Journal of Environmental Management 342 (2023) 118315

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Review

Forest fuel type classification: Review of remote sensing techniques, constraints and future trends

Abolfazl Abdollahi [a,*], Marta Yebra [a,b,**]

[a] Fenner School of Environment & Society, College of Science, The Australian National University, Canberra, ACT, Australia
[b] School of Engineering, College of Engineering and Computing Science, The Australian National University, Canberra, ACT, Australia

ARTICLE INFO

Keywords:
Fuel type classification
Fuel modeling
Fuel mapping
Forest fuel
Remote sensing

ABSTRACT

Improved forest management plans require a better understanding of wildfire risk and behavior to enhance the conservation of biodiversity and plan effective risk mitigation activities across the landscape. More particularly, for spatial fire hazard and risk assessing as well as fire intensity and growth modeling across a landscape, an adequate knowledge of the spatial distribution of key forest fuels attributes is required. Mapping fuel attributes is a challenging and complicated procedure because fuels are highly variable and complex. To simplify, classification schemes are used to summarize the large number of fuel attributes (e.g., height, density, continuity, arrangement, size, form, etc.) into fuel types which groups vegetation classes with a similar predicted fire behavior. Remote sensing is a cost-effective and objective technology that have been used to regularly map fuel types and have demonstrated greater success compared to traditional field surveys, especially with recent advancements in remote sensing data acquisition and fusion techniques. Thus, the main goal of this manuscript is to provide a comprehensive review of the recent remote sensing approaches used for fuel type classification. We build on findings from previous review manuscripts and focus on identifying the key challenges of different mapping approaches and the research gaps that still need to be filled in. To improve classification outcomes, more research into developing state-of-the-art deep learning algorithms with integrated remote sensing data sources is encouraged for future research. This review can be used as a guideline for practitioners, researchers, and decision-makers in the domain of fire management service.

1. Introduction

Wildfires are a recurring threat in forested areas worldwide, destroying countless socioeconomic and environmental resources annually. Wildfires are a major disturbance element in forests, producing land cover change, erosion, and water quality deterioration (Cano-Crespo et al., 2015; Eva and Lambin, 2000). Wildfires also affect ecosystem function, structure, distribution, and adaptation (Pausas and Keeley, 2009), although they are beneficial to plant succession and biodiversity (Archibald et al., 2018). Annually, 4–4.5 million km^2 of land is projected to be burned around the world (Lizundia-Loiola et al., 2020). These lands contain pasture, agricultural burns, and wildfires, which have a significant economic and societal impact. Indeed, due to the consequences of climate change, the world's wildfire vulnerability has lately increased (Moreira et al., 2011; San-Miguel-Ayanz et al., 2013).

Human or natural (mostly lightning) causes can be the origin of wildland fires (Aragoneses and Chuvieco, 2021). Appropriate topographic and meteorological conditions must be satisfied for fires to spread. In addition, heat and oxygen transfer are essential for ignition as well as dead or live fuel continuity that is dry enough to retain the fire (Pettinari and Chuvieco, 2020). The physical properties of the dead and live biomass (e.g., bulk density, size, and loading) that influence the severity and spread of wildfires are used to define fuels (Andrews and Queen, 2001). Describing all the physical properties for all fuels in a region is difficult. Thus, the characterization of those fuel attributes pertinent to fire propagation and fire danger assessment is based on classification schemes that summarize a huge number of vegetation features. Typically, these classification schemes are known as fuel types. Fuel type, which is the main element in wildfire behavior modeling, is defined by Merrill and Alexander (1987) as "an identifiable association of fuel elements of distinctive species, form, size, arrangement, and

* Corresponding author.
** Corresponding author. Fenner School of Environment & Society, College of Science, The Australian National University, Canberra, ACT, Australia.
E-mail addresses: Abolfazl.Abdollahi@anu.edu.au (A. Abdollahi), Marta.Yebra@anu.edu.au (M. Yebra).

https://doi.org/10.1016/j.jenvman.2023.118315
Received 5 February 2023; Received in revised form 25 May 2023; Accepted 31 May 2023
Available online 6 June 2023

continuity that will exhibit characteristic fire behavior under defined burning conditions." As a result, fuel type mapping is vital for characterizing wildfire risk and plays a significant role in wildfire risk management. Therefore, having high-quality fuel type maps that can be readily updated is crucial (Marino et al., 2016). Fuel type models, which are commonly employed in fire risk assessment and behavior programs, are numerical descriptions of every fuel type's physical property that entail fuel type parameterization to predict fire behavior (Chuvieco et al., 2003). There have been numerous attempts to establish methodologies for generating and mapping fuel types. The methodologies utilized to determine fuel types and their features are highly reliant on the input data, work scale detail, and ultimate use (Chuvieco et al., 2003). The percentage of area covered by vegetation, canopy bulk density, forest canopy density, apparent crown density, number of trees by area, crown base height, crown height, biomass, vegetation arrangement (horizontal and vertical continuity), live and dead fuel load and fuel moisture content are vegetative features that are commonly used to describe fuel types (Chuvieco et al., 2003; Pettinari and Chuvieco, 2020).

In recent decades, multiple fuel type classification systems have been presented worldwide (Table 1). The most widely used fuel type models have been developed in Canada and USA such as the Canadian Fire Behavior Prediction (FBP) System (Taylor et al., 1996), Northern Forest Fire Laboratory (NFFL) (Albini, 1976), National Fire Danger Rating System (NFDRS) (Deeming, 1972) and the classifications from Anderson (1981). Also, regional models have been established in Australia (Matthews et al., 2019; McArthur, 1966, 1967), the Mediterranean region (Prometheus, 1999) and Southeast Asia (Dymond et al., 2004). However, generating fuel maps is complex and expensive. First of all, fuels are difficult to categorize because they are structurally complicated and have a wide range of physical characteristics that lead to different fire behavior, and impacts. Thus, the developed fuel type models have shown some limitations on their classification. For example, they are site-specific, what means that every fuel type classification model is only valid in similar geographic areas and cannot be applied to other areas (Fogarty et al., 1998). Fuel types can change over time due to disturbances such as fire and given the dynamic nature of fuels, fuel type maps and related parameters should be updated frequently to improve wildland fire appraisal, risk management, and decision-making (Chuvieco et al., 2009). However, updating these maps and parameters in a cost-effective way is challenging (Arroyo et al., 2008).

Arroyo et al. (2008) carried out a synthesis review on fuel type mapping highlighting that as early as the mid-1960s, some authors foresaw that fuel type mapping would be revolutionized through remote sensing technologies (Adams et al., 1995). This is because remote sensing technologies can better estimate fuel type at various scales on the basis of satellite systems with various spectral, temporal, and spatial properties (Arroyo et al., 2008). In addition, Gale et al. (2021) made a broader review on the use of remote sensing for different forest fire fuel characterization briefly describing the various types of remote sensing data and classification methods used for fuel type mapping. Both studies found that integration of different remote sensing sources is a complementary way to improve fuel type classification. Arroyo et al. (2008) also found a lack of data and remote sensing techniques to derive vertical forest information which is relevant to fuel type mapping.

In this study, we provide a comprehensive review of the research conducted on remote sensing between 2008 and 2022 that explicitly maps forest fuel types using innovative modeling approaches and remote sensing data. Previous reviews in this field were conducted by Arroyo et al. (2008) and Gale et al. (2021). While Gale et al. (2021) conducted a broader review of remote sensing applications for different forest fire fuel characterizations, briefly describing the various types of remote sensing data and classification methods used for fuel type mapping, Arroyo's review needs to be updated. Therefore, we extensively discuss the classification methods used in mapping fuel types from remote sensing products, highlighting their limitations, and explain how state-of-the-art machine learning techniques such as convolutional neural networks (CNNs) can address the issues of traditional methods.

Table 1
The characteristics of standardized fuel type classification systems.

Standardized fuel classification systems	Number of fuel types	Country	Fire model with specific fuel classification	Description	Citation
FBP Fuel Types	16	Canada	Canadian Forest Fire Behavior Prediction System	The FBP system is based on simple mathematical models, which are partly based on experimental and physical models. Fuels are categorized by the system into five main groups (grass, slash, mixed wood, deciduous, coniferous)	Taylor et al. (1996)
NFFL Fuel Types	13	USA	BEHAVE and FARSITE	A local scale system which incorporates surface fuel and crown fire behavior models. This fuel model classifies 13 fuel types by taking into account the properties and structure of the vegetation.	Albini (1976)
NFDRS Fuel Types	20	USA	Rothermel's fire spread model	A broad-scale and essentially seasonal weather system that uses an organized set of weather records to determine daily conditions. A combination of satellite imagery used to create a land cover database with 20 classes and derive the fuel type map.	Deeming (1972)
AFDRS Fuel Types	8	Australia	The Australian Fire Danger Rating System	Eight different vegetation types (e.g., forest, grassland, grassy woodland, spinifex, shrubland, mallee, buttongrass, and pine), which have different structural characteristics and a specific fire behavior model	Matthews et al. (2019)
McArthur Fuel Types	2	Australia	McArthur Fire Danger Rating System	The system is developed for forest and grassland fuel types, which associates fire behavior with weather and fuel parameters from opportunistic wildfire observation and experimental fires.	McArthur (1967)
Prometheus Fuel Types	7	Mediterranean countries	Rothermel's fire spread model	The Prometheus system is primarily based on the height and type of propagation element, which divides fuels into seven types.	Prometheus (1999)
Fuel Classification System (FCS)	8	Southeast Asia (Malaysia and western Indonesia)	_____	The system is based on a template of fuel characteristics from temperate fuel classification systems as well as data gathered from the field and literature. It considers eight fuel types: primary rainforest, forest plantation, secondary forest, slash from agroforestry, slash from land clearing, shrublands, seasonal agriculture, and grassland.	Dymond et al. (2004)

Moreover, we demonstrate the importance of recent remote sensing technologies, such as new active sensors at local and global scales, in producing accurate and up-to-date fuel type maps. These technologies enable the derivation of vertical forest information, which is crucial in fuel type classification. We hypothesize that with the availability of recent remote sensing data and new robust deep learning (DL) models, integration of remote sensing resources has been adopted over the last 15 years in the remote sensing community for better characterization of fuel types, addressing the shortcomings of conventional modeling approaches identified by Arroyo et al. (2008) and Gale et al. (2021).

2. Meta-analysis process

A systematic review method was applied to recognize and choose relevant literature resources on the basis of the statement of preferred reporting items for systematic reviews and meta-analyses (PRISMAm) (Moher D et al., 2009; Moher et al., 2009). This review method can ensure the chosen papers' authenticity and quality.

Google Scholar (GS) and Web of Science (WoS) databases were utilized to search for the appropriate literature articles. We selected WoS and GS for collecting the papers because they are standard databases and preferred options used by most of the organizations (Alcaraz and Lopez, 2012; Wen et al., 2020). PRISMA method first needs the description of a representative set of keywords. We limited the outcomes to peer-reviewed manuscripts such as conferences and journals to assure the reliability and quality of the results. We utilized the principal expressions such as "Fuel Type Mapping", "Fuel Type Classification", "Fuel Type Mapping and Remote Sensing", and "Fuel Type Classification and Satellite Imagery" from 2008 to 2022 to collect the articles over the last 15 years. The overall methodology of research is shown in Fig. 1. Each step of the methodology is described as follows:

Research and relevant paper selection: According to the paper's scope explained in the introduction, the previous works and approaches developed for fuel type classification using remote sensing techniques were selected and reviewed in this research.

Qualification of criteria: To distinguish the prior subjects and works according to the objective, we determined a collection of inclusion and exclusion criteria. The criteria of exclusion are described as follows:

i) Publishers do not provide the full text of the manuscript
ii) Not written in English

The criteria of inclusion are defined as below:

i) Studies that develop a remote sensing approach for fuel type mapping
ii) Papers that are written in English
iii) Journals and conferences peer-reviewed publications
iv) Published over the last 15 years (2008–2022 inclusive)

Exploitation and combination of data: we presented different compositions of the aforementioned key search phrases to exploit the appropriate studies. As Fig. 2 shows, we initially recognized 26 records. For the next stage, we eliminated the repeated publications and works that do not use remote sensing, in which 23 records remain. Finally, 19 records were included to synthesize the results after sieving process and validating the qualification of records (e.g., assessing the title, abstract, and key search phrases).

Combination of outcomes: we classified the achieved manuscripts based on the goal and expressed the results in more detail in the next sections. We also discussed the principal findings, including the advantages and disadvantages of current methods for fuel type classification based on remote sensing datasets, the evidence for every principal result, and some suggestions for future works.

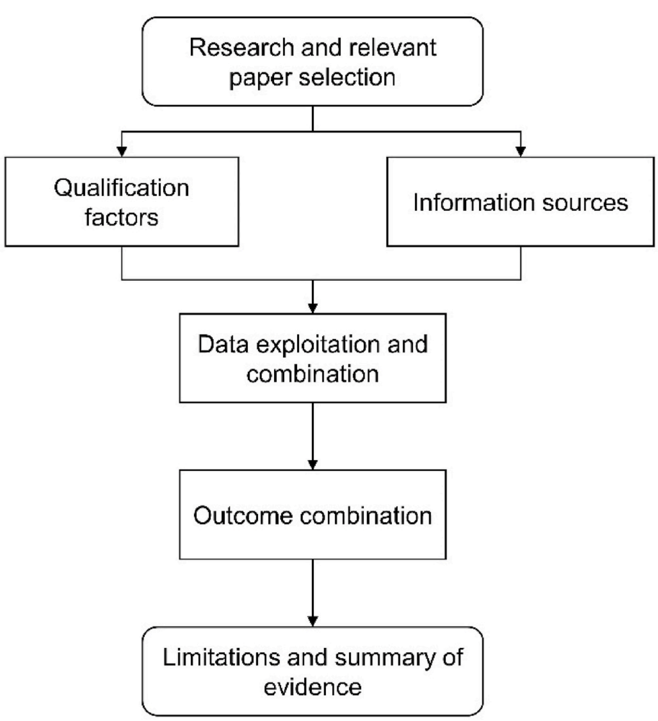


Fig. 1. Research methodology.

3. Remote sensing sensors for fuel type mapping

Fuel types are generally difficult to characterize and map due to their physical characteristics and inherent complexity. Remote sensing provides a diverse set of sensors that can facilitate fuel mapping. The most common remote sensing sensors found to be used in the literature for fuel type mapping include passive sensors such as multispectral, hyperspectral, and very high-resolution (VHR), or active sensors such as light detection and ranging (LIDAR) and RADAR data.

Multispectral data was the most common remote sensing data among the 19 studies found to use remote sensing to classify fuel type (Fig. 3). Multispectral data have acquired a lot of attention in research because of their global coverage and are freely available and downloadable. In addition, Fig. 4 depicts the geographical distribution of several articles published worldwide that investigated various remote sensing data for fuel classification during the study period. Based on the figure, the number of works exploring different remote sensing images for fuel type mapping in Spain and Greece was highest among the other regions.

The most frequently used satellites for fuel type classification and their parameters are included in Table 2. For assessing fuel types and how they change over time, these images are a good source of data. The most common multispectral data that have been used for fuel type mapping are Landsat-8 OLI (Operational Land Imager), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), Sentinel-2, and Sentinel-3 (Aragoneses and Chuvieco, 2021; Mitri et al., 2011; Stefanidou et al., 2020; Stergiopoulos et al., 2007; Tompoulidou et al., 2016). Multispectral images contain fewer but broader spectral bands, which do not allow the separation of items with minor spectral reflecting differences and cannot identify small details on the land's surface. However, they are beneficial in terms of data availability (Thomas et al., 2008). In comparison, a wide range of narrow spectral bands (e.g., visible, near-infrared, medium, and thermal infrared) found in the electromagnetic spectrum can be captured by hyperspectral remote sensing sensors (Paoletti et al., 2019). The bands on these sensors are narrow and continuous, enabling a more in-depth investigation of Earth's features and details. In hyperspectral imaging, two types of platforms are used: satellite-based (e.g., Hyperion) and aircraft (e.g., Multispectral Infrared and Visible Imaging Spectrometer (MIVIS),

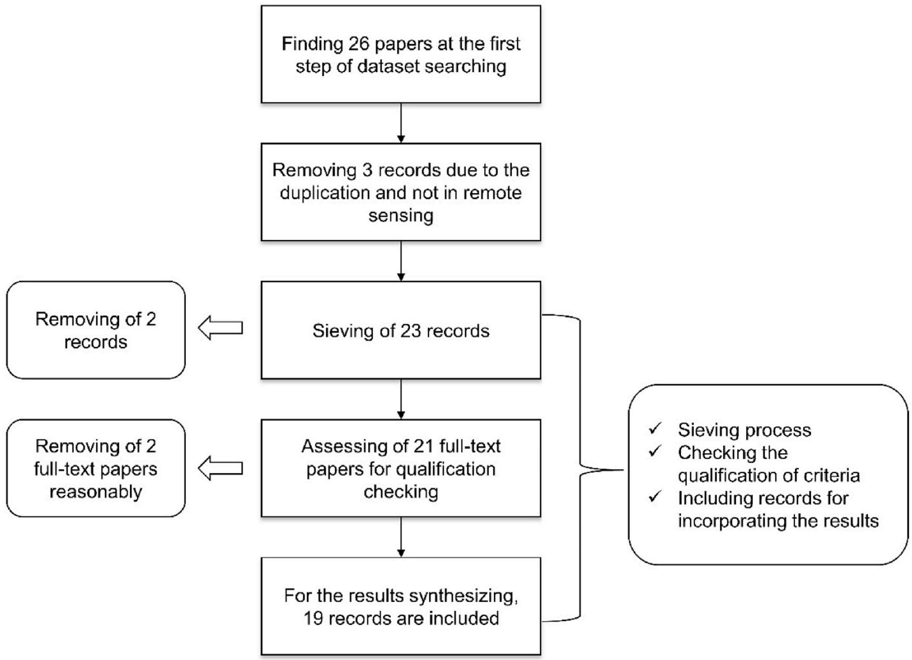


Fig. 2. Process of data extraction.

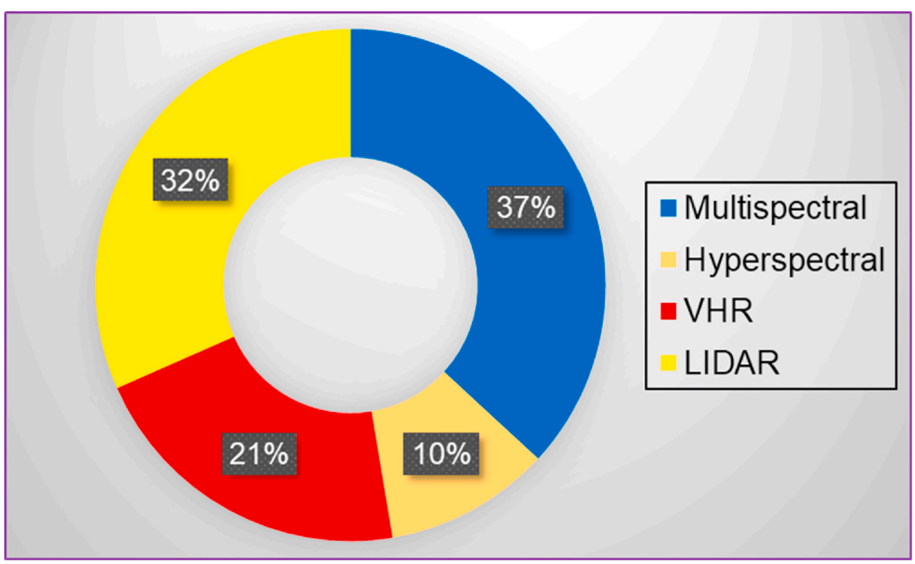
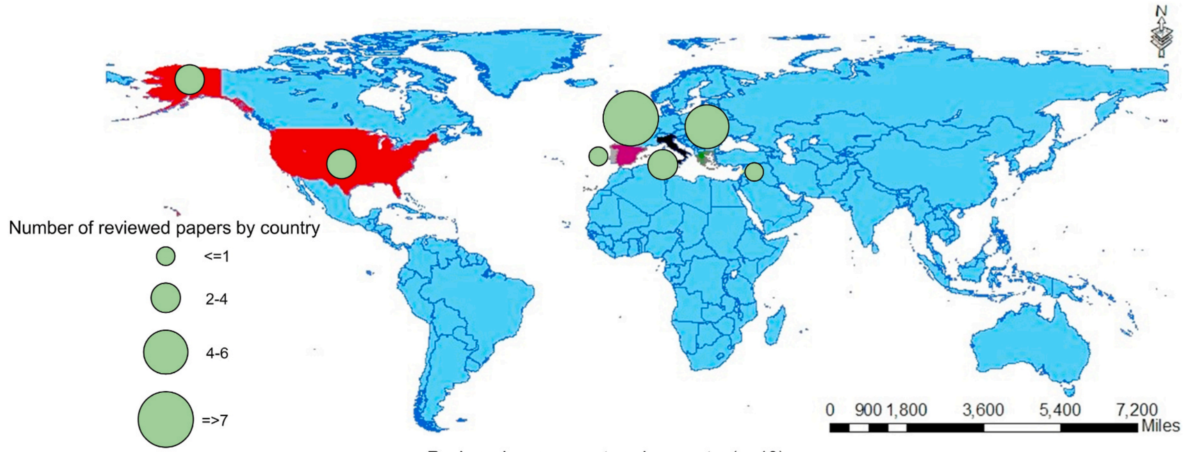


Fig. 3. Percentage of different remote sensing data used for fuel type mapping.

Airborne Visible/Infrared Imaging Spectrometer (AVIRIS). The vast majority of hyperspectral sensors are mounted on aerial platforms, with only a few mounted on satellites (Adão et al., 2017; Seydi and Hasanlou, 2018). To capture VHR images, more advanced satellite sensors, including IKONOUS, QuickBird and WorldView are becoming available as earth observation technology progresses. More spatial distribution and surface characteristics information can be provided through VHR images compared to the low and medium-resolution data (Benediktsson et al., 2012). For fuel type mapping, remote sensing sensors measure other physical properties rather than directly measuring fuel types. For example, the majority of low and medium-resolution multispectral techniques identify fuels by first categorizing an image into vegetation types, then allocating fuel attributes to each class (Chuvieco et al., 2003). Multispectral and hyperspectral remote sensing technologies are efficient for the spectral and spatial differentiation of vegetation characteristics such as vegetation density, green canopy closure, vegetation cover, and live to dead plant materials proportion that are important for classification (Ustin et al., 2004). However inability of passive sensors to distinguish between the different layers of vegetation is a primary drawback (Lechner et al., 2020). Also, these sensors cannot estimate vegetation height, which is crucial in differentiating various fuel types. In contrast, active sensors can penetrate forest canopies and derive some fuel attributes. For instance, LIDAR systems can directly estimate canopy height, base height, bulk density, biomass, leaf area, etc. (Béland et al., 2014; Chamberlain et al., 2021; Chuvieco et al., 2010; Luo et al., 2018; Simard et al., 2011), which can be used to characterize various fuel types. In addition, microwave sensors (e.g., RADARSAT, SAR, JERS-1) have been used to estimate forest characteristics such as tree height, tree volume, foliar biomass, and canopy closure that are crucial for accurate fuel type mapping (Gama et al., 2010; Garestier



Reviewed papers per type by country (n=19)

	Multispectral	Hyperspectral	VHR	LIDAR
Spain	14.3%	0.0%	25.0%	83.3%
Italy	0.0%	50.0%	0.0%	16.7%
Greece	42.9%	0.0%	50.0%	0.0%
Lebanon	14.3%	0.0%	0.0%	0.0%
USA	14.3%	50.0%	25.0%	0.0%
Portugal	14.3%	0.0%	0.0%	0.0%

Fig. 4. The geographical distribution of a number of articles published around the world that investigated various remote sensing data for fuel classification. Blue color show countries that have not investigated remote sensing datasets for fuel type classification, while other colors indicate countries that have looked into remote sensing products for fuel type mapping. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 2
The most commonly used remote sensing satellites for fuel type classification.

Satellite/ Sensors	Revisit (day)	Year	Country	Spatial Resolution (m)	Number of Bands
Multispectral Data					
Landsat-8 OLI	16	2013	USA	MS:30 m Pan:15 m TIRS:100 m	11
ASTER	16	1999	USA	15–90 m	14
Sentinel-2	5	2015	ESA	10,20,60 m	13
Sentinel-3	27	2016	ESA	300 m	21
Hyperspectral Data					
AVIRIS	–	1993	USA	20 m	224
PRISMA	–	2019	Italy	30 m	239
VHR Data					
QuickBird	2.4–5.9	2001	USA	MS:2.61 m	4
WorldView-2	1.1	2009	USA	MS:1.8 m Pan:0.46 m	8
Worldview-3	1	2014	USA	MS:1.24 m Pan:0.3 m	8

et al., 2007; Lavalle and Khun, 2014).

3.1. Multispectral images

Several researchers have endeavored to map fuel type using multispectral remote sensing data. For example, Mitri et al. (2011) used ASTER images for generating fuel type maps with 6 classes on a regional scale in North Lebanon's central forested area based on the object-based image analysis (OBIA) method. In the research area, they used field data to train the classification method and evaluate the classification outcomes. The results demonstrated the method could achieve an overall accuracy (OA) of 70% in a heterogeneous vegetated region using ASTER imagery's spectral and spatial information. There was not enough information regarding the forest understory in this study. In contrast, combining ASTER data with VHR images such as QuickBird and IKONOS would give users the information they need to recognize every of the Prometheus categorization system's fuel type classes (Mitri et al., 2011). Also, height data from an active sensor (e.g., LIDAR) in a similar region could provide considerably more specific information for a more precise categorization outcome (Mitri et al., 2011). To detect 14 fuel types from ASTER imagery in the Canary Islands, Spain, Alonso-Benito et al. (2012) used four classification methods, including an OBIA and three pixel-based techniques such as maximum likelihood (ML), neural network (NN), and support vector machine (SVM). In terms of allocation disagreement and quantity disagreement, the algorithms' effectiveness was evaluated and compared. The OBIA provided the most accurate maps with an OA of 95%, 1% of quantity disagreement, and 4% of allocation disagreement. Also, the SVM method produced the highest accuracies in pixel-based classifications, with an OA of 83%, 3% quantity disagreement, and 14% allocation disagreement. With the addition of context information to the object-based classification, fuel types with comparable spectral behavior can be identified better (Alonso-Benito et al., 2012).

In another work, Tompoulidou et al. (2016) used Landsat-8 OLI data and an object-oriented categorization method to map fuel type with 7 classes on a national scale in the Chalkidiki case study, northern Greece. They also evaluated the model's transferability to the Preveza and Attica's regional units. They acquired Landsat-8 OLI data during the winter and summer seasons and calculated additional features such as spectral and textural properties and vegetation indices for both seasons. The findings indicate that the proposed object-oriented technique was effective in obtaining highly accurate fuel type maps, which could achieve an OA of 89.47% and Kappa of 84.4% for the case study of Chalkidiki. The model could also produce an OA of 91.74% and Kappa of 86.7% for Preveza and OA of 80.30% and Kappa of 70.6% for Attica. Consequently, the findings demonstrated that the suggested methodology has high transferability qualities, allowing the model to be implemented across the country. Stefanidou et al. (2018) utilized Landsat-8 OLI satellite data, data from the disaster monitoring constellation, and OBIA method to map 10 fuel types at a regional scale in northern Greece. The use of the OBIA technique combined with OLI satellite data resulted in a highly accurate fuel type map with an OA of 85.43%. The findings reveal that data from both Landsat-8 OLI and disaster monitoring constellation can be utilized with OBIA analysis to generate accurate fuel type maps. However, only the OLI images can be considered operational for regional mapping of Mediterranean fuel types. He et al. (2019) used field data and Landsat 8 images to map the fractional coverages of 3 major fuel type components in the Alaskan tundra on a regional scale. To quantify the fractional vegetation cover of herbaceous, nonvascular, and woody components at the subpixel level, they used a multi-step random forest (RF) technique. They indicated a remarkable capacity to detect these component types using multi-seasonal spectral information. Their mapping outputs show the aforementioned component's spatial distribution across Alaskan tundra at subpixel resolution, which might be useful for investigating wildland fire danger and behavior. In another study, Stefanidou et al. (2020) utilized Sentinel-2 satellite data and OBIA methodology to improve the accuracy of the national fuel type map with 10 classes in Greece. They found that Sentinel-2 data might likely increase the reliability and resolution of national fuel type maps and enhance mapping effectiveness for operational reasons, as seen by the average OA of 84.43%. To improve wildland fire risk assessment, Aragoneses and Chuvieco (2021) applied an approach for creating fuel maps with 6 classes across European regions like Spain and Portugal. Sentinel-3 data, biogeographic areas, horizontal vegetation continuity, and biomass data were used to map fuel type on a regional-continental scale. With an OA of 85%, a vegetation map for the Balearic Islands and Iberian Peninsula was created. The results proved the efficiency of the proposed technique and Sentinel-3 data for fuel type classification. These studies demonstrated the transferability of the mapping techniques across different regions and at a national scale, which is essential for the efficient management of wildland fires. The accuracy of fuel type maps could be improved further by incorporating additional data, such as height and biomass data and vegetation continuity, to capture the variability in fuel types across the landscape.

3.2. Hyperspectral images

Hyperspectral remote sensing technologies use a huge number of contiguous spectral bands to measure emitted or reflected electromagnetic radiation. This data has been demonstrated to be beneficial for spatial and spectral differentiation of various fuel types. For instance, Smith et al. (2021) created boreal forest vegetation fire fuel maps with 19 classes on a local scale in inland Alaska using AVIRIS-NG hyperspectral data with high spectral and spatial resolution. Compared to the LANDFIRE's existing vegetation type (EVT) product obtained from Landsat 8 data with 33% accuracy, the results from RF showed an accuracy of 80% based on their field plot data. Whereas the EVT product only recognized 8 dominant vegetation classes, the proposed method identified 20 classes within the research area and classified fire fuels more precisely. This research demonstrates that accurate and detailed fuel maps can be generated where there is accessible AVIRIS-NG data, and this information can help fire managers to make better decisions while fighting wildfires. Shaik et al. (2022) applied a semi-supervised machine learning technique for fuel type mapping with 18 classes on a regional scale utilizing hyperspectral imaging from hyperspectral precursor of the application mission (PRISMAs), the Italian Space Agency's recently launched satellite. A new era of hyperspectral imaging spectroscopy has been ushered in by PRISMAs, which is capable of capturing a continuous range of spectral bands spanning from 400 to 2500 nm at a spatial resolution of 30 m. The sensor is equipped with 173 bands in the shortwave infrared (SWIR) range, which covers 920–2500 nm, and 66 bands in the visible near-infrared (VNIR) range, which spans from 400 to 1010 nm. They used a single spectral signature per class as input data for sample generation and pseudo labeling, a fully constrained linear mixing method for unmixing mixed pixels, and biomass and digital elevation model (DEM) maps for distinguishing typical vegetation from mountainous and sparse vegetation. Then, according to the Joint Research Center (JRC) Anderson Codes, the technique for converting a classified map to a fuel map was provided (Toukiloglou et al., 2013). As a result, the classified map was validated with an OA of 87%. According to this study, training samples for the machine learning method can be produced using the proposed semi-supervised method when no single go-to dataset is accessible as well as PRISMA imagery showed significant capability for wildfire fuel mapping. The aforementioned studies demonstrate the potential of hyperspectral remote sensing technologies for fuel type mapping, with Shaik et al. (2022) introducing a better methodology that improves upon previous approaches.

3.3. Very high-resolution images

Satellites images such as WorldView and QuickBird, have been frequently used in vegetation assessment as they enable high spatial (1–3 m) resolutions (Mallinis et al., 2008a). Mallinis et al. (2008b) employed Quickbird imagery to evaluate the spatial distribution of 8 fuel types in a forested region in Northern Greece. The multiscale components of the scene were identified using a segmentation method after the image was preprocessed for geometric error correction. A classification and regression trees (CART) method was used to allocate the image objects to their corresponding fuel types, which obtained an OA of 80%. The combination of object-based classification with CART analysis was demonstrated to be quite effective in reliably identifying fuel complexes. Also, Mallinis et al. (2014) compared the spatial and spectral information of Quickbird data with 2.4 m spatial resolution, Landsat TM with 30 m spatial resolution, and EO-1 Hyperion imagery with 30 m spatial resolution for mapping Mediterranean (Greece) 7 fuel types based on SVM method on a regional scale. The proposed method could obtain an OA of 69.50%, 70%, and 74.27%, for the Landsat TM, EO-1 Hyperion, and Quickbird. This study showed that in Mediterranean fuel type mapping, high spectral resolution data might be less decisive than high spatial resolution data. Alonso-Benito et al. (2016) examined the potential of using WorldView-2 (WV2) and LIDAR data with OBIA for classification of 7 fuel types in a local area of Tenerife's island, Spain, with complicated vegetation distribution. Field data was utilized to evaluate the precision of the fuel maps. The derived maps' accuracy ranged from 76.23% to 85.43%. The maps created by data fusion were substantially more accurate than the maps created only from the WV2 data. Sesnie et al. (2018) used Worldview-3 (WV3) and Landsat-8 OLI data for fuel type mapping on the Buenos Aires National Wildlife Refuge (BANWR) in southern Arizona. Using WV3 images with high spatial resolution, land cover classification for 11 cover classes demonstrated an OA of 80%. Generally, WV3 and OLI yielded similar estimates of fine-fuel biomass, albeit WV3 demonstrated higher efficiency in characterizing fine-scale variations in fuel type and continuity throughout the research region. These studies show the potential of high-resolution satellite imagery and OBIA for fuel type classification and vegetation assessment.

3.4. LIDAR data

LIDAR technology is proving to be a viable alternative for solving the main challenges that come with mapping fuels using passive optical imagery. Fuel factors utilized in fire behavior modeling, such as crown bulk density and canopy-based height, and biomass, which are useful for fuel types discrimination, can be obtained using LIDAR data (Chen et al., 2017). Huesca et al. (2019) were among the first to demonstrate the utility of LIDAR data for fuel type discrimination. They classified LIDAR data using three spectral mapping techniques: Multiple Endmember Spectral Mixture Analysis (MESMA), Spectral Angle Mapper (SAM), and SMA to calculate the vertical structure of vegetation for Cabañeros National Park's fuel type mapping in Spain. The main spatial patterns for the 7 fuel types were well represented, highlighting the significance of these new LIDAR data spectral mapping techniques. Building on this foundational work, García-Cimarras et al. (2021) utilized the Prometheus classification system on the basis of conditional principles, which represent the vertical profile of vegetation cover for fuel management and ecological objectives to analyze vegetation changes and map 7 fuel types from the distribution of LIDAR heights across the region. The links between ecological parameters like forest vegetation cover types, topographic aspects, and distinct stand structures were also investigated. An OA of 81.26% with a Kappa coefficient of 0.73% was obtained for the final classification map. This cost-effective technique demonstrated that LIDAR yields direct measurements, with good agreement between estimated and visually examined fuel type classes in the majority of cases. Finally, Revilla et al. (2021) investigated the applicability of low-density small-footprint airborne laser scanning (ALS) and discrete anisotropic radiative transfer (DART) framework for 7 fuel types mapping on a local scale in the central Ebro valley, north-east of Spain. The LIDAR data were simulated on the basis of sensor and flight characteristics of low-density ALS data taken by the Spanish National Plan and field data in two different dates (2011 and 2016). For the years 2011 and 2016, the classification's OA was 88% and 91%, respectively. DART's utility in simulating generalizable 3D data for mapping fuel type provides essential information for forest managers to prevent wildfires. The studies reviewed above collectively demonstrate the potential of LIDAR technology and different modeling approaches, especially DART framework for accurate fuel type mapping.

3.5. Integrated sensors

We will now put more of an emphasis on the fusion of several mapping approaches in an integrated approach, as opposed to earlier parts that showed the advancements of various remote sensing techniques and products when they are used independently. There have been studies of forest fuels that combined data from more than one source to solve the drawbacks of using a single mapping technique. For example, García et al. (2011) proposed a methodology for 6 fuel types mapping in La Rioja, Northern Spain, based on merging multispectral airborne thematic mapper (ATM) and LIDAR data with the SVM classifier. They used LIDAR measurements for separating additional fuel types using vertical data. They showed that the utilization of LIDAR data in conjunction with optical data had been proven to help decrease the ambiguity that can arise when assessing fuel types based solely on optical data. Also, Chirici et al. (2013) combined IRS LISS-III multispectral imagery with ALS data for 9 forest fuel types classification on a reginal scale in Sicily, Italy. They tested three non-parametric classification methods such as stochastic gradient boosting (SGB), CART, and RF approach. They found that combining multispectral imagery with ALS data could help the models achieve satisfactory fuel type mapping accuracy. Domingo et al. (2020) also used ALS data, Sentinel-2 data, and field plots as ground truth to classify fuel types among Spanish municipalities on a local scale. In order to classify 7 fuel types, two non-parametric classification algorithms and two metric selection methods were examined. The application of adapted structural diversity indices obtained from ALS data and integrating data from passive and active remote sensing sensors showed classification accuracy enhancement. The proposed method demonstrated its utility in fuel type mapping at a regional scale under complicated and heterogeneous Mediterranean forests. According to the studies reviewed above, the integration of data from multiple sources has proven to be effective in reducing ambiguity and enhancing classification accuracy. A succinct overview of the various fuel type classification studies reviewed in the preceding sections is presented in Table A1 (Appendix A).

4. Discussion

We have reviewed the recent remote sensing approaches used for fuel type classification. In this section, the accuracies, limitations and benefits of various remote sensing data for fuel classification, along with opportunities and future directions for improving the fuel maps are highlighted and discussed.

4.1. Accuracy of various remote sensing datasets for fuel type mapping

The classification accuracy of the different types of remote sensing data for fuel mapping varies. Among the multispectral sensors, the accuracy for Landsat ASTER and Sentinel-2data was between 80.30% and 91.74%, 70%–95%, and 84.43%–85%, respectively. For hyperspectral sensors, the accuracy ranged from 80% to 87%. Also, fuel type classification maps had accuracies from 74.27% to 85.43%, 81.26%–89.5% and 84%–92.8% for VHR, LIDAR data and integrated sensors, respectively. According to the previous sections, which presented the various classification methods and remote sensing products for fuel type classification, the accuracy and efficiency in fuel type classification using remote sensing data can be scaled on the basis of the study area, classification method, the amount of the training data, processing capability, and model complexity.

4.2. Challenges in fuel type mapping from satellite data

The benefits and drawbacks of the diverse remote sensing techniques used for the classification of fuel types around the world is shown in Table 3. For example, because of their global coverage and availability, multispectral images have received a lot of attention in research. Also, they are one of the most important data sources for fuel type mapping because they provide good spectral information. However, they are restricted in spatial resolution what makes the pixel information be a mixture of both the canopy and the surface materials. This can make it difficult to accurately identify the surface fuels for example, as the signal is influenced by the presence and properties of the canopy. As a result, multispectral imaging can be limited in its ability to provide accurate information about the surface fuels. In contrast, VHR data can provide detailed information regarding surface properties because of their high spatial resolution. However, the primary trade-off with VHR sensors is their limited temporal resolution and spatial extent. This can result in difficulty in monitoring changes over time and capturing large-scale spatial patterns. Hyperspectral images, mostly from airborne sensors, provide more spectral information, which can identify finer differences, allowing it to reveal the precise composition of different fuel types. Also, this data can be used for spectral evaluation of fuel status as well as spectral and spatial differentiation of fire-related vegetation features. However, the fundamental drawback of airborne hyperspectral sensors is their limited spatial coverage. In addition, some fuel type classification techniques are challenging to handle because of the hyperspectral

Table 3
The benefits and limitations of various remote sensing data applied to fuel types mapping.

Data	Benefits	Limitations
Multispectral Data	• Reasonable cost • Easy accessibility • Provide good spectral information • Mapping of physical components	• Restricted spatial resolution • Restricted to canopy • Cloud cover may limit the use of this type of data
VHR Data	• Detailed information • High spatial resolution • Mapping of physical components	• Computing demanding • Restricted spectral information • Cloud cover may limit the use of this type of data
Hyperspectral Data	• Rich in spectral information • Mapping of biophysical components • Adapted to fuel properties	• High dimensionality • Restricted area coverage • Complex data processing • Cloud cover may limit the use of this type of data
LIDAR	• Canopy and Subcanopy structure information • Direct measurements of height and other structural properties of fuel • Reasonable cost than manual inventory for small areas	• Costly • Covering a limited area

image's high dimensionality. LIDAR data can penetrate into the canopy and obtain information on surface fuels. It also can be utilized to determine fuel heights and other structural properties of fuels, which is useful information for fuel type differentiation. However, LIDAR data has limited spatial coverage and is costly.

4.3. Improving fuel type mapping through integrated sensors

As previously discussed, each the use of each sensor for mapping fuel type comes with its own set of advantages and disadvantages, therefore, there are opportunities to improve the classification results by integrating multiple data sources (Gale et al., 2021). Most studies on fuel characterization with LIDAR data have used airborne sensors on limited geographic areas and narrow temporal coverage given the expense of acquisition making it difficult to analyze fuel dynamics (García et al., 2017). Spaceborne LIDAR sensors, including the Global Ecosystem Dynamics Investigation (GEDI) (Dubayah et al., 2021) or ICESat-2/ATLAS (Gwenzi et al., 2016) can overcome this limitation in dynamic estimation of fuel characteristics, which can help discriminating various fuel types. For example, high-resolution maps of forest structure, including vertical profiles of vegetation height and canopy structure can be derived from GEDI that can be used for improving fuel type classification. Although none of the studies reviewed here used microwave technologies, they could offer valuable insights into fuel type classification. For example, microwave data could be an ideal supplement to airborne or terrestrial LIDAR measurements as it is less expensive to obtain and allows for the analysis of wider areas (Kaasalainen et al., 2015) and a better characterization of fuel types dynamic (Keane A et al., 2001). Microwave sensors can also supplement optically data given its success to estimate forest parameters such as canopy closure, tree volume, foliar biomass, and tree height, which are important for fuel type mapping (Garestier et al., 2007; Kaasalainen et al., 2015; Smith-Jonforsen et al., 2007). In addition, active microwave data such as radio detection and ranging (RADAR) and interferometric synthetic aperture radar (InSAR) tehcniques can be used to measure the height of vegetation, biomass, and the structure of forests, which can also be useful in fuel type classification (Lavalle and Khun, 2014).

Although our review focused on studies that used airborne or spaceborne remote sensing data to map fuel types at resolutions of 1 m or greater, it is important to note that high-resolution fuel type mapping techniques such as those using ground-based LIDAR, photogrammetry, and uncrewed aerial vehicle (UAV) data can provide even finer spatial resolution outputs. For example, studies by Hiers et al. (2009) and Bright et al. (2016) used ground-based LIDAR and photogrammetry to classify fuel types at fine spatial scales with at a 10-cm resolution, respectively. However, the use of high-resolution remote sensing techniques can often be resource-intensive and impractical for large-scale mapping projects. Furthermore, different fuel types and ecosystems pose diverse challenges for remote sensing-based fuel mapping. Accuracy and efficiency of fuel type classification using remote sensing data depend on various factors. For instance, mapping fuel types in dense tropical forests is difficult due to limited spectral contrast between the canopy and understory vegetation. Similarly, shrubland ecosystems present challenges due to complex three-dimensional vegetation structure. In contrast, fuel mapping in grasslands is relatively easier due to uniform vegetation structure and limited vertical stratification. Recent studies show promising results in mapping dense vegetation and complex ecosystems using hyperspectral and LIDAR data. LIDAR data offers high-resolution, three-dimensional information about vegetation and terrain, including height and density. This data is valuable for accurately classifying fuel types like forests or shrublands. Hyperspectral data, on the other hand, provides detailed spectral information, making it useful for classifying fuel types with a high number of classes. It can identify and differentiate fuel types based on their unique spectral signatures. Hyperspectral data also helps identify subtle differences in reflectance, aiding in the classification of vegetation and surface fuels. So, this data can provide valuable information for the classification of fuel types. Therefore, integrating multiple types of remote sensing data can be crucial in improving the accuracy of fuel type classification results.

4.4. Improving fuel type mapping using state-of-the-art modelling approaches

The classification results of fuel types can be improved by applying state-of-the-art classification techniques such as deep learning (DL) architectures, which have recently gained significance in the remote sensing field (Abdollahi and Pradhan, 2021; Guo et al., 2020; Vali et al., 2020). The classification methods which were extensively applied to the multispectral for fuel type classification were traditional pixel-based machine learning techniques such as NN, SVM, ML, etc. (Table 3). These methods contend that a single pixel is independent, and that processing doesn't consider its spatial interactions with nearby pixels (Cleve et al., 2008). However, because the individual pixels in images no longer take the features of classification purposes, a "salt and pepper" influence is always present in the classification findings (Tompoulidou et al., 2016; Yu et al., 2006). Object-based image analysis (OBIA) is another common method implemented mostly to the VHR images for fuel type mapping. The primary distinguishing feature of OBIA is integrating a range of textural, spatial, and spectral information in the classification process by employing multi-scale image segmentation, which considerably enhances accuracy (Alonso-Benito et al., 2016). However, it is difficult and complex to use OBIA because it requires a range of input variables. In addition, two significant challenges still exist during the OBIA process: identifying suitable scale for image segmentation and choosing proper features for image classification (Mallinis et al., 2008b; Puissant et al., 2014). The most used techniques for mapping fuel types in hyperspectral images were conventional spectral mixture analysis (SMA) and classification approaches. Narrow-band spectra from hyperspectral images can give detailed information about the Earth's surface. Since the spectra of the materials might be subjected to complicated interactions, separating the constituent materials (i.e., endmembers) and their fractions (i.e., abundances) that contribute to the measured hyperspectral data is a fundamental step (Lei et al., 2021). Due to the limitations of hyperspectral sensors, they can thus be blended in various fractions, which makes it more challenging to solve the issue caused by these scattering effects. In order to more easily evaluate the data, spectral unmixing tries to determine the fractions of the elements from the mixed data in a blind manner (Ozkan and Akar, 2018). However, the methods used in the literature for fuel type classification from hyperspectral images could not properly simplify the mixture data, and the models remained weak and underestimated the solution.

Recent advances in DL techniques, notably deep convolutional neural networks (CNN) architectures, have improved the state-of-the-art in a variety of remote sensing applications since CNN's frameworks have demonstrated excellent feature extraction capacity (Abdollahi and Pradhan, 2023; Kattenborn et al., 2021). As a result, these sophisticated deep learning techniques have addressed the main difficulties with conventional machine learning algorithms for fuel type mapping (e.g., inefficient performance and time-consuming). Also, deep learning approaches can automatically obtain meaningful representations (LeCun et al., 2015), which can improve the limitations of conventional machine learning techniques in fuel type mapping. Moreover, different kinds of processing approaches such as spectral unmixing (Bioucas-Dias et al., 2012) and classification (Wang et al., 2016) have been developed to efficiently investigate the rich spectral and spatial information included in hyperspectral images. The spectral unmixing approach can be effectively combined with deep learning-based classification task, which amplify the training set and simplify the classification method. This enhances the fuel type classification performance.

On the other hand, we recognize the potential for integrating physical-based models and deep learning methods in fuel type classification for future research. While physical-based models accurately simulate light-vegetation interactions, resulting in more detailed and precise vegetation properties, their use is limited by the high computing demands required for model inversion. On the other hand, deep learning methods can learn complex relationships between input features and output labels and provide computing efficient algorithms, making them complementary to physical-based models if used together. However, deep learning models require large amounts of data to prevent underfitting, which may not always be available. To overcome this challenge, future studies can explore the use of physical-based models to simulate remote sensing data, which could then be used to train deep learning models to estimate input parameters. By integrating physical-based models and deep learning methods, the accuracy and effectiveness of mapping forest fuel types could be improved, ultimately enhancing forest fire management strategies. Therefore, it is critical to introduce new robust approaches associated with fuel type classification, and studies on various suggested approaches using cutting-edge technology are growing.

5. Conclusion

The common remote sensing-based fuel type classification techniques were reviewed to provide an overview of remote sensing image classification data sources and algorithms for fuel type mapping, including their advantages and disadvantages. For fire models and fire management systems, the knowledge of fuel types distribution and their properties are critical. This is because it can be utilized to calculate fire behavior, risk, and impacts. However, it is challenging to classify and map fuel types because of their high variability and complexity. Fieldwork has typically been used to map the different types of forest fuels, which is costly and time-consuming. Nonetheless, field surveys still play a critical role and serve as a valuable supplement to remote sensing techniques. This is because they provide the necessary sources for calibrating and validating maps created with remote sensing data. Remote sensing techniques, in contrast, have several advantages. For example, they can provide cost-effective techniques with broader temporal and spatial coverage to map fuel type and analyze wildfire threats in near real-time. Various remote sensing techniques have been presented for mapping fuels, but each has demonstrated challenges in distinguishing fuel types and providing reliable classification maps, particularly in complicated backgrounds. Integrating several data sources and fuel mapping methodologies is one feasible strategy for producing accurate fuel maps and improving classification results with existing technology. To develop the most effective maps, future fuel mapping techniques will need to include state-of-the-art methodologies and multiple remote sensing technologies. For instance, fuel mapping tasks can be significantly improved by combining passive sensors with newly developed active sensors such as LIDAR (GEDI) or RADAR (Sentinel-1). This is because these sensors can penetrate the forest canopy and perceive ground complexity, which is required for precise surface and crown fuel mapping. In addition, deep neural networks (DNNs) have grown in popularity as a technique for recognizing characteristics at several levels of representation in remote sensing studies. DNNs can learn a hierarchical feature representation from the data through a series of interconnected layers, and efficiently encode spatial and spectral information from raw data without requiring any preprocessing. Thus, future research should concentrate on developing state-of-the-art deep learning techniques as promising tools for addressing the issues of conventional fuel classification approaches and improving the classification results.

Author contributions

A.A. and M.Y. conceptualized the study; A.A. wrote and edited the manuscript; M.Y. supervised, edited and improved the manuscript.

Funding

This research is funded by the Australian Research Data Commons (ARDC).

Conflicts of interest

The authors declare no conflict of interest.

Data availability

No data was used for the research described in the article.

Appendix A

Table A1
Overview of fuel type classification studies reviewed.

Category	Data	Modelling Approach	Number of Classes	Study Area Size	Accuracy Assessment Method	Overall Accuracy (%)	Citation
Multispectral	Landsat-8	Supervised Classification Methods (e.g., ML, NN, SVM), Fuzzy Set Methodology, Object-Based Image Analysis (OBIA)	7–10	Regional/National	On screen/field measurement	80.30–91.74	(Tompoulidou et al., 2016), (Stefanidou et al., 2018), (He et al., 2019)
	ASTER		6–14	Regional	On screen/field measurement	70–95	(Mitri et al., 2011), (Alonso-Benito et al., 2012),
	Sentinel-2		10	National	On screen	84.43	(Stefanidou et al., 2020),
	Sentinel-3		6	National	On screen	85	Aragoneses and Chuvieco (2021)
Hyperspectral	AVIRIS	Spectral Mixture Analysis (SMA), Classification Approaches (e.g., MLC, RF)	19	Local	Field measurement	80	Smith et al. (2021)
	PRISMA		18	Regional	On screen	87	(Shaik et al., 2022)
VHR	QuickBird	Object-oriented Classification Approaches, Classification and Regression Trees (CART)	8	Regional	Field measurement	74.27–81.5	(Mallinis et al., 2008b),
	WorldView-2		7	Local	Field measurement	85.43	(Mallinis et al., 2014),
	Worldview-3		11	Regional	Field measurement	80	(Alonso-Benito et al., 2016), Sesnie et al. (2018)
LIDAR	LIDAR	Spectral Mapping Techniques (e.g., MESMA, SAM, SMA), Discrete	7	Local	On screen/Field measurement	81.26–89.5	(Huesca et al., 2019), (García-Cimarras et al., 2021), (Revilla et al., 2021)

(continued on next page)

Table A1 (*continued*)

Category	Data	Modelling Approach	Number of Classes	Study Area Size	Accuracy Assessment Method	Overall Accuracy (%)	Citation
Integrated Sensors	LIDAR and multispectral images	Anisotropic Radiative Transfer (DART) Supervised Classification Methods (SGB, CART, SVM, and RF)	6–9	Reginal	Field measurement	84–92.8	(García et al., 2011), (Chirici et al., 2013), (Domingo et al., 2020)

References

Abdollahi, A., Pradhan, B., 2021. Urban vegetation mapping from aerial imagery using explainable AI (XAI). Sensors 21, 4738.

Abdollahi, A., Pradhan, B., 2023. Explainable artificial intelligence (XAI) for interpreting the contributing factors feed into the wildfire susceptibility prediction model. Sci. Total Environ. 879, 163004.

Adams, J.B., Sabol, D.E., Kapos, V., Almeida Filho, R., Roberts, D.A., Smith, M.O., Gillespie, A.R., 1995. Classification of multispectral images based on fractions of endmembers: application to land-cover change in the Brazilian Amazon. Rem. Sens. Environ. 52, 137–154.

Adão, T., Hruška, J., Pádua, L., Bessa, J., Peres, E., Morais, R., Sousa, J.J., 2017. Hyperspectral imaging: a review on UAV-based sensors, data processing and applications for agriculture and forestry. Rem. Sens. 9, 1110.

Albini, F.A., 1976. Estimating Wildfire Behavior and Effects. Department of Agriculture, Forest Service, Intermountain Forest and Range.

Alcaraz, C., Lopez, J., 2012. Analysis of requirements for critical control systems. Int. J. Critical Infrastruct. Prot. 5, 137–145.

Alonso-Benito, A., Arroyo, L.A., Arbelo, M., Hernández-Leal, P., 2016. Fusion of WorldView-2 and LiDAR data to map fuel types in the canary islands. Rem. Sens. 8, 669.

Alonso-Benito, A., Arroyo, L.A., Arbelo, M., Hernández-Leal, P., González-Calvo, A., 2012. Pixel and object-based classification approaches for mapping forest fuel types in Tenerife Island from ASTER data. Int. J. Wildland Fire 22, 306–317.

Anderson, H.E., 1981. Aids to Determining Fuel Models for Estimating Fire Behavior. US Department of Agriculture, Forest Service, Intermountain Forest and Range.

Andrews, P.L., Queen, L.P., 2001. Fire modeling and information system technology. Int. J. Wildland Fire 10, 343–352.

Aragoneses, E., Chuvieco, E., 2021. Generation and mapping of fuel types for fire risk assessment. Fire 4, 59.

Archibald, S., Lehmann, C.E., Belcher, C.M., Bond, W.J., Bradstock, R.A., Daniau, A.-L., Dexter, K.G., Forrestel, E.J., Greve, M., He, T., 2018. Biological and geophysical feedbacks with fire in the Earth system. Environ. Res. Lett. 13, 033003.

Arroyo, L.A., Pascual, C., Manzanera, J.A., 2008. Fire models and methods to map fuel types: the role of remote sensing. For. Ecol. Manag. 256, 1239–1252.

Béland, M., Widlowski, J.-L., Fournier, R.A., 2014. A model for deriving voxel-level tree leaf area density estimates from ground-based LiDAR. Environ. Model. Software 51, 184–189.

Benediktsson, J.A., Chanussot, J., Moon, W.M., 2012. Very high-resolution remote sensing: challenges and opportunities. Proc. IEEE 100, 1907–1910.

Bioucas-Dias, J.M., Plaza, A., Dobigeon, N., Parente, M., Du, Q., Gader, P., Chanussot, J., 2012. Hyperspectral unmixing overview: geometrical, statistical, and sparse regression-based approaches. IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 5, 354–379.

Bright, B.C., Loudermilk, E.L., Pokswinski, S.M., Hudak, A.T., O'Brien, J.J., 2016. Introducing close-range photogrammetry for characterizing forest understory plant diversity and surface fuel structure at fine scales. Can. J. Rem. Sens. 42, 460–472.

Cano-Crespo, A., Oliveira, P.J., Boit, A., Cardoso, M., Thonicke, K., 2015. Forest edge burning in the Brazilian Amazon promoted by escaping fires from managed pastures. J. Geophys. Res.: Biogeosciences 120, 2095–2107.

Chamberlain, C.P., Meador, A.J.S., Thode, A.E., 2021. Airborne lidar provides reliable estimates of canopy base height and canopy bulk density in southwestern ponderosa pine forests. For. Ecol. Manag. 481, 118695.

Chen, Y., Zhu, X., Yebra, M., Harris, S., Tapper, N., 2017. Development of a predictive model for estimating forest surface fuel load in Australian eucalypt forests with LiDAR data. Environ. Model. Software 97, 61–71.

Chirici, G., Scotti, R., Montaghi, A., Barbati, A., Cartisano, R., Lopez, G., Marchetti, M., McRoberts, R.E., Olsson, H., Corona, P., 2013. Stochastic gradient boosting classification trees for forest fuel types mapping through airborne laser scanning and IRS LISS-III imagery. Int. J. Appl. Earth Obs. Geoinf. 25, 87–97.

Chuvieco, E., Aguado, I., Yebra, M., Nieto, H., Salas, J., Martın, M., Vilar, L., Martınez, J., Martın, S., Ibarra, P., 2010. Development of a framework for fire risk assessment using remote sensing and geographic information system technologies. Ecol. Model. 221, 46–58.

Chuvieco, E., Riaño, D., Van Wagtendok, J., Morsdof, F., 2003. Fuel Loads and Fuel Type Mapping, Wildland Fire Danger Estimation and Mapping: the Role of Remote Sensing Data. World Scientific, pp. 119–142.

Chuvieco, E., Wagtendonk, J., Riaño, D., Yebra, M., Ustin, S.L., 2009. Estimation of Fuel Conditions for Fire Danger Assessment, Earth Observation of Wildland Fires in Mediterranean Ecosystems. Springer, pp. 83–96.

Cleve, C., Kelly, M., Kearns, F.R., Moritz, M., 2008. Classification of the wildland–urban interface: a comparison of pixel-and object-based classifications using high-resolution aerial photography. Comput. Environ. Urban Syst. 32, 317–326.

Deeming, J.E., 1972. National Fire-Danger Rating System. Rocky Mountain Forest and Range Experiment Station, Forest Service, US.

Domingo, D., de la Riva, J., Lamelas, M.T., García-Martín, A., Ibarra, P., Echeverría, M., Hoffrén, R., 2020. Fuel type classification using airborne laser scanning and Sentinel 2 data in mediterranean forest affected by wildfires. Rem. Sens. 12, 3660.

Dubayah, R., Hofton, M., Blair, J., Armston, H., Tang, H., Luthcke, S., 2021. GEDI L2A Elevation and Height Metrics Data Global Footprint Level V001 [Data Set]. NASA EOSDIS Land Processes DAAC. Available online: https://lpdaac. usgs. gov/products/gedi02_av001/. (Accessed 24 October 2020).

Dymond, C.C., Roswintiarti, O., Brady, M., 2004. Characterizing and mapping fuels for Malaysia and western Indonesia. Int. J. Wildland Fire 13, 323–334.

Eva, H., Lambin, E.F., 2000. Fires and land-cover change in the tropics: a remote sensing analysis at the landscape scale. J. Biogeogr. 27, 765–776.

Fogarty, L., Pearce, H., Catchpole, W., Alexander, M., 1998. Adoption vs. adaptation: lessons from applying the Canadian forest fire danger rating system in New Zealand. In: Proceedings, 3rd International Conference on Forest Fire Research and 14th Fire and Forest Meteorology Conference. Luso, Coimbra, Portugal, pp. 1011–1028.

Gale, M.G., Cary, G.J., Van Dijk, A.I., Yebra, M., 2021. Forest fire fuel through the lens of remote sensing: review of approaches, challenges and future directions in the remote sensing of biotic determinants of fire behaviour. Rem. Sens. Environ. 255, 112282.

Gama, F.F., Dos Santos, J.R., Mura, J.C., 2010. Eucalyptus biomass and volume estimation using interferometric and polarimetric SAR data. Rem. Sens. 2, 939–956.

García-Cimarras, A., Manzanera, J.A., Valbuena, R., 2021. Analysis of mediterranean vegetation fuel type changes using multitemporal LiDAR. Forests 12, 335.

García, M., Riaño, D., Chuvieco, E., Salas, J., Danson, F.M., 2011. Multispectral and LiDAR data fusion for fuel type mapping using Support Vector Machine and decision rules. Rem. Sens. Environ. 115, 1369–1379.

García, M., Saatchi, S., Casas, A., Koltunov, A., Ustin, S.L., Ramirez, C., Balzter, H., 2017. Extrapolating forest canopy fuel properties in the California Rim Fire by combining airborne LiDAR and Landsat OLI data. Rem. Sens. 9, 394.

Garestier, F., Dubois-Fernandez, P.C., Papathanassiou, K.P., 2007. Pine forest height inversion using single-pass X-band PolInSAR data. IEEE Trans. Geosci. Rem. Sens. 46, 59–68.

Guo, Q., Jin, S., Li, M., Yang, Q., Xu, K., Ju, Y., Zhang, J., Xuan, J., Liu, J., Su, Y., 2020. Application of deep learning in ecological resource research: theories, methods, and challenges. Sci. China Earth Sci. 63, 1457–1474.

Gwenzi, D., Lefsky, M.A., Suchdeo, V.P., Harding, D.J., 2016. Prospects of the ICESat-2 laser altimetry mission for savanna ecosystem structural studies based on airborne simulation data. ISPRS J. Photogrammetry Remote Sens. 118, 68–82.

He, J., Loboda, T.V., Jenkins, L., Chen, D., 2019. Mapping fractional cover of major fuel type components across Alaskan tundra. Rem. Sens. Environ. 232, 111324.

Hiers, J.K., O'Brien, J.J., Mitchell, R., Grego, J.M., Loudermilk, E.L., 2009. The wildland fuel cell concept: an approach to characterize fine-scale variation in fuels and fire in frequently burned longleaf pine forests. Int. J. Wildland Fire 18, 315–325.

Huesca, M., Riaño, D., Ustin, S.L., 2019. Spectral mapping methods applied to LiDAR data: application to fuel type mapping. Int. J. Appl. Earth Obs. Geoinf. 74, 159–168.

Kaasalainen, S., Holopainen, M., Karjalainen, M., Vastaranta, M., Kankare, V., Karila, K., Osmanoglu, B., 2015. Combining lidar and synthetic aperture radar data to estimate forest biomass: status and prospects. Forests 6, 252–270.

Kattenborn, T., Leitloff, J., Schiefer, F., Hinz, S., 2021. Review on convolutional neural networks (CNN) in vegetation remote sensing. ISPRS J. Photogrammetry Remote Sens. 173, 24–49.

Keane, A.R.E., Burgan, R., Wagtendonk, J.v., 2001. Mapping wildland fuels for fire management across multiple scales: integrating remote sensing, GIS, and biophysical modeling. Int. J. Wildland Fire 10, 301–319.

Lavalle, M., Khun, K., 2014. Three-baseline InSAR estimation of forest height. Geosci. Rem. Sens. Lett. IEEE 11, 1737–1741.

Lechner, A.M., Foody, G.M., Boyd, D.S., 2020. Applications in remote sensing to forest ecology and management. One Earth 2, 405–412.

LeCun, Y., Bengio, Y., Hinton, G., 2015. Deep learning. Nature 521, 436–444.

Lei, Z., Zeng, Y., Liu, P., Su, X., 2021. Active deep learning for hyperspectral image classification with uncertainty learning. Geosci. Rem. Sens. Lett. IEEE 19, 1–5.

Lizundia-Loiola, J., Otón, G., Ramo, R., Chuvieco, E., 2020. A spatio-temporal active-fire clustering approach for global burned area mapping at 250 m from MODIS data. Rem. Sens. Environ. 236, 111493.

Luo, L., Zhai, Q., Su, Y., Ma, Q., Kelly, M., Guo, Q., 2018. Simple method for direct crown base height estimation of individual conifer trees using airborne LiDAR data. Opt Express 26, A562–A578.

Mallinis, G., Galidaki, G., Gitas, I., 2014. A comparative analysis of EO-1 Hyperion, Quickbird and Landsat TM imagery for fuel type mapping of a typical Mediterranean landscape. Rem. Sens. 6, 1684–1704.

Mallinis, G., Koutsias, N., Tsakiri-Strati, M., Karteris, M., 2008a. Object-based classification using Quickbird imagery for delineating forest vegetation polygons in a Mediterranean test site. ISPRS J. Photogrammetry Remote Sens. 63, 237–250.

Mallinis, G., Mitsopoulos, I.D., Dimitrakopoulos, A.P., Gitas, I.Z., Karteris, M., 2008b. Local-scale fuel-type mapping and fire behavior prediction by employing high-resolution satellite imagery. IEEE J. Sel. Top. Appl. Earth Obs. Rem. Sens. 1, 230–239.

Marino, E., Ranz, P., Tomé, J.L., Noriega, M.Á., Esteban, J., Madrigal, J., 2016. Generation of high-resolution fuel model maps from discrete airborne laser scanner and Landsat-8 OLI: a low-cost and highly updated methodology for large areas. Rem. Sens. Environ. 187, 267–280.

Matthews, S., Sauvage, S., Grootemaat, S., Hollis, J., Kenny, B., Fox-Hughes, P., 2019. Implementation of Models and the Forecast System for the Australian Fire Danger Rating System.

McArthur, A., 1967. Fire behaviour in eucalypt forests. In: Leaflet No. 107. Forest Research Institute, Forestry and Timber Bureau, Canberra.

McArthur, A.G., 1966. Weather and Grassland Fire Behaviour. Forestry and Timber Bureau, Department of national Development, Commonwealth Commonwealth of Australia, p. 100.

Merrill, D., Alexander, M., 1987. Glossary of forest fire management terms. In: National Research Council of Canada, Canadian Committee on Forest Fire Management, 26516. Publication NRCC No, Ottawa, Ontario, p. 91.

Mitri, G., Nader, M., Salloum, L., 2011. Fuel type mapping in the Mediterranean region of north Lebanon using object-based image analysis of aster imagery. In: Advances in Remote Sensing and GIS Applications in Forest Fire Management from Local to Global Assessments, 39.

Moher, D., Liberati, A., Tetzlaff, J., Dg, A., 2009. PPreferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. BMJ 339: b2535. Ann. Intern. Med. 151, 264.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D.G., The, P.G., 2009. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. PLoS Med. 6, e1000097.

Moreira, F., Viedma, O., Arianoutsou, M., Curt, T., Koutsias, N., Rigolot, E., Barbati, A., Corona, P., Vaz, P., Xanthopoulos, G., 2011. Landscape–wildfire interactions in southern Europe: implications for landscape management. J. Environ. Manag. 92, 2389–2402.

Ozkan, S., Akar, G.B., 2018. Improved Deep Spectral Convolution Network for Hyperspectral Unmixing with Multinomial Mixture Kernel and Endmember Uncertainty arXiv preprint arXiv:1808.01104.

Paoletti, M., Haut, J., Plaza, J., Plaza, A., 2019. Deep learning classifiers for hyperspectral imaging: a review. ISPRS J. Photogrammetry Remote Sens. 158, 279–317.

Pausas, J.G., Keeley, J.E., 2009. A burning story: the role of fire in the history of life. Bioscience 59, 593–601.

Pettinari, M.L., Chuvieco, E., 2020. Fire danger observed from space. Surv. Geophys. 41, 1437–1459.

Prometheus, S., 1999. Project: management techniques for optimization of suppression and minimization of wildfire effects, System validation. European Comission. Contract Number ENV4-CT98-0716.

Puissant, A., Rougier, S., Stumpf, A., 2014. Object-oriented mapping of urban trees using Random Forest classifiers. Int. J. Appl. Earth Obs. Geoinf. 26, 235–245.

Revilla, S., Lamelas, M.T., Domingo, D., de la Riva, J., Montorio, R., Montealegre, A.L., García-Martín, A., 2021. Assessing the potential of the DART model to discrete return LiDAR simulation—application to fuel type mapping. Rem. Sens. 13, 342.

San-Miguel-Ayanz, J., Moreno, J.M., Camia, A., 2013. Analysis of large fires in European Mediterranean landscapes: lessons learned and perspectives. For. Ecol. Manag. 294, 11–22.

Sesnie, S.E., Eagleston, H., Johnson, L., Yurcich, E., 2018. In-situ and remote sensing platforms for mapping fine-fuels and fuel-types in Sonoran semi-desert grasslands. Rem. Sens. 10, 1358.

Seydi, S.T., Hasanlou, M., 2018. Sensitivity analysis of pansharpening in hyperspectral change detection. Applied Geomatics 10, 65–75.

Shaik, R.U., Laneve, G., Fusilli, L., 2022. An automatic procedure for forest fire fuel mapping using hyperspectral (PRISMA) imagery: a semi-supervised classification approach. Rem. Sens. 14, 1264.

Simard, M., Pinto, N., Fisher, J.B., Baccini, A., 2011. Mapping forest canopy height globally with spaceborne lidar. J. Geophys. Res.: Biogeosciences 116.

Smith-Jonforsen, G., Folkesson, K., Hallberg, B., Ulander, L.M., 2007. Effects of forest biomass and stand consolidation on P-band backscatter. Geosci. Rem. Sens. Lett. IEEE 4, 669–673.

Smith, C.W., Panda, S.K., Bhatt, U.S., Meyer, F.J., 2021. Improved boreal forest wildfire fuel type mapping in interior Alaska using aviris-ng hyperspectral data. Rem. Sens. 13, 897.

Stefanidou, A., Dragozi, E., Stavrakoudis, D., Gitas, I., 2018. Fuel type mapping using object-based image analysis of DMC and Landsat-8 OLI imagery. Geocarto Int. 33, 1064–1083.

Stefanidou, A., Gitas, I.Z., Katagis, T., 2020. A national fuel type mapping method improvement using sentinel-2 satellite data. Geocarto Int. 1–21.

Stergiopoulos, I., Mallinis, G., Gitas, I., 2007. Fuel type mapping using medium resolution imagery and GIS, considering radiometric, spatial and spectral enhancements of the original dataset. TowardsOperat. Use Rem. Sens. Forest Fire Manag. 107.

Taylor, S.W., Pike, R., Alexander, M.E., 1996. Field Guide to the Canadian Forest Fire Behaviour Prediction (FBP) System.

Thomas, C., Ranchin, T., Wald, L., Chanussot, J., 2008. Synthesis of multispectral images to high spatial resolution: a critical review of fusion methods based on remote sensing physics. IEEE Trans. Geosci. Rem. Sens. 46, 1301–1312.

Tompoulidou, M., Stefanidou, A., Grigoriadis, D., Dragozi, E., Stavrakoudis, D., Gitas, I., 2016. National Fuel Type Mapping Methodology Using Geographic Object Based Image Analysis and Landsat 8 Oli Imagery.

Toukiloglou, P., Eftychidis, G., Gitas, I., Tompoulidou, M., 2013. ArcFuel Methodology for Mapping Forest Fuels in Europe, First International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2013). SPIE, pp. 482–500.

Vali, A., Comai, S., Matteucci, M., 2020. Deep learning for land use and land cover classification based on hyperspectral and multispectral earth observation data: a review. Rem. Sens. 12, 2495.

Wang, L., Shi, C., Diao, C., Ji, W., Yin, D., 2016. A survey of methods incorporating spatial information in image classification and spectral unmixing. Int. J. Rem. Sens. 37, 3870–3910.

Wen, W., Timmermans, J., Chen, Q., van Bodegom, P.M., 2020. A review of remote sensing challenges for food security with respect to salinity and drought threats. Rem. Sens. 13, 6.

Yu, Q., Gong, P., Clinton, N., Biging, G., Kelly, M., Schirokauer, D., 2006. Object-based detailed vegetation classification with airborne high spatial resolution remote sensing imagery. Photogramm. Eng. Rem. Sens. 72, 799–811.