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Monitoring Change in Vegetation Cover and LST due to Forest Fires Occurred at the Regional Level Using Satellite Imagery

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Abstract: Remote sensing techniques have been extensively used for surveying post fire effects of forest fires and to analyse them. Forest fires occur due to anthropogenic activities of people whichinfluence greatly the forest structure, wild life and vegetation. The land surface temperature gets greatly affected with the change of vegetation cover over the region due to these forest fires. The forest range covering in and around Tirupati region (Andhra Pradesh, INDIA) was selected as the area of studyfor the present work. The LST was estimated using mono-window algorithm forLandsat8 imagery collected forFebruary and March, 2014 (the year in which many forest fire events had occurred) and observed the change in mean temperatures.In this present work, it is estimated that about 19.86% of chosen area has suffered from forest fires and LST has raised more than 10^{o}C after the occurrence of forest fires with the loss of vegetation cover which ultimately indicates a negative correlation.

Key words: Change Detection, Forest fires, Land Surface Temperature (LST), Normalised Difference Vegetation Index (NDVI), Remote sensing.

Introduction

Remote sensing is the process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance from the targeted area. Forest fires are recognised as a major driver of the global change in terrestrial ecosystems [1]. Remote sensing helps to map large forest fires from space, allowing rangers to see a much larger area than from the ground. The emission of energy in the form of light and heat during the burning process can be easily detectable in electromagnetic (EMR) spectrum. The changes in the reflectance spectrum before (standing vegetation) and after combustion (ash and char) can be measured using sensors on remote platforms [2].When vegetation is burned, there is, at the spatial resolution of most satellite sensors (pixel size >30 m), a drastic reduction in visible-to-near-infrared surface reflectance (i.e. 0.4–1.3μm) associated with the charring and removal of vegetation [3-5]. The destruction of vegetation by forest fires can affect the land surface and the hydrologic cycle, by increasing the surface albedo, surface runoff, and decreasing the evapotraspiration [6]. Remote sensing data acquired in the thermal infrared region is a very attractive alternative for detection of fires as it is capable of supplying a continuous record of very small temperature changes. Eva and Lambin (1998a) [4] mapped burns in central Africa during the 1994–1995 dry season using 1-km ATSR imagery by matching decreases in shortwave infrared (SWIR) reflectance with increases in surface temperature. Barbosa et al. (1999) [7] used daily 5-km AVHRR imagery to map burned areas in Africa based on changes occurring in reflectance, brightness temperature, and a vegetation index (VI). Kasischke and French (1995) [8], for example, applied differencing to 15-day AVHRR Normalized Difference Vegetation Index (NDVI) composite imagery to detect burns in Alaskan boreal forests during 1990 and 1991.

There are methodsavailable in literature for measuring the temperatureof these fire zones. Airborne thermal infrareddata have been widely used for fire detection. Satellite data due to its synoptic and repetitive coverage provide valuable information in such studies[9-10].

Forest fires in the range of Tirupati city in March, 2014 serves as a case study in this work. Landsat 8, with a spatial resolution of30mand a temporal resolution of 16 days is used for analysing the change in the vegetation cover and land surface temperature (LST), as it would be ideal for forest fire monitoring. Two datasets corresponding to pre fire event and post fire event are used to identify the effects. LST is an essential factor in many areas like global climate change studies, urban land use/land cover, geo-/biophysical and also a key input for climate models [11]. LST would be high when the forest fire occurs and it would take time to get back to the normal temperatures which is hazardous to the wild life to survive. Hence in this present study an attempt is made to estimate LST before the event and after the event of forest fires occurred in Tirupati WLM division using mono window algorithm[11]. The technique was developed using ERDAS IMAGINE 2016 and LST is estimated from Landsat 8 data for both the data sets. Validation of the areas affected by forest fires was done by collecting the information from Wild Life Management System of Tirupati Division.

Study area and Data

The study area chosen for the present work is part of Tirupati WLM division of Tirupati, India. Tirupati WLM division spreads over part of southern part of AP i.e, north eastern part of Chittoor district and southern part of Kadapa district. It lies between latitudes $13^{o}36'18''$ and $13^{o}56'55.68''$ N and longitudes $79^{o}07'51.96''$ and $79^{o}30'18.36''$ E. The geographical area of the division is about 755.17km^{2}and land use pattern of the division is as shown in Table 1 [Source: Andhra Pradesh State of Forest Report 2014].

Table 1 Land Use Pattern of the Division

S.No.	Land Use	Area in km^2	Percentage
1.	Forest including scrub	689.81	91.34
2.	Agriculture	0.00	0.00
3.	Land with scrub	3.82	0.51
4.	Fallow lands	35.73	4.73
5.	Grass lands	0.00	0.00
6.	Settlements	4.39	0.58
7.	Vegetation outside forest	19.18	2.53
8.	Water bodies	2.31	0.31
	Total	755.17	

The climate of the division is dry with temperatures ranging from 19^{o}C to 44^{o}C and annual rainfall is about 934mm,which is mainly due to north-east monsoons.

The notified forest area of the division is 714.33 km^2 which is 98.38% of the geographical area. The Division consists of the Sri Venkateswara Wildlife Sanctuary and Sri Venkateswara National Park. The division wise forest cover changes are shown in Figure 1[Source: Andhra Pradesh State of Forest Report 2014].

Landsat 8 imagery is used in the present work since the spatial resolution is of 30m. The satellite data for two dates i.e, 04.02.2014 and 24.03.2014 were taken from USGS portal. The dates were chosen such that the first dataset was acquired before the forest fire and the other dataset after the occurrence of forest fire. In between the two dates, many forest fires were recorded. Since the temporal resolution of Landsat 8 is 16 days, the dates mentioned were chosen. The datasets considered is presented in the Table 2.

Landsat 8 has two sensors called Operational Line Image (OLI) and Thermal Infrared Sensor (TIRS). The band designations of Landsat 8 are shown in Table 3. Following January 6, 2014, instructions of USGS of not using TIRS band 11 due to its larger calibration unreliability, only band 10 was considered in the technique [11].

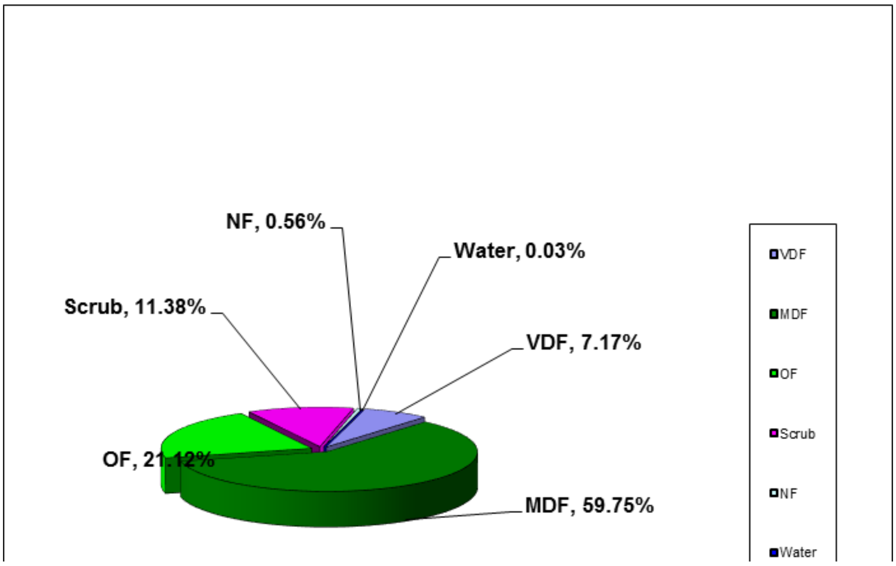

Figure1. Forest Cover Distribution of the Division

- MDF- Moderate Dense Forest
- VDF- Very Dense Forest
- OF- Open Forest
- Scrub- Scrub Forest
- NF- Non Forest
- WB- Water body

The area around the holy place, Tirumala which falls in Tirupati WLM division is chosen for the study. The study area is shown in Figure2.

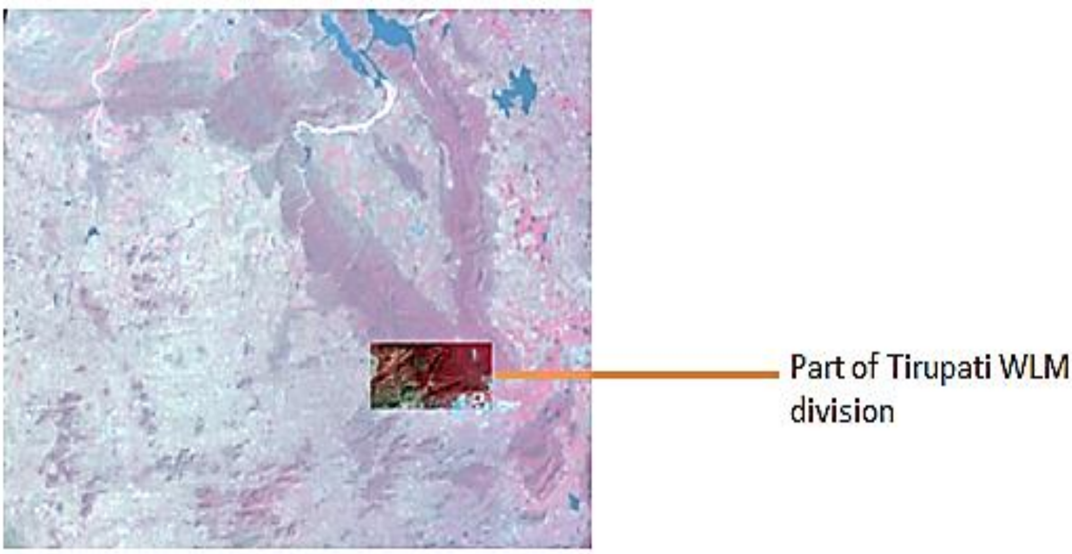

Figure2. Study area

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Table 2. Details of the two datasets collected from USGS

Sensor	Path/Row	Resolution (m)	Date of Acquisition	Time of Acquisition
Landsat 8	143/50	30 30	04.02.2014 24.03.2014	05:05:19 05:04:38
	143/51	30 30	04.02.2014 24.03.2014	05:05:42 05:05:01

Table 3. Band Designations of LANDSAT 8

Band Designations	Wavelength(μm)	Resolution (m)
Band 1 (Coastal Aerosal)	0.43 - 0.45	30
Band 2 (Blue)	0.45 - 0.51	30
Band 3 (Green)	0.53 - 0.59	30
Band 4 (Red)	0.64 - 0.67	30
Band 5 (Infrared)	0.85 - 0.88	30
Band 6 (Short wave infrared)	1.57 - 1.65	30
Band 7 (Short wave infrared)	2.11 - 2.29	30
Band 8 (Panchromatic)	0.50 - 0.68	15
Band 9 (Cirrus)	1.36 - 1.39	30
Band 10 (Thermal infrared)	10.6 - 11.19	100
Band 11 (Thermal infrared)	11.50 - 12.51	100

Methodology

The primary objective of this work is estimate the area of percentage affected due to forest fires and to retrieve the LST over that region from LANDSAT 8 imagery. For this purpose the pre images and post images were processed and detected the change. Image differencing is one of the most accurate change detection methods [12-13]in which the difference between pre image and post image is identified and analysed the effects of forest fires.Image differencing is probably the most widely applied change detection algorithm for a variety of geographical environments.

The post-event temperatures over the affected region increases abruptly compared to the pre-event temperatures. To estimate these LSTs,Mono window technique [11,14,15] is used which utilises the brightness temperature of the thermal band 10 of LANDSAT 8 imagery. Even though the band 11 is also thermal band, it is not considered because of its calibration unreliability (as per Instructions of USGS vide January 6, 2014).Before using the technique, pre-processing of data has to be performed. Pre-processing can be done by performing Geometric correction and radiometric correction [16].

Geometric correction

The images were resampled using nearest neighbor method. All the data are re-projected to a Universal Transverse Mercator (UTM) coordinate system, datum WGS84, zone 44. This process is known as Geo-referencing.

Radiometric Correction

Usually the satellite data received have the Digital Numbers as pixel values for the convenience of transmitting with less errors. These DN values are to be further converted into at sensor spectral radiance using equation (1)[16].

$$L_\lambda = \frac{(L_{max} - L_{min})*Q_{cal}}{(Q_{calmax} - Q_{calmin})} + L_{min} - O_i \qquad (1)$$

Where,
L_{max} is the maximum radiance ($Wm^{-2}sr^{-1}\mu m^{-1}$)
L_{min} is the minimum radiance ($Wm^{-2}sr^{-1}\mu m^{-1}$)
Q_{cal} is the DN value of pixel
Q_{calmax} is the maximum DN value of pixels
Q_{calmin} is the minimum DN value of pixels
O_i is the correction value for band 10
Brightness temperature (BT) of the thermal band 10 is evaluated using the thermal constants given in the metadata file given along with the band information. The equation for calculating BT is given in equation (2)

$$BT = \frac{K2}{\ln[(\frac{K1}{L\lambda}) + 1]} - 273.15 \qquad (2)$$

Where K1 and K2 are the thermal constants of TIRS band 10 which can be identified in the metadata file associated with the satellite image.To have the results in Celsius, it is necessary to revise by adding absolute zero which is approximately equal to -273.15.
Two of most eminent indices related to environmental studies and, especially, to forest fires and floods are the Normalized Difference Vegetation Index (NDVI) and Surface Temperature (ST) [6]. A mathematical function of the visible and infrared parts of the electromagnetic spectrum can be an indicator of the presence and condition of the vegetation. This leads us to the concept of Normalized Difference Vegetation Index (NDVI), which is an indication ofthe amount of green vegetation. NDVI can be derived using the equation (3). The NDVI values range between +1.0 to -1.0.

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)} \qquad (3)$$

Where NIR is the near infrared band value of a pixel and RED is the red band value of the same pixel.
The researcher who analyses the change of vegetation in a burned area usually has no information on the fire severity experienced by the vegetation soon after the fire event. The application of supervised techniques like classification requires knowledge of the fire spread. Studying fire events of past years, for which in-field information obtained in the weeks after the fire, is insufficient, the usefulness of the bi-temporal NDVI (difference between the index value before and after the fire) dNDVI in the discrimination of burned areas has been proven with the results of the works mentioned, but, the ultimate challenge is to be able to generalize the results of some fires to others, at least in a regional context. Image differencing of pre and post-fire NDVI gives the change detection in the evolution of vegetation over the area of interest which can be obtained using the equation (4)

$$dNDVI = NDVI_{prefire} - NDVI_{postfire} \qquad (4)$$

After obtaining a change image, a further analysis is required to identify change and no change pixels and to produce a classified map. Histogram thresholding is a simple approach for identifying the change pixels. Pixels that show no significant change tend to be grouped around the mean while pixels with significant change are found in tails of the histogram distribution. This approach is known as direct multidate classification technique or composite analysis[17].
Proportional vegetation cover (P_v) is one of the biophysical parameters involved in the surface processes, which is also necessary requirement for regional and global climate modelling, and global change monitoring. It is also a key parameter in thermal remote sensing, since it is one of the basic parameters from which surface emissivities can be estimated which varies with the NDVI [18,19].P_v is calculated with the use of equation (5)

$$P_v = \left(\frac{NDVI - NDVI_s}{NDVI_v - NDVI_s}\right)^2 \qquad (5)$$

Where $NDVI_s = 0.5$ and $NDVI_v = 0.2$

Land surface emissivity (LSE) is another parameter required to estimate LST which is a proportionality factor that calibrates the black body radiance (Plank's law) needed to estimate emitted radiance and it is the ability of transmitting thermal energy across the surface into the atmosphere [14]. Since the emissivity depends on the wavelength, the NDVI threshold method (NTM) [14] can be used to estimate the emissivity of different land surfaces.

$$\varepsilon_\lambda = \begin{cases} \varepsilon_{s\lambda}, & NDVI < NDVI_s \\ \varepsilon_{s\lambda} P_v + \varepsilon_{s\lambda}(1 - P_v) + C_\lambda, & NDVI_s \le NDVI \le NDVI_v \\ \varepsilon_{s\lambda} + c_\lambda, & NDVI > NDVI_v \end{cases} \quad (6)$$

Where ε_v and ε_s are the vegetation and soil emissivities respectively, and C is the surface roughness taken as a constant value of 0.005[15].Finally LST is calculated using the brightness temperature (BT) of thermal band 10 and LSE given by the equation (7)

$$T_s = \frac{BT}{\{1 + [(\lambda BT/\rho)\ln \varepsilon_\lambda]\}} \quad (7)$$

Where, Ts is the LST in Celsius (^oC), BT is at- sensor BT (^oC), λ is the average wavelength of band 10, ε_λ is the emissivity calculated from equation (6) and ρ is ($h\ x\frac{c}{\sigma}$) which is equal to 1.438×10^{-2} m K in which, σ is the Boltzmann constant (1.38×10^{-23} J/K), h is Plank's constant (6.626×10^{-34}) and c is the velocity of light (3×10^8 m/s).

The interaction between climate change and forest fire is like a feedback system. As climate change has an impact on forest fire, the forest fire may also have an impact on climate change. Firstly, the surface temperature rises drastically which affect the soil moisture, canopy and wild life soon after the forest fire. Hence it is required to estimate the change in the forest cover and rise in the temperature.

Results

NDVI and LST are estimated for the two datasets to identify the change in the vegetation cover and rise in surface temperature due to forest fires. Forest fires occur mostly during February to April. In the year 2014, most of the fires occurred between February and March. The study area chosen is covered with moderate dense forest, open forest and scrub forest. The area is chosen such that it surrounds the holy place "Tirumala" which is visited by many people throughout the year. This region falls under Tirupati WLM division of wild life management.

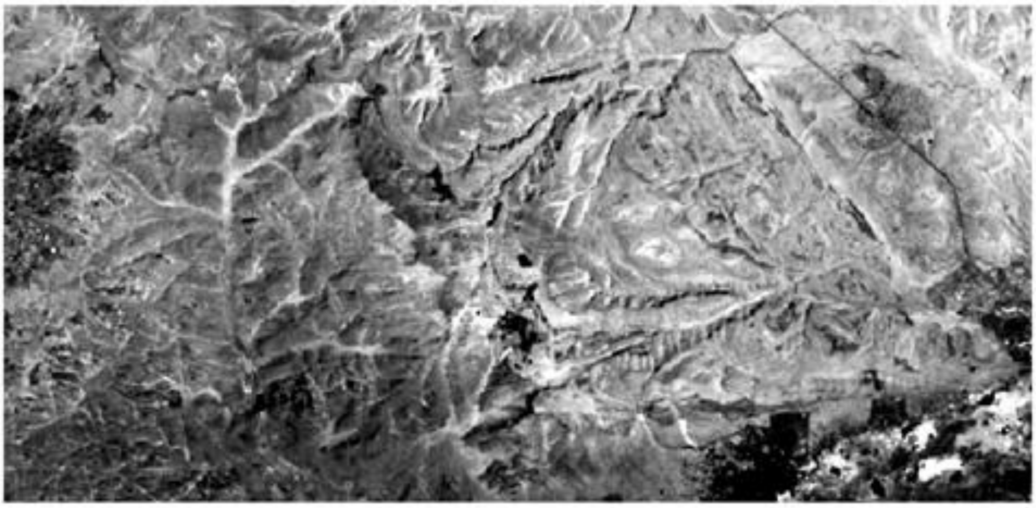
Table 4. Mean and Standard deviation of NDVI and LST for the two datasets

Date	NDVI				LST			
	Min	Max	Mean	Std. Dev	Min	Max	Mean	Std. Dev
04.02.2014	-0.091	0.488	0.251	0.057	18.3	34.26	25.21	2.31
24.03.2014	-0.109	0.508	0.187	0.056	24.46	58.6	36.62	2.91

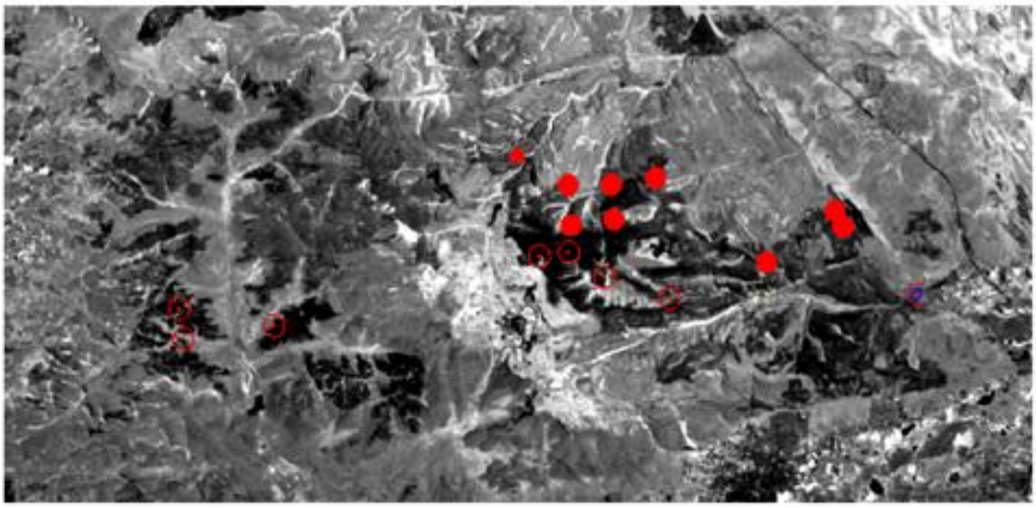
The thermal band of Landsat 8 is used to estimate the LST before and after the event with change in the vegetation cover (NDVI). The results obtained after processing the data using ERDAS IMAGINE 2016 is presented in the Table 4. From the table it can be observed that the mean of the NDVI has fallen from 0.251 to 0.187 after the occurrence of fire and there was an immediate rise in LST mean with a difference of more than 10^oC i.e., mean has changed from 25.21^oC to 36.62^oC.

LST is estimated using mono-window algorithm with the help of thermal band 10. Figure 3 and Figure 4 shows the images of NDVI and LST respectively. Figures 3a and 4a represents the estimated values of NDVI and LST of the study area before the forest fires and figures 3b and 4b represents the estimated values after forest fires along with the validation points collected from Wild Life Management Division. The burnt area has a sudden rise in surface temperature of about more than 10^oC. Many Forest fires have been recorded during the period of

February and March, 2014. Each type of point on the images indicates the date of event occurred [Source: Wild Life Management Division of Tirupati]



(a)



(b)

Figure 3. NDVI images of (a) before and (b) after forest fire in 2014

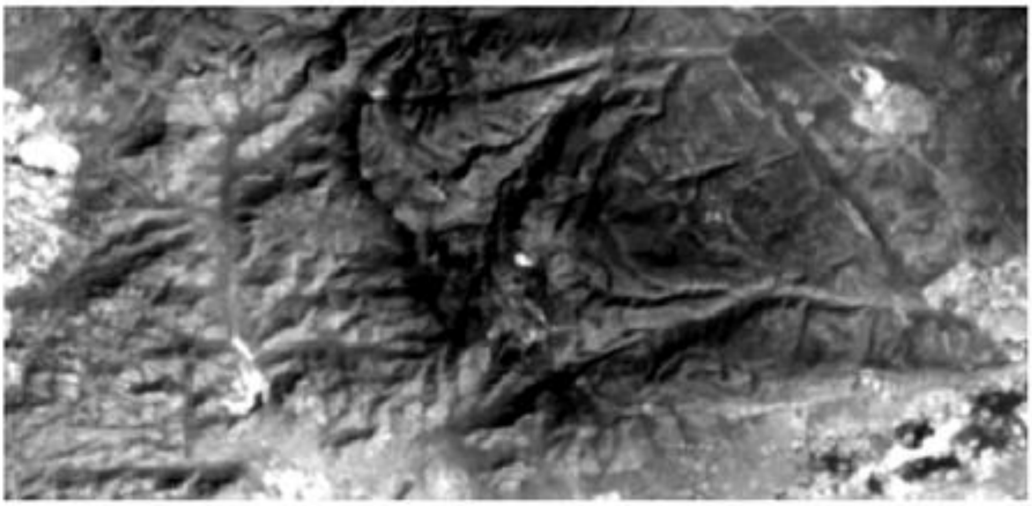
Forest fires were occurred on

02.03.2014

16.03.2014

18.03.2014

Figure 5 shows the change occurred in NDVI. It shows about 19.86% of area, has been affected due to forest fires in the area of interest. The highlighted regions in the NDVI image represent the loss of vegetation cover in the region of interest after forest fire. And increased temperatures are highlighted in LST map.



(a)

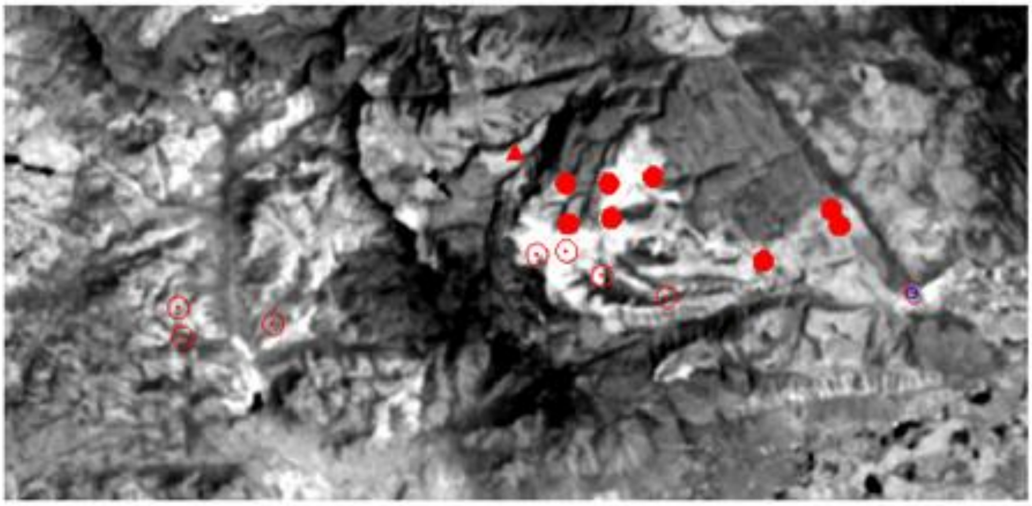


Figure 4. LST images of (a) before and (b) after forest fires in 2014

Conclusion

Remote sensing provides a better source of identifying the burnt area from the space using weather satellites like Landsat 8 which has a better resolution. In the present study, the burnt areas were identified by estimating LST and the change seen in the vegetation cover after the events. This kind of approach helps us to analyse the impact of forest fire on climate change, bio-diveristy and ecology system. Tirupati WLM is having good resources of medicinal plants, red sandal trees and many wild lives. Dueto these forest fires, the vegetation is being affected and the animals do suffer a lot because of the trace gas emissions and rise in temperature. In this study, an attempt is made to identify the places where there is change of temperature more than 10^{o}C i.e., increases of more than 40% of surface temperature compared to before event, using remote sensing and verified the obtained results with that of the coordinates collected from Wild Life Management Division of Tirupati.

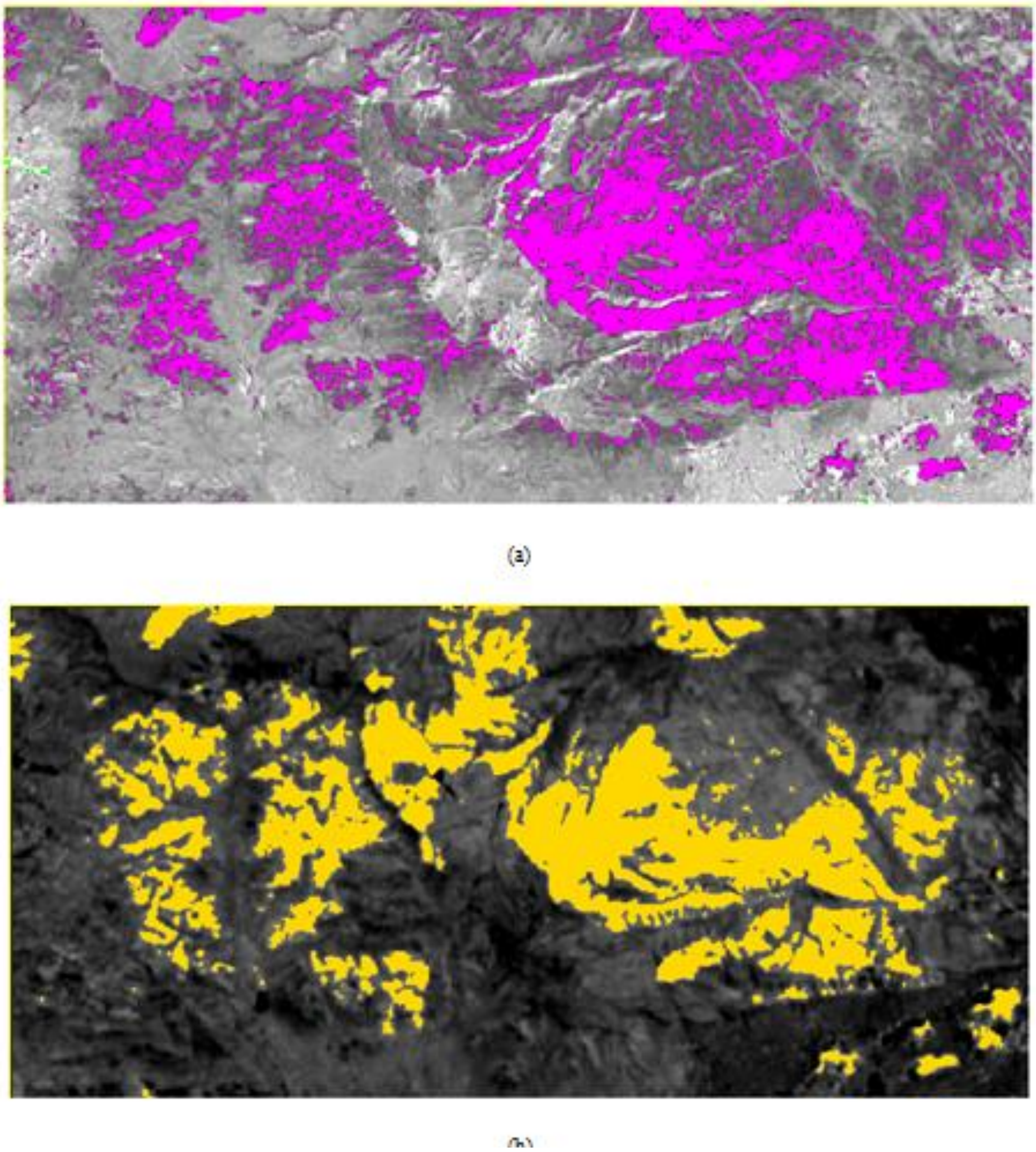


Figure 5. Change observed in (a) NDVI and (b) LST after forest fires

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