Automation of Forest Fire Danger Index from the Near Real Time Satellite Datasets

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ABSTRACT. Forest fire is a major ecological disaster, which has economic, social and environmental impacts on humans and also causes the loss of biodiversity. Forest officials issue the warnings to the public on the basis of fire danger index classes. There is no fire danger index for the country India due to the sparsely distributed meteorological stations. In this study, we have made an attempt to integrate both the Static and Dynamic fire danger indices and also used the near real time data sets that can be available for download through Earthdata website after one hour of the satellite overpass and also automated the entire procedure. Static Fire Danger Index (SFDI) is a constant over the study area, computed from the MODIS Land cover type yearly L3 global 500 m SIN grid (MCD12Q1) and ASTER GDEM datasets. In this study, Dynamic Fire Danger Index (DFDI) has been calculated from the Near Real Time (NRT) Level 2 MODIS Terra Land Surface Temperature datasets (MOD11_L2) and MODIS TERRA NRT surface reflectance dataset MOD09. DFDI has been developed from three parameters i.e., Potential surface temperature, Perpendicular Moisture Index and Modified Normalized Difference Fire Index (MNDFI). Finally, The Forest Fire Danger Index (FFDI) has been developed from the static and dynamic fire danger indices by the additive model and the overall accuracy was ranging from 86% to 95% and Area under Curve (AUC) values ranging from 0.81 to 0.91 during the major fire episode of 2018. Thus, the FFDI has been useful to assess the fire danger accurately over the study area and can be useful anywhere, where the meteorological stations are un-available. The procedure of calculating the DFDI and FFDI has been automated in R studio environment in near real time and therefore, the fire danger maps can be disseminated to fire officials in near real time for the quick actions to suppress the fire activities.

Keywords: forest fire, MODIS, forest fire danger index, DFDI, SFDI, MOD14

1. Introduction

The Fire Danger indices are used as a tool by decision makers to issue warnings to the public, based on the level of fire danger classes i.e., No danger, Low, Moderate, High and very High, for implementing the mitigation measures to control the fires. The Fire Danger index is an integration of both the dynamic and static fire danger indices. Fire danger indices are broadly classified into two types viz. long-term indices (structural indices) and short-term indices. Long-term indices are indicators of vegetation and topographic conditions as well as the anthropogenic factors that favor the occurrence of forest fires. Long term indices vary periodically like monthly and yearly and gives a clear understand about the spatial pattern of the fire events. Therefore, long-term indices have been used to determine the forest areas with high probability of fire occurrence. The variables for long-term indices are topography (elevation, slope, and aspect), vegetation type, proximity to settlements, distance to the roads, rail networks, and fire history. Whereas, short-term indices mainly consider parameters that changes sud-

denly and depend on factors influencing ignition and spreading the forest fires. The short-term variables are air temperature, relative humidity, wind speed and rainfall.

Fire Danger Models can be used to predict the probability of occurrence of forest fire based on the forest fuel characteristics, weather and topography. These are used in decision making for better management and control of forest fire. It can also be used as a tool to train and improve skills of firefighters and also to visualize, estimate and explain the behavior of fire, its spread and the control measures. At present, Canadian FWI (Fire Weather Index) approach was adapted in other countries such as Argentina, USA, and Alaska (Alexander and Cole, 2001; Taylor, 2006), Indonesia (De Groot et al., 2007), Malaysia (De Groot et al., 2007), Mexico (Lee et al., 2002); New Zealand (Alexander and Fogarty, 2002), Portugal (San-Miguel-Ayanz et al., 2003), Spain (Viegas et al., 1999) and Sweden (Granström, 2001) around the world for forecasting the fire danger on daily basis. The FWI calculation needs a set of automatic weather station parameters, such as air temperature, wind speed, and relative humidity during the mid-day; and point locations data of 24-h accumulated rainfall. The problem with the FWI is it employs the interpolation techniques, and it is evident that different interpolation techniques (for example, spline, kriging, IDW) may possibly generate different outputs even using the same set of data inputs. In other studies (Molders, 2008; Safi and

Bouroumi, 2013), statistical Numerical Weather Prediction model was used to calculate the Canadian CFFDRS danger indices and the US NFDRS danger indices at a spatial resolution of one degree to one degree i.e., $\sim 110 \times 110$ km^2, where the main problem is the low spatial resolution.

In this regard, geospatial techniques are useful with improved spatial and temporal resolutions for monitoring and forecasting the fire danger conditions (Ceccato et al., 2002; Bajocco et al., 2010; Leblon et al., 2017). Understanding the importance of satellite datasets, researchers started using the satellite derived parameters for fire danger estimations. These satellite based products are: "Normalized Difference Vegetation Index (NDVI)" (Leblon et al., 2007), "Enhanced vegetation index (EVI)" (Bisquert et al., 2012, 2014), "Vegetation Index green (VI green)", "Normalized Difference Infrared Index (NDII)" (Peterson et al., 2008; Sow et al., 2013), "Global Vegetation Moisture Index (GVMI)" (Sow et al., 2013), "Visible Atmospheric Resistant Index (VARI)" (Schneider et al., 2008), "Normalized Multiband Drought Index (NMDI)" (Wang et al., 2008) and "Normalized Difference Water Index (NDWI)" (Stow et al., 2005) as well as meteorological vari-ables such as "surface temperature" (T_S) (Oldford et al., 2006; Leblon et al., 2007), air temperature (T_a) (Nieto et al., 2011), Relative Humidity (RH) (Nieto et al., 2011).

The AVHRR-derived NDVI and TS images have been used in the calculation of the fire danger codes of the FWI system i.e., 'Fine Fuel Moisture Content, Duff Moisture Code, Drought Code, BuildUp Index, and 'Fire Weather Index code' (Oldford et al., 2006; Leblon et al., 2007) and the correlation shows that they have similar pattern, but it was observed that there is no direct relationship between these parameters. NDVI and surface temperature (T_S) were used to determine the live fuel moisture in the vegetation (Chuvieco et al., 2002). Live moisture can also be determined using greenness indices such as NDVI, VARI, VIgreen, EVI, and NDWI (Dennison et al., 2005; Dasgupta et al., 2007; Peterson et al., 2008) as these indices are more sensitive to changes in water content as well as the chlorophyll status in vegetation (Peterson et al., 2008). MSG-SEVIRI generated weather variables such as Ta and RH were used to determine the dead fuel moisture (Nieto et al., 2011).

Soil moisture is also an indicator for estimating the drought and forest fire danger. Soil moisture is an important variable for the growth of vegetation as well as the plant functionalities (Hari and Nojd, 2009) and indicate the weather and drought conditions in the forests (Fennessy and Shukla, 1999). In general, soil moisture can be estimated from the ground-based methods either direct or indirect, but, direct methods are time consuming and do not have the spatial variability. Surface wetness conditions can be estimated based on the relation between the vegetation index (VI) and Ts, the scatter plot of VI-Ts is to be a triangle or trapezoidal shape and surface wetness was calculated from the edges (Moran et al., 2004; Carlson, 2007; Petropoulos et al., 2009). Hassan et al. (2007) developed the "Temperature Vegetation Wetness Index (TVWI)" by using the potential surface temperature instead of

Ts to eliminate the effect of Terrain elevation and then combined with NDVI (Hassan et al., 2007; Hassan and Bourque, 2009).

In the studies carried out by Schneider (2008) and Huesca (2009), various indices such as "NDVI, VARI, and NDWI" were used as a substitute to live fuel moisture in determining the "fire potential index" (Schneider et al., 2008; Huesca et al., 2009). The results suggested that the indices "VARI" and "NDWI" have shown the best results of measuring the live fuel moisture conditions when compare to the "NDVI". Another index, "Normalized Multiband Drought Index (NMDI)" was used in assessing the drought conditions and can be computed as follows (Wang and Qu, 2007, 2009; Wang et al., 2008).

A very few studies have been carried out on the use of satellite data for the determination of probability of fire occurrence. Vidal and Devaux-Ros (1995) calculated the water deficit index (WDI) by relating NDVI and the difference between T_a and T_s and it effectively predicted the onset of fires (Vidal and Devaux-Ros, 1995). Guangmeng and Mei (2004) used MODIS-derived surface temperature over the forested regions of northeast China. They observed that surface temperature values were increased at least 3 days before the occurrence of fires, but, the rate of increase of the T_s values for fire occurrence were not quantified. Oldford et al. (2003) utilized the NOAA AVHRR-derived T_s and NDVI parameters over the northern boreal-forested regions of the Northwest Territories in Canada. The results of the study showed increased trend of the surface temperature values at least 3 days before the fire occurrences similar to previous study (Guangmeng and Mei, 2004), while NDVI did not show any indication of the fire occurrence (Oldford et al., 2003).

Akther and Hassan (2011) utilized the 8-day MODIS derived composites of "surface temperature", "Temperature Vegetation Wetness Index (TVWI)", and NMDI, over the boreal forested regions of Alberta, Canada for the years from 2006 to 2008 (Akther and Hassan, 2011). They found an accuracy of 91.6% of the fire pixels in "very high" to "moderate" danger classes. Chowdhury and Hassan (2015) used the MODIS derived parameters such as T_S, NDVI, NMDI, and Precipitable Water (PW). They revealed that 95.51% of the fires fell under "extremely high" to "moderate" danger classes. MODIS TERRA 16-day composite EVI datasets from 2001 to 2006 were used by Bisquert et al. (2012) for the computation of fire occurrence over Galicia, Spain and achieved an overall accuracy of 58.2% when compared with the actual occurrence of fires.

In light of above discussion, the present study describes the development of satellite-based forest fire danger index for Uttarakhand state of India as it does not have the sufficient number of meteorological stations especially in and around the forest. The developed forest fire danger index is an integration of the static and dynamic fire danger indices. The static fire danger index is based on the static variables like the forest types, topography and terrain characteristics whereas the dynamic fire danger index is based on the dynamic variables like air temperature, moisture conditions.

The forests of Uttarakhand state of India, are prone to forest

fires, causing loss of biodiversity and degradation of the environment. Most of the valuable plant and animal species are depleted due to the frequent occurrence of forest fires (Babu et al., 2016, 2018) The near real time fire alerts are being generated at National Remote Sensing Centre (NRSC), and Forest Survey of India (FSI) using the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor on TERRA and AQUA satellites and Visible Infrared Imaging Radiometer Suite data from the Suomi National Polarorbiting Partnership (SNPP-VIIRS). Active fire location information is disseminated to state forest departments within half an hour after the satellite overpass and also uploaded on the respective website. But hitherto operational fire danger rating system has not been developed in India except zonation of risk areas in protected areas. In this study, an attempt has been made to develop the Forest Fire Danger Index (FFDI) by integrating the static and dynamic fire danger indices by an additive model.
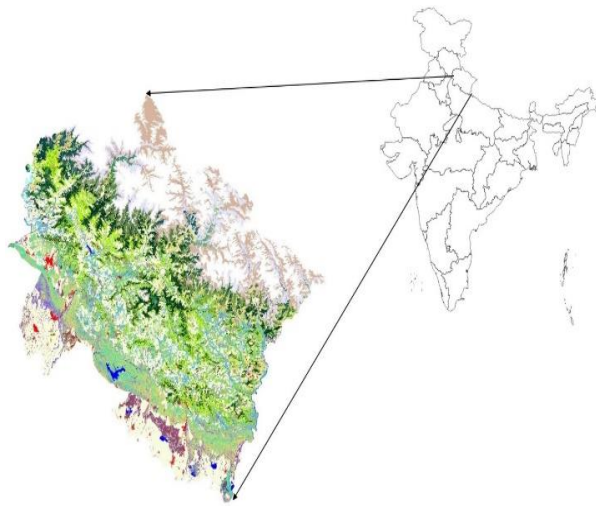

Figure 1. Study area – Uttarakhand state.

2. Study Area

Uttarakhand is a hill state in India, which shares an international border with China in the north and Nepal in the east. Uttarakhand lies between 28°43' N to 31°27' N latitude and 77°34' E to 81°02' E longitude. It has an area of 53,483 km² or 10.3% total geographical area of the Himalaya inhabited by 10.1 million persons living in 16,583 villages and 86 urban centers in 159 density per sq.km. At present, the state is administrated in 2 divisions, i.e., Kumaon and Garhwal comprising 13 districts: Almora, Bageshwar, Nainital, Champawat, Pithoragarh, U S Nagar (Kumaon), Dehradun, Haridwar, Pauri, Tehri Garhwal, Uttarkashi, Chamoli, and Rudraprayag (Garhwal). Further, these districts are divided into 52 Tehsils and 97 development blocks. Districts Haridwar and Udhamsingh fall into a plain area, whereas Nainital and Dehradun falls into both foothills and plain areas and rest nine districts totally lie in hill area. Uttarakhand has recorded forest area of 34,651 km², which is 64.79% of its geographical area

(ISFR, 2015) and Figure 1 shows the study area.

Uttarakhand is largely a rocky mountainous region, where the altitudes dramatically fluctuate between 300 to 7,817 m. As a result, high mountain ridges and deep river valleys are common features in the mountain area and great plain in the southern part of the state. This abrupt altitudinal variation has obviously resulted in a complex but interesting diversity in topography, meteorology, flora, fauna, demography etc. from the Gangetic plain in the south a comparatively less elevated rain shadow zone of Trans-Himalaya in the north. The large variations in altitudes, the slope, aspect, presence of glaciers, forests, and its geographical locations has resulted in varying climates in different parts of Uttarakhand state, even at the micro or local levels.

3. Satellite Datasets

MODIS is one of the widely used satellite sensors on board NASA TERRA and AQUA satellite datasets that scientists have been using for global and regional studies. Table 1 show the datasets used in this study to develop the Forest Fire Danger Index (FFDI). The datasets were taken during the major fire episode of Uttarakhand state i.e., April 16, 2018 to May 2, 2018.

Table 1. Satellite Datasets

Name of Datasets	Product ID	Spatial Resolution	Temporal Resolution
Land Surface Temperature	MOD11NRT	1 km	Daily
Surface Reflectance	MOD09GA NRT	500 m	Daily
Geolocation fields	MOD03	1 km	Daily
Digital Elevation Model	ASTER	30 m	-
Fire and Thermal Anomalies	MCD14	1 km	Daily

4. Methodology

In this study, Dynamic Forest Fire Danger index and Static Fire Danger Index has been integrated to develop the Forest Fire Danger Index. The Static Fire Danger Index (SFDI) was developed from the fuel type danger index, slope danger index, aspect danger index, elevation danger index, and terrain ruggedness danger index. Whereas the Dynamic danger index has been developed from three parameters viz. Potential surface temperature, Perpendicular Moisture Index and Modified Normalized Difference Fire Index using the near real time datasets, available through NASA Earthdata website after one hour of the satellite overpass. Figure 2 shows the methodology of the study.

4.1. Static Fire Danger Index (SFDI)

Static Fire Danger Index has been derived from the static parameters i.e., fuel, topographic and terrain characteristics,

which influence the spread of forest fires. SFDI was computed from the ASTER GDEM dataset and MODIS TERRA & AQUA land cover type product (MCD12Q1) (Babu et al., 2016 b). The SFDI was computed from the integration of five distinct indices i.e., Fuel type danger index, Terrain ruggedness danger index, Slope danger index, Aspect danger index and Elevation danger index (Babu et al., 2016b). Figure 3 shows the computation of SFDI by using packages raster, rgdal, Rcpp, sp, tiff, jpeg, EBImage, png, and locfit in R studio environment.
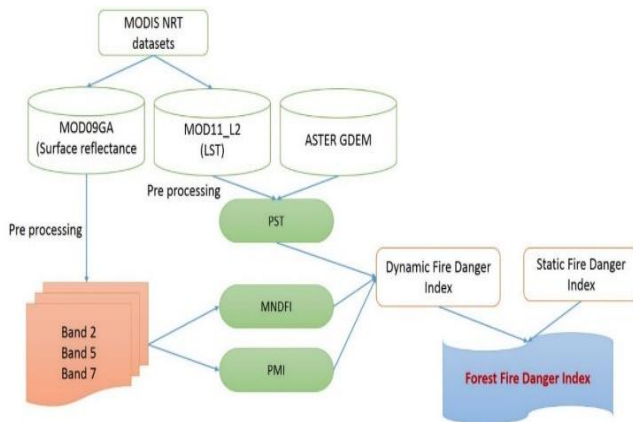

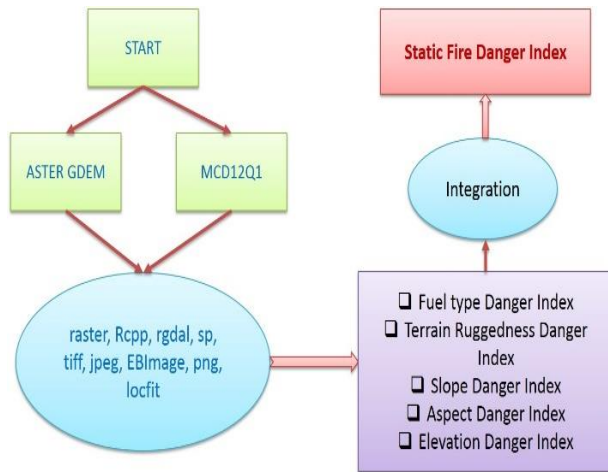**Figure 2.** Flow chart showing the methodology.

Figure 3. Structure of SFDI.

4.2. Dynamic Fire Danger Index (DFDI)

Dynamic forest fire danger index has been developed by integrating three parameters such as potential surface temperature, Perpendicular Moisture Index (PMI) and Modified Normalized Difference Fire Index (MNDFI), which were derived from the MODIS TERRA and ASTER DEM satellite datasets. Uttarakhand has variable hilly terrain so, elevation influences the Land Surface Temperature (LST) because LST decreases with the increase of elevation due to the pressure drops with the increasing of elevation. Hence, Potential Surface Temperature (PST) i.e., terrain corrected temperature has been computed

from the Near Real Time (NRT) Level 2 MODIS Terra Land Surface Temperature datasets (MOD11_L2) and ASTER GDEM using the Barometric formula. MODIS TERRA NRT surface reflectance dataset MOD09 has been used for generating the PMI and MNDFI.

This methodology has been taken from our previously published work (Babu et al., 2016a). The main difference from the previous work is temporal resolution and the level of satellite dataset processing. In this study, Near Real Time datasets have been used instead of the 8-day composite datasets. These near real time datasets are available within 1 hour of the observation time of satellite overpass, downloaded through an FTP website. In this study, individual parameters were computed and have assigned the danger values from 1 to 5 based on the danger classes. The DFDI has been computed by adding the individual parameters i.e., PST, PMI and MNDFI.

LANCE (The Land, Atmosphere Near Real Time Capability for EOS) supports the application users across the globe, who are working on the monitoring of natural resources and managing the disasters. LANCE NRT data available much quicker than general processing time, including the data and imagery from the sensors such as MODIS, AIRS, AMSR2, MISR, MLS, MOPITT, OMI, OMPS, and VIIRS (Earthdata website). DFDI has been computed from the Near Real Time (NRT) MODIS TERRA datasets, available through ftp server (ftp://nrt3.modaps.eosdis.nasa.gov/). Figure 4 shows the workflow to compute the DFDI in near real time by using R studio environment.
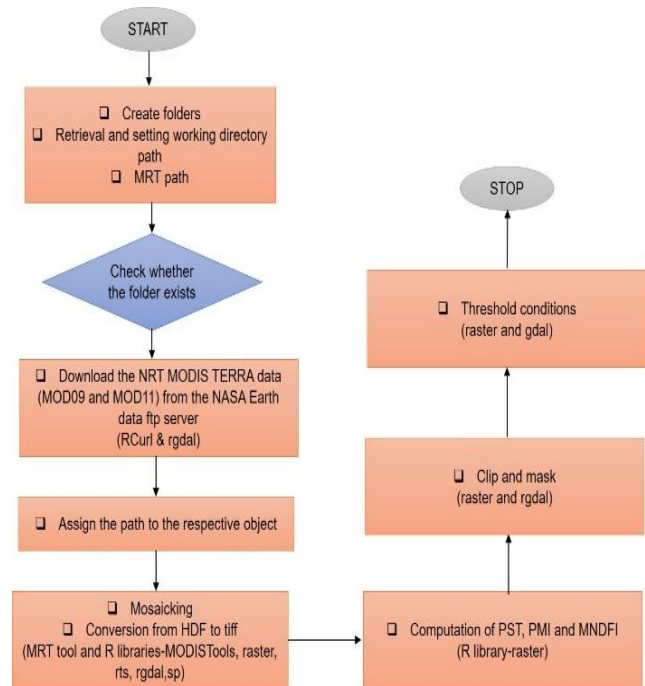

Figure 4. Workflow diagram of DFDI.

In the first step, MODIS NRT datasets can be downloaded from the http site or Earthdata website in tiles format. The Ut-

tarakhand state covers in 4 MODIS tiles i.e., h24v05, h24v06, h25v05, and h25v06. MOD09GA and MOD11_l2 data can be downloaded tiles wise and saved into local directory for further analysis. The downloaded MODIS datasets are in HDF-EOS format and in different 4 tiles for the Uttarakhand. The datasets have to be converted into easily readable format i.e., GeoTIFF and also mosaic to get the datasets in a single seamless file. MOD09 consists of several parameters such as Bands from 1 to 7 in 500 m spatial resolution, information about the band quality, solar zenith angle, view zenith angle. Bands 2, 5, and 7 are required to compute the indices PMI and MNDFI. MODIS Reprojection Tool (MRT), an open source tool developed by LPDAAC, has been used to read the hdf files. Next step shows the entire preprocessing of MODIS NRT datasets in R studio environment.
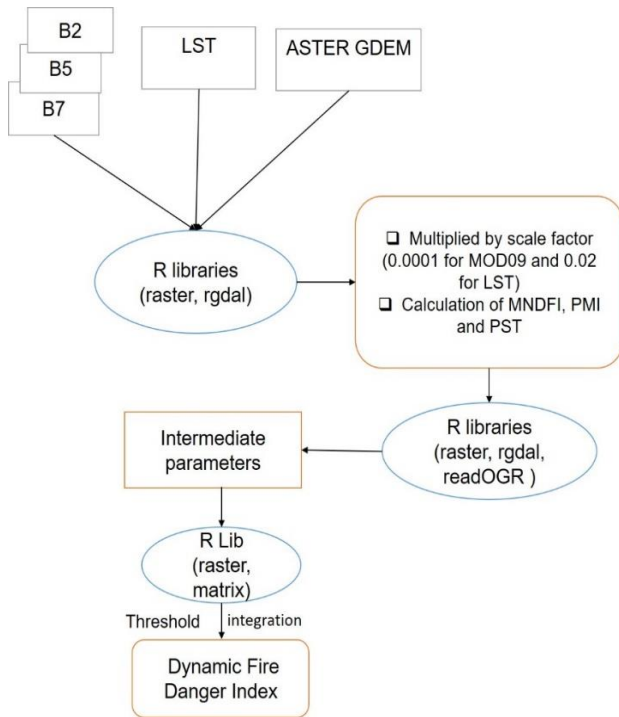

Figure 5. Steps involved in calculation of DFDI.

MOD11 dataset consists of the parameters such as land surface temperature (LST) of day and night, emissivity of band 31 and band 32, view time of day and night etc. The LST of day time has been extracted from MOD11 in similar way as like spectral bands. After getting the required datasets i.e., LST, Bands 2, 5, and 7 for each day, have been used to calculate the parameters PST, MNDFI, and PMI. The MODIS reflectance bands have to be multiplied by the scale factor 0.0001 to get the surface reflectance of B2, B5 and B7. Figure 5 shows the calculation of intermediate parameters and finally calculation of DFDI.

PMI (Maffei and Meneti, 2014) and MNDFI (Vermote et al., 2002; EijiNunohiro et al., 2007) has been calculated by using the Equations 1 and 2 respectively:

$$PMI = -0.73 \times (R5 - 0.94R2 - 0.028) \tag{1}$$

$$MNDFI = \left[\frac{Band7 - Band2 - 5\%}{Band7 + Band2 + 5\%} \right] \tag{2}$$

where R5 and R2 are the MODIS spectral bands 5 and 2 respectively.

PST can be computed from the MOD11_L2 NRT datasets by using the Barometric formulae:

$$p = p_0(1 - \frac{Lz}{T_o})^{\frac{gM}{RL}} \tag{3}$$

$$\theta_s = T_s \left[\frac{p_0}{p} \right]^{\frac{R}{Cp}} \tag{4}$$

4.3. Forest Fire Danger Index (FFDI)

The FFDI has been calculated by integrating the static fire danger index and individual dynamic forest fire danger index on each day because each index has its own influence on fire danger. The FFDI has been categorized into 5 fire danger classes such as "very high, high, moderate, low and no fire danger" and Table 2 shows the value of forest fire danger and the corresponding danger classes.

Table 2. Fire Danger Classes Assigned to FFDI

| S No	Forest Fire Danger Index value	Danger class
1	≤ 8	No fire danger
2	$9 \sim 16$	Low
3	$17 \sim 24$	Moderate
4	$25 \sim 32$	High
5	> 32	Very High

5. Results and Discussion

MODIS active fire hotspots have been used for validating the fire danger model in various studies as a proxy for the actual occurrence of fires (Chuvieco et al., 2008; Maeda et al., 2011; Adab et al., 2013; Eskandari and Chuvieco, 2015; Babu et al., 2016a, b). Similarly, in the present study, MODIS active fire product MCD14 has been used for the validation. FFDI has been computed daily by integrating both SFDI and DFDI after computing the DFDI from the NRT MOIDS TERRA datasets and categorized into 5 classes based on the threshold conditions as shown in Table 2. Figure 6 shows the forest generated fire danger maps overlaid with the fire hotspots during the major fire episode in 2018.
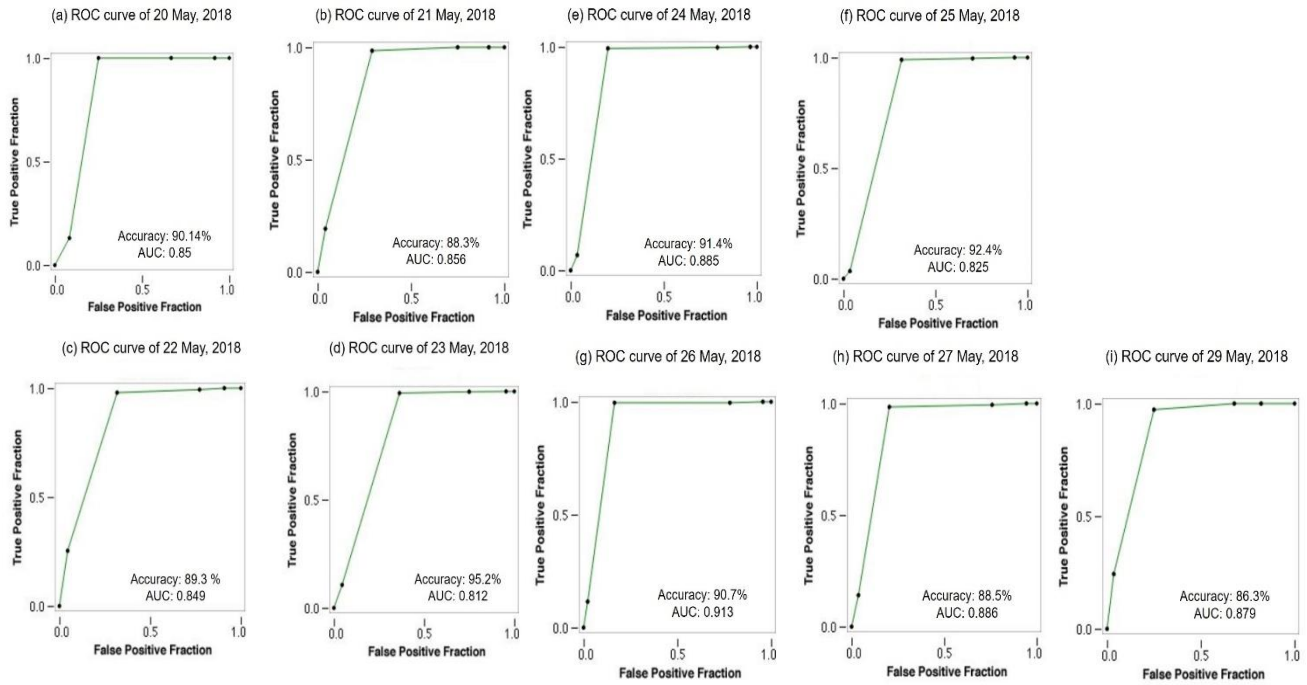
5.1. Fire Danger Index (FDI) - Validation

The number of fire hot spots in each fire danger class from no fire to very high danger classes were extracted. It would be
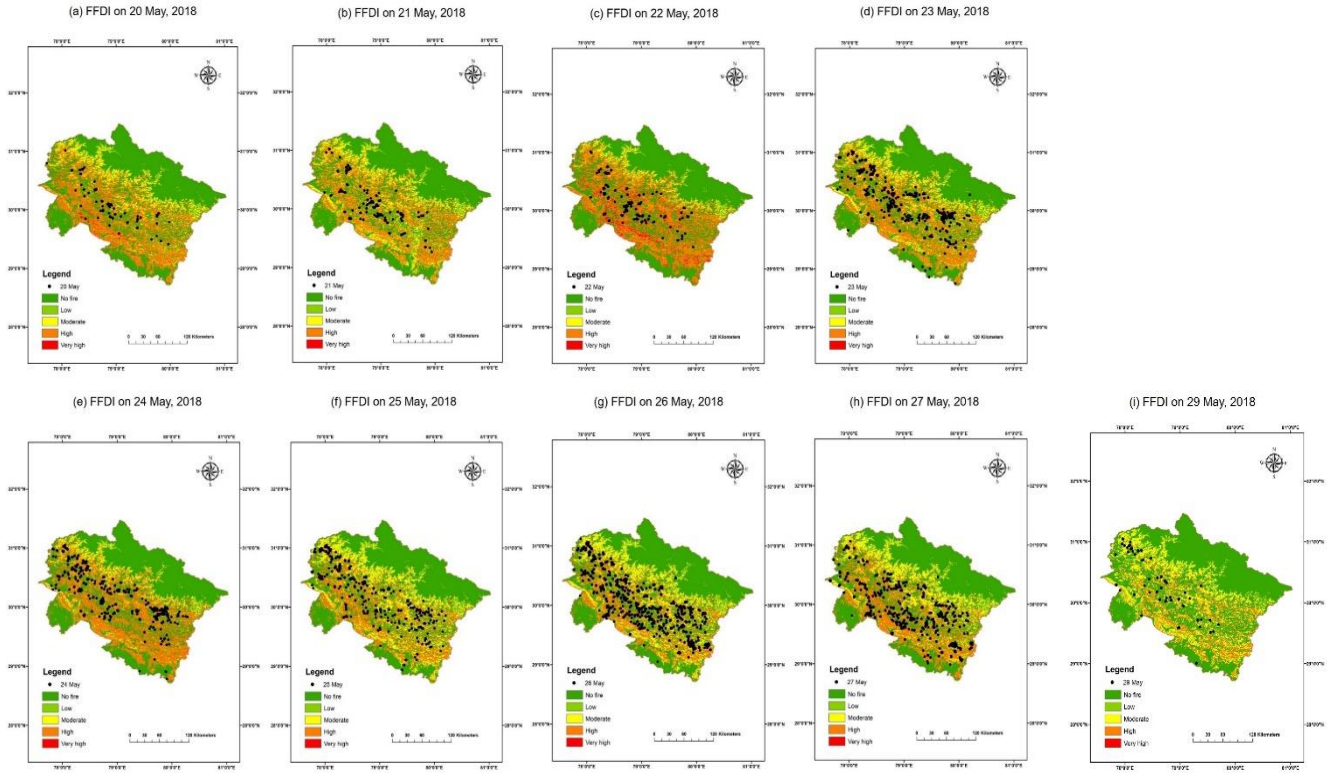
Figure 6. Forest Fire Danger Index images of 2018 were overlaid with corresponding active fire location data. (a) 20 May, (b) 21 May, (c) 22 May, (d) 23 May, (e) 24 May, (f) 25 May, (g) 26 May, (h) 27 May, (i) 29 May, 2018.

Figure 7. ROC curves and the AUC. (a) 20 May, (b) 21 May, (c) 22 May, (d) 23 May, (e) 24 May, (f) 25 May, (g) 26 May, (h) 27 May, (i) 29 May, 2018.

acceptable that the most of the fire hotspots should fell in high and very high danger classes rather than other classes of fire danger namely, no fire, low and moderate. It was assumed that the fires fell in high and very high fire danger classes are exactly predicted by the index, otherwise not predicted by the index. Receiver Operating Characteristic (ROC) technique is used for the effective validation of developed Fire Danger Index. ROC represents the probability curve while, the area under ROC curve (AUC) represents the degree of separability between classes and also expresses the quality of a prediction model (Yesilnacar and Topal, 2005). If the value of AUC is close to 1, then the result of model is excellent, where as the result of model is fairer when the AUC is near to 0.5. Figure 7 shows the ROC curves for the fire episode in 2018 i.e., 20 May ~ 29 May, 2016.

Figure 7, the accuracies and AUC during the fire event (May 20 ~ 29, 2018) are: 90.14%, 0.85 (May 20); 88.3%, 0.856 (May 21); 89.3%, 0.849 (May 22); 95.2%, 0.812 (May 23); 91.4%, 0.885 (May 24); 92.4%, 0.825 (May 25); 90.7%, 0.913 (May 26); 88.5%, 0.886 (May 27); 86.3%, 0.879 (May 29). It is clearly evident that the developed Fire Danger Index have the AUC values ranging from 0.81 to 0.91, that means close to one. If the result of the output is close to 1, the model performance was good, therefore, the FDI is useful to predict the fire danger accurately over the study area.

6. Conclusion

In this study, Forest Fire Danger Index (FFDI) has been developed from the static fire danger index and dynamic danger index. Static fire danger rating index has been developed from the terrain characteristics i.e., fuel type, slope, aspect, elevation, Terrain ruggedness danger index and danger levels have been assigned based on the historical fire data. MODIS Land cover type (MCD12Q1) and ASTER GDEM have been used to develop the static fire danger index. The SFDI is useful to understand the spatial pattern of fire occurrence in the study area and used to determine areas of high fire danger due to the fundamental conditions that leads to fire occurrence. The Dynamic fire danger index (DFDI) has been computed from the Near Real Time satellite datasets such as MODIS Terra Daily surface reflectance product (MOD09), MODIS Terra Daily land surface temperature (MOD11_L2), and ASTER Digital Elevation Model (DEM). Three parameters Potential Surface Temperature (PST), Perpendicular Moisture Index (PMI), and Modified Normalized Difference Fire Index (MNDFI) have been calculated and were used to generate the dynamic fire danger index.

The computed accuracy was ranging from 86% to 95% and AUC values ranging from 0.81 to 0.91, close to one i.e., the FFDI performance was good. Thus, the developed index has the potential for predicting the forest fires using the satellite derived products. The Forest Fire Danger Index has been computed from the near real time datasets, which can be downloaded from the HTTP server after the pass within one hour. The fire danger maps can be disseminating the forest fire danger maps to the forest officials for the controlling activities of forest fires. We are planning to upload the fire danger maps into the web portal in near real time so that fire danger maps can be accessed by public for precaution measures to control forest fires.

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