International Journal for Innovative Engineering and Management Research
A Peer Revieved Open Access International Journal
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IJIEMR Transactions, online available on 24th Apr 2022. Link
:http://www.ijiemr.org/downloads.php?vol=Volume-11&issue=ISSUE-04

DOI: 10.48047/IJIEMR/V11/I04/97

Title **FOREST FIRE MONITORING BY REMOTE SENSING USING SATELLITE DATA**

Volume 11, Issue 04, Pages: 622-629

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FOREST FIRE MONITORING BY REMOTE SENSING USING SATELLITE DATA

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ABSTRACT:

Forest fires are one of the most important disasters since past. The necessary preventions should be taken promptly to prevent these disasters. Remote sensing, which is a very effective and practical tool, is one of these tools that provide a timely receipt of measures with the development of technology. Sentinel 2 images were used in order to detect forest fire risk class. Normalized Burn Ratio (NBR), Differenced Normalized Burn Ratio (dNBR), Relativized Burn Ratio (RBR) spectral indices and Normalized Difference Vegetation Index (NDVI) were used in order to determine the forest area damaged by fire and to establish fire risk classes. According to the results of the study, the size of the vegetation area that was destroyed due to fire determined, and the probability of forest fire exposure of these areas established.

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

RemoteSensing:

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.

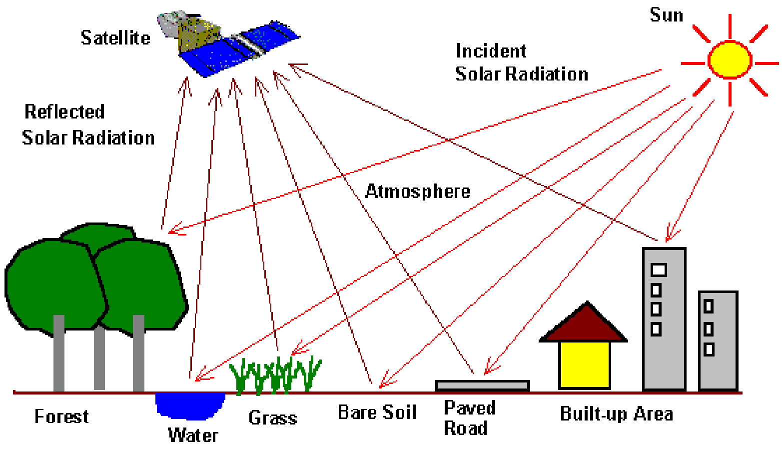

Fig.RemoteSensingProcess

Remote sensing method is classified into 2 types:

1. Passive Remote sensing
2. Active Remote sensing

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)

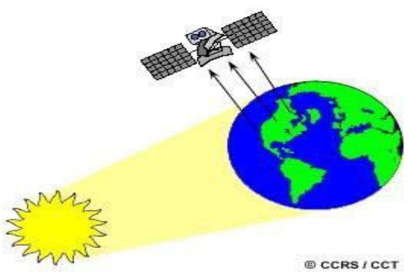

Fig: Passive Remote Sensing

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 fluoro sensor and a synthetic aperture radar (SAR).).

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Fig Active Remote Sensing

2. LITERATUREREVIEW:

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).

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

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steps, segmentation and classification (Baatz, Hoffmann, & Willhauck, 2008). Multiresolution 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 objectbased 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)

2. PROPOSEDSYSTEM

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.

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.

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

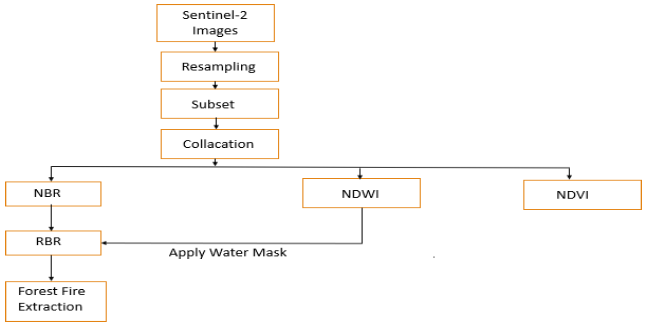

Fig .Block Diagram

Calculate Normalized Burn Ratio (NBR)

The Normalized Burn Ratio (NBR) is an index designed to highlight burnt areas in large fire zones. The formula

$$\mathrm{NBR} = 1 + \frac{NIR - SWIR}{\mathrm{NIR} + \mathrm{SWIR}}$$

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.

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 responses of healthy vegetation and burnt areas reach their peak in the NIR and the SWIR regions of the spectrum.

APPLYWATERMASKONNBRTOGET BURNAREAS

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.

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.

OpenandDisplaySentinel-2Image:

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.

4. RESULTS

PRE-EVENTIMAGARY:

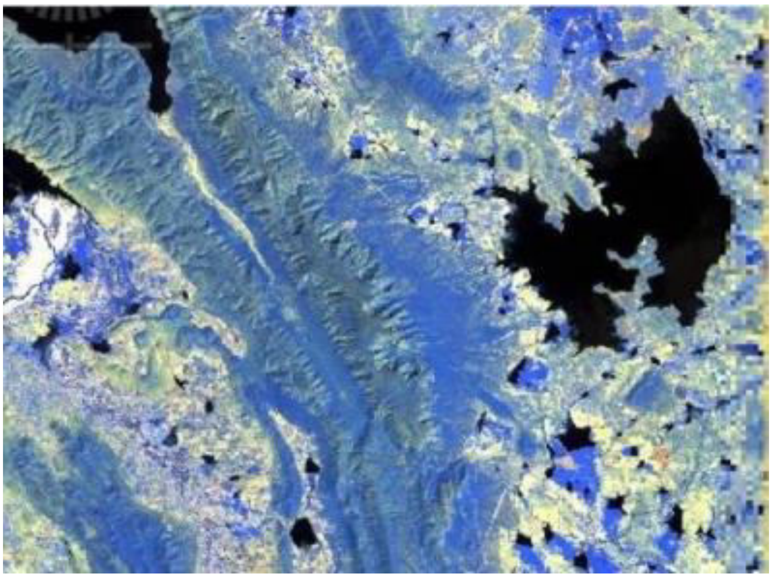

Fig : Pre-event image before forest fire on 27-02-2021in Nellore and Kadapa Region

5. 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 classified as high severity maybe water (Bolton et al., 2015). However, since there is no water body in the study area, a water mask was not performed. According to the fire risk maps, it is seen that the areas with high forest fire risk in the study area are quite low. This is due to the fact that the study area consists of a mixture of urban texture together with the sparse forest 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 out for natural reasons.

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