Comparative analysis of mapping burned areas from landsat TM images

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Abstract. Remote sensing is a major source of mapping the burned area caused by forest fire. The focus in this application is to map a single class of interest, i.e. burned area. In this study, three different data combinations were classified using different classifiers and quantitatively compared. The adopted classifiers are Support Vector Data Description (SVDD), a one-class classifier, Binary classifier Support Vector Machines (SVMs) and traditional Maximum Likelihood classifier (ML). At first, the Principal Component Analysis (PCA) was applied to extract the best possible features from the original multispectral image (OMI) and calculated spectral indices (SI). Then the resulting subset of features was applied to the classifiers. The comparative study has undertaken to find firstly, the best possible set of features (data combination) and secondly, an effective classifier to map the burned areas. The best possible set of features was attained by data combination- II (i.e., OMI information). Furthermore, the results of the SVM showed the high classification accuracies than ML. Experimental results demonstrate that even though the SVDD for mapping the burned areas doesn’t showed the higher classification accuracy than SVM, but it shows the suitability for the cases with few or poorly represented labelled samples available. The parameters should be further optimized through the use of intelligent training for improving the accuracy of SVDD.

1. Introduction
Land cover change is regarded as one of the most important variables of global change affecting ecological systems [1]. Wild fires are a key ecological disturbance factor of natural ecosystems, affecting the distribution of the land use and land cover and threatening environmental systems and infrastructure worldwide. Thus, information on the spatial distribution of the burned areas is of vital importance and required by both environmental scientist and policy makers. Satellite remote sensing is an important source for mapping burned areas. Burned patches are very complex to detect automatically due to their spatial and spectral diversity caused by the severity of the fire and other factors. Landsat thematic Mapper (TM) and Enhanced Thematic Mapper plus (ETM+) images have been widely used in mapping the burned areas at local and regional scales [2], [3]. The existing methods for mapping burned areas in these studies showed the relatively high accuracy for the specific sites, but didn’t present any generalized algorithm applicable to other sites with different input conditions. The global algorithms have also been developed for coarse resolution images by considering the wide range of burning conditions but the high accuracy from these algorithms are not sure in general. An alternative approach to enhance the discrimination of burned areas is to use several spectral indices. Some studies used the most sensitive input bands to discriminate between burned and unburned pixels [4]-[11]. The two problems, so far has been observed from these studies firstly, the methods used to discriminate the
burned areas are case dependent and secondly, only spectral indices (SI) were used to discriminate burned areas, but not the original multispectral image (OMI) information. No study did the comparison of SI and OMI information to map the burned areas. Therefore, the first objective of this study is to compare the OMI, SI and the combination of these two to analyze how OMI and SI perform in mapping the burned areas individually and in combination. Secondly, to see whether the additional information of SI to the OMI improves the accuracy of a classifier. Three classifiers have been used for the comparative analysis.

The conventional supervised classifiers (e.g. Maximum Likelihood) typically requires the analyst to train the classifier on each and every class that is in study area to satisfy the assumption of an exhaustively defined set of classes, even most are of no interest for the analysis. The conventional classifiers aim to optimize the classification accuracy over all the land cover classes rather than focus on that specific class of interest. Thus, when a specific class is of interest, it is preferable to adopt an alternative to the standard multiclass classifiers. One approach is to adopt binary classifiers to separate the class of interest from all the other classes [12], [13]. Further refinement to this approach is to use one-class classification. A series of one-class classifiers have been introduced to map those remotely sensed images, where only a specific class is of interest to improve the classification accuracy [14]. One-class classifiers require no statistical assumption regarding the distribution of the data and it only focuses on the class of interest for selecting the training samples. Hence by comparing the capacity of Conventional Maximum Likelihood (ML), Binary Support Vector Machine (SVM) and One-class Support Vector Data Descriptor (SVDD) for optimizing training in the classification, the efficient monitoring of burned areas can be achieved.

The rest of the paper is organized in four sections. The classifiers are described in Section III under the methodology after introducing the study site in Section II. The results obtained and discussion revealed in Section IV. Finally Section V summarizes the observations and the concluding remarks to end this paper.

2. Study Site
The Landsat 5 Thematic Mapper (TM) images of the test site before and after the fire acquired on July 05, 2009 and October 25, 2009 respectively were obtained from U.S. Geological Survey (USGS). Figure 1 shows the dataset covered some part of Los Angeles, California. The six non-thermal spectral bands with a spatial resolution of 30m were acquired for both the images. These images are located on the satellite path and row 041 036. The spectral band 6 was discarded while doing the analysis.

![Figure 1](image_url) Location of the study site. (a) Before Fire and (b) After Fire.
3. Methodology

Many authors have recognized that burned patches do not present a specific spatial pattern [15] and therefore the discrimination of these areas should be based on either the spectral or temporal contrast or on both. The detection of the burned areas is not an easy task as the wide variety of spectral characteristics contributes within the burned territory. The methodology adopted in this study is to extract the features appropriate for mapping burned areas and to find an effective classifier in terms of accuracy. The methodology adopted in this study mainly consists of three steps: (a) extraction of the best possible features (b) comparison of classification methods and (c) assessment of accuracy.

3.1. Feature extraction

In this study, both original multispectral images and derived spectral indices were used. Three data combinations were compared: (1) derived spectral indices (Data-I); (2) original multispectral data only (Data-II); (3) combination of both spectral indices and multispectral data (Data-III).

The spectral data from bitemporal Landsat 5 TM images contain 12 non-thermal multispectral bands. The indices used in this study were Normalized Difference Vegetation Index (NDVI), Burned Area Index (BAI), Normalized Burn Ratio (NBR), Burned Area Index Improved (BAIM), MIRBI, GEMI, NBR_L and BAIM_L. The indices NBR_L and BAIM_L use the long SWIR variation instead of Short SWIR variation of the NBR and BAIM. The number of spectral indices from bitemporal images is 16 (8 for each). Thus, the third data combination contains 28 bands (12 from bitemporal multispectral images and 16 from bitemporal spectral indices). To reduce the dimensionality of each data combination and choose the best subset of the original features, Principal component analysis (PC) was adopted in this study.

3.2. Selection of training pixels

The training pixels acquired for the classification of the Landsat TM data set follows a manual selection procedure, whereby randomly selected samples from each land cover class were used as training data set. As the class of interest (burned class) is relatively smaller in size than the non-burned class, 9,807 pixels out of total 31,411 pixels were selected from burned class, while 21,604 from the other land cover classes were used as samples of non-burned class. The training data set was later used to train the ML and SVM classifiers. However, the SVDD used only the samples for burned area (target class) (i.e. 9,807 pixels). Using this training data set, a variety of the parameter combinations ($\gamma$, $\alpha$) were tested to attain the optimal parameter combination set for the SVDD classification. The aim was to find the set of parameters that provide the effective hyper-sphere (represent the burned areas) in feature space.

3.3. Image classification

Three classification methods are adopted to classify the burned areas from the Landsat TM imagery. Maximum Likelihood (ML) is the parametric classifier based on the assumptions of the normality of data distribution for each class and exhaustively selected set of classes. For mapping the land cover areas, a number of studies used the ML classifier as a benchmark to compare its classification accuracy with the other newly developed classifiers. It is considered as a standard approach to thematic mapping from the remotely sensed imagery. In real life applications hardly the nature of the distribution is known. It is preferable to use the non-parametric classifiers that are free from assumptions. For the sake of comparison of the classification accuracies and to validate the suitability of the non-parametric classifier for mapping the burned areas in this study, ML classification is conducted.

Support Vector machines (SVM) for the classification of multispectral remote sensing images gains a sky-scraping attention now a day [16], [17]. Vapnik introduced the concept of the SVM for the first time [18]. SVM is a non-parametric binary classifier that locates the optimal hyper plane between the two classes to separate them in a new high-dimensional feature space by taking into account only the training samples that lie on the edge of the class distributions known as support vectors. Support vectors are the samples that lie closest to the decision boundary; this means that only the extreme cases are used by the SVM to separate the classes. This is the primary benefit of using SVM over the other classifiers.
In addition SVM results in high classification accuracies and holds very good generalization abilities. In general, the SVMs are much more effective than other conventional non-parametric classifiers in terms of classification accuracy, computational time and stability to parameter setting. Moreover, it shows the less sensitivity to the problem occur by the curse of dimensionality. The details regarding the SVM execution can be found in [17], [19]. This study only deals with the application of the SVM.

The one-class classification method used in this study is Support Vector Data Descriptor (SVDD). The term one-class classification is coined from [14]. One-class classification proved to be valuable in variety of research areas. It does not require the parametric assumption to be fulfilled that is the chosen set of classes is exhaustively defined. In this way only the training samples from the class of interest are chosen to train the classifier resulting in reducing the amount of training data as well as high accuracy of a classifier will be anticipated. The SVDD is a one-class classifier based on the principles of the SVMs [20]. Analogous to SVM, it too only uses the training set (support vectors) from the class of interest but instead of optimizing a hyper plane between two classes it calculates an optimal hyper sphere with the smallest radius that makes a tighter boundary around the target class and separates it from novel data (outlier data) or any other possible class. Therefore, it models (or trains) only the boundary of a target class instead of modeling a complete density distribution. In this study the SVDD is used to train the classifier with the different model parameter combinations to reach the optimal accuracy level. All the three classifiers were used to classify an image by using original multispectral information, spectral indices and the combination of these two.

3.4. Accuracy assessment
The confusion matrix was used to assess the accuracy measures for all the three classification procedures by using the ground truth pixels as the reference. The Overall accuracy (OA), Kappa coefficient (K), Producer’s accuracy (PA) and the User’s accuracy (UA) were used. The overall accuracy is the percentage of all validation pixels correctly classified, whereas the users and producers accuracy provide information about the commission and omission errors associated with the individual classes, respectively. Unlike the overall accuracy, Kappa takes into account the possibility of agreements occurring by chance in a random classification [21]. The accuracies of the both the burned and the outlier class (non-burned area) were evaluated but the particular attention was focused on the class of interest (burned area).

4. Results and discussion
The output from three classifications is the binary map illustrating the burned areas for all three situations as shown in figure 2. Only the SVDD classification maps with the optimum parameters $\gamma = 10$ and $\alpha = 5\%$ is shown here.

By visually comparing the results shown in figure 2 and original images figure 1, it is easily found that the ML significantly overestimated the burned area, i.e. many non-burned areas were wrongly identified as burned areas. The SVDD also slightly overestimated the burned areas for the Data-I but underestimate for Data-II and Data-III. However, the binary SVM obtained relatively accurate classification results, using different data combinations (figure 2).

To compare the accuracy measurements the confusion matrix calculated for ML, SVDD and SVM for all data combinations are shown in Table 1, Table 2 and Table 3, respectively. The best classification result in this study was obtained by the binary classifier SVM for the Data combination-II as shown in the middle of figure 2, which resulted in the Kappa coefficient of 92.58%. Moreover, it showed the better tradeoff between the producer’s and user’s accuracy in comparison to the other two classifiers for the burned class.

The following discussion concerns the details and the comparison of the classification results used for mapping the burned areas in this study.
Figure 2. Classification results. Data combination-I shows the classification results by using spectral indices (SI), Data combination-II shows the classification results obtained by the original multispectral image (OMI) and Data combination-III shows the results obtained by combining the spectral indices and the original multispectral image (combined SI and OMI) for all the three classifiers.
Table 1. Confusion Matrix for Conventional ML.

| (%)       | Data-I       | Data-II     | Data-III     |
|-----------|--------------|-------------|--------------|
|           | Spectral Indices | Multispectral image | Combined     |
| Burned    | Unburned     | Burned      | Unburned     | Burned      | Unburned |
| PA        | 88.63        | 91.93       | 92.23        | 98.77       | 93.58     | 97.79 |
| UA        | 46.79        | 99.02       | 85.74        | 99.37       | 77.23     | 99.48 |
| OA        |              | 91.68       | 98.29        | 97.47       |           |
| K         |              | 57.08       | 87.94        | 83.26       |           |

The accuracy of the ML classifier was calculated for all three data combinations as it provides the benchmark for the assessment of the SVM based classifications. The classification result of ML by using original multispectral information only, shows the best Kappa (87.94%) among all the three data combinations. Moreover, the user's accuracy (i.e. 85.74%) is also higher than the other two data combinations, which shows that the commission error is least for Data-II (14.26%) as compared to the Data-I (53.21%, i.e. 1-46.79%) and Data-III (22.77%, i.e., 1-77.23%). It can be further observed from table I that the users accuracy for Data-I that is ML classification by using spectral indices only showed the commission error of 53.21%, which means that the burned area is largely over estimated. Hence, the use of spectral indices for classifying the burned areas is not recommended in this study. Even though the commission error is least for Data-II as compared to others but still 14.26% is the high percentage of classifying non-burned pixels as burned pixels. It can also be evident from (figure 2(a)).

From this, we conclude that the ML classification approach is improper to map the burned areas in this study, since the class of interest is substantially over estimated by all the three data combinations. In order to monitor any loss in the environmental and the ecosystem, an accurate classification of the burned area is of crucial interest.

Table 2. Confusion Matrix for One-class SVDD.

| (%)       | Data-I       | Data-II     | Data-III     |
|-----------|--------------|-------------|--------------|
|           | Spectral Indices | Multispectral image | Combined     |
| Burned    | Unburned     | Burned      | Unburned     | Burned      | Unburned |
| PA        | 88.42        | 97.55       | 85.46        | 99.585      | 84.13     | 99.58  |
| UA        | 74.32        | 99.06       | 94.27        | 98.84       | 94.18     | 98.74  |
| OA        | 96.87        | 98.54       | 98.44        |             |
| K         | 79.07        | 88.87       | 88.04        |             |

A real potential for the saving in resources was demonstrated through the use of a one-class SVM i.e. SVDD, as it trains the classifier by using the samples only from the class of interest (burned area). In this case study, confusion matrix for the SVDD of optimal parameter combination is shown in table 2. The best result in terms of accuracy is attained by Data-II (using original multispectral image only) for one-class SVDD. The Kappa coefficient for this is 88.87% showing the high agreement with the burned areas. Also the high user’s accuracy (94.27%) indicates that the error of commission is quite low as compared to the other data combinations. Moreover, Data-II by SVDD classification showed the good tradeoff between users and producers accuracy.
Table 3. Confusion Matrix for Binary SVM.

|             | Data-I     |       | Data-II     |       | Data-III    |       |
|-------------|------------|-------|-------------|-------|-------------|-------|
|             | Spectral Indices | Multispectral image | Combined |       |             |       |
|             | Burned | Unburned | Burned | Unburned | Burned | Unburned |       |       |
| PA          | 91.00  | 96.83   | 92.64  | 99.49   | 92.79  | 99.47    |       |       |
| UA          | 69.69  | 99.26   | 93.62  | 99.41   | 93.39  | 99.42    |       |       |
| OA          | 96.40  | 98.98   | 98.98  |         |        |          |       |       |
| K           | 77.00  | 92.58   | 92.54  |         |        |          |       |       |

The binary SVM obtained the Kappa value of 92.58% for Data-II, higher than the ML and SVDD in general. The user’s and the producer’s accuracies for the burned class, are also high, i.e. 93.62% and 92.64%, (table 3). By using only the original multispectral image (Data-II) in SVM classification, the commission and omission errors both are reduced by 6.38% and 7.36%, respectively.

In this case study the user’s accuracy is given weight-age since it indicates the capacity of the classifier for identifying the occurrences of the outlier class on the ground. In this regard, SVM showed much higher accuracy than the ML and SVDD method. Moreover, SVM showed the best classification results for Data-II.

It has been observed that the accuracy measurements for Data II and Data III in table 2 are not significantly different. The use of original multispectral image and the combined dataset provides more or less the same classification accuracy measurements for mapping burned areas. Moreover, the same pattern can be observed in table 3.

5. Conclusion

In this case study the Data-II i.e. the original multispectral image (OMI) showed the best features to discriminate the burned and outlier (un-burned) classes. The spectral indices calculated in this study do not have significant impact on the burned areas classification accuracy. Other significant spectral indices and vegetation indices should be taken into account to extract the more suitable features appropriate for mapping the burned areas. Moreover, the Binary classifier SVM showed the potential for the accurate mapping of burned areas. In general SVM and SVDD both provide better accuracy than the parametric ML classifier. However, the SVDD performs not well than the SVM in this case study, although SVDD has an advantage of using the training samples only from the class of interest. To get a reliable classifier by only having few labeled pixels is very difficult. In particular for one-class SVM i.e. SVDD, this task is even more harder because the free parameters of the model need to be finely adjusted, but no clear criterion can be adopted. Further work is required to find an algorithm for the optimization of parameters. Moreover, the different remotely sensed images can be used to further rely on the findings of this study.

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