg NDI_b7_b5_savg NDI_b8_b7_savg RVI_b3_b2_savg b1_savg b6_diss b6_svar b8_savg	DVI_b5_b4_savg DVI_b6_b2_savg DVI_b6_b4_savg NDI_b7_b6_savg NDI_b8_b2_savg NDI_b8_b3_savg RVI_b7_b2_prom

Table A-10 Selected features for crop 5 based on mono-temporal features

	Fisher	**InfFS**	**FFS**	**MKL**
MAY	RVI_b5_b2 NDI_b5_b2 b7_savg NDI_b5_b2_savg NDI_b6_b2_var	LBP_b2_prom LBP_b5_prom LBP_b4_prom LBP_b7_prom LBP_b6_prom LBP_b3_prom LBP_b8_prom RVI_b6_b4_prom RVI_b6_b3_prom	b4_savg b7_savg NDI_b5_b2_savg NDI_b6_b2_var NDI_b6_b2_savg RVI_b6_b3_prom	b3_savg b4_savg b7_savg b8_savg DVI_b6_b2_savg DVI_b7_b3_shade NDI_b5_b2_savg NDI_b6_b2_var RVI_b6_b3_prom
OCT	DVI_b6_b2 DVI_b6_b3 b6 b6_savg b7_savg DVI_b6_b2_savg DVI_b6_b3_savg DVI_b6_b4_savg DVI_b7_b3_savg NDI_b6_b3_savg	LBP_b5_prom LBP_b8_prom LBP_b2_prom LBP_b7_prom LBP_b4_prom	DVI_b6_b2_savg DVI_b6_b3_savg DVI_b6_b4_savg DVI_b7_b3_savg b6_savg b7 b7_savg	NDI_b6_b3 b6_savg DVI_b6_b3_savg DVI_b7_b2_savg NDI_b6_b3_savg RVI_b6_b3_savg RVI_b6_b5_var RVI_b7_b3_savg RVI_b8_b6_savg DVI_b6_b3 RVI_b6_b2 RVI_b6_b5 b6_savg b7 b7_savg b8_savg
NOV	NDI_b6_b3_savg NDI_b7_b3_savg RVI_b6_b3_savg NDI_b8_b3_savg DVI_b6_b5_savg DVI_b6_b4_savg TCARI	LBP_b4_prom LBP_b7_prom LBP_b3_prom LBP_b6_prom LBP_b5_prom LBP_b8_prom	LBP_b7_savg NDI_b6_b3_savg NDI_b7_b2_savg b7_diss MSAVI2_savg	b5_savg DVI_b6_b5_savg DVI_b7_b4_savg NDI_b4_b2_savg NDI_b6_b5_savg RVI_b6_b2_savg RVI_b6_b5_savg RVI_b7_b2_savg RVI_b8_b4_savg MSAVI2_savg SAVI_savg