A Multi-Sensor Approach For Burned Area Extraction Due To Crop Residue Burning Using Multi-Temporal Satellite Data

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A Multi-Sensor Approach For Burned Area Extraction Due To Crop Residue Burning Using Multi-Temporal Satellite Data

by

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Abstract

The agricultural burning in the Indo-Gangetic plain causes a variety of effects ranging from human health problems to large carbon emissions. There are high amount of uncertainties associated in estimating the carbon emissions, which is mainly due to inaccurate information about total area affected by fire. The spatial and temporal variations in the distribution of burnt areas in the study area is very high, so the accurate assessment of total burned area from the field records in not possible. Hence, there is need to use the remotely sensed data for accurate assessment of burnt areas at regular intervals.

Various earth observation satellites are providing information for monitoring and assessment of biomass burning activities. Remotely sensed data acquired from a variety of sensors (LISS-III, LISS-IV, MODIS and AVHRR) has been used in the quantitative measurements of burned areas in the parts of Punjab region. The multi-temporal image difference technique using three different indices (NDVI, NBR and GEMI3) was used for extracting the burned areas using the statistical threshold. The performance of the indices was evaluated using spectral separability analysis and was found the performance of GEMI3 as the best in spectral discrimination of burned and unburned surface.

Fine resolution LISS-III (23.5m) data provides accurate estimation of burned area affected by fire, but frequent assessment is not possible due to low temporal resolution (24 days). On the other hand, the coarse resolution of MODIS (500m) and AVHRR (1000m), results in high degree of bias in area estimation, but provides frequent coverage. This bias is taken care by the use of sub-pixel technique in the area estimation. The information from both fine and coarse resolution sensors however was used in combination to reduce the bias in area estimation. As agricultural burnt areas are fragmented and small enough to be detected by MODIS (500m) and AVHRR (1000m), therefore, the most reliable strategy for sub-pixel burned area estimation from coarse resolution sensors is multi-sensor approach. The burned area estimates from coarse spatial resolution data are calibrated on the basis of fine spatial resolution estimates, using regression estimator approach.

The sub-pixel burned area estimation at spatial resolution of 500m (MODIS) was compared with 5.8m (LISS-IV) for 2007 at 9 different field locations using regression algorithm. Good correspondence was observed, with value of coefficient of determination ($R^2 = 0.771$). An overall linear regression fit with data for whole LISS-IV image was compared with sub-pixel estimates at 1000m of AVHRR and the results revealed that there is strong relationship between AVHRR and LISS-IV burned areas, with $R^2 = 0.817$. Finally, it is suggested that, for crop residue burning multi-sensor approach is very effective for improving the accuracy of burned area estimation at coarser resolution.

Key Words: Burned area estimation, MODIS, AVHRR, LISS-III, LISS-IV, Regression estimator approach, Separability analysis, and Accuracy assessment.
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1. Introduction

During the past decades, the significant increase in the occurrence and extent of biomass burning (including forest fire and crop residue burning) has been observed all over the world and is becoming an increasingly important global environment issue. It has been estimated that globally around 350 Mha (million hectare) of area is affected by vegetation fires in the year 2000 (Tansey et al., 2000). The biomass burning release large amount of trace gases like CO$_2$, CO, CH$_4$, N$_2$O and aerosols, which are considered as a major cause for local and global climatic change. Biomass burning has been estimated to contribute up to 40% of the annual carbon released into the atmosphere by human activities. Estimation of burned area (at regional to global level) holds importance in quantifying the total biomass burned and the trace gas emissions. Burned area extraction is one of the major factors contributing to the uncertainty in estimating amount of total burnt and emitted gases at the regional and global levels (Levine, 1991). Large scale burned area estimates have been mainly based on extrapolation of areas obtained from smaller scale results or use of national statistics, which may have been inaccurate due to insufficient resources. These all introduce errors in the overall burnt area estimation. It is observed that information extracted from real time satellite data provides more accurate estimation of burnt areas. An increasing amount of efforts has been put into investigating suitable materials and methods for burned area estimation for different fire regimes and to produce global estimates using satellite data (Roy et al., 2005), Silva et al., 2005).

1.1. Agricultural residue burning

Large quantities of agricultural wastes are produced, from farming systems worldwide, in the form of crop residue. The amount of agricultural wastes produced varies by country, crop and management system. Burning of agricultural waste in the fields is a common practice in the developing world, primarily to clear remaining straw and stubble after harvest and to prepare the field for next cropping cycle. The statistical facts in Table 1-1 show that in Asia, the annual biomass is burned at a very large scale and the contribution of crop residue burning in total residue is very predominant in China and India specially. In Southeast Asia, burning is the major disposal method for rice straw, which accounts for about 31 per cent of the agricultural waste in the developing world. It has been estimated that as much as 40 per cent of the residue produced in developing countries may be burned in fields, while percentage is lower in developed countries. Agricultural burning can produce a large amount of smoke in a short amount of time and hence concerns over impact to public health, safety and the environment have led to stronger regulation, monitoring and burn severity assessment of this activity.
Table 1-1: Annual Amounts of Biomass Burned in Asian Countries in 2000 (Tg)

<table>
<thead>
<tr>
<th>Country</th>
<th>Grassland (Tg)</th>
<th>Forest (Tg)</th>
<th>Crop Residue (Tg)</th>
<th>Total Residue (Tg)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bangladesh</td>
<td>0.0</td>
<td>8.5</td>
<td>11.0</td>
<td>19.5</td>
</tr>
<tr>
<td>Bhutan</td>
<td>0.0</td>
<td>0.7</td>
<td>0.0</td>
<td>0.7</td>
</tr>
<tr>
<td>Cambodia</td>
<td>7.6</td>
<td>5.4</td>
<td>0.9</td>
<td>13.9</td>
</tr>
<tr>
<td>China</td>
<td>52.0</td>
<td>25.0</td>
<td>110.0</td>
<td>180.0</td>
</tr>
<tr>
<td>India</td>
<td>8.6.0</td>
<td>37.0</td>
<td>84.0</td>
<td>130.0</td>
</tr>
<tr>
<td>Indonesia</td>
<td>21.0</td>
<td>68.0</td>
<td>5.8</td>
<td>94.8</td>
</tr>
<tr>
<td>Thailand</td>
<td>12.0</td>
<td>36.0</td>
<td>7.7</td>
<td>55.7</td>
</tr>
<tr>
<td>Vietnam</td>
<td>12.0</td>
<td>15.0</td>
<td>6.1</td>
<td>33.1</td>
</tr>
<tr>
<td>Mongolia</td>
<td>23.0</td>
<td>9.2</td>
<td>0.0</td>
<td>32.2</td>
</tr>
</tbody>
</table>

(Source: Streets, 2003)

1.2. Role of Satellite Remote Sensing in monitoring biomass burning

Satellite remote sensing is a very useful technology for monitoring the biomass burning at regional and global level. It provides us with means to measure the extent of burnt areas and potentially the proportions of burned surface in fire affected areas. The burned area mapping, aims at detecting and delineating the scars left by fires using their spectral signature. The burned area mapping provides the assessment of area affected by fire. During the last ten years, large scale burnt area mapping has been widely studied with ERS ATRS, NOAA AVHRR, SPOT VEGETATION and Terra/Aqua MODIS satellite sensors. These sensors have a high temporal resolution (almost daily) due to wide viewing swaths (512km-3000km), while their spatial resolution varies between 250m (two bands in MODIS) and around 1 km (all other sensors) and include spectral bands of varying bandwidths (Eva and Lambin, 1998). Low spatial resolution (250m – 1000m) however restricts the capability to detect the small burned areas, and therefore questions the reliability of large scale burned area mapping in areas where small burn scars strongly contribute to the total burnt area. The recent advancements in sensor characteristics at finer resolution give the way out to resolve the shortcomings of coarse resolution sensors. Regional level studies related to biomass burning, using medium to finer spatial resolution sensors (IRS-P6 AWiFS 56m to IRS-P6 LISS III 23.5m with spatial coverage of 370 km and 141km respectively) resolves the problem in detecting even the small burned areas effectively but provides restriction in frequent assessment & monitoring of agricultural burning activity due to its low repetivity (24 days in case of IRS P6).

1.3. Problem Definition

The phenomenon of crop residue burning is quite different from the forest burning in terms of temporal and spatial extent. Use of fine spatial resolution satellite data resolves the issues related to map the burnt areas. However, it is impossible to achieve a regional coverage at weekly basis from fine spatial resolution data. On the other hand coarse resolution satellite data gives the mixed pixels, aggregated with other landuse classes; which may lead to a bias in the estimate of the proportion of area burned. The magnitude of this bias depends on: i) the size of coarse resolution cells, ii) the burned
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA

area proportion at a fine spatial resolution, iii) the spatial pattern of burned areas, iv) the spectral contrast between burned areas and their surrounding landcover types and v) the algorithm used to map burned areas (Eva and Lambin, 1998). To overcome the limitations of fine and coarse resolution sensors, a sample of fine spatial resolution data could however be used in combination with coarse resolution data. The above concept gives rise to a new approach called as multi-sensor approach. Hence, the main objective of this study is to minimize the inherent biases involving the fine and coarse resolution satellite data by using multi-sensor approach. The main task of this approach is to first identify the burnt pixels by applying the threshold to different vegetation indices and then select the best indices on the basis of ground validation and separability analysis. The threshold technique may introduce commission errors, which could eventually lead to an overestimation of the burnt areas. Developing the regression algorithm for estimating the area fraction of pixel that has been burnt will compensate for these commission errors. Hence, methodology would be to formulate and derive the feasibility of multi-resolution satellite data for accurate estimation of burnt area fraction in a pixel using regression estimator approach (by calibrating the coarse resolution data of MODIS (500m) and AVHRR (1100m) with fine resolution data of LISS III (23.5m)).

1.4. Research Objectives

This study is being conducted to evaluate the performance of multi-temporal image difference technique based on three different vegetation indices for extracting burned areas at different resolutions and then developing the algorithm for sub-pixel burned area estimation at coarse resolution. The accuracy assessment of sub-pixel burned area estimation will then be done, based on field data. The objectives of the present study are:

- To study and estimate the area under cultivation in summer season.
- To study the algorithms for extracting the burned areas using IRS-P6 LISS-III, Terra/MODIS and NOAA/AVHRR and their comparison.
- To refine the burned area estimation of Terra/MODIS and NOAA/AVHRR using IRS-P6 LISS-III data.

1.5. Research Questions

Some of the research questions to be addressed in order to reach the objectives are:

1. Which algorithm is capable of extracting the burned patches accurately?
2. What are the factors affecting the accuracy?
3. How to utilize the active fire and scar datasets for estimating the burned area?
4. How to increase the accuracy of burned area estimation from NOAA/AVHRR and Terra/MODIS using IRS-P6 LISS III data?
5. How do the uncertainties affect the outcome?
2. Literature Review

This chapter reviews the previous work done for burned area estimation. The remotely sensed information from various earth observation satellites for monitoring and assessment of area affected by fire, has been widely used for different fire regimes. Previously, the different techniques were evaluated for burned area mapping depending upon the characteristics of burning activity. The chapter is having different sections, which explores the use of multi-resolution sensors and different algorithms for burned area mapping for different eco-systems.

2.1. Burned area estimation using coarse spatial resolution sensors

Imageries from the numerous satellites at various resolutions have been employed for identifying burnt areas and for estimating their extent. The NOAA (National Oceanic and Atmospheric Administration) series of satellites have been the most widely used for this purpose, specially the Advanced Very High Resolution Radiometer (AVHRR). Coarse spatial resolution of 1 km offers the potential for regional studies with high temporal repetivity. (Pereira et al., 2003) provides an opportunity to review his studies on the burnt area assessment using Advanced Very High Resolution Radiometer (AVHRR). ATSR data have also been used on a few occasions for burnt area extraction using artificial neural technique (Eva and Lambin, 1998). In recent studies, the use of MODIS (Moderate Resolution Imaging Spectroradiometer) and SPOT–VGT is increasing. The MODIS sensor on board the Terra and Aqua satellites was designed to enhance fire-mapping capabilities. Thirty-six spectral bands of MODIS with spatial resolution ranging from 250 to 1000 meters. Spectral bands of MODIS in near infrared wavelengths provides the better spectral discrimination among burnt and unburned areas (Loboda et al., 2007). MODIS produces full global coverage everyday for all areas except the equatorial region, where repeat frequency is approximately 1-2 days. This is important for burn scar detection in cloudy regions as it provides many alternative days for analysis.

2.2. Burned area estimation using fine spatial resolution sensors

Burnt areas have been mapped, from Landsat TM and SPOT data (Pereira and Setzer, 1993). The wide spectral range of TM data and, in particular, the availability of middle infrared spectral band (1.55-1.75 mm) makes this data particularly appropriate for this application. Due to early morning overpass and low time frequency of observation, Landsat data are unsuitable for the monitoring of active fires. A very few attempts have been made for the utilization of (Linear Imaging Self Scanner) LISS–III on board Indian Remote Sensing Satellite. (Roman-Cuesta et al., 2005) has conducted a study to compare the methods for classifying burn areas with LISS – III imagery. Several methods have been proposed for accurate estimation of burnt area extent using WiFS and LISS sensor (Vazquez et al., 2001).

2.3. Methods of estimating burned area extent

Several methods have been proposed over the years for burnt area extraction using coarse and fine resolution satellite images. There are range of algorithms to detect burnt area i.e. threshold based detection algorithm (Vafeidis and Drake, 2005) algorithms for active fire detection. (Eva and Lambin,
1998) and (Giglio et al., 2003) have been focused on fire detection based on theoretical analysis, fixed
threshold method or contextual algorithms using NOAA Advanced Very High Resolution Radiometer
and MODIS instrument on board Terra and Aqua. These contextual algorithms are not very sensitive
to small fires. An enhanced contextual fire detection algorithm (Giglio et al., 2003) was recently used
for MODIS Version 4 fires products in which the sensitivity to detect small fires increased. The
MODIS fire detection algorithm has a weakness for regional fire detection, as it is designed for global
fire monitoring. Taking into consideration, the temporal distribution of crop residue burning, the fire
events are concentrated in just 2 weeks, beginning after harvesting of paddy crop. As farmers burn
their fields according to their time schedule, the spatial distribution of active fires is changing every
hour. Therefore; MODIS active fire algorithm may not detect the active fires accurately in this case.

The spatial pattern of active fire does not carries a memory of previous biomass burning events, while
the spatial pattern of burned area does carries a memory for a certain time period. Hence, burned area
mapping gives the most accurate assessment of total area effect by the fire activity. It leads to lower
time frequency observations for burnt area detection than active fires (Eva and Lambin, 1998).
Regarding burned area estimation, (Razafimpanio et al., 1995) has proposed a. two methods. The first
method employs channel 2 reflectance and is based on nearly linear relationship between the fraction
of pixel burned and channel 2 reflectance. The second method employs the normalized difference
vegetation index (NDVI) derived from channel 1 and channel 2 reflectance and is based on non-linear
relationship between NDVI and fraction burned (P), where P = f(NDVI), a polynomial of order 2 in
NDVI. The mean relative error on the fraction of area burned is about 20 % for linear method and 10%
for the non-linear method, when applied to uniform pixels. The linear method gives better results for
non-uniform pixels, but neither method can be used when the pixel contains low reflectance
backgrounds (e.g., water).

In addition to using single post-fire images to map burned areas, some researchers have included pre-
fire images and used change detection methods. (Boschetti, 2003) has developed a multi-temporal
algorithm for the detection of burned areas using daily SPOT-VEGETATION multispectral remotely
sensed data. The algorithm exploits the fact that a vegetation fire drastically changes the spectral
characteristics of the local environment and by looking at pre-burn and post-burn conditions, these
changes can be identified. Another studies have also shown that burned areas can be identified using
multi-temporal images of Multi Spectral Scanner (MSS) or TM data (Pereira and Setzer, 1993). The
discrimination between burned and unburned areas is however limited by other surfaces that give
similar response to burned surface (i.e. water) and shadows. The performance of multi-temporal image
compositing algorithms for burned area were analysed using AVHRR sensor Jeffries-Matusita distance
was used to quantify spectral separability of the burned and unburned classes in the composite images.
The commonly used NDVI maximum value compositing procedure was found to be least appropriate
to produce composites to be used for burned area mapping. The best spectral separability is provided
by the minimum channel 2(m2) compositing approach. (Pereira, 1999) addressed problems associated
with the use of vegetation indices for burnt-pixel identification when employing single-date AVHRR
imagery. He adopted the potential of the middle infrared channel (Kaufman and Remer, 1994) and
replaced channel 1 with the reflective component of channel 3 in the NDVI and the global
Environment monitoring Index (GEMI) vegetation indices. In this way he produced two indices.
GEMI3 from GEMI and dNBR from NDVI.

\[
NDVI = \frac{(R_2 - R_1)}{(R_2 + R_1)}
\]
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\[ \text{GEMI 3} = n (1-0.25n) - (\rho_3 - 0.125) / (1- \rho_3) \]

Where \( n = [2(\rho_2^2 - \rho_3^2 + 1.5 \rho_2 + 0.5 \rho_3)] / (\rho_2 + \rho_3 + 0.5) \)

\[ \text{dNBR} = (\rho_2 - \rho_3) / (\rho_2 + \rho_3) \]

Where \( \rho_1 \) is reflectance in the visible range, \( \rho_2 \) the reflectance in the near-infrared and \( \rho_3 \) the reflectance in the middle infrared. It was found that new indices outperformed the NDVI in terms of the degree of spectral separability that the burnt pixel demonstrated over the background with the GEMI 3 being the best discriminator for burnt surfaces.

2.4. Burned area extraction using Hotspot datasets and spectral index

(Frazer et al., 2000) presents HANDS (Hot Spot and NDVI Differencing Synergy), a new satellite based algorithm for boreal burned area & mapping. HANDS synergistically combines two methods commonly used for burn assessment i.e. hotspot detection and multi-temporal NDVI differencing. Both the techniques overcome the deficiency of each other in order to assess the burn areas in an accurate manner. Recently (Loboda et al., 2007) has presented algorithm which has a strong potential for regional specific burned area mapping application. The algorithm is based on Normalized Burned ratio differencing (dNBR) and Modis Active fire product (MOD14), shows high levels of accuracy in comparison with burn scar information from Landsat ETM + imagery

2.5. Sub-pixel burned area estimation

The burnt area detection algorithms as mentioned earlier assume that pixel is either totally burnt or unburnt and many of the techniques use visually or empirically determined threshold to define this decision. Sub-pixel estimation is more necessary in case of coarse resolution sensors particularly when the burnt area is less than the resolution of sensor in order to avoid the over-estimation of burnt area. Several attempts have been made in order to overcome these limitations. Both (Eva and Lambin, 1998) and (Silva et al., 2005) suggested calibration of coarse resolution burnt area results by high-resolution satellite data. This approach enables estimation of total burnt area but the exact locations of burn scars are not known and therefore further monitoring of burn scars following the fire is not possible. It is important to thoroughly understand the variation of fire regimes in the region, in order to reliably calibrate the amount of burnt area. Two methodologies for the estimation of sub pixel burnt area was proposed and developed by (Razafimpanio et al., 1995). One method gives the burnt fraction of a pixel as a linear function of the top to the atmosphere (TOA) of AVHRR channel – 2 reflectance. Other method provides burnt fraction of a pixel as a non-linear function (expressed as a second-order polynomial) of the normalized difference vegetation index (NDVI) before and after the fire event. Both the methods gave accurate estimates of burnt areas when applied to pixels with uniform backgrounds and with burnt percentage exceeding 20% but NDVI method clearly outperformed the linear method for pixels with higher burnt percentage. (Sa et al., 2003) has assessed the sub-pixel burned area mapping technique in miombo woodland lands using MODIS data. A highly accurate map of burned areas at high spatial resolution (Landsat ETM+) was produced and was validated with ground data. The map was spatially degraded to match the MODIS pixel size. Correlation of MODIS reflective data with the burned area fraction map revealed that MODIS channel 2 (0.86 µm), 5 (1.24 µm) and 6 (1.64 µm) are the better single predictors of sub-pixel burned area extent. A regression tree model developed to predict burned area fraction as a function of seven MODIS reflective channels confirmed those results.
3. Study Area

As per the objectives of the study, requirement is to take an area where agricultural residue burning is under taken. Study area was decided after analyzing the agricultural pattern and the technique used for harvesting of paddy and wheat. The criteria for choosing the area were a) availability of large homogenous agriculture fields b) mechanized harvesting technique used by farmers c) burning of left over paddy straw after harvesting.

3.1. Introduction

In India, the Rice-wheat cropping system (RWS) is widely practiced on the Indo-Gangetic Plains (IGP), which accounts for nearly 12 million hectares. IGP is composed of the Indus (areas in Pakistan, and parts of Punjab and Haryana in India) and the Gangetic Plains (Uttar Pradesh (UP), Bihar, and West Bengal in India, Nepal and Bangladesh). In 2000, the total agricultural residue production in India was 347 million tons, of which rice and wheat straw accounted for more than 200 million tons. For every 4 tons of rice or wheat grain, about 6 tons of straw is produced (Gupta et al., 2004). The area chosen for the study is Punjab, which produces enormous amount of crop residue (see Table 3-1). Punjab, which is famous for agriculture and called as “Granary of India”.

Table 3-1: Rice and Wheat crop production and residue generation from major states in India in 1994 (Gg)

<table>
<thead>
<tr>
<th>States</th>
<th>Rice Production</th>
<th>Rice Residue</th>
<th>Wheat Production</th>
<th>Wheat Residue</th>
<th>Total Production</th>
<th>Total Residue</th>
</tr>
</thead>
<tbody>
<tr>
<td>UP</td>
<td>10326</td>
<td>13284</td>
<td>22126</td>
<td>33189</td>
<td>32452</td>
<td>46473</td>
</tr>
<tr>
<td>Punjab</td>
<td>7688</td>
<td>9890</td>
<td>13501</td>
<td>20251</td>
<td>21189</td>
<td>30141</td>
</tr>
<tr>
<td>MP</td>
<td>6308</td>
<td>8115</td>
<td>7151</td>
<td>10727</td>
<td>13459</td>
<td>18842</td>
</tr>
<tr>
<td>Bihar</td>
<td>6251</td>
<td>8041</td>
<td>4296</td>
<td>6443</td>
<td>10547</td>
<td>14484</td>
</tr>
<tr>
<td>Haryana</td>
<td>2185</td>
<td>2810</td>
<td>7285</td>
<td>10928</td>
<td>9470</td>
<td>13738</td>
</tr>
<tr>
<td>Maharashtra</td>
<td>2419</td>
<td>3112</td>
<td>1097</td>
<td>1646</td>
<td>3516</td>
<td>4758</td>
</tr>
<tr>
<td>Gujarat</td>
<td>916</td>
<td>1179</td>
<td>1704</td>
<td>2555</td>
<td>2620</td>
<td>3734</td>
</tr>
<tr>
<td>HP</td>
<td>110</td>
<td>141</td>
<td>553</td>
<td>829</td>
<td>663</td>
<td>970</td>
</tr>
<tr>
<td>All India</td>
<td>81435</td>
<td>88474</td>
<td>64285</td>
<td>96428</td>
<td>145720</td>
<td>184902</td>
</tr>
</tbody>
</table>

(Source: (Gupta et al., 2004))
Punjab, lies between 29º 30' N to 32º 32' N latitude and 73º 55' E to 76º 50' E longitude (Figure 3-1). Punjab located between the Indus and Ganges rivers, is largely an alluvial plain irrigated by canals. Its arid southern border edges the Thar or Great Indian Desert. The Shivalik Ranges rise majestically in the north. Four rivers, i.e. Ravi, Beas, Satluj and Ghaggar flow across the state in the southwest direction. Punjab occupies 50,362 sq. km area i.e 1.54% of India’s total geographical area, but contributes about 22% of wheat, 12% rice to the country. At present, over 84% of the total geographical area of the state stands cultivated and only about 28,000 ha land is classified as cultivable waste. The state looks like a vast farmstead with only 16% of its geographical area under cities, towns, villages, rivers, canals, roads, buildings, wastes, forests, etc (Appendix 1).

Figure 3-1: Location of study area in map of India and coverage of LISS-IV
There are very few studies attempted on spatial and temporal monitoring and assessment of crop residue burning. (Gupta et al., 2004) found that in India RWS (rice-wheat system) leave behind large quantities of straw in the field for open burning of residue. Such burnings results in perturbations to the regional atmospheric chemistry due to emissions of trace species like CO2, CO, CH4, NO2, and aerosols. Recently, (Badrinath et al., 2006) has demonstrated the potential of satellite remote sensing datasets for burnt area estimation and GHG emissions. Indian Remote Sensing Satellite (IRS-P6) Advanced Wide Field Sensor (AWiFS) data during May and October 2005 have been analysed for estimating the extent of burnt areas from crop residue burning. The results suggest that AWiFS data with band in the short-wave infrared together with ground data can be effectively used to estimate the extent of agricultural crop residue burning in fields

3.2. Agricultural Pattern

Agricultural pattern of Punjab is still based on the rice-wheat crop rotation. The total area under rice and wheat cultivation is 2,647 and 3,481 thousand hectares respectively (Table 3-2). The land holdings are ranging from small (1-2 Hectares) to large (10 Hectares and above) (Figure 3-2). The major crops in the State are wheat, maize (corn), rice, pulses (legumes), sugarcane, cotton, and exotic vegetables. Average annual rainfall of the state is 462.8 mm and over 70% of the annual rainfall occurs during the monsoon season, i.e. from July to September. Weather remains dry during the October and November months. Rice is grown during warm, humid season between June and October and wheat in cool, dry season between November and March. Punjab is highly mechanized state in terms of agriculture in which all farm operations from sowing to harvesting is done mechanically. There is little time available between harvesting of rice and planting of wheat and moreover, performance of wheat crop is highly susceptible to any delay in planting. This has resulted in mechanizations of harvesting and introduction of combine harvesters (Figure 3-3). Due to the use of combine harvesters, there has been a sharp increase in the amount of residue that is left in the field, as it leaves major portion of the residue, including husk in the field. The tentative estimates shows that in Punjab 75–80% rice is machine-harvested, which leaves behind enormous quantities of organic matte about 5-7 tons/ha (Gupta et al., 2004). Wheat straw is mainly used as animal feed, whereas rice straw is inferior in feeding quality and hardly used for fodder, at least in Punjab and mainly is left in the field, and burnt by the farmers. In Punjab there is little scope for horizontal expansion of crop cultivation but vertically, the intensity of cropping is over 186% (yes, there is crop rotation practice so, that one field can be used more than once in each calendar year).
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Figure 3-2: Large paddy fields in Sangrur district of Punjab (30th September 2007)

Figure 3-3: Combine Harvester in operation to harvest the paddy crop (last week of October, 2007)
3.3. Paddy Straw Burning

Punjab has about 2,647 thousand hectares under paddy cultivation that yields roughly 100 million tonnes of rice straw and about 70-80 million tonnes of rice is disposed-off by burning (Badrinath et al., 2006). The main options left for proper management of left over straw area is in situ incorporation and burning in the field. In situ incorporation is not feasible as the decomposition of residue takes a long time and affects the growth of wheat crop. Thus, for a farmer it is economical and easier to burn the residue in the field. Residue burning in open field has resulted in pollutant emission, loss of nutrients, diminished soil biota, and reduced total N and C in the topsoil layer (Figure 3-4). This wasteful burning results in a gigantic waste of energy besides contributing to global warming. It is also a health hazard to local inhabitants.

Figure 3-4: (a) Paddy field during burning and (b) Field covered with ash after burning

This year it was reported “Air in the entire district, particularly in the rural belt, is heavily laden with noxious fumes of paddy straw, which continues to be burnt rampantly despite a complete ban by the Government. During a random survey today, suffocating thick smoke and paddy stubbles in fields were witnessed all over the district. Tarsem Singh, a farmer, said, “Farmers don’t burn the paddy residue because they are against environment. They don’t have an alternative for its disposal because they have to prepare the fields for the next crop. The Government or agriculture monitoring agencies have, till date, not given us any viable method for disposal of paddy residue.” The UNEP scientists in the past have pointed out that the build-up of the haze, a mass of ash, acids, aerosols and other particulars, is disturbing the weather cycle, including rainfall and the haze phenomenon is set to intensify over the next 30 years. Its implications are dangerous for agriculture.” (Tribune News Service, Chandigarh Edition, Vol. 127 No. 297, of October 26, 2007).

It is difficult to conduct this study for whole Punjab area, due to limitation of moderate resolution Remote Sensing data to cover the whole Punjab in one scene. It has been decided to conduct this study on Ludhiana and Sangrur districts, which are one of the prominent areas under paddy cultivation. The decision has been taken on the basis of area under paddy cultivation in these two districts (Table 3-2) and availability of satellite data for these regions on required dates in month of September and October (pre-burn and post-burning period) in 2006.
Table 3-2: District wise distribution of area under Paddy and Wheat cultivation (year 2005)

<table>
<thead>
<tr>
<th>District</th>
<th>Area under Paddy cultivation</th>
<th>Area under Wheat cultivation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gurdaspur</td>
<td>202</td>
<td>227</td>
</tr>
<tr>
<td>Amritsar</td>
<td>334</td>
<td>372</td>
</tr>
<tr>
<td>Kapurthala</td>
<td>105</td>
<td>115</td>
</tr>
<tr>
<td>Jalandhar</td>
<td>145</td>
<td>171</td>
</tr>
<tr>
<td>Nawang Shehar</td>
<td>50</td>
<td>76</td>
</tr>
<tr>
<td>Hoshiarpur</td>
<td>58</td>
<td>145</td>
</tr>
<tr>
<td>Rupnagar</td>
<td>51</td>
<td>89</td>
</tr>
<tr>
<td><strong>Ludhiana</strong></td>
<td><strong>247</strong></td>
<td><strong>258</strong></td>
</tr>
<tr>
<td>Firozpur</td>
<td>238</td>
<td>386</td>
</tr>
<tr>
<td>Faridkot</td>
<td>88</td>
<td>114</td>
</tr>
<tr>
<td>Muktsar</td>
<td>86</td>
<td>199</td>
</tr>
<tr>
<td>Moga</td>
<td>164</td>
<td>173</td>
</tr>
<tr>
<td>Bathinda</td>
<td>102</td>
<td>241</td>
</tr>
<tr>
<td>Mansa</td>
<td>75</td>
<td>167</td>
</tr>
<tr>
<td><strong>Sangrur</strong></td>
<td><strong>367</strong></td>
<td><strong>397</strong></td>
</tr>
<tr>
<td>Patiala</td>
<td>250</td>
<td>266</td>
</tr>
<tr>
<td>Fatehgarh Sahib</td>
<td>85</td>
<td>85</td>
</tr>
<tr>
<td><strong>Total Area</strong></td>
<td><strong>2,647</strong></td>
<td><strong>3,481</strong></td>
</tr>
</tbody>
</table>
4. Methodology

This chapter clearly explains various steps followed during pre-processing of satellite data, generation indices, deriving threshold technique for burned area extraction, downscaling approach and validation procedure followed.

4.1. Satellite Data

The study is based on the utilization of multi-resolution sensor characteristics for burned area extraction. For this purpose a variety of remotely sensed images, from different sensors, that offer a range of spatial and spectral resolution, were taken. As study is concentrated on paddy straw burning, the images of two dates are acquired i.e pre-burning period (30th September, 2006) and post-burning (24th October, 2006). The images of LISS-III, MODIS and AVHRR are acquired, which offers spatial resolutions of 23.5m, 500m and 1100m respectively.

4.1.1. Satellite Data Acquisition

As this study is based on utilization of multi-sensor characteristics to detect the burned areas accurately, it was mandatory to acquire all the three satellite datasets of same dates. MODIS and AVHRR are global datasets and the temporal resolution is very high. The medium resolution LISS-III sensor is having the repetitivity of 24 days. After, deciding the pre-burning and post burning dates and also on which the LISS III was available, 30th September 2006 and 24th October 2006 was selected as pre-burning and post-burning dates respectively. MODIS surface reflectance product was downloaded through FTP server from LPDAAC (Land process Distributed Active Archive Center) data link and AVHRR raw images were downloaded from CLASS (The Comprehensive Large Array-data Stewardship System) for the same dates. Class is an electronic library, which provides on-line facility for distribution of NOAA environment data. For validation purpose, real time data of LISS-IV sensor of spatial resolution of 5.8m was acquired for same date (24th October) for 2007 on a special request to the NDC (NRSA Data Center, Hyderabad).

4.1.2. Sensor Characteristics

MODIS (Moderate Resolution Imaging Spectrometer)

MODIS is an important sensor onboard NASA’s Terra (EOS AM) and Aqua (EOS PM) satellites. MODIS sensor combines the characteristics of AVHRR and Landsat sensors to provide improved monitoring of the Earth’s surface at global scales. Terra is a polar orbiting spacecraft that when cloud is at its daily minimum (10:30 AM, descending). It is having swath of 2330km with temporal resolution of 1 day. MODIS provides 36 bands in wide range of wavelength from visible to thermal infrared region of spectrum. MODIS provides different products for Land, Atmosphere and Ocean related studies at resolution 250m, 500m and 1000m. In this study, MODIS land surface reflectance product at 500m is being used. The MODIS surface reflectance product is having seven land bands ranging from visible to short wave infrared. The spectral characteristics of each band are Band 1 (620nm-670nm), Band 2 (841nm-876nm), Band 3 (459nm-479nm), Band 4 (545nm-565nm), Band 5 (308nm-382nm), Band 6 (1638nm-1731nm), and Band 7 (2130nm-2350nm).
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(1230nm-1250nm), Band 6 (1628nm-1652nm) and Band 7 (2105nm-2155nm). These all seven bands are corrected for atmospheric effects with an algorithm that uses aerosol and water vapour information collected by sensor. The algorithm corrects for thin cirrus clouds, aerosols, and atmospheric gases. The result is an estimation of surface reflectance as if it had been measured on the surface, without the effects of atmospheric absorption or scattering.

RESOURCESAT –1 (IRS-P6)

The RESOURCESAT-1 (IRS-P6) is envisaged as the continuity mission to IRS-1C/1D, with enhanced capabilities both in the payload and the platform, to meet the increasing demands of the user community.

LISS-III

LISS-III onboard RESOURCESAT-1 (IRS-P6) is a multi-spectral sensor operating in four spectral bands, three in the visible and near infrared and one in SWIR region. The new feature in LISS-III camera is the SWIR band (1550nm to 1700 nm), which provides data with a spatial resolution of 23.5m. The spectral range for four different bands are Band 1 (620nm-670nm), Band 2 (841nm-876nm), Band 3 (459nm-479nm) and Band 4 (1550nm-1700nm). It provides the swath of 141 km and repetivity of 24 days.

LISS-IV

The LISS-IV camera is a multi-spectral high-resolution camera with a spatial resolution of 5.8m at nadir. The swath at multi-spectral mode is 24 km and at mono mode is 70 km. This camera can be operated in two modes of Mono and Multi-spectral. In the Multi-spectral mode, data are collected in three spectral bands Band 1 (520nm - 590 nm), Band 2 (620nm-680nm) and Band 3 (760nm-860nm).

AVHRR (Advanced Very High Resolution Radiometer)

The six channel Advanced Very High Resolution Radiometer (AVHRR/3) on board NOAA-17 is used originally to provide global cloud imagery for meteorological purposes. That objective is still retained, but many other applications have developed around the use of this versatile instrument. The instrument has an instantaneous field-of-view (IFOV) of 1.3 milliradians providing a nominal spatial resolution of 1.1 km at nadir. It provides the data at Global Area Coverage (GAC, 4x4 km) and Local Area Coverage (LAC, 1x1 km) with swath width of 3000km. Data from five of the channels are transmitted continuously and in full 1.1 km resolution within the HRPT (High Rate Picture Transmission) data stream. The wavelength range of five spectral bands are Band 1 (580nm-680nm), Band 2 (725nm-1100nm), Band 3A (1580nm-1640nm), Band 3B (3550nm-3930nm), Band 4 (1030nm-1130nm) and Band 5 (1150nm-1250nm).
4.2. **Flow Chart**

![Flow chart showing the most important steps of overall methodology](image)

*Figure 4-1: Flowchart showing the most important steps of overall methodology*
4.3. Pre-processing

The pre-processing of data includes atmospheric correction, radiometric enhancement, and geometric correction of satellite data. During the burning period, the atmosphere is normally affected by haze and smoke, so it is necessary to apply the atmospheric correction to LISS III datasets. MODIS surface reflectance product which is being used in the study, is already corrected for atmospheric effects.

4.3.1. Atmospheric Correction

Earth Observation systems recorded the signals, which is always get obstructed by the atmospheric profile. The atmospheric contributions to the signals recorded from satellite become more critical in case where surface characteristics of landuse class is to be studied. To enable quantitative studies of the earth surface, atmospheric perturbations need to be removed from the observed signal. The process of removing atmospheric contributions is commonly referred as atmospheric correction.

The atmospheric correction has been applied to LISS-III raw data of 30th September 2006 and 24th October 2006. During agricultural residue burning period, the smoke and haze is commonly seen over the entire study area as seen in LISS III image of 24th October, 2006 (Figure 4-2 (a) and (b)). Surface information under haze regions cannot be retrieved with optical sensors, because the signal contains no radiation component being reflected from the ground. So, in order to retrieve the ground reflectance of all the land use classes, the haze removal technique was applied to whole image. In some parts of the image, the thin cloud shadows are seen which resembles the burned areas and may give false signal during the burned area extraction. So, de-shadowing technique is also used in order to remove the shadows.

![Figure 4-2: LISS III image of 24th October 2006 showing (a) Smoke and (b) Haze](image)

4.3.1.1. Software Used

The LISS III images were atmospherically corrected using Satellite ATCOR software. The ATCOR software was developed by DLR (German Aerospace Center) and the Standalone IDL version is licensed to ReSe for commercial marketing. ATCOR is useful for processing bands in the solar region from 400-2500nm. Satellite ATCOR is equipped with Haze removal deshadowing technique. The atmospheric correction can be done in two modes ATCOR-2 and ATCOR-3. ATCOR-2 is used for flat
terrain and removes the shadows due to buildings and clouds, whereas ATCOR-3 is used for mountainous terrain and removes the shadows in the mountain areas.

4.3.1.2. Haze Removal

Figure 4-3 is showing the LISS III image before and after haze removal.

![LISS-III (Before Haze Removal)](image1) ![LISS-III (After Haze Removal)](image2)

**Figure 4-3: LISS III image of 24th October 2006, before and after haze removal**

The Haze removal has been done during the atmospheric correction process by giving some parameters listed below:

- **ATCOR2 (flat terrain)**
  - Scene acquisition date (dd/mm/year): 24/10/2006
  - Solar zenith angle [degree] = 44.3
  - Solar azimuth angle [degree] = 160.5
  - Sensor tilt angle [degree] = 0.0
  - Sensor view azimuth angle [degree] = 90.0
  - Water vapour category: Tropical (water vapour column: 4.11 cm for sea level)
  - Aerosol type: Rural
  - Constant scene visibility
  - Input visibility [km] = 23.0
  - Final visibility [km] = 20.0
  - Haze removal: yes

- **Haze Processing Parameters:**
  - Correlation coefficient for visible bands = 0.94
  - ihot_mask (1=compact, 2=larger area mask) = 1
  - ihot_dynr (1=small, 2=large dynamic range) = 1
  - Haze HOT level range = 21 to 35
4.3.1.3. De-shadowing

In shadow areas, however, the ground-reflected solar radiance is always a small non-zero signal, because the total radiation signal at the sensor contains a direct and reflected component. Figure 4-4 shows, even if the direct solar beam is completely blocked in shadow regions, the reflected diffuse flux will remain. Therefore, an estimate of the fraction of direct solar irradiance for a fully or partially shadowed pixel can be the basis of a compensation process called de-shadowing.

Figure 4-4: Cloud shadow geometry

The de-shadowing technique works for multispectral and hyperspectral imagery over land acquired by satellite/ airborne sensors. The method requires a channel in the visible and at least one spectral band in the near-infrared (0.8-1 µm) region, but performs much better if bands in the short-wave infrared region (1.6 to 2.2 µm) are available as well. It is fully automatic algorithm, which employs masks for cloud and water. These areas are identified with spectral criteria and thresholds. The interactive session of the de-shadowing method enables the setting of three parameters.

1. a threshold \( \phi_T \) for the unscaled shadow function \( \phi = \Phi_U \) to define the core size of the shadow regions (Figure 4-5).
2. the maximum range \( \phi_{\text{max}} \) for re-scaling the unscaled shadow function \( \phi = \Phi_U \) into the (0,1) interval of the scaled shadow function.
3. the last parameter sets the minimum value of the scaled shadow function \( \phi^* = \Phi_S \), typically in the range \( \Phi_S = 0.02-0.10 \), i.e., the darkest shadow pixels of the scene are being illuminated with a fraction \( \Phi_S \) of the direct solar irradiance.
De-shadowing has been implemented by setting the following parameters, which are found suitable in this case. These parameters are found during the two iteration process for providing the best output. The final result of de-shadowing is shown in Figure 4-6.

1. Threshold for core shadow areas = -0.20
2. Unscaled shadow function = -0.10
3. Scaled shadow function = 0.15
4. Stretch function (1=linear, 2=exponential) = 1

Figure 4-6: Shows the unscaled shadow function

Before Shadow Removal

After De-shadowing

Figure 4-6: LISS III images before and after de-shadowing technique
After the atmospheric corrections, there was a considerable decrease in the reflectance in percentage of water pixels in red and infrared bands. Also, the reflectance values for vegetation class after the atmospheric correction decrease in Red band and there is an increase in Infrared band. For urban feature showing the increase in reflectance in Red and Infrared band (Table 4-1).

Table 4-1: Mean reflectance values before and after atmospheric corrections over some selected pixels on LISS III data.

<table>
<thead>
<tr>
<th>Features</th>
<th>Before AC</th>
<th>Before AC</th>
<th>After AC</th>
<th>After AC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Red</td>
<td>Infrared</td>
<td>Red</td>
<td>Infrared</td>
</tr>
<tr>
<td>Water</td>
<td>6.25 %</td>
<td>6.49 %</td>
<td>3 %</td>
<td>2.75 %</td>
</tr>
<tr>
<td></td>
<td>5.97 %</td>
<td>6.78 %</td>
<td>2.25 %</td>
<td>0.75 %</td>
</tr>
<tr>
<td>Urban</td>
<td>11.37 %</td>
<td>15.32 %</td>
<td>9.75 %</td>
<td>16.25 %</td>
</tr>
<tr>
<td></td>
<td>11.02 %</td>
<td>15.56 %</td>
<td>10.76 %</td>
<td>18.25 %</td>
</tr>
<tr>
<td>Vegetation</td>
<td>5.18 %</td>
<td>29.95 %</td>
<td>1.75 %</td>
<td>39.5 %</td>
</tr>
<tr>
<td></td>
<td>4.75 %</td>
<td>27.58 %</td>
<td>1.5 %</td>
<td>37 %</td>
</tr>
<tr>
<td></td>
<td>4.98 %</td>
<td>27.32 %</td>
<td>1.5 %</td>
<td>38.5 %</td>
</tr>
</tbody>
</table>

4.3.2. Geometric Correction

After applying the atmospheric correction to the raw DN values of LISS-III images, the reflectance images were geometrically corrected with respect to the Survey of India toposheets No. 44 N and No. 53 B at scale 1: 250,000. The permanent features like road crossing, bridges and canal crossings were located in both toposheet and image as ground control point. 12 GCPs were selected over the entire scene for final geo-correction. The root mean square error during the geo-correction was 0.23 pixels. The transformation projection selected was geographic, which later on re-projected to UTM Zone 43 and WGS84 datum using nearest-neighbour resampling method.

4.3.3. Masking out Study Area

The vector layer of Area of Interest was prepared and then this layer was used to subset the study area from whole LISS-III scene, as shown in Figure 4-7.
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA

4.3.4. Classification

Classification of pre-burn image (30\textsuperscript{th} September 2006) was done for fulfilment of two conditions:

- To estimate the total area under cultivation of paddy crop for two districts and further comparison with agricultural statistics.
- To generate the mask of agriculture class, in order to eliminate the urban, forest and fallow land use class from images generated using different indices.

The LISS-III image was classified in ERDAS 8.7 software using the supervised classification technique. Supervised classification was based on signatures of different land use classes. The signature library was created using signature editor toolbox. The level-1 classified scheme was adopted. Finally the image was classified using the parametric rule of maximum likelihood.

4.3.5. Calibration of MODIS

MODIS/Terra Surface Reflectance Daily L2G Global 500m SIN Grid (MOD09GHK) was downloaded via FTP server. The product is available in HDF format, which is directly imported into ENVI HDR format using MODIS Conversion Toolkit, which is downloaded from ITT Visual Information Solutions (Figure 4-8).
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA

4.3.6. Calibration of AVHRR

The pre-processing of AVHRR data having five spectral bands ranging from visible to thermal infrared was done using ENVI software. The data download via ftp link was first imported into ENVI through calibration utilities and then after providing the parameters for calibration (Figure 4-9), the raw image was converted into reflectance image.

Figure 4-8: Converting the HDF format to surface reflectance values using MODIS Conversion toolkit

Figure 4-9: Parameters used for calibration of AVHRR data
4.4. Generation of Indices for detecting the burned pixels

The performance of three different indices was evaluated for burned pixel identification. These are NDVI, DNBR and GEMI3. These indices were selected on the basis of previous work done by various authors for detecting the burnt scars (Chuvieco et al., 2002) NDVI is most commonly used index for various vegetation related studies, but also being tested on quite number of occasions for burned area detection over different vegetation regimes. The other two indices i.e NBR and GEMI3 utilize the mid-infrared region of the spectrum for burnt area detection. Mid-infrared region of spectrum is considered as the most predominant region for detecting burn scars due to forest fire. The GEMI3 is selected, as it is specifically designed to minimize problems of contamination of the vegetation signal by critical factors, such as the atmosphere and the soil background.

4.4.1. Normalized Difference Vegetation Index (NDVI)

The spectral contrast offered by red and near-infrared channels in case of healthy vegetation and burned areas, provides the basis for using this technique for burned area extraction. The NDVI is linked to different physiological variables such as the green biomass and could also be an indicator of the moisture content of the vegetation (Fernandez et al., 1997). Healthy vegetation tends to give rise to high NDVI values, because it has a high reflectance in the near infrared and a low in the visible; burned surface give rise to lower NDVI values because the reflectance of the burned vegetation increases in the visible and decreases in the infrared. The NDVI images of pre-burning period (30th September, 2006) and post-burning period (24th October, 2006) for all the satellite data were generated using the following equation

\[ \text{NDVI} = \frac{(R_2 - R_1)}{(R_2 + R_1)} \]

Where \( R_1 \) and \( R_2 \) are satellite reflectance in the visible (red) and in the near- infrared, respectively.

4.4.2. Normalized Burn Ratio (NBR)

Normalized Burn Ratio (NBR) is another band ratio similar to the NDVI, which utilizes the near-infrared and mid-infrared bands. Imagery collected over a agriculture in a pre-fire condition will have high NIR band values and very low mid-infrared band values. Image collected over a agriculture after a fire is having low NIR band values and high mid-infrared band values. (Pereira et al., 1999) found that mid-infrared bands are less affected by atmospheric scattering. In addition, as many natural materials have a broader range of reflectance in the mid-infrared bands than the visible bands, it is easier to differentiate between land cover types. The comparison of field observations to dNBR (NBR\text{pre-burn} - NBR\text{post-burn}) for fires throughout the western United States that burned during 2003 and illustrated that dNBR values consistently described vegetation burn severity. The USDA Forest Service and U.S Geological Survey use the dNBR method to map post fire burn severity. In previous studies, dNBR found to be the most practical tool for burns mapping and applicable across ecosystems.

The following equations are used for generating the pre-burn and post-burn NBR images and finally difference NBR (dNBR) image was generated for all satellite data.

\[ \text{NBR} = \frac{(\rho_2 - \rho_3)}{(\rho_2 + \rho_3)} \]

\[ \text{dNBR} (\text{NBR}_{\text{pre-burn}} - \text{NBR}_{\text{post-burn}}) \]

\( \rho_2 \) the reflectance in the near- infrared and \( \rho_3 \) the reflectance in the middle infrared
4.4.3. Global Environment Monitoring Index (GEMI3)

GEMI is a non-linear index to monitor global vegetation from satellites, which had been developed by B. Pinty and M. M. Verstraete at Joint Research Centre, Ispra (VA), Italy in 1992. GEMI was specifically designed to minimize the atmospheric and soil effects for burned area extraction. It represents the new generation of indexes. The non-linear design of GEMI provides a significant built-in attenuation of atmospheric effects, which is considered very important for remote sensing of burned areas. It was seen that, when the atmospheric optical thickness increases from clear to more turbid conditions, the range of ‘transmission’ which is defined as the ratio of the vegetation index at the top of the atmosphere over its value at the surface, of simple ratio and NDVI is larger than that of GEMI (Pinty and Verstraete, 1992). GEMI3 is the modified version of GEMI where visible channel is replaced by middle infrared channel. The new GEMI3 combines the atmospheric insensitivity of the MIR range with the non-linear design of the GEMI. The Pre-burn and Post-burn images from GEMI3 was generated for all satellite data using the following equation.

\[
\text{GEMI 3} = n (1-0.25n) - \frac{(\rho_3 - 0.125)}{(1-\rho_3)}
\]

Where \( n = \left[ 2(\rho_2^2 - \rho_3^2 + 1.5 \rho_2 + 0.5 \rho_3) \right] / (\rho_2^2 + \rho_3 + 0.5) \)

Where \( \rho_1 \) is reflectance in the visible range, \( \rho_2 \) the reflectance in the near-infrared and \( \rho_3 \) the reflectance in the middle infrared.

After generating the pre-burn and post-burn images from NDVI, NBR and GEMI3 indices, the change in land cover due to fire activities is observed by pre-burn and post-burn difference images for each index used. The difference image statistics is further studied for defining threshold value for each index separately.

4.5. Threshold Approach

The thresholds determination is very important to flag the pixels as burned pixels. Thresholds may be chosen using field validation data, by visual interpretation, using statistically based techniques or by adopting the fixed threshold. Visual, determination is often superior to statistical methods. But sometimes visual interpretations is not very helpful in hazy conditions, particularly for small agricultural burns. Classification of the burnt pixels in the previous studies has been predominantly based on the setting of fixed thresholds (Kasischke et al., 1993). Pixels whose values fall below or above the set thresholds are classified as burned or unburned. In the previous studies, the fixed thresholds were suggested for mapping the burned areas due to forest fire. As forest burning activity differs from that of agricultural burning, and due to variations in viewing, atmospheric and surface conditions at different places and times, it is not usually possible to use the same fixed threshold to classify pixels as burned and unburned for crop residue burning. The fixed thresholds may produce questionable results. Other possibility is to use a statistical approach, considering pixels located more than a particular numbers of standard deviations from mean value of difference image. This value varies from image to image and largely depends upon spatial extent of different landuse classes. Considering the images of same dates, having same conditions, still the statistics of the images varies with spatial resolution. This method is based on the probability of extracting from a normal population, an individual outside the interval given by \( \mu \pm Y\sigma \) (where \( \mu \) is the population mean and \( Y \) is a value, usually 1 or 2). The value of \( Y \) is a variable and is very uncertain; therefore field validation data have been used to determine the appropriate threshold for different indices.
4.6. Active Fire Database Generation

The active fire data were generated for the purpose to confirm, whether the burned areas, which has been detected by the image difference technique, had actually experienced the active burning. The buffer zone of 500m radius was created around each active fire point created. The active fire buffer layer generated will be overlaying with the burned areas detected. Also the spatial distribution of burned areas can be compared with of active fire points.

The active fire layers had been created from period of 30th September 2006 to 24th October 2006 (Figure 4-11) using MODIS MOD14 (fire) Direct Broadcast algorithm, which was developed by Scanex Company in Russia. It requires the MODIS level 1B product of calibrated radiance of 1km and geolocation file. The algorithm generates the hotspot data file in HDF format for Terra or Aqua. The HDF file is then opened in HDF inspector for retrieving the center latitude and longitude of fire pixel. Each hotspot detection represents the center of a 1km pixel flagged as containing one or more active hotspots/fires within that pixel. The location is the center point of the pixel, not necessarily the coordinates of the actual fire, which is shown in Figure 4-10.

4.7. Field Investigations

The field investigations are emphasized and carried out in order to understand the ground reality and to make the results authenticated with actual situation. The two field visits were planned, one before and other after burning period for the purpose of ground truth data collection, which is required for setting the threshold for burned area detection and for locating the burned areas for validation of results.

4.7.1. Field Visit before burning period

Pre-burning field visit during 23rd September to 30th September was planned for the purpose of marking of some field locations, which later on can be used as a base to analyse the extent of burning
on that locations. Homogeneous paddy fields of 500x500 m² were identified in LISS-III image and finally located on ground using GPS. After locating the homogenous patch of paddy crop, the Ground Control Points were collected at four corners of each 500x500 m² size field. 21 sample fields were located in the whole study area, as shown in Figure 4-11. The spectral reflectance of paddy field was also measured at five different field locations. The GCP’s collected at four corners of each field were later on transferred to LISS-III imagery of 30th September.

![Legend](image)

**Figure 4-11:** Showing field boundary of 500x500 m² located in the LISS III image of 30th September 2006.

### 4.7.2. Field Visit after burning period

The post-burning visit was restricted to the same field locations, as identified during the pre-burning visit. The burned areas were located and identified on pre-defined field locations. The GCP’s of burned areas were collected using GPS, for validation of the results. The extent of burning in 500x500 m² fields was later on mapped on real time LISS-IV image of 2007. The spectral reflectance of burned surface at same five locations were also measured.

### 4.7.3. Sampling Plan

The random sampling approach is being used in order to locate homogeneous field sites of 500 x 500m². As agricultural pattern is same in whole study area, 21 field sites were selected randomly, which can be easily located in LISS-III image. The majority of field sites are selected in those areas, which are under the coverage of LISS-IV data of 2007, so that these samples can be later on used for validation for 2007 MODIS and AVHRR data.

### 4.7.4. Field Spectra collection

The field spectra data are used as one of the major inputs for setting up the threshold for different algorithms for extracting the burned areas. As agricultural burning activity is having high degree of spatial variability, the fields, which were burn in 2006 till 24th October, may not burn in 2007 till 24th October. This uncertainty encourages the spectral collection of different land use classes, especially the burn areas and vegetation, because the spectral variability hardly varies with time, considering the
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA

same type of crop burn every year. As the datasets used in the present study is of 2006, field spectra collection was done on the same dates in 2007 and at same solar time.

4.7.4.1. Instrumentation

In order to make measurements of surface reflectance of paddy crop and burned area samples, an Analytical Spectral Device (ASD) a FieldSpec®-Pro spectroradiometer, was used. The spectroradiometer is a portable array-based spectrometer consisting of a spectrometer unit, computer interface, and fiber optic probe. The instrument has two integrated radiometers covering 350 to 2500nm. The radiometer consists of one silicon photodiode array and two fast scanning thermoelectrically (TE) cooled spectrometers with a spectral resolution 10nm. The instrument was operated with 5 full-field-of-view (FFOV) fore optics. A laptop interface with the instrument allows real time viewing of the spectrum recorded. The ASD instrument meets the requirement of different datasets used in this study. Table 4-2 shows the specification of the instrument used.

Table 4-2: Specifications of FieldSpec®-Pro Spectroradiometer

<table>
<thead>
<tr>
<th>Spectral Range</th>
<th>350 – 2500 nm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral Resolution</td>
<td>FWHM 3 nm for 350-1000 nm</td>
</tr>
<tr>
<td></td>
<td>FWHM 10 nm for 1400 – 2100 nm</td>
</tr>
<tr>
<td>Sampling Interval</td>
<td>1.4 nm for 350 – 1050 nm</td>
</tr>
<tr>
<td></td>
<td>2 nm for 1000 – 2500 nm</td>
</tr>
<tr>
<td>Scanning Time</td>
<td>100 milliseconds</td>
</tr>
<tr>
<td>Detector</td>
<td>One 512 element (Si photodiode array 350 – 1000 nms)</td>
</tr>
<tr>
<td></td>
<td>Two separate, TE cooled, InGaAs (Indium-Gallenium-Arsenide) photodiodes 1000 – 2500 nm</td>
</tr>
<tr>
<td>Input device</td>
<td>Foreoptics gun</td>
</tr>
</tbody>
</table>

(Source: FieldSpec®-Pro User Guide)

The spectral data collection requires instrument calibration using a reference panel (“Spectralon” white reference) provides along with the instrument. During the white reference collection, a reference 100% line is available to the user to check the status of the instrument performance. White reference collection includes dark current correction and was repeated every 20 minutes during the collection of sample spectra. Actually, a certain amount of electrical current is generated by thermal electrons within the ASD and always added to the incoming photons of light during spectra collection. This adversely affects the spectra collection and has to be removed. This process is known as “Dark Current Correction”. This minimizes the effect of the changing lighting conditions on the recorded spectra. The calibration was repeated several times during the sampling period to establish changing light conditions or instrument drift

4.7.4.2. Spectral data collection

There are homogenous paddy fields available all over the study area. At five different locations in the study area Figure 4-12, spectral reflectance of 15 samples of paddy crop and bare soil and water were collected. The field spectra collections were undertaken within 2 hours before solar noon, to simulate the similar illumination conditions as during the satellite pass. During the burning season, at same locations, spectral reflectance of 20 samples of burned residue, bare soil, and standing residue were collected. The spectra collected during the field visit, Figure 4-13 were processed further using the
inbuilt software. The 35 samples of spectra were exported in text format and spectral reflectance curves were plotted using the ENVI software.

Figure 4-12: Sample points distribution in the study area

Figure 4-13: Collecting the spectra (a) Paddy crop and (b) burned areas

4.8. Downscaling Approach

The spatial aggregation of burned areas in coarse resolution pixels may lead to a bias in the estimation of the proportion of area burned. Therefore downscaling approach is being adopted in this study for the purpose of reducing bias in estimation of proportion of burned areas at spatial resolution of 500m (MODIS) and 1000m (AVHRR). A linear regression estimator approach is being used to estimate the burned area from low resolution data. The LISS-III burned area image is considered as reference
image to calibrate the low resolution burned area images of MODIS and AVHRR. The LISS-III data was spatially degraded to match the MODIS and AVHRR pixel size using aggregate function in ArcGIS. The relationship was developed between the aggregated mean value of LISS-III with MODIS and AVHRR pixel values. Another relationship is built between the aggregated LISS-III values and burned fraction in 500m x 500m and 1000m x 1000m window size, which moves linearly throughout the image. The linear regression approach provides an assessment of the quality of low-resolution burned area estimates and then used for validation of results. The main advantage of this approach is that it quantifies the bias in burned estimation present in low resolution burned area maps (Silva et al., 2005).

The potential of sub-pixel algorithm given by (Razafimpanilo et al., 1995) is also being evaluated for agricultural burning. The algorithm expresses the burnt fraction of a pixel as a second-order NDVI polynomial whose coefficients are estimated as non-linear functions of the NDVI of a region before the fire event (equation (4-1)). The comparative evaluation of burned area algorithm developed by using linear regression estimator approach with the algorithm developed by Razafimpanio for sub pixel estimation is being performed.

\[ P = A_0 + A_1 \text{NDVI}_b + A_2 (\text{NDVI}_b)^2 \]  

(4-1)

Where P is the burnt fraction as a function of the NDVI of the area that has burnt (NDVI_b) and A_0, A_1 and A_2 are coefficients of following polynomials:

\[ A_0 = 2.822 + 765.136x - 2398.331x^2 + 5398x^3 - 3658.492x^4 \]

\[ A_1 = -770.844 + 4030.346x - 8347.035x^2 + 6358.168x^3 \]

\[ A_2 = -1416.609 + 4603.778x - 4569.151x^2 \]

x is the maximum NDVI of the unburnt region before the fire (Razafimpanilo et al. (1995))
5. RESULTS AND DISCUSSION

This chapter explains on the results of the objectives undertaken in the study. To classify the landuse/landcover features using satellite data, knowledge of ground is necessary. An extensive field visit and ground truth collection was performed and spectral libraries were build. Atmospheric corrections and haze/shadow removal techniques were performed on satellite data to retrieve the true surface reflectance of different land cover classes. The chapter is arranged to highlights the results obtained in implemented the overall objectives.

5.1. Analysis of Landuse/Landcover classification

The study area is dominated by agriculture with only 16 % of its geographical area under cities, towns, villages, rivers, canals, roads, buildings, wastes, forests landuse class (Appendix 1). The study area is dominated by large homogeneous paddy fields, as found during the field visits. For the purpose of generating the agriculture mask of study area and to estimate the total area under paddy cultivation, the LISS III image of 30th September 2006 was classified into five different classes (Figure 5-1a) as explained in section 4.3.4.

5.1.1. Classification Accuracy

The classification accuracy assessment was done in ERDAS software by making use of 21 reference ground control points of different land use classes collected during the field visits. The producers and users accuracy was calculated for urban, water, forest, fallow and agriculture and overall classification accuracy of 76.19% was obtained with overall Kappa statistics of 0.5661. After masking out the agriculture class from the classified image Figure 5-1(b). According to agricultural statistics report for 2004-2005, the total area under paddy cultivation is 61400 hectares. The area under paddy cultivation for year 2006 was estimated from classified LISS III image of 30th September 2006 is 701,877.6091 hectares. There is a difference of 12.53% in the area estimation from LISS-III image which is attributed to mainly two reasons. Firstly, in the satellite image of the area, there is possibility of classifying fodder or other crops with paddy which increases the overall paddy area and secondly, the comparison of crop statistics has been done with that 2004-05 which may lead to some error.

Table 5-1: Classification Accuracy for different classes

<table>
<thead>
<tr>
<th>Class Name</th>
<th>Reference Totals</th>
<th>Classified Totals</th>
<th>Number Correct</th>
<th>Producers Accuracy</th>
<th>Users Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>--------</td>
<td>--------</td>
</tr>
<tr>
<td>Urban</td>
<td>4</td>
<td>4</td>
<td>3</td>
<td>75.00%</td>
<td>75.00%</td>
</tr>
<tr>
<td>Forest</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>--------</td>
<td>--------</td>
</tr>
<tr>
<td>Agriculture</td>
<td>14</td>
<td>12</td>
<td>11</td>
<td>78.57%</td>
<td>91.67%</td>
</tr>
<tr>
<td>Fallow</td>
<td>3</td>
<td>5</td>
<td>2</td>
<td>66.67%</td>
<td>40.00%</td>
</tr>
<tr>
<td>Totals</td>
<td>21</td>
<td>21</td>
<td>16</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA

**Legend**

- Agriculture
- Fallow
- Forest
- Unclassified
- Urban
- Water

![Figure 5-1: Classified Image of LISS III (30th September, 2006) and Agriculture mask of study area.](image)

5.2. **Generation of difference images**

The indices described in Chapter 4 are used to generate the difference image from (pre-burn image – post-burn image) for all satellite data used in the study. For MODIS spectral bands of Spectral bands of Visible (620-670 nm), Infrared (841-876 nm) and Short wave infrared (1628-1652 nm) were used for generation of all three indices. It is found that short wave infrared band 6 was substantially used in previous studies for burn scar mapping and considered as the most suitable band for detection of burn scars. The difference images for all the three indices were derived; using same equations of NDVI, NBR and GEMI3 as described Chapter 4. The difference image was generated in order to detect the change in the vegetation due fire activities. The burned areas can detect in lighter tones of grey, where the difference in index values area higher. The darker tones of grey indicated areas with small or no changes. The lighter tone of grey represents the maximum change in land cover after fire. The histogram shows the image statistics with mean and standard deviations.
5.2.1. Difference Images of LISS-III

Figure 5-2: Difference image and Histogram of NDVI
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA

Legend

nbr_agri

Value

High : 1.17816

Low : -0.934783

Histogram showing mean and ± 1 standard deviation

Figure 5-3: Difference image and Histogram of dNBR
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA

Figure 5-4: Difference image and Histogram of GEMI3

Histogram showing mean and ± 1 standard deviation
5.2.2. Difference Images of MODIS

Figure 5-5: NDVI difference image and histogram showing mean and standard deviation
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA

Histogram showing mean and ± 1 standard deviation

Figure 5-6: dNBR difference image and histogram showing mean and standard deviation
Figure 5-7: GEMI3 difference image and histogram showing mean and standard deviation
5.2.3. Difference Images of AVHRR

Figure 5-8: NDVI difference image and histogram showing mean and standard deviation
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA

Figure 5-9: dNBR difference image and histogram showing mean and standard deviation
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA

Figure 5-10: GEMI3 difference image and histogram showing mean and standard deviation
5.3. Spectral characteristics of burned and unburned surface

The spectral reflectance of different landuse classes was collected at different field locations. The soil spectra differ significantly from those of vegetation and ash Figure 5-11(a). The reflectance of soil considerably increases from visible to NIR region. Dry paddy straw shows high reflectance values due to the absence of chlorophyll content, whereas water shows near to zero reflectance for infrared and short-wave infrared bands.

Paddy crop represents the pre-fire surface, as only paddy straw has been burnt in the field every year. Post –fire surface consisted of only black ash, unburned biomass, and bare soil. Figure 5-11(a) and (b) shows the field reflectance spectra of each pre-fire and post-fire surface component. The spectral reflectance measured between 350 to 2500nm was strongly affected by atmospheric water absorptions, which occurs at the wavelength 1450, 1950 and 2500 nm. After pre-processing the random noise has been removed.

The spectral differences within each pre-fire spectra (Figure 5-11(a)) is very marginal at five different locations, which due to the homogeneity of Paddy crop before fire as described in the agricultural pattern of study area. The maturity stage of Paddy crop was almost same in the whole study area, at the time of pre-fire visit. The spectral reflectance of paddy crop increases drastically in the infrared region of 700 to 1300 nm due to presence of chlorophyll content, but there is a decrease in the reflectance beyond 1300 nm.

The spectral reflectance of the post-fire burned surface contrast strongly with that of the pre-fire counterparts as shown in Figure 5-11(b). These observations were recorded at same field locations. The burned surface is covered with black ash, which is produced by complete combustion of plant materials in the presence of oxygen. The black ash has a very low spectral reflectance in the visible range of 400 to 700 nm. At the wavelength greater than that of 700 nm (infrared bands), there is considerable increase in the reflectance values. Even in middle infrared region of spectrum, the reflectance is higher than in the visible spectral region. The nature of spectral curves has been compared with those of the spectral reflectance’s found over black ash studied over African Savannahs by (Smith et al., 2005) and have been found to have similar spectral nature.

The random noise signals were observed in both spectral profiles of paddy crop and burned surface. These noise signals are concentrated at 1400 nm, 1850 nm and 2500 nm wavelength region, which correspond to water vapour absorption bands. The measured signal consists of following components:

Measure signal = true signal + dark current + stray light + random noise.

Dark current can easily be recorded and subtracted so that it is a negligible contributor. Computed reflectance = (true target signal + stray light + random noise)/(true reference signal + stray light + random noise) (ASD Technical Guide 3rd Ed. Section 4-2)

Computed reflectance is ratio of random noise to the random noise at the time of target measurement to the random noise at the time of reference measurements. In certain case, if the random noise signal at the time of target measurement increase from 3DN to 6DN, then computed reflectance at a particular wavelength would be 200 percent. Graphically, this would be a vertical line that shoots upward from the last wavelength channel with a non-zero measurement signal. Likewise let’s say that at the 1850nm wavelength channel the random noise levels are such that the ration is near zero. Graphically, this would be another vertical line next to the last one that shoots straight down to zero.
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA

(a)

Endmember Collection Spectra

(b)

Endmember Collection Spectra
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA

Figures 5-11: Spectral reflectance of the different land use classes collected at the field sites using FieldSpec®-Pro spectroradiometer (a) Spectral reflectance of paddy straw and soil during the burning period. (b) Spectral reflectance of the pre-fire Paddy crop at different field sites. (c) Spectral reflectance of the post-fire burned surface at same field locations.

5.4. Comparison of spectral curves

To evaluate the performance of atmospheric corrections applied to LISS-III images, the comparison of reflectance spectra from field measurements has been done with image reflectance values at corresponding field locations. The ASD instrument records the spectra in 1251 bands at 2 nm bandwidth as discussed in (section 4.7.4.1). To compare the ground measurement spectra collected from ASD with that of atmospherically corrected image spectra, the ASD spectra were re-sampled to LISS-III bandwidth. A spectral library of re-sampled ASD spectra was created Figure 5-12(a)-(b). The spectra from the ASD library were used as standard to compare image reflectance spectra. The comparison was done for each site location as shown in Figure 5-12. Table 5-2 shows marginal difference between image and ground reflectance values for paddy crop and burned areas. The reflectance values obtained from satellite image are comparable with that of field measurements at all different locations. Such comparison for site 1 is shown in Figure 5-13. This result is further very useful for deriving the ground-based threshold for burned area algorithm.
Figure 5-12: The re-sampled spectral reflectance to LISS-III bandwidth (a) re-sampled reflectance of paddy at different sites. (b) re-sampled reflectance of burned areas at same sites.
Figure 5-13: Shows the comparison of Paddy and Burned reflectance spectra recorded from FieldSpec instrument and image pixels at Site 1

<table>
<thead>
<tr>
<th>Wavelength</th>
<th>558 (nm)</th>
<th>652</th>
<th>813 (nm)</th>
<th>1620 (nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Site 1</td>
<td>IMAGE</td>
<td>0.040</td>
<td>0.030</td>
<td>0.40</td>
</tr>
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<td></td>
<td>GROUND</td>
<td>0.056</td>
<td><strong>0.044</strong></td>
<td><strong>0.439</strong></td>
</tr>
<tr>
<td>Site 2</td>
<td>IMAGE</td>
<td>0.045</td>
<td>0.029</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td>GROUND</td>
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<td><strong>0.026</strong></td>
<td><strong>0.454</strong></td>
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<tr>
<td>Site 3</td>
<td>IMAGE</td>
<td>0.039</td>
<td>0.027</td>
<td>0.41</td>
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<tr>
<td></td>
<td>GROUND</td>
<td>0.042</td>
<td><strong>0.037</strong></td>
<td><strong>0.434</strong></td>
</tr>
<tr>
<td>Site 4</td>
<td>IMAGE</td>
<td>0.049</td>
<td>0.032</td>
<td>0.37</td>
</tr>
<tr>
<td></td>
<td>GROUND</td>
<td>0.09</td>
<td><strong>0.041</strong></td>
<td><strong>0.428</strong></td>
</tr>
<tr>
<td>Site 5</td>
<td>IMAGE</td>
<td>0.043</td>
<td>0.033</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td>GROUND</td>
<td>0.053</td>
<td><strong>0.025</strong></td>
<td><strong>0.338</strong></td>
</tr>
</tbody>
</table>
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA

<table>
<thead>
<tr>
<th></th>
<th>Wavelength</th>
<th>558 (nm)</th>
<th>652</th>
<th>813 (nm)</th>
<th>1620</th>
</tr>
</thead>
<tbody>
<tr>
<td>Site 1</td>
<td>IMAGE</td>
<td>0.05</td>
<td>0.06</td>
<td>0.11</td>
<td>0.15</td>
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<tr>
<td></td>
<td>GROUND</td>
<td>0.072</td>
<td><strong>0.059</strong></td>
<td><strong>0.112</strong></td>
<td><strong>0.140</strong></td>
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<tr>
<td>Site 2</td>
<td>IMAGE</td>
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<td>0.065</td>
<td>0.10</td>
<td>0.156</td>
</tr>
<tr>
<td></td>
<td>GROUND</td>
<td>0.059</td>
<td><strong>0.056</strong></td>
<td><strong>0.12</strong></td>
<td><strong>0.131</strong></td>
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<tr>
<td>Site 3</td>
<td>IMAGE</td>
<td>0.064</td>
<td>0.069</td>
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</tr>
<tr>
<td></td>
<td>GROUND</td>
<td>0.072</td>
<td><strong>0.061</strong></td>
<td><strong>0.127</strong></td>
<td><strong>0.166</strong></td>
</tr>
<tr>
<td>Site 4</td>
<td>IMAGE</td>
<td>0.061</td>
<td>0.081</td>
<td>0.11</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>GROUND</td>
<td>0.076</td>
<td><strong>0.058</strong></td>
<td><strong>0.121</strong></td>
<td><strong>0.162</strong></td>
</tr>
<tr>
<td>Site 5</td>
<td>IMAGE</td>
<td>0.069</td>
<td>0.073</td>
<td>0.13</td>
<td>0.15</td>
</tr>
<tr>
<td></td>
<td>GROUND</td>
<td>0.08</td>
<td><strong>0.057</strong></td>
<td><strong>0.116</strong></td>
<td><strong>0.160</strong></td>
</tr>
</tbody>
</table>

Table 5-2: Comparison of reflectance values of field measurement and LISS III image (a) Comparison of reflectance values of Paddy (b) comparison of reflectance values of burned pixels

5.5. Deriving the threshold for burned pixel identification

The urban, forest, water and fallow land classes are masked out from the LISS-III image leaving only agriculture (Figure 5-1 (b)), to highlight only paddy and burned classes to be further used in refining the threshold. The pixel values are calculated using difference technique (pre-burn – post-burn) for three indices using the field measured reflectance data. The values obtained for pixels at different locations as shown in Table 5-3 are used to refine the threshold based on image statistics. The field values are calculated in order to confirm whether the pixel values that has been burned lies in the range of ±1*standard deviation or ± 2*standard deviation from the mean value of the image statistics. The values marked as red (Table 5-3) are minimum values obtained at different locations which signifies that if a pixel is having difference values greater than the minimum value, the pixel (in ground) has been detected as burned. It is observed from the mean and +1*standard deviation of the difference images shown in (Figure 5-2, 5-3 and 5-4), that the values obtained from field reflectance data lies above the +1*standard deviation from the mean values of the images. Therefore considering well distribution of field observations and homogeneity of burning activity all over the study area, for LISS-III difference images, the threshold of +1*standard deviation has been used for extracting burned pixels. Similar threshold has been used to detect burnt pixel using the algorithm from MODIS and AVHRR data.
Table 5-3: Values of different indices obtained using ground measured reflectance at selected locations

<table>
<thead>
<tr>
<th></th>
<th>NDVI difference</th>
<th>NBR difference</th>
<th>GEMI3 difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Site 1</td>
<td>0.508</td>
<td>0.518</td>
<td>0.385</td>
</tr>
<tr>
<td>Site 2</td>
<td>0.528</td>
<td>0.488</td>
<td>0.394</td>
</tr>
<tr>
<td>Site 3</td>
<td>0.491</td>
<td>0.693</td>
<td>0.490</td>
</tr>
<tr>
<td>Site 4</td>
<td>0.477</td>
<td>0.479</td>
<td>0.392</td>
</tr>
<tr>
<td>Site 5</td>
<td>0.521</td>
<td>0.558</td>
<td>0.356</td>
</tr>
</tbody>
</table>

5.5.1. Burned area images from LISS-III

The image statistical approach, verified by field data is being used in order to classify the burned and unburned pixels. The statistical threshold of mean + 1*standard deviation is used to extract the burned areas from LISS-III derived indices. The pixels having values more than mean + 1*standard deviation are labelled as burned. The burned areas images for LISS-III derived indices are shown in Figure 5-14.
Figure 5-14: Burned area obtained from LISS III (23.5m) using (a) NDVI, (b) NBR and (c) GEMI3 difference techniques

5.5.2. Burned area images from MODIS

As the MODIS data was acquired for the same date and of the same area as that of LISS-III, the conditions are assumed to be similar, hence used the same threshold (mean + 1*standard deviation) is used to label as burned pixels. Unlike LISS-III, for coarse resolution MODIS (500m) and AVHRR (1000m), which include water, forest, fallow landuse class as mixed pixels, it was difficult to classify different landuse classes with high accuracy, therefore extracting pure paddy class in case of MODIS and AVHRR is not possible. Three burned area images for each indices are derived using same statistical threshold technique (Figure 5-15).
5.5.3. Burned area images from AVHRR

In case of AVHRR also, the burned pixels are identified using same threshold (mean + 1*standard deviation). Three burnt area images for each indices are derived using same statistical threshold technique Figure 5-16.
5.6. Separability Analysis

Visual inspection of a gray scale image containing burned surfaces is not an adequate methodology for assessing the discriminate capability of spectral index. It is necessary to quantify this ability, taking into account both the magnitude of interclass differences as well as the magnitude of interclass variance, for some predefined set of land cover classes, one formed by surface burned. In this study, it is decided to consider only two classes, one formed by burnt surface and another containing all remaining land cover types.

5.6.1. Spectral Discrimination Index M

It is a measure used to quantify the effectiveness of each vegetation index to separate burned surfaces from the unburned background environment (Pereira, 1999). The spectral discrimination index (M) is given by following equation:

\[ M = \frac{\mu_u - \mu_b}{\sigma_u + \sigma_b} \]

Where:
- \( \mu_u \) = mean value for the unburned background class;
- \( \mu_b \) = mean value for burned class;
- \( \sigma_u \) = standard deviation of values for unburned background class;
- \( \sigma_b \) = standard deviation of values for burned class.

![Figure 5-16: Burned area obtained from AVHRR (1km) using (a) NDVI, (b) NBR and (c) GEMI3 difference technique](image)
Values of M larger than one indicate good separability, while value lies between 0-1 represents a large degree of histogram overlap between the two classes. This measure is analogous to the signal to noise ratio concept previously used to evaluate the performance of various Vegetation index as predictors of fractional vegetation cover. Here, the difference between mean values of the two classes represents the burned area detection signal, while the sum of the standard deviations measures the level of noise. Figure 5-17, 5-18 and 5-19 shows the histogram of the burned and unburned classes, which are useful in understanding the behaviour of each vegetation index for burned area detection and mapping. The distance between the mean values for the two classes, the amount of spread in the data, and the consequent extent of histogram overlap determine the values of the spectral discrimination index M. Figure 5-17 shows the results of separability analysis for LISS-III derived indices, which shows that GEMI3 displays the largest discriminate power (M = 1.06). Hence shows better separability than NBR (M = 0.89). The NDVI (M = 0.70) is giving the lowest separability index of three vegetation index tested. This outcome provides strong support to the fact that contributing the SWIR band gives better spectral separability to the burnt areas as compared to the NIR band. The results of separability analysis in case of MODIS suggested GEMI3 (M= 0.99) as a better discriminating index as compared to NDVI (M= 0.79) and NBR (M = 0.86) (Figure 5-18).

### 5.6.1.1. Spectral Discrimination Index M for LISS III derived indices

![Histogram of NDVI](image.png)

![Histogram of NDVI](image.png)

**Unburned**

**Burned**

\[ M = 0.70 \]
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Figure 5-17: Histograms of the burned and unburned classes of LISS III for (a) NDVI, (b) NBR and (c) GEMI3

(a) No. of Pixels

(b) NBR

M = 0.89

(c) GEMI3

M = 1.06

Figure 5-17: Histograms of the burned and unburned classes of LISS III for (a) NDVI, (b) NBR and (c) GEMI3
5.6.1.2. Spectral Discrimination Index $M$ for MODIS derived indices

The separability analysis for MODIS data has been performed to test the ability of each index to discriminate between burned and unburned class (Figure 5-18).

![Histogram of NDVI](image)

- **NDVI**
  - $M = 0.79$
  - Unburned
  - Burned

![Histogram of NBR](image)

- **NBR**
  - $M = 0.86$
  - Unburned
  - Burned
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA

Figure 5-18: Histograms of the burned and unburned classes of MODIS for (a) NDVI, (b) NBR and (c) GEMI3

The analysis performed has given the same results as in case of LISS-III, with GEMI3 being the best index to separate the burned class with respect to the background as compared to other indices. The value of M for GEMI3 index decreases to 0.99 as compared to GEMI3 for LISS-III. The decrease in the value of M may be due to the limited capability of coarse spatial resolution of 500m to discriminate between burned and unburned areas.

5.6.1.3. Spectral Discrimination Index M for AVHRR derived indices

The spectral discrimination index (M) is derived for each index using AVHRR data (Figure 5-19).
The result of the analysis reveals that the value of $M$ for GEMI3 is still decreases from 0.99 at 500m resolution to 0.92 at 1000m resolution. Although the value for GEMI3 is less than 1, but still as compared to NDVI and NBR, it gives better separability.
5.7. Assessment of burn area extraction

In order to assess the potential of each index to map the burned areas accurately, the high resolution LISS-IV having spatial resolution of 5.8m was used. LISS-IV data of 24th October 2007 was acquired, so there is always a spatial mismatch between burned area extracted by three indices using 2006 data and LISS-IV burned areas of 2007. The spatial viability of agricultural burning is very high in this region as discussed earlier, so in order to overcome this problem only selected fields are used to compare the burned area estimates. The fields were selected based on the fact that agricultural burning is anthropogenic activity and fire doesn’t go beyond the boundary of field belonging to a particular farmer, and hence, there is a strong possibility to detect the same burned field in LISS-IV image of 2007 as it was detected as burned area in 2006 Figure 5-20. In this case, the information from farmer itself is being used, whether he has burned the same field last year before 24th October, as he has done this year. On the basis of information collected from the farmer during field survey and burned area location in LISS-IV image, seven fields are selected, which were burned in 2006 and in 2007 also.

Each boundary of burned fields identified in the LISS-IV image, was digitized representing one polygon, using Arc GIS software by visual interpretation. The area of each polygon was calculated as shown in Table 5-4. The comparative evaluation of burned areas estimated at same fields locations by three indices using high resolution LISS-IV image was done Table 5-5. The estimated areas by three indices were correlated with reference area estimates of LISS-IV Figure 5-21. The correlation coefficient of burned area extraction using GEMI3 is very high as compared to other two indices used. So, considering the results at few field locations, the accuracy assessment of burned area extraction of GEMI3 difference technique is the best between other two techniques for burned area extraction due crop residue burning.

<table>
<thead>
<tr>
<th>FID</th>
<th>Shape'</th>
<th>Id</th>
<th>Field_Id</th>
<th>Area</th>
</tr>
</thead>
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<td>Polygon</td>
<td>1</td>
<td>2</td>
<td>37650.316532</td>
</tr>
<tr>
<td>2</td>
<td>Polygon</td>
<td>2</td>
<td>2</td>
<td>7903.976681</td>
</tr>
<tr>
<td>3</td>
<td>Polygon</td>
<td>3</td>
<td>6</td>
<td>122462.516365</td>
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<tr>
<td>4</td>
<td>Polygon</td>
<td>4</td>
<td>9</td>
<td>22862.614419</td>
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<tr>
<td>5</td>
<td>Polygon</td>
<td>5</td>
<td>10</td>
<td>74999.194958</td>
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<td>0</td>
<td>Polygon</td>
<td>7</td>
<td>12</td>
<td>74275.314866</td>
</tr>
</tbody>
</table>

Table 5-4: Burned area estimation of each polygon digitized by visual interpretation in LISS IV image
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA

Figure 5-20: Burned area detected in (a) LISS-III 2006 (resolution 23.5m) and (b) LISS-IV 2007 (resolution 5.8m)
The burned areas extracted at 7 different field locations from LISS-III image using NDVI, NBR and GEMI3 indices. The area in meters sq. extracted by each index at selected locations are compared with the area statistics of high resolution reference LISS-IV image (Table 5-5).

<table>
<thead>
<tr>
<th>Polygon_Id</th>
<th>LISS IV</th>
<th>NDVI (LISS III)</th>
<th>NBR (LISS III)</th>
<th>GEMI3 (LISS III)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>57658.52</td>
<td>45292.00</td>
<td>49885.00</td>
<td>58136.00</td>
</tr>
<tr>
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<td>7903.97</td>
<td>43264.00</td>
<td>20813.00</td>
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</tr>
<tr>
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<td>122462.52</td>
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<td>145332.00</td>
<td>123032.00</td>
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<tr>
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</tr>
<tr>
<td>5</td>
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<td>94886.00</td>
<td>84500.00</td>
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<tr>
<td>6</td>
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<tr>
<td>7</td>
<td>74275.31</td>
<td>78416.00</td>
<td>81456.00</td>
<td>85176.00</td>
</tr>
</tbody>
</table>

Table 5-5: Comparison of burned area estimated in meter sq. by different indices used with reference to digitized burned areas of LISS-IV
As per the results and outcome of discussion in section 5.4 and 5.5, GEMI3 is the best index for burned area extraction in Agricultural burning regime for LISS-III sensor. The burned area map of GEMI3 is being further used as a reference image for further analysis and selection of best-burned areas image for MODIS and AVHRR datasets. Previous studies (Pereira, 1999) also suggested that GEMI3 performs quite well for overall burning regimes, but especially over the agricultural and sparse evergreen oak landscapes and was clearly the best of all indexes tested for the purpose of segmenting images into burned and unburned areas.
5.8. Utilization of Active fire datasets

The active fire layers from MODIS algorithm was generated as discussed earlier (section 4.6) for the whole study area. The results of active fire generation are shown in Figure 5-22.

Figure 5-22: Active Fire Locations in the study area

The agricultural burning results in large degree of spatial variation in terms of fire activity. The active fire can only be detected at the time of satellite pass. MODIS, onboard TERRA and AQUA satellites having the capability to detect the active fire twice a day, TERRA (10:30 am) and AQUA (2:30 pm). The active burning in the individual’s field, remains for only short time (few hours) as compared to forest fire (few days), so satellite detection mainly missed large number of active fires. Hence, particularly for agricultural burning the active fires does not represent the actual burning pattern. Moreover, the MODIS algorithm detects the active fire with in 1km pixel size, but the exact location of fire remains uncertain. Hence, there is very limited scope to utilize the active fire layers for burned area estimation, rather it can be used for monitoring the spatial variability of fires in whole burning period. The only possibility, to utilize the active fire information occurred in case of validation of burned areas. The buffer zone of 500m radius around the central pixel location is created. The active fire buffer zone layer is overlayed with detected burned areas. The burned areas that lies within the buffer zone, indicates that the area is affected by fire activity (Figure 5-23).
Figure 5-23: Burned area overlayed with buffer zone of 500m
5.9. **Sub-pixel burned area estimation using MODIS and AVHRR**

The burned area images of MODIS (GEMI3) and AVHRR (GEMI3) derived in section 5.3.2 and 5.3.3 are calibrated as described in (section 4.6). The burnt fraction images are generated from reference image of LISS-III GEMI3 to calibrate with MODIS and AVHRR. The LISS-III image is reclassified into burnt class and background. Then burned percentage is calculated within the window size of 500 m and 1000 m to match with pixel of MODIS (500m) and AVHRR (1000m) respectively. The window moves linearly throughout the image to calculate the fraction of burned pixels in percentage within the size of moving window Figure 5-24. The relationship has been developed between the MODIS pixel values and mean of pixel values of LISS-III aggregated 500m shown in Figure 5-25. Another relationship has been developed between mean of pixel values of LISS-III aggregated 500m and proportion of area burned within 500 window size of LISS-III (Figure 5-26). Similar procedure has been followed to derive such relationships for AVHRR data (Figure 5-27 and 5-28). It has been concluded from the relationships that, sub-pixel burned area can be estimated using the above regression estimator approach, but the accuracy for sub-pixel estimates depends largely upon the difference in the resolution between the reference image. High resolution image of AVHRR is not giving the linear relationship. The coefficient of regression existing on the lower side, the possible reason for that may be the large pixel size of 1km contains effect of landuse classes other than burned surface. In case of MODIS, the relationship is linear and is much better; it may give good accuracy at sub-pixel level.

![Figure 5-24: Burned fraction images generated from LISS III at (a) window size of 500 m and (b) window size of 1000 m](image-url)
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Figure 5-25: Relation between aggregated LISS III to 500m and MODIS 500m

Figure 5-26: Relation between aggregated LISS III to 500m and Percentage burned within 500m pixels
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA

Figure 5-27: Relation between aggregated LISS III to 1000m and AVHRR

Figure 5-28: Regression analysis between aggregated LISS III to 1000m and Percentage burned within 1000m pixels
The regressions equations are used to calculate the sub-pixel burned areas for MODIS and AVHRR. It is calculated from regression equation derived from MODIS GEMI3 and LISS-III GEMI3, that threshold of mean + 1*standard deviation applied on MODIS GEMI3 identifies the burnt pixels with more than 26 % fraction burnt actually. This means if the MODIS pixels are having burned percentage of more than 26%, then it is considered to be fully burnt. This results in high degree of overestimation in overall burned area. Therefore, the regression algorithm is being used to compensate for high degree of overestimation of areas in MODIS pixels. Similarly, in case of AVHRR also, the pixels having burned fraction more than that of 25% is considered as fully burned and later on this bias in area estimation can be reduced using the regression algorithm for AVHRR data.

5.9.1. Accuracy assessment of sub-pixel burnt area estimates

The burned areas estimated from MODIS sub-pixel algorithm defined by (Razafimpanilo et al., 1995) and MODIS regression algorithm is compared with reference image of LISS III at same field locations as used in section 5.5. The field size of 500m x 500m was taken as reference to match with MODIS pixel size of 500m. The burned area estimation by MODIS at these field locations using Razafimpanilo sub pixel algorithm and algorithm derived from regression estimation approach was compared with LISS IV estimation at those field locations. The comparison reveals that MODIS sub-pixel algorithm overestimate the actual burned area. The overestimation is quite large at every field measurement, therefore doesn’t depict the burned areas accurately. The burned area estimates from regression estimator approach gives underestimation for burnt area proportion less than 20% and slight overestimation in burned areas for proportion more than 20% (Table 5-6).

<table>
<thead>
<tr>
<th>FIELD ID</th>
<th>LISS IV Burned Area (% burned in 500m x 500m field size)</th>
<th>LISS III (GEMI3)</th>
<th>MODIS (Razafimpanilo Sub pixel Algorithm)</th>
<th>MODIS (Regression Algorithm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>65662.48 (26.22%)</td>
<td>71656.00</td>
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</tr>
<tr>
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<td>189800.00</td>
<td>142225.00</td>
</tr>
<tr>
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<td>21632.00</td>
<td>58625.00</td>
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</tr>
<tr>
<td>10</td>
<td>74999.19 (30%)</td>
<td>84500.00</td>
<td>168100.00</td>
<td>85300.00</td>
</tr>
<tr>
<td>15</td>
<td>53712.37 (21.48%)</td>
<td>61200.00</td>
<td>149675.00</td>
<td>71500.00</td>
</tr>
<tr>
<td>12</td>
<td>74275.31 (29.71%)</td>
<td>85176.00</td>
<td>120575.00</td>
<td>58575.00</td>
</tr>
</tbody>
</table>

Table 5-6: Comparison of sub-pixel burned area estimation from MODIS
The LISS-III burned estimate also varies with respect to the burned area obtained from reference image (LISS-IV). The error of LISS-III estimates of burned area considering the LISS-IV data as the reference, i.e. the LISS-III error was obtained as error estimates given by (Silva et al., 2005)

\[
\text{LISS-III Error} = \frac{(\text{LISS-III} - \text{LISS-IV})}{\text{LISS-IV}}
\]

The error of MODIS estimates of burned area considering the LISS-III data as the reference was obtained as:

\[
\text{MODIS Error} = \frac{(\text{MODIS} - \text{LISS-III})}{\text{LISS-III}}
\]

The MODIS sub-pixel regression algorithm is derived using the reference LISS-III data. This means we can only estimate the error in MODIS with respect to the LISS-III datasets. But we have already found that in LISS-III has also some error with respect to high resolution LISS-IV (Table 5-7). Therefore, indirectly we can say that mean error of 7.74% in area estimates of LISS-III also propagating in MODIS sub-pixel estimates.

<table>
<thead>
<tr>
<th>BURN AREA (m²)</th>
<th>LISS-IV Burned Area with percentage burn in (500x500 m²) field</th>
<th>LISS-III (GEMI3) (Error %)</th>
<th>MODIS (Sub pixel) (Error %)</th>
<th>MODIS (Regression Alg) (Error %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>65562.48 (26.22 %)</td>
<td>+9.29</td>
<td>+123.22</td>
<td>-49.62</td>
</tr>
<tr>
<td>5</td>
<td>122462.51 (48.98 %)</td>
<td>+0.46</td>
<td>+54.9</td>
<td>+16.13</td>
</tr>
<tr>
<td>9</td>
<td>22662.61 (9.06 %)</td>
<td>-4.54</td>
<td>+158.68</td>
<td>-100.00</td>
</tr>
<tr>
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<td>+124.13</td>
<td>+13.73</td>
</tr>
<tr>
<td>15</td>
<td>53712.37 (21.48 %)</td>
<td>+13.90</td>
<td>+178.66</td>
<td>+33.11</td>
</tr>
<tr>
<td>12</td>
<td>74275.31 (29.71 %)</td>
<td>+14.67</td>
<td>+62.33</td>
<td>-21.13</td>
</tr>
</tbody>
</table>

Table 5-7: Error estimation in MODIS and LISS-III

It is concluded that MODIS regression algorithm gives the high degree of underestimation when the burned percentage within the 500m x 500m is less than 20%. It proved more accurate results when the burned percentage is large (more than 30%). Figure 5-29 gives the clear overview that in case of MODIS, the error in area estimates decreases when the MODIS pixel is having large burned percentage. But LISS-III gives the slight overestimation with respect to the high resolution LISS-IV. The ± 1*standard deviation error bars showed in the graph signifies that the area estimates from the MODIS is affected by high degree variation in the error as compared to the LISS-III. Hence, the result signifies that the regression algorithm reduces the bias in area estimation for MODIS with mean error of -17 % at selected sites.
Comparison of percentage error in area estimation by LISS-III and MODIS with reference to LISS-IV

Figure 5-29: Comparison of percentage error in LISS-III and MODIS at 1*standard deviation

5.10. Validation and comparison of Burned Areas derived from MODIS and AVHRR with reference of LISS-IV for 2007

The burned area algorithm that has been developed using regression estimator approach for MODIS and AVHRR is being tested over the datasets of 2007. The burned area estimates were derived from MODIS and AVHRR preserving the original spatial resolution of the different data i.e 500m and 1km respectively. MODIS estimates were compared at 9 different fields of size (500m x 500m) corresponding to high resolution LISS-IV data. The analyses were performed using burned fraction image of LISS-IV at 500 m pixel size and 1km pixel size (Figure 5-30). The burned polygons area digitized by visual interpretation and area of each polygon is calculated as shown in Table 5-8.

Figure 5-30: Burned Fraction images generated at (a) 500m and (b) 1000m pixel size
Table 5-8: Burned area estimation of each polygon digitized by visual interpretation in LISS-IV image

<table>
<thead>
<tr>
<th>Field_Id</th>
<th>LISS-IV (500 x 500 m²)</th>
<th>MODIS (m²)</th>
<th>MODIS Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>105157.46 (42.06 %)</td>
<td>128350</td>
<td>+22.05</td>
</tr>
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<td>2</td>
<td>120093.67 (48.03 %)</td>
<td>100500</td>
<td>-16.31</td>
</tr>
<tr>
<td>3</td>
<td>119501.06 (47.8 %)</td>
<td>142000</td>
<td>+18.82</td>
</tr>
<tr>
<td>4</td>
<td>59498.58 (23.79 %)</td>
<td>39500</td>
<td>-33.61</td>
</tr>
<tr>
<td>5</td>
<td>239458.58 (95.78 %)</td>
<td>195800</td>
<td>-18.23</td>
</tr>
<tr>
<td>6</td>
<td>78631.84 (31.45 %)</td>
<td>47250</td>
<td>-39.90</td>
</tr>
<tr>
<td>7</td>
<td>74882.33 (29.95 %)</td>
<td>46750</td>
<td>-37.56</td>
</tr>
<tr>
<td>8</td>
<td>170272.92 (68.10 %)</td>
<td>145825</td>
<td>-14.35</td>
</tr>
<tr>
<td>9</td>
<td>122847.96 (49.14 %)</td>
<td>64175</td>
<td>-47.76</td>
</tr>
</tbody>
</table>

Table 5-9: Estimates of burned area derived from MODIS sub-pixel algorithm and reference LISS-IV image
The MODIS sub-pixel estimate results obtained at selected field locations, signifies that there is a strong correlation exists between estimated burned areas and reference burned area with coefficient of correlation $R^2 = 0.771$ (Figure 5-13). It is observed from the MODIS error values, that the area estimates is largely affected by burned fraction within the pixel. Large burned percentage gives more accurate area estimates as compared to small burned areas. The mean error over all the sites is -5.3 %, which gives more accurate result in total area estimated over a certain region. It is concluded that is MODIS sub-pixel algorithm may give more accurate results for total area estimation as compared to the selected sites.

As the 500 m x 500 m field size is taken in the field for validation purpose, the sub-pixel estimation for AVHRR (1000m) cannot be compared at the same selected field locations. Hence, the sub-pixel burned area estimation for AVHRR is compared for whole image of LISS-IV using regression analysis. The burned fraction image generated from LISS-IV (Figure 5-30 (b)) is taken as reference. The results of regression analysis is showed in Figure 5-32. According to the $R^2 = 0.817$, there is strong correlation exists between the observed and estimated burned percentage. But, there high degree of bias in estimates. It is clearly seen that for burned percentage less than 25%, results in high degree of underestimation, but for high burned percentage of more than 40%, the algorithm gives overestimation. Hence, small and fragmented burned areas leads to underestimation and large burned areas leads to overestimation.
Figure 5-32: Comparison of burned proportions estimated by AVHRR with respect to actual burned percentage within 1000m pixels
6. Conclusions and recommendations

This chapter gives the conclusions arrived at, after a detailed study on evaluating the performance of multi-temporal image difference technique using different vegetation indices for extracting the burned areas. This study also intended to develop technique for sub-pixel burned area estimation at coarse resolution of 500m and 1000m. The following sections states the conclusion arrived during the study.

6.1. Conclusions

The study was carried out on extraction of burnt areas over agricultural residue burning region using multi-sensor approach. In the first step of the investigation, the potential of three indices NDVI, NBR and GEMI3 for estimating the statistical threshold and sensitiveness towards accurate extraction of burnt areas using LISS-III, MODIS and AVHRR sensors was evaluated. The statistical threshold has been implemented keeping in view the spectral characteristics of burned surface and fire regimes in the region. The results revealed the use of spectral bands for deriving various indices over pre-burn and post-burn conditions with different accuracies in estimating the total burned area of the region. This variation was taken into account for selecting the best indices to derive total burnt area. The separability analysis was performed and it was found that GEMI3 as the best in spectral discrimination of burned and unburned surface. The performance of different indices for LISS-III was evaluated for mapping the burned areas at 7 selected field locations and it was compared with LISS-IV revealing that there is a strong correlation for LISS-III (GEMI3) and LISS-IV with coefficient R² = 0.976 as compared to NBR (R² = 0.876), NDVI (R² = 0.482).

It is observed that agricultural burning leaves behind fragmented and smaller burned areas, which restricts the capability of coarser resolution sensors to detect the burned area. Therefore, in second step the coarse resolution burnt area images (500m and 1000m) were calibrated with fine resolution LISS-III (23.5m) to estimate the burned area at sub-pixel level. This helps to reduce the bias in burned area estimation. The sub-pixel burned area estimation at spatial resolution of 500m (MODIS) was compared with 5.8m (LISS-IV) for 2007 at 9 different field locations using regression algorithm. Good correspondence was observed, with value of coefficient of determination (R²) = 0.771. The percentage error in area estimation was also calculated to quantify the bias in burned area estimation. It was found that, when burned percentage in a pixel is less than 20%, there is underestimation of burned area ranging from -16.31% to -47.76% and when large burned area dominates in a pixel, there is slight overestimation ranging from +18.82% to +22.05%. An overall linear regression fit with data for whole LISS-IV image was compared with sub-pixel estimates at 1000m of AVHRR and the results revealed that there is strong relationship between AVHRR and LISS-IV burned areas, with R² = 0.817. The results showed that AVHRR underestimates the burned area for fragmented and small burned areas, whereas for large and compact burned areas, there is overestimation. Keeping in view of high cost and limited availability of high-resolution satellite data, it is suggested that the most reliable way to map the burned areas due to crop residue burning with optical remote sensing data would be to use multi-sensor approach by combining the low and high-resolution datasets.
The following questions were answered to meet the objectives of the study:

6.1.1. **Which algorithm is capable of extracting the burned patches accurately?**

Multi-temporal image difference technique was applied using NDVI, NBR and GEMI3 indices. Separability analysis and accuracy assessment for mapping burned area were the two criteria’s selected to evaluate their performance. The multi-resolution satellite data of LISS-III, MODIS and AVHRR were utilized in order to evaluate the performance of each index. The results of separability analysis showed that for all three sensors, GEMI3 index is being best discriminator for burned areas. The results of the accuracy assessment for mapping the burned areas at selected locations using the LISS-III was compared with LISS-IV, which reveals that GEMI3 index gives better accuracy for area estimation as compared to other indices with strong correlation coefficient $R^2 = 0.976$ as compared to NBR ($R^2 = 0.876$), NDVI ($R^2 = 0.482$). Due to non-linear structure of GEMI3, the burned area mapping accuracy is not affected by the atmospheric effects, which makes its importance in detecting even the small burned areas accurately. Hence, image difference technique using GEMI3 index is capable for extracting the burned patches accurately.

6.1.2. **What are the factors affecting the accuracy?**

There are various factors, which affects the accuracy of burned area mapping. Some of them are related to the sensor characteristics and other related to the spatial variability of burned areas. The factors related to sensor characteristics are spatial and spectral resolution. The accuracy of burned area mapping largely depends upon the spatial resolution of the sensor. The agricultural burning leaves behind small and scattered burned areas, which may not be detected even with LISS-III. The comparison of burned area estimation using high resolution LISS-IV and moderate resolution LISS-III shows that there is a mean error of 7.74% in area estimation (compared on selected field locations) in case of LISS-III image (LISS-IV as reference). The spatial resolutions of MODIS and AVHRR sensors are very coarse to extract the burned patches, as sizes are smaller than the spatial resolution (500m and 1000m).

The spectral properties of the sensor determines the degree to which, burned areas can be discriminated with respect to the background. The results of separability analysis, shows that the GEMI3 index gives Spectral Discrimination Index (M) of 1.06 for LISS-III, 0.99 for MODIS and 0.92 for AVHRR, which indicates good spectral separability between burned and unburned areas. The results suggested that contribution of short-wave infrared band gives better discrimination between burned and unburned class, as compared to the visible band. Hence, the sensor with spectral bands in middle and short-wave infrared range are ideal for burned area extraction, particularly using the image difference technique (ex. GEMI3 index).

The variability in spatial pattern of burned areas also affects the accuracy of sub-pixel burned area estimates at coarser resolution. In case, when burned percentage in a pixel is less than 30%, there is underestimation of burned area ranging from -16.31% to -47.76% and when large burned area dominates in a pixel, there is slight overestimation ranging from +18.82% to +22.05%. Hence large clusters of burned areas leads to higher accuracy and slight overestimation, whereas underestimation occurs where burned areas are small and scattered.

6.1.3. **How to utilize the active fire and scar datasets for estimating the burned area?**

The active fire datasets are generally used to monitor the spatial and temporal variability of the fire activity. These datasets only gives the instantaneous information about the occurrence of fire that is at
time of pass of the satellite. The active fire layers from MODIS fire product were generated for both Terra and Aqua satellites from 30 September 2006 to 24 October 2006. The active fire layer does not carry the information about the extent of burned areas; it can only be used in order to monitor the spatial variability of the fires. Burned areas possess the property of carrying the historical information about the extent of burned areas. This property holds the key for the assessment of the total area affected by fire. The MODIS fire algorithm detects the fire within the pixel size of 1 km, therefore, by creating the buffer zone of 500m radius around that point; the validation of burned areas can be done by overlaying the buffer zone layer to the burned areas. It is concluded that for agricultural burning, where the spatial pattern of fire changes every hour, and leaving behind the fragmented and small burned areas, active fire detections cannot be utilized to estimate the burned areas. It can only be used to validate the burned areas at some of the burned sites, by overlaying with 500m buffer zone of active fire points.

6.1.4. How to increase the accuracy of burned area estimation from NOAA/AVHRR and Terra/MODIS using IRS-P6/LISS III data?

The low spatial resolution of MODIS and AVHRR restricts the capability to detect small fraction of burned areas at the sensor’s pixel. The statistical threshold applied to coarse resolution sensor gives bias results in overall area estimation. It has been observed that the threshold (mean + 1*SD) in case of MODIS detects pixels more than 26% as burned and for AVHRR the pixels with more than 43% burned areas were detected as burned, which leads to high degree overestimation in overall area. In order to reduce the overestimation, burned areas are calibrated with high-resolution satellite data. The linear regression estimator approach is being used for sub-pixel burned area estimation. This approach enables the estimation of total burned area, but the exact location of burned areas cannot be derived. The regression estimation approach gives the better results as compared to the algorithm developed by (Razafimpanio et al, 1995) for burned areas detected in the field and area estimated by real-time data of LISS-IV. For MODIS, the regression algorithm is giving the error in sub-pixel area estimation for selected locations in the range of (-49% to + 33.11%). The comparison of sub-pixel area estimates for AVHRR with respect to LISS-IV was done for whole image of LISS-IV 2007 and it was found that the regression algorithm under-estimates the burned areas with burned percentage less than 20% in 1km x 1km pixel and overestimates the burned area as the burned percentage increases beyond 30%. This shows that the regression based approach increases the accuracy for estimating burned areas using coarser resolution data.

6.1.5. How do the uncertainties affect the outcome?

There are certain uncertainties associated with input parameter, which affects in the overall area estimation. The indices derived for extracting the burned areas largely depends upon the range of reflectance values, which is the input parameter. The reflectance values are generally very sensitive to the atmospheric conditions. If the pre-burn and post-burn atmospheric conditions are same then indices derived using the multi-temporal image difference technique, may give reliable results. But in case, when the pre-burn atmospheric conditions differ from the post-burn, due to smoke and haze and if they are considered then there would be a bias in the values of indices. It is estimated that ± 5% deviation in GEMI3 values obtained after subtracting the pre-burn and post-burn GEMI images, results in ± (15-20) % error in outcome of area estimation. This shows that the area estimation (from the GEMI3) is very sensitive to change in reflectance values if the image is not corrected to atmospheric corrections. For MODIS and AVHRR, the same deviation of ± 5% in GEMI3 values, gives ± (3-5) % and ± (2-3)
% error in the sub-pixel estimates respectively. Hence, reflectance values provide uncertainties in the output results of area estimation particularly in case of LISS-III.

6.2. Recommendations

This study has been aimed at improving the accuracy of burned area estimation at coarse resolution in this region.

- The potential of other vegetation indices can be evaluated, using the same methodology.

- This methodology has to be applied and tested over a larger area in agriculture burned regions.

- Further, total area estimation derived from the methodology could be used and tested in the quantification of Green House Gas emissions at regional level with increased accuracies which would be a challenging task.
7. References


**APPENDIX-1 Landuse classification of Area in Punjab**

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<th>Total a</th>
<th>Forest</th>
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<th>Land Put to 6</th>
<th>Culturable Waste</th>
<th>Permanent Pastures &amp; other Grazing Land</th>
<th>Curren t Fallow</th>
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**Districts**

- Gurdas 356 35 37 -- 2 -- (a) (a) 2 8
- Amrits 508 50 13 2 3 (a) -- 3 4 8
- Kapurt 163 16 2 (a) 2 (a) -- (a) 1 8
- Jaland 266 26 4 -- 2 -- -- -- 2 9
- Nawan 119 12 16 4 7 3 -- 2 9 7
- Hoshiar 340 33 10 1 2 (a) 1 1 2 5
- Rupnag 216 21 51 8 1 7 3 2 1 5
- Ludhia 368 36 10 (a) 4 -- -- 3 3 8
- Firozpu 585 52 12 1 3 -- -- (a) 4 9
- Faridko 144 14 2 (a) 1 -- -- 2 1 8
- Muktsa 263 26 2 5 1 2 -- 19 2 8
- Moga 168 22 2 (a) 2 -- -- (a) 2 9
- Bathin 334 33 7 -- 3 -- -- -- 2 8
- Mansa 219 21 3 (a) 1 (a) -- 9 1 8
- Sangru 502 50 7 7 4 1 (a) 3 4 8
- Patiala 368 37 15 5 4 -- (a) 5 3 8
- Fatehg 117 11 1 (a) 1 (a) (a) -- 1 9
A MULTI-SENSOR APPROACH FOR BURNED AREA EXTRACTION DUE TO CROP RESIDUE BURNING USING MULTI-TEMPORAL SATELLITE DATA