DEVELOPING FOREST FIRE DANGER INDEX
USING GEO-SPATIAL TECHNIQUES

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by

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CERTIFICATE

This is to certify that Mr. Suresh Babu K V, Ph.D. has carried out dissertation entitled "**Developing Forest Fire Danger index using geo-spatial techniques**" in partial fulfillment of the requirements for the award of Doctoral degree in Spatial Informatics. This work has been carried out under the supervision of Dr. Arijit Roy, Head, Scientist/Engineer-SF, Disaster Management Studies, Indian Institute of Remote Sensing, ISRO, Dehradun and Dr. P. Ramachandra Prasad, Assistant Professor, Lab for Spatial Informatics, International Institute of Information Technology, Hyderabad, India.

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Dedicated

to

My Lovely parents

Satyanarayana and Kalavathi

&

My Inspiration

Supriya

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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 warnings to the public on the basis of fire danger index classes. Generally, fire danger indices are developed based on the meteorological stations in countries like Canada, United States of America, Australia, etc. Geospatial techniques such as satellite remote sensing based approaches can be useful to develop the fire danger indices in those countries that lack sufficient meteorological stations. In general, fire danger indices have been developed based on the parameters which are associated for the cause of ignition and spreading of forest fires. These properties include forest fuel type, topographic conditions and moisture conditions. Vegetation and topographic conditions are static, i.e. they do not change frequently, whereas moisture conditions are dynamic. Dynamic properties such as air temperature, relative humidity, moisture conditions changes regularly in a day. In this study, Static Fire danger Index has been developed using MODIS (Moderate Resolution Imaging Spectro Radiometer) Land cover type yearly L3 global 500 m SIN grid (MCD12Q1) and ASTER Global Digital Elevation Model datasets. International Geosphere-Biosphere Programme (IGBP) land cover type has been generated from MCD12Q1, which has been used to compute the forest fuel type index based on historical fire data. Fuel type danger index, Terrain ruggedness danger index, Slope danger index, Aspect danger index and Elevation danger index were computed from the ASTER GDEM datasets. Uttarakhand state has very few meteorological stations so geospatial techniques can be useful to derive the fire danger indices. Several authors developed the fire danger indices based on satellite derived parameters such as land surface temperature, vegetation and moisture indices such as "Normalized Difference Vegetation Index, Normalized Difference Water Index, Normalized Multiband Drought Index, Visible Atmospheric Resistant Index" etc. In this study, Dynamic Fire Danger Index (DFDI) has been developed from three parameters i.e. potential surface temperature, Perpendicular Moisture Index (PMI) and Modified Normalized Multiband Fire Index (MNDFI) using the MODIS Terra satellite datasets. 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). Finally, Forest Fire Danger Index (FFDI) has been developed by integrating both the Static and Dynamic fire danger indices and also used the near real time data sets that can be available for download through NASA FTP server

after one hour of the satellite overpass. The overall fire danger prediction accuracy was around 81.27% for the year 2016. 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 entire procedure of calculating FFDI from NRT datasets was semi-automated so that the fire danger maps will be disseminated to the fire officials for taking timely action in controlling the forest fires.

Keywords: Forest fire, Forest fire danger index, MODIS, MCD12Q1, ASTER GDEM.

Contents

List of Abbreviations

ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advanced Very High Resolution Radiometer
COMS	Communication, Ocean, and Meteorological Satellite
DDI	Disaster Disturbance Index
DFDI	Dynamic Fire Danger Index
ENSO	El Niño Southern Oscillation
EVI	Enhanced Vegetation Index
FFDI	Forest Fire Danger Index
GOES	Geostationary Operational Environmental Satellite
GPS	Global Positioning System
GVMI	Global Vegetation Moisture Index
IGBP	International Geosphere-Biosphere Programme
LAI	Leaf Area Index
LST	Land Surface Temperature
MNDFI	Modified Normalized Difference Fire Index
MODIS	Moderate Resolution Imaging Spectroradiometer
MSG	Meteosat Second Generation
NDI	Normalized Difference Index
NDII	Normalized Difference Infrared Index
NDWI	Normalized Difference Water Index
NDVI	Normalized Difference Vegetation Index
NMDI	Normalized Multiband Drought Index
NIR	Near Infra-red
NOAA	National Oceanic and Atmospheric Administration's
PMI	Perpendicular Moisture Index
PST	Potential Surface Temperature
RH	Relative Humidity
RS	Remote sensing
SAVI	Soil Adjusted Vegetation Index
SFDI	Static Fire Danger Index
SWIR	Short wave Infra-red
TVWI	Temperature Vegetation Wetness Index
VI	Vegetation Index
VI green	Vegetation Index green
VARI	Visible Atmospheric Resistant Index
VIIRS	Visible Infrared Imaging Radiometer Suite

List of Tables

List of Figures

Chapter 1: Introduction

Forest fires, either natural or anthropogenic occur throughout the world, causing adverse environmental, economic and ecological impacts (Pyne et al., 1996, Crutzen & Andreae, 1990; Penner et al., 1992; Cochrane, 2003). Forests play a crucial part in the quality of life on the earth as they comprise a most of the renewable natural resources as well as provide ecosystem goods and services. Forests serve as a primary source of many non-timber and timber products and plays significant role to sustain human life on the earth by maintaining the suitable environmental conditions. According to a UN study, the earth had about 4128 million ha of forest area in 1990; and had decreased to 3 999 million ha by 2015, Which means a reduction from 31.6 % (1990) of global land area to 30.6 % (2015) (FAO, 2015). One of the factors which are resulting in the degradation of forests is the forest fires or wild fires.

Most of the forest fires around the world are caused by anthropogenic activities. The most common natural cause of forest fires is the lightning (Higgins, 1984). "Fire being a good servant and a poor master" (Viro, 1974), has been responsible for the huge destruction of forest resources including wildlife, soil bio-constituents and biota, endangering human life and property (Trollope Winston & Trollope Lynne, 2004); though fire has been used as a tool to manage land clearance for centuries as well as the source of forest regeneration and nutrient recovering especially nitrogen. The UN World Conference on Disaster Risk Reduction has established GP- STAR ("Global Partnership using Space Technology Applications for Disaster Risk Reduction") in Sendai, Japan, on March 15, 2015. GP-STAR is a platform aims to foster the use of Space based Technologies and Applications as well as Earth observations in the background of the Sendai Framework for the reduction of disaster risk during 2015-2030 (www.unisdr.org).

Presently, there is a good system for forest fire alerts using geo spatial technology but, not for forest fire danger prediction. . So, there is a need to develop a modelling framework for forest fire danger to predict the chances for forest fire occurrence so that necessary mitigation measures are taken to control the fire spread to other forest areas. Fire danger can be defined as the result of both static (fuel and topographic characteristics) and dynamic (weather parameters) factors of fire environment affecting the initiation, propagation of fire and potential to do destruction (Chandler

et al., 1983). "Fire Danger Rating System" (FDRS) is a Decision Support System (DSS) which takes into consideration of all the factors affecting the fire danger and indexing them into different classes for the purpose of issuing warnings to the public, implementing the mitigation measures for controlling fires and for setting up measures to protect valuable forest resources. Fire Danger Index (FDS) is categorized into danger classes to provide a rating such as "low, moderate, high, very high and extreme".

1.1 Types of forest fire

Fires can be categorized into 4 types based on the geographical location, where the fire started. These are creeping, ground, surface and crown fires. Creeping fires spread gently over the forest ground surface burning with a low intensity flame. In ground fires, most of combustion process happens underground. These fires occur when decomposition of leaves and other plant material along with other dead flora become dry sufficient to initiate fire. Ground fires move very slowly on forest floor, but, it is very difficult to suppress as it is subsurface and can burn longer days to months also. The common type of forest fire is the surface fire, it may be primarily confined to the forest surface, spreads along the ground floor as the litter catches the fire and are surrounded by the spreading flames. Surface fires spread so quickly due to high susceptibility of the fuel in smaller area. So, these fires are reasonably easy to control by stopping the continuous fuel supply through constructing firelines. Crown fire is the most destructive among all types, in which the crown of trees and shrubs burn. However, crown fires do not burn all the biomass due to the fact that tree trunk and woods need to burn for longer times before they turn into ashes. These types of forest fires are very dangerous, particularly in coniferous forests as these trees have a large amount of resins and sap, which burns very quickly and they grow much closer together.

From the above, it is clear that crown fire is very difficult to control, especially under strong wind condition, Aerial suppression by dropping water and fire retardant from specially designed airplanes is the only effective method to control these fires. In most cases, crown fire will continue to burn until it consumes all the organic matter (fuel) or there is a sudden change in weather conditions such as rain, snow, etc. Figure 1.1 shows the different types of forest fires occur throughout the world.

Fig 1.1 Types of Forest fires (Satendra and Kaushik, 2014)

1.2 Global fire scenario

Fires occur in various parts of the earth and maximum of these fires are caused by anthropogenic activities, including illegal activities and very few natural causes of ignition. Forest fires are most occurring event in North America, Asia, Europe, Africa, South America and Australia. The Figure 1.2 shows the occurrence of forest fires during the time period from March 12 to 17, 2017.
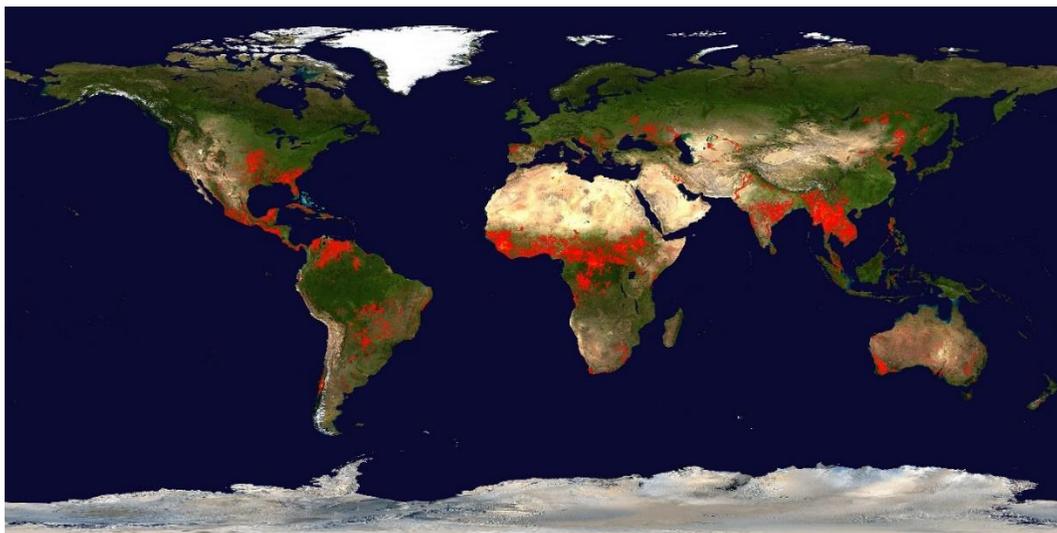
Fig 1.2 Forest fire hotspots during March 12-21, 2017 (source: Lance MODIS)

1.2.1 North America

Canada has about 9% of the world's forests as per the reports of Natural resources of Canada. Forest fire is natural phenomena in Canada especially in boreal region, which has the largest forested area in the country. The total forest burned area in Canada varies from year to year, but on an average about 2.5 million ha of forest burn annually. Fire management activities such as fire suppression and controlling measures costs ranged from $500 million to $1 billion a year over the last 10 years in Canada (Natural Resources Canada). Crown fires are more dominant in the boreal landscape. In USA, extreme drought conditions, high winds and combustible fuel types play a major part in the behavior of high-intensity forest fires. A number of systems have been used over time in classifying fire regimes in the USA (Hendee et al., 1978; Agee, 1993; Morgan et al., 1994; Frost, 1998). Fire severity has been the basis for classifying the fire regimes (Brown & Smith, 2000) as fire regimes directly relates to the effects of disturbance, especially on the type and structure of the prevailing forest cover. According to the newspaper reports, forest fires burned more than 119,000 ha in eight states and smoke was released through most of the Southeast US in the year 2016.

1.2.2 Europe

Similar to US, forest fire is considered as one of the main disasters in European countries, especially in countries like France, Portugal, Italy, Greece and Spain. During 1971 to 2000, number of forest fires in a year has increased from 40,000 (1971-1980) to 95,000 (1991-2000). In the historical record, one of the largest forest fires occurred in 1888; it started in the suburb of Maroussi near Athens in Greece burned more than 16,000 ha and suppressed only when it reached the sea (Tedim et al., 2015). In the year 1949, the largest fires occurred in Landes forest in southwest France burned about 50,000 ha of maritime pine forests and 82 firefighters lost their lives in trying to control the fire (Tedim et al., 2015). In Portugal, about 2,660 ha forest area burned during the fire of Serra de Sintra, and killed 26 firefighters in the year 1966 (Tedim et al., 2015). In another fire incident in West Germany (1975), about 7,418 ha of forest mainly of pines was burned, killing 6 firefighters (Tedim et al., 2015).

1.2.3 Africa

Africa has some of the driest and most fire prone ecosystems in the world. UNESCO defined three major vegetation formations Sudanian, Guineo-congolia/sudania and Guineo-congolia in the Central African Republic (White, 1983). These three vegetation formations of dry and wet savannahs in north, central and south are covered by humid forests of the Central African Republic (International Forest Fire News, 2001). Fires have been a regular occurrence throughout tropical savannas and forests for more than hundred years (Goldammer, 1990). Fire season starts around November in the northeast of the country, and reaches peak in the month of December or January following the Harmattan winds in the southwest of the country. Fire season in African continent terminates with the onset of rains in the month of March.

1.2.4 Asia

Asia which has a huge population also has some of the most pristine forests in the world. This includes the countries like India, China, Indonesia, Sir Lanka and Malaysia. China has rich forest resources with total forest cover of about 158.9 million ha in the year 2002, which is 16.55 % of the total geographical area of the country (Lifu & Xiaorui, 2002). Forest fire has been a major threat to forests of China and was evident after massive forest fire occurred in Daxing'anling Mountain in Heilongjiang Province during May 1987. This fire has burnt about 1330 ha of forest area and resulted in the death of 213 persons (Shu et al., 2003). The number of forest fires occurred in 5 provinces (Heilongjiang, Yunnan, Inner Mongolia, Guizhou and Guangxi) are about 42.5 % of the countrywide and 75% of the damaged area affected by forest fire in the China during the period of 1950 to 1998. The extent of decrease in forest cover in these regions was 14.5% i.e. from 76% to 61.5% (Zhang & Qingwen, 2008). Damaged area due to annual fire is about 0.8% of the entire forest area of the country, and experiences more than 8 times damage extent annually compared to the world average (Zhao, 2003).

In Indonesia, fire has long been used as a tool to clear forest area for agriculture. The first large forest fire in Indonesia was reported in the second half of the 20th century, happened during the "E1 Niño-Southern Oscillation (ENSO)" event of 1982 to 1983. World Wildlife Fund (WWF) and the "Canadian International Development Research Centre's Economic and Environment project in South East Asia (EEPSEA)" estimated that, the economic loss due to fires that covered three

countries (Indonesia, Singapore and Malaysia) reached 1.45 billion dollars during the period 1997-98 (Detri Karya et al., 2017). According to the report of Indonesian government, 2.6 million ha of forest area burned between June and October 2015 (Glauber et al., 2016). The World Bank estimated that the forest fires in 2015 cost Indonesia as a minimum of USD 16.1 billion (IDR 221 trillion), which is nearly 1.9 % of GDP of that year (Glauber et al., 2016).

In Malaysia, most of the forest fires occurred mainly in the Pinus forest types during the year 1970 and in *Acacia mangium* type during the year 1980 (IFFN, 1988). Fires occur occasionally in natural evergreen rainforests, while the forest areas those connected to cultivated locations are also prone to fires. The major forest fires experienced were during 1982 to 1983, nearly 1 million ha of forest burned in Sabah (International Forest Fire News, 1988). Forest fire incidents occurred mainly in the forest plantations and degraded peat swamp forests. The occurrence of forest fires also increased considerably during the ENSO period of years, due to elongated dry conditions.

1.2.5 Australia

The most forest fire prone continent is Australia, where wild fires mainly occur in deserts and rainforests. Fires occur throughout the year in some part of the continent. Southeast corner of the country is one of the most fire prone regions across the world. This is due to the presence of dominant species Acacia and Eucalyptus. Climate of Australia ranges from monsoon tropics of the north to mid-latitude Mediterranean in the south. Whereas the vegetation ranges from grasslands and open woodland in the north while the southern region consists of Eucalyptus forests and scrublands. Hence the forest fires are common throughout the year in some regions due to the combination of climate and vegetation.

1.2.6 India

Forest fire is considered as one of the major causes of degradation to forests in India. The forest area prone to fires in the states of India is between 33% to 90% annually (Roy, 2003). The first ever evidence of forest fire in India occurred about 200 million years ago (Narendran, 2001). As per the state forest report, the forest cover in India is 70.82 M ha, constituting 21.54 % of its geographical area, represented by 9.81 M ha (2.99 %) of very dense forest, 30.83 M ha (9.38%) of moderate dense forest and 30.17 M ha (9.18 %) of open forest (ISFR, 2017). In India, forest

vegetation composition varies from tropical evergreen forests in the Andaman and Nicobar islands and in the Brahmaputra basin in Northeast India, to alpine forests in the Himalayas. These forests further sub divided into Semi-evergreen forests, sub-tropical broad-leaved hill forests, deciduous forests, sub-tropical montane temperate forests, and sub-tropical pine forests. The most common forest types are tropical dry deciduous (38.7%) and tropical moist deciduous (30.9%), which are extensively affected by forest fires (ISFR, 2003). According to Forest Survey of India (FSI), about 53 % forest cover is prone to a range of fire regimes heavy to light (ISFR, 1997) and 6.17% of the forests cover to huge fire damage in India. The forest departments carry out controlled firing along fire lines of 5 to 10 m width, which have the most probability of fire occurrence due to the human activities.

According to the International Forest Fire News (IFFN)-2002 report, the environmental and economic consequences of forest fires in India include: Loss of fuel wood, fodder and valuable timber products (teak, Deodar, Sal, Chir-pine, Rosewood etc.), bio-diversity, wildlife habitat, carbon sink, natural regeneration and increase in global warming, and soil erosion, loss of, loss of and finally forest cover reduction (IFFN, 2002). Vegetation type, topography and the climatic conditions are the main factors for the vulnerability of forests to wild-fires. The coniferous forests are the most prevalent forest types in the Himalayan region, consisting of fir (*Abies*spp), spruce (*Piceasmithiana*), Deodar (*Cedrusdeodara), Chir*-Pine (*Pinusroxburgii)* and Blue-Pine (*Pinuswallichiana)* etc. and are most susceptible to fire. Deciduous forests dominated in other parts of the country are also more vulnerable to fire.The fire season varies with the different regions of the country. They occur between the months of February to June in the northern and central part of India. While in the hills of northern states fire season starts in the month of March and continue till the mid of June. In the southern part of the country, fire season starts from January to May.

In India, most of the fires are of anthropogenic origin (Bahuguna, 2002) and natural causes are very few. A significant number of forest fires, may be intentional due to the socioeconomic conditions prevalent in the region (Roy, 2003) such as: (1) to promote better growth of grass in the next season, (2) collection of minor forest products and (3) grazing activities. In addition to these, negligence of the tourists is also responsible for initiating the forest fires.

1.3 Impacts of Forest Fires: Ecology, Economy and Environment

Forest fires have numerous direct and indirect impacts on global forest resources. Fire directly influences on vegetation development where the landscape experienced frequent fire episode (Covington & Moore, 1994; Goldammer & Seibert, 1990; Morgan et al., 2001). Forest fires have serious consequences on human health and on the socio-economic status of the countries that are affected by fires.

The annual average loss estimated due to the forest fires is Rs.440 crore (US$ 100 million) in India (IFFN, 2002). It's very difficult to quantify the economic loss due to the forest fires, but, "Economy and Environment Programme for Southeast Asia", estimated the cost of damages during Southeast Asian fires due to various causes in greater than $4 billion. According to the study conducted on the Economic Analysis of Indonesia's 2015 fire crisis, about 2.6 million ha of land burned during the months from June to October in the year 2015, an area equal to the four and half times the size of Bali, and estimated loss is around USD 16.1 billion (Glauber et al., 2016). The estimated loss of forest in Uttarakhand state was around 4000 ha during April to May, 2016.

Smoke emitted from forest fire consists of a mixture of "carbon dioxide" (CO_2), "water vapour" (H_2O), "carbon monoxide" (CO), organic components such as "formaldehyde" and "acrolein", "nitrogen oxides" (NOx) and numerous minerals and suspended particles. Greenhouse gases such as CO_2, NOx along with CO and organic components in significant large quantities are a cause of serious health risk to humans, residing close proximity to the location of forest fires (Bowman & Johnston, 2005). Studies suggest that 20 million people were in danger of breathing problems due to Southeast Asia forest fires during 2015. The smoke and particulate matter from Indonesian forest fires during 1997-98 had affected health of 70 million people in Indonesia, Malaysia and Singapore (Kinnaird & O'Brien, 1998).

Another major consequence of forest fires is their impact on climate change through contribution of biomass burning to release the greenhouse gases such as CO_2, CO, CH_4, NO_2, O_3 and carbon constituents. Biomass burning is considered as an important worldwide source of emissions and contributes around 40% of CO_2 and 38% of ozone (Levine, 1991). Forest fires also increase the air pollutants and the instantaneous concentration of particulate matters (PM) in the atmosphere during the period of forest fires and pose serious health risks (Sofowote & Dempsey, 2015).

1.4 Factors responsible for fire occurrence and spread

For forest fires to occur, the presence of factors conducive to fire occurence is essential. The conditions conducive to forest fire risk can be broadly categorized into two types as ignition factors and spreading factors - responsible for initializing and spread of forests fires.

Ignition factors: Forest fires are initiated either naturally or by anthropogenic activities (Negi, 1986). Anthropogenic activities are two types i.e. intentional and unintentional. Anthropogenic causes, which may be due to negligence or deliberate or unintentional. The main causes of intentional forest fires are: Burning of forest floor purposefully to enrich soil with nutrients so that the productivity increases in the following season; for shifting cultivation; setting fires around forests for recreation; sometimes forest fire are induced to flush out wild animals by villagers or by smugglers. While the unintentional fires are due to human carelessness without having knowledge to set fire such as uncontrolled campfires by tourists, workers etc.; Spark of fire from wheels of railway engines or locomotives; burning bidis, matchsticks, cigarettes etc. left behind by travelers, grazers and forest workers; negligence of forest staff during the controlled burning by the forest department.

Natural factors: lighting, volcanic eruption, rolling stones etc. Lightening can cause fires, especially hot lightening, which can last for a very long time and produce a spark that can result in igniting the fuel content in the forest either the standing wood or the litter. Hot burning lava from the volcanic eruptions also causes forest fires especially in the volcanic active regions of the world like Hawaii, Barren Island, etc.

1.5 Fire spread factors

Three main factors are considered to be responsible for the spread of forest fires:
(1) The fuel, which includes forest type, fine fuel moisture content and inflammability of fuel. (2) Topography is an important parameter, wherein slope, aspect and elevation play a major role in spread of forest fire. (3) Weather, which is a dynamic factor influences fire ignition and spread and involve parameters like relative humidity, air temperature, wind speed and rainfall (Roberto Barbosa et al., 2010).

Vegetation cover and fuel: There is a strong relationship between the vegetation type and forest fire intensity and frequency as each vegetation type has different fire proneness due to flammability of vegetation. In general, coniferous forest is more prone to fires than deciduous forests, because of the lesser moisture content and higher resin/oil content in coniferous vegetation. Fuel is an important parameter because it influences the ignition potential as well as the intensity of forest fire (Pyne et al., 1996). The state and type of the fuel describes the characteristic of forest fires. Fuel can be either living organic material like grass, shrubs, trees or dead material like fallen branches, leaves, needles, twigs etc. The size, moisture content, chemical composition of fuel influences the fire behavior and intensity.

Topography features such as slope, aspect, elevation can influence the fire spread and behavior. Generally, fire travels up the slope as compared to down the slope and influences rapid increase of the fire spread (Kushla & Ripple, 1997; Butler et al., 2007). Steepness of the slope influences the intensity of solar radiation and fuel moisture and also the rate of fire spread. Aspect represents the direction of the slope, and based on the northern or southern hemisphere the amount of solar radiation and the type of vegetation present is determined. In the northern hemisphere, southern slopes receive more solar radiation as compared to the northern slopes so vegetation starts to dry by February-March in slopes on the southern aspect and are highly dried during the summer season. In contrast, slopes in the northern aspect are cooler and moist so drying up the vegetation is relatively slower. Elevation influences the amount of precipitation as well as the wind speed and therefore affects the fire behavior along with the drying period of the vegetation. In lower elevations, vegetation tends to dry out sooner as compared to the higher elevations due to higher temperatures and lower precipitation in the lower altitudes.

Weather being a dynamic factor in the fire environment triangle changes regularly. "Temperature", "relative humidity", "wind speed" and "precipitation" are the main weather factors for fire occurrence. These influence how much time and to what degree the vegetation dry out during the summer season. Longer time periods of low relative humidity and higher wind speeds rapidly dry the vegetation. This resulting fuel with low moisture content is highly susceptible to fire incidents and rapid spread. The variation in temperature and relative humidity influence the intensity and rate of fire spread under a given set of meteorological conditions.

Air temperature (AT) is an essential variable, describing the fire behavior as it directly influences the temperature of the fuel and indirectly influences the relative humidity and loss of moisture in the vegetation. Air temperature plays significant effect on the fire spread and intensity in South African grasslands and savannas (Mapiye et al., 2008; N'Dri et al., 2018). RH influences the moisture content of the vegetation and is positively correlated with fuel moisture content of the vegetation. Wind speed influences the fire behavior as it provides oxygen for fire spread and also forces the angle of fire flames into the unburned forest area and increase the rate of fire spread (Kennedy et al., 1994).

1.6 Global fire prevention methods

Fire prevention methods refer to the approaches of reducing the danger of forest fire as well as controlling its spread. Timely detection of forest fire is the key to forest fire management. In US, the fire watch towers were installed to detect the fires in the early 19th century and were reported using mobiles and heliographs (Alkhatib, 2014). In 1950s, aerial and terrestrial photographs were used and then infrared (IR) scanning was developed in the 1960s for the detection of forest fires. However, analyzing the information and dissemination was delayed in this communication technology.

A fire prevention system involves integration of different systems that can incorporate the satellite remote sensing data, aerial photography and Global Positioning System (GPS) information in near real time for monitoring of forest fire and its dissemination through either satellite based or terrestrial communication system. Satellite and aerial based monitoring provide a synoptic cover and provide critical information to monitor large areas. Satellite sensors such as "Envisat's Advanced Along Track Scanning Radiometer" and "European Remote-Sensing Satellite's Along-Track Scanning Radiometer" can measure IR radiation emitted by fires, identifying fire hot spots which are higher than 39°C (102 °F). The "National Oceanic and Atmospheric Administration's (NOAA)" Hazard Mapping System combines satellite data of sensors such as "Geostationary Operational Environmental Satellite (GOES)", "Moderate-Resolution Imaging Spectroradiometer (MODIS)", and "Advanced Very High Resolution Radiometer (AVHRR)" for the fire and smoke plume detection.

1.7 Controlling forest fires in India

There has been a long history of forest fire incidences in Indian forestry. The traditional methods of fire protection cover an intricate network of forest fire lines, fire watch towers, and guidelines (Roy et al., 2012). One forest guard watches the 500 ha of forests and it is not sufficient to detect and prevent forest fires efficiently through human intelligence alone. On the other hand, vast tracts of deciduous forests in the Indian landscape coupled with the increasing biotic pressure like grazing, fuel wood extraction makes fire management more challenging complex. Current statistics of forest fire episodes and their ecological as well as the economic impacts stress the need to have a well-managed system in monitoring and mitigation of fires which include a suite of space-based and ground-based season. Several state forest departments, FSI, Universities and different scientific institutions are carrying out research and studies towards scientific and efficient forest fire management in India. These studies are mostly local specific and address the regional and national perspectives of fire management to a limited extent. Thus, there is an urgent need for national level for generating information on fire monitoring, damage assessment and mitigation planning by integrating   information for fire management in India.

1.8 The Indian Forest Fire Response and Assessment System (INFFRAS)

Under the disaster management activities of the Department of Space, a comprehensive system "Indian Forest Fire Response and Assessment System (lINFFRAS)" was initiated to integrate different sensors satellite data and ground data through geospatial techniques. The activity has been carried out during the fire season of India, every year to provide the needs of the state forest departments for mitigation and management of fires. Presently, INFFRAS has been integrated with BHUVAN and daily fire alerts are being provided by NRSC through BHUVAN portal. The BHUVAN portal is designed to reach the below three requirements of the Indian forest departments.

1) Pre fire: Preliminary planning for controlling the forest fires; 2) During fire: active fire detection and monitoring in near real time during the fire season i.e. Feb to June, every year 3) Post fire: Damage and recovery assessment based on the satellite datasets and mitigation planning for controlling the fires.

Daytime near real time forest fire alerts are based on MODIS sensor on board "Terra" and "Aqua" satellites and VIIRS sensor on board NASA/NOAA Suomi National Polar-orbiting Partnership (SNPP) satellite datasets. Night time alerts are based on DMSP-OLS data received from the US National Geophysical Data Centre under ISRO-NASA-NOAA collaboration. Indian Remote sensing Satellite data has been used to develop information on burnt area assessment. Figure 1.3 show the forest fire alerts in Bhuvan portal.

Also, NRSC & Forest Survey of India (FSI) have been disseminating the fire alerts to the State Forest Departments and other registered users, detected by the MODIS sensor on board Terra and Aqua Satellites of NASA since 2004. From 2017, FSI has also started disseminating the fire alerts obtained from SNPP-VIIRS sensor, which has a better resolution (375 m) compared to MODIS (1 km). These alerts are disseminated up to beat level for the states, namely Andhra Pradesh, Bihar, Himachal Pradesh, Jharkhand, Karnataka, Maharashtra, Mizoram, Punjab, and Telangana & Tripura and up to Range Level for Kerala.
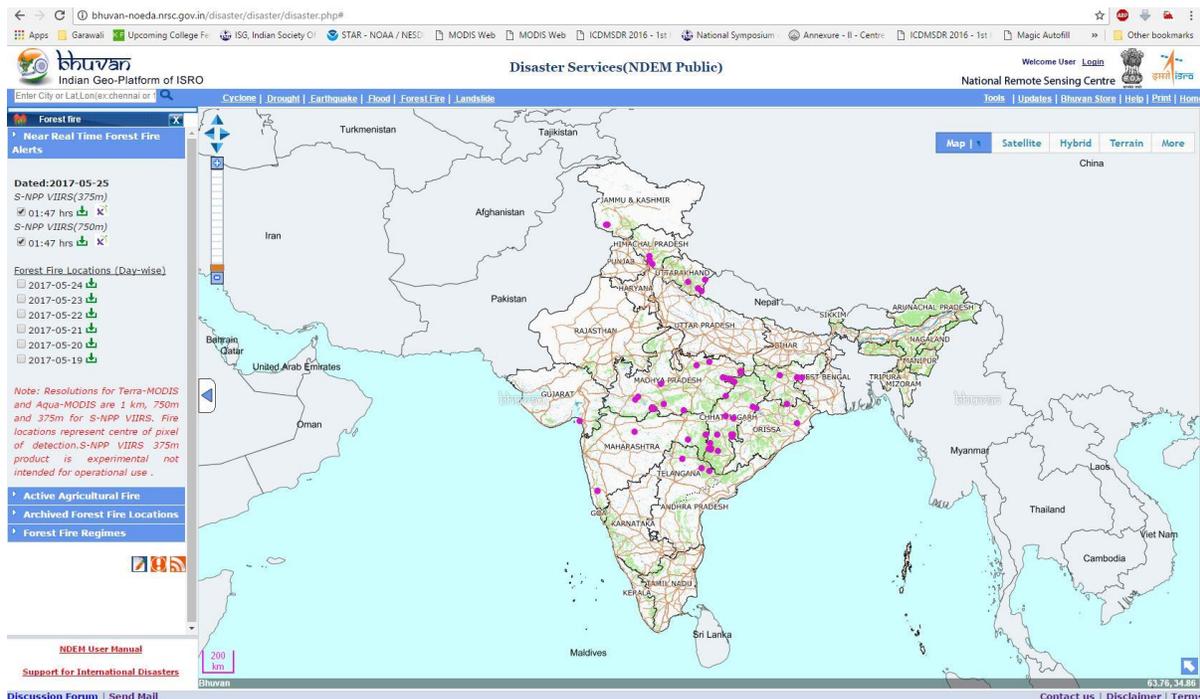
Fig 1.3 NRSC Bhuvan portal

1.9 Modeling of forest fire danger Index

The term "fire hazard" can be considered as phenomenon which can cause harm to the forest resources, humans and the environment due to fire. The term "fire danger" describes the probability that a fire can occur due to the natural causes and anthropogenic activities (Bachmann & Allgower, 2001; Hardy, 2005). The prediction of forest fire danger is essential for the fire management and strategic planning of forest protection. Fuel properties, Terrain features and the weather conditions are the main factors for the initiation and the spread of forest fires. The essential part of the strategic planning is to identify the fire potential risk zones i.e. sites where a forest fire most probable to start and from where, the fires can spread to other forests, at local level and sometimes at regional level (Jaiswal et al., 2002).

There are five different approaches proposed to model the forest fire risk, some of them are:

1. Qualitative and quantitative approach based on the expert knowledge i.e. classify the fire danger variables using a numerical scale based on the weights, derived from the review of literature, experts opinion and field based observations and reclassify into a level of risk or danger like high, medium and low (Chuvieco & Salas, 1996)

2. Multi-criteria based quantitative models that involves expert opinions, but, reduces the subjectivity when selecting the weights. This method though helps to make agreement among the experts when there is difference of opinions (Chen et al., 2001).

3. Statistical models (Chuvieco & Salas, 1996; Hernandez-Leal et al., 2006) depend on spatial characteristics of the study area. So, these models cannot be extrapolated to other areas. Linear regression, poisson distribution and logistic regression are the examples of statistical models. These models also include neural network based approaches.

4. Fire dispersion models i.e. fire spreading models such as Behave, FARSITE etc.

5. Physical models that are based on the scientific principles and extensive ground studies.

1.10 Remote sensing based fire danger rating techniques

At present, Canadian Fire Weather Index approach was adapted in other countries such as Argentina, USA and Alaska (Taylor, 2006; Alexander & Cole, 2001), Indonesia (De Groot et al., 2007), Malaysia (De Groot et al., 2007), Mexico (Lee et al., 2002); New Zealand (Alexander & 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 location data of 24-h accumulated rainfall. The problem with the FWI is that 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. The studies carried out by Molders, (2008); Safi & Bouroumi, (2013), used statistical Numerical Weather Prediction model 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. ~110 × 110 km^2, where the main problem is low spatial resolution because these indices does not detect the small fires.

In this regard, geospatial techniques are useful with improved spatial and temporal resolutions for monitoring and forecasting the fire danger (Leblon et al., 2017; Ceccato et al., 2002; Bajocco et al., 2010). Understanding the importance of satellite datasets, researchers started using 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; Bisquert et al., 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 variables such as "surface temperature" (T$_S$) (Leblon et al., 2007; Oldford et al., 2006), air temperature (T$_a$) (Nieto et al., 2011), RH (Nieto et al., 2011).

The AVHRR-derived NDVI and T$_S$ image 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, Build up 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 is observed that there is no 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; García, 2008). Live moisture can also be determined using the 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 air temperature (Ta) and relative humidity (RH) were used to determine the dead fuel moisture (Nieto et al., 2011).

Very few studies have been carried out on the use of satellite data for the determination of probability of fire occurrence. Vidal & Devaux-Ros (1995) calculated water deficit index (WDI) by relating NDVI and the difference between surface temperature and air temperature and it effectively predicted the onset of fires (Vidal & Devaux-Ros, 1995). Guangmeng & Mei (2004) used MODIS- derived surface temperature over the forested regions of northeast China and they observed that surface temperature values were increased at least 3 days before the occurrence of fires, but, the rate of increase of the surface temperature values for fire occurrence were not quantified. Oldford et al., (2003) utilized the NOAA AVHRR-derived surface temperature 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 same as like the previous study (Guangmeng & Mei, 2004), while NDVI did not show any indication of the fire occurrence (Oldford et al., 2003).

Akther & Hassan (2011) utilized the 8 day MODIS derived composites of "surface temperature", and "Temperature Vegetation Wetness Index" (TVWI) and NMDI over the boreal forested regions of Alberta, Canada during the years from 2006 to 2008 (Akther & Hassan, 2011). They found an accuracy of 91.6% of the fire pixels in "very high" to "moderate" danger classes. Chowdhury & 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 as it does not have the sufficient number of meteorological stations. The developed forest fire danger index is an integration of the static and dynamic fire

danger indices. SFDI is based on the static variables like the type of forests, topography and Terrain characteristics whereas the DFDI is based on the dynamic variables like air temperature, moisture conditions.

1.11 Rationale of the study

Forest fire is one of the major causes of degradation of forests in Himalayan region and is a regular feature every year causing large scale destruction of the forest ecosystems. In India, most of fires are ignited due to anthropogenic activities and very few natural causes of fires such as lightning (Bahuguna, 2002). As per Sendia framework priorities, there is a need to shift from Disaster Monitoring to Disaster Risk assessment. Fire danger rating systems are significant tools for fire officials in the management of fire controlling activities and can help to achieve the Sendai Framework initiatives. Till now, there is no operational fire danger system for India except few case studies related to fire risk zonation maps.

Forest fire alerts are disseminating and uploading into the Bhuvan and Forest Survey of India websites during the fire season of India for the management of forest fire activities. But, there is a limitation of fire alerts are: Fires which are actively burning at the time of satellite overpass can be detected and fires which are taken places between the passes are missed. So, there is a need of comprehensive fire danger system to forecast the fire danger for the Uttarakhand state. In India, there is no fire danger system to forecast the fire danger.

Global fire danger rating systems such as "Canadian Forest Fire Danger Rating System", "McArthur Forest Fire Danger Index" and "US National Fire Danger Rating System" provide a global framework but are not very accurate at local and regional levels. These systems require large datasets consisting of different time period daily automatic weather stations data and along with ground investigation data. Various meteorological based and drought indices such as Nesterov index, Angstrom Index etc. have been used to determine the fire danger across the world. All the above mentioned fire danger systems and indices require the daily, hourly meteorological parameters such as temperature (T), relative humidity (RH), rainfall and wind speed. It's very difficult to develop the forest fire danger index based on the meteorological station data in the tropical region and the Himalayas, especially in the mountainous state like the Uttarakhand state,

due to the less number of available meteorological stations. So, the satellite remote sensing derived parameters can be useful to model the fire danger indices. In this study, FFDI has been developed from the satellite derived datasets for the state of Uttarakhand in India.

1.12 Problem statement

India has two forest fire alert monitoring systems provided by National Remote Sensing Centre and Forest Survey of India. Forest fires burning at the time of satellite overpass can be detected and fires which have taken place between the passes are missed. Therefore, there is a need of fire danger index for the country India for the effective management of fire activities.

1.13 Objectives

The forest fire danger index is an integration of both the static and dynamic fire danger indices. Forest type and Terrain characteristics are the static i.e. does not change with the time, while, weather parameters are dynamic, changes all the time with respect to time. So, the objectives of current study are:

- To calculate the Forest Fire Danger Index from the static and dynamic fire danger indices and human activities.
- To automate the procedure of computing the Forest Fire Danger Index from the Near Real Time (NRT) MODIS Terra satellite datasets.

Chapter 2: Literature review

Satellite remote sensing with its multi sensor, multi-temporal and synoptic potential in conjunction with Geographic Information System (GIS) has been considered as one of the powerful mechanism to provide input for the fire management activities. Satellite remote sensing techniques are useful for the fire management activities such as fire detection, assessment of fire burnt area and the generation of fire danger indices.

2.1 Fire detection

An accurate and real time detection of forest fire is critical to protect the forest resources from the destruction. Satellite remote sensing having the capability of synoptic data capture enables to image large areas at low cost compared to traditional methods that has been utilized for forest fire monitoring since 1980s (Wang et al., 2012). There are several satellite sensors that have been designed and used for the fire detection and monitoring with different spatial and temporal resolutions (Prins et al., 1998; Li et al., 2000; Justice et al., 2002). Different sensors onboard polar, sun synchronous satellites such as "National Oceanic and Atmospheric Administration (NOAA)"/ "Advanced Very High Resolution Radiometer" (AVHRR) (Flasse & Ceccato, 1996; Li et al., 2000), "EOS- "Moderate Resolution Imaging Spectroradiometer" (MODIS) (Justice et al., 2002; Giglio et al., 2003; Morisette et al., 2005; Csiszar et al., 2006), "Advanced Spaceborne Thermal Emission and Reflection Radiometer" (ASTER; Schroeder et al., 2008), the "Environmental Protection & Disaster Monitoring Constellation" (HJ; Wang et al., 2012) and "SUOMI NPP Visible Infrared Imaging Radiometer Suite (VIIRS)" (Schroeder & Giglio, 2016) has been providing information on the fire occurence globally on a regular basis. Geostationary satellite sensors such as "Geostationary Operational Environmental Satellite" (GOES; Xu et al., 2010), "Meteosat Second Generation (MSG)" (Hassini et al., 2009) and "Communication, Ocean and Meteorological Satellite" (COMS; Kim et al., 2014), "Himawari-8" (Bessho et al., 2016) Indian INSAT-3D/3DR (Ahmed et al., 2015) were also designed to detect forest fires sensitive to thermal radiation. Generally, fire detection algorithms involve the brightness temperatures obtained at approximately 4 and 11 micro meters respectively since fire results in emission of strong infrared radiation in those regions help discriminating fire pixels from surrounding pixels using the temperature threshold criteria (Flasse & Ceccato, 1996; Giglio et al., 2003).

Sensor based contextual algorithms have been operationally used across the world to detect the forest fires as this method provides flexibility to determine the temperature thresholds (Manyangadze, 2009). These contextual algorithms introduces a background characterization, which compares the each pixel temperature with the pixels of neighboring background pixel temperatures (Flasse & Ceccato, 1996) assuming that brightness temperature of background pixels obeys a normal distribution. The threshold conditions are determined and validated by extensive ground truthing to detect the fires locally because each region has distinctive characteristics of forest fire. The fire alerts thus generated are disseminated to the foresters and officials involved in the management of forest fires for further action. The active fires during the satellite overpass can be recorded but cannot detect the fires which have taken place between the two passes.

2.2 Burnt area mapping methods

Burnt area products derived from satellite data provide a comprehensive assessment of the damage to the forest than the active fire detection. Vegetation damage because of fire event results in significant change in the reflectance due to the difference in the structure of forest vegetation and soil properties. NOAA-AVHRR data were used to map the burnt areas during the 1990's based on the multi- temporal comparison of spectral index "Normalized Difference Vegetation Index" (NDVI) (Kasischke & French, 1993; Martin & Chuvieco, 1995). Later, global burnt area products generated from the "SPOT Vegetation" and the "ATSR-2" on the board of European Remote Sensing -2 satellite (Grégoire et al., 2003; Simon et al., 2004) became available. These global burnt area products were validated partially at regional and national level by numerous researchers (Roy et al., 2005; Roy & Boschetti, 2009). After the launch of "MODIS" sensor on board Terra and Aqua, regional burnt area maps on daily basis were generated with medium spatial resolution (500m) (Justice et al., 2002). Since, MODIS provides the daily data with a higher radiometric resolution, it is easier to discriminate the burnt areas and also enable accurate mapping with increase in number of revisits. MODIS burnt area product that are available monthly with 500 m spatial resolution and validated for regional level (Roy et al., 2008), were observed to detect around 75% of fire affected area as compared to the Landsat images (Roy & Boschetti, 2009).

Currently there are wide range of satellite based products from medium (30 m) to high (10 m) spatial resolution that makes it possible to accurately map the burnt areas from regional to local

level. However, the increase in spatial resolution results in decrease in temporal resolution and vice versa, which results in small burnt areas being left out. Burnt area mapping with high spatial resolution has been carried out with Landsat series satellite imagery (Chuvieco & Congalton, 1989; Michalek et al., 2000) and the "LISS-3" sensor of the IRS Indian satellite occasionally (Chuvieco, 2008). The range of satellites of high to very high spatial resolutions such as "QUICKBIRD", "RAPIDEYE", "FORMOSAT", "IKONOS", "EARLYBIRD" have also been using for the quick, immediate and localized fire events (Leblon et al., 2017).

2.3 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 the clear understand of the spatial pattern of the fire events. Therefore long-term indices have been used to determine forest areas with high probability of fire occurrence. The variables for long-term indices are topography (elevation, slope and aspect), vegetation type, vicinity to settlements, distance to the roads, rail networks and fire history. Whereas, short-term indices mainly consider parameters that changes suddenly and depend on factors influencing ignition and spreading of 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 in the study site 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 to save the time, money and lives. The well-known forest fire danger rating systems have been explained in the following sections.

2.3.1 Canadian Forest Fire Danger Rating System (CFFDRS)

The CFFDRS was developed by Canadian Forestry Service (CFS) in the year 1920, and is the Canadian national fire danger rating system (Stocks et al., 1989; Alexander et al., 1996; Van Nest & Alexander, 1999). CFFDRS consists of 2 primary subsystems (Fig 2.1) i.e. the "Canadian

Forest Fire Weather Index" (FWI) and the "Canadian Forest Fire Behavior prediction (FBP) system". The other two systems are the "Accessory fuel moisture system" and the "Fire Occurrence Prediction (FOP) system", that have been developed for regionally but not for entire Canada. The Accessory fuel moisture system is used to support other three subsystem applications while the FOP is proposed to predict the lighting and human caused fires.
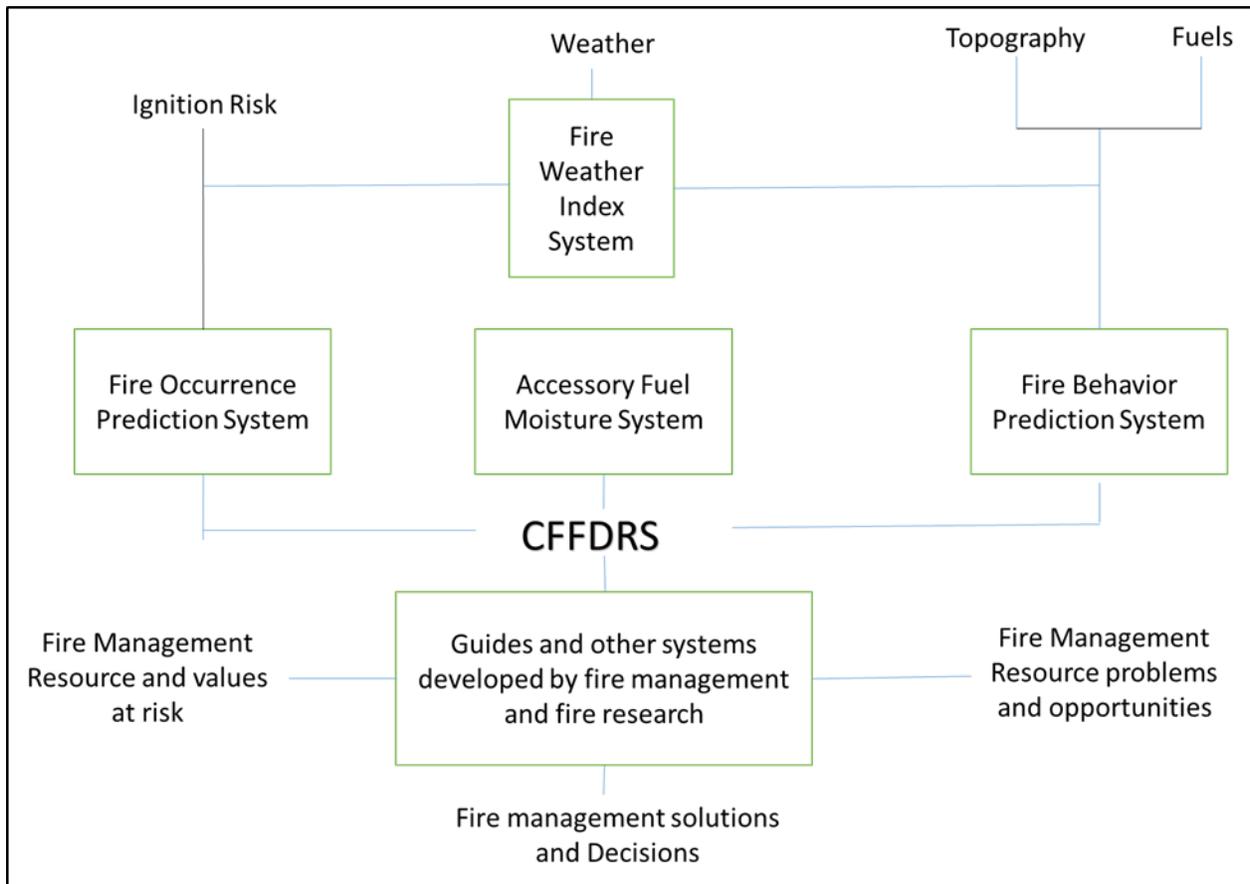
Fig 2.1 Canadian Forest Fire Danger Rating system (source: Canadian Forest Service, 1984)

The CFFDRS model has been developed based on the vast field experiments and fire behavior characteristics in a wide range of vegetation types. The most standard forest fuel type studied has been the generalized across pine forest, nearly the jack pine and lodge pole pine forest which are most prevalent across Canada (Van Wagner, 1987). These forest types have been used as the standard fuel type in the computation of FWI and it requires various inputs like daily air temperature, relative humidity, rainfall of previous day and wind speed. Early Canadian fire danger system just used the FWI as the basis for fire management. FWI has 3 basic and 2 intermediate

sub components and finally, one output. The basic components of FWI are Fine "Fuel Moisture Code" (FFMC), Duff Moisture Code (DMC) and "Drought Code" (DC)", these codes are mainly focus on the moisture conditions in different types of fuels (Van Wagner, 1987). The first 3 codes represents the variation of moisture content of fuels with different time responses i.e. time lag fuels such as FFMC indicates for short term, DMC for midterm and DC for long term dryness conditions (Van Wagner, 1987). The two intermediate indices "Initial Spread Index" (ISI) and "Buildup Index" (BUI) are based on the basic codes (FFMC, DMC and DC). ISI depends on FFMC and WS calculates the initial spread rate of a forest fire without taking into account of fuel characteristics. While the BUI depends on the DMC and DC estimates the quantity of dry fuel available for spreading the forest fire. Finally, "FWI" is calculated from the intermediate indices ISI and BUI, which estimates the overall fire danger and is used to classify fire danger (Fig 2.2).
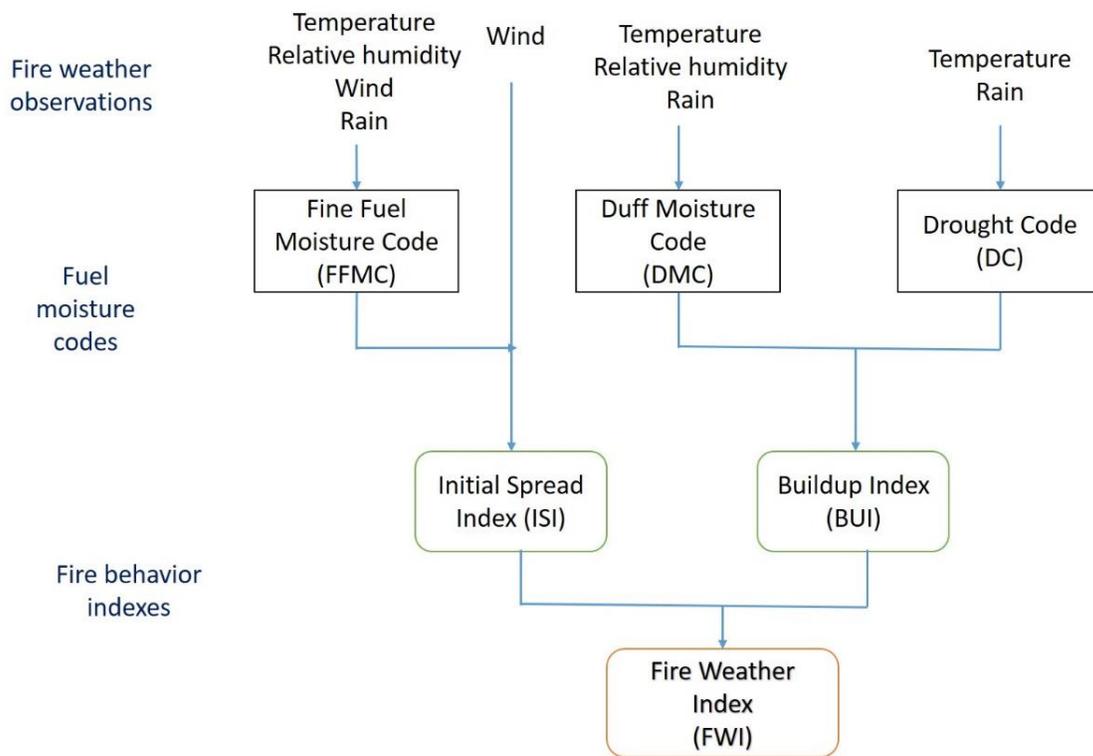
Fig 2.2 Canadian Fire weather index system (source: Canadian Forest Service (1984))

Based on the final FWI value, fire danger is categorized into six classes i.e. "very low, low, moderate, high, very high and extreme", Several studies undertaken in different countries across the world (Haines et al., 1986; Viegas et al., 1999) showed the strong correlations between human

caused fire and FFMC; burnt area and the ISI. The CFFDRS has been adopted in some other countries like New Zealand, Fiji, Venezuela, Mexico, Southeast Asia, Argentina, Chile, Florida, Alaska and Europe (Bytnerowicz et al., 2008).

2.3.2 US- National Fire Danger Rating System (NFDRS)

Evolution of development of fire danger rating system was first attempted around 1968 in US, based on the scientific data and engineering principles rather than local observations previously used by different researchers (Deeming, 1977; Bradshaw et al., 1984). This system integrates the fundamental laws of physics such as combustion and constants developed from lab experiments and coefficients establishing the relationships between different fuels, weather parameters, topographic characteristics and danger conditions to develop the fire danger rating system. NFDRS is applicable throughout USA. The first version of NFDRS was released around 1972 while an automated version of the NFDRS in 1975 (Schlobohm & Brain, 2002). It consists of computer system "Administrative and Forest Fire Information Retrieval and Management System" (AFFIRMS). The initial version was released in the year 1978 while modified version was released in 1988 that include fuel moisture variation during the drought periods and precipitation. The AFFIRMS system was replaced by "Weather Information Management System" (WIMS) in 1993 as the processor of fire danger information. Numerous private companies integrated the NFDRS computer code in desktop based software programs.

The data used to calculate daily based fire danger rating indices and components were daily weather based observations and the parameters that the fire managers sets to control the real calculations within the NFDRS processor. Generally, NFDRS has been operated on either observed data from manual and automatic weather stations to produce fire danger indices and components indicating the current day conditions or on forecasted data to predict next day fire danger conditions. Weather forecasters develop the predicted data using methods that applied to observed conditions within the zone. This forecasted information then applied in an automatic way within the processor to current conditions at all AWS within the region to calculate the forecasted conditions. Fire danger calculations were determined at 1 PM local standard time conditions. This system requires hourly measurements of accumulated precipitation. In addition, reading of hourly air temperature has been taken and 10 minute averages has been computed for the following

variables: "relative humidity, wind direction, and wind speed" along with 60 minute average solar radiation.

The NFDRS calculation has 2 types of outputs viz., intermediate outputs and indices - components (Fig 2.3). Intermediate outputs served as constituents for the next day calculations whereas the fire danger indices and components determine the actual fire danger in the region (Schlobohm & Brain, 2002). The NFDRS has three components viz. "Ignition Component" (IC), "Spread Component" (SC), "Energy Release Component" (ERC) and has four indices viz. "Lightening Occurrence Index" (LOI), "Human Caused Fire Occurrence Index" (MCOI), "Burning Index" (BI), "Fire Load Index" (FLI) (Schlobohm & Brain, 2002). In NFDRS, fire danger classes have been classified into five classes i.e. "Low, Moderate, High, Very High and Extreme". The NFDRS processor not only calculates the fire danger but also computes the class rating based on the user information.
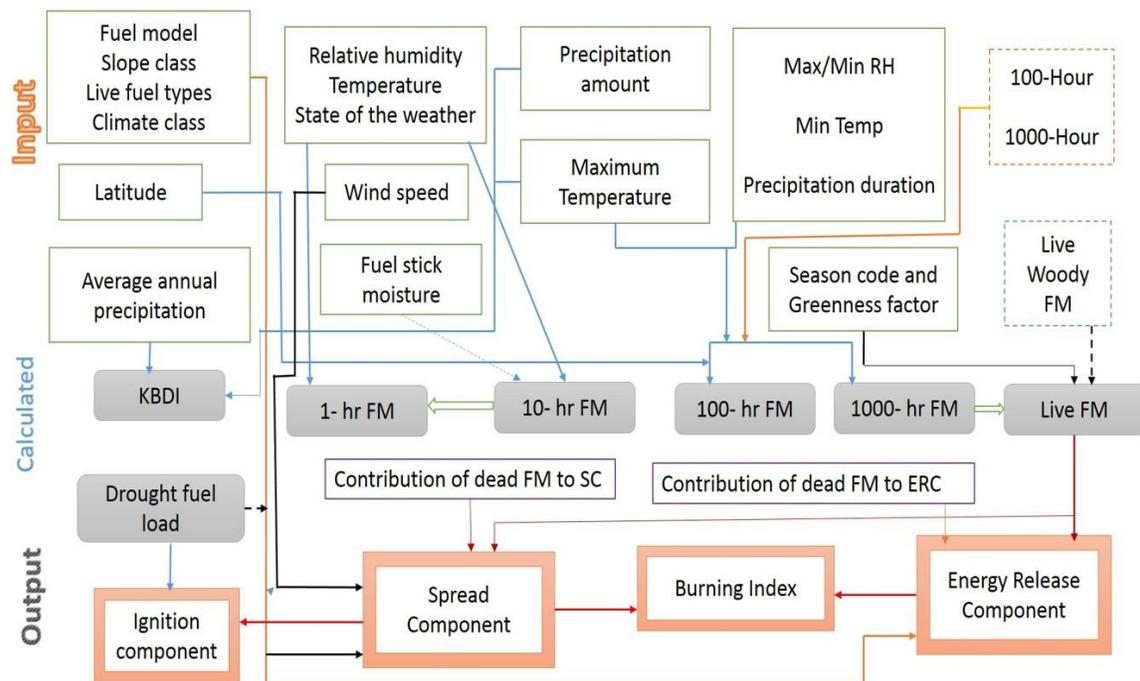
Fig 2.3 United States National Fire Danger Rating System (NFDRS) (source: National Wildfire Coordinating Group (NWCG))

2.3.3 McArthur's Forest Fire Danger System

The "McArthur Forest Fire Danger Index" was evolved in the year 1958 (McArthur, 1958, 1962, 1966, 1967). McArthur further modified fire danger system after taking several empirical

wild land fire observations. The re-developed fire danger system includes four sub-models (Fig 2.4). The first one is called "Drought Factor", which represents the fine fuel availability of the surface fuels on the forest floor. Drought factor is measured from meteorological parameters such as rainfall and number of days since last rainfall. It also uses "Keetch–Byram drought index" (KBDI) , which is determined from parameters like daily maximum temperature, precipitation and annual precipitation. The second sub-model is "Surface Fine Fuel Moisture", which is estimated based on daily T and RH values. The third sub-model is "Rate of Spread", which is the combination of above two sub-models – "Drought Factor" and "Surface Fine Fuel Moisture sub-model". The wind speed (ws) value is added to fine fuel moisture determined from the second sub-model. Final and fourth sub-model is the "Suppression Difficulty sub-model", depends on the relationship between the fire spread which is derived from "ws" and "surface fine fuel moisture content" (San-Miguel-Ayanz et al., 2003).

There are three sub-components in McArthur's modified fire danger index (Camia et al., 1999) i.e. "Mark3 Grassland Fire Danger Meter", "Mark5F Forest Fire Danger Meter" and "Mark5 Fuel Moisture Content" in Grassland Fire Danger Meter. "Mark3 Grassland Fire Danger Meter" and "Mark5F Forest Fire Danger Meter" have been used in Australia for measuring fire danger rating and fire behavior assessment and are represented by following equations respectively.

$$F = 2.0 \times e^{\left[-23.6 + 5.01 \times \ln(c) + 0.0281 \times T - 0.0226 \times \sqrt{H} + 0.633 \times \sqrt{V}\right]} \qquad (1)$$

Where F is "Mark3 component", C is degree of curing (%), T is temperature (°C), H is relative humidity (%) and V is wind speed (km/h).

$$F = 2.0 \times e^{\left[-0.450 + 0.987 \times \ln(D) + 0.0338 \times T - 0.0234 \times V\right]} \qquad (2)$$

Where F is "Mark5F component" and D is "Drought factor".

Mark5 represents the estimation of "fuel moisture content" included in the equation derived by Noble et al., (1980) and Camia et al., (1999), from the "Mark 3 McArthur's fire danger meter" for grassland. Equation (3) represents the fuel moisture content in percentage.

$$M = \frac{(97.7 + 4.06 \times H)}{(T + 6.0)} - 0.00854 \times H + \frac{3000.0}{C} - 30.0 \qquad (3)$$
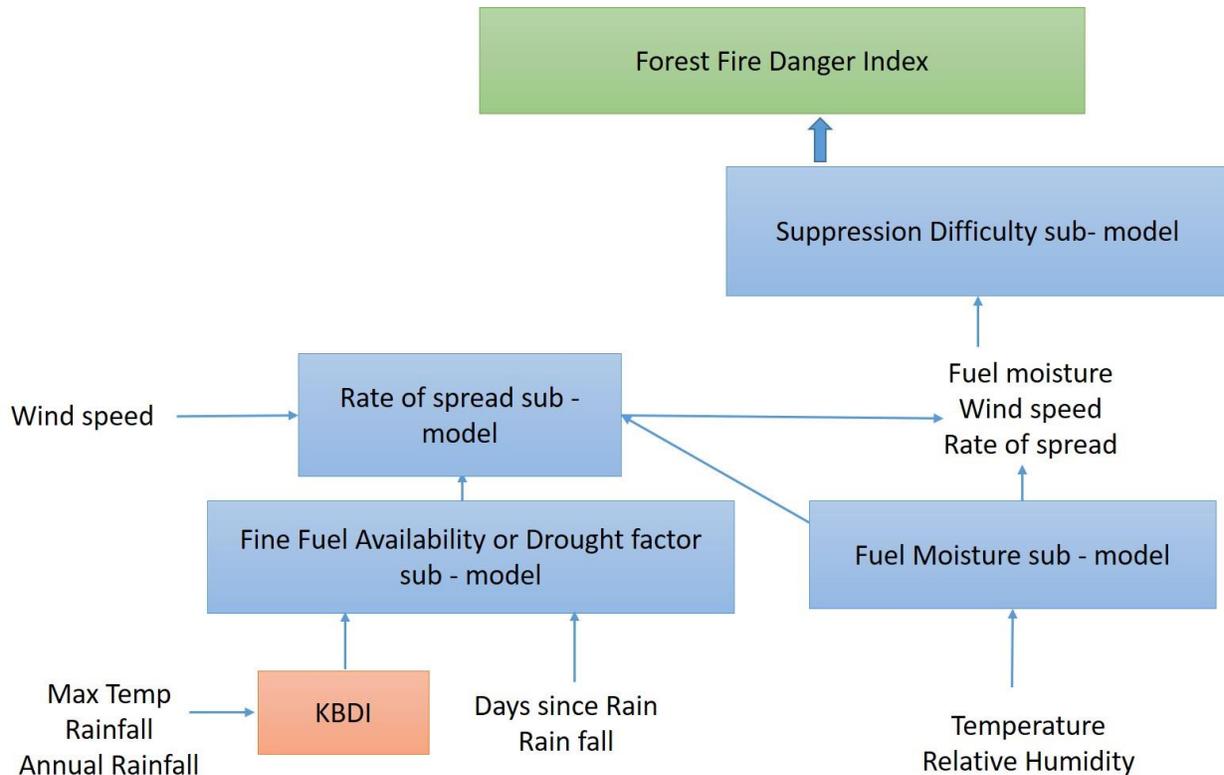
Fig 2.4 Structure of McArthur Fire Danger Index (McArthur, 1958)

The above mentioned four major fire danger rating indices mainly uses the Automatic Weather stations (AWS) data parameters such as "temperature, relative humidity, wind speed and rainfall" as inputs. Besides these fire danger rating systems, a number of meteorological indices and drought indices being used around the world for measuring the forest danger and are described in the subsequent sections.

2.3.4 Meteorological and Drought indices

The well-known meteorological and drought indices around the world are explained in the below with their input variables and applications.

The simple fire danger rating index is the "Angstrom Index" or "Swedish Angstrom index" (Willis et al., 2001; Ganatsas et al., 2011), was developed in Sweden and has been using across

Scandinavia. This index takes "T" and "RH" in its computation and provides an indication of the occurrence of forest fires. The index value ranges from 0 to 4, if the index value is low (0), then fire risk is higher while values above 4 represents no fire risk (Chandler et al., 1983). The Angstrom index is an indication of the air dryness, but, it does not include the fuel moisture content or rainfall and wind speed, as both variables play a significant role in fire triangle.

The USSR Ignition Index is also a basic index and was developed in Russia (Willis et al., 2001). The index not only uses temperature and relative humidity as in Angstrom Index but also incorporates the effect of current day rainfall on the fine fuel flammability. If the rainfall is more than 3 mm, then fire will not occur, and the index value returns to zero. Fire danger has been classified into 4 danger classes based on the value of USSR ignition index as no fire danger if the index value range between 0-300, 301-1000 - moderate fire danger, 1001-4000high and more than 4000 as a chance of extreme fire danger.

Baumgartner Index (BI) is measured from amount of "precipitation" and the "potential evapotranspiration" and is used in Germany (Skvarenina et al., 2003). This index is divided into the 5 fire danger classes depending on the month of fire season (Skvarenina et al., 2003).

French Fire Danger Index or Thornthwaite's Index was developed for France and it combines the drought effects with the wind speed (ws) to assess the fire danger (Viegas et al., 1999; Willis et al., 2001). Dryness is measured seasonally by soil moisture capacity estimation and adding to or subtracting from it according to the daily "evapotranspiration" balance. Thornthwaite's formula is used to calculate the "Potential evapotranspiration". This index provides a measure of potential of ignition as well as fuel availability and also includes wind speed and fire spread rate.

"Fosberg's Fire Weather Index" (FFWI) is also a basic index. It correlates the linear relationship between relative humidity and wind speed combination with fire behavior (Goodrick, 2002). FFWI calculations are based on Byram flame length model (1959) and Rothermel spread model (1972) and was calculated on an hourly basis. The value of FFWI ranges from 0 to 100 and if the index is greater than 100, it returns to 100. The maximum limit of FFWI is set to 100, if and only if moisture content is zero and the WS is 30 kmph.

The "Lowveld Fire Danger System" has been used in some parts of South Africa and was developed by Michael Laing in Zimbabwe in the year 1968 (Meikle & Heine, 1987). This index uses temperature and relative Humidity as inputs, which are used to create a model that can compute integers easily rather than complex calculations (McArthur, 1967). The Burning Index (BI) is calculated by using nomogram using T and RH or computer programs. A value is added to adjust BI for wind, according to the present wind conditions at 2 pm. Fine fuel availability is included in the form of "rainfall correction factor" (RCF), that uses the past rainfall conditions to adjust the BI.

Professor V.G. Nesterov developed Nesterov index in the year 1967 for Russia and is an accumulative index, which adds the calculated index value to the last day's value till there is a certain amount of precipitation (> 3mm), later it is set back to zero. It takes the weather parameters like T, RH and the rainfall and its impact on the fine fuel flammability (Groisman et al., 2005a; Willis et al., 2001; Skvarenina et al., 2003, Alexander et al., 2010, Ganatsas et al., 2011). Based on the calculated Nesterov index value, fire risk has been classified into five different classes i.e. "no fire risk, low risk, medium risk, high risk and extremely high risk" (Skvarenina et al., 2003).

"Fuel Moisture Index" (FMI) is a very basic index, developed by Sharples et al (2009) and it takes the meteorological parameters such as temperature and relative humidity. It has shown very good performance in comparison to other fuel moisture indices (Sharples et al., 2009, Liu et al., 2010). FMI has values ranging from 0 to 30. If the index value is smaller, then there is a chance of high fire danger and there is no fire danger classification.

The Modified Nesterov index is the Nesterov index by a reduction factor as Zhdanko index used in similar manner (Groisman et al., 2005 a). The index takes inputs such as mid-day temperature, relative humidity and the precipitation. The Fire Risk level has been classified into 5 classes such as "very low, low, moderate, high and extreme".

Zhdanko index is also a drought index, used to measure the probable fire danger for the warm snow-free period in Russia. It is similar to Nesterov index, suggested by Zhdanko in 1965 (Groisman et al., 2005 a). This index values are ranging from 0 to 1 based on the precipitation occurs on the day.

The Portuguese Index is a modified version of Nesterov index and was developed by the "Portuguese meteorological and geophysical national institute" (Goncalves & Lourenco, 1990). This index is based on the evaluation of meteorological conditions in relation to the fuel layer and is composed of three numerical indices i.e. Index of ignition, Cumulative index and Final danger index and takes the inputs such as air temperature, dew point temperature, wind speed during the noon time and the previous day rainfall.

"Italian fire danger index" (IFDI) is derived from the McArthur's models in the Australian Forest Fire Danger Meter. Results showed that this index is applicable only to the Mediterranean part of Italy (Palmieri & Cozzi, 1983). IFDI calculation consists of two steps. First step is to compute soil water deficit and drought index and is a function of rainfall amount, days since last rain and maximum air temperature. Second step is measure of danger index and it depends on drought index, WS, RH and T (Palmieri et al., 1992).

The "Keetch-Byram drought index" (KBDI) was designed specifically for assessment of fire potential by Keetch and Byram in 1968 (Keetch & Byram, 1968; Heim, 2002; Dennison et al., 2003; Dimitrakopoulos & Bemmerzouk, 2003). This index is based on weather parameters and an empirical relation between moisture depletion in the upper part of soil and surface litter levels (Keetch & Byram, 1968; Janis et al., 2002). KBDI is used as a tool for estimating forest fire potential (Janis et al., 2002) and it requires weather stations data such as "maximum daily temperature", "total daily precipitation" and the "average annual precipitation". Table 2.1 shows the comparison of fire danger indices across the world.

Table2.1 Different fire danger indices across the world

Weather based indices	Country	Weather parameters				
		AT	RH	WS	RF	DPT
Portuguese Index	Portugal	Yes		Yes	Yes	Yes
Italian Fire Danger Index	Italy	Yes	Yes	Yes	Yes	
US -NFDRS	USA	Yes	Yes	Yes	Yes	
Canadian Fire Weather Index	Canada, New Zealand, Fiji, Venezuela, Mexico, Southeast Asia, Argentina, Chile, Florida, Alaska	Yes	Yes	Yes	Yes	
McArthur Fire Danger Rating System	Australia	Yes	Yes	Yes		
Angstrom Index	Sweden, Scandinavia	Yes	Yes			
USSR Ignition Index	Russia	Yes			Yes	Yes
Baumgartner Index	Germany	Yes			Yes	
French Fire Danger Index	France	Yes		Yes		
Fosberg"s Fire Weather Index	USA	Yes	Yes	Yes		
Lowveld Fire Danger System	South Africa	Yes	Yes	Yes		
Nesterov Index	Russia	Yes			Yes	Yes
Fuel moisture Index	Australia	Yes	Yes			
Modified Nesterov Index	Russia	Yes			Yes	Yes
Zhdanko Index	Russia				Yes	Yes
Keetch-Byram Drought Index	Australia	Yes			Yes	

[AT: Air Temperature; RH: Relative Humidity; WS: Wind Speed; RF: Rain Fall (Precipitation); DPT: Dew Point Temperature.]

2.4 Remote sensing based forest fire danger rating methods

In most of the studies, satellite based vegetation and moisture indices are usually used to assess the potential of fire danger conditions. Commonly used indices are "Normalized Difference Vegetation Index" (NDVI) (Leblon et al., 2007), "Enhanced vegetation index" (EVI) (Bisquert et al., 2012; Bisquert et al., 2014), "Vegetation Index green" (VI green), "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., 2007; Wang et al., 2008), "Normalized Difference Water Index" (NDWI) (Stow et al., 2005) and their formulations are below.

$$NDVI == \frac{(\rho_{NIR} - \rho_{Red})}{(\rho_{NIR} + \rho_{Red})} \tag{4}$$

$$EVI = \frac{2.5 * (\rho_{NIR} - \rho_{Red})}{(\rho_{NIR} + \rho_{Red} - \rho_{Blue} + 1)} \tag{5}$$

$$VI_{green} = \frac{(\rho_{Green} - \rho_{Red})}{(\rho_{Green} + \rho_{Red})} \tag{6}$$

$$VARI = \frac{(\rho_{Green} - \rho_{Red})}{(\rho_{Green} + \rho_{Red} - \rho_{Blue})} \tag{7}$$

$$NDWI == \frac{(\rho_{NIR} - \rho_{SWIR})}{(\rho_{NIR} + \rho_{SWIR})} \tag{8}$$

Where ρ is the "surface reflectance" of NIR, red, green, SWIR and the blue spectral bands. These indices have been using globally to assess the fire danger conditions.

The parameters such as "NDVI" and "surface temperature" (Ts), derived from the AVHRR were used in the computation of "Canadian Fire Weather Index" (FWI) system components i.e. "fine fuel moisture content, duff moisture code, drought code, buildup index and fire weather index" (Oldford et al., 2006; Leblon et al., 2007). The correlation between the NDVI and the FWI components showed the similar variation, but, no direct relationship between them.

The live fuel moisture conditions were measured as a combination of NDVI and T_s (Chuvieco et al., 2002) or a combination of vegetation greenness indices such as "NDVI, EVI, VIgreen, VARI"; wetness indices such as NDWI (Dennison et al., 2005, Peterson et al., 2008). The dead fuel

moisture conditions were determined by combing the weather variables such as air Ta and RH, derived from the MSG-SEVIRI (Nieto, 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 & Nojd, 2009) and indicate the weather and drought conditions in the forests (Fennessy & 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 & Bourque, 2009).

In the studies carried out by Schneider, (2008); 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". 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 & Qu, 2007, Wang et al., 2008, Wang & Qu, 2009).

$$NMDI = \frac{[\rho_{860nm} - (\rho_{1640nm} - \rho_{2130nm})]}{[\rho_{860nm} + (\rho_{1640nm} - \rho_{2130nm})]} \qquad (9)$$

The above mentioned studies used satellite remote sensing based indices for monitoring of fire danger conditions and not for forecasting the forest fires. A limited number of studies determine the probability of fire occurrences. For example, the study of Vidal and Devaux-Ros (1995), calculated the "water deficit index" (WDI) by combining "NDVI" and the difference between the "Ts" and "Ta" and the results showed its efficiency in predicting the forest fires. The studies Oldford et al., (2003) and Guangmeng & Mei, (2004) reported that the mean surface temperature values showed an increasing trend as the fire incidences date is approaching.

2.5 Summary

In the above sections, the major forest fire danger rating systems across the world, i.e. CFFDRS, US NFDRS and McArthur FFDI have been explained with their input variables and applications. It is observed that a large number of weather stations dataset are required such as hourly, daily and also extensive ground datasets. So, it's difficult to adapt these systems in developing countries like India, as it requires installing dense weather stations especially in the forest areas. The standalone meteorological and drought indices like "Nesterov index", "Keetch-Byram drought index", "Angstrom Index", "Baumgartner Index" etc. are also explained briefly mentioning their input datasets. These indices are simple and take two or more meteorological parameters only to compute the fire danger and do not include the ignition and spreading factors such as type of vegetation, topographic characteristics. The major limitation of fire danger indices based on meteorological stations is the lower spatial resolution and the fire danger map generated from the interpolation of individual input point weather parameters. Remote sensing techniques are used to develop the fire danger indices with higher spatial resolution after launching the moderate resolution sensors onboard satellites. These remote sensing based fire danger indices are based on the vegetation and moisture indices such as NDVI, NDWI, NMDI, PMI, VARI etc.

It was concluded from this chapter that, remote sensing based fire danger indices are having higher spatial resolution and can predict the fire danger more accurately as compared to the automatic weather stations based fire danger indices. In India, near real time fire alerts have been uploaded into the Bhuvan portal and Forest Survey of India geoportal by using the MODIS TERRA & AQUA and SNPP-VIIRS sensors. Actively burning forest fires during the time of satellite overpass can be detected and fires which have taken places between the passes are not identified. Fire danger index has not developed in India, So, my main objective is to develop the fire danger index.

Chapter 3: 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 Km^2 or 10.3% total geographical area of the Himalaya inhabited by 10.1 million persons living in 16583 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 Km^2, which is 64.79 % of its geographical area (ISFR, 2015). Fig 3.1 shows the study area.
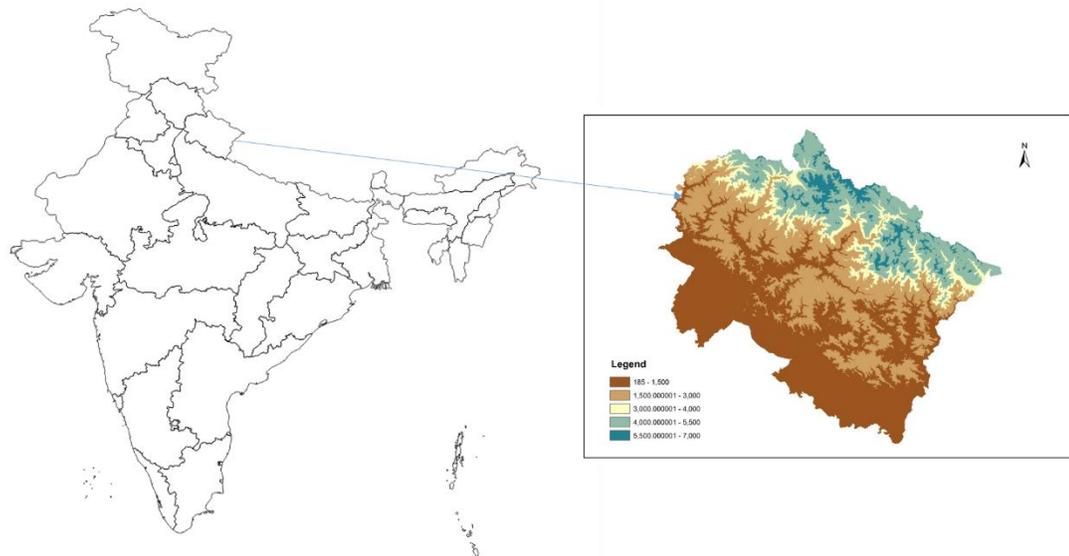

Fig 3.1 Study area

3.1 Terrain

Uttarakhand is largely a rocky mountainous region, where the altitudes dramatically fluctuate between 300 m to 7817 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.

3.2 Water resources

The Uttarakhand state is drained by the mighty and holy river Ganga and its main tributaries namely Yamuna, Tons, Kali, Sharda and Ramganga. The entire state, except for its southern part, holds the perpetual reservoir of water and hence acts as the water tower of the northern India. The runoff from all rivers of the state is estimated to be around 25 million cubic meters, which can generate up to 40,000 MW power.

3.3 Climate

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. The climatic condition is hot and moist in the sub Himalayan zone and in river valleys below 600 m elevation, whereas the climate is sub-tropical from 600 m up to an elevation of 1200 m. between 1200 - 1800 m the climate is temperate and cold temperature between 1800 to 2400 m altitudes. The climate is cold frigid above altitudes more than 2400 m elevation above mean sea level. Tree line of Uttarakhand state is around 3200 m elevation msl.

3.4 Population

The total population of the state is 1,01,16,752 persons as per census report of 2011 (http://censusindia.gov.in), about 69.45% is distributed in the rural areas while only 30.55% is accounted in urban areas. The distribution of population in the mountainous area is mainly due to the natural factors such as relief, soil, climate, availability of water and agricultural land etc.

3.5 Vegetation

The natural forest cover in Uttarakhand is 44.76% of the state's geographical area which constitutes. 3.5% of the country's forest cover. The maximum forest cover exists in Nainital and Champawat districts (>60%) while Pithoragarh district has relatively less extent of forest cover viz. 28.87%.

3.5.1 Forests

There are 4 major forest types distributed in Uttarakhand state, which include the Alpine meadows in the in the higher elevation above treeline, Temperate forest in the Himalaya ranges, Tropical deciduous forests in the lesser Himalaya and mixed deciduous and thorny vegetation in the Shiwalik range and in some parts of the Terai.

According to the Uttarakhand forest statistical report of 2012 – 13, forest is divided in various categories on the basis of landuse and requirements of the people and managed by the various administrative units. According to the report, geographical area of the state is 53,483 Km^2 in which 37,999.532 Km^2 of area is occupied by various forest types . Total number of Panchayati forests under Van Panchayats are 12,089 and consists of an area of 7350.857 Km^2. Permanent pastures occupies lesser portion of the Uttarakhand state land area. The trees like Chir pine, Oak and Sal are the dominating tree species in the state. According to Champion and Seth (1968), Uttarakhand state has 37 forest types, which belong to 8 forest type groups (Table 3.1; ISFR, 2011).

Table 3.1 Forest type groups and their area (ISFR, 2011)

Group number	Forest type	Area (%)
9	Subtropical Pine Forest	28.72
5	Tropical dry and deciduous forest	6.38
3	Tropical moist deciduous forest plantation	18.71
16	Dry alpine scrub	0.16
15	Moist alpine scrub	0.69

14	Sub alpine forest	6.82
13	Himalayan dry temperate forest	1.81
12	Himalayan moist temperate forest	36.71

3.6 Forest fires in Uttarakhand

Forest fire is a regular feature in Uttarakhand forest ecosystems and most valuable plant and animal species can be depleted due to the frequent incidences of forest fires. More than 50% of Himalayan forests in Uttarakhand are prone to high incidence of fire, during the months from March to June in every year. The main causes of forest fires in western Himalayas of India are : Forest ground is being burnt by nearby villagers for hoping to get good grass in the following season; burning of wild grass or undergrowth in the forest in search of game animals, use of fire for collecting forest products like honey, gum etc. and to destroy stumps of illegal felling activities., Accidental fires are also due to carelessness of humans, such as throwing of cigarettes and fire spread from recreational spots.

According to reports of the forest department, the state of Uttarakhand lost 2000 ha (1998), 60,000 ha (1999), 2320 ha (2000), 1144 ha (2001), 3494 ha (2002), 4750 ha (2003), 4750 ha (2004) and 3652 (2005). The state has lost 1595.35 ha in 2008. In 2012, about 1409 ha of forests were affected by fires, by the end of fire season. According to the forest department of Uttarakhand, forest fires occur frequently during the months of March to June, causing loss of valuable timber resources, endangered species and extensive damage to forest ecology as well as the landscape of the area. So, the effective forest fire management is necessary to mitigate these occurring forest fires in Uttarakhand Himalayas.

3.6.1 Major forest fire episode of Uttarakhand state

In the year 2016, the pine forests of Uttarakhand and Himachal Pradesh caught severe fire, over 4,500 hectares was damaged in Himachal Pradesh, some 40% more than the 3,185 ha in Uttarakhand. This fire costs 7 human lives in Uttarakhand state apart from the flora and fauna.

Maximum number of fires in Uttarakhand occurred in the Chir pine (*Pinus roxburghii*) forests because leaves of this forest type catch fire quickly, despite the fact that the Chir pine is more resistant to the fire itself.

3.6.2 Reasons for the fires

Generally, the forest fires in Uttarakhand are: for the purpose of collection of forest products such as resin, honey, timber, Sal seeds etc. The forests are rich in Banj Oak trees which are source of a kind of resin. People set the surface fires so that pine needles can be removed and it's easy to collect the resin. Further, the forest fires are also ignited by smugglers to mask their operations. However, in the year 2016, natural reasons (high temperatures, no atmospheric moisture and vapour pressure deficit) might have intensified the problem. Some also link the forest fires to El Nino (which is usually used to explain almost every climatic problem in India), that resulted in high temperature and no rainfall (Parliament of India, Rajya Sabha, 2016). Therefore, there is a need of forest fire danger index for effectively controlling the forest fires in this region.

Chapter 4: Developing the Static Fire Danger Index

4.1 Introduction

Ignition and spread factors which are responsible for forest fires were explained in the Introduction chapter. Ignition and spread factors depends on the type of vegetation, topographic characteristics, Terrain properties as well as the moisture condition and weather parameters. The factors such as vegetation type, slope, aspect, elevation and Terrain heterogeneity are static in nature that means they cannot change in short time spans and almost constant over the study area. The Fire Danger Rating System is a Decision Support System, which takes into consideration of all the factors affecting the fire danger such as fuel type, weather parameters and Terrain characteristics and indexing into different classes of fire danger based on the value viz. No danger, Low, Moderate, High and very High for the purpose of issuing warnings to the public, implementing the mitigation measures for controlling fires. The Fire Danger Rating system is an integration of dynamic and static fire danger rating indices. Dynamic fire danger index (DFDI) is based on weather parameters such as moisture conditions, temperature while Static fire danger index (SFDI) is based on the constant parameters such as fuel characteristics, topographic conditions. In this chapter, SFDI has been developed from the fuel type danger index, slope danger index, aspect danger index, elevation danger index and Terrain ruggedness danger index.

4.2 Satellite datasets

For developing the Static Fire Danger Index (SFDI), MODIS Terra and Aqua land cover type product (MCD12Q1) and ASTER GDEM datasets have been used. The Moderate Resolution Imaging Spectroradiometer (MODIS) is a sensor on board NASA Terra and Aqua satellites since 1999 and 2002 respectively. The MCD12Q1 is a global land cover annual product of 500 m spatial resolution, it provides the five land cover schemes i.e. IGBP global vegetation classification scheme; University of Maryland scheme; Leaf Area Index/ fraction of photosynthetically active radiation (LAI/FPAR) scheme; Net Primary Production scheme (NPP) and Plant Functional Type (PFT) scheme (LPDAAC). The IGBP classified scheme is the primary land cover scheme and it consists of 17 land cover types (Belward et al., 1999; Friedl et al., 2010). The MODIS product MCD12Q1 pertaining to the years from 2001 to 2014, were downloaded from the REVERB (https://reverb.echo.nasa.gov/reverb/) website. Advanced Spaceborne Thermal Emission and

Reflection Radiometer Global Digital Elevation Model Version 2 (ASTER GDEM V2) product was developed by the NASA & Japan Ministry of Economy, downloaded from the global data explorer (https://gdex.cr.usgs.gov/gdex/). The MCD14 provides the thermal anomaly and fire location information, which can be derived from the MODIS 4 μm and 11 μm radiances. The MCD14 data have been downloaded from the Fire Information for Resource Management System (FIRMS) website (https://firms.modaps.eosdis.nasa.gov/active_fire/).

4.3 Methods

The static fire danger index was generated from the MODIS land cover type product (MCD12Q1) and ASTER GDEM datasets, which were downloaded from the NASA REVERB ECHO website. ISRO vegetation type map was also used. A detailed description of the methodology is given in the following subsections (Fig 4.1). This chapter was published as an article in the IEEE conference proceedings (Babu et al., 2016 b).
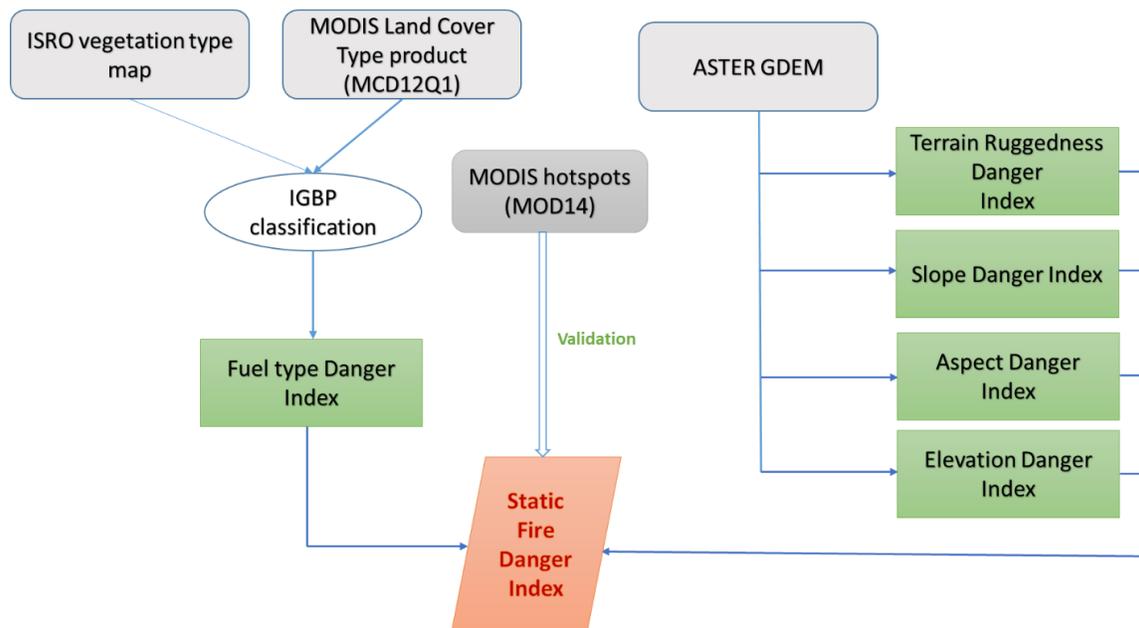
Fig 4.1 Flow chart showing the methodology

4.3.1 Historical forest fire hotspot data

The MODIS Terra and Aqua fire hotspot product MCD14 were downloaded for the study area Uttarakhand from 2010 to 2014. The product consists of fire location information, date and time of acquisition, brightness temperature and Fire Radiative Power (FRP) on each day. Grey

Relativity Analysis has been used to evaluate the weights of the each factor, influencing the fire danger. This method is an effective technique to solve the uncertainty problems consists of distinct datasets with less information (Chan & Tong, 2007; Zhai et al., 2009; Gai et al., 2011).

4.3.2 Fuel type Danger Index

The MODIS land cover type product (MCD12Q1) provides five global land cover classification systems along with a land cover type assessment, quality control information (LPDAAC). "International Geosphere-Biosphere Programme" (IGBP) land cover type has been generated from MCD12Q1 using "HDF-EOS to GeoTiff conversion tool" (HEG) software. The historical fire data were downloaded for the corresponding years (2010 to 2014) and these fires data were overlaid on the IGBP land cover type map to determine the type of land cover that is more vulnerable to fire. The percentage of fire incidents were calculated for each land cover type in each year so that the actual vulnerability of each land cover type has been determined during the fire season irrespective of the number of fire incidents. The mean of the percentages was calculated for the entire years and the danger levels were categorized into 5 types as shown in the Table 4.1.

Table 4.1 Description of different danger levels

S. No	Normalized score (%)	Name of the danger level	Description
1	< =5	No fire	Un favorable conditions
2	5-10	Low	Possible chances of fire
3	10-15	Moderate	Quite possible chances of fire
4	15-20	High	More favorable
5	>20	Very high	Most favorable

Table 4.2 shows the number of fire incidents in different landcover classes of IGBP classification for the years from 2010 to 2014.

Table 4.2 Fire incidents in different landcover classes of IGBP classification

IGBP classes	2010	2011	2012	2013	2014
Evergeen needleaf forest	3	1	14	1	1
Evergeen Broadleaf forest	0	0	4	3	0
Deciduous Needleleaf Forests	0	0	0	0	0
Deciduous Broadleaf Forests	0	0	2	0	0
Mixed Forests	661	103	1378	180	757
Closed Shrublands	7	2	5	1	4
Open Shrublands	0	0	1	0	0
Woody Savannas	216	35	397	66	223
Savannas	0	0	0	0	2
Grasslands	19	6	49	10	1
Permanent Wetlands	0	0	0	0	0
Cropland	213	85	324	48	51
Urban and Built-up	9	0	4	5	4
Cropland/Natural Vegetation Mosaics	185	32	233	34	98
Snow and Ice	0	0	0	0	0
Barren	0	0	0	0	0
Water bodies	0	0	0	0	0

Percentage of fires were calculated for each year and the normalized score was calculated for each landcover type (Table 4.3) and danger levels were assigned based on the table 1 and Fig 4.2 showing the fuel type danger index.

Table 4.3 Fire danger level of different land cover types

IGBP classes	Normalized score (%)	Danger level
Evergeen needleaf forest	0.31	No danger
Evergeen Broadleaf forest	0.21	No danger
Deciduous Needleleaf Forests	0	No danger
Deciduous Broadleaf Forests	0.02	No danger
Mixed Forests	52.92	Very high
Closed Shrublands	0.43	No danger
Open Shrublands	0.01	No danger
Woody Savannas	16.94	High
Savannas	0.04	No danger
Grasslands	1.74	No
Permanent Wetlands	0.00	No danger
Cropland	16.02	high
Urban and Built-up	0.53	No danger
Cropland/Natural Vegetation Mosaics	10.85	Moderate
Snow and Ice	0	No danger
Barren	0	No danger
Water bodies	0	No danger
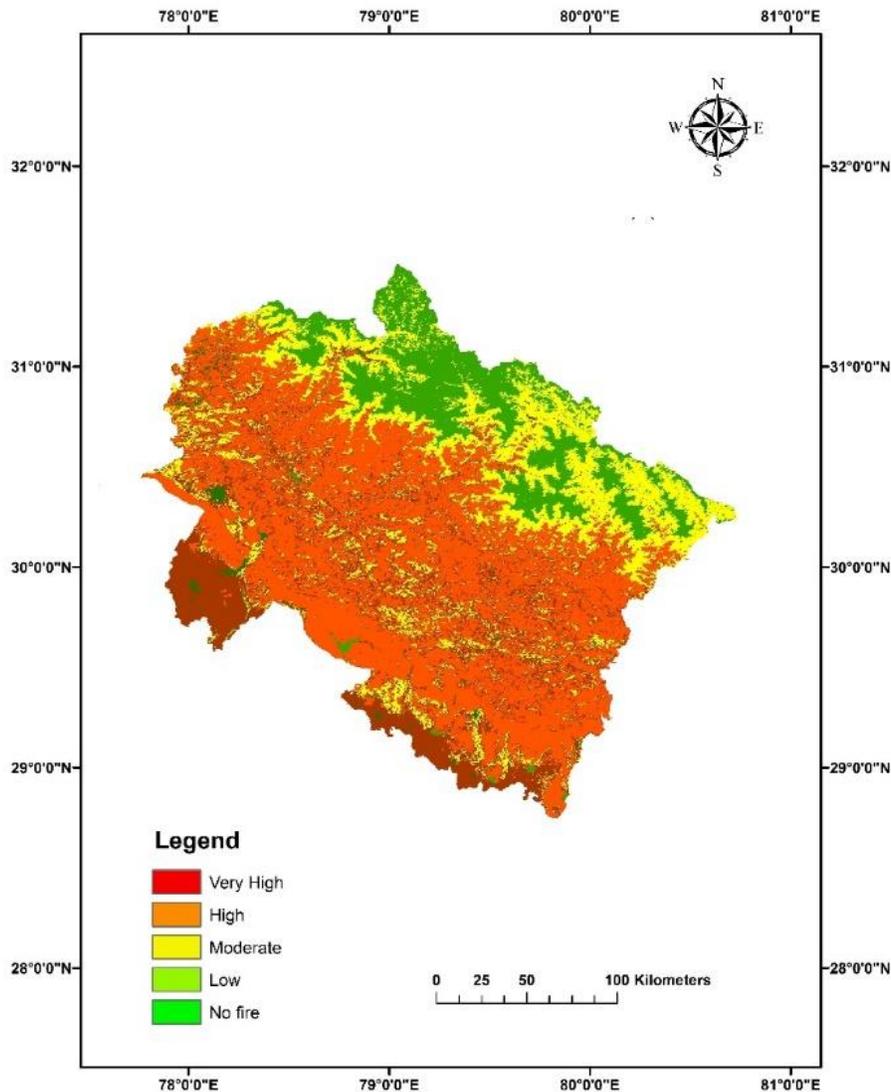
Fig 4.2 Fuel type danger index

Vegetation type map was downloaded from the ISRO Biodiversity Information System (BIS website) and has been used to generate fuel danger index based on the number of fire hotspots in each of the vegetation type. Fire hotspots were counted in each vegetation type for the years 2010 to 2014 (Table 4.4) and normalized to know the type of vegetation which more vulnerable to fire. The fire danger levels were assigned to each vegetation type based on the normalized score, as shown in the table 4.5.

*Table 4.4 Fire incidents in different vegetation types*

vegetation type	2010	2011	2012	2013	2014
Himalayan moist temperate	53	14	220	21	13
Sub alpine	6	1	1	0	3
Sal mixed moist deciduous	306	51	399	55	24
Dry deciduous	148	10	79	16	26
Temperate coniferous	14	2	8	1	2
Sal	222	44	350	44	223
Pine	206	62	512	66	313
Fir	0	0	0	0	0
Oak	8	1	2	1	0
Deodar	2	0	2	0	2
Teak	7	5	22	9	6
Eucalyptus	7	2	12	7	4
Mixed plantation	27	12	40	13	15
Degraded forest	32	5	22	6	45
Scrub	2	0	5	0	3
Dry evergreen scrub	3	0	0	1	2
Dry deciduous scrub	111	25	308	20	163
Ziziphus	4	0	3	1	5
Wet grasslands	15	3	15	5	32
Riverine grasslands	28	2	27	1	3
Moist alpine pasture	2	2	3	0	2
Agriculture	102	19	360	67	237
Barren land	5	2	2	0	3
River bed	13	2	19	6	16

Table 4.5 Fire danger levels assigned to vegetation types of Uttarakhand

Vegetation type	Normalized score (%)	Danger levels
Himalayan moist temperate	5.15	Low
Sub alpine	0.23	No danger
Sal mixed moist deciduous	15.45	High
Dry deciduous	5.05	Low
Temperate coniferous	0.52	No danger
Sal	16.09	High
Pine	21.42	very high
Fir	0	No danger
Oak	0.27	No danger
Deodar	0.08	No danger
Teak	1.30	No danger
Eucalyptus	0.84	No danger
Mixed plantation	2.68	No danger
Degraded forest	2.19	No danger
Scrub	0.12	No danger
Dry evergreen scrub	0.14	No danger
Dry deciduous scrub	10.16	moderate
Ziziphus	0.23	No danger
Wet grasslands	1.43	No danger
Riverine grasslands	0.91	No danger
Moist alpine pasture	0.24	No danger
Agriculture	14.06	moderate
Barren land	0.30	No danger
River bed	1.14	No danger

Fig 4.3 showing the Fuel type Danger Index generated from the vegetation type map of Uttarakhand state.

Fuel type danger index from both the MODIS IGBP land cover type map and ISRO vegetation type were map compared based on the fire hotspots of 2015. The accuracy of Fuel type danger index from the Biodiversity Information System (BIS) vegetation map was good and therefore the fuel type danger index from the ISRO vegetation map was used to generate the Static Fire Danger Index.
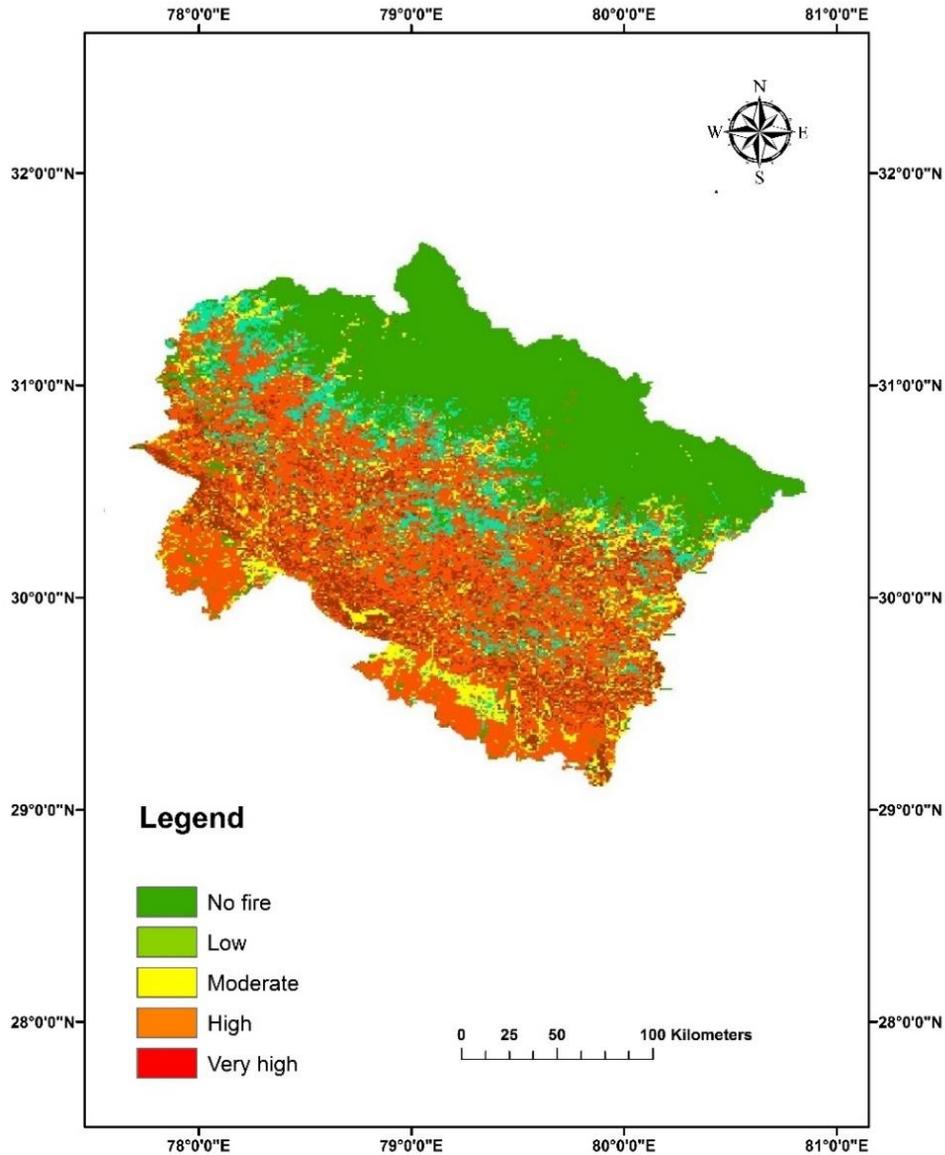
Fig 4.3 Fuel type Danger Index from ISRO vegetation type map

4.3.3 Terrain Ruggedness Danger Index (TRDI)

Terrain heterogeneity is an important parameter for describing the species diversity in the mountainous area. Terrain Ruggedness Index (TRI) provides an objective quantitative measure of topographic heterogeneity and is derived from digital elevation model (DEM) (Riley et al., 1999). It is the difference between the values of a cell and the mean of an eight neighborhood surrounding cells. Terrain has been classified into 7 classes: Level, nearly level, slightly rugged, intermediately rugged, moderately rugged, highly rugged and extremely rugged based on TRI values (Riley et al., 1999; Moreno et al., 2004) and the danger levels were assigned according to the procedure followed as in the fuel type danger index. Table 4.6 shows the number of fire points in different TRI class levels. Percentage mean was calculated for the years 2010 to 2014 as shown in the table 4.7 and fire danger classes were assigned based on their normalized score and Fig 4.4 shows the Terrain ruggedness danger index.

Table 4.6 Fire hotspots occurred in different TRI class levels

TRI	TRI class	Year				
		2010	2011	2012	2013	2014
0-80	Level	552	308	1607	201	853
81-116	Nearly Level	69	9	48	18	4
117-161	Slightly Rugged	97	6	22	12	7
162-239	Intermediately Rugged	167	36	365	47	72
240-497	Moderately Rugged	425	95	858	97	316
498-958	Highly Rugged	14	3	8	1	7
>958	Extremely rugged	0	0	0	0	0

Table 4.7 Terrain ruggedness danger index

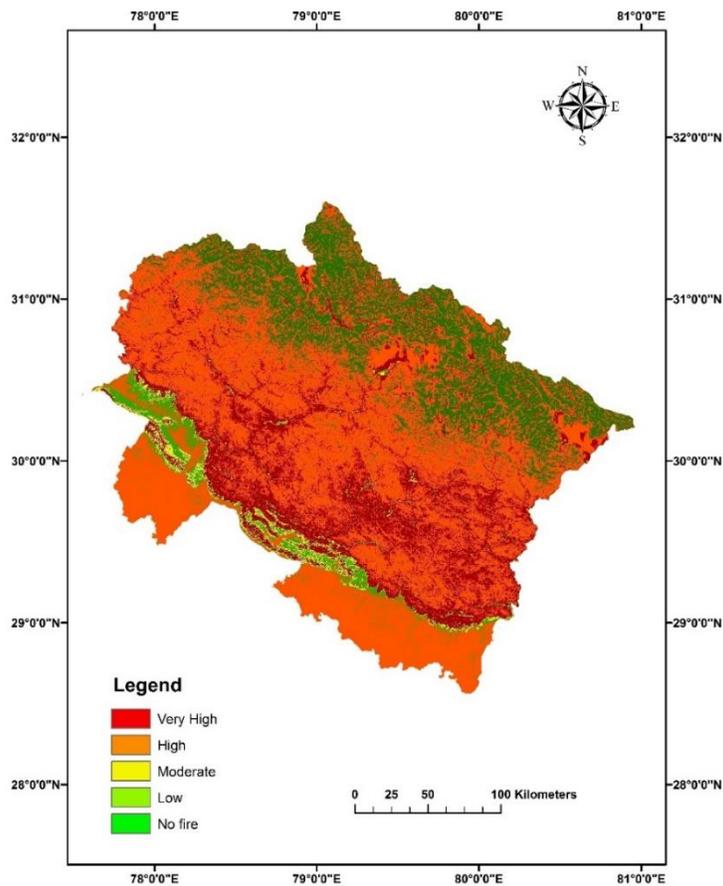| TRI	Name of the class	Normalized Score (%)	Danger class
0 – 80	Level	57.11	Very high
81 - 116	Nearly Level	2.79	No danger
117 – 161	Slightly rugged	2.63	No danger
162 – 239	Intermediately rugged	10.25	Moderate
240 – 497	Moderately rugged	26.66	High
498 - 958	Highly rugged	0.56	No danger
>958	Extremely rugged	0	No danger

Fig 4.4 Terrain Ruggedness Danger Index

4.3.4 Topography

Topography is an essential physiographic factor, which influences the wind speed and behavior and hence, affects the spreading of fire (Rothermel, 1983). Topography is the most stable factor of the fire triangle and easier to predict its influence on other factors: weather and fuel. Topographic factors are slope, aspect and elevation.

4.3.4.1 Slope Danger Index

Slope is the main factor in any fire danger analysis due to the fact that fire travels up slope faster than down (Chuvieco & Congalton, 1989; Jaiswal et al., 2002). In general, steeped slopes tend to increase the rate of fire spread as compared with flat surfaces or lower steeped slopes. In this study, historical fire data from 2010 to 2014 have been used to measure the slopes which are more vulnerable to fire. Table 4.8 shows the fire incidents occurred in different slopes of the study area.

Table 4.8 Fire hotspots occurred in different slopes

Slope (Degrees)	Year				
	2010	**2011**	**2012**	**2013**	**2014**
< 3	221	118	275	92	93
3 – 5	135	13	48	23	17
5 – 10	116	9	61	18	28
10 – 15	176	25	271	26	86
15 – 20	183	18	276	17	142
20 – 25	192	25	497	48	185
25 – 30	160	27	443	67	153
30 – 35	91	20	329	23	149
35 – 40	26	5	126	7	73
40 – 45	14	2	66	2	31
>45	9	4	21	2	10

From the table 4.8, it is evident that a larger number of fire incidences occurred below 3 degrees and minimum above 40 degrees, which is against the general hypothesis for the spread of fire (Chuvieco & Congalton, 1989; Dong et al., 2005; Rathaur, 2005). After the field visit to entire forests of Uttarakhand state, it is concluded that the higher litter content with driest condition and longer time of sunlight received in down the slope were the main cause of the higher incidence of fires, that support surface fires in the Uttarakhand Himalayas. Accessibility is the main reason for the larger number of fires in the lesser slopes (< 3 degrees) as the humans can easily climb and ignite the fires either intentional or unintentional ways. Mean number of fire incidents calculated in each year for the above slope intervals and normalized to determine the fire danger levels. Table 4.9 shows the danger levels assigned to the different range of slopes for the generation of slope danger index (Fig 4.5).

Table 4.9 Fire danger levels for different range of slopes

Slope (Degrees)	Normalized score (%)	Danger class
< 3	22.08	Very high
3 – 5	5.18	Low
5 – 10	4.62	No danger
10 - 15	10.17	Moderate
15 – 20	10.39	Moderate
20 – 25	15.68	High
25 – 30	15.41	High
30 – 35	10.10	Moderate
35 – 40	3.75	No danger
40-45	1.67	No danger
>45	0.94	No danger
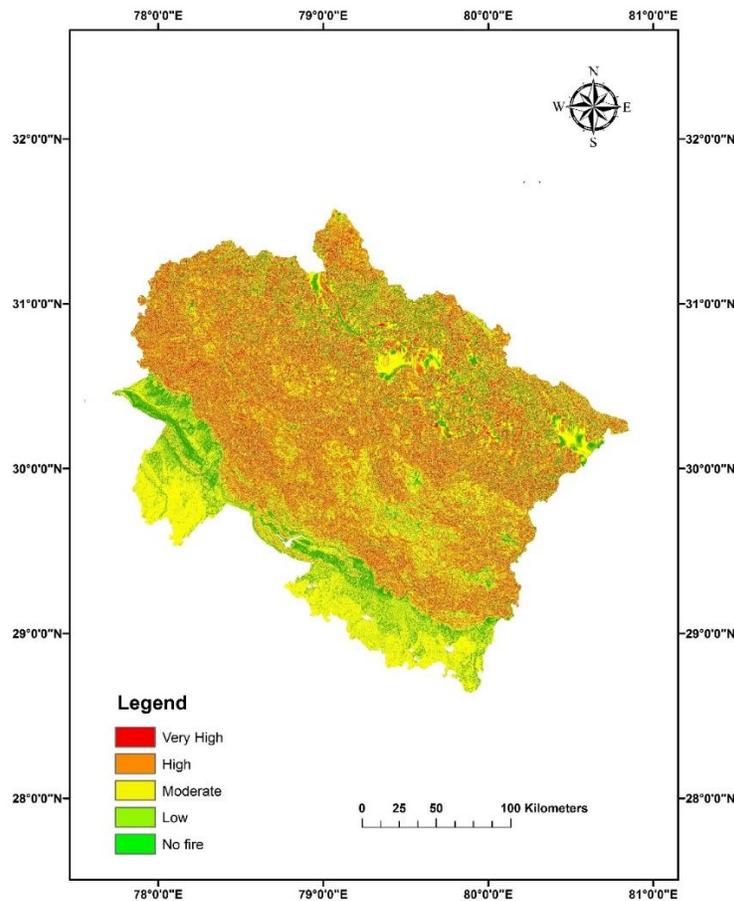
Fig 4.5 Slope Danger Index

4.3.4.2 Aspect Danger Index

Aspect is the direction of slope change and it determines the effect of solar radiation, moisture and air temperature (Chuvieco & Congalton, 1989). As the state Uttarakhand is in the Northern Hemisphere, the south facing slopes receive more solar radiation which results in lower humidity, less moisture and higher fuel temperatures creating suitable condition for initiation of forest fires. Fire incidents from 2010 to 2014 were used to compute the Aspect Danger Index. Aspect map of Uttarakhand was generated from the ASTER GDEM and is categorized into 10 classes viz. flat (-1), North (0 - 22.5), Northeast (22.5-67.5), East (67.5-112.5) Southeast (112.5-157.5), south (157.5-202.5), southwest (202.5-247.5), west (247.5-292.5), northwest (292.5-337.5) and north (337.5-360). Total number of fire incidents in each of the aspect class was extracted for the period 2010-14 during fire season (Table 4.10).

Table 4.10 Fire incidents in different aspects

S. No.	Name of the aspect classes	Year				
		2010	**2011**	**2012**	**2013**	**2014**
1	Flat	0	0	0	0	0
2	North	40	8	115	9	53
3	Northeast	120	12	250	21	89
4	East	100	20	271	16	113
5	Southeast	119	74	501	72	199
6	South	340	74	501	72	199
7	Southwest	346	75	495	105	169
8	west	142	27	233	36	103
9	Northwest	79	6	173	31	67
10	North	34	6	78	6	40

The total number of fire points were normalized into 1 to 100 to estimate which aspect class was more susceptible to fire and the mean of normalized score was computed. Table 4.11 shows the mean normalized score and the corresponding danger levels and Fig 4.6 shows the generated aspect danger index. According to the reports (Anand et al., 2012), in the month of March and April, most prominent wind direction is northwest in the morning and southwest in the evening whereas in the month of May and June, both morning and evening wind directions are south and southeast.

Table 4.11 Aspect danger Index

S. No	Aspect degree	Mean normalized score (%)	Danger class
1	Flat	0	No danger
2	North	3.82	No danger
3	Northeast	7.95	Low
4	East	8.62	Low
5	Southeast	11.29	Moderate
6	South	23.53	Very high
7	Southwest	25.06	Very high

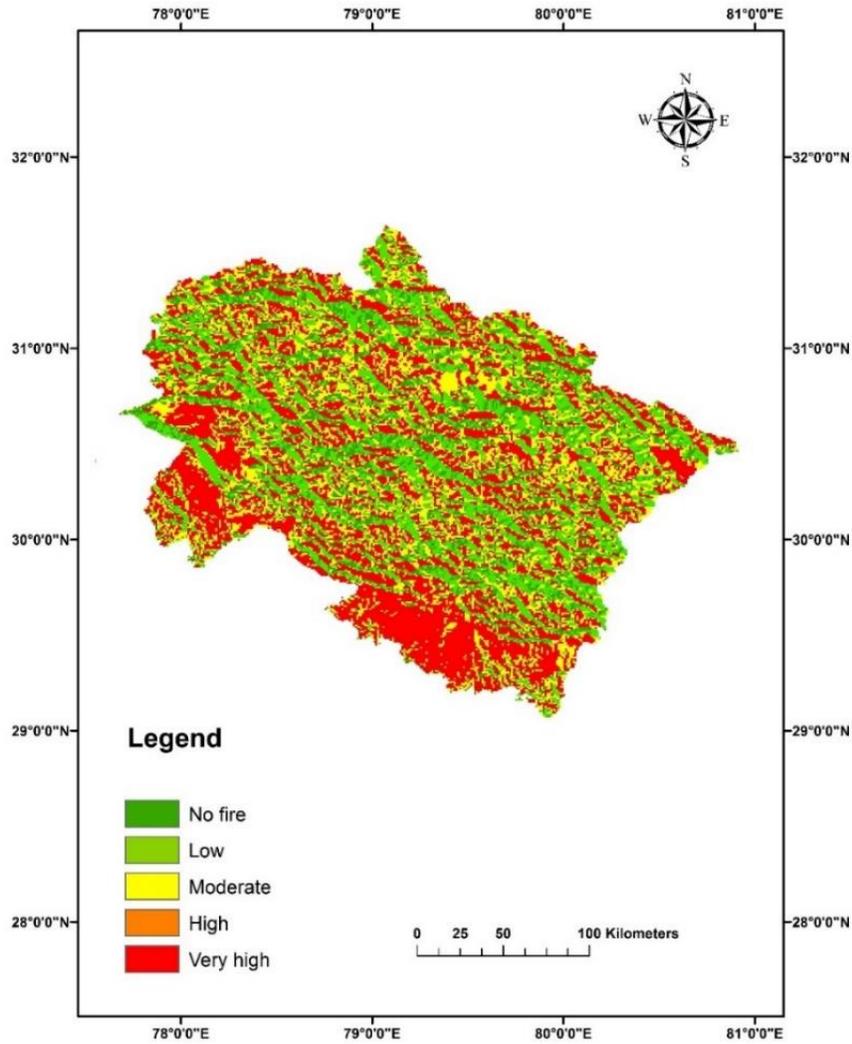| 8	**West**	10.5	Moderate
9	**Northwest**	6.39	Low
10	**North**	2.82	No danger

Fig 4.6 Aspect Danger Index

4.3.4.3 Elevation Danger Index

The variable elevation is considered as an important factor of forest fire because it influences the precipitation and temperature. The weather is hot and moist in the sub – Himalayan zone and in river valleys below 600 m in elevation whereas the climate becomes sub-tropical up to the elevation of 1200 m. Elevations of Uttarakhand were categorized into different ranges to

know the vulnerability of forest fires. Table 4.12 shows the fire incidents occurred in different elevation ranges of the study area. Tree line of the Uttarakhand state is 3200 m.

Table 4.12 Fire hotspots occurred in different elevation ranges

Elevation	Year				
	2010	**2011**	**2012**	**2013**	**2014**
0-600	308	53	308	68	148
601-1200	546	130	786	148	296
1201-1800	190	32	212	28	166
1801-2400	192	28	242	77	312
2401-2700	71	21	158	5	42
2701-3200	17	3	9	0	0
>3200	0	0	0	0	0

From the table 4.12, it was clear that maximum number of fires occurred in the elevation ranges from 0 to 1200 m above mean sea level, followed by elevation ranges from 1200 to 1800 m and less or very few fires in the ranges from 2700 to 3200 m, no fires in the altitudes above 3200 m. Anthropogenic activities were the main cause of occurrence of highest fire incidences in the elevations below 600 m and 600 to 1200 m and presence of pine forests are the responsible for highest number of fires in the elevation ranges 1200 to 2400 m. There are lesser or no fires in the elevations greater than 2700 m because the climate is cold frigid. Number of fire points in each year was normalized into 1 to 100 and mean of all 5 years were calculated to assign danger levels based on the value to generate elevation danger index (Table 4.13; Fig 4.7).

Table 4.13 Elevation danger Index

Elevation (m)	Mean of Normalized score (%)	Danger class
0 - 600	19.46	High
601 - 1200	42.37	Very high
1201-1800	12.90	Moderate
1801 - 2400	19.02	High

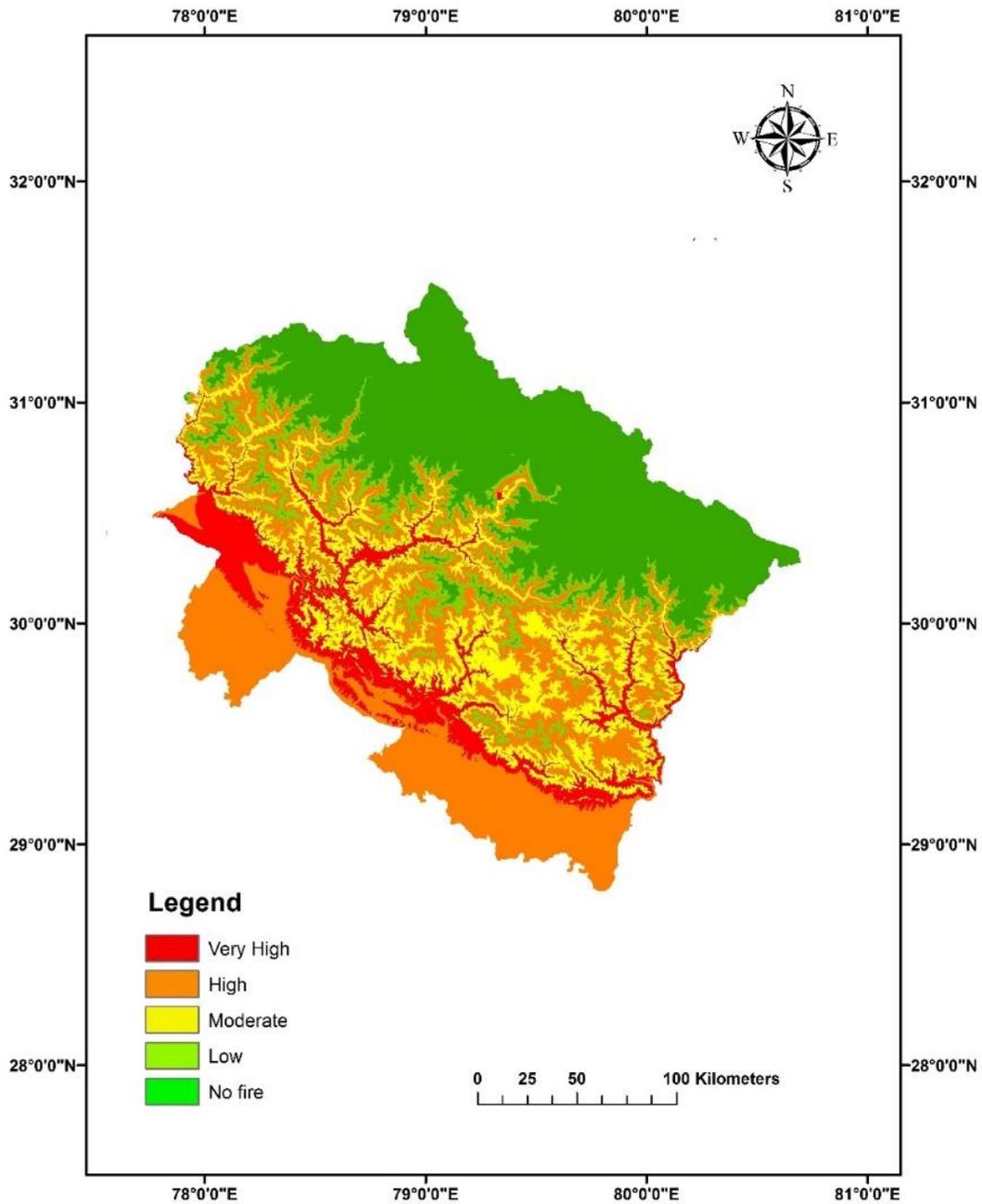| 2401 - 2700	5.67	Low
2701-3200	0.59	No danger
>3200	0	No danger

Fig 4.7 Elevation Danger Index

4.4 Results and Discussion

Hitherto in the studies carried out by various researchers (Brass et al., 1983; Chuvieco & Salas, 1996; Dong & Rathur, 2005; Orozco et al., 2009), danger levels were assigned randomly to each factor based on the hypothesis of forest fire spread without consideration of characteristics of the study area and historical fire records. So, Analytical Hierarchical Process (AHP) method was used to calculate the forest fire risk in the above mentioned studies. In this study, weights were assigned to each parameter based on the historical fire occurence. Therefore, Static Fire Danger Index (SFDI) was developed by combining all the five individual danger indices i.e. Fuel type danger index, Terrain Ruggedness Danger Index, Slope danger index, Aspect danger index and Elevation danger index as the each individual index was generated based on the historical fire incidents and the field investigation.

The SFDI has been categorized into fire danger classes viz. no fire, low, moderate, high and very high based on the Table 4.14.

Table 4.14 SFDI danger classes

S. No	SFDI	Danger level
1	<=5	No fire
2	6-10	Low
3	11-15	Moderate
4	16-20	High
5	>20	Very high

MODIS Terra and Aqua active fire hotspot data (MCD14) during the fire season of 2015, 2016 and 2017 were downloaded from the FIRMS website and has been used to estimate the accuracy of the SFDI. Figs 4.8 – 4.10 shows the map of static fire danger index overlaid with active fire data of 2015, 2016 and 2017. Fig 4.11 represents the number of fire incidents in different danger classes of SFDI for the years 2015, 2016 and 2017.
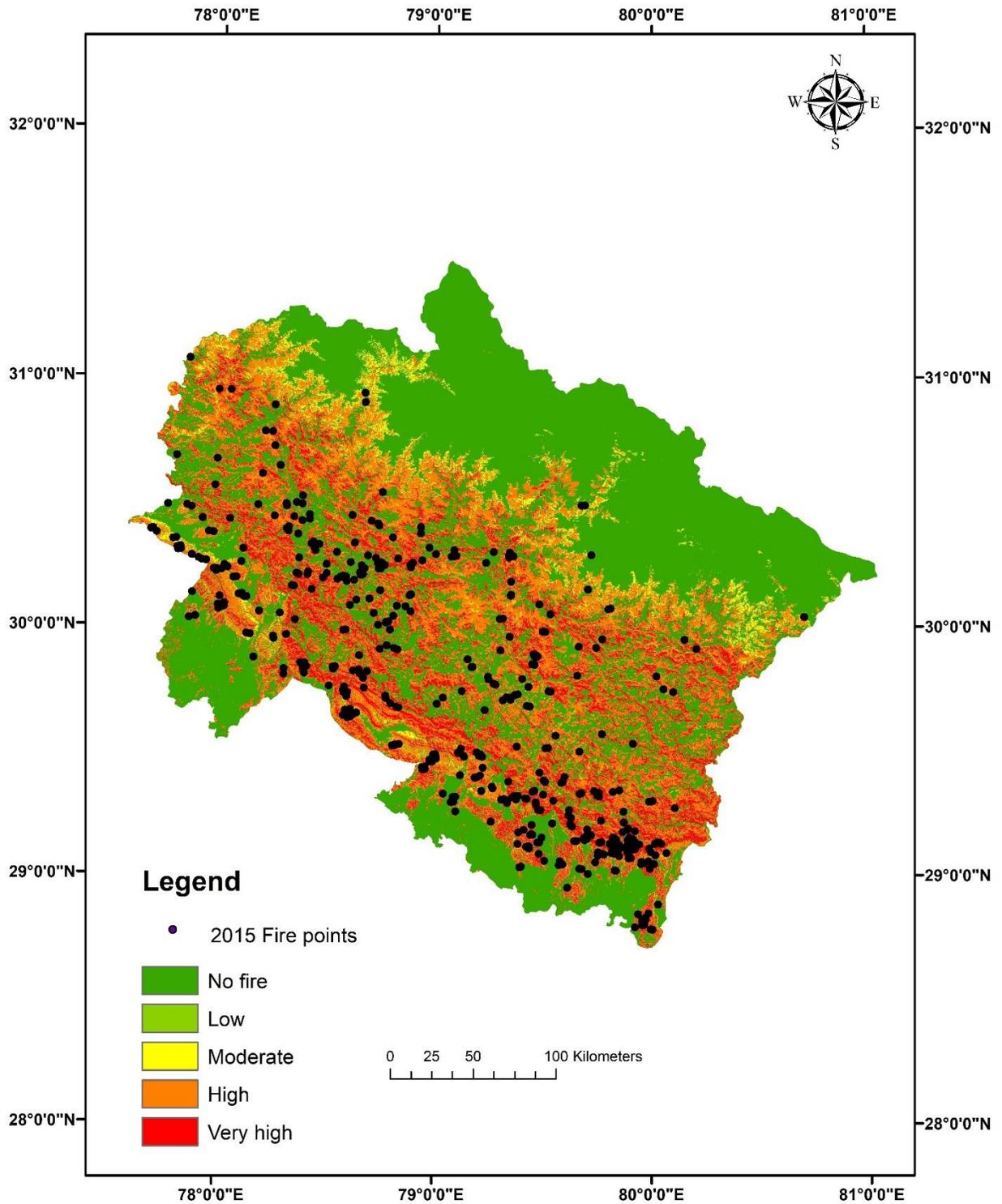
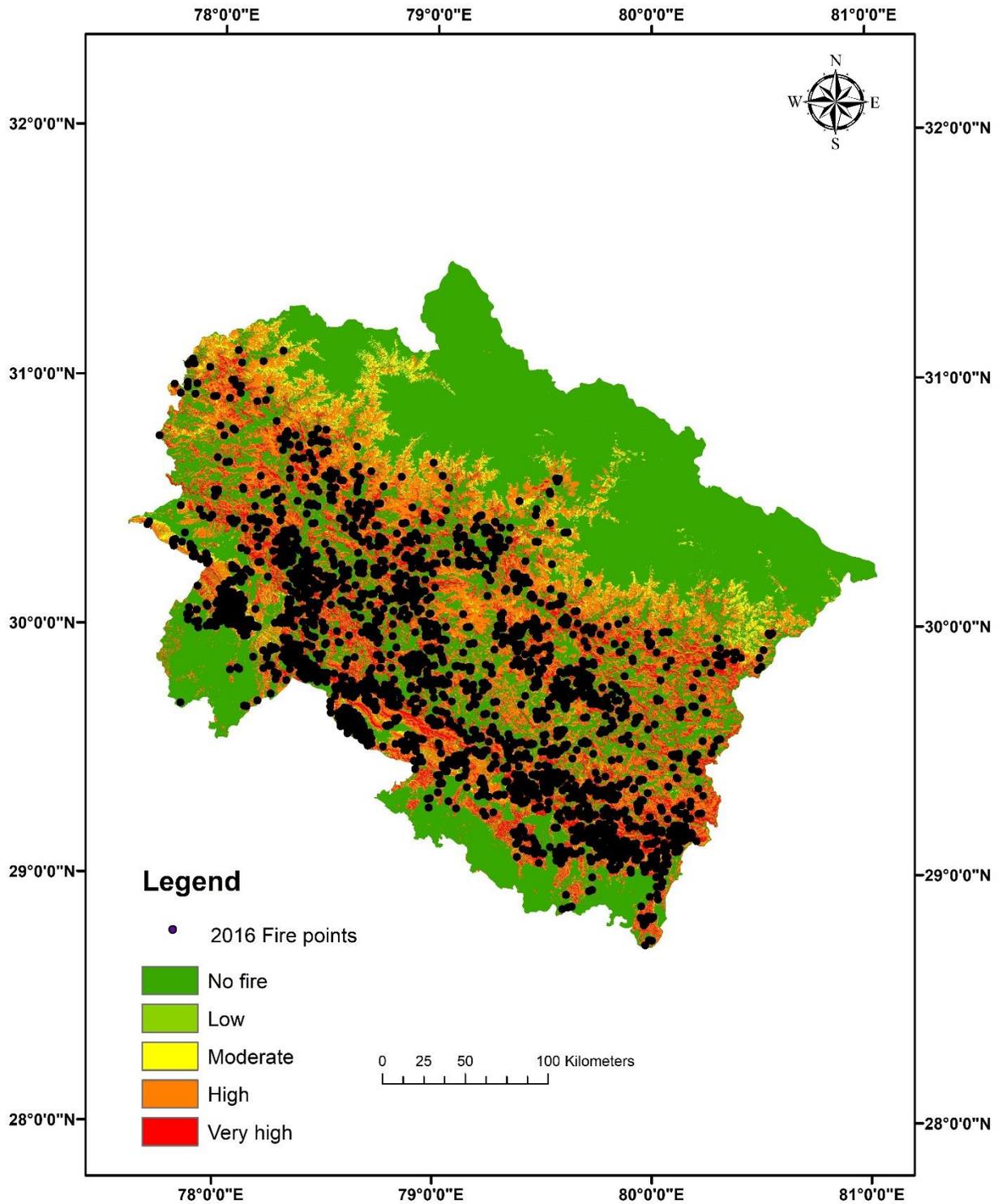*Fig 4.8 Static Fire Danger Index overlaid with fire hotspots of 2015*

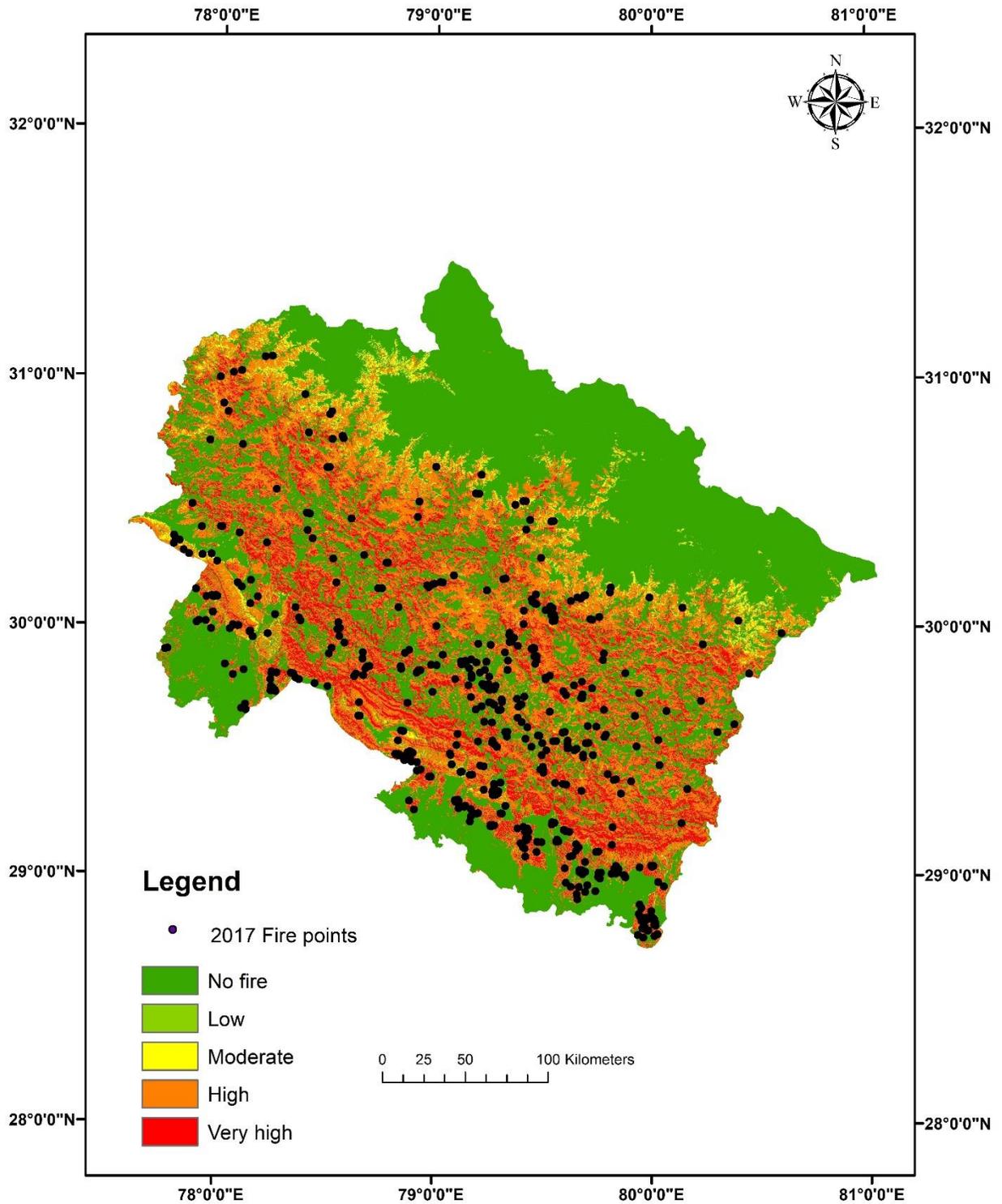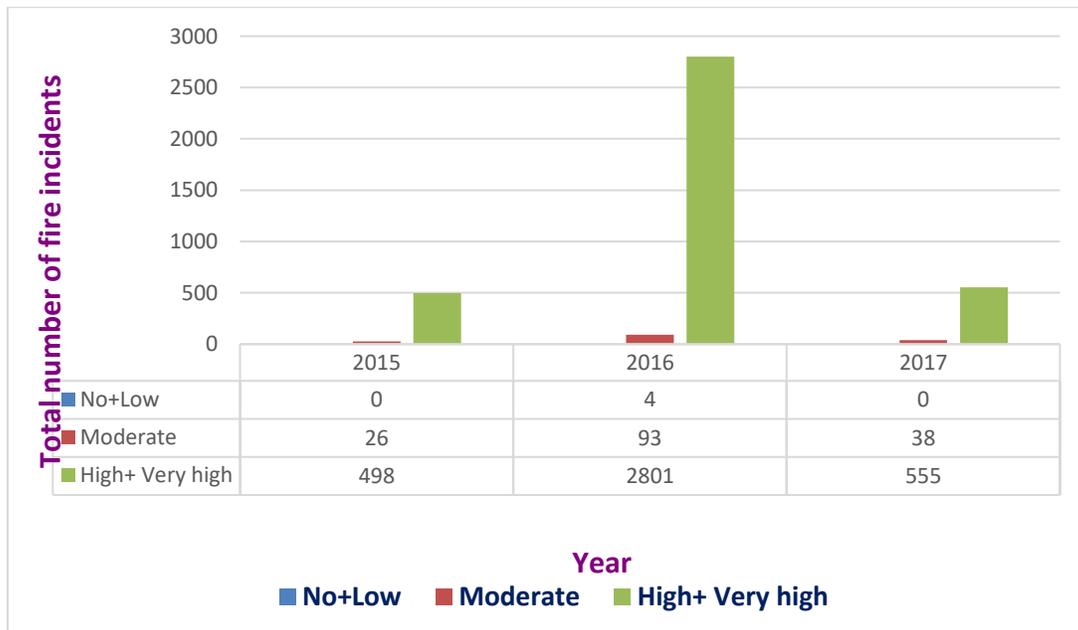*Fig 4.9 Static Fire Danger Index overlaid with fire hotspots of 2016*

Fig 4.10 Static Fire Danger Index overlaid with fire hotspots of 2017

MODIS active fire hotspots were used as a proxy to the actual occurrence of fires for calculating the accuracy of fire danger models (Chuvieco et al., 2008; Vadrevu et al., 2010; Maeda et al., 2011; Adab et al., 2013; Eskandari & Chuvieco, 2015). Similarly in the present study, MODIS active fire product MCD14 has been used for the validation for SFDI. In most of the studies, accuracy was estimated based on the number of fire incidents fell in different fire danger classes (Alexander et al., 2008; Vadrevu et al., 2009; Maeda et al., 2011; Adab et al., 2013; Sitanggang et al., 2013; Eskandari & Chuvieco, 2015; Mitri et al., 2017). They counted the number of fires fell in each fire danger classes and the classes "low" and "very low" classes were considered as "no fire is predicted"; the classes "high", "very high" and "extreme" classes were considered as "a fire is predicted". But, in current study, fires fell in "No fire danger", "Low" and "Moderate" were considered as fire is not predicted and otherwise predicted.

Accuracy of SFDI was estimated based on the number of fire incidents in different danger classes and calculated from the below equation (1) (Babu et al., 2016 a ,b).

$$Accuracy = \frac{Total\ number\ of\ fire\ incidences\ in\ High\ and\ very\ high\ danger\ classes}{Total\ number\ of\ fire\ incidents\ in\ all\ classes} * 100 \qquad (1)$$

	2015	2016	2017
No+Low	0	4	0
Moderate	26	93	38
High+ Very high	498	2801	555

Year

No+Low   Moderate   High+ Very high

Fig 4.11 Fire incidents in different fire danger classes from 2015-17

Accuracy of SFDI for the years 2015, 2016 and 2017 were 95%, 96.7% and 93.6% respectively. Therefore SFDI accurately represents the distribution of fire danger over the study area. Further analysis was carried out to analyze the SFDI on the basis of elevation ranges and forest types of Uttarakhand state.

4.5 Static Fire Danger Index versus forest types

Vegetation type map of Uttarakhand derived from LISS-III data (Roy et al., 2012) was used to cross tabulated the SFDI for the distribution of fire danger classes in different forest types of the state. Fig 4.12 represents the areal distribution of five danger classes viz. no fire, low, moderate, high and very high in different vegetation classes and it was evident that Pine forests have the highest distribution in the high fire danger class of the SFDI, followed by the Sal mixed moist deciduous, and then Sal forest type. This is exactly matches with the forest fire trends in the Uttarakhand state and also attributed to the surface fine fuel availability in these forest types.
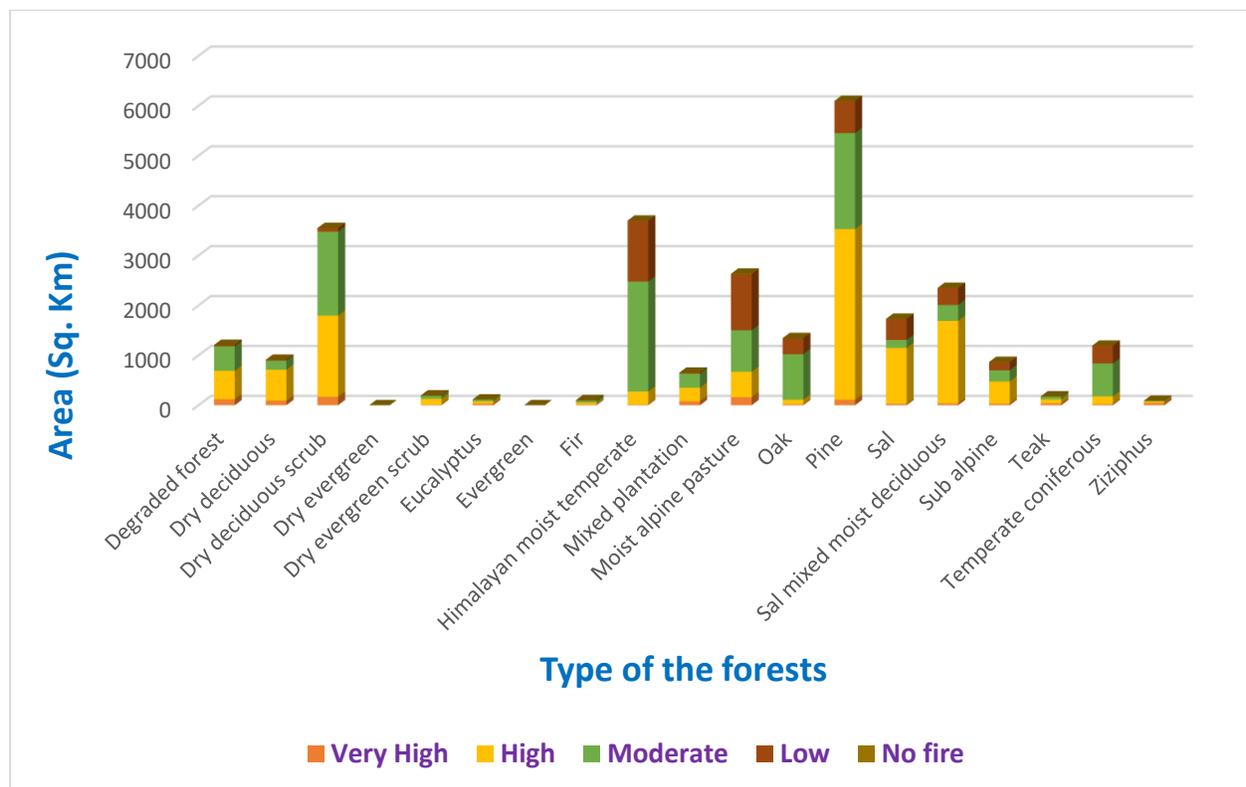

Fig 4.12 SFDI danger classes versus forest types

4.6 Conclusions

Static fire danger index has been developed from the static parameters such as 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 in this study. Fuel type danger index was generated from the IGBP product, which was extracted from the MODIS Terra and Aqua dataset MCD12Q1. ASTED GDEM was used for the computation of TRDI, ADI, SDI, EDI based on the historical fire location data as well as ground investigation. SFDI was computed by combining all the individual indices and fire incidents for the years 205, 2016 and 2017 have been used for the validation.

Accuracy of SFDI for the years 2015, 2016 and 2017 were 95%, 96.7% and 93.6% respectively. The Static fire danger index 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.

Chapter 5. Dynamic Forest Fire Danger Index

5.1 Introduction

Forest fire danger is the resultant of both the factors i.e. static and dynamic. Static parameters such as the type of the forest, Terrain characteristics, and topographic conditions are constant over the time, Whereas the dynamic parameters (meteorological parameters) like "air temperature", "relative humidity", "wind speed" and "rainfall" vary with the time. Fire Danger Rating Systems computes the fire danger based on the meteorological parameters from weather stations and predicts the fire danger using the forecasted parameters (Canadian FWI, US NFFDRS, and McArthur FDI). In India, meteorological stations are very sparse and also very far from the forests. Therefore, the fire danger rating systems has not been developed in India to forecast the fire danger. In this chapter, Dynamic Fire Danger Index (DFDI) has been developed from the satellite datasets.

In this chapter, MODIS Terra satellite datasets i.e. MOD09A1 (8 day Surface Reflectance product), MOD11A2 (8 day Land Surface Temperature/Emissivity product), MCD14 (MODIS Terra and Aqua thermal anomaly product) and ASTER digital Elevation Model (GDEM) were used to develop the DFDI. Three parameters Modified Normalized Difference Fire Index (MNDFI), Perpendicular Moisture Index (PMI) and potential surface temperature were calculated from the above mentioned satellite based products. MNDFI has been used for determining whether the thermal anomaly location has fire or not and PMI is for the estimation of live fuel moisture content in the vegetation and litter. Potential surface temperature was calculated from the MODIS LST and ASTER GDEM.

5.2 Materials and Methods

Table 5.1 shows the information about the satellite datasets used in this study such as product ID, spatial resolution and temporal resolution. MODIS Terra Satellite data sets i.e. MOD09A1, MOD11A2 were downloaded from the REVERB site and the entire study area covering the 4 tiles (h24v05, h24v06, h25v05 and h25v06) were processed using "HDF-EOS to GeoTIFF Conversion Tool (HEG)" software and ERDAS imagine software. ASTER Terra product (ASTGTM -ASTER Global Digital Elevation Model V002) was downloaded from the REVERB

website for the state Uttarakhand.

Table 5.1 Satellite datasets used in this study

S. No	Name of Datasets	Product ID	Spatial Resolution	Temporal Resolution
1	Land Surface Temperature	MOD11A2	1 km	8 days
2	Surface Reflectance	MOD09A1	500 m	8 days
3	Fire and Thermal Anomalies	MCD14	1 km	Daily
4	Global Digital Elevation Model	ASTER	30 m	-

The MOD09A1 dataset is a MODIS surface reflectance product at 500 m pixel resolution, consists of seven bands (Band 1 to 7) and the product is processed to level 3 gridded using a sinusoidal projection. The processing corrects for the effects of atmospheric gases and aerosols resulting in a band-wise estimate of surface reflectance as it would have been measured at ground level. The MOD11A2 products provide per-pixel temperature and emissivity values in a sequence of swath-based on grid-based global products in the Sinusoidal projection, and produced daily at 1 km spatial resolution (LPDAAC). Table 5.2 shows the day of MODIS datasets used in this chapter.

Seven spectral reflectance bands and Land Surface Temperature were derived from MOD09A1 and MOD11A2 data using HEG tool and multiplied by a scale factor (0.0001 for reflectance and 0.02 for LST) to generate the final data products. The resulting products i.e. Land Surface Temperature and Reflectance products have been clipped to the Uttarakhand boundary for calculation of dynamic parameters.

Table 5.2 Julian day and corresponding date of temporal MODIS datasets

Julian day	Date
81	22-March-2015
89	30-March-2015
97	07-April-2015
105	15-April-2015
113	23-April-2015
121	01-May-2015
129	09-May-2015
137	17-May-2015
145	25-May-2015
153	2-June-2015
161	10-June-2015

5.3 Methods

The corrected MODIS reflectance bands 2, 5 and 7 and Land surface temperature were used to compute three parameters viz. Potential surface temperature, Modified Normalized Difference Fire Index (MNDFI) and Perpendicular Moisture Index (MSI). Fig 5.1 shows the methodology flow to compute fire danger model based on MODIS Terra and ASTER satellite datasets.
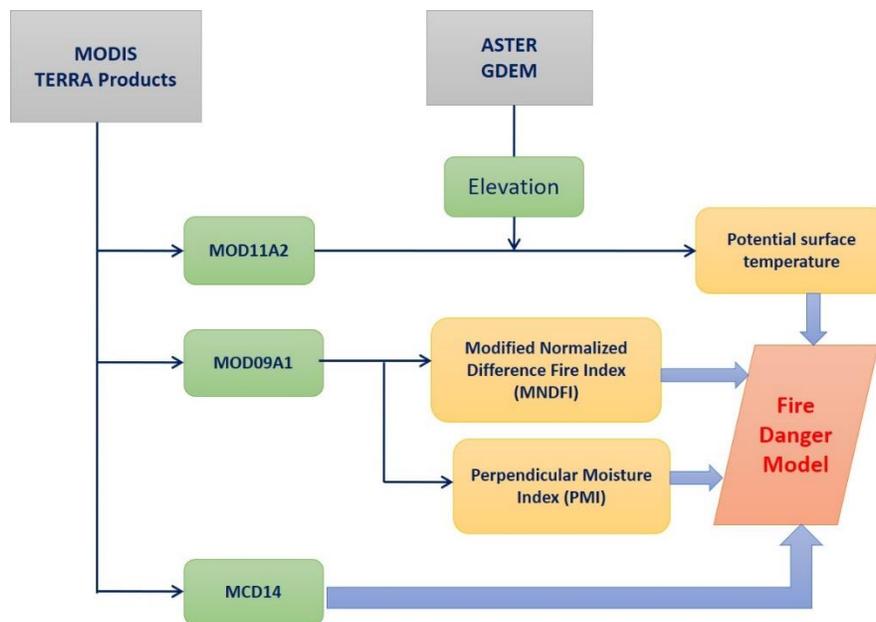
Fig 5.1 Methodology for modeling the fire danger

5.3.1 Potential Surface Temperature

Potential surface temperature for each day during the fire season was computed from the MOD11A2 product by the following equations. Using the Barometric formula, we can find the relationship between Atmospheric Pressure and Digital Elevation Model (DEM) over the study area at every pixel.

$$p = p_0 \left(1 - \frac{Lz}{T_0}\right)^{\frac{g.M}{R.L}} \tag{1}$$

Where p: Atmospheric pressure; p_0 is the Standard atm. pressure at mean sea level (101.3 kPa); z is the elevation above mean sea level; L: Temperature lapse rate (0.0065 K/m); R: Gas constant (8.31447 J/ mol-K); g: Earth-surface gravitational acceleration (9.80665 m/s^2) ; M: Molar mass of dry air (0.0289644 kg/mol) and T_0: Sea level standard temperature ($20°C$)

Pressure data (30m resolution) was converted to 1 km spatial resolution data using Reproject tool in ERDAS. Potential surface temperature for each day was computed from the following equation (2):

$$\theta_s = T_s \left[\frac{p_0}{p}\right]^{\frac{R}{C_P}} \tag{2}$$

Where

T_s: Surface temperature (in K)

R: Gas constant (287 J kg^{-1} K^{-1})

C_P: Specific heat capacity of air (~1004 J kg^{-1} K^{-1})

θ_s: Potential surface temperature (in K)

5.3.2 Perpendicular Moisture Index (PMI)

Vegetation moisture is one of the factors that dictate the susceptibility to fire ignition and propagation in forests. Several spectral indices were developed based on a function of NIR and SWIR reflectance such as Normalized Difference Infrared Index (Hardisky et al., 1983), the Normalized Difference Water Index (Gao, 1996), and the Global Vegetation Moisture Index (Ceccato et. al., 2002) for the assessment of vegetation equivalent water thickness (EWT).

However, many fire models depend on live fuel moisture content (LFMC) as a measure of vegetation moisture. Perpendicular Moisture Index (PMI) (Maffei & Meneti, 2014) was proposed as direct measure of LFMC.

Perpendicular Moisture Index (PMI) was computed from MODIS bands 2 (0.86 µm) and 5 (1.24 µm) according to the following formula (Maffei & Meneti, 2014).

$$PMI = -0.73 * (R5 - 0.94 * R2 - 0.028) \qquad (3)$$

R2 and R5 are spectral reflectance of Band 2 and 5 respectively. The PMI values increases with increasing values of LFMC, so, the higher PMI values imply a lower fire spread and vice versa.

5.3.3 Modified Normalized Difference Fire Index (MNDFI)

Modified Normalized Difference Fire Index (MNDFI) was proposed by Yasuda and Park of Tokyo university of Information sciences (Park et al., 2006) to determine whether a location has the higher temperature or not. There is a high correlation between MODIS Band 2 and the chlorophyll content in the vegetation. MODIS Band 7 provides the information about reflective and radiation factors of the earth's surface. In case of forest fires, Band 2 value decreases with the decreasing amount of chlorophyll and the Band 7 value increases with rising temperature.

MNDFI can be determined from the following formula (Vermote et al., 2002; EijiNunohiro et al., 2007) and these have values ranging from -1 to 1.

$$MNDFI = \left[\frac{MODIS Band\ 7 - MODIS\ Band\ 2 - 0.05}{MODIS\ Band\ 7 + MODIS\ Band 2 + 0.05}\right] \qquad (4)$$

As discussed in above methods, the potential surface temperature, Modified Normalized Difference Fire Index (MNDFI) and Perpendicular Moisture Index (PMI) were calculated and the generated datasets were reprojected into 1 km resolution for the integration. The resulting images were then clipped to the boundary of the study area.
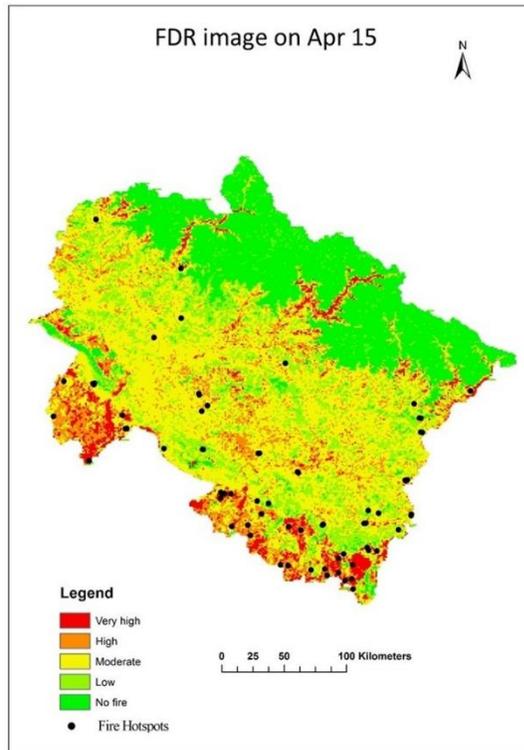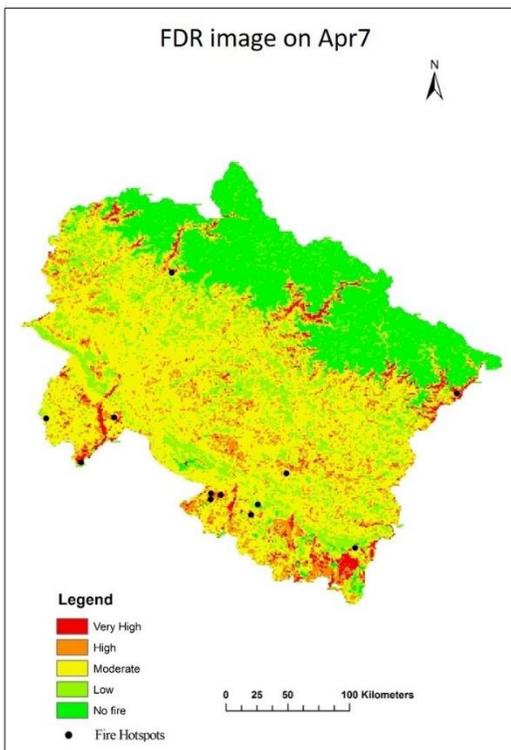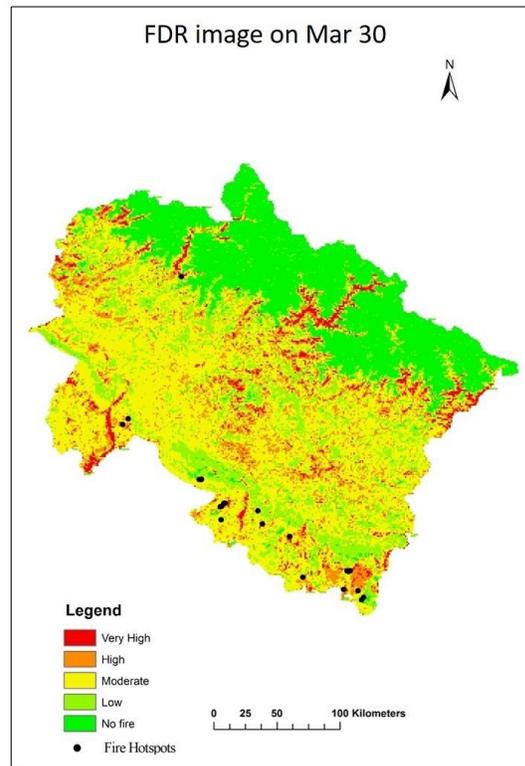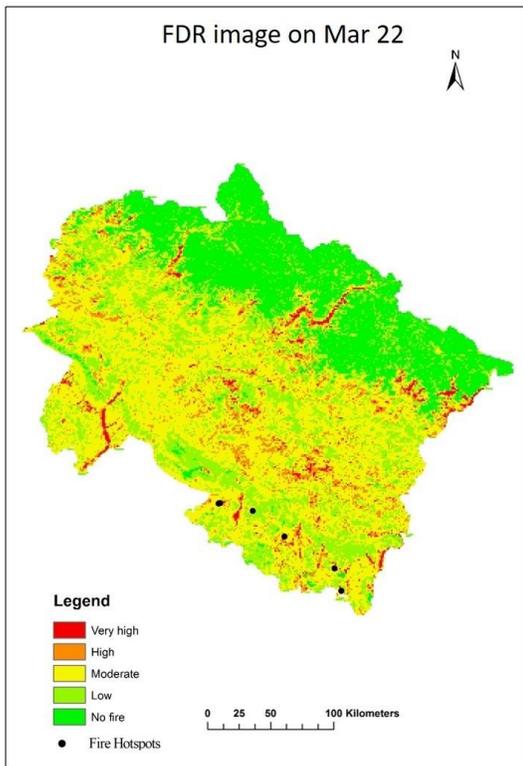
5.4 Results and Discussions

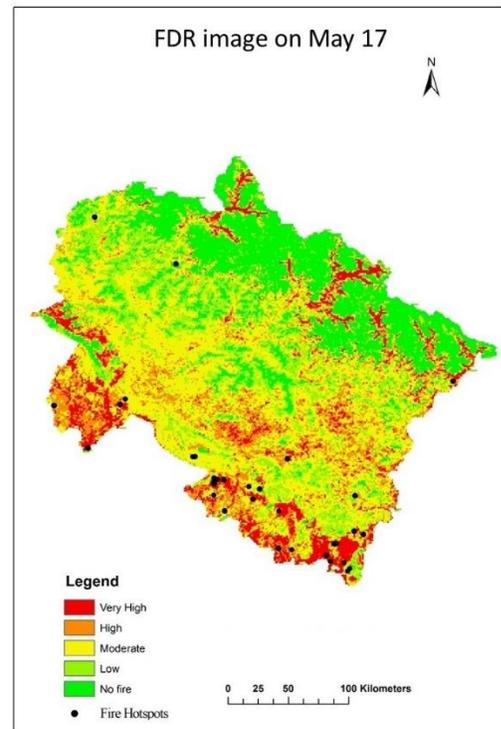Dynamic fire danger index was developed based on the above three parameters by applying criterion condition as shown in the Table 5.3 and integrated all the parameters after applying
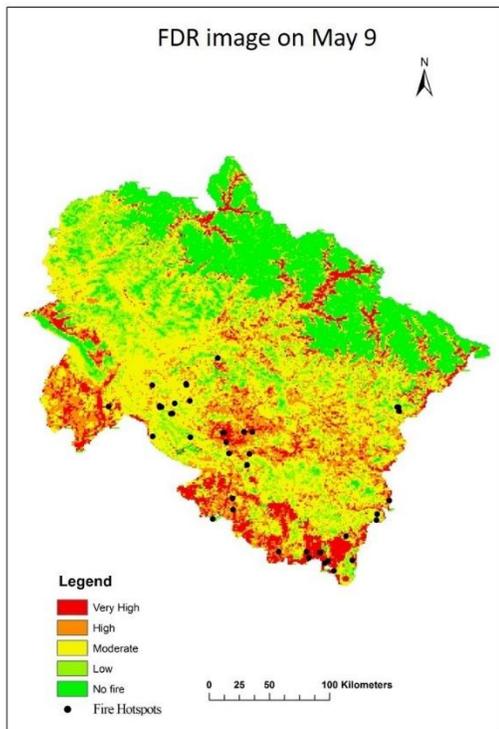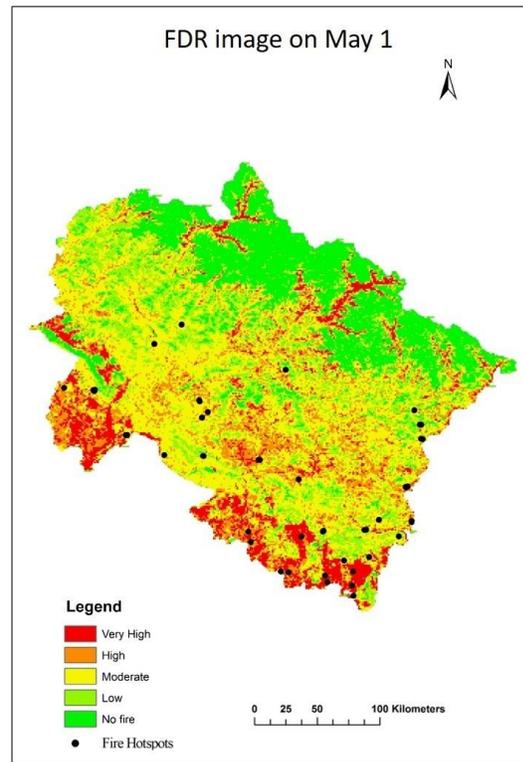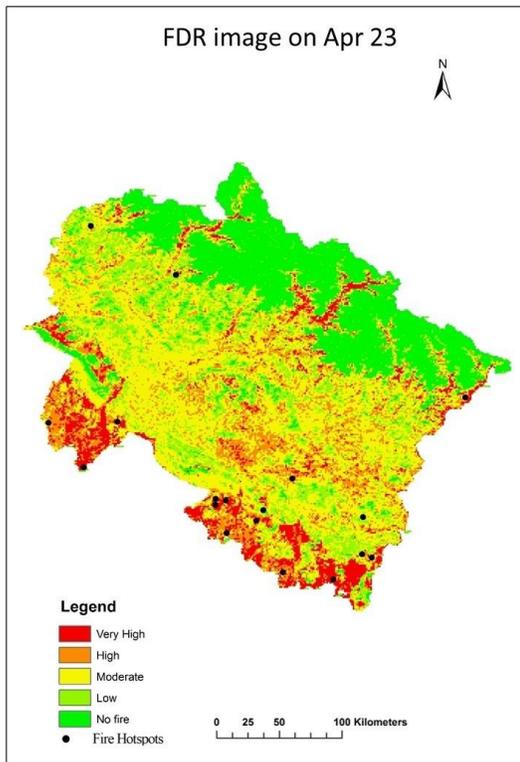
threshold conditions. Final fire danger images were regrouped into 5 fire danger classes such as "very high, high, moderate, low and no fire danger" (Table 5.3). Active forest fire location data (MCD14) were downloaded from the FIRMS website for the corresponding days. These are the active fire location computed from MODIS thermal anomaly data and were overlaid on fire risk maps to estimate the accuracy of model based on potential surface temperature, Perpendicular Moisture Index and Modified Normalized Difference Fire Index. MODIS Terra and Aqua active fire location data have been used for the validation due to the lack of ground fire data for the entire study area. Fig 5.2 showing the fire danger maps generated for eight day interval during fire season overlaid with corresponding composite active fire locations.

Table 5.3 Fire danger rating assigned to each parameter

Parameters	classes	Fire danger rating
LST	<284	No fire
PMI	>0.7	
MNDFI	>0.45	
LST	284-294	Low
PMI	0.3-0.7	
MNDFI	0.20-0.45	
LST	294-310	Moderate
PMI	0.2-0.3	
MNDFI	0-0.20	
LST	310-320	High
PMI	0-0.2	
MNDFI	0 to -0.2	
LST	>320	Very high
PMI	<0	
MNDFI	<-0.2	

FDR image on Mar 22

FDR image on Mar 30

FDR image on Apr7

FDR image on Apr 15

FDR image on Apr 23

Legend
Very High
High
Moderate
Low
No fire
• Fire Hotspots

FDR image on May 1

Legend
Very High
High
Moderate
Low
No fire
• Fire Hotspots

FDR image on May 9

Legend
Very High
High
Moderate
Low
No fire
• Fire Hotspots

FDR image on May 17

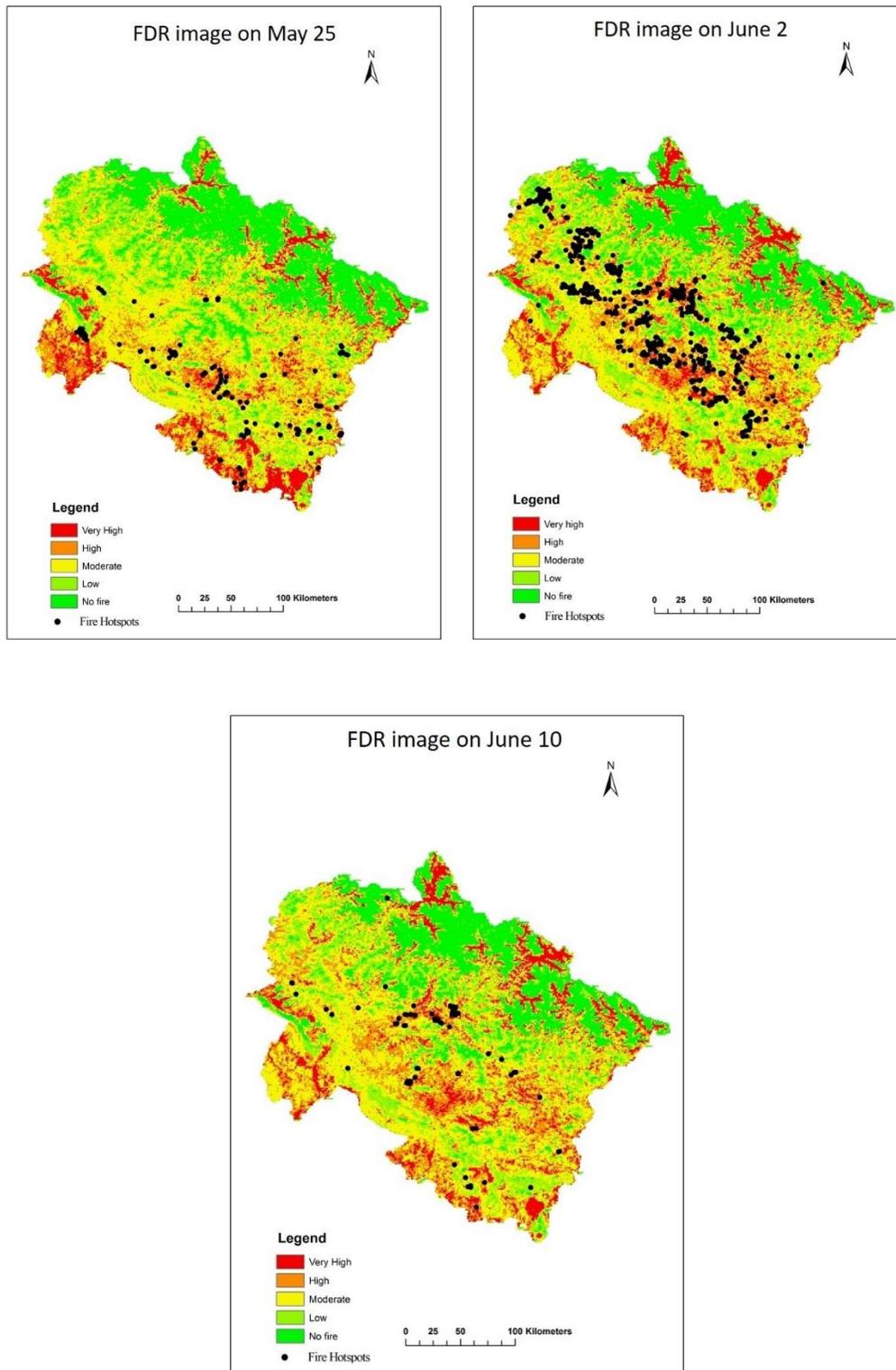Legend
Very High
High
Moderate
Low
No fire
• Fire Hotspots

Fig 5.2 Potential Fire Danger images overlaid with corresponding fire thermal anomaly product during fire season

Accuracy assessment was done for each individual fire danger image on the basis of overlaid active fire point locations. The modeled fire danger map showed an accuracy of 80% to 95% indicating most of the fires fell in High to Very High fire danger classes. Table 5.4 shows the accuracies of fire danger model for different time periods during the fire season over the study area.

The fire danger classes were merged into three classes for accuracy assessment wherein no fire and low fire classes were considered together, and high and very high as one group whereas the moderate fire danger class remained separate based on their probability of fire danger. It was justified that more number of fire hotspots should fell in the high and very high fire danger classes as compared with other classes. There are less number of fires in very high fire danger classes because area occupied by this class was low as it should satisfy all the threshold criterion. From the table 5.4, it was evident that maximum number of fire locations fell in high to very high danger classes while less or zero fires fell in No fire to Low fire danger classes and a few fires in Moderate danger class.

Table 5.4 Accuracies of fire danger model

Date	No. of fire points in different fire danger classes			Accuracy (%)
	No Fire + Low	Moderate	High +Very High	
22-March-2015	0	1	11	91.66
30-March-2015	0	2	13	86.66
07-April-2015	0	4	22	84.61
15-April-2015	3	3	36	85.71
23-April-2015	0	4	26	86.66
01-May-2015	2	4	31	83.78
09-May-2015	0	9	51	85
17-May-2015	0	4	44	91.66
25-May-2015	0	6	83	93.25
2-June-2015	0	12	120	90.90
10-June-2015	0	2	39	95.12

Accuracy was computed for each day, assuming that fires fell in No fire, Low and moderate fire regions were as un- identified fire points by the model. Accuracy was computed using the equation 5.

$$Accuracy\ (\%) = \frac{Active\ fires\ fell\ in\ High\ and\ very\ high\ fire\ danger\ classes}{Total\ number\ of\ active\ fire\ points\ on\ that\ day} \qquad (5)$$

Computed accuracy ranged from a minimum of 80% to a maximum of 95% and overall accuracy estimated from the table 5.4 was 87.31%. So, integrating the three parameters Potential surface temperature, Perpendicular moisture index and Modified normalized difference fire Index i.e. the fire danger model accurately predicts the potential fire risk over the Uttarakhand state. DFDI was tested with daily MODIS TERRA satellite datasets (MOD11A1 & MOD09GA) for the years 2016 to 2018 and the accuracy is found to be more than 85%.

5.4.1 Influence of forest types on potential fire danger

Fire hotspots during the fire season of 2015 for Uttarakhand Himalayan forests downloaded from the FIRMS website and these are active fire location data in shape-file format. Vegetation type of Uttarakhand state was downloaded from the ISRO Biodiversity Information System. Vegetation type map of the study area was overlaid with fire hot spots to determine which type of vegetation type was more prone to fires in 2015.

It is observed from Fig 5.3 that pine forests in the study area are most prone to fire followed by dry deciduous shrub forests and others since a significant number of fires were in agriculture; these were removed from analysis subsequently. Due to the surface level fine fuel availability for the mentioned forest types and they are more susceptible to forest fire.

a single composite potential fire danger image of 2015 was generated from the individual potential fire danger images. Vegetation type map of Uttarakhand derived from LISS-III data (Roy et al., 2012) were crossed with the composite potential fire danger map to generate a summary. Fig 5.4 shows the area statistics of proportion of fire danger classes in different vegetation types.
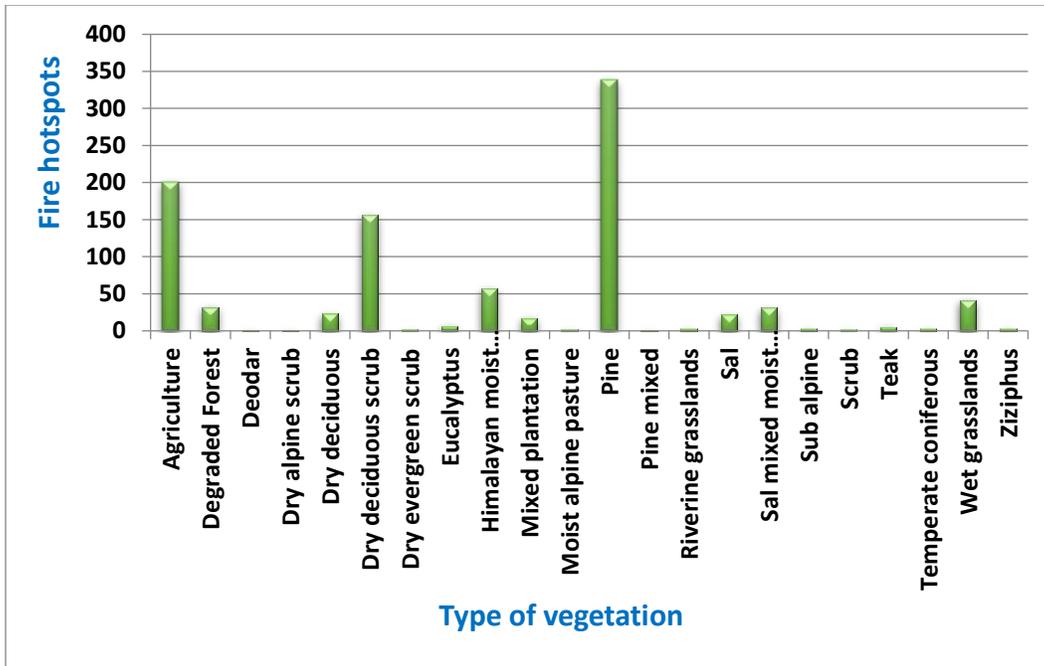
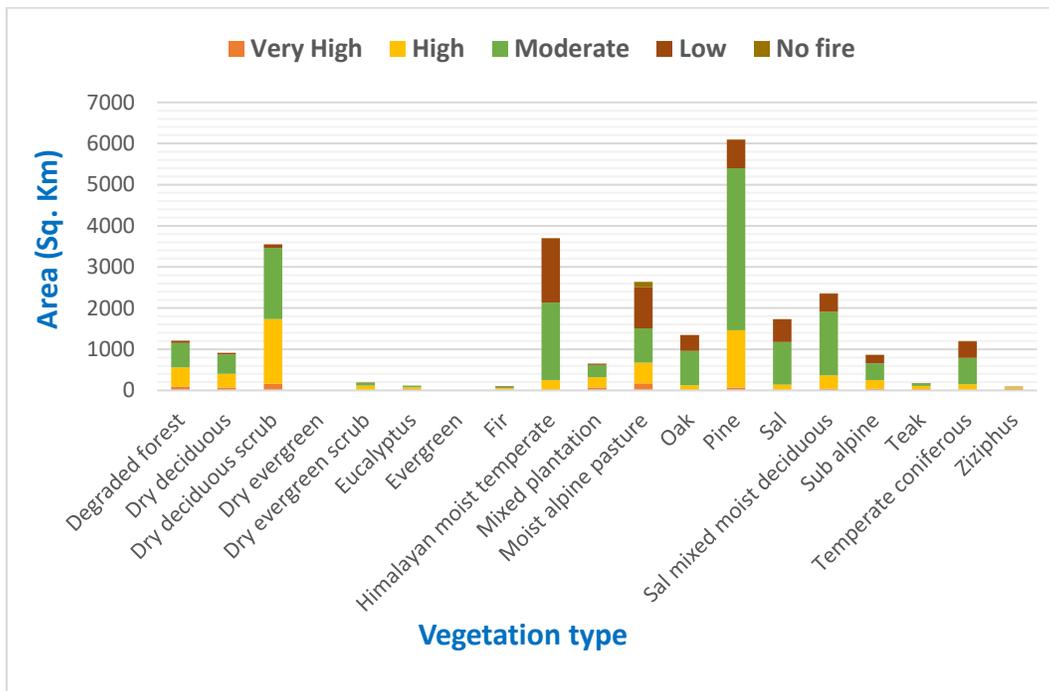*Fig 5.3 Forest fire hotspots versus forest type of the study area*

Fig 5.4 Potential fire danger area of different forest types

Fig 5.4 clearly shows that pine forests in Uttarakhand have a high probability of fire danger followed by dry deciduous scrub according to the model. This exactly matched with the results of actual fire locations in the respective forest types of Uttarakhand as in Fig 5.3. Therefore, the DFDI based on PST, MNDFI and PMI could accurately model the fire danger in Uttarakhand.

5.6 Conclusions

This chapter shows the use of satellite derived products such as MODIS Terra surface reflectance product (MOD09A1), MODIS Terra land surface temperature (MOD11A2) and ASTER Digital Elevation Model (DEM) for calculating the Dynamic Fire Danger Index (DFDI). Three parameters Potential surface temperature, Perpendicular moisture index and Modified normalized difference fire index computed from the above mentioned MODIS and ASTER sensor products can be successfully used to generate the Dynamic fire danger index. Results showed an accuracy of 80% to 95% indicating its robustness and accuracy and the DFDI was also able to correctly predict the regions more prone to fire. The DFDI was tested for the years 2016 and 2017 fire season and estimated accuracy was around more than 80% in each day during that fire season. Therefore, the DFDI can be useful to estimate the fire danger accurately over the study area.

Chapter 6. Developing the Forest Fire Danger Index and Near Real Time Forest Fire Danger system

6.1 Introduction

In this chapter, an attempt has been made to develop the Forest Fire Danger Index (FFDI) by integrating the static and dynamic fire danger indices by a additive model. 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 fire 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 FTP server after one hour of the satellite overpass.

6.2 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 6.1 shows the datasets used in this study to develop the forest fire danger rating index. The NASA Shuttle Radar Topographic Mission (SRTM) provides the digital elevation data (DEM) for the entire earth and data is freely available. SRTM DEM (1 km) of study area was downloaded from the USGS Earth Explorer website (https://earthexplorer.usgs.gov/). The datasets were taken during the major fire episode of Uttarakhand i.e. 20 April 2018 to 30, April 2018.

6.3 Methodology

The Fire Danger Rating (FDR) indices have been using across the world, which takes into consideration of all the factors affecting the fire danger and indexing into different classes of fire danger viz. no danger, low, moderate, high and very high for the purpose of issuing warnings to the public as well as implementing the mitigation measures for controlling fires. Examples of most sophisticated fire danger rating systems across the world are Canadian forest fire danger rating system (CFFDRS) (Canadian Forest Service, 1984), US National Fire Danger Rating System (NFDRS) (NWCG) and McArthur's Forest Fire Danger System (McArthur, 1958), explained in detail in the literature review chapter. CFFDRS is a combination of Fire Weather Index system,

Fire Behavior Prediction system and Fire Occurrence Prediction system, in which first system is the dynamic and other systems are static (Stocks et al., 1989; Alexander et al., 1996; Van Nest & Alexander, 1999).

US NFFDRS calculations are based on the daily weather based intermediate outputs, indices ("Ignition Component, Spread Component, Energy Release Component") and static components ("Lightening Occurrence Index, Human Caused Fire Occurrence Index, Burning Index, Fire Load Index") (Schlobohm & Brain, 2002). Therefore, in this chapter, DFDI, SFDI as well as disturbance danger index has been integrated to develop the Forest Fire Danger Index (Fig 6.1). Disturbance danger index is included as the forest fires are initiated by humans either intentionally or un-intentionally.

Table 6.1 Satellite datasets

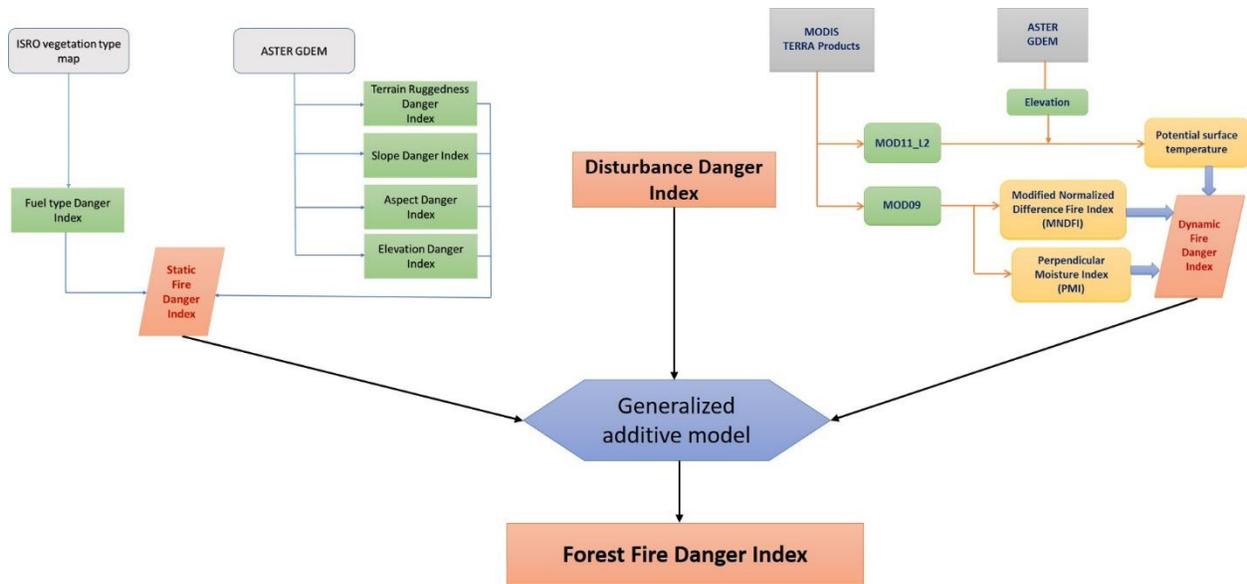| Name of Datasets	Product ID	Spatial Resolution	Temporal Resolution
Land Surface Temperature	MOD11NRT	1 km	Daily
Surface Reflectance	MOD09GA NRT	500 m	Daily
Geolocation fields	MOD03	1 km	Daily
Vegetation type map	LISS 3	-	-
Digital Elevation Model	SRTM	1 km	-
Disaster index map	LISS 3	-	-
Fire and Thermal Anomalies	MCD14	1 km	Daily

Fig 6.1 Flow chart showing the methodology- FFDI

6.3.1 Dynamic Fire Danger Index (DFDI)

DFDI has been developed by integrating three parameters such as PST, MNDFI and PMI, which were derived from the MODIS Terra and ASTER GDEM 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., 2016 a) and explained in the chapter 5. The main difference from the previous work is temporal resolution of the satellite datasets 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. Further, 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.

6.3.2 Static Fire Danger Index (SFDI)

The 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 developed from the ASTER GDEM dataset and ISRO Biodiversity vegetation type map. The SFDI was computed from the integration of five distinct indices that are explained in the chapter 4 (Babu et al., 2016 b).

Fig 6.2 shows the computation of SFDI by using packages raster, rgdal, Rcpp, sp, tiff, jpeg, EBImage, png and locfit in R studio environment.
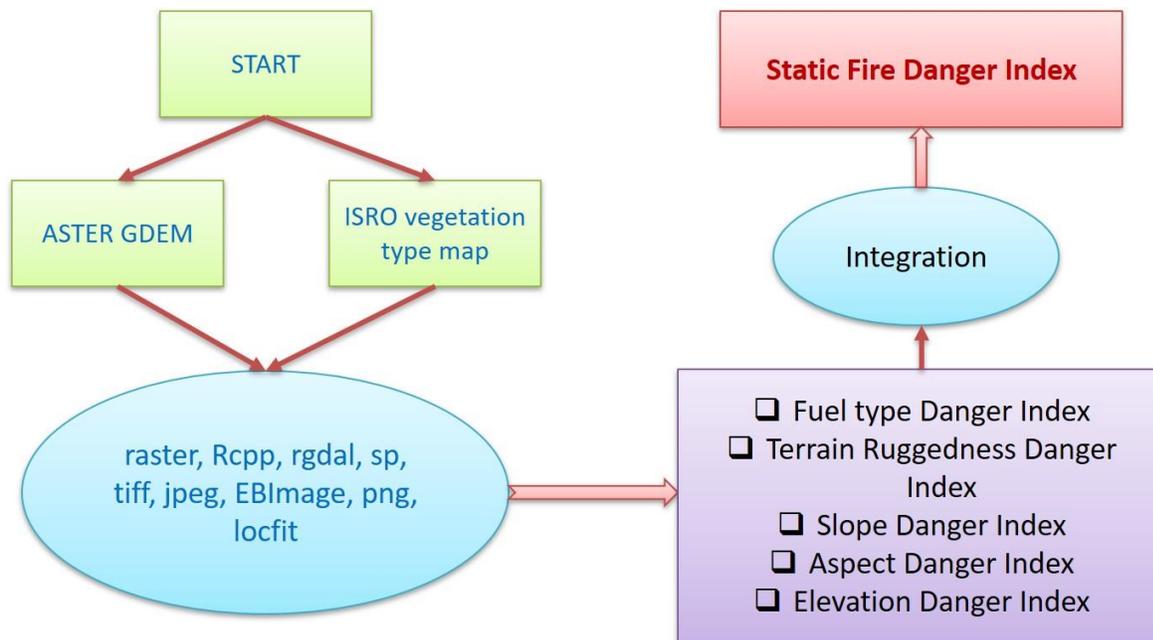

Fig 6.2 Structure of SFDI

6.3.3 Disturbance Danger Index (DDI)

In India, about 90% of the fires are initiated by humans while natural causes are very less (Roy, 2003). Disturbance danger index was generated from the disturbance index map that can be downloaded from the ISRO Biodiversity Information System (Fig 6.3). Disturbance index

provides the level of anthropogenic activities in the vegetated areas of the country and has a range from 0-72 (Roy et al., 2012). The level of danger class has been assigned to the value of disturbance index based on the historical fire location data and disturbance danger index lookup table (table 6.2).

Table 6.2 Fire danger classes assigned to the Disturbance Danger Index

S. No.	Value of Disturbance Index	Danger class
1	<=10	No danger
2	11 to 18	Low
3	19 to 24	Moderate
4	25 to 28	High
5	>28	Very high
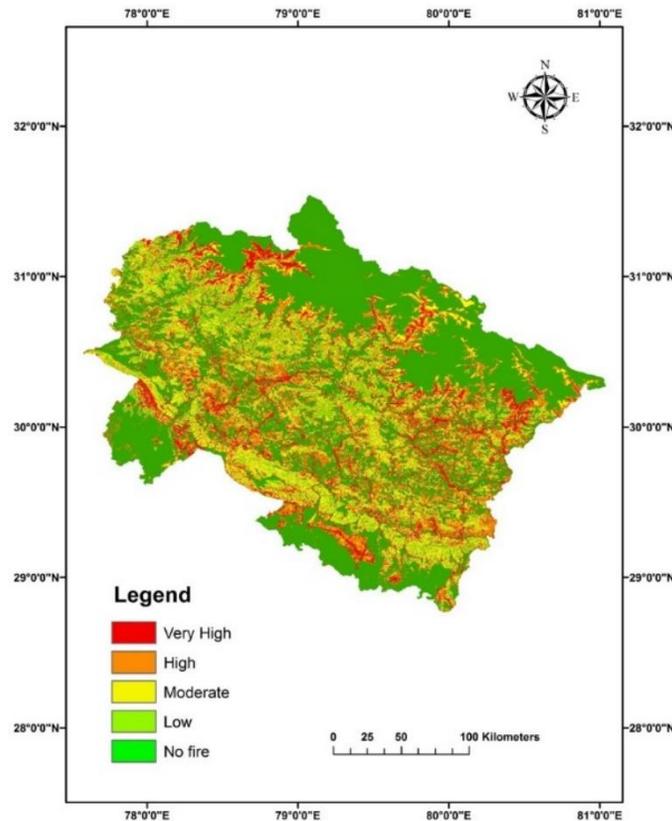
Fig 6.3 Disturbance Danger Index
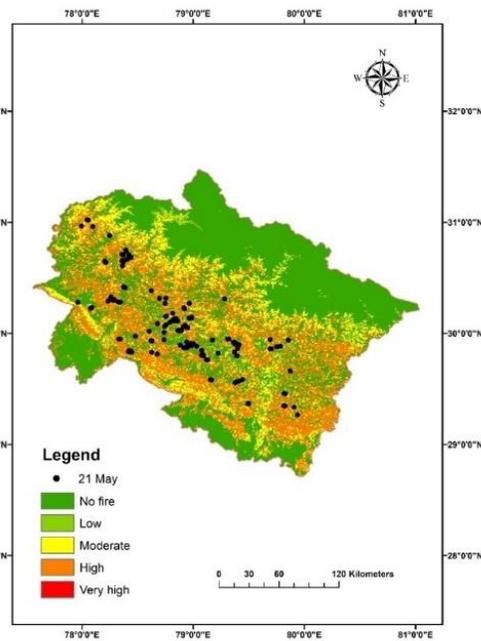
6.3.4 Forest Fire Danger Index (FFDI)

The FFDI has been calculated by integrating SFDI, DDI and individual dynamic forest fire danger index on each day because each index has its own influence on forest fire danger conditions over the study area. The FFDI has been categorized into 5 fire danger classes such as "very high, high, moderate, low and no fire danger" and Table 6.3 shows the value of forest fire danger and the corresponding danger classes. Fig 6.4 shows the computed forest fire danger index images overlaid with corresponding active fire hotspots, downloaded from the NASA FIRMS website.

Table 6.3 Fire danger classes assigned to FFDI

S No	FFDI value	Danger class
1	<=9	No fire danger
2	10-18	Low
3	19-27	Moderate
4	28-36	High
5	>36	Very High
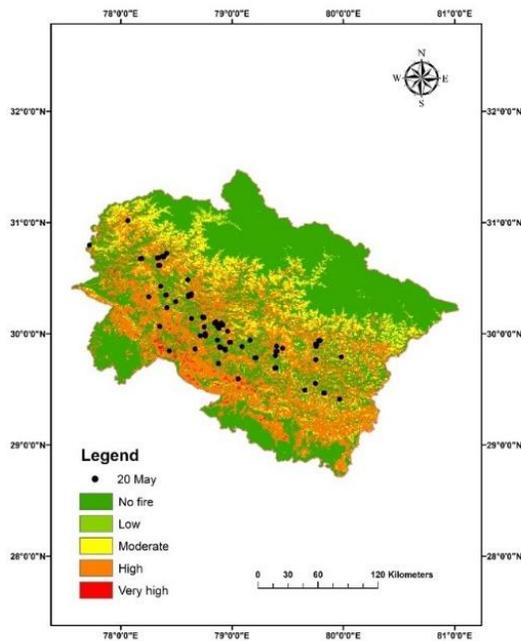
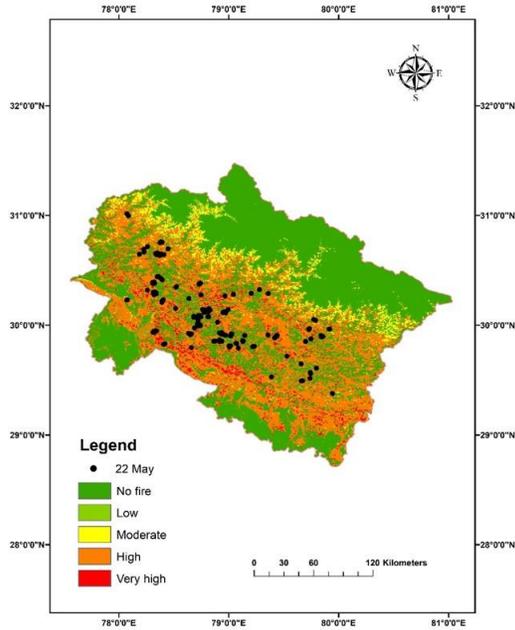**FFDI of 19 May 2018 overlaid with 20 May active fire points**

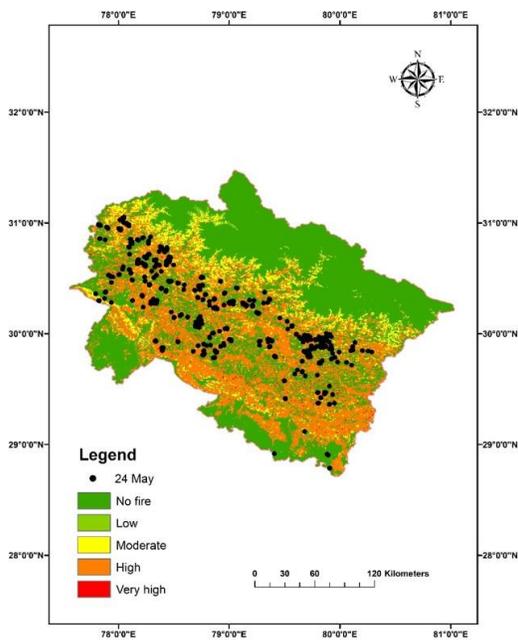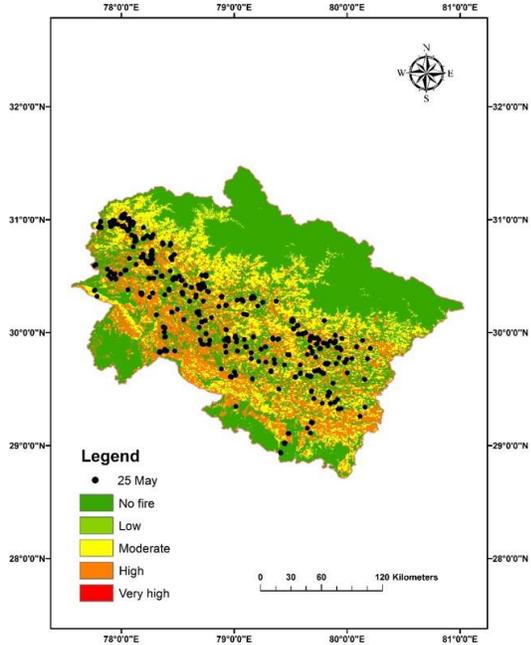**FFDI of 20 May 2018 overlaid with 21 May active fire points**

FFDI of 21 May 2018 overlaid with 22 May active fire points
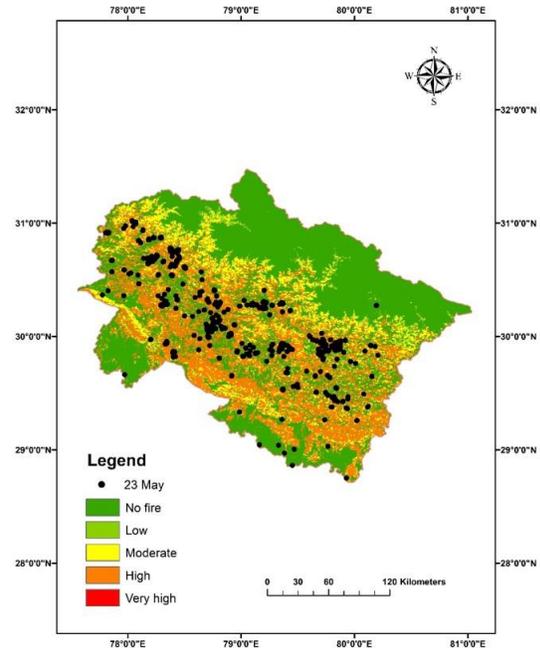
FFDI of 22 May 2018 overlaid with 23 May active fire points

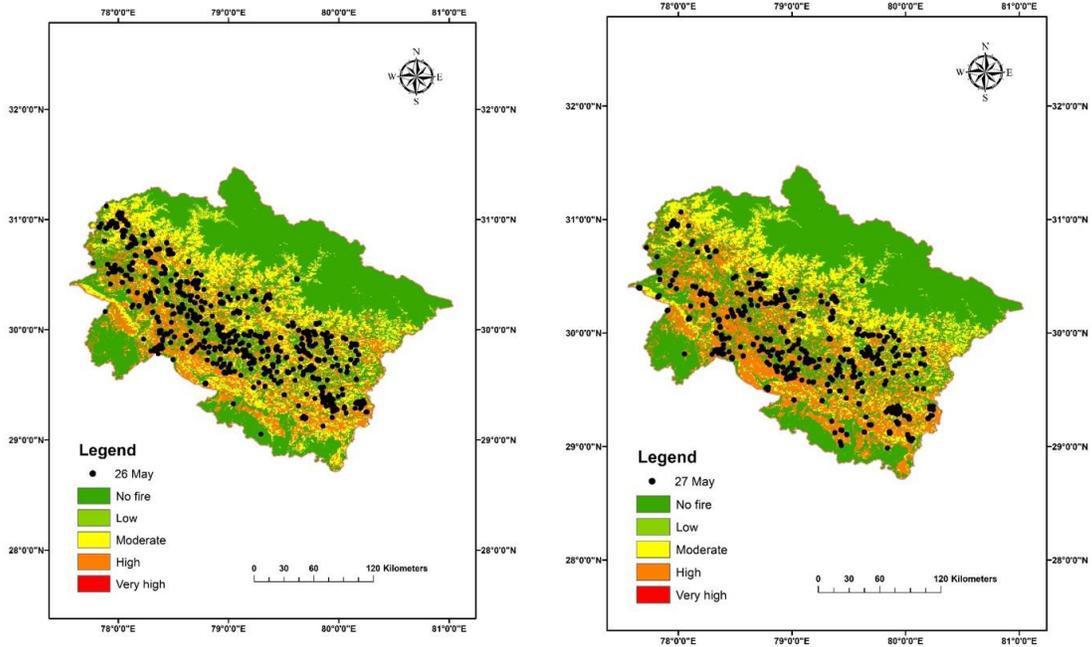**FFDI of 23 May 2018 overlaid with 24 May active fire points**

FFDI of 24 May 2018 overlaid with 25 May active fire points

FFDI of 25 May 2018 overlaid with 26 May active fire points

FFDI of 26 May 2018 overlaid with 27 May active fire points

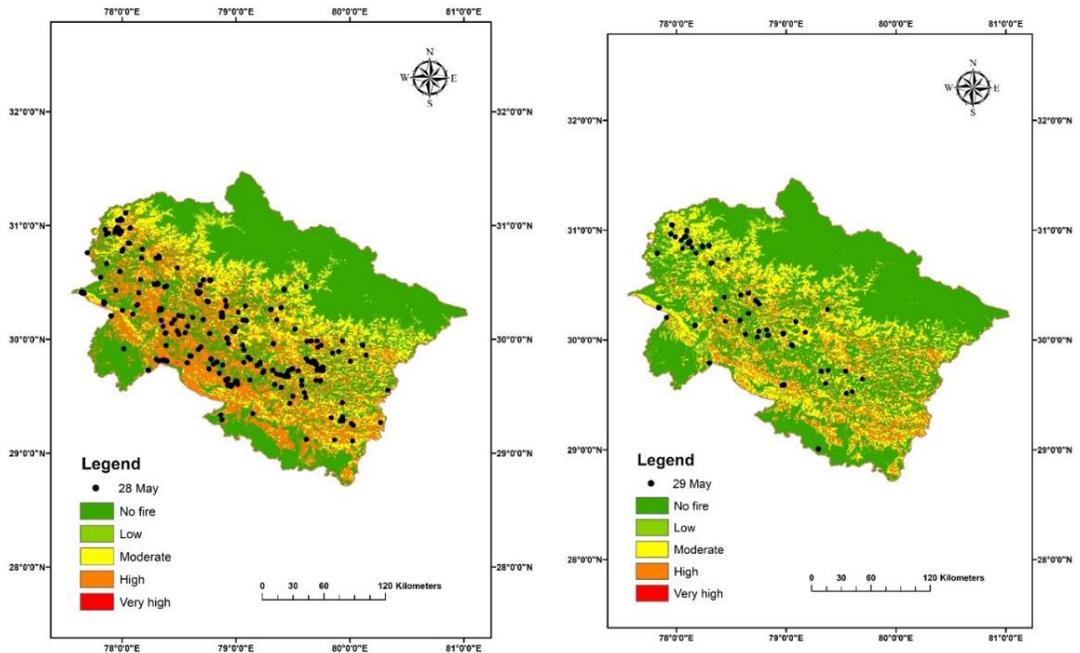FFDI of 27 May 2018 overlaid with 28 May active fire points
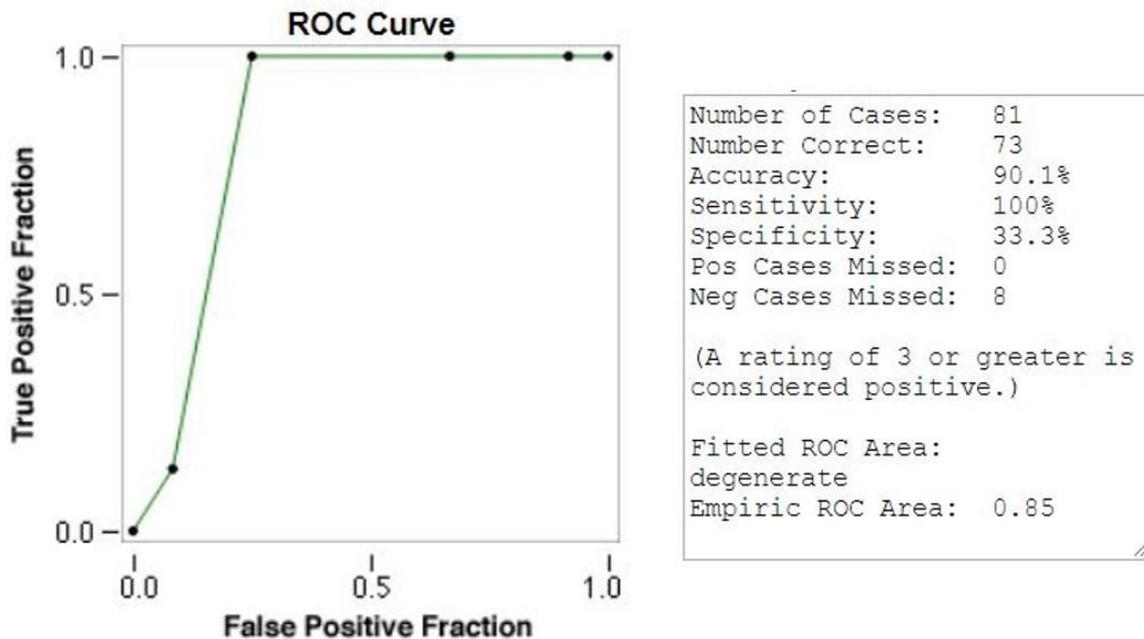
FFDI of 28 May 2018 overlaid with 29 May active fire points

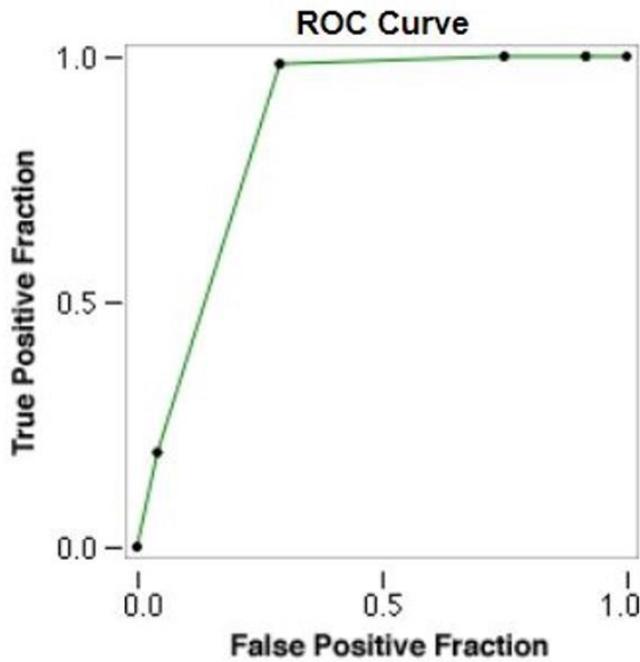*Fig 6.4 Forest Fire Danger Index images were overlaid with next day active fire location data*

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 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 & 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. Fig 6.5 shows the ROC curves for the fire episode in 2018 i.e. 19 May - 28 May, 2018.

19 May 2108


```
Number of Cases:      81
Number Correct:       73
Accuracy:             90.1%
Sensitivity:          100%
Specificity:          33.3%
Pos Cases Missed:     0
Neg Cases Missed:     8

(A rating of 3 or greater is
considered positive.)

Fitted ROC Area:
degenerate
Empiric ROC Area:     0.85
```

20 May 2108


```
Number of Cases:      154
Number Correct:       136
Accuracy:             88.3%
Sensitivity:          100%
Specificity:          25%
Pos Cases Missed:     0
Neg Cases Missed:     18

(A rating of 3 or greater is
considered positive.)

Fitted ROC Area:      0.903
Empiric ROC Area:     0.856
```

22 May 2108


```
Number of Cases:      168
Number Correct:       150
Accuracy:             89.3%
Sensitivity:          99.3%
Specificity:          22.7%
Pos Cases Missed:     1
Neg Cases Missed:     17

(A rating of 3 or greater is
considered positive.)

Fitted ROC Area:      0.908
Empiric ROC Area:     0.849
```

23 May 2108

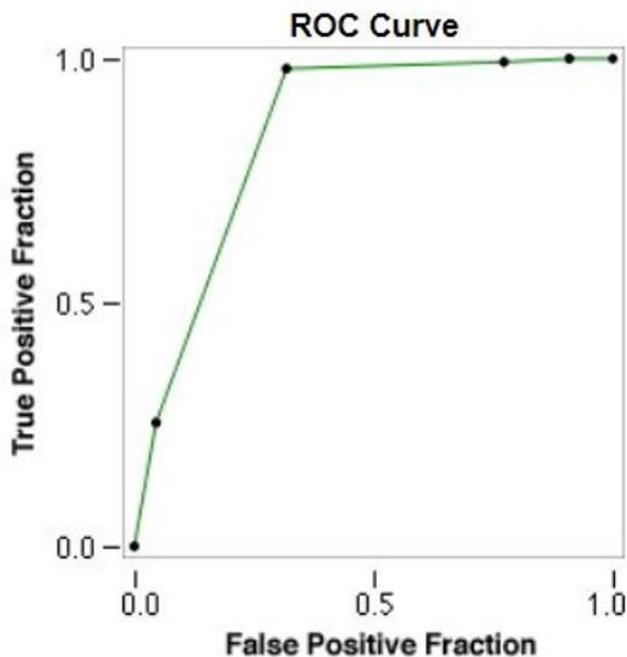ROC Curve

Number of Cases: 702
Number Correct: 668
Accuracy: 95.2%
Sensitivity: 99.8%
Specificity: 25%
Pos Cases Missed: 1
Neg Cases Missed: 33

(A rating of 3 or greater is considered positive.)

Fitted ROC Area: 0.89
Empiric ROC Area: 0.812

24 May 2108

ROC Curve
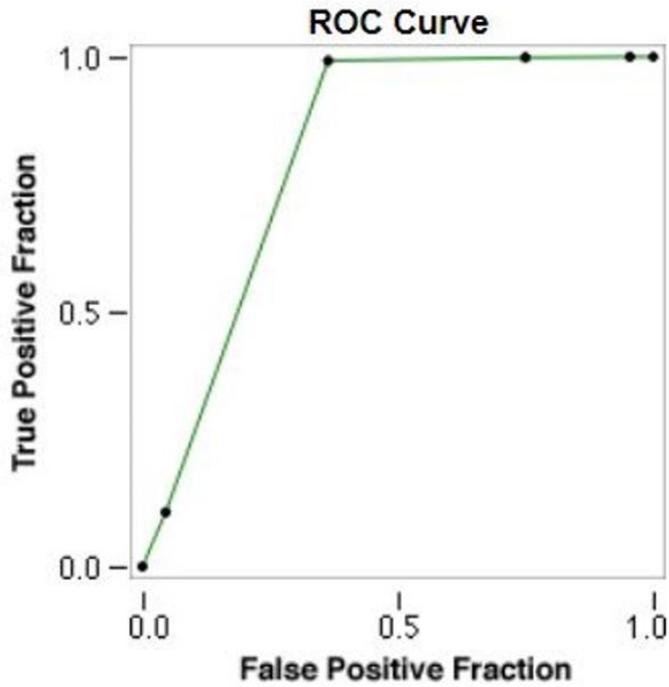


```
Number of Cases:      804
Number Correct:       735
Accuracy:             91.4%
Sensitivity:          99.7%
Specificity:          21.2%
Pos Cases Missed:     2
Neg Cases Missed:     67

(A rating of 3 or greater is
considered positive.)

Fitted ROC Area:      NaN
Empiric ROC Area:     0.885
```

25 May 2108

ROC Curve
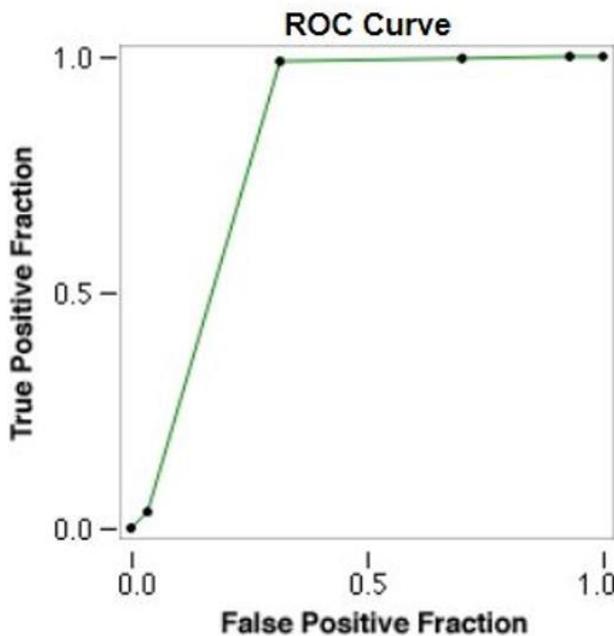

```
Number of Cases:      552
Number Correct:       510
Accuracy:             92.4%
Sensitivity:          99.6%
Specificity:          29.8%
Pos Cases Missed:     2
Neg Cases Missed:     40

(A rating of 3 or greater is
considered positive.)

Fitted ROC Area:      NaN
Empiric ROC Area:     0.825
```
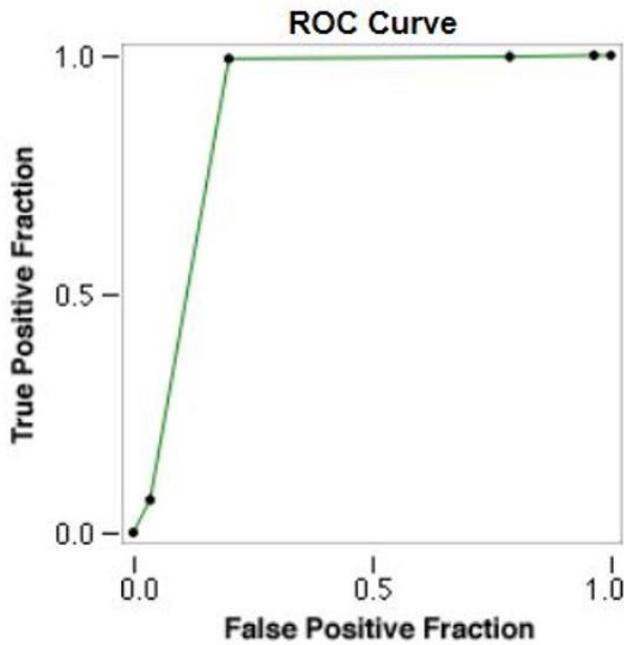
26 May 2108

ROC Curve


```
Number of Cases:      796
Number Correct:       722
Accuracy:             90.7%
Sensitivity:          99.6%
Specificity:          22%
Pos Cases Missed:     3
Neg Cases Missed:     71

(A rating of 3 or greater is
considered positive.)

Fitted ROC Area:      NaN
Empiric ROC Area:     0.913
```

27 May 2108

ROC Curve
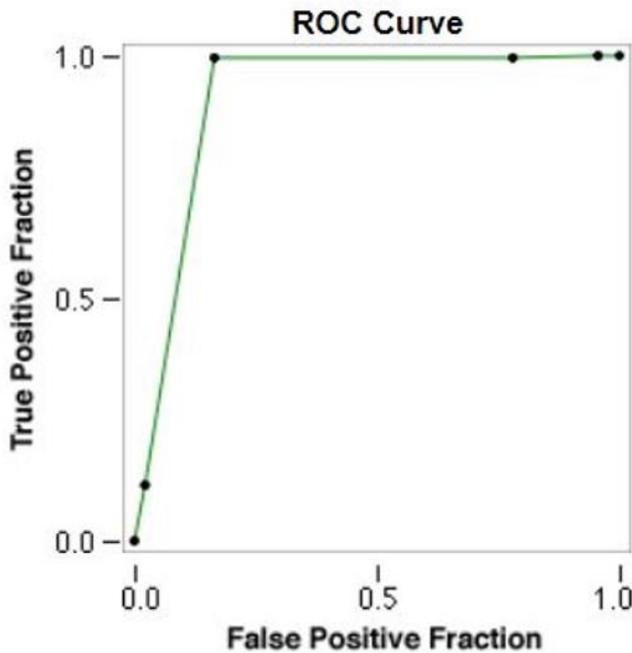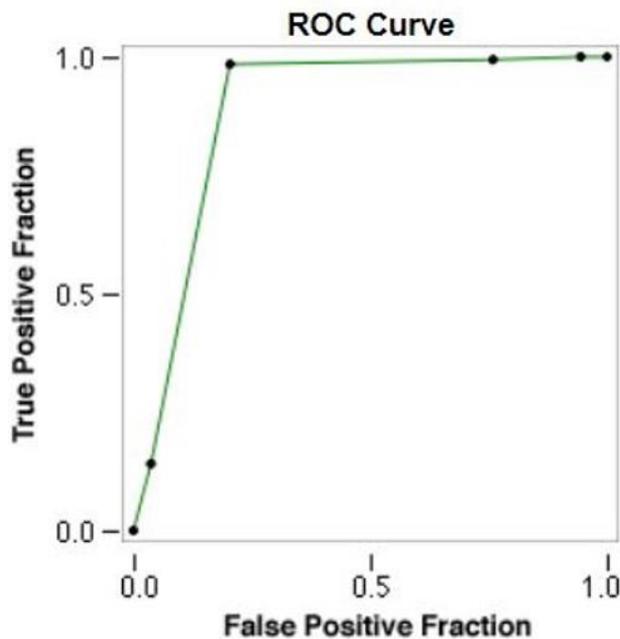


```
Number of Cases:      373
Number Correct:       330
Accuracy:             88.5%
Sensitivity:          99.4%
Specificity:          24.1%
Pos Cases Missed:     2
Neg Cases Missed:     41

(A rating of 3 or greater is
considered positive.)

Fitted ROC Area:      NaN
Empiric ROC Area:     0.886
```

28 May 2108

ROC Curve


```
Number of Cases:    139
Number Correct:     120
Accuracy:           86.3%
Sensitivity:        100%
Specificity:        32.1%
Pos Cases Missed:   0
Neg Cases Missed:   19

(A rating of 3 or greater is
considered positive.)

Fitted ROC Area:    0.916
Empiric ROC Area:   0.879
```
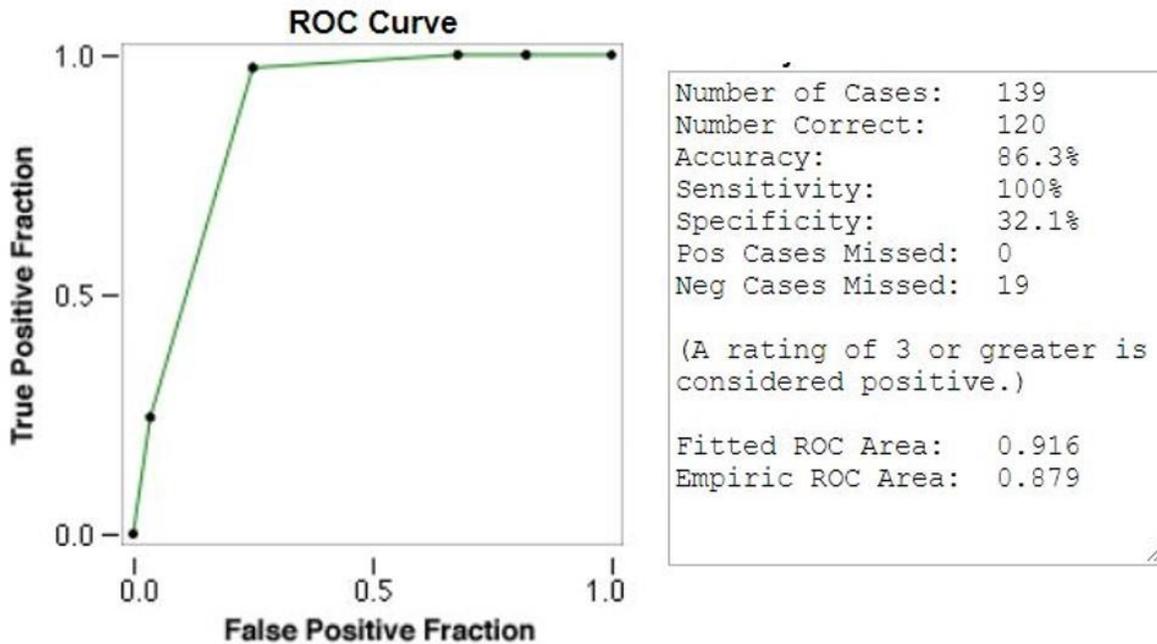
Fig 6.5 ROC curves and the area of AUC during May 19 to May 28, 2018

Fig 6.5, the accuracies and AUC during the fire event (May 19-28, 2018) are: 90.14%, 0.85 (May19); 88.3%, 0.856 (May 20); 89.3%, 0.849 (May22); 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 28). 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 studyarea.

Accuracy comparison of FFDI and DFDI

The cumulative fire danger indices FFDI and DFDI were calculated by adding the individual indices during the above mentioned time period and categorized into different fire danger classes.

The number of fire hotspots during that period were overlaid with each cumulative index and Fig 6.6 shows the extracted fire hotspots in each of the classes of DFDI and FFDI.
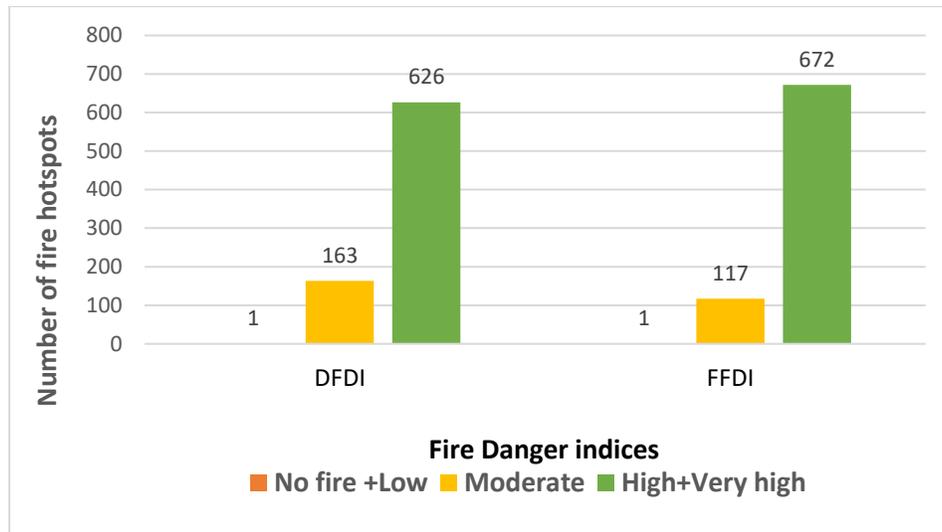

Fig 6.6 Total number of fire points in fire danger classes of DFDI and FFDI

From Fig 6.6, it was evident that more number of fire points fell in high and very high fire danger classes of FFDI as compared to DFDI. Accuracy of FFDI and DFDI were 85.06% and 79.24% respectively.

Further analysis was carried out by using the forest fire danger class areas of FFDI and DFDI and Fig 6.7 shows the forest fire danger class areas of different fire danger classes.

It is observed from Fig 6.7 that, DFDI has categorized more area under high and very high danger classes as compared to FFDI and also less area under low and no fire danger classes. The accuracy of DFDI (79.24%) is less compared to FFDI (85.06%). Hence, the FFDI is more accurately predicted the fire danger as compared with DFDI. So, the integration of static and dynamic danger indices are most accurate index to represent the fire danger. The FFDI has been tested during the major fire episode of Uttarakhand in the year 2016 and also tested for the years 2015 and 2016 fire season and found that an overall accuracy is more than 85%.
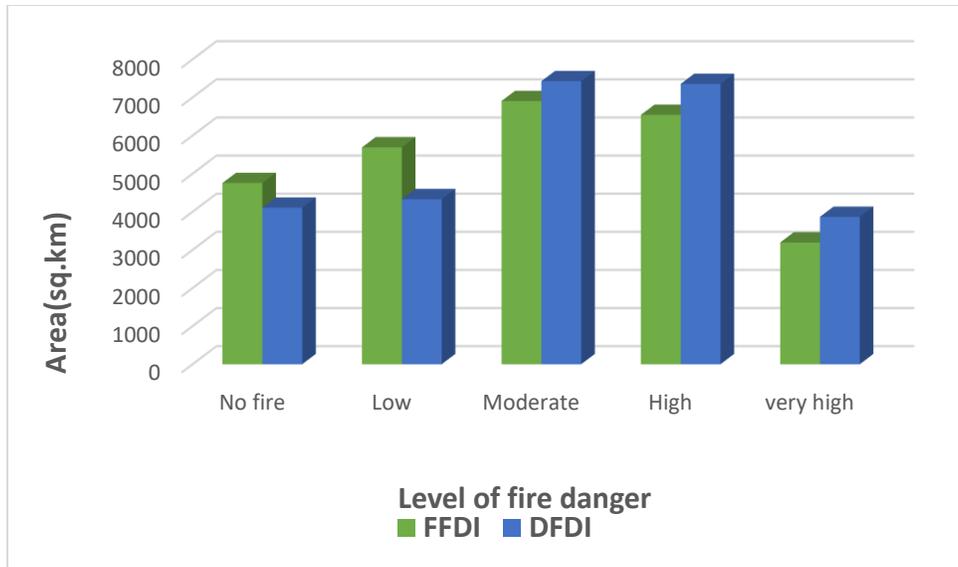
Fig 6.7 Areal statistics of forest fire danger estimated by FFDI and DFDI

6.4 Near Real Time Forest Fire Danger system

Based on the above findings, FFDI is more accurate as compare to DFDI and also DFDI can be computed from the datasets such as MODIS Terra NRT Land Surface Temperature datasets (MOD11_L2) and MODIS Terra NRT surface reflectance dataset MOD09. FFDI is an integration of both the DFDI and SFDI, the former can be calculated in near real time whereas the latter is static. Therefore the procedure of automation of NRT FFDI will be useful to tackle the forest fires effectively and explained in the following steps and Fig 6.8 shows the architecture of NRT Forest Fire Danger System (NFFDS).

Thus the procedure of FFDI has automated so that fire danger prediction maps disseminated to the fire officials in each day during the fire season. In this chapter, automation of FFDI will be explained in the following sections.
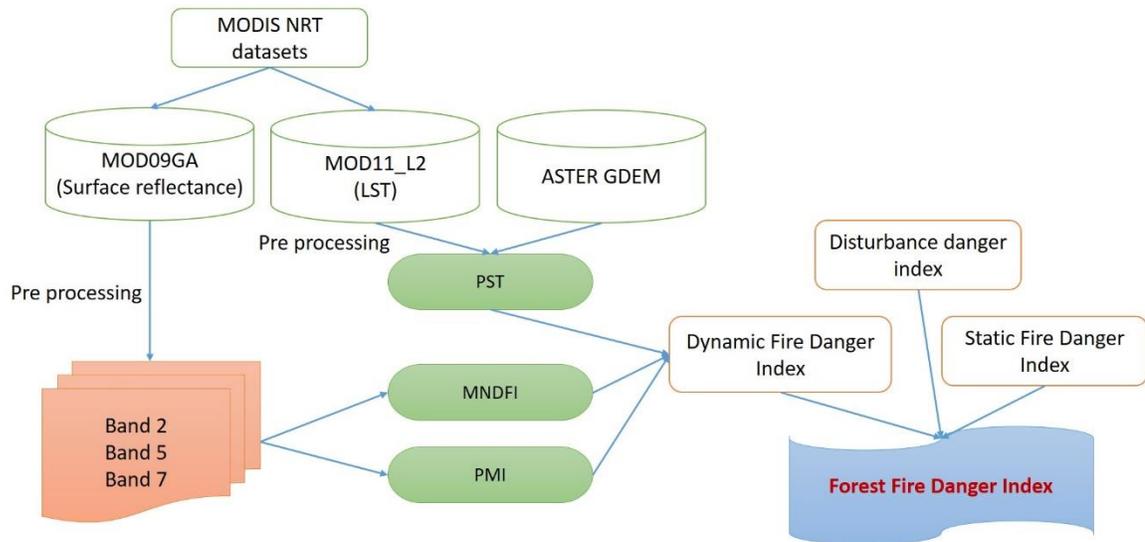
Fig 6.8 NFFDS architecture

6.4.1 System Requirements (Software/Hardware)

The software and hardware requirements are shown below.

Software: R , R Studio, Q-GIS, MRT SWATH and MRT

Hardware: Minimum 8GB RAM, Internet Connectivity, Minimum 2 GB Graphics Card and
Windows 8 Operating System.

6.4.2 Procedure of calculating Near Real Time Dynamic Fire Danger Index (DFDI)

LANCE (The Land, Atmosphere Near real time capability for EOS) supports the application users across the world, 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 (https://earthdata.nasa.gov/earth-observation-data/near-real-time). DFDI has been computed from the Near Real Time (NRT) MODIS Terra datasets, which can be available to download through ftp server (ftp://nrt3.modaps.eosdis.nasa.gov/). Fig 6.9 shows the workflow to compute the DFDI in near real time.
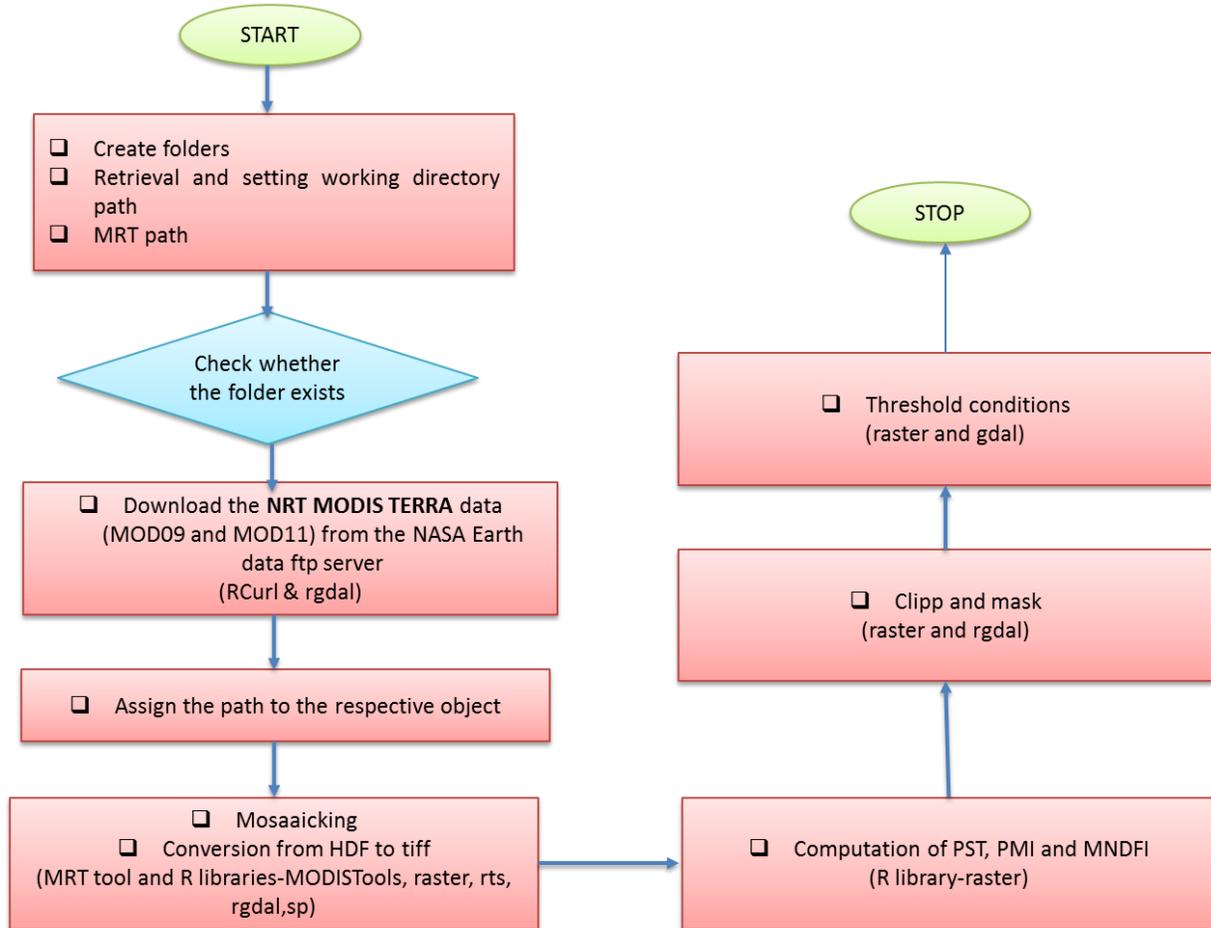
Fig 6.9 workflow diagram of NRT DFDI

The procedure of computation of DFDI as explained sequentially in the below. The following steps had performed sequentially for downloading the MODIS NRT datasets.

- get the list of directories
- you get the folders (and files) but the folder names are in the form of a unix directory listing
- get the last word of any lines that start with "d":
- get the directory names and create a new data frame:
- get the list of *.hdf files:
- Download tile by tile (example: h24v05)
- write up the file names back to the dates.txt:
- Download the block from the list to a local drive.

The Uttarakhand covers in 4 MODIS tiles i.e. h24v05, h24v06, h25v05 and h25v06. So, four tiles have to be downloaded in each day. MOD09 and MOD11_l2 data can be downloaded tiles wise and saved into local directory for further analysis and the work flow is shown in the Fig 6.10.
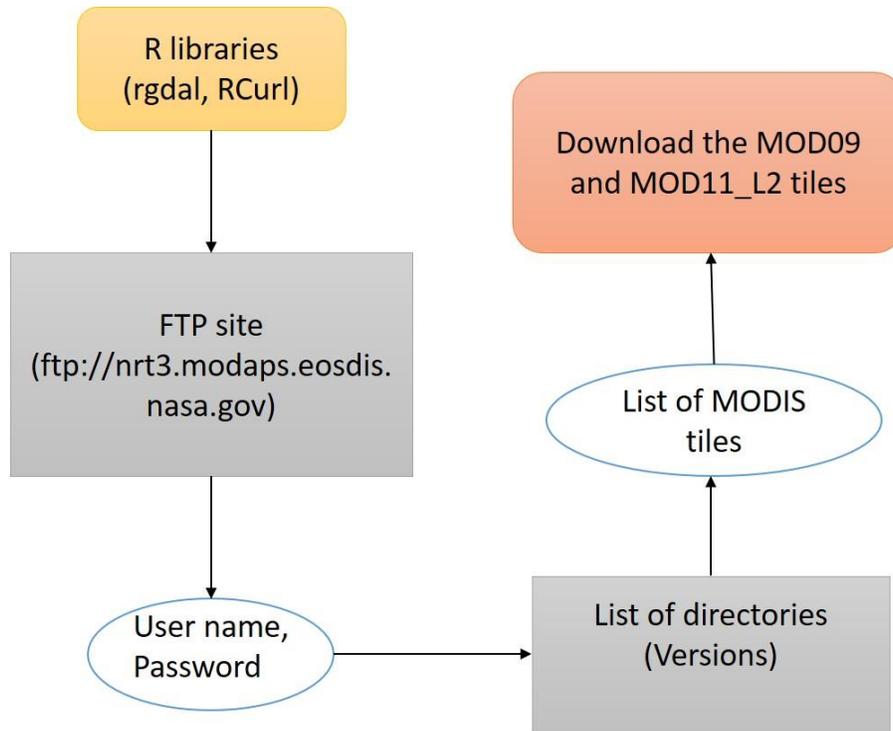
Fig 6.10 Flow diagram showing the downloading MODIS datasets

Conversion from hdf to tiff and mosaicking

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 etc. (LPDAAC). In this chapter, bands 2, 5 and 7 are required to compute the indices PMI and MNDFI. The below code snippet shows the extracting of the specific bands. MODIS Reprojection Tool (MRT), an open source tool developed by LPDAAC, has been used to read the hdf files (https://lpdaac.usgs.gov/tools/modis_reprojection_tool).

MOD11 dataset consists of the parameters such as LST of day and night, emissivity of band 31 and band 32, view time of day and night etc.(https://lpdaac.usgs.gov). The LST of day time has been extracted from MOD11 in similar way and the Fig 6.11 represents the procedure to convert from hdf to tiff format.
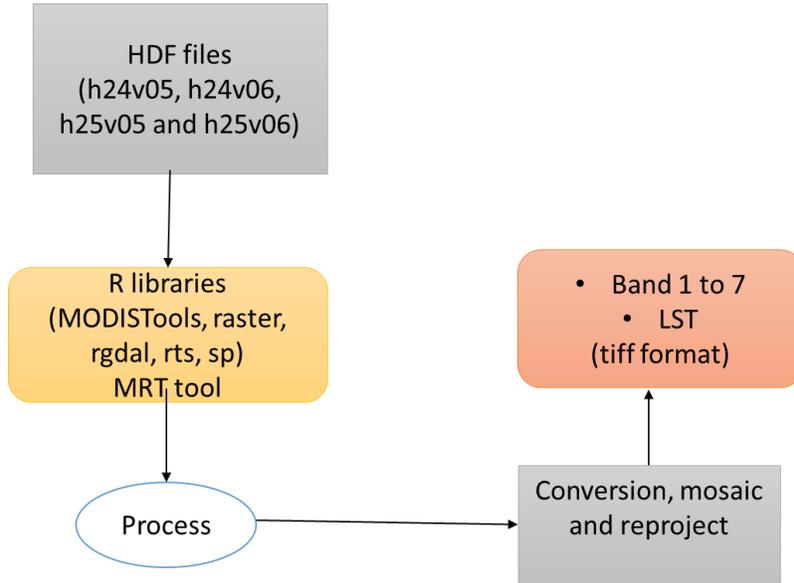
Fig 6.11 Flowchart showing the datasets conversion from hdf to till format

Generation of NRT Dynamic Fire Danger Index

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. PMI and MNDFI have been calculated by using the equation 1 and 2 respectively.

$$PMI = -0.73 * (R5 - 0.94 * R2 - 0.028) \qquad (1)$$

$$MNDFI = \left[\frac{Band\ 7 - Band\ 2 - 5\%}{Band\ 7 + Band2 + 5\%}\right] \qquad (2)$$

PST is computed from the MOD11_L2 NRT datasets by using the following equations as already explained in the previous chapters.

$$p = p_0 \left(1 - \frac{L_z}{T_0}\right)^{\frac{g.M}{R.L}} \tag{3}$$

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

Fig 6.12 shows the calculation of NRT Dynamic Fire Danger Index from the intermediate parameters PST, MNDFI and PMI.
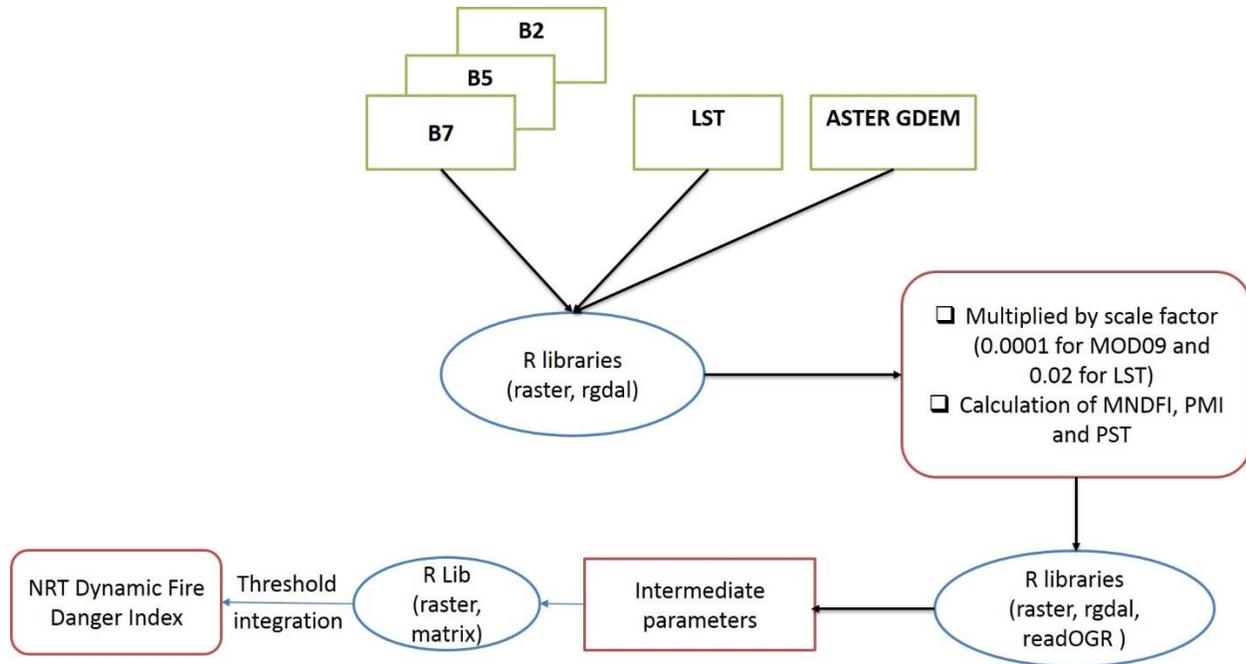
Fig 6.12 Flowchart showing the calculation of NRT DFDI

Forest Fire Danger Index (FFDI)

FFDI has 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 explained in the above sections. The entire procedure was automated from steps to download the NRT MODIS Terra datasets, conversion, mosaicking, calculation of the intermediate parameters, calculation of NRT DFDI and finally integration of both the SFDI and NRT DFDI to generate FFDI in near real time, within one hour of the satellite overpass. The resultant fire danger maps have been disseminated to the fire managers for the quick actions to control the forest fires during the fire season.

The entire procedure was carryout in near real time in two days 18 March, 2018 and 19 March, 2018 to test the FFDI. The results were shown in Fig.s 6.13 and 6.14 and overlaid with the actual fire hotspots in fig 6.15 and 6.16.
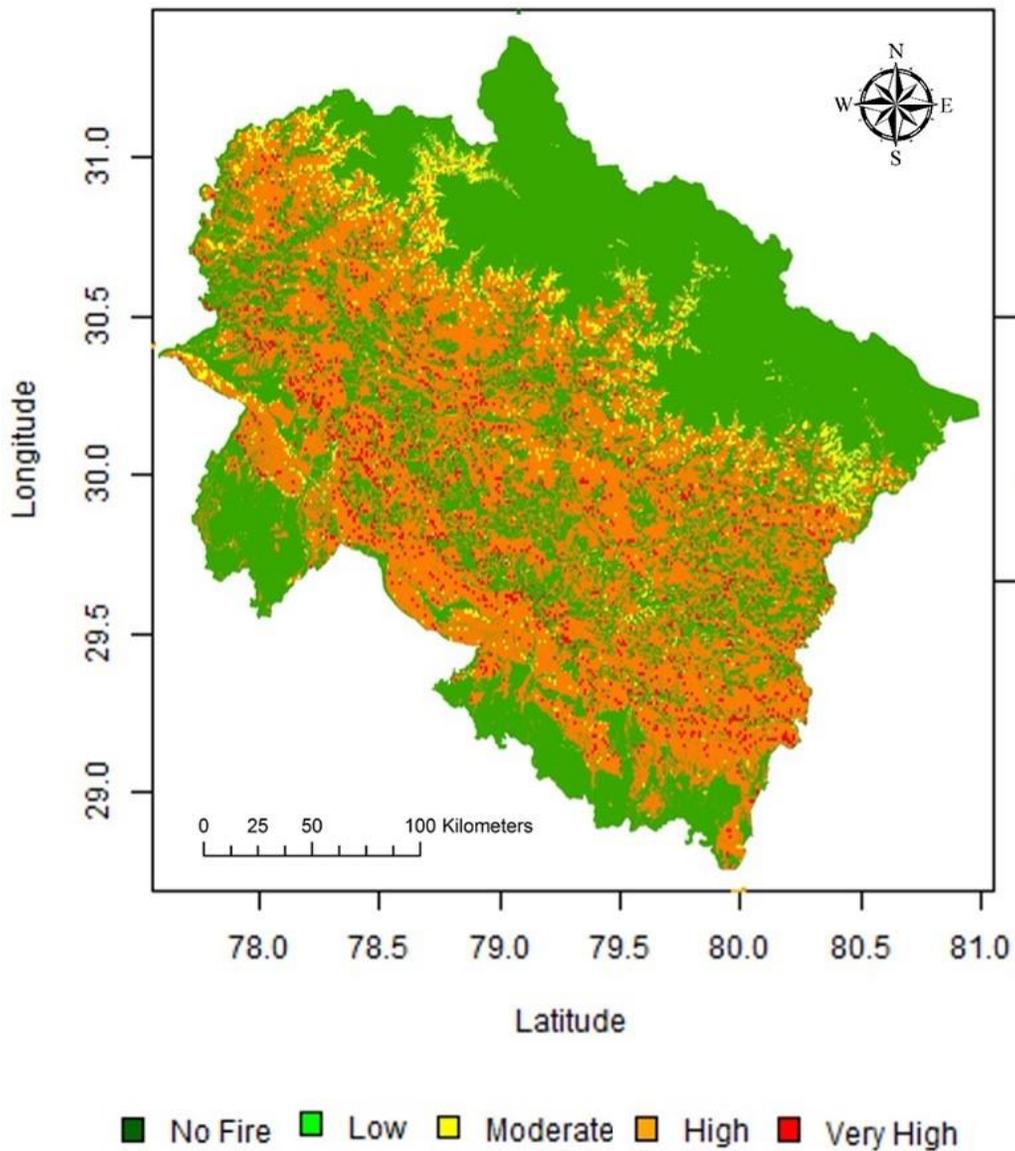
Fig 6.13 FFDI map generated on Mar 18, 2018
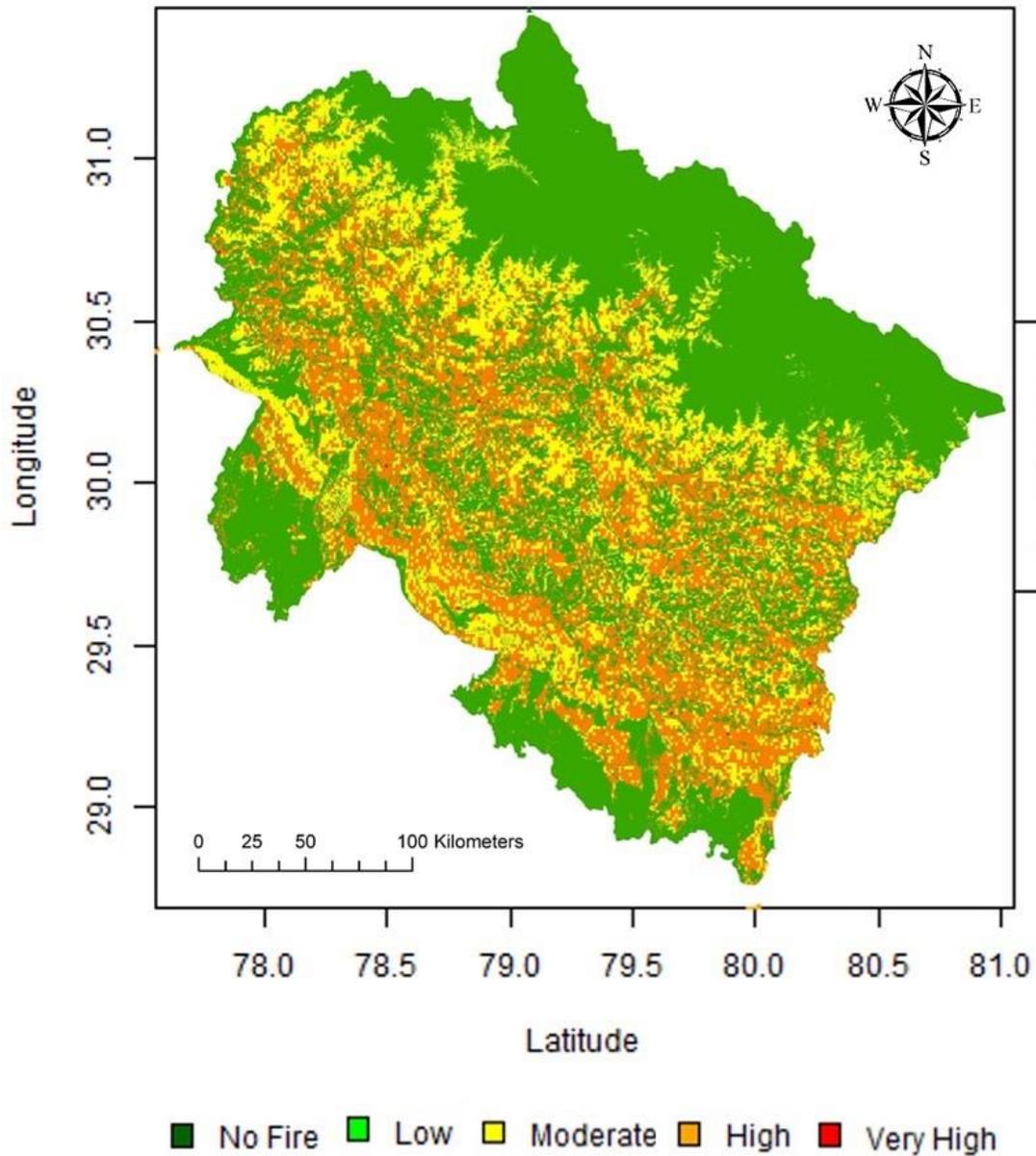
Fig 6.14 FFDI map generated on Mar 19, 2018

MODIS active fire hotspot data (MCD14) for the days Mar 18, Mar 19, 2018 downloaded and overlaid on the corresponding FFDI map and these are shown in the Fig.s 6.15 and 6.16 respectively. Estimated accuracy was around 89.25% and 91.60%.
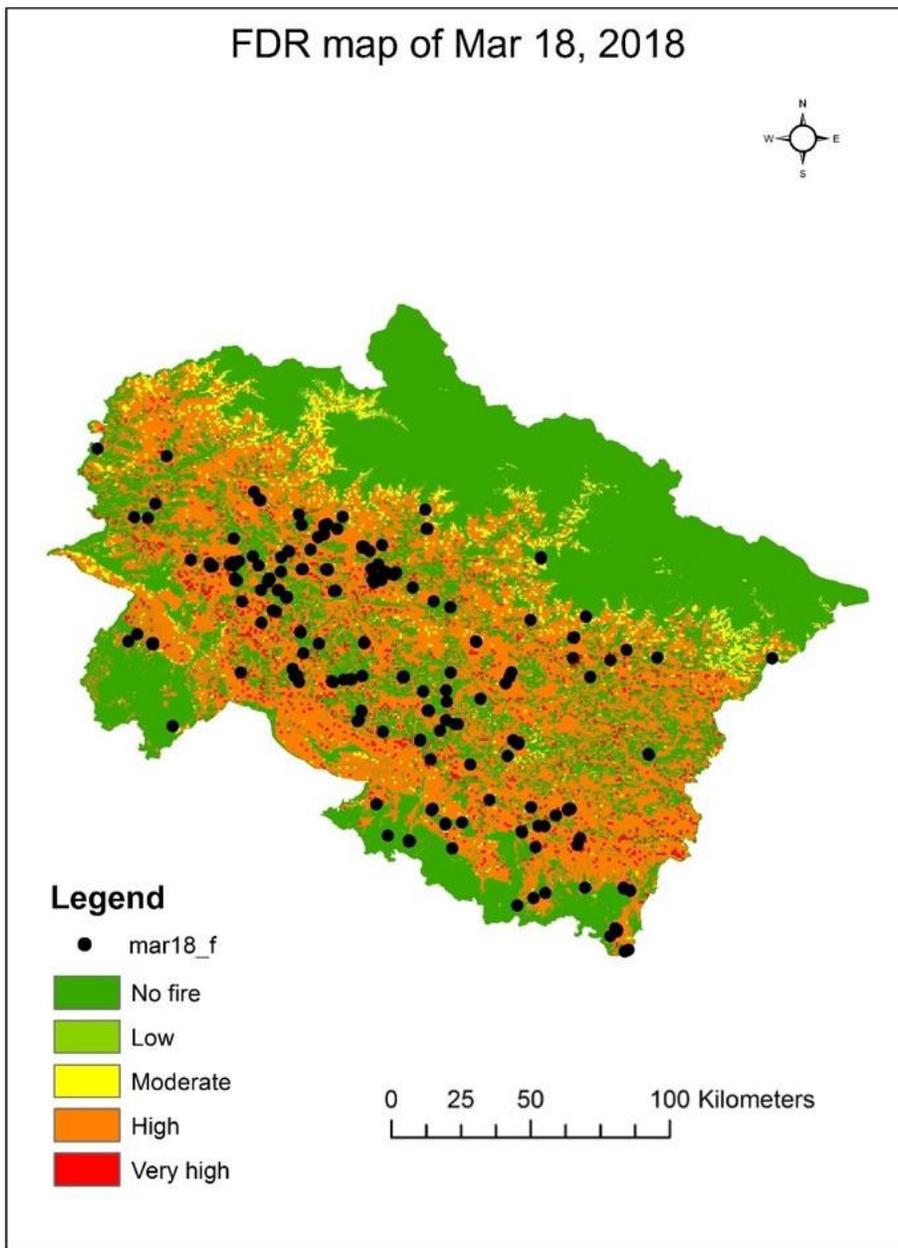
Fig 6.15 Fire hotspots overlaid with FFDI map of Mar 18, 2018
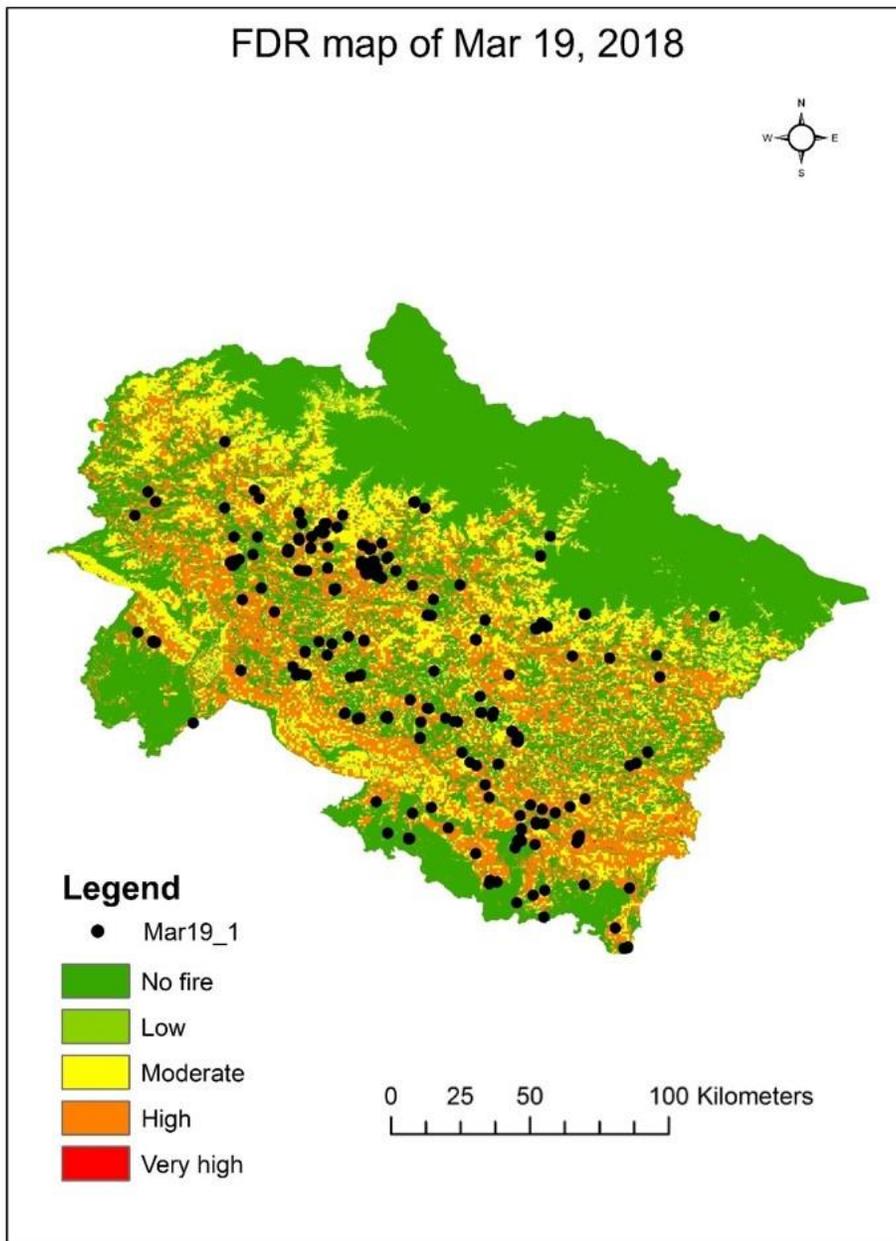
Figure 6.16 Fire hotspots overlaid with FFDI map of Mar 19, 2018

6.5 Conclusions

The NRT Forest Fire Danger Index is semi-automated in the current study as the downloading of MODIS Terra LST (MOD11_L2) has not automated because the data is in swath format and has to download manually due to the change of scenes in each day for the study area. MOD09 data is in tiles format, so, downloading of fixed tiles data was automated. Therefore, developed NRT FFDI is semi-automated and can be useful to predict the fire danger during the fire season not only in Uttarakhand state but any area under study.

Chapter 7. Summary and Conclusions

Forest fires are considered as one of the major disaster in India especially in Uttarakhand Himalaya. Three major fire disasters were occurred in the years 2013, 2016 and 2018. Near real time fire alerts have been disseminating during the fire season by NRSC Bhuvan and FSI by using MODIS Terra, Aqua and VIIRS satellite datasets. The limitation of fire alerts are fires which are actively burning at the time of satellite overpass can be detected and fires which have taken place between the passes cannot be recorded.

Fire danger indices are important tools for the management of forest fires effectively by using the early warnings to the public and fire officials for suppressing forest fires effectively. Fire danger index is an integration of the static and dynamic parameters, which are responsible for the ignition and spreading of fires. Fire danger indices generally calculated by using the meteorological stations data and ground data. In this study, forest fire danger index has been developed from the parameters derived from satellite due to the lack of meteorological stations data.

The Static Fire Index 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 static fire danger rating index has been developed from the MODIS land cover type product (MCD12Q1) and ASTER GDEM datasets, which were downloaded from the NASA REVERB ECHO website. International Geosphere-Biosphere Programme (IGBP) land cover type has been generated from MCD12Q1, which has been used to develop forest fuel type danger index based on the historical fire location data of years 2010 to 2014. Terrain Ruggedness danger index, Slope danger index, Aspect danger index, Elevation danger index has been generated from the ASTER GDEM datasets based on the historical fire location data. Finally, the Static fire danger index has been developed by integrating the aforementioned indices.

Dynamic forest fire danger index has been developed from three biophysical parameters such as potential surface temperature, Perpendicular Moisture Index and Modified Normalized Difference Fire Index. Uttarakhand has hilly Terrain, so, the potential surface temperature, that means Terrain corrected temperature has been computed from the daily MODIS Terra Land Surface Temperature datasets (MOD11A1) and ASTER GDEM using the Barometric formula. MODIS Terra surface reflectance dataset MOD09GA has been used for generating the Perpendicular Moisture Index

(PMI) and Modified Normalized Difference Fire Index (MNDFI). Dynamic fire danger index has been developed by integrating the above mentioned parameters. Finally, the fire danger rating index has been developed from the static fire danger index and dynamic fire danger index by generalized additive model.

The entire procedure of forest fire danger index has been automated by using the near real time MODIS Terra satellite datasets, which are available for download from the ftp server after half an hour of the satellite overpass over the study area. This entire procedure was automated in R studio environment i.e. downloading NRT MODIS Terra satellite datasets (MOD09, MOD11), pre-processing, conversion, calculation of intermediate parameters, integration of static and dynamic fire danger indices to generate the fire danger map. In future, the fire danger maps will be disseminated in near real time. There is a limitation study is missing pixels in the datasets due to the cloud cover, but, there are very few missing pixels during the summer season of Uttarakhand state. The forest fire danger index will also be adapted to entire Western Himalaya for the better management of fires. Thus, the forest fire danger index was developed for the Uttarakhand state by using the satellite datasets.

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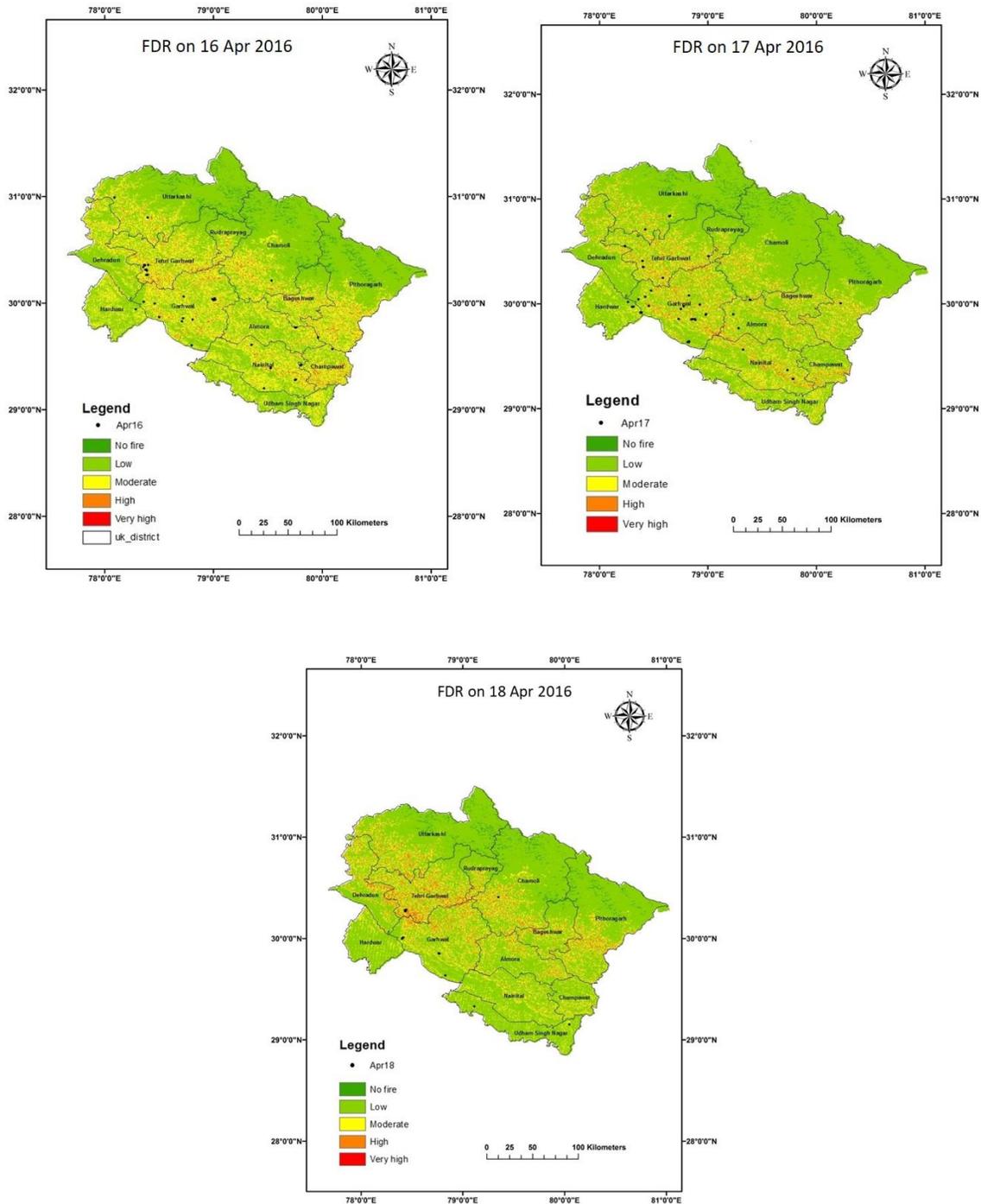
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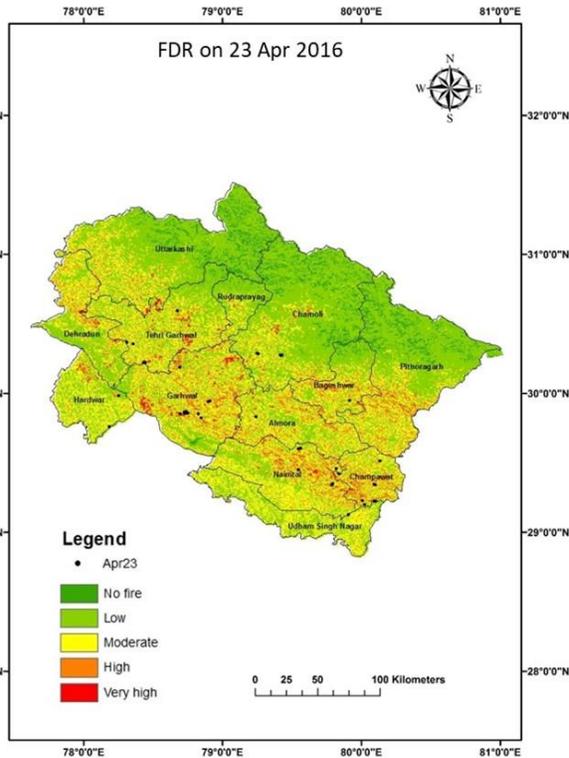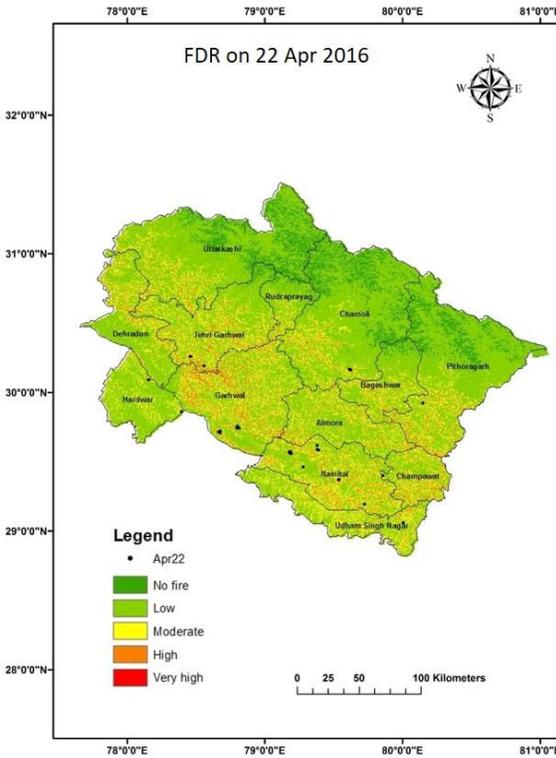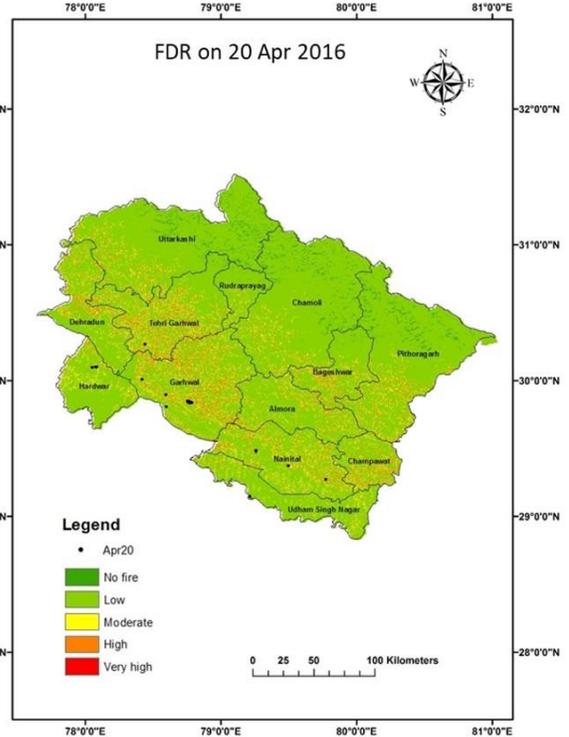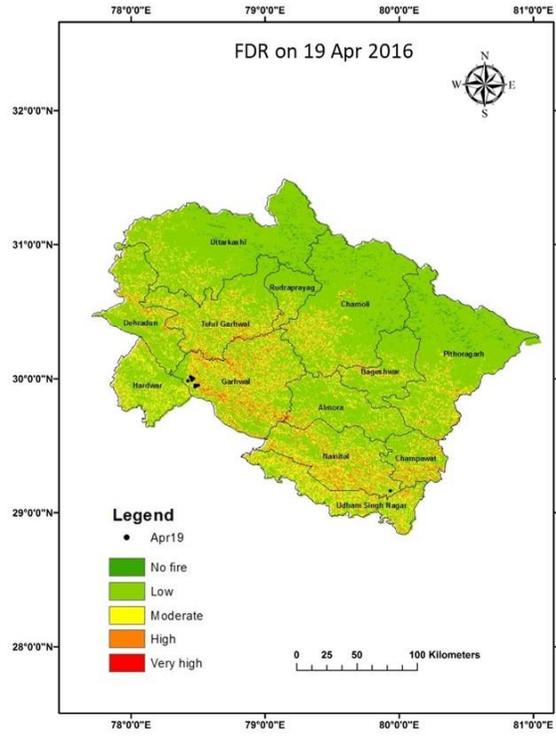
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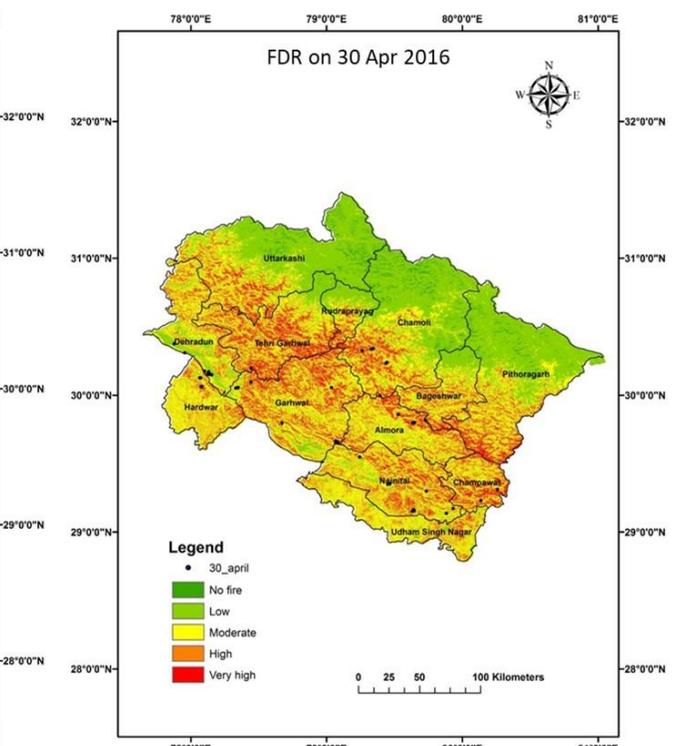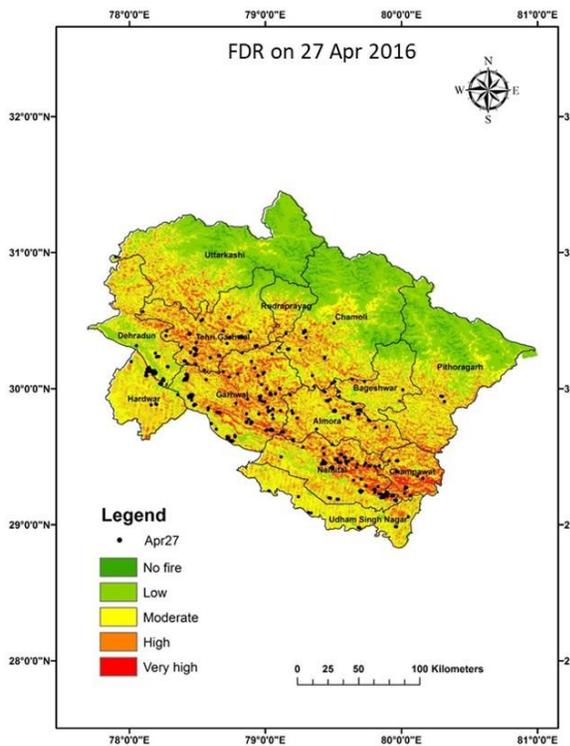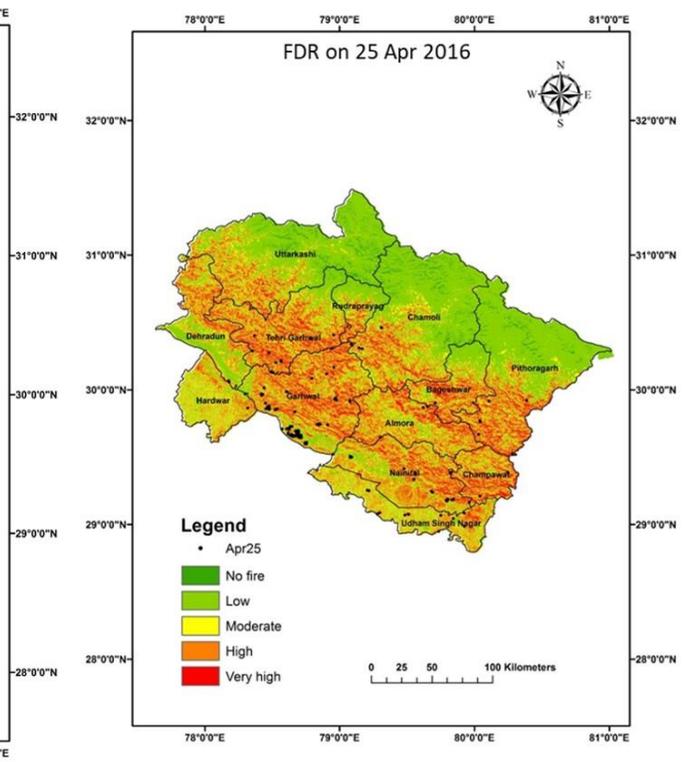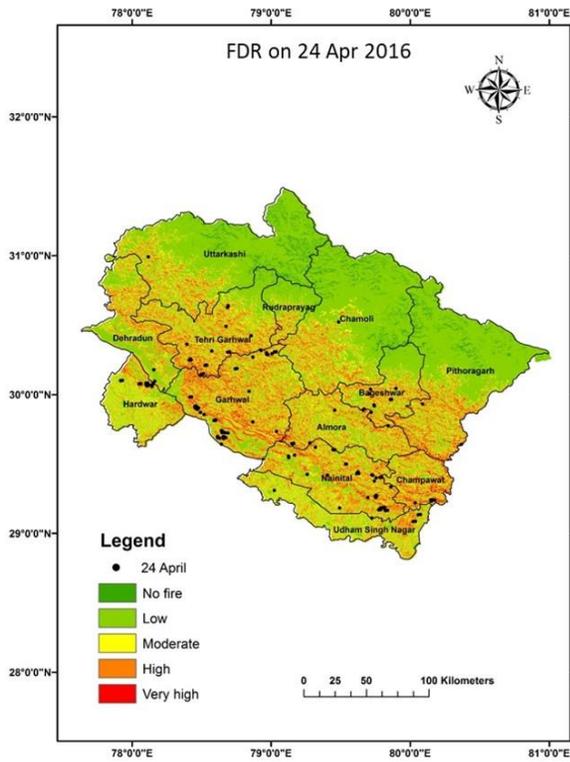
Appendix 1

The forest fire danger index was calculated during the major fire episode of 2016 i.e. 16 Apr 2016 to 4 May 2016 and the results were shown in below Appendix Figure1 and accuracy was shown in Appendix Table 1
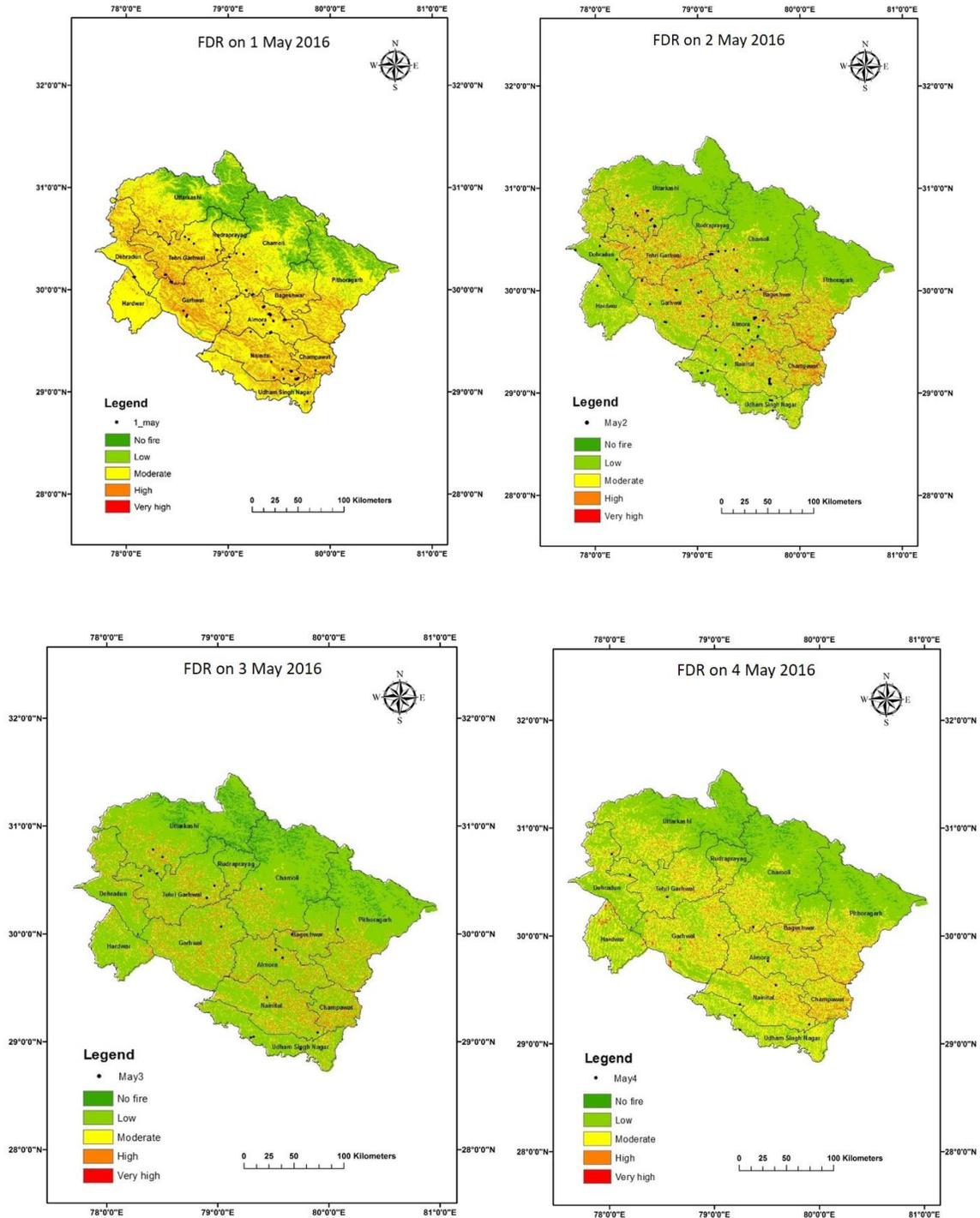
FDR on 19 Apr 2016

Legend
- Apr19
- No fire
- Low
- Moderate
- High
- Very high

0 25 50 100 Kilometers

FDR on 20 Apr 2016

Legend
- Apr20
- No fire
- Low
- Moderate
- High
- Very high

0 25 50 100 Kilometers

FDR on 22 Apr 2016

Legend
- Apr22
- No fire
- Low
- Moderate
- High
- Very high

0 25 50 100 Kilometers

FDR on 23 Apr 2016

Legend
- Apr23
- No fire
- Low
- Moderate
- High
- Very high

0 25 50 100 Kilometers

Appendix Fig: Forest Fire Danger Index images were overlaid with corresponding active fire location data

Appendix Table: Accuracy of the Forest Fire Danger Index during the fire episode of 2016

S. No.	Date	Total no. of fire incidents		Accuracy (%)
		No, Low, and Moderate classes	High and Very High classes	
1	16-04-16	7	32	82.05
2	17-04-16	8	34	80.95
3	18-04-16	3	10	76.92
4	19-04-16	2	7	77.77
5	20-04-16	5	13	72.22
6	22-04-16	7	21	75
7	23-04-16	8	34	80.95
8	24-04-16	16	92	85.18
9	25-04-16	14	89	86.40
10	27-04-16	21	142	87.11
11	30-04-16	4	40	90.90
12	1-05-16	7	62	89.85
13	2-05-16	8	76	90.47
14	3-05-16	5	12	70.58
15	4-05-16	3	8	72.72

Appendix 2

Forest types effected by forest fires as observed from field inventory.

Figure 1: Pine dominated Forests near Hairakhan

Figure 2: one of the cause of forest fire- Resin collection

Figure 3: Saal dominated Forests near Kaladhungi

Figure 4: Forest fire in Nainital district

Figure 5: Pine forests affected by Forest Fire in 2018

Figure 6: Pine forests affected by Forest Fire in 2018