Chapter

Remote Sensing and GIS Applications in Wildfires

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Abstract

Wildfires are closely associated with human activities and global climate change, but they also affect human health, safety, and the eco-environment. The ability of understanding wildfire dynamics is important for managing the effects of wildfires on infrastructures and natural environments. Geospatial technologies (remote sensing and GIS) provide a means to study wildfires at multiple temporal and spatial scales using an efficient and quantitative method. This chapter presents an overview of the applications of geospatial technologies in wildfire management. Applications related to pre-fire conditions management (fire hazard mapping, fire risk mapping, fuel mapping), monitoring fire conditions (fire detection, detection of hot-spots, fire thermal parameters, etc.) and post-fire condition management (burnt area mapping, burn severity, soil erosion assessments, post-fire vegetation recovery assessments and monitoring) are discussed. Emphasis is given to the roles of multispectral sensors, lidar and evolving UAV/drone technologies in mapping, processing, combining and monitoring various environmental characteristics related to wildfires. Current and previous researches are presented, and future research trends are discussed. It is wildly accepted that geospatial technologies provide a low-cost, multi-temporal means for conducting local, regional and global-scale wildfire research, and assessments.

Keywords: wildfires, GIS, remote sensing, multispectral sensors, lidar, UAV, mapping

1. Introduction

Forest fires (term used in Europe to designate the unwanted fires burning forests and wildlands) are considered as one of the main environmental hazards worldwide. Forest fires are periodic disturbance events that dramatically affect the structure and distribution of global forest ecosystems, altering soil erosion, causing loss of biodiversity, habitat, production and productivity, endangering human life, and disrupting livelihoods [1].

The impacts of climate change are becoming more evident each year. Forest fires are more frequent and extreme, as also confirmed by the recent report of the International Panel on Climate Change (IPCC) "Climate Change 2022: Impacts, adaptation and vulnerability" [2] and the recent United Nations Environment Program report "Spreading like wildfire: The rising threat of extraordinary landscape fires" [3].

In Mediterranean basin, natural forest fires are common and are an integral part of the terrestrial ecosystems (**Figure 1**). Fire has been used by man as management tool since early times. Mediterranean region is the most affected area from wildfires in Europe. Approximately 85% of the total burnt area occurs in the EU Mediterranean region [4]. This vulnerability of Mediterranean basin to be affected by fire is linked to its climate, which is characterized by rainy and mild winters followed by warm and dry summers [5]. Extreme weather conditions in summer (high temperature, strong wind, low relative humidity and drought) are a key factor in the ignition and spread of large forest fires [6–8].

Geospatial technologies such as remote sensing (RS) and geographic information systems (GIS) have been used for the management of forest fires several years ago with the use of aerial photographs and have been increasing as new type of sensors become available varying from spaceborne sensors to the newly era of UAVs sensors. Remote sensing provides the data used through the GIS or other decision support systems.

Three main levels can be distinguished, in which remote sensing and GIS provide results that can be applied directly to the subject of forest fires: pre-fire conditions (fire risk assessment, vegetation mapping, topography, risk of fire spreading, etc.), monitoring fire conditions (fire detection, detection of hotspots, fire thermal parameters, etc.) and post-fire (burnt area mapping, success of forest regeneration, flood risk, etc.). Different types of remote sensing platforms and sensors are used for data acquisition as satellites to UAVs and active sensors (SAR, Lidar) to passive sensors (optical, thermal infrared, multispectral).

The purpose of this chapter is to present a wide outline of the use of remote sensing and GIS in wildfire management. The chapter examines research in the

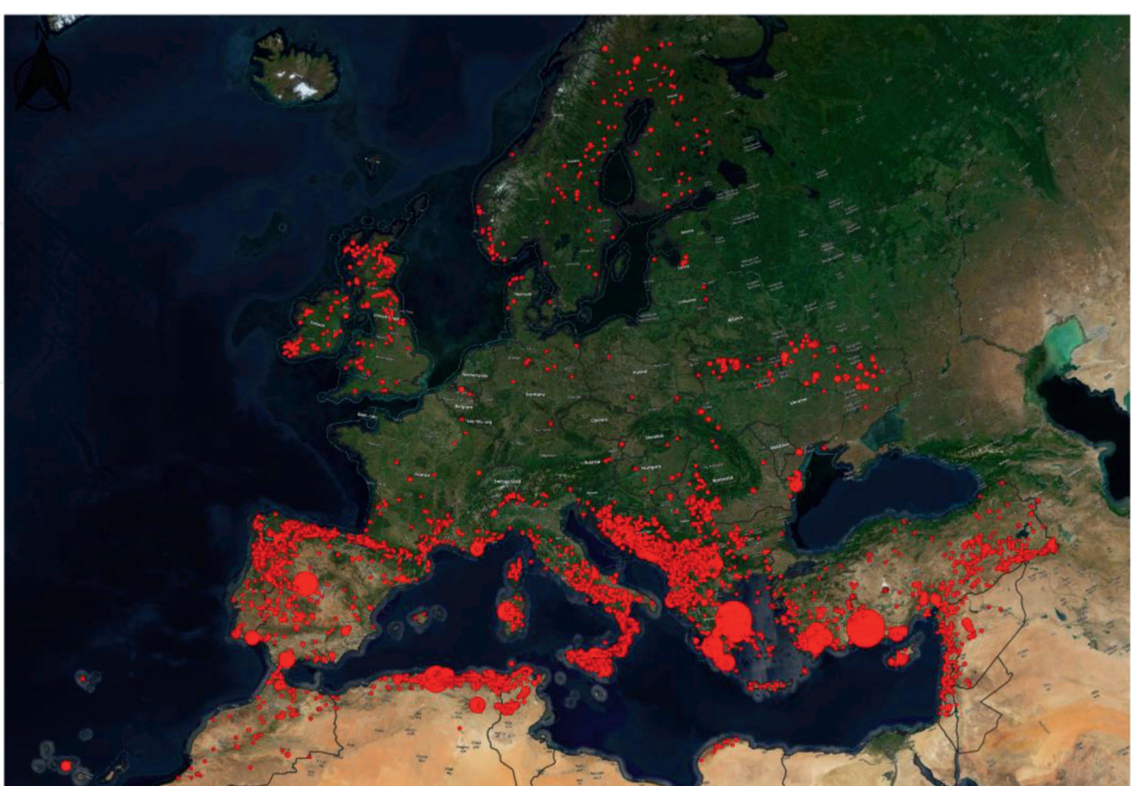

Figure 1.
Forest fires in the pan-European region in 2021 © EU, 2022.

three main levels and within each level, and sub-level, current research trends and case examples are presented, divided by the platform and sensor type used. The goal of this chapter is to provide the reader with a broad view of the current applications of remote sensing and GIS technologies and techniques in the field of wildfire management.

2. Pre-fire condition management

A forest fire results from a complex interaction of biological, meteorological, physical and social factors that influence the likelihood of a forest fire breaking out, its propagation and intensity, duration and extent, and its potential to cause damage to economies, the environment, and society [3]. Terms such as fire hazard, fire risk or danger and severity have been introduced to define risk, hazard and the characteristic (or uncharacteristic) nature of forest fires [9].

Fire risk or danger is a term used to represent the vulnerability of an area to the ignition and spread of fire. This fire vulnerability is influenced by various factors that are dynamic and static in both spatial and temporal dimensions; therefore, it is a complex concept to measure [10]. Furthermore, fire risk factors are both biotic and abiotic [11]. Biotic conditions are aimed at studying the morphological (i.e., fuel biomass load, species composition, height and density) and physiological (i.e., moisture status and chemical properties) characteristics of vegetation, while abiotic indicators are related to the study of external conditions such as topography and meteorological factors on the other hand [11, 12].

Fire risk assessments involve identifying the potentially contributing variables and integrate them into mathematical expression known as "index" [13]. Several risk indices have been developed for fire risk evaluation based on either the temporal scale [14, 15] or the variable data sources [16].

Mapping is used to visualize the fire risk assessments, and this is accomplished through two primary methods: (i) point-wise meteorological data-based operating systems and (ii) the use of remote sensing technologies and geographic information systems (GIS) [17].

The early methods, which assess fire danger, were based on meteorological factors since they have significant role in the occurrence of severe fire episodes [18, 19], including the Nesterov index for use in the former Soviet Union [20], the Forest Fire Danger Index (FFDI) for eastern Australia [21], the National Fire Danger Rating System for the USA [22] and the Canadian Forest Fire Weather Index (FWI) System [23]. These systems use meteorological data such as temperature, precipitation, humidity and wind speed to assess fire danger over extent geographic regions. However, these systems suffer from several limitations as the need for an extent network of weather stations or the need for interpolation to generate fire danger maps. Since the geoinformatic technologies as remote sensing/GIS have the ability to obtain continuous data for an area, the ability to analyze those data is recognized as an effective alternative or addition for the creation of fire risk maps [15, 24].

2.1 Fire hazard mapping

Fire hazard divers from fire danger as it does not include a meteorological component in the assessment [9]. Fire hazard or susceptibility maps are important in land use planning [25, 26], and that maps are useful as a valuable reference to reduce vulnerability and could help to improve decision-making planning in ecological risk prevention [27]. Another potential use is in the insurance markets [28].

Several pre-fire conditions used in the fire hazard maps can be monitored using remote sensing [29]. Vegetation mapping (including fuel loads) is one of the first pre-fire conditions contributing to fire hazard models that are produced usually from high spatial resolution optical or radar images [30, 31]. The fuel maps may range from global-continental products derived from coarse-resolution sensors (AVHRR, Modis, Vegetation) to regional-local inventories, based on higher-resolution data (Landsat TM/ETM, radar or even Ikonos) [32].

Description of fuel properties is critical in all phases of fire management and fire science: prevention, fire danger estimation; suppression: fire behavior modeling; fire effect assessment: trace gas emissions and vegetation recovery after fire [33]. Several fuel characteristics are critical for fire propagation studies: crown bulk density, crown base height, canopy height, canopy closure, surface area to volume ratio, vertical and horizontal continuity, dead and live fuel loads, live woody loads and size of particles referring to vegetation geometry to the fuel type, which can be mapped, like classical vegetation mapping, from high spatial resolution optical or radar images [34].

Depending on the remote sensing data sources used different vegetation characteristics can be interoperated because of the different spatial, spectral and temporal resolution (**Table 1**).

Multispectral remote sensing provides fundamental inputs for the mapping of fire hazard [15, 35]. Land cover type plays an important role in evaluating the risk of a given area to fire events as it is related to fuel types and characteristics; usually, classification is fulfilled using vegetation indices. The simplest form of vegetation index is simply a ratio between two digital values from independent spectral bands. The Normalized Difference Vegetation Index (NDVI=NIR R/NIR + R), the most commonly used ratio transformation for vegetation studies, is used to monitor photosynthetic activity and provides information on vegetation biomass and phenology [36–38]. Biomass is also estimated using various remote sensing data [39, 40].

Usually low or medium spatial resolution multispectral sensors such as Landsat-TM [41, 42] or MODIS-ASTER [43, 44], and hyperspectral sensors, such as Hyperion [45], AVIRIS [46] or MIVIS (Multispectral Infrared Visible Imaging Spectrometer) [47] and lately the Sentinel-2A [48].

High resolution commercial satellites, such as Quickbird, Pleiades-1A, IKONOS, GeoEye-1, WorldView-2,3, have become operational over the past decades, offering data at finer than 10-m spatial resolution have also been used for fuel mapping [44, 49]. Arroyo et al. [50] explored the utility of high resolution (4 m^2) satellite imagery for the production of fuel type maps using a different data processing approach and object-oriented classification, which allows for considering spatial context of adjacent pixels in the eventual generation of the fuel map. It was concluded that this approach produced higher accuracies than would have been generated using traditional maximum-likelihood classifiers. Such data can be used for pre-fire studies, but hurdles such as high cost per scene and the limitation common to most of optical sensors, the inability to penetrate forest canopies [51].

Beyond optical remote sensing satellites active sensors such as SAR and Lidar have been used to estimate vegetation characteristics that are critical for fuel type mapping, such as foliar biomass, tree volume, tree height and canopy closure [52, 53]. Lidar data is used in combination with other remote sensing data airborne or space-borne to estimate vegetation characteristics [49, 54].

Sensor	Spatial resolution	Temporal resolution	Advantages	Disadvantages	Info
Landsat MSS,TM, ETM+, OLI	15–30 m	16 days	Free and easily accessible	Lack of canopy penetration, low temporal resolution	https://landsat.gsfc.nasa.gov/satellites/landsat-8/
Sentinel-2	10–60 m	5 days	Free, relatively high spatial and temporal resolution, multiple near-infrared (NIR) bands	Lack of canopy penetration	https://sentinels.copernicus.eu
MODIS	250 m–1 km	1 to 2 days	Free and easily accessible, high temporal resolution, large area analysis	Lack of canopy penetration, coarse spatial resolution limits analysis of smaller areas	https://modis.gsfc.nasa.gov/about/
Pleiades Neo	0.3–1.2 m	1–3 per day	High spatial resolution	High cost	https://earth.esa.int/eogateway/missions/pleiades-neo
AVIRIS	4–20 m	Airborne	High spatial resolution, hyperspectral sensor	High cost, complicated data processing	https://aviris.jpl.nasa.gov/
AVIRIS-NG	0.3–4.0 m	Airborne	High spatial resolution, hyperspectral sensor	High cost, complicated data processing	https://avirisng.jpl.nasa.gov/aviris-ng.html
Hyperion	10–30 m	16 days	Free and easily accessible, hyperspectral sensor	Decommissioned 2017	https://www.usgs.gov/centers/eros/science/usgs-eros-archive-earth-observing-one-eo-1-hyperion
UAV	High centimeter-level	Airborne	High spatial resolution, hyperspectral sensor, lidar sensors	Cost it depends from the sensor, low endurance for areas 1–10 km^2	

Table 1.
List of sensors commonly used or with potential usage in forest fires research.

Remote sensing provides also topographic data as slope, aspect and elevation that all influence the risk of an area to fire ignition and/or spread [55]. In terms of terrain factors, altitude and slope can affect the moisture loss of vegetation, and in contrast, the aspect affects the amount of solar radiation received by vegetation, directly affecting the vegetation drying degree. For forests, terrain differences lead to differences in wind, water balance and heat transfer between different areas, affecting the spread of fire [56].

Another pre-fire condition that remote sensing systems provide is the historical statistical data about the date and time of the fire, fire location (administrative district), fire size by land use category and fire cause [57, 58]. Historical data can be used to evaluate the accuracy of the fire hazard maps or the fire risk maps and the models used. Examples of remote-sensed databases of fire activity include the World Along Track Scanning Radiometer (ATSR) Fire Atlas [59], the MODIS and the VIIRS Active Fire Products [60] and the LSA SAF Fire Products [61].

In the last decade, unmanned aerial vehicles (UAVs) have become more affordable and one of the most important remote sensing data sources in various natural resource management applications [62–64]. UAV can use a variety of sensors, including visible light, near infrared (NIR), shortwave infrared (SWIR), thermal infrared (TIR), SAR and Lidar sensors. UAV optical sensors, including visible, NIR and SWIR, also record data as multispectral or hyperspectral bands [65, 66]. Since the sensor technology advances, increasingly smaller, lighter and cheaper sensors have become available for UAV remote sensing applications. Manfreda et al. [67] and Constantine and Rey [68] provide detailed introductions to various UAV remote sensing systems. Also, Dainelli et al. [69] provide a systematic review analysis of unmanned aerial vehicle (UAV)-based forestry research papers.

Remote sensing provides data about proximity to human settlement/infrastructure to identify areas at risk of fire occurrence. Forest fires in the Mediterranean Europe and in Mediterranean basin in general are mostly related to human activities. More than 90% of fires originate from either deliberate or involuntary causes [70] Mapping ignition risk is an important tool for managers, helping to improve the effectiveness of fire prevention, detection and firefighting resource allocation [71, 72].

In Mediterranean basin, in California and in Australia, electric power infrastructure has ignited several of the most destructive wildfires in recent history, even if there is a gap in published research work on wildfire prediction when the root cause of the fire is linked to the power grid infrastructure—despite the fact that some of the most devastating wildfires were sparked by power grids [73]. Remote sensing (RS) and geographic information system (GIS) technologies and their derived applications are effective tools for power line surveillance and disaster prevention [74]. UAVs can be used for detailed map of electric power grid and for identifying utility systems that pose a fire risk [75, 76].

Several methods have been used widely for forest fire occurrence. Based on the literature, there are two main methods and techniques for this aim, namely, data-based (machine learning (ML)) and knowledge-based methods [77]. Numerous studies used knowledge-based methods for forest fire susceptibility mappings, such as fuzzy logic [78], the analytic hierarchy process (AHP) [79] and the analytical network process [80]. In recent years, an obvious trend in the use of machine learning algorithms is in a wide range of natural hazard assessment disciplines [81, 82]. Machine learning (ML) methods, such as logistic regression [83], artificial neural networks [84, 85] and Random Forest [86, 87], are also used for forest fire hazard mapping.

An example of fire hazard mapping is Fire Hazard Severity Zones Maps in California USA and it is produced by State of California and the Department of Forestry and Fire Protection. The Fire Hazard Severity Zone (FHSZ) maps are developed using a science-based and field-tested model that assigns a hazard score based on the factors that influence fire likelihood and fire behavior. Many factors are considered such as fire history, existing and potential fuel (natural vegetation), predicted flame length, blowing embers, terrain, and typical fire weather for the area. There are three levels of hazard in the State Responsibility Areas: moderate, high and very high (**Figure 2**) [88].

2.2 Fire risk mapping

Fire risk mapping also includes dynamic variables such as weather and vegetation conditions. The result is a map that displays varying degrees of fire risk ranging from very low to very high. Fire risk maps in short term normally provide risk estimates that are only appropriate for a short period (days-weeks) after their creation. They use many of the same inputs as fire hazard maps but also include variables that are continuously changing such as fuel moisture content, weather conditions and vegetation conditions [9, 89]. Live fuel moisture content (LFMC) is one of the critical factors affecting fire ignition and fire propagation, and therefore is taken into account in most fire danger and fire behavior modeling systems [90]. Dead fuel moisture conditions also affects fire ignition and fire propagation and the computation is easily estimated from weather data and fuel characteristics, because dead fuel moisture is in balance with that of the surrounding atmosphere [91, 92]. Several studies conducted in a wide range of ecosystems have found a significant correlation between burned area and LFMC [93, 94]. Accurate and comprehensive spatial and temporal estimations of LFMC are essential to assess wildfire danger [95] and to develop early warning systems for the evolution of critical conditions [96]. Field-based estimations of LFMC are labor and time intensive as well as costly, and they cover small areas and are difficult to be frequent.

Remote sensing methods cover large areas and this is why remotely sensed images have been used extensively for estimation of the LFMC using various methods, which

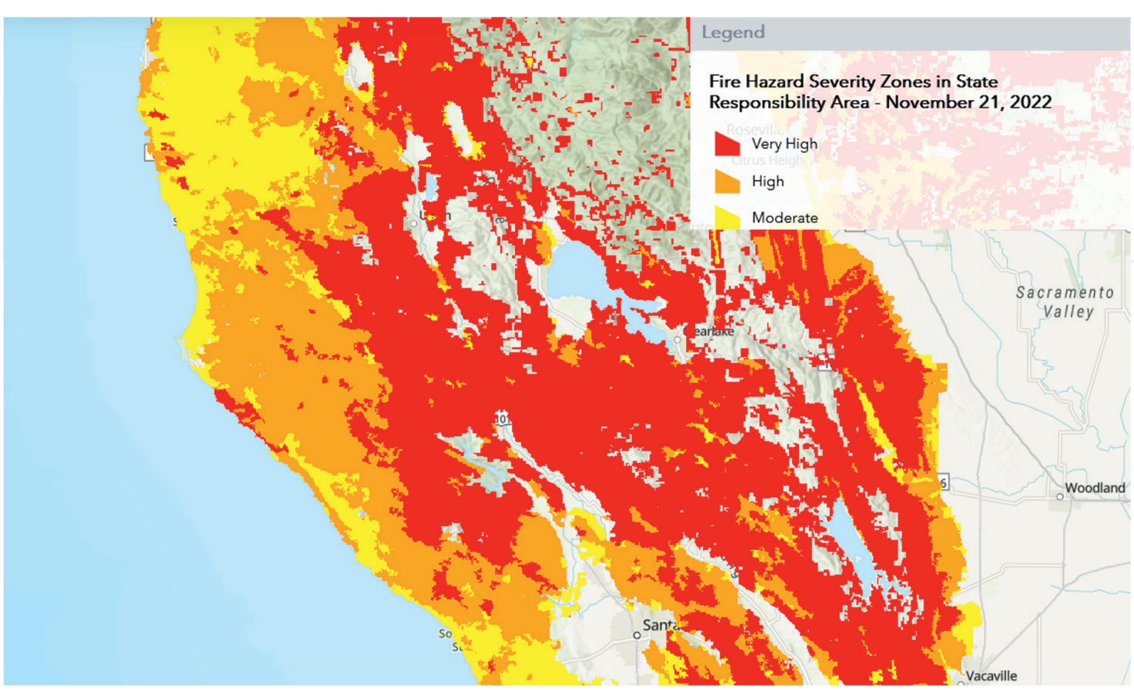

Figure 2.
California fire Hazard severity zone viewer web mapping application.

may be generally classified into statistical (empirical) [97, 98], physical model-based approaches [99, 100] and recently machine learning approaches [101, 102].

The use of satellite data in LFMC estimation has been focused on coarse spatial resolution remote sensing data such as moderate resolution Imaging Spectroradiometer (MODIS) and Advanced Very High-Resolution Radiometer (AVHRR). Combinations of spectral indices have been successfully employed to estimate LFMC [94, 97, 103] usually including the reflectance in the near infrared and the reflectance in the 1.6-μm region [104, 105]. Other studies implement also thermal data to estimate LFMC [106], different satellite data (Sentinel-2) in combination with meteorological variables or without [107, 108] and microwave remote sensing [102, 109, 110]. Yebra et al. [111] reviewed the use of remotely sensed data for estimating LFMC with particular interesting toward the operational use of LFMC products for fire risk assessment.

Fire Weather Index (FWI) module of the Canadian Forest Fire Danger Rating System (CFFDRS) is widely used in several countries such as Alaska, USA [112]; Indonesia and Malaysia [113]; Portugal [114]; Spain [115]; and others. It is also part of the European Forest Fire Information System (EFFIS) (**Figure 3**) [116]. The FWI System has six components rating fuel moisture content and potential fire behavior in a common fuel type (i.e., mature pine stand) and in no slope conditions.

Calculations are based on daily noon measurements of air temperature, relative humidity, wind speed and previous 24-h precipitation. Despite the global acceptance of the FWI, it has an inherent problem in delineating the spatial dynamics of the danger conditions, as it employs geographic information system (GIS)-based interpolation techniques [117]. Sirca et al. [118] assessing the performance of several fire danger indexes in the Mediterranean area concluded that FWI yielded better predictions than the other indexes.

In Italy, the Civil Protection adopted the RISICO model, which is a fire danger rating system that was developed specifically for the vegetation cover of the Mediterranean [119]. RISICO integrates meteorological observations and forecasts from an NWP (Numerical Weather Predication) Limited Area Model (LAM) and ECMWF-Integrated Forecasting System (IFS) with vegetation cover and topography data. Another project developed in Sardinia, Italy called Daily Fire Hazard Index (DFHI) [120], the index is computed using satellite images and the meteorological data.

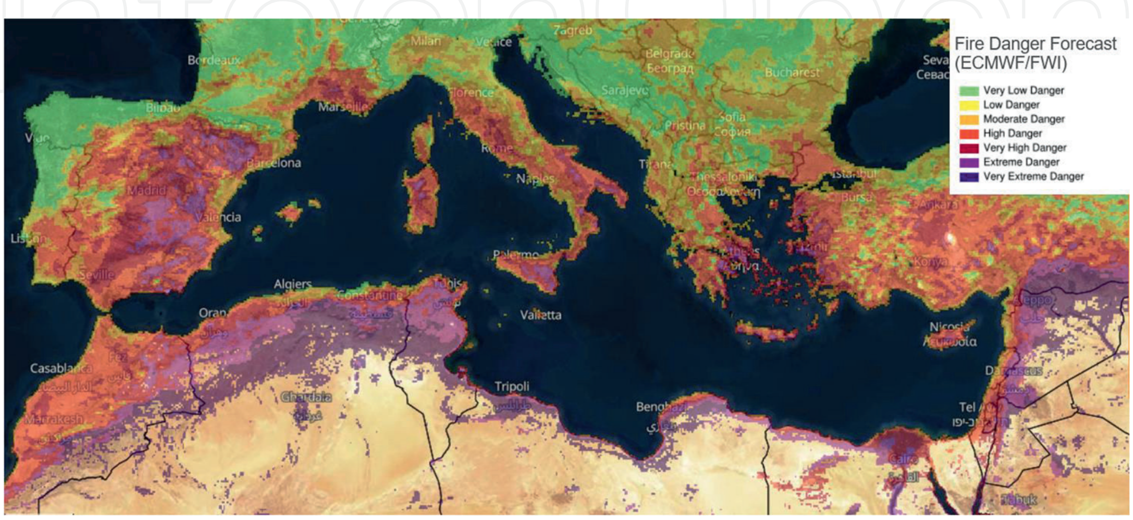

Figure 3.
Forest fire danger forecast in the pan-European region for 02 Jun 2022 © EU, 2022.

3. Fire detection and monitoring fire conditions

Fire detection is the earliest critical stage of forest fires management, which is aimed at either fighting or monitoring the fire. For firefighting the early detection is essential; so far, fire detection is based on human observation, the use of fixed optical cameras to monitor the surrounding environment or aerial survey [29]. The temporal and spatial analysis capabilities provided by current satellite sensors are not considered sufficient for firefighting operations by forest fire mangers.

3.1 Spaceborne multispectral sensors

Several of geo-stationary satellite sensors have been used for active fire detection and monitoring including but not only: Advanced Very High-Resolution Radiometer (AVHRR), Meteosat Second Generation, Spinning Enhanced Visible and Infra-red Imager (MSG-SEVIRI), Himawari-8, Geostationary Operational Environmental Satellite (GOES), DMSP OLS (US Air Force Defence Meteorological Satellite Programme – Operational Line-scan System), Visible Infrared Imaging Radiometer Suite (VIIRS) and moderate resolution imaging spectroradiometer (MODIS) [121–123]. Early attempts of active fire detection and monitoring started during 80′ with the US Forest Service using NOAA satellites to identify forest fires in the western US [124]. AVHRR was the primary sensor system for active fire detection and monitoring until the eventual launch during 1999 of the MODIS sensors onboard the Terra and Aqua platforms [125]. MODIS Terra and Aqua have become the primary sensors at regional to global scales for active fire detection and monitoring due to their high temporal resolution and special channels designed for fire monitoring. The Aqua MODIS instrument acquires data twice daily (1:30 PM and AM), as does the Terra MODIS (10:30 AM and PM). These four daily MODIS fire observations serve to advance global monitoring of fire processes and their effects on ecosystems, the atmosphere and climate [126]. Serval operational fire monitoring systems using MODIS active fire detection include the Canadian Wildland Fire Information System (CWFIS) (http://cwfis.cfs.nrcan.gc.ca), the USA Active Fire Mapping Service or the European Forest Fire Information System (EFFIS) (http://effis.jrc.ec.europa.eu). In the case of EFFIS, post-processing filters based on landcover ancillary data are applied to the MODIS product to reduce the number of false alarms produced by non-fire hot surfaces (e.g., industrial areas, hot ground soils) and therefore increase the reliability of the active fire detection [116]. **Figure 4** shows active fires monitoring in the wider Mediterranean region.

Several studies found that MODIS fire detection algorithms had trouble detecting smaller/cooler fires and frequently detected false alarms [127, 128]. Validation of MODIS and AVHRR active fire products used higher spatial resolution sensors such as Landsat TM and ASTER to evaluate the performance of the MODIS and AVHRR products [129, 130]. The accuracy of fire detection is calculated in terms of commission and omission errors as well as error distributions over various locations. Commission and omission errors have been reported by many studies errors of omission represent "failure to detect fires" and errors of commission represent "false alarms or false positives" pixels identified as fires [130]. Schroeder et al. [127] found errors of commission of approximately 35% over areas of active deforestation, and similarly, Forghani et al. [130] report that overall commission errors of MODIS and AVHRR hotspots over the 5% sample data were 15 and 68%, respectively, and overall omission errors of MODIS and AVHRR hotspots were 17 and 23%, respectively. An interesting comparison of the

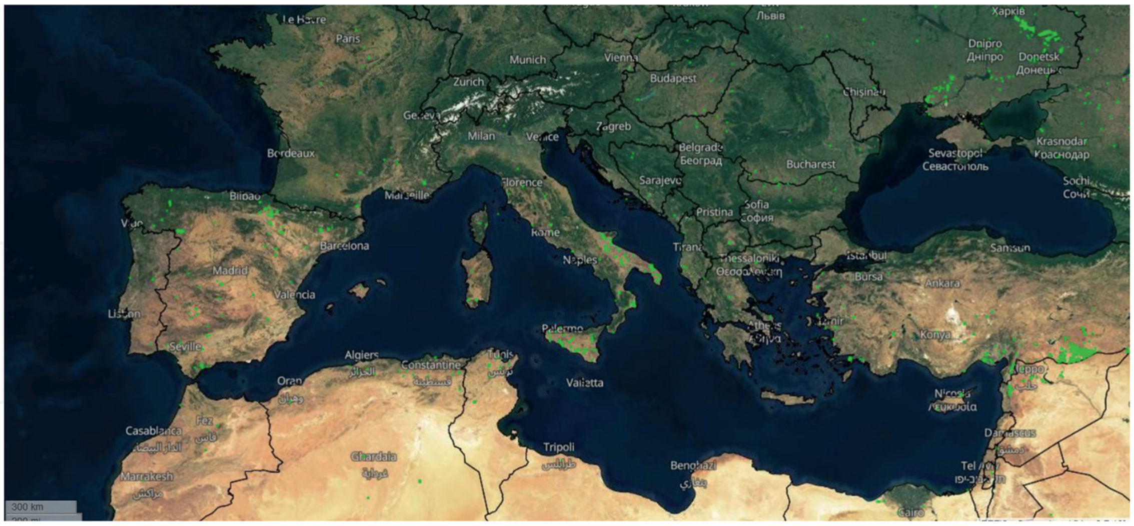

Figure 4.
Active fires from MODIS during June 2022 © EU, 2022.

suitability of some of geo-stationary satellite sensors (AVHRR, MODIS, DMSPOLS) for fire detection was carried out by Cahoon et al. [131]. They found in their study that the minimum size for a detectable fire was approximately 213 m2 for MODIS, 435 m2 for AVHRR and 45 m2 for DMSP-OLS, for a nominal fire front temperature of 1000 K and a background temperature of 305 K. Maier et al. [132] determined a minimum fire size of 100–300 m2 for the detection by the MODIS algorithm. Evaluation of the MODIS active fire product to quantify detection rates of both Terra and Aqua MODIS sensors was carried out by Hawbaker et al. [133]. Finally, MODIS had the ability to capture large fires in the US, but may under represent fires in areas with high cloud, rapid burning or small- and low-intensity fires that are often undetected.

To address these limitations found during evaluation of the MODIS fire detection algorithm, NASA's Earth Observing System periodically reprocesses the raw instrument data archive using newer fire detection algorithms. In the MODIS version 3 active fire detection algorithm's sensitivity to small fires was sacrificed to reduce false alarms over certain surface types during the day [134]. The MODIS 4, contextual fire detection algorithm was enhanced, which increased the ability to detect small cool fires [60]. For the recently released Collection 6 MODIS fire products, bands 1 (red), 2 (near infrared), 7 (short-wave infrared), 21 (thermal infrared over a wide-range centered on 4 μm), 22 (thermal infrared in a narrow-range centered on 4 μm), 31 (thermal infrared at 11 μm) and 32 (thermal infrared at 12 μm) are used to identify 1-km "fire pixels" that contain at least one active fire at time of acquisition [128].

Further than MODIS, recent studies have used data from the Landsat 8 Operational Land Imager (OLI) [135] and Sentinel-2 sensors [136]. Also, the use of geostationary weather satellites and their ability to detect active fires have been a research topic of great interest for several years [137–139].

Active fires can be detected by a wide variety of spectral sensors, but as active fire products are usually used to monitor ongoing fires and the ideal sensors for detecting them will possess a high temporal resolution; at the same time that kind of sensor have low spatial resolution. While sensors with higher spatial resolution like Landsat satellites and Sentiel-2 satellites work well for detecting active fires, their low temporal resolution makes them less than ideal. This is the reason why most active fire products are generated from sensors such as MODIS and VIIRS, as these sensors have a very short revisit time (<2 days) allowing for the active fire products to be rapidly updated [17]. Geostationary satellites have even higher temporal resolution, with updates every few hours or less. However, these high temporal resolutions come at the cost of lower accuracies due to the omission of smaller/cooler fires and commission errors caused by activities such as deforestation [127, 132, 140].

3.2 UAVs

The MODIS satellite imagery with the high temporal resolution (1–2 days revisiting time) is commonly applied in forest fires detection and monitoring. However, the low spatial resolution of MODIS is insufficient for this task at local scales [65]. During the last decade, we have seen a great progress in the field of using unmanned aerial vehicles (UAVs) for forest fire monitoring, detection and even fighting [141]. UAVs have become smaller, more affordable and now have better computation capabilities than in the past making them reliable tools for remote sensing missions in hostile environments [142]. UAVs provide rapid, mobile and cost-effective sensor systems that are currently being adopted for fire detection and monitoring [143, 144]. In their review of UAVs applications for forest fire monitoring, detection and fighting, Yuan et al. [144] define fire monitoring as involving the active search for possible fire occurrences, while fire detection involves the identification of fires in progress. UAVs used for fire monitoring and detection rely on sensors operating in the visible and thermal infrared wavelengths. In a more recent review of UAVs usage in forest fires, Akhloufi et al. [145] present a survey of different approaches for the development of UAV fire assistance systems. They conclude that UAVs can play an important role in the fight against wildland fires in large areas and with the decrease in their prices and their wider commercial availability, new applications in this field will emerge. However, limitations remain such as autonomy, reliability and fault tolerance; also security issues are a concern, as there are risks associated with having UAVs flying over firefighters or close to aircraft carrying water and fire retardants [145].

4. Post-fire condition management

The application of remotely sensed imagery to monitor and assess the impacts of fire on local and regional environments can be broadly divided into several applications such as burnt area mapping, burn severity assessments, vegetation recovery monitoring, effects on soil erosion, and general fire effects on air quality, soil, vegetation and fauna.

4.1 Burnt area mapping

Remotely sensed data have been extensively used for burnt area mapping at local, regional and global scales [146, 147]. Burned area mapping is critical importance for forest managers, climate scientist and policy makers; they provide accurate spatial representations of fire extents and perimeters. Accurate maps of the areas affected by forest fire are needed for rehabilitation planning, calculating the economic and environmental cost of fires, and for regional and global scale estimates in gas and particulate emissions [148, 149].

Fires produce a significant change in the structure and the reflectance of vegetation and the soil properties within the burnt area that are noticeable in the microwave, visible and especially the infrared part of the electromagnetic spectrum [29]. The sensors used for burned area mapping differ depending on scale and purpose of the assessment. Since the 1980s, the majority of techniques have been developed for data acquired from the AVHRR sensor, and as such were restricted to a limited number of reflectance and thermal bands; most commonly method used is multi-temporal comparison of NDVI [150, 151]. Although data from the AVHRR sensor have low spatial resolution (i.e., 1.1 km), global data have been obtained from a series of different satellites since the 1980s allowed the long-term monitoring of large-scale fires in remote and isolated areas. During 2000s, other global burnt area datasets were derived from SPOT Vegetation and the ATSR-2 on board of Envisat [152–154]. Partial validations of the global burnt area products were performed by Roy et al. [155], Boschetti et al. [156] and Roy and Boschetti [157]. Pereira et al. [150] showed that the accuracy of the results for mapping burnt areas with AVHRR data in the Mediterranean region of Europe was about 80% for large fires. The methods were considered suitable only for fires larger than 1000 ha and reliable for fires larger than 2000 ha. However, the mapping of those fires would correspond only to approximately 30 and 21%, respectively, of the total yearly burnt area in the European Mediterranean region.

Until the launch of the MODIS sensor on board of the TERRA and AQUA satellites, there was not a space-based system design specifically to “look” at terrestrial Earth. MODIS sensors add a new capability for regional mapping of burnt areas, the availability of free data of medium spatial resolution from the MODIS sensors since 2000 provided a definite impulse for the use of remote sensing at the regional and global scales [134]. The higher spectral information and the better radiometry of the MODIS sensor in comparison with the previous sensor systems (e.g., AVHRR—an atmospheric mission), provided the right data for the mapping of burnt areas at these scales. At the global scale, the MODIS program has used to produce a standard product on burned areas based on a multi-temporal change detection approach to analyze differences between modeled and actual reflectance, using an algorithm based on Bidirectional Reflectance Distribution Function (BRDF) change detection approach [155]. Giglio et al. [147] created an algorithm for burned area mapping using 1 km MODIS data, the normalized burn ratio (NBR) and temporal texture. The resulting algorithm (MCD64) was assessed based on Landsat-derived burned area maps for central Siberia, the western US and southern Africa. They found that the algorithm performed well overall, except in a closed canopy subregion in southern Africa where it underestimated burned area. In general, global burned area products have been shown to exhibit relatively large errors of omission and commission. The accuracies of several of these burned area products were compared by Padilla et al. [158]. Six global burned area products were compared using stratified random sampling in the first attempt to implement a statistically designed sample to validate burned area products on a global scale. The products used in this study included MCD45, MCD64, Geoland2, MERGED_cci, MERIS_cci and VGT_cci. The study found MCD64 to be the most accurate, followed by MCD45; however, all the products possessed burned area commission errors above 40% and omission errors above 65%.

At regional scale, MODIS is operationally used in systems such as Canadian CWFIS and the European EFFIS. Two full mosaics of MODIS data are received and processed daily in EFFIS to provide near-real time monitoring of wildfires and map burnt areas. The systems are thus updated up to two times daily, providing accurate information of fire impacts in Europe [159]. Rapid Damage Assessment (RDA) module of EFFIS was initially implemented in 2003 to map burned areas during the fire season, by analyzing MODIS daily images at 250-m spatial resolution. Since the

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year 2016, the RDA incorporates the mapping of active fires and burnt areas from the VIIRS Sensor, onboard the NASA Suomi National Polar-orbiting Partnership (SNPP) and the NOAA-20, which allows the update of burnt areas maps one more time, every day. The EFFIS from 2018 is started using also Sentinel-2 imagery at 20-m resolution, which allows the detection of fires below the 30-ha threshold and it is estimated that the areas mapped in EFFIS represent about 95% of the total area that burns in the EU every year. **Figure 5** shows the extent of burnt areas as they were mapped from MODIS and Sentinel-2 imagery during the last fire season and **Figure 6** shows details about the area burnt (dates, location, area, type of vegetation affected).

At national to local scales, the wide variety of remotely sensed products at high to moderate resolution (1-m to 30-m ground spatial resolution) makes it possible the accurate mapping of burnt areas. Optical image satellites such as the Landsat-8 and Sentinel-2 constitute the latest generation Earth observation missions of the United States Geological Survey and European Space Agency, respectively. The Landsat-8 satellite, launched on February 11, 2013, has 11 bands ranging in spatial resolution from 15 m (panchromatic) to 30 m (visible, near infrared, short-wave infrared) and then to 100 m (thermal). Within 16 days' temporal resolution, Landsat-8 provides 30-m spatial resolution optical imagery on eight spectral bands *via* the Operational Land Imager sensor, which can be accessed freely [160, 161]. Landsat-8 30-m products can map small and spatially fragmented burned areas greater than 40 ha in size witch its more detail than other satellite sensors, such as the MODIS 500 m [162]. Sentinel 2 is a high-resolution multispectral imaging satellite composed of Sentinel-2A and Sentinel-2B satellites. The Sentinel-2 satellite covers 13 spectral bands with ground resolutions of 10 m, 20 m and 60 m and provides red-edge spectral bands, the satellite temporal resolution 10 days [163]. Filipponi [164] using threshold-based classification for burnt area mapping of on the 2017 Italy forest fires based on Sentinel-2 time series data reported the methodology generated commission error of around 25% and an omission error of around 40%.

Since the Sentinel-2 and Landsat-8 have similar wavelengths and the same geographic coordinate system, several studies combined both sensors for burnt area mapping [162, 165, 166]. Syifa et al. [166] using SVM and SVM–ICA algorithms for burned area mapping for the Camp Fire (California, USA) report that the SVM–ICA

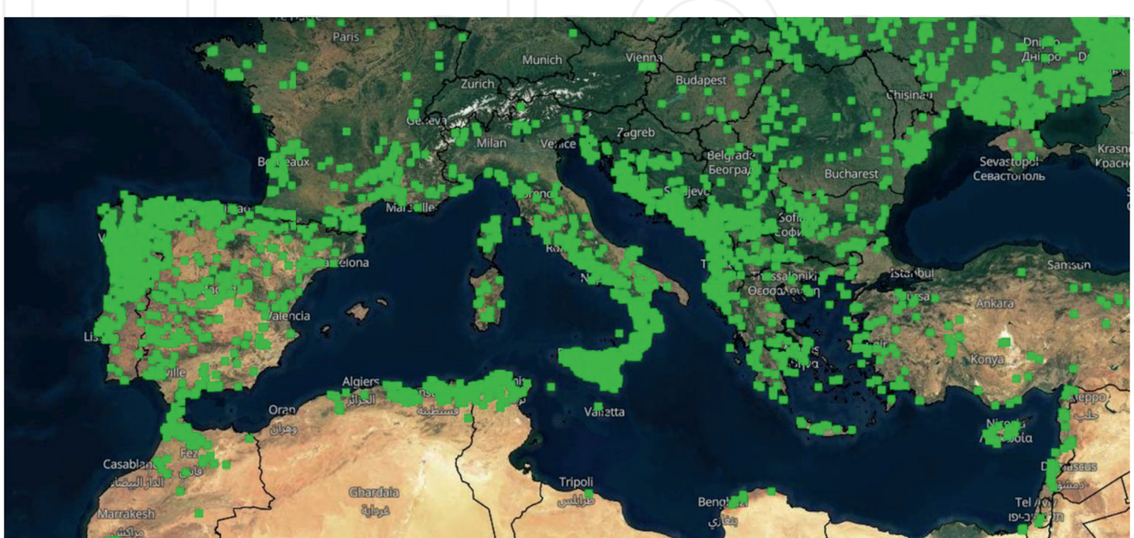

Figure 5.
Burnt area mapping MODIS/SENTINEL2 from the last fire season © EU, 2022.

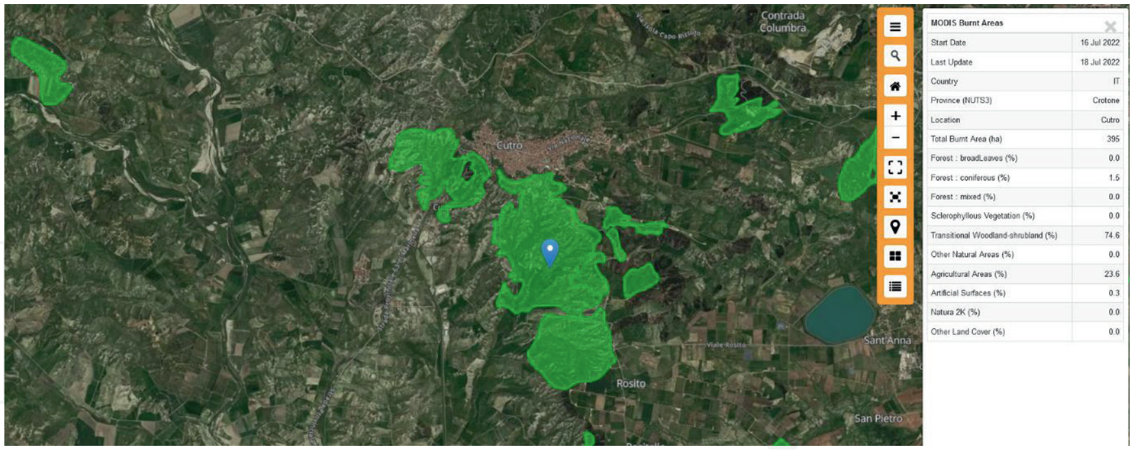

Figure 6.
Burnt area mapping from a fire occurred at July 16, 2022 near Cutro, Crotone, Italy © EU, 2022.

produced a better accuracy (overall accuracies of 83.8 and 83.6% for pre- and post-wildfire using Landsat-8, respectively; 90.8 and 91.8% for pre- and post-wildfire using Sentinel-2, respectively), compared to SVM without optimization (overall accuracies of 80.0 and 78.9% for pre- and post-wildfire using Landsat-8, respectively; 83.3 and 84.8% for pre- and post-wildfire using Sentinel-2, respectively). Different methods of satellite-based burned area detection have been developed, including threshold-based methods using multi-spectral bands or spectral indices such as Normalized Difference Vegetation Index (NDVI), the Soil-adjusted Vegetation Index (SAVI), and the Normalized Burned Ratio (NBR), supervised classification, logistic regression, random forest, etc. [162, 165, 167]. Reviews of burned area mapping algorithms are found in the studies by Boschetti et al. [168] and Chuvieco et al. [169]. Synthetic Aperture Radar (SAR) was also used for burned area mapping mainly in boreal or tropical regions [170, 171], but some examples for the Mediterranean area exist [172, 173]. Also, SAR data have been used in combination with optical data for burned area mapping [174].

4.2 Burn severity and soil erosion assessments

The term fire or burn severity was born out of the need to provide a description of how fire intensity affected ecosystems, particularly following forest fires where direct information on fire intensity was absent and effects are often quite variable within and between different ecosystems [175]. Burn severity impacts vegetation mortality and soil nutrient composition, and causes increased run-off due to decreased of organic matter in the soil and the aboveground vegetation [176, 177]. Burn severity is usually measured in the field using the composite burn index (CBI), which involves an optical assessment of burned areas to determine the fire impacts on ecological conditions. Due to the need for a systematic approach to estimate burn severity across different environments, this approach uses a measure called the composite burn index (CBI) designed to provide a single index to represent many different phenomena of interest to land managers [178]. The CBI combines fire severity metrics and ecosystem responses that include resprouting of herbs, shrubs and hardwood trees, and seedling colonization. The CBI was created to allow for visual estimates to be conducted by rating the degree of damage done by the fire, as well as the estimated vegetation recovery for the area, on a 0 to 3 scale [179].

Various remote sensors (e.g., MODIS, AVIRIS) have been tested for their ability to match field measurements of severity and the Landsat Thematic Mapper sensor was widely accepted as most appropriate for this task [180–182].

Spectral indices, such as the Normalized Burn Ratio (NBR) and NDVI, have been widely used for assessing burn severity through remote sensing in boreal regions [183–186]. The NBR has mostly replaced the NDVI as the standard index for burn severity assessment and been widely used as a means for approximating the burn severity and burned area using satellite imagery also in the Mediterranean basin [187, 188]. The NBR is calculated using NIR and SWIR data, with the SWIR wavelength interval generally within the 2.08–2.35-μm range [189]. A numerous differenced indices for burn severity assessment using multi-temporal satellite data and bi-temporal image differencing techniques have been used in boreal regions, such as the Differenced Normalized Burn Ratio (dNBR) [186, 190], the Differenced Normalized Difference Vegetation Index (dNDVI) [191, 192] and a relative version of the dNBR (RdNBR) [193]. The majority of this indices used NIR and SWIR data, where the NIR wavelengths are sensitive to the leaf structure of live vegetation, while the SWIR is sensitive to moisture content and some soil conditions [189, 194]. Vegetation affected by a fire show decreased NIR reflectance and increased SWIR reflectance [187].

Temporal differences in land surface albedo (LSA) and land surface temperature (LST) have been used to estimate burn severity [195, 196]. Quintano et al. [195] found that changes in LST showed high agreement with field-measured CBI when used to map burn severity for an ecosystem dominated by maritime pine (Pinus pinaster) in Sierra del Teleno, Spain. Zheng et al. [196] conclude that the results indicated that the deltaLST/EVI performed relatively better than some commonly used burn severity indices, and its performance was stable and steady across regional forest areas of different eco-type after fires. However, Veraverbeke et al. [197] and Quintano et al. [195] found that while changes in LSA and LST were highly related to burn severity they were highly dependent on seasonality.

With the launch of the Sentinel-2 sensors by the European Space Agency (ESA), with specific spectral bands to record data in the vegetation red-edge spectral domain, which is one of the best radiance-based descriptors of chlorophyll content [198], allowed for the development and application of new spectral indices to discriminate burn severity.

Fernández-Manso et al. [199] used Sentinel-2A imagery to examine capabilities of red-edge spectral indices in the context of burn severity in central-western Spain. The area is a mixed of shrubs and trees, with maritime pine (*Pinus pinaster*) and Pyrenean oak (*Quercus pyrenaica*) being the dominate species. Results indicated that the red-edge spectral indices calculated using red-edge 1(B5) and red-edge 3(B7)/NIR(B8) were most suitable for burn severity assessment. Filipponi [164, 200] tested Burned Area Index for Sentinel-2 (BAIS2, BAIS2α), based on Sentinel-2 spectral bands on various study cases in Italy for summer 2017 fires, and results show a good performance of the index and highlighted critical issues related to the Sentinel-2 data processing. Burn severity assessments require imagery with a high to moderate (<100 m) spatial resolution such as Landsat series and the Sentinel-2 sensors, and the limitation of these sensors is the long temporal resolution, which can make the rapid acquisition of data on post-fire conditions difficult.

With the use of more advanced remote sensing technologies, such as hyperspectral imagery, lidar, radar and UAVs, important fire effects may be more accurately and consistently inferred from imagery with higher spectral, spatial and temporal resolutions [201]. Lidar sensors provide a relative new technology, which can be used for burn severity assessments. Lidar data can provide pre- and post-fire vegetation structure profiles, which can be used for severity of burning estimations. Wang and Glenn [202] showed the potential for lidar-derived burn severity estimates is sagebrush steppe rangelands using average vegetation height change. This method outperformed the dNBR index estimations, with an overall accuracy of 84%, and proved to be sensitive to differences between moderate and high severity burns. Wulder et al. [203] compared changes in boreal forest structure, obtained by lidar returns, to post-fire conditions, estimated using spectral indices for the Boreal Plains ecozone in Alberta, Canada. The researchers found that absolute and relative changes in post-fire forest structure exhibited a high correlation with post-fire conditions. The synergy of lidar with multispectral sensor data for burn severity assessment is a topic of ongoing research [204–206]. Viedma et al. [206] crossed high-resolution lidar data, acquired from an UAV after the fire and fire severity levels based on the relativized burnt ratio (RBR) derived from Sentinel 2A images acquired a few months before and after fire. They conclude that lidar metrics derived from vertical canopy profiles (VCPs) demonstrated promising potential for characterizing fine-grained post-fire plant structures and fire damage when crossed with satellite-based fire severity metrics, turning into a promising approach for better characterizing fire impacts at a resolution needed for many ecological processes.

UAV technologies have seen an important progression in the last decade and they are now used in a wide range of applications. This technology has recently been applied to research focusing on burn severity assessment using various sensors [206–213]. Ye et al. [211] used object-oriented method to determine the optimal segmentation scale for forest burn severity and a multilevel rule classification and extraction model is established to achieve the automatic identification and mapping. The imagery was obtained by a small, multi-rotor near-ground UAV and the results show that the method mentioned above can recognize different types of forest burn severity: unburned, damaged, dead and burnt with overall accuracy been 87.76%. Carvajal-Ramírez et al. [207] employed an UAV carrying a high-resolution multi-spectral sensor including green, red, near-infrared and red-edge bands. Flights were carried out pre- and post-controlled fire in a Mediterranean forest. The products obtained from the UAV were a Digital Surface Model (DSM) and multispectral images orthorectified in both periods, temporal differences (d) between pre- and post-fire values of the Excess Green Index (EGI), Normalized Difference Vegetation Index (NDVI) and Normalized Difference Red Edge (NDRE) index, where used to after reclassification to produce fire severity classes. It was concluded that dNDVI was the index that best estimated the fire severity according to the UAV flight conditions and sensor specifications.

Forest fires can negatively impact water catchments, contaminating, increasing soil erosion, changing soil composition and slope stability for extensive periods. A major reason for post-fire assessments of fire or burn severity is that it is used as an important indicator of the potential water runoff and erosion [214–216], the loss of vegetation exposes soil to erosion and makes burned areas more vulnerable to runoff and then susceptible to flood [217].

Several studies used fire or burn severity data derived from remote sensing applications or/and GIS applications for post-fire soil erosion assessment [217–219]. Lanorte et al. [218] used a distributed model based on the Revised Universal Soil Loss Equation (RUSLE) to estimate potential post-fire soil loss for four different fire events occurred in Basilicata region (Southern Italy) during 2017. GIS techniques and remote sensing data have been adopted to build a prediction model of post-fire soil erosion risk. Results show that this model is not only able to quantify post-fire soil loss but also to identify the complexity of the relationships between fire severity and all the factors that influence soil susceptibility to erosion. Fox et al. [217] used POSTFIRE a GIS-based model that maps the burn scar and quantifies fire impacts on runoff and soil erosion. The model used pre-fire and post-fire satellite images, calculates the impact of a fire on total rainfall event runoff, and maps soil erosion rates. Additionally, the model requires a Digital Elevation Model (DEM), a mask of the general contour of the fire, land cover map, and tables of runoff coefficients and sediment concentration values for the land covers. Preliminary results from two fires in SE France indicate the model is simple to use, adaptable to local conditions, and provides realistic outputs for the burn scar, discharge and soil erosion maps after a forest fire. UAV imagery has also been used for soil erosion modeling in various types of landscape [220–222].

4.3 Post-fire vegetation recovery monitoring

Vegetation recovery after a fire event is an important measurement for the determination of the long-term impacts that fire has on an ecosystem. During the process of recovery, vegetation may also be influenced by several environmental factors, such as fire severity/damage and climatological extreme events. Vegetation recovery depends on several climate factors, such as the occurrence of droughts, which may inhibit vegetation growth, but also on precipitation of high intensity, which contributes to nutrient loss and erosion by runoff [223]. Anthropogenic factors such as grazing can also affect vegetation recovery [224, 225].

Monitoring post-fire vegetation recovery is crucial, as it provides valuable information for analyzing ecosystem resilience, for determining landscape dynamics and for forest management purposes. Post-fire monitoring of vegetation recovery can be conducted on the field using plots sampling where they measure seedling germination, plant survival and restoration, and vegetation characteristics [226–228], or with the use of remote sensing technologies. Since field measurements of post-fire vegetation recovery are a very challenging and expensive task, remote sensing techniques are a time- and cost-effective way to monitor post-fire ecosystem recovery [229]. Remote sensing techniques for estimating vegetation recovery can be grouped into three categories: (1) image classification, (2) vegetation indices (VIs) and (3) spectral mixture analysis (SMA) [230].

The most practical way to monitor changes over large areas and periods is through image-processing techniques based on change detection or classification techniques [231]. Stueve et al. [232] used supervised classification to identify patterns of alpine tree recovery in Mount Rainer National Park, Washington, USA. They performed classification analysis of 1970 satellite imagery and 2003 aerial photography to delineate establishment. Local site conditions were calculated from a lidar-based DEM, ancillary climate data and 1970 tree locations in a GIS. The supervised classification method proved successful, which can be credited to the very high spatial resolution of the data used in this study. Salvia et al. [233] used a combination of unsupervised classification and field data to successfully examine the influence of burn severity on vegetation cover and soil property recovery in the wetlands of the Paraná River Delta, Argentina.

Geographic object-based image analysis (GEOBIA) is an alternative method for image classification and uses geographic objects instead of pixels as the spatial unit of analysis [234]. GEOBIA are techniques that use both spectral response and contextual information to assess post-fire vegetation characteristics in groups of pixels (geographic objects generated by image segmentation). Polychronaki et al. [235] performed GEOBIA-based classification on multi-temporal Système Pour l'Observation de la Terre (SPOT) and European Remote-Sensing (ERS) (C-band VV) images covering the time period from 1993 to 2007 of Thasos, Greece, to estimate forest regeneration after two different forest fires occurred 19 and 23 years ago. Using data from field-stratified sampling, they found that the classification results were validated, achieving an overall accuracy of 90.5%. In the same area, Mitri and Gitas [236] used GEOBIA on a combination of very high spatial (VHS) resolution (QuickBird) and hyperspectral (EO-1 Hyperion) imagery to investigate *Pinus brutia* and *Pinus nigra* regeneration. After classification of the segmented imagery, validation showed an overall accuracy of 83.7%.

In relation to post-fire vegetation recovery, these indicators used generally rely on greenness measurements of red-near-infrared (R-NIR) vegetation indices [237, 238]. Several spectral indices based on the NIR is used for post-fire vegetation recovery estimations; nevertheless, the Normalized Difference Vegetation Index (NDVI), the Enhanced Vegetation Index (EVI) and the Normalized Burn Ratio (NBR) are the ones used most frequently [239]. Veraverbeke et al. [240] tested the utility of 13 red-near infrared (R–NIR) vegetation indices (VIs) spectral indices to detect and estimate vegetation recovery. The study found that the soil-adjusted vegetation index (SAVI) outperformed the NDVI in areas with a single type of vegetation, NDVI outperformed the SAVI in areas with heterogeneous vegetation cover and a single soil type, and overall, the NDVI was the most robust VI for assessing vegetation recovery. Several studies of post-fire vegetation responses are based on the discrimination of spectral bands and vegetation indices (mostly NDVI, dNBR and EVI) by MODIS, Landsat, SPOT and Sentinel multi-temporal imagery in different regions and forest ecosystems of the world [241–245].

Spectral mixture analysis (SMA) have also used in vegetation recovery monitoring [246, 247]. SMA studies have shown high correlation between mapped vegetation recovery and field sampling [248, 249]. There is disagreement on whether the SMA or spectral index-based approach is most effective at estimating vegetation recovery [17]. Specific nature of the vegetation's spectral response and the different components of forest recovery, the use of a single method may not be the best option, requiring multiple methods to be deployed in each ecosystem. Riaño et al. [248] and Vila and Barbosa [250] compared Spectral Mixture Analysis (SMA) against quantitative vegetation indices (NDVI and Modified Soil Adjusted Vegetation Index (MSAV)), in different types of ecosystems, such as chaparral shrub communities SMA performed better in the contrary NDVI was most accurate applicable to coniferous forests with maquis.

Further than passive remote sensing active synthetic aperture radar (SAR) has been used for post-fire vegetation recovery assessments [30, 251–254]. Laurin et al. [30] used Cosmo-SkyMed data in a Mediterranean protected area covered by maquis to detect the burnt area extension and to conduct a mid-term assessment of vegetation regrowth. The positive results obtained in this research highlight the importance of the very high-resolution continuous acquisitions and the multi-polarization information provided by COSMO-SkyMed for monitoring fire impacts on vegetation. Several studies also confirmed that the combination of SAR and optical information was essential for estimation of regeneration stages in different forest ecosystems [255–257] and for post-fire vegetation regrowth [258, 259]. De Luca et al. [259] integrating the use of Synthetic Aperture Satellite Radar (SAR) (Sentinel-1) and optical (Sentinel-2) image time series in a Mediterranean ecosystem. They conclude that the use of optical short-wave infrared (SWIR) and SAR C-band-based data revealed that some ecological characteristics, such as the woody biomass and structure, recovered at slower rates, comparing to those suggested by using near-infrared (NIR) and red-edge data and they proposed the optimized burn recovery ratio (BRR) for the estimation and mapping the spatial distribution of the degree of vegetation recovery.

Lidar sensors are capable of penetrating through vegetation and recording forest structural characteristics [260] makes the system ideal for monitoring vegetation recovery. Sato et al. [261] estimated post-fire changes in forest canopy height and biomass using airborne Lidar in western Amazonia. Comparing burned and unburned as control sites found that even 10 years after the occurrence of an understory fire event, burned forests had significantly lower biomass and height than control sites. Gordon et al. [262] used lidar data to measure post-fire mid-story vegetation regrowth of open forests in Australia using also field surveys. They found that the metrics computed with the lidar data had moderate to strong positive associations with field-derived metrics and provided a suitable representation of post-fire vegetation cover. Several studies also have examined the combined use of optical sensor imagery and lidar data [205, 263–266]. Viana-Soto et al. [266] combine lidar with Landsat imagery to extrapolate forest structure variables over a 30-year period (1990–2020) to provide insights on how forest structure has recovered after fire in Mediterranean pine forests. They found that less than 50% of the area completely recovered to the pre-fire structure within 26 years, and the area subjected to fire recurrence showed signs of greater difficulty in initiating the recovery. They conclude that the use of Landsat data provides a unique opportunity to analyze the evolution through decades, but the 30-m pixel size may conceal a larger structural variability within. Even so, cover and height are important indicators of forest recovery that can be derived to larger areas, providing useful information to support post-fire restoration activities [267].

In addition to satellite or the conventional airborne sensors, the value of using unmanned aerial vehicles (UAV) for estimation and monitoring of post-fire forest recovery has also been incised with the use of a variety of sensors [206, 210, 268–274]. Pádua et al. [268] evaluated effectiveness for Post-Fire Monitoring of Sentinel-2 time series data in comparison with high-resolution UAV-based data in an area affected by a fire in north-eastern Portugal. Sentinel-2 images with 10-m resolution, different spatial resolutions of the UAV-based data (0.25, 5 and 10 m) were used and compared to determine their similarities. The results demonstrated the effectiveness of satellite data for post-fire monitoring, even at a local scale as more cost-effective than UAV data. Talucci et al. [273] evaluate the ability of two vegetation indices derived from UAV imagery, one based on the visible spectrum (GCC; Green Chromatic Coordinate) and one using multispectral data (NDVI; Normalized Difference Vegetation Index), to predict field-based vegetation measures collected across post-fire landscapes of high-latitude Cajander larch forests. Findings show the utility of UAV data for NDVI in this region as a tool for quantifying and monitoring the post-fire vegetation dynamics in Cajander larch forests.

UAV systems can also be used to deliver temporal digital surface models (DSM) to detect post-fire changes in vegetation recovery, and the DSMs are produced either from lidar or using photogrammetric approach from digital imagery. Qi et al. [210] used drone laser scanning (DLS) and mobile laser scanning (MLS) to describe post-fire forest structures. There results demonstrate that fused DLS-MLS point clouds can be effective in quantifying post-fire tree structures, which facilitates foresters to develop site-specific management plans. Aicardi et al. [272] used change detection analysis through a time sequence (2008–2015) of DSMs obtained from lidar and digital images (UAV), for a forest stand composed primarily of Scots pine (Pinus sylvestris) in the Aosta Valley Region, Italy. They conclude that these preliminary results highlight the usefulness of low cost, highly flexible UAV systems within areas affected by natural or anthropogenic disturbances, given the possibility to fly on-demand (e.g., immediately after the event) and quickly repeat measures when requested for environmental monitoring.

5. Discussion and conclusions

This chapter aimed to provide a wide review of remote sensing and GIS applications in the field of forest fires—wildfires. The topics include fire hazard and fire risk mapping, fuel mapping, active fire detection and monitoring, burned area estimations, burn severity assessments and mapping, soil erosion assessments and post-fire vegetation recovery assessments and monitoring. Fire hazard mapping can be improved with better mapping and monitoring of manmade Infrastructure like power lines using UAVs with active (lidar) or passive sensors. For fire risk mapping alternative geocomputational techniques as neural networks, classification and regression trees (CARTs), fuzzy modeling, and other machine learning techniques are currently a research subject [275]. Locally fuel mapping can be delivered from UAVs with active (lidar) or passive sensors in more detailed resolution than satellite data. Active fire detection and monitoring is limited from the low temporal or spatial resolution of the available satellite sensors. Smaller and cooler fires have proven difficult to detect in global active fire datasets and by geostationary sensors [132, 140]. Probably, in the near future, geostationary satellites with higher spatial resolutions may become available, allowing for near real-time detection and monitoring of small/cool fires, already new generation satellites for forest and grassland fire detection have been launched such as the Himawari-8 launched by Japan, GOES-R/S/T by the United States and Geo-Kompsat-2A (GK-2A) by South Korea, compared with the previous satellites, and these new-generation geostationary meteorological satellites have been improved in spatial resolution and observation frequency [276]. UAVs equipped with infrared or thermal or RGB cameras can be used where data can provide live feeds and be used to predict information such as propagation of a fire [277]. For burned area estimates mostly Landsat, MODIS, Sentinel, AVHRR and SPOT satellites are used, with the NDVI and dNBR the most frequently used vegetation indices compared to other indices. Relatively newer sensors as Sentinel-2 have improved the high rates of omission errors, common when using other satellite sensors, and allow the detection of small fires (< 100 ha) accounting for a significant proportion of total burned area globally [278]. Currently, burn severity assessments and mapping are mostly based using spectral indices such us dNBR (difference of the Normalized Burn Ratio) or relative differenced Normalized Burn Ratio (RdNBR), and classified according to the ground reference values of the CBI (Composite Burn Index). UAVs equipped with lidar or hyperspatial sensors allowed the rapid burn severity assessments and further research is needed to utilize the hyperspatial data provided from UAV sensors. Also, lidar technology derived from UAVs are able to provide forest structure parameters and become increasingly available. Similar erosion assessments can improve with the use of UAVs since they are able to provide higher spatial data. The use of remote sensing to analyze vegetation recovery is expected to grow even further in application and prominence as new sensors become available (i.e., UAVs and new satellites) and bring enhanced

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spatial, spectral and temporal resolutions to the observations [239]. Current and future trends are the combination of remote sensing data from passive and active sensors either spaceborne or airborne. With the availability of several spaceborne sensors (passive and active) and the emerging improvements of UAVs technologies (flight endurance, sensors, affordability), the development of algorithms that can monitor changes through time irrespective of the characteristics of each platform [279] will improve the overall accuracy of the assessments in almost all the reviewed topics. Finally, recent advances in artificial intelligence (AI) will play a growing role in geospatial technologies as remote sensing (RS) applications [280–282].

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