JAWAHARLAL NEHRU TECHNOLOGICAL UNIVERSITY

ANANTAPUR

FOREST FIRE MONITORING BY REMOTE SENSING USING SATELLITE DATA

A project report Submitted to the

Jawaharlal Nehru Technological University Ananthapur

In partial fulfilment for the Award of the degree of

BACHELOR OF TECHNOLOGY
IN
ELECTRONICS AND COMMUNICATION ENGINEERING

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SREE VENKATESWARA COLLEGE OF ENGINEERING

NAAC 'A' Grade Accredited Institution, An ISO 9001::2015 Certified Institution

(Approved by AICTE, New Delhi and Affiliated to JNTU, Anantapur)

NORTHRAJUPALEM(VI), KODAVALURU(M), S.P.S.R NELLORE (DT) – 524 316

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CERTIFICATE

Certified that the project entitled **"FOREST FIRE MONITORING BY REMOTE SENSING USING SATELLITE DATA"** submitted by **K. UMA MAHESH (H.T. No. 19JN1A0473) , M. UMA GANESH (H.T. No. 19JN1A04A0) , N. SUDHARSHAN RAO (H.T. No. 19JN1A04B5) , M. VENKATA SAI SRAVAN (H.T. No. 19JN1A0498) & M. MASTHAN BABU (H.T. No. 19JN1A04A2)** in partial fulfilment for the award of degree **of BACHELOR OF TECHNOLOGY in ELECTRONICS AND COMMUNICATION ENGINEERING** by **Jawaharlal Nehru Technological University, Anantapur** during the academic year **2022-2023**. It is certified that all corrections/suggestions indicated for internal assessment have been incorporated in the report. The project report has been approved as it satisfies the academic requirements in respect of project work prescribed for the said degree.

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DECLARATION

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NDWI	**-**	**NORMALIZED DIFFERENCE WATER INDEX**
NBR	**-**	**NORMALIZED BURN RATIO**
DNBR	**-**	**DIFFERENCE NORMALIZED BURN RATIO**
RBR	**-**	**RELATIVIZED BURN RATIO**
NIR	**-**	**NEAR INFRARED**
SWIR	**-**	**SHORT WAVE INFRARED**
S2TBX	**-**	**SENTINEL-2 TOOL BOX**
MSI	**-**	**MULTI SPECTRAL IMAGERY**

ABSTRACT

Forest fires have been a significant disaster for many years. It is crucial to take the necessary measures promptly to prevent these disasters from occurring. Technology has advanced, and one of the effective and practical tools that aid in detecting forest fire risk class is remote sensing.

With the development of technology, remote sensing has become a very effective and practical tool to provide timely measures to prevent forest fires. One of the applications of remote sensing in forest fire management is the use of Sentinel 2 images. These images can be used to detect forest fire risk class and to identify the damaged areas.

To determine the forest area damaged by fire and establish fire risk classes, various spectral indices such as Normalized Burn Ratio (NBR). Differenced Normalized Burn Ratio (DNBR). Relativized Burn Ratio (RBR), and Normalized Difference Vegetation Index (NDVI) are used. By applying these spectral indices on the Sentinel 2 images, it is possible to determine the severity of the fire and the probability of forest fire exposure.

The study conducted showed that the size of the vegetation area destroyed due to the fire could be determined, and the probability of forest fire exposure of these areas established. The use of remote sensing technology along with spectral indices provides a fast and accurate assessment of the damage caused by forest fires. These techniques can be used to establish prevention strategies to reduce the damage caused by forest fires.

CHAPTER – 1
INTRODUCTION

1.1: INTRODUCTION

Wildfire is a very important component in many forest ecosystems and it has contributed to the development of biomes since its widespread occurrence which began approximately 400–350 million years ago. Though fire played an important role in the evolution and distribution of present ecosystems, anthropogenic activities coupled with climate change have caused alteration of fire regimes globally, making many ecosystems vulnerable. Wildlife is one of the major factors causing loss and degradation of forest, its biodiversity, and ecosystem functions besides unbearable damage to human health, lives and property. In addition to the direct effect, wildfire also affects the livelihood of local people by limiting forest resources on which they depend for their survival. Wildfire is one of the major factors that has caused the loss of 6 million square kilometers of forest in the world in the last two centuries.

While preventing forest fires requires a very important environmental management, identifying forest fire risk areas is another pillar of environmental management. With the identification of risk areas, necessary precautions will be taken on time, the number of forest fires will be reduced or minimized. Remote sensing could be used to identify areas damaged by forest fires, and besides, these areas could be classified according to forest fire possibility. Remote sensing also provides speed, practicality, and efficiency in detecting and monitoring forest fire risk areas. Nowadays, with the development of technology, the use of remote sensing in the detection of forest fires, damage detection studies and the detection of risky areas has increased gradually.

Climate change can exacerbate the wildfire and its effect (Art´es et al., 2019). The extent of damage by wildfire is increasing in many areas and also occurring in areas where it was not occurred in the past. The intensity and behavior of fire depend on a diverse array of factors on human disturbance and the climatic conditions of a region. Many evidences in support that climate change may modify the dynamic of fire, reducing the vegetation moisture and leaving many forests in a stressed condition where a severe wildfire could occur. Besides, weather affects the fire triangle i.e., oxygen, heat, and fuel ignite the fire, and these are affected by the topography, vegetation and distance from the settlement. The duff moisture code (DMC) and drought code (DC) are used as the Fire Weather Index (FWI) to estimate fire danger (Martell and Sun, 2008; Art´es et al., 2019).

Remote sensing is widely used to evaluate and predict fire danger. Many studies analyzed the time series of optical spectral indices such as Burgan et al. (1998) in the United States of America, Maselli (2003) in Mediterranean areas, Bajocco et al. (2015) in the role of the vegetation seasonal dynamics on fire ignition patterns in southern Italy, Menenti et al. (2016) studied the response of terrestrial vegetation to climate variability in a lake in the Yangtze River Basin, Jang et al. (2006) evaluated the thermal and water stress of the vegetation canopy in Southern Que'bec, Canada, Pan et al. (2016) in Shanxi Province of Chinato relate estimation of plant-water stress and fire activity, Maffei et al. (2018) explored the potential of the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard Terra and Aqua satellites. Another approach is the estimation of moisture content by using spectral indices such as the Global Vegetation Moisture Index (GVMI) (Ceccato et al., 2002), the Perpendicular Moisture Index (PMI) (Maffei and Menenti, 2014), and the Normalized Difference Water Index (NDWI) (Gao, 1996; Abdollahi et al., 2018).

1.2: Remote Sensing

Remote Sensing is basically a multi-disciplinary science which includes a combination of various disciplines such as optics, spectroscopy, photography, computer, electronics and telecommunication, satellite launching etc. All these technologies known as the Remote Sensing System are integrated to act as a complete system in itself. Remote Sensing is a way to obtain data about an object's characteristics without physical contact with it. It is a technology for examining electromagnetic radiation, acquiring and interpreting non-immediate geospatial data from which information on the characteristics of the objects on the earth's surface, oceans and atmosphere is extracted. Remote sensing offers useful information on resources, meteorology and climate in a short time, leading to better management of resources and thus speeding up domestic growth. As can be seen from the Figure 1.1, the sun's radiation falls on all objects on the Earth. The outgoing radiation from the object depends on its nature and properties.

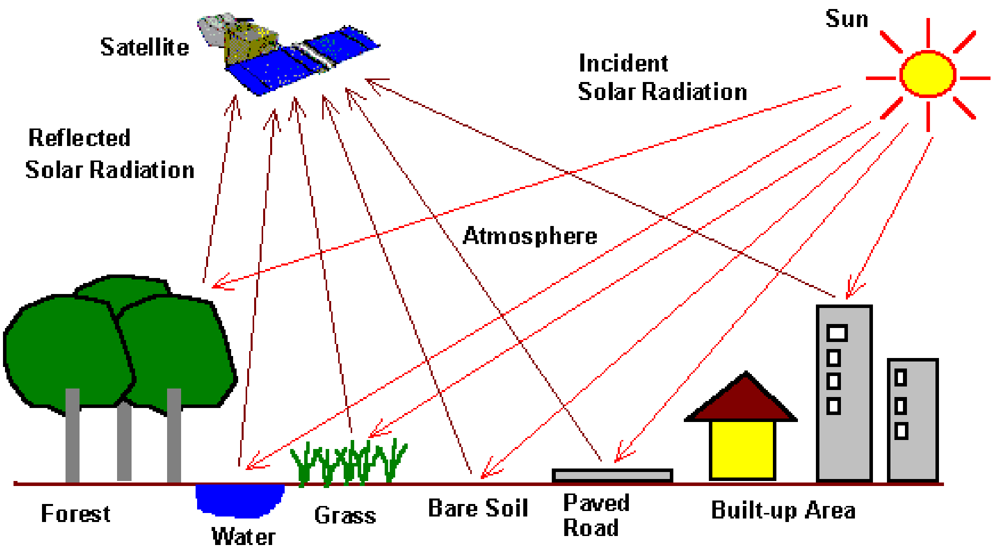


Fig 1.2: Remote Sensing Process

Remote sensing method is classified into 2 types:

1. Passive Remote sensing
2. Active Remote sensing

1.2.1: Passive Remote sensing Method

Remote sensing systems which measure energy that is naturally available are called passive sensors. Passive sensors can only be used to detect energy when the naturally occurring energy is available (SUN).

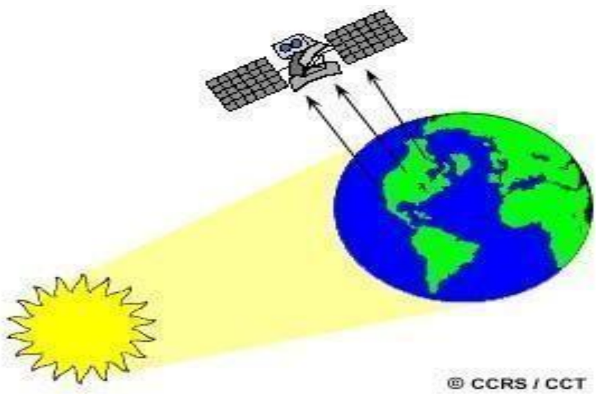


Fig 1.2.1: Passive Remote Sensing

1.2.2: Active Remote Sensing Method

Active sensors, on the other hand, provide their own energy source for illumination. The sensor emits radiation which is directed toward the target to be investigated. The radiation reflected from that target is detected and measured by the sensor.

Some examples of active sensors are a laser fluorosensor and a synthetic aperture radar (SAR).

Fig 1.2.2: Active Remote Sensing

1.3: Organisation of Thesis

Chapter 1 gives an insight to the selection of the topic and its importance. The objectives and scope of the present work is identified in this chapter.

Chapter 2 gives a brief idea about the literature review that has been performed before undertaking the project.

Chapter 3 reviews the methodology of the process forest fire mapping of the study area.

Chapter 4 gives the machine learning algorithm.

Chapter 5 Conclusion of the study is done in this chapter.

CHAPTER – 2

MATERIALS AND METHODS

2.1 STUDY AREA

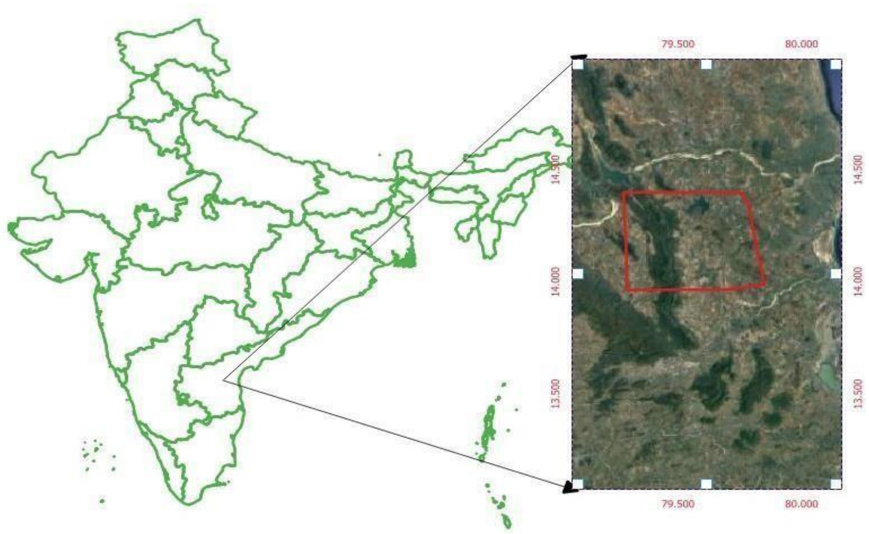


Fig 2.1: Study Area

The study is located between the latitude 14-14.5^0N and 79.5-80^0 longitudes which cover a dense forest of area 1460 sq. kms extended between west of Nellore to north of YSR Kadapa district.

2.2: AIM AND OBJECTIVES OF THE STUDY

This study aims to detect the area destroyed by fire with remote sensing and also to evaluate the fire risk of other areas. In this context, Sentinel 2 satellite images and Normalized Burn Ratio (NBR), Differential Normalized Burn Ratio (DNBR), Relativized Burn Ratio (RBR) spectral fire indices were used to create fire risk classes with the help of multi-temporal Sentinel-2 images. In addition, Normalized Difference Vegetation Index (NDVI) was utilized to identify the forest area damaged by fire.

2.3: DATA USED

The main objective of Sentinel 2 satellite are providing data for risk management, land use and land cover mapping, change detection, natural hazards, water management. Sentinel-2 gives global coverage every five days. It is equipped with a multispectral imager (MSI) with 13 bands.

Each SENTINEL-2 satellite weighs approximately 1.2 tonnes. SENTINEL-2A and SENTINEL-2B have both been launched with the European launcher VEGA. The satellite lifespan is 7.25 years, which includes a 3 month in-orbit commissioning phase. Batteries and propellants have been provided to accommodate 12 years of operations, including end of life de-orbiting manoeuvres.

Two identical SENTINEL-2 satellites operate simultaneously, phased at 180° to each other, in a sun-synchronous orbit at a mean altitude of 786 km. The position of each SENTINEL-2 satellite in its orbit is measured by a dual-frequency Global Navigation Satellite System (GNSS) receiver. Orbital accuracy is maintained by a dedicated propulsion system.

The SENTINEL-2 satellite system was developed by an industrial consortium led by Astrium GmbH (Germany). Astrium SAS (France) is responsible for the Multi Spectral Instrument (MSI).

The MSI works passively, by collecting sunlight reflected from the Earth. New data is acquired at the instrument as the satellite moves along its orbital path. The incoming light beam is split at a filter and focused onto two separate focal plane assemblies within the instrument; one for Visible and Near-Infra-Red (VNIR) bands and one for Short Wave Infra-Red (SWIR) bands . The spectral separation of each band into individual wavelengths is accomplished by stripe filters mounted on top of the detectors.

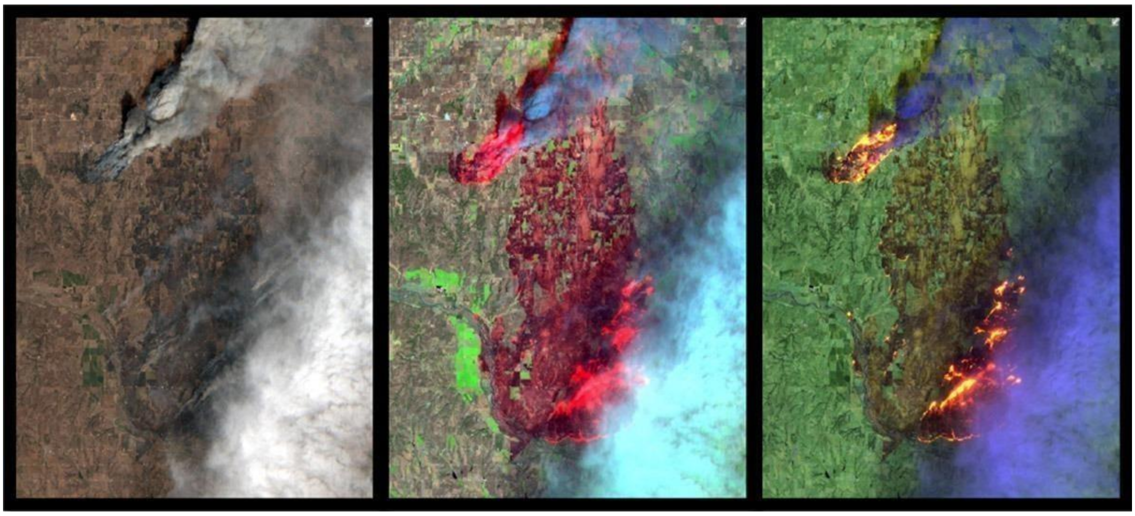


Fig 2.3.1: Sentinel 2 Image

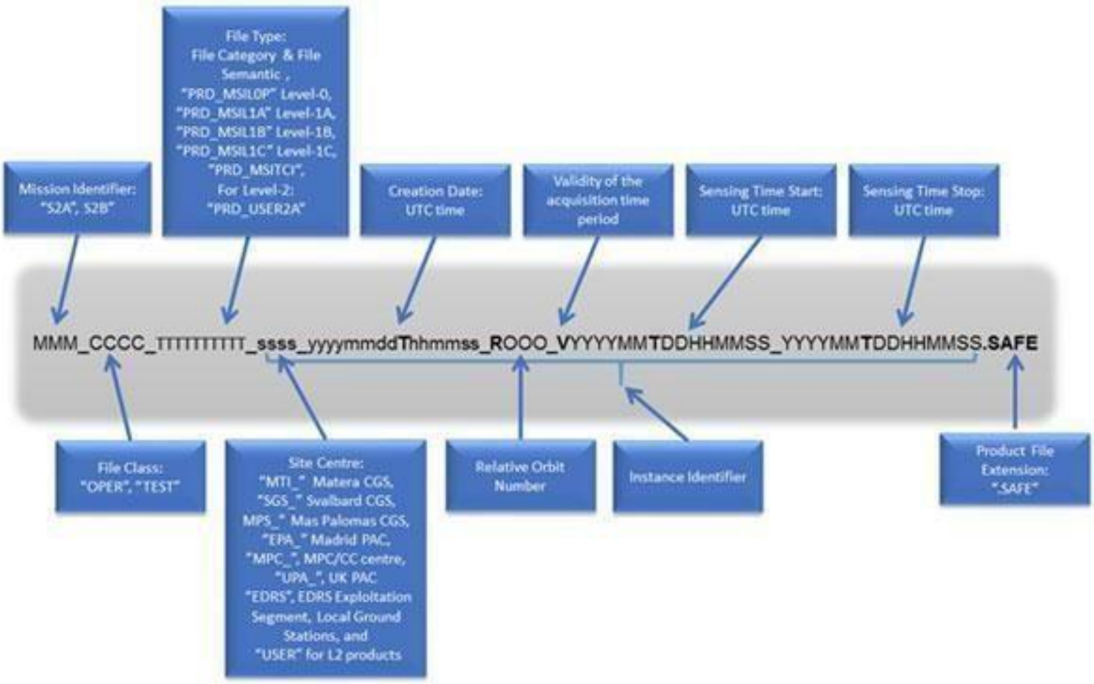


Fig 2.3.2: Sentinel 2 Naming Convention

2.4: TOOLS USED

2.4.1: SNAP Tool Box

The Sentinel-2 Toolbox (S2TBX) consists of a collection of processing tools, data product readers and writers and a display and analysis application to support the large archive of data from ESA SAR missions including Sentinel-2, ERS-1 & 2 and ENVISAT, as well as third party SAR data from ALOSPALSAR, Terra SAR-X, COSMO-Sky Med and RADARSAT-2. The Toolbox includes tools for calibration, speckle filtering, co-registration, orthorectification, mosaicking, data-conversion, polarimetry and interferometry.

The Sentinel-2 Toolbox is being developed for ESA by Array in partnership with DLR, Brockmann Consult and Ocean Data Lab.

The SNAP platform looks like this where we can do all the processing steps in easy way which is free of cost.

Features:

- Common architecture for all Toolboxes
- Very **fast image display and navigation** even of giga-pixel images
- Graph Processing Framework (GPF): for creating user-defined processing chains
- Advanced **layer management** allows adding and manipulation of new overlays such as images of other bands, images from WMS servers or ESRI shape files
- Rich **region-of-interest** definitions for **statistics** and various **plots**
- Easy **bit mask** definition and overlay
- Flexible **band arithmetic** using arbitrary mathematical expressions
- Accurate **reprojection** and **ortho-rectification** to common map projections,
- Geo-coding and rectification using **ground control points**
- Automatic SRTMDEM download and tile selection
- Product library for scanning and cataloguing large archives efficiently
- Multithreading and Multi-core processor support
- Integrated World Wind visualization

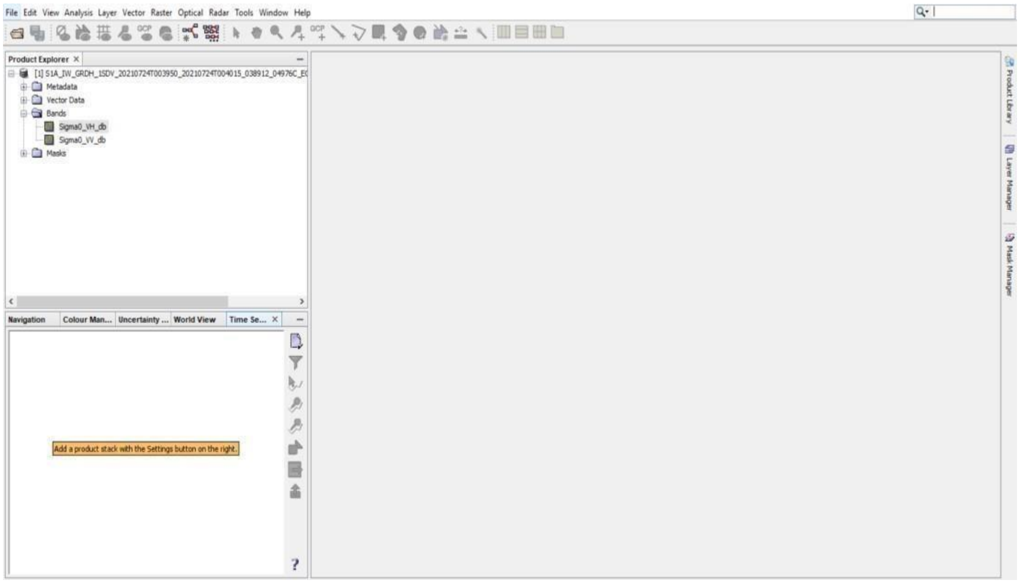


Fig2.3.1: SNAP Platform

2.4.2: Coper Nicus Open Access Hub

Anyone can register online via self-registration. The self-registration process is automatic and immediate. Registration grants access rights for searching and downloading Sentinels products. Sentinel's products are available at no cost for anybody. The data available through the Data Hub is governed by the Legal Notice on the use of Copernicus Sentinel Data and Service Information , which the User is deemed to have accepted by using the Sentinel data. It is free and open data source access.

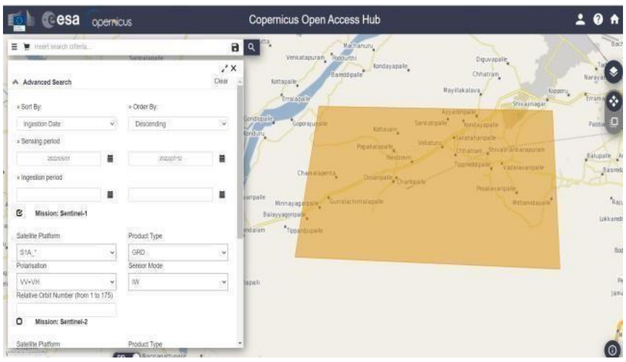


Fig2.3.3.1: Coper Nicus Open Access

2.5: LITERATURE REVIEW

Satellite remote sensing has offered great advantages in the monitoring and mapping of burned areas since the 1980s(Flannigan & Haar, 1986). Optical satellite data has been especially successful in generating a burned area inventory on the continental scale (Barbosa, Grégoire, & Pereira, 1999), regional scale (Giglio, Loboda, Roy, Quayle, & Justice, 2009; Loboda, O'neal, & Csiszar, 2007) and national scale (Palandjian et al., 2009). Many image analysis techniques, such as vegetation and burn index (Chuvieco, Martin, & Palacios, 2002; Epting, Verbyla, & Sorbel, 2005; Escuin, Navarro, & Fernandez, 2008; Loboda et al., 2007; Pereira, 1999), supervised classification (Palandjian et al., 2009), logistic regression (Bastarrika, Chuvieco, & Martín, 2011), spectral angle mapper and artificial neural network (Petropoulos, Vadrevu, Xanthopoulos, Karantounias, & Scholze, 2010), Neuro-fuzzy (Mitrakis, Mallinis, Koutsias, & Theocharis, 2012) and support vector machine (Petropoulos, Kontoes, & Keramitsoglou, 2011), have been successfully applied to pixel based satellite data of various resolutions.

Pixel based image analysis (PBIA) and object based image analysis (OBIA) techniques are the two main image analysis approach in satellite image classification. While PBIA approach works on each individual pixel for extracting information from satellite images, OBIA approach uses image objects that consist of homogenous pixel groups. While pixel based approach has generally applied to medium and low spatial resolution images, OBIA has applied to high and very high spatial resolution images. There were many studies that applied to OBIA to medium and low resolution images for burned area mapping (Gitas, Mitri et al. 2004, Polychronaki and Gitas 2012, Katagis, Gitas et al. 2014, Kavzoglu, Erdemir et al. 2016), (Gitas, Mitri et al. 2004). Analyzing the studies using medium resolution satellite images to compare these two approaches, OBIA gives more accurate results than PBIA (Estoque, Murayama, & Akiyama, 2015; Gao, Mas, Kerle, & Pacheco, 2011; Gilbertson, Kemp, & van Niekerk, 2017; Varamesh, Hosseini, & Rahimzadegan, 2017). Also, OBIA reduce the salt and pepper effect that cause misclassified pixel on satellite images (Phiri & Morgenroth, 2017) (Gao et al. 2011).

Object-based classification of burned areas has been applied to very high-resolution images (Dragozi, Gitas, Stavrakoudis, & Theocharis, 2014), high-resolution images (Sertel & Alganci, 2016), medium resolution images (Katagis, Gitas, & Mitri, 2014; Kavzoglu, Erdemir, & Tonbul, 2016; Mitri & Gitas, 2004; Polychronaki & Gitas, 2012), low resolution images (Gitas, Mitri, & Ventura, 2004) and SAR images(Polychronaki, Gitas, Veraverbeke, & Debien, 2013). The OBIA has two main steps, segmentation and classification (Baatz, Hoffmann, & Willhauck, 2008). Multi-resolution segmentation used in the segmentation phase is a preferred method (Benz, Hofmann, Willhauck, Lingenfelder, & Heynen, 2004). The classification process is carried out by rule-based or supervised classification.

In many studies, rule-based classification methods have been used to map burned areas along with object based classification methods. The rule-based classification has two limitations, although it does not yield successful results in the removal of burned areas. These are, (i) the difficulty in deciding which descriptive properties are really important within a large number of object metrics in large data sets, and (ii) its limited applicability to different environmental conditions and different data types (Stumpf & Kerle, 2011). Therefore, in the extraction of burned fields from complex datasets and data sets with a large number of variables, there is a need to implement other classification algorithms.

Machine learning algorithms such as random forest (Breiman, 2001) provide effective solutions for the analysis of complex datasets. Random forest has been successfully applied to areas such as mapping landslides (Breiman, 2001; W. Chen, Li, Wang, Chen, & Liu, 2014; Stumpf & Kerle, 2011), gene selection (Díaz-Uriarte & De Andres, 2006), land cover classification (Gislason, Benediktsson, & Sveinsson, 2006) and hyperspectral image classification (Ham, Chen, Crawford, & Ghosh, 2005). Also, it has been used forest fire studies such as fire occurrence modeling (Gislason et al., 2006), forest and woodland severity analysis (Dillon et al., 2011; Holden, Morgan, & Evans, 2009). There is only one study is available in the literature for the mapping of burned areas with the random forest based classifier. This classifier was developed to extract the burned areas on the global scale from the MODIS images (Ramo & Chuvieco, 2017).

CHAPTER - 3
METHODOLOGY

3.1: DATA ACQUIRED AND SOURCE

For the present study, multispectral, multi-temporal Sentinel-2 satellite data of Nellore and Kadapa forest region were acquired for two years namely, 2016 and 2021. All the Sentinel-2 images have been taken from USGS Earth Explorer.

Sentinel-2

The Copernicus Sentinel-2 mission comprises a constellation of two polar-orbiting satellites placed in the same sun-synchronous orbit, phased at 180° to each other. It aims at monitoring variability in land surface conditions, and its wide swath width (290 km) and high revisit time (10 days at the equator with one satellite, and 5 days with 2 satellites under cloud-free conditions which results in 2-3 days at mid- latitudes) will support monitoring of Earth's surface changes.

SENTINEL-2 mission objectives are to provide:

- Systematic global acquisitions of high-resolution, multispectral images allied to a high revisit frequency
- Continuity of multi-spectral imagery provided by the SPOT series of satellites and the USGS LANDSAT Thematic Mapper instrument
- Observation data for the next generation of operational products, such as land-cover maps, land-change detection maps and geophysical variables.

Sentinel 2 Bands and Combinations

There are 13 Sentinel 2 bands in total. Each band is 10, 20, or 60 meters in pixel size.

Sentinel 2 consists of 2 satellites. First came Sentinel 2A which was launched in 2015. Next came Sentinel 2b in 2017.

Sentinel-2 carries the Multispectral Imager (MSI). This sensor delivers 13 spectral bands ranging from 10 to 60-meter pixel size.

- Its blue (B2), green (B3), red (B4), and near-infrared (B8) channels have a 10-meter resolution.
- Next, its red edge (B5), near-infrared NIR (B6, B7, and B8A), and short-wave infrared SWIR (B11 and B12) have a ground sampling distance of 20 meters.
- Finally, its coastal aerosol (B1) and cirrus band (B10) have a 60-meter pixel size.

Band	**Resolution**	**Central Wavelength**	**Description**
B1	60 m	443 nm	Ultra Blue (Coastal and Aerosol)
B2	10 m	490 nm	Blue
B3	10 m	560 nm	Green
B4	10 m	665 nm	Red
B5	20 m	705 nm	Visible and Near Infrared (VNIR)
B6	20 m	740 nm	Visible and Near Infrared (VNIR)
B7	20 m	783 nm	Visible and Near Infrared (VNIR)
B8	10 m	842 nm	Visible and Near Infrared (VNIR)
B8a	20 m	865 nm	Visible and Near Infrared (VNIR)
B9	60 m	940 nm	Short Wave Infrared (SWIR)
B10	60 m	1375 nm	Short Wave Infrared (SWIR)
B11	20 m	1610 nm	Short Wave Infrared (SWIR)
B12	20 m	2190 nm	Short Wave Infrared (SWIR)

Table 1: Sentinel Bands and the resolutions

Sentinel Band Combinations

We use band combinations to better understand the features in imagery. The way we do this is by rearranging the available channels in creative ways.

By using band combinations, we can extract specific information from an image. For example, there are band combinations that highlight geologic, agricultural, or vegetation features in an image.

Natural Color (B4, B3, B2)

The natural color band combination uses the red (B4), green (B3), and blue (B2) channels. Its purpose is to display imagery the same way our eyes see the world. Just like how we see, healthy vegetation is green. Next, urban features often appear white andgrey. Finally, water is a shade of dark blue depending on how clean it is.

Color Infrared (B8, B4, B3)

The color infrared band combination is meant to emphasize healthy and unhealthy vegetation. By using the near-infrared (B8) band, it’s especially good at reflecting chlorophyll. This is why in a color infrared image, denser vegetation is red. But urban areas are white.

3.2: SOFTWARE USED IN THE STUDY

SNAP 8.0 – This was used for displaying images and mosaicking and geo-referencing the images.

CHAPTER - 4

PROPOSED SYSTEM

The proposed system is forest fire monitoring using multi-temporal sentinel data. This helps us to estimate the amount of land were effected due to the forest fire.

4.1: Methodology

- Preprocessing was performed on the satellite data.
- Calculate NBR for extraction of burned area.
- Calculate NDWI for extraction of water bodies.
- Apply water mask on NBR to get burnt areas.

4.1.1: Preprocessing

- Resampling,
- ensures that images of each band have the same resolution and number of pixels
- Atmospheric Correction and
- Atmospheric/Topographic Correction
- Subset selection
- Re-choosing specific areas of interests
- Classification
- Index-based classification - NDVI, NDWI, NBR.

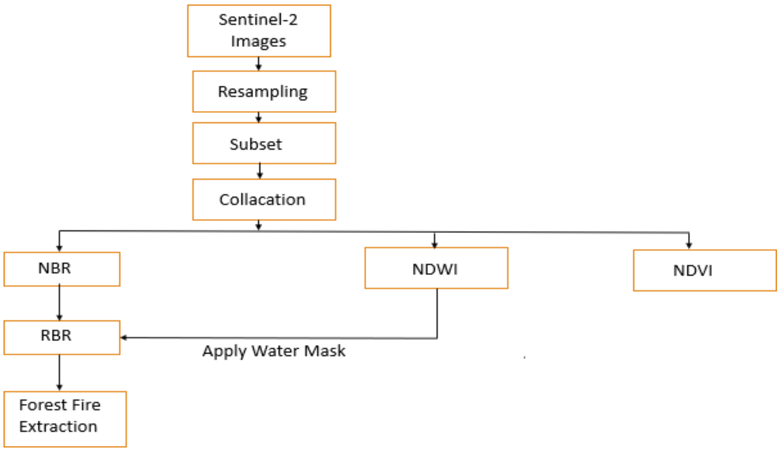


Fig 4.1.1: Block Diagram

4.1.2: Calculate Normalized Burn Ratio (NBR)

The Normalized Burn Ratio (NBR) is an index designed to highlight burnt areas in large fire zones. The formula is similar to NDVI, except that the formula combines the use of both near infrared (NIR) and shortwave infrared (SWIR) wavelengths.

Healthy vegetation shows a very high reflectance in the NIR, and low reflectance in the SWIR portion of the spectrum (Figure 2) - the opposite of what is seen in areas devastated by fire. Recently burnt areas demonstrate low reflectance in the NIR and high reflectance in the SWIR, i.e. the difference between the spectral responsesof healthy vegetation and burnt areas reach their peak in the NIR and the SWIR regions of the spectrum.

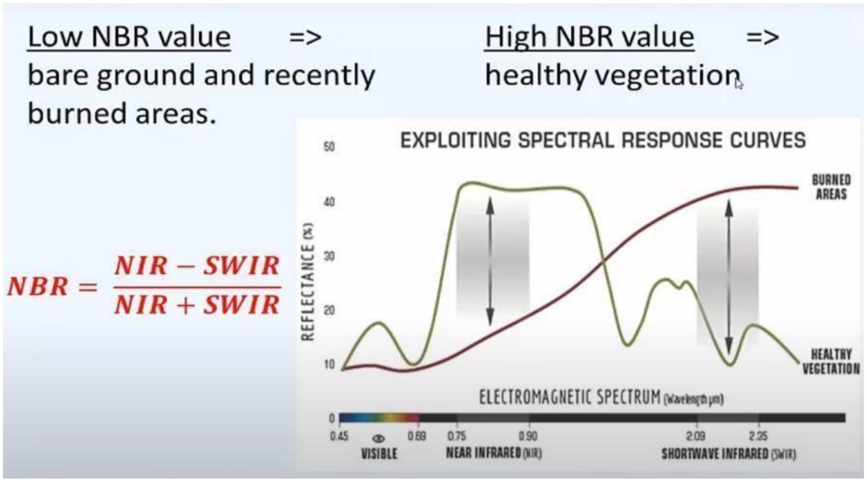


Fig 4.1.2.1: Comparison of the spectral response of healthy vegetation and burned areas. Source: U.S. Forest service.

To benefit from the magnitude of spectral difference, NBR uses the ratio between NIR and SWIR bands, according to the formula shown below. A high NBR value indicates healthy vegetation while a low value indicates bare ground and recently burnt areas. Non-burnt areas are normally attributed to values close to zero.

$$NBR = \frac{NIR-SWIR}{NIR+SWIR}$$

Burn Severity:

The difference between the pre-fire and post-fire NBR obtained from the images is usedto calculate the *delta* NBR (DNBR or ΔNBR), which then can be used to estimate the burn severity. A higher value of DNBR indicates more severe damage, while areas with negative DNBR values may indicate regrowth following a fire. The formula used to calculate DNBR is illustrated below:

$$\text{dNBR or } \Delta\text{NBR} = \text{PrefireNBR} - \text{PostfireNBR}$$

DNBR values can vary from case to case, and so, if possible, interpretation in specific instances should also be carried out through field assessment; in order to obtain the best results. However, the United States Geological Survey (USGS) proposed a classification table to interpret the burn severity.

4.1.3: Calculate Normalized Difference Water Index (NDWI)

NDWI = (G-NIR)/(G+NIR)

The Normalized Difference Water Index (NDWI) is derived from the Near-Infrared (NIR) and Green (G) channels. This formula highlights the amount of water in water bodies.

An alternate method of calculation uses the NIR and Short Wave Infrared (SWIR) channels [(NIR-SWIR)/(NIR+SWIR)]. The amount of water present in vegetation primarily affects the spectral reflectance in the SWIR channel. The information about vegetation contained in the SWIR channel is unique.

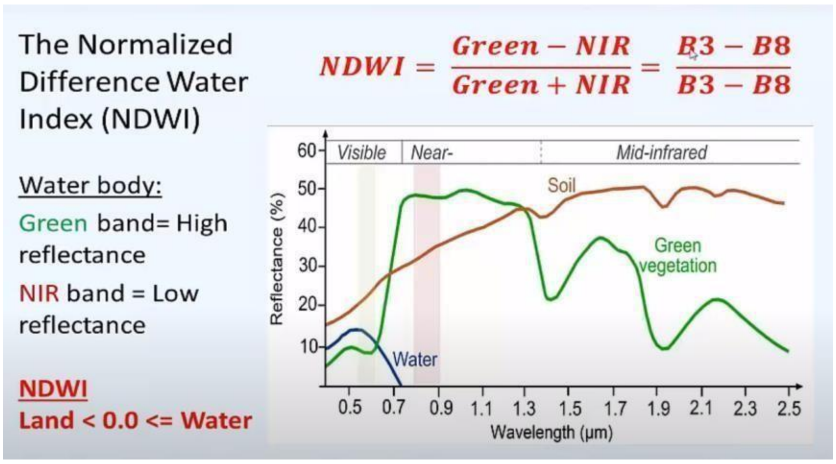


Fig 4.1.3: Graph for NDWI, NBR and NDVI

4.1.4: APPLY WATER MASK ON NBR TO GET BURN AREAS

The NDWI results from the following equation: Index = (NIR - MIR) / (NIR + MIR) using Sentinel-2 Band 8 (NIR) and Band 12 (MIR). The NDWI is a vegetation index sensitive to the water content of vegetation and is complementary to the NDVI. High NDWI values show a high water content of the vegetation.

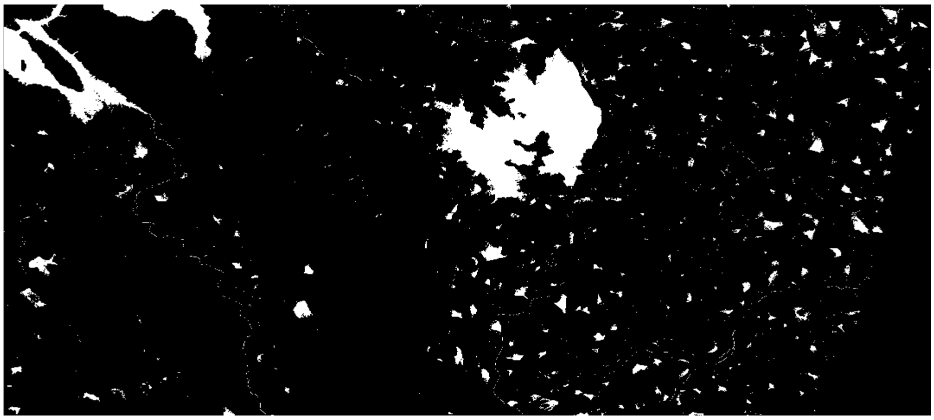


Fig 4.1.4.1: Extraction of water bodies using NDWI

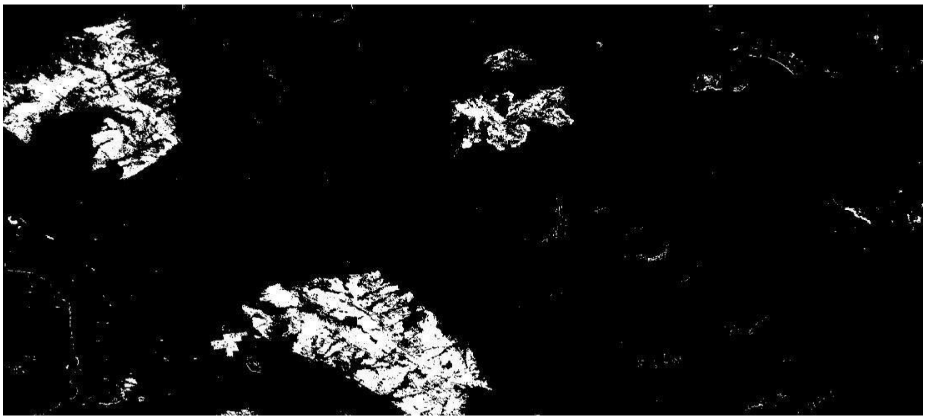


Fig 4.1.4.2: Extraction of Burnt Areas

4.2: WORK FLOW

A standard generic work flow to preprocess Copernicus Sentinel-2 GRD data is presented here. The workflow was created in order to be used within the Sentinel application platform (SNAP), a common architecture for all Sentinel satellite toolboxes. The processing graph in 'xml' format allows the processing of Sentinel-1 GRD using the command line graph processing framework, which allows for batch processing of large datasets. The preprocessing work flow consists of seven processing steps, designed to best reduce error propagation in subsequent processes, described here after in separate subsections. The code to perform the preprocessing work flow is available on the GitHub repository and in the Supplementary Materials as Computer Code1.

Open and Display Sentinel-2 Image

1. Initiate the SNAP tool
2. In the SNAP interface, go to File menu >> Open Product
3. Select the folder that contains the Sentinel-2 data.
4. Open the image.
5. Double click the file name to view the directories within the file.
6. Open the pre and post event images and click on MTD_MSL 1C.

Fig 4.2: SNAP (Sentinel Applicaton Platform) Tool Image

4.2.1: Open RGB Image Window for Pre and Post Events

Sentinel 2 MSI Natural colours and click on OK.

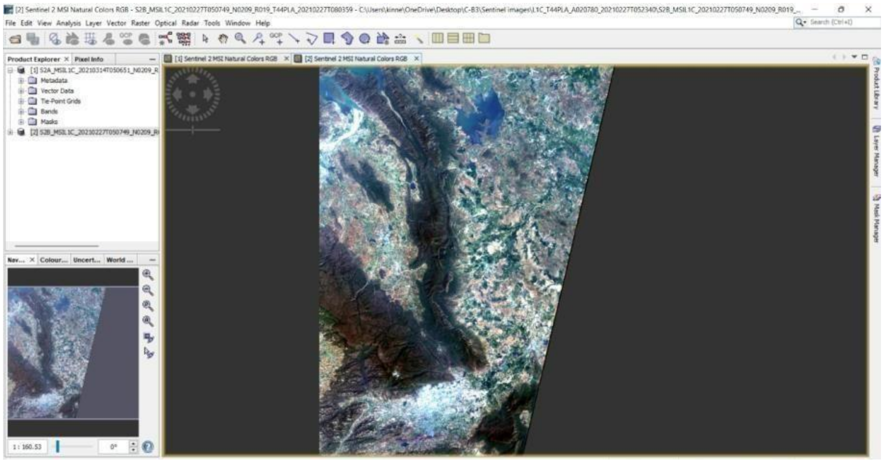


Fig 4.2.1.1: Sentinel-2 MSI Natural Colour Image for Pre-Event

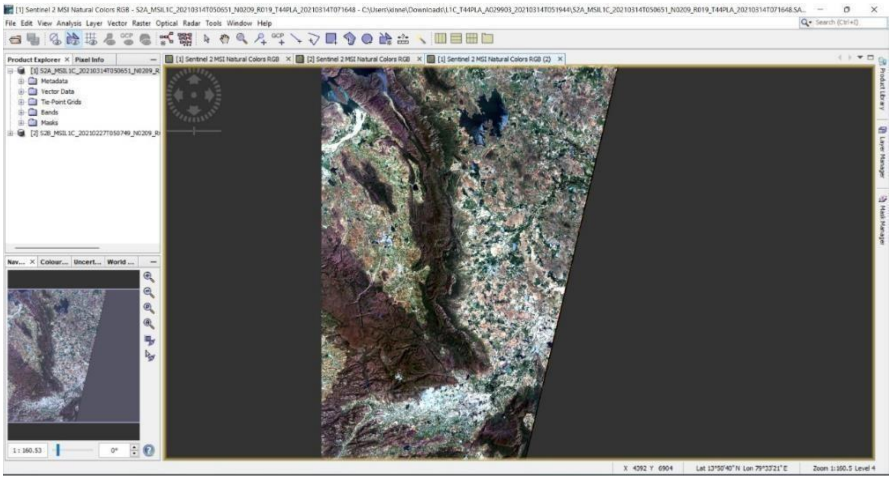


Fig 4.2.1.2: Sentinel-2 MSI Natural Colour Image for Post-Event

4.2.2: Resampling

The tool is found under Raster > Geometric Operations > Resampling. You get more information in the Help file.

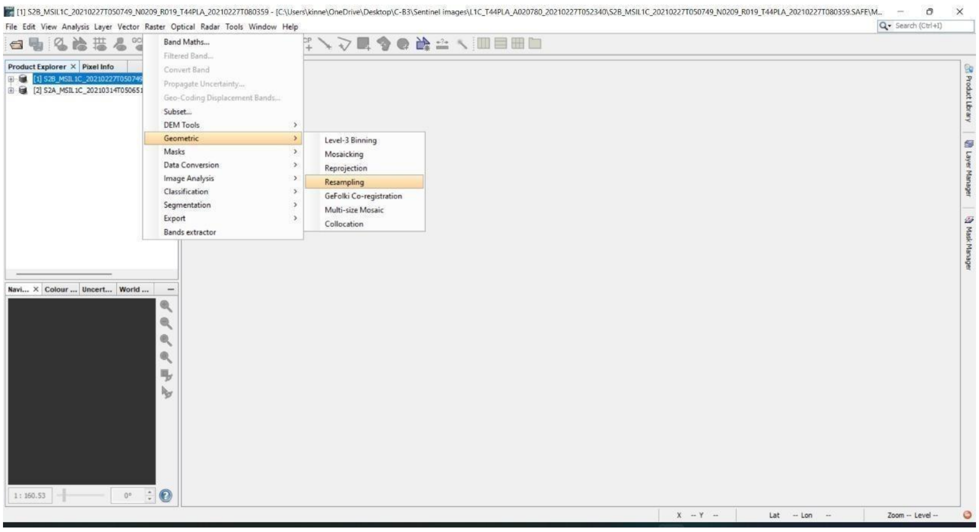
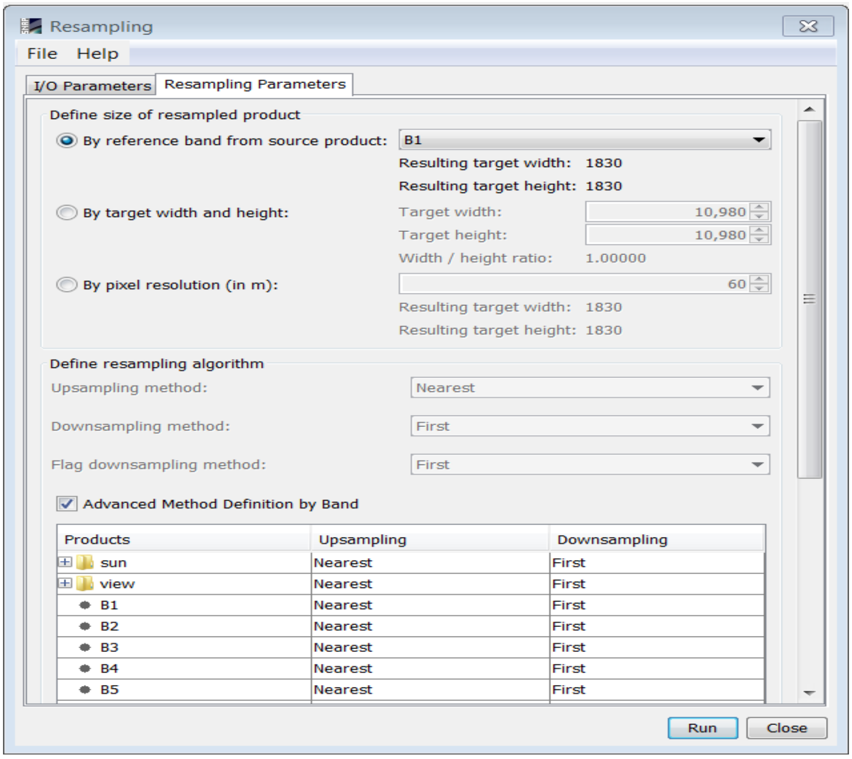


Fig 4.2.2: Resampling Process

Here you can resample a multi-size product to a single-size product. A multi-size product is a product in which bands are of different sizes and/or resolutions. This can be useful for those instances when a SNAP feature is not supported for a multi-size product.

After the new product has been created, you can change to the Product Explorer in order to open an Image View for a band of the new product. After the resampling is completed all the bands are in same resolution. Save the resampled images on the desktop.

Fig 4.2.2.2: Resampling Parameters



Now right click on resampled image > Open RGB image > Now we can change the bands.

4.2.3: Resolution of the Band

- Select Red as B12 Green as B11 Blue as B8.
- Expressions are valid. We can see that the expressions are valid. Then click on OK.

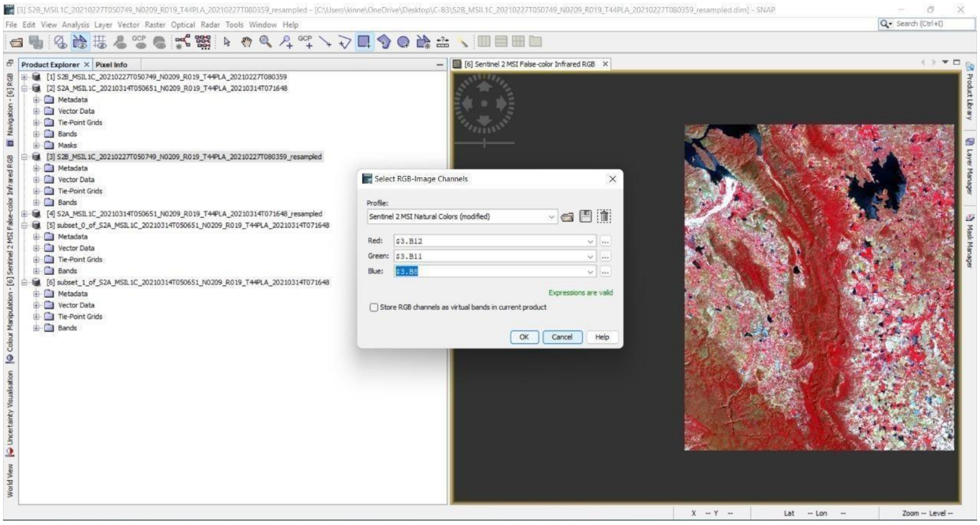


Fig 4.2.3.1: Changing Image colour from Natural to False Colour Image

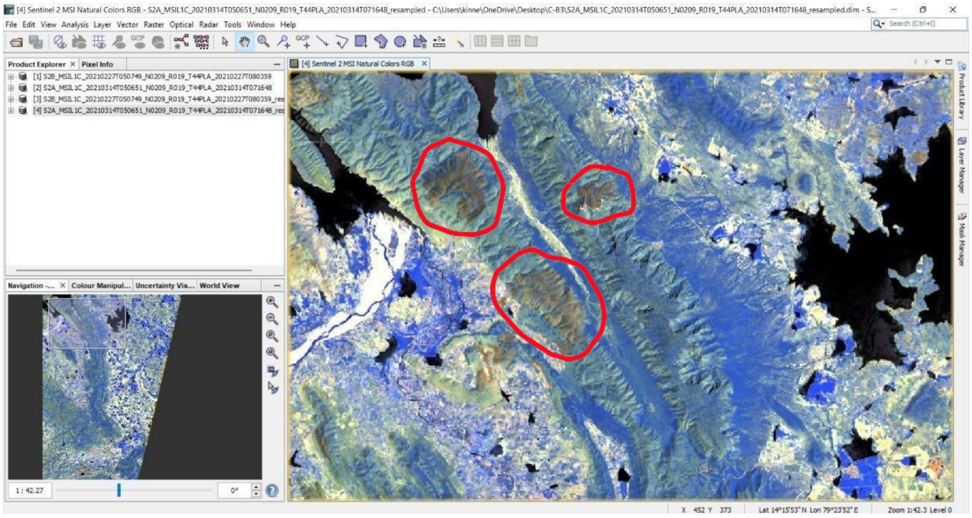


Fig 4.2.3.2: Resampled Image of Post-Event

From the above figure we can see the marked area is the burnt area.

4.2.4: Calculation of NBR in SNAP TOOL

We can calculate the value of NBR in SNAP tool.

$$NBR = \frac{NIR\text{-}SWIR}{NIR+SWIR}$$

To calculate NBR for the burnt area Right click on the resampled image > Select Band Maths > Click on Edit the expression > write the formula as follows.

As per the formula here, NIR => B8 band

SWIR => B12 band

then, (B8 – B12)/(B8 + B12)

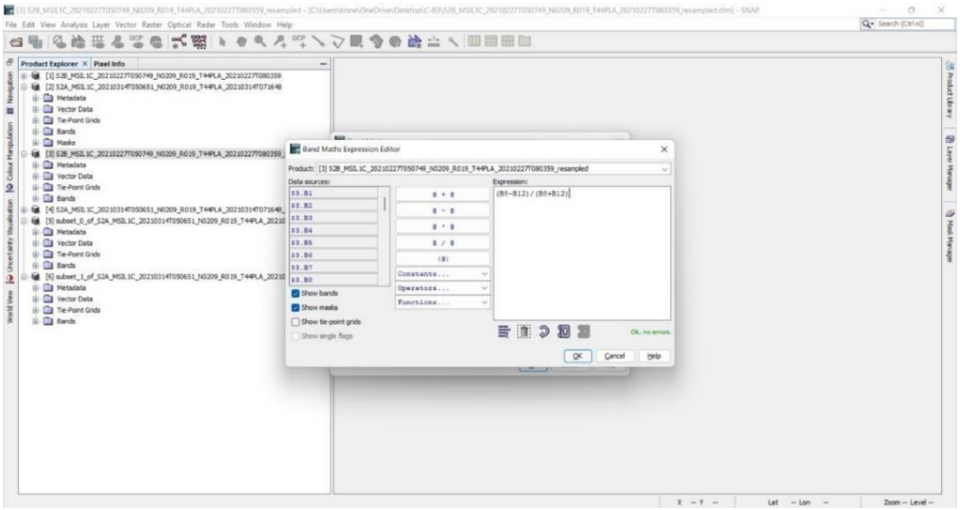


Fig 4.2.4.1: Expression for calculating NBR

After entering the formula > Click on OK.

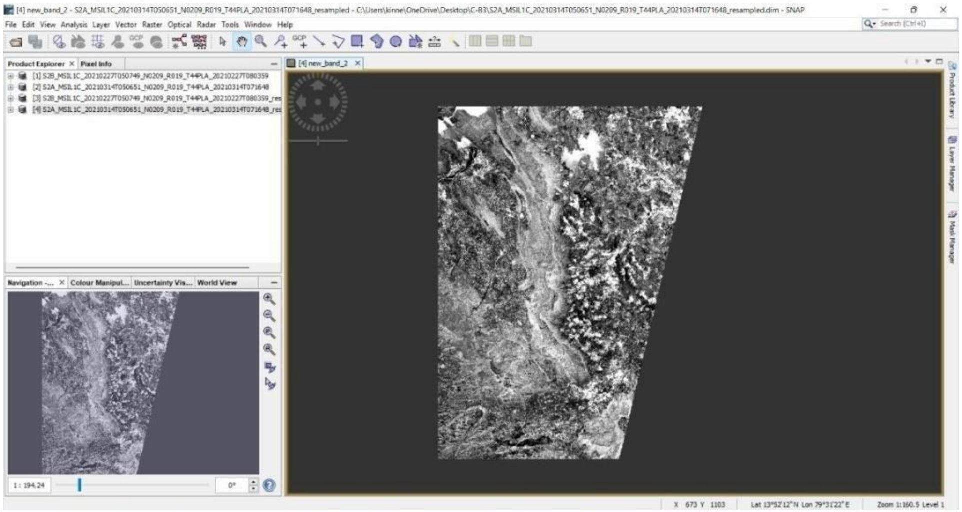


Fig 4.2.4.2: Image to estimate Burn Severity

Now by changing the band colours , we can estimate the burn severity.

4.2.5: Calculation of NDWI

To calculate NDWI, Right click on the resampled image > Select Band Maths > Click on Edit the expression > write the formula as follows.

$$NDWI = \frac{Green - NIR}{Green + NIR} = \frac{B3 - B8}{B3 + B8}$$

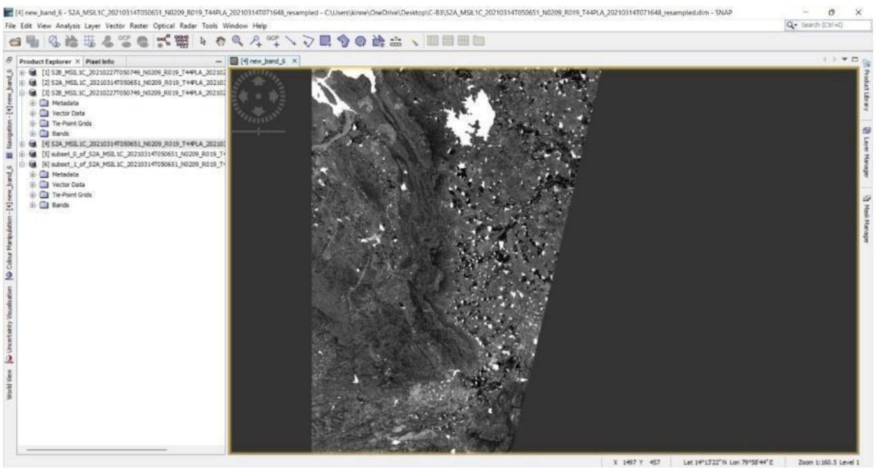


Fig 4.2.5: Image obtained after calculating NDWI

4.2.6: Masking the water bodies

After masking the water bodies, finally we get the extraction of burnt area is done.

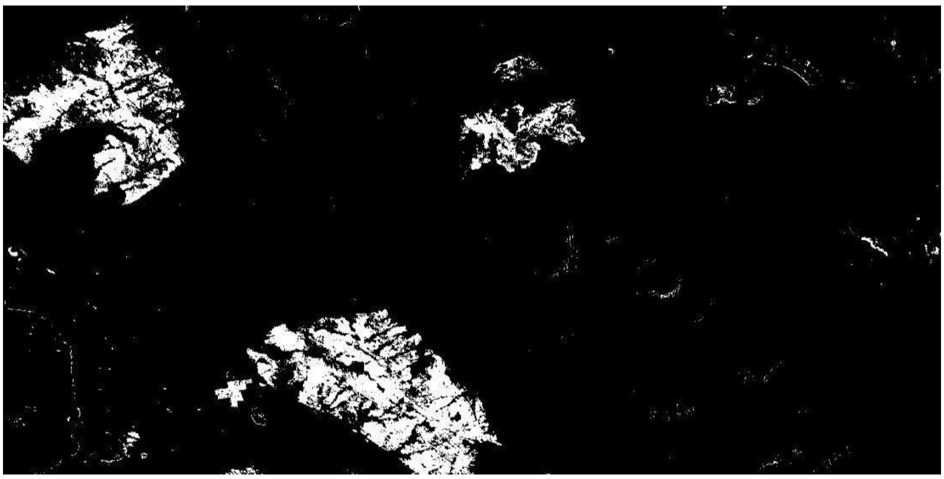


Fig 4.2.6: Image of Burnt Area.

CHAPTER - 5

MACHINE LEARNING ALGORITHM

5.1: Random Forest Algorithm

Random Forest is a machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML.It is based on the concept of ensemble learning, which is a process of combining multipleclassifiers to solve a complex problem and to improve the performance of the model.

"Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that data-set. "Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

5.2: What is the use of Random Forest?

- It takes less training time as compared to other algorithms.
- It predicts output with high-accuracy, even for the large data set it runs efficiently.
- It can also maintain accuracy when a large proportion of data is missing.

Random Forest works in two-phase first is to create the random forest by combining N decision tree, and second is to make predictions for each tree created in the first phase.

5.3: Working of Random Forest Algorithm

The Working process can be explained in the below steps and diagram:

Step-1: Select random K data points from the training set.

Step-2: Build the decision trees associated with the selected data points (Subsets).

Step-3: Choose the number N for decision trees that you want to build

Step-4: Repeat Step 1&2.

Step-5: For new data points, find the predictions of each decision tree, and assign the new data points to the category that wins the majority votes.

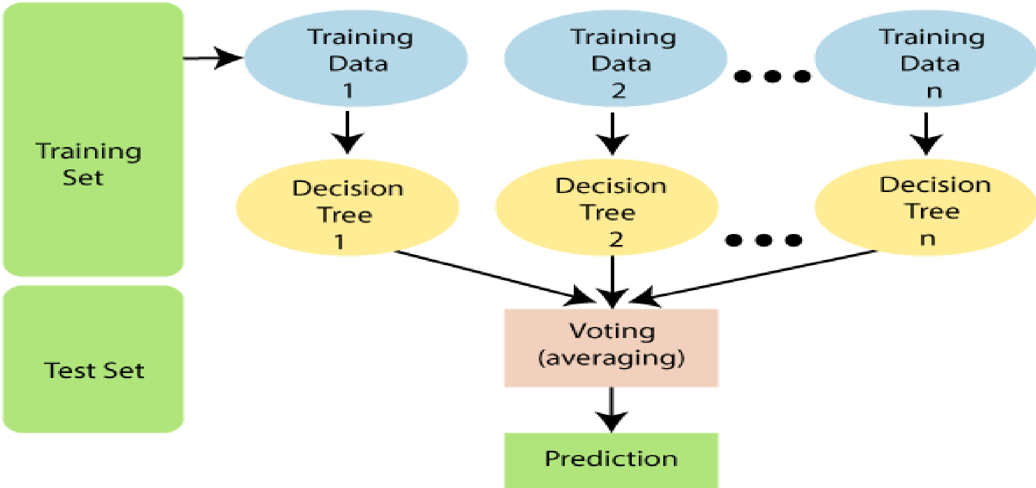


Fig 5.3: Working of the Random Forest algorithm

5.4: Advantages of Random Forest

- Random Forest is capable of performing both Classification and Regression tasks.
- It is capable of handling large data sets with high-dimensionality.
- It enhances the accuracy of the model and prevents the over fitting issue.

CHAPTER - 6

ADVANTAGES

- More dynamic and wider detection as compared to fixed sensors.
- Reduction in cost.
- Unreachable areas can now be controlled and monitored.
- Satellite data in more realistic.
- Proposed methods are very convenient and can easily detect.

CHAPTER - 7

RESULTS

7.1: PRE-EVENT IMAGARY :

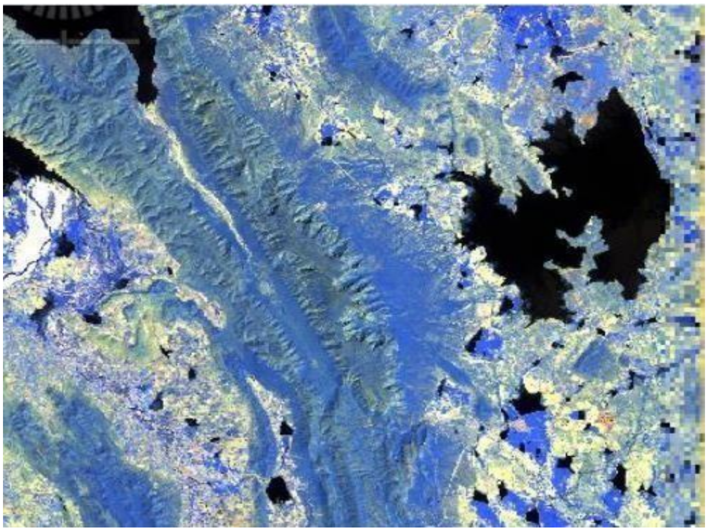


Fig 7.1: Pre-event image before forest fire on 27-02-2021 in Nellore and Kadapa Region

7.2: POST – EVNET IMAGARY:

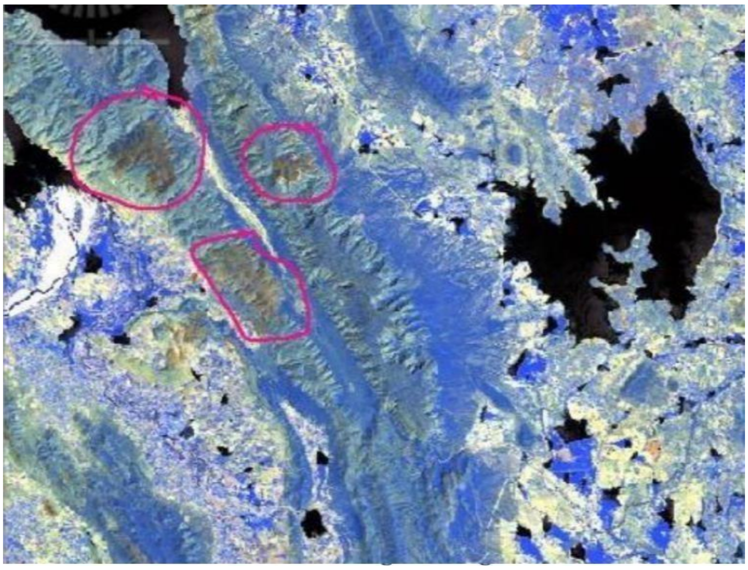


Fig 7.2: Post-event image after forest fire on 14-03-2021 in Nellore and Kadapa Region

CHAPTER – 8

SCOPE AND FUTURE WORK

All three datasets considered are of dry season when forest fires are expected. The seasonal variations and climatic conditions over the period of study are not considered in this study. However, being the same season data, such variations are not likely to significantly affect the results. Further fine tuning of results could be done by corrections for sun angle. Future study can be taken up for time series data with suitable time intervals to examine the vegetation recovery cycle and resultant fall in temperature under different soil conditions and seasonal regimes.

CHAPTER – 9

CONCLUSION

According to index results, it was understood that the RBR generates more sensitive results in determining the forest fire risk classes according to the DNBR. Also, it has been understood that the classified pixels in RBR pose more risk in terms of a forest fire risk than the same classified pixels in DNBR.

DNBR is a powerful tool to detect burned area but also it is sensitive to water and thus sometimes, pixels that are classifiedas high severity maybe water (Bolton et al., 2015). However, since there is no water bodyin the study area, a water mask was not performed. According to the fire risk maps, it isseen that the areas with high forest fire risk in the study area are quite low. This is due tothe fact that the study area consists of a mixture of urban texture together with the sparseforest cover. In addition, the fact that both forest and urban texture within one pixel in some pixels have affected the results by causing mixed pixel problems. On NDVI maps,these regions are classified as moderate vegetation and sparse vegetation.

As supported by the results obtained from the fire index maps, it was concluded that a forest fire that may occur in this region is quite difficult to come outfor natural reasons.

CHAPTER – 10

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