



Invited Review

Wildfire Fuels Mapping through Artificial Intelligence-based Methods: A Review

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ABSTRACT

Understanding fire behavior is a crucial step in wildfire risk assessment and management. Accurate and near real-time knowledge of the spatio-temporal characteristics of fuels is critical for analyzing pre-fire risk mitigation and managing active-fire emergency response. Geospatial modeling and land cover mapping using remote sensing combined with artificial intelligence techniques can provide fuel information at regional scales with high accuracy and resolution, as evidenced by the extensive recent work in the literature that appeared with increasing volume in the open literature. This paper provides a comprehensive survey of the state-of-the-art in wildfire fuel mapping, focusing on the research frontier of fire fuel models, fuel mapping methods, remote sensing data sources, existing datasets/reference maps, and applicable artificial intelligence techniques. The main findings highlight the increasing research on fire fuel mapping worldwide, with a considerable emphasis on multispectral imagery and the Random Forest classifier for its efficacy with limited data. The majority of these studies concentrate on relatively limited geographical scales spanning a small variety of fuel types, thus leaving a gap in regional and national-scale mapping. Further, this review focuses on identifying the major challenges in wildfire fuel mapping and viable solutions as they relate to (i) ground truth data scarcity, (ii) mapping understory vegetation, (iii) temporal latency, and (iv) lack of uncertainty-aware models. Lastly, this paper identifies potential AI-driven solutions that promise a significant leap in fuel mapping and discusses the latest developments and potential future trends in AI-based fuel mapping applications.

1. Introduction

Wildfires result from a complex interaction of ecobiological, meteorological, biophysical, and social factors (Lévi-Strauss, 1969; Scott and Burgan, 2005a). The frequency and intensity of fires are increasing, likely due to climate change (Littell et al., 2009) and anthropogenic factors (Bowman et al., 2020). Wildfire management and decision-making rely on a realistic understanding of the fire behavior (Bond et al., 2005; Bowman et al., 2011), which partially depends on the available biomass fuel. Characterizing burnable biomass involves defining the physical parameters of dead and live surface and canopy biomass, such as fuel load, depth, heat content, moisture, etc. These

characteristics contribute to the spread, intensity, and severity of wildland fires (Arroyo et al., 2008; Scott and Burgan, 2005a).

The wildland fuel bed comprises three stratified fuel layers: ground, surface (within 2 m above the ground, including downed woody biomass, duff, litter, and standing vegetation), and canopy fuels (above 2 m ground, like foliage, branches, mosses, etc.) (Keane, 2015b, 2015c). The position of the ground line, which separates ground fuels from surface fuels, is contentious due to challenges in distinguishing litter and duff in the field (Reinhardt et al., 2006). Geospatial maps describing the spatial pattern of fuels, or fuel maps, are critical for spatially explicit fire simulation and analysis and fire risk assessment. Knowledge of fuels is essential to predict fire behavior and inform decision-making regarding

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fire risk mitigation and emergency response. A variety of approaches have been utilized to generate fuel maps, including biophysical modeling (Falkowski et al., 2005; Keane and Reeves, 2012), field reconnaissance (Anderson, 1982; Anderson, 1981; Brown, 1982), and aerial and satellite remote sensing (Rollins, 2009), and the integration of one or more of these techniques (Arroyo et al., 2008). The variability of temporal fuel conditions requires frequent field survey efforts to keep fuel maps up to date, which is not economical and time-consuming. Therefore, remote-sensing methods for fuel mapping have emerged as a cost-effective alternative due to their large-scale coverage. Satellite remote sensing has become a major data source not only for fuel and fire mapping (Fernández-Álvarez et al., 2019; Shaik et al., 2022) but also for fire danger rating prediction (Laneve et al., 2020), fire monitoring (Priya and Vani, 2019; Yuan et al., 2015), and fire ecology (Szapkowski and Jensen, 2019) research. Satellite remote-sensing techniques provide a grid-like structure to model fuel data, offering refined spatial coverage and temporal resolution (in days) to update fuel maps more efficiently and timely than traditional aerial photography and/or fieldwork. Therefore, this survey paper focuses on remote sensing-based fuel mapping, which can be incorporated into fire behavior models (Arroyo et al., 2008; Krasnow et al., 2009; Lasserre et al., 2011).

Artificial intelligence (AI) is increasingly influencing remote sensing (RS) research, offering applications from initial image processing to high-level data interpretation and knowledge discovery. While empirical models were conventionally used to estimate fuel parameters using remote sensing data (Yebra et al., 2008), AI is now replacing these conventional approaches. Machine Learning (ML) models require extraction of meaningful features—such as Normalized Difference Vegetation Index (NDVI) (Jia et al., 2014), Enhanced Vegetation Index (EVI) (Jiang et al., 2008), Normalized Burn Ratio (NBR) (Miller et al., 2009)—from raw remote sensing data. These features are typically grounded in biophysical understanding and require expert knowledge for extraction. In contrast, deep learning (DL) techniques, which gained substantial popularity recently, automate feature extraction without expert guidance to learn unknown variables using filters in data extraction to achieve optimal performance. This paper provides a comprehensive review of the utilization of AI in RS and highlights the associated challenges and opportunities.

In this paper, we provide a comprehensive review of research conducted on fuel mapping during the past two decades, from 2002 to 2022, with a specific focus on studies that provide estimates of forest fuel types by using AI techniques over RS data. Previous notable reviews in this field were conducted by Arroyo et al. (2008), Gale et al. (2021), and Abdollahi and Yebra (2023). The earliest review, by (Arroyo et al., 2008), is naturally lacking recent developments due to the rapid expansion of AI techniques in recent years. On the other hand, (Gale et al., 2021) focused on remote sensing applications for different forest fire fuel characterizations, whereas Abdollahi and Yebra (2023) reviewed various types of remote sensing data and classification methods used in fuel type mapping. In addition to the specific focus on the use of AI, the present effort differs from these relevant prior studies in that it employs an extensive scoping review methodology to summarize the recent research findings, track trends, and identify challenges in fuel mapping from the published literature. In this context, we address the absence of critical reviews on challenges faced in fuel mapping and viable solutions for the challenges identified.

The structure of this manuscript is as follows: Section 2 describes the adopted meta-analysis procedure for examining prior literature, followed by the surveys of studies on fire behavior fuel models, fuel mapping approaches, ML approaches in fuel mapping, and existing wildfire fuel datasets. Section 3 provides the identified research challenges—namely, ground truth data scarcity, mapping understory vegetation, temporal latency, and lack of uncertainty-aware models, and AI-based potential solutions to them. Section 4 covers our findings and perspectives on the future of fuel mapping research, and section 5 concludes the paper.

2. Literature Survey

2.1. Meta-analysis Procedure

The combination of remote sensing data and AI techniques has yielded diverse potential solutions to real-world problems. A scoping review methodology is adopted herein to categorize the published work in this particular area. Scoping reviews are necessary, especially when literature on a specific topic has not yet been extensively reviewed, and the related concepts are complex and heterogeneous (Pham et al., 2014). Scoping reviews also help in the identification of research gaps. In this context, the absence of critical reviews on current challenges faced in fuel mapping and the identification of viable solutions for those challenges are also addressed in this paper.

The literature survey was conducted using the Web of Science (WoS) and Google Scholar (GS) databases based on two keyword groups provided in Table 1. We opted for WoS and GS due to their widespread use and recognized status as standard databases many organizations prefer (Alcaraz and Lopez, 2012; Wen et al., 2020). A total of 59 relevant publications on the topic of wildfire fuel mapping were identified, including one prior review paper. Fig. 1 displays the distribution of these papers based on their publication dates, revealing a clear increase in the number of wildfire fuel mapping articles in recent years.

Fig. 2 provides the histogram of fuel mapping publications leveraging sensor types, while Fig. 3 shows the histogram of target spatial resolutions used for fuel mapping. Figs. 2 and 3 show that multispectral data and a target resolution of 30 m are the most employed combinations in wildfire fuel mapping literature. This preference can be attributed to the accessibility and availability of multispectral data. Landsat imagery has been a prominent choice for remote sensing data in numerous publications due to its consistency, quality, and widespread availability. The Landsat program has launched eight satellites since 1972, providing four types of images: (i) multispectral scanner (MSS) by Landsat 1, 2, and 3, (ii) thematic mappers (TM) by Landsat 4 and 5, which also include MSS, (iii) enhanced thematic mappers (ETM+) by Landsat 7, and (iv) operational land imagers (OLI) by Landsat 8 (Tavora et al., 2023). To ensure data continuity, Landsat 9 is set to launch in 2023 with improved qualities, featuring 14-bit quantization (increased from 12-bits in Landsat 8) (Shahfahad Talukdar et al., 2023). Researchers have utilized Landsat MSS, TM, ETM+, and OLI, all with 30 m resolutions, for fuel mapping based on various classification methods.

Depending on the goals of the fuel mapping effort, studies may focus on either surface fuels, canopy fuels, or both. Fig. 4 summarizes the number of publications focusing on each fuel type, indicating that fewer studies concentrate on simultaneously estimating surface and canopy fuels. Most previous research efforts to map surface fuels focus on categorizing them into specific fuel models. Fuel models are defined as a complete set of fuel characteristics required by fire behavior models, such as Rothermel's rate of spread model (Andrews, 2018). They are developed to aid the determination of fuel characteristics for fire behavior simulations.

Fig. 5 shows a histogram of fuel mapping publications based on their target fuel models, including Anderson (Anderson, 1982), Scott and Burgan (Scott and Burgan, 2005b), Prometheus (Domingo et al., 2020),

Table 1
Literature survey database and keywords.

Database	Keyword Group	Keywords
Scopus and Google Scholar	1	Fuel Mapping, Fuel Characterization, Fire Fuels, Grassland Mapping, Forest Canopy Mapping, and Forest Understory Mapping
	2	Artificial Intelligence, Machine Learning, Deep Learning, Reinforcement Learning, Neural Networks, Support Vector Machine, Algorithm, Decision Trees, and Random Forests

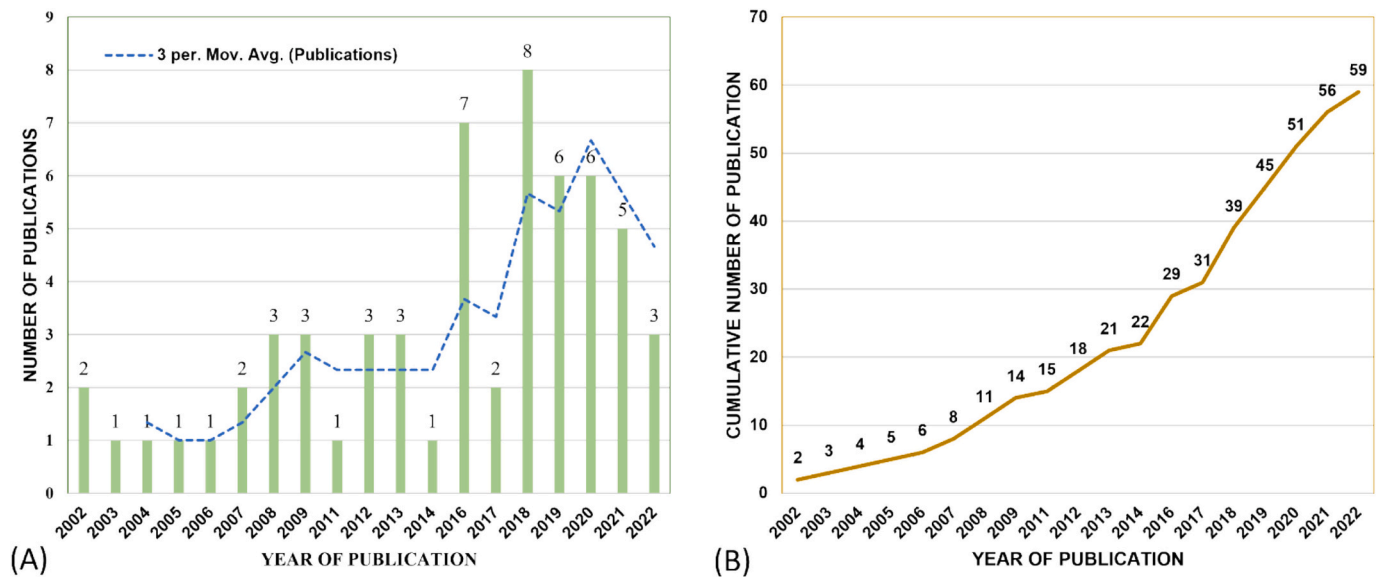


Fig. 1. (A) Number of publications per year retrieved from the literature search and (B) Cumulative curve for the publications over the 20 years.

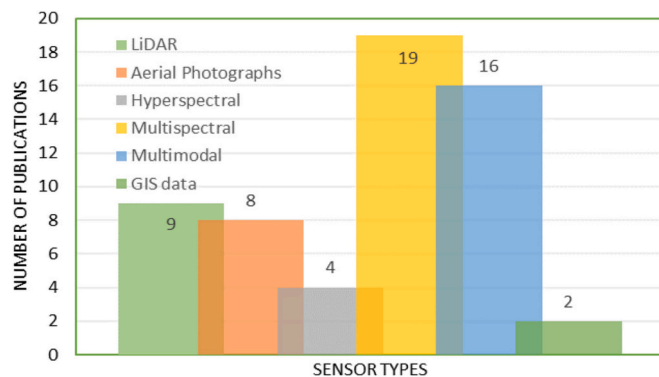


Fig. 2. Number of publications per sensor type for fuel mapping (excluding review paper).

Canadian (Tymstra et al., 2010), and selected fuel types such as grass, shrubs, grass-shrubs etc. These fuel models are briefly introduced later in this study. As seen, most of the articles are focused solely on selected fuel types, mainly because mapping the entire set of fuel types in any standard fuel model is challenging.

In addition to studies that targeted mapping fuels into fuel models, few articles focused on advanced fuel characterization were published in recent years. These studies examined the variability in fuel mass as a function of fuel type and depth class (Rowell et al., 2020; Prichard et al., 2020; Prichard and Rowell, 2023). They analyzed three-dimensional fuel metrics to establish relationships between structural metrics (e.g., porosity, bulk density, and surface area) and fine-scale mass (Rowell et al., 2020).

The extraction of meaningful features from remote sensing data requires expert knowledge and careful consideration of appropriate indices and transformations. In the context of fuels mapping, optical multispectral data has been extensively utilized, with certain spectral indices proving particularly effective. The Normalized Difference

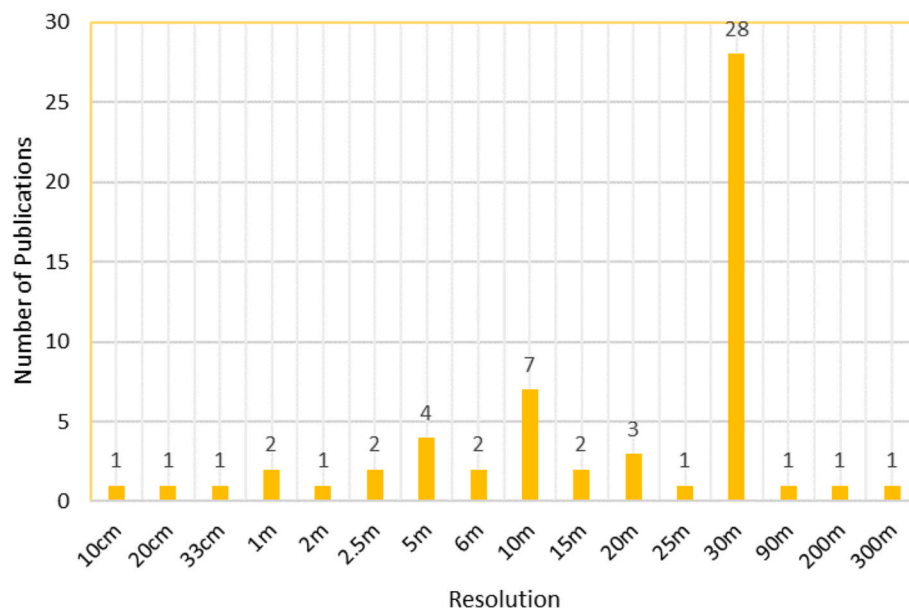


Fig. 3. Number of publications per fuel map resolution.

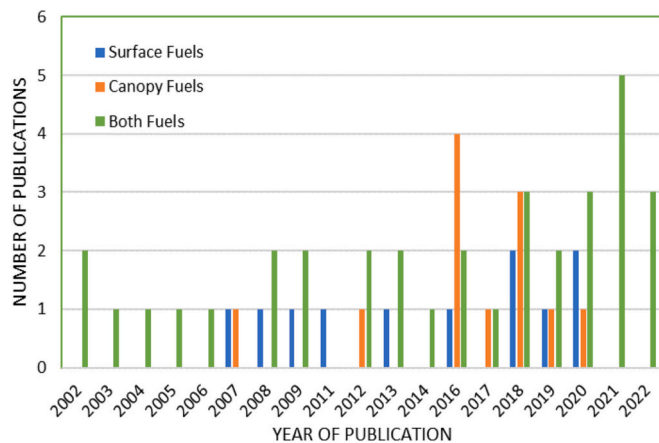


Fig. 4. Number of publications for surface and canopy fuels.

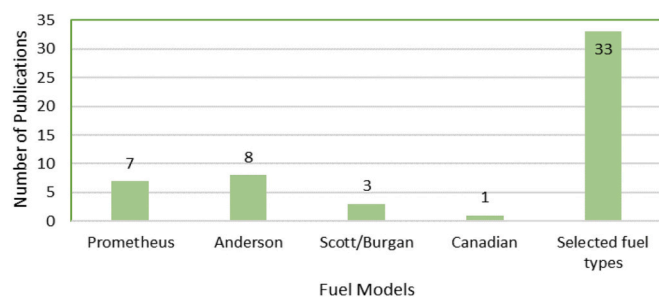


Fig. 5. Number of publications per fuel model.

Vegetation Index (NDVI) (Jia et al., 2014) emerges as one of the most employed indices, followed closely by the Enhanced Vegetation Index (EVI) (Jiang et al., 2008). These indices provide critical insights into vegetation health, density, and biomass, which are essential for characterizing fuel properties. NDVI is calculated using the near-infrared (NIR) and red bands, while EVI incorporates the NIR, red, and blue bands to correct for atmospheric and canopy influences.

Additionally, the Tasseled Cap Transformation indices, including brightness (TCB), greenness (TCG), and wetness (TCW), have been applied successfully in fuels mapping to extract information about surface reflectance and vegetation structure (Pickell et al., 2021). The Soil Adjusted Vegetation Index (SAVI), which accounts for soil brightness influences, is another valuable tool highlighted in literature (Alonso-Benito et al., 2013). SAVI is calculated using the NIR and red bands, with an additional soil brightness correction factor.

For Synthetic Aperture Radar (SAR) data, various polarimetric bands have been widely used in fuels mapping. These include Vertical-Vertical (VV), Vertical-Horizontal (VH), Horizontal-Horizontal (HH), and Horizontal-Vertical (HV) polarizations (Saatchi et al., 2007). The Radar Vegetation Index (RVI) has also been frequently employed to assess vegetation structure and moisture content (Shaik et al., 2025). SAR data captures different properties of Earth's surface compared with optical data due to the penetration and polarization of microwaves, sensitivity to vegetation structure, and sensitivity to dielectric properties that reflect moisture content. As a result, SAR data contributes to a more comprehensive assessment of fuel characteristics by providing additional dimensions of information, such as canopy height and biomass, even under challenging conditions like cloud cover or low light. Together, these spectral indices and SAR-derived features represent critical tools in remote sensing for fuels mapping.

The aspects reviewed in Table 2 are further introduced in the following subsections, which include fuel models, remote sensing data used in fuel mapping, existing datasets and reference maps, and AI

methods used in fuel mapping. An overview of each of these subsections is illustrated in Fig. 6.

2.2. Fire behavior fuel models

As mentioned earlier, the majority of surface fuel mapping literature aims to map surface fuels to specific fuel models. Currently, various fuel models exist for distinct locations around the world, including the U.S., Canada, Australia, and Europe. In the U.S., the most commonly used fuel models are the “Anderson 13” (Anderson, 1982) and “Scott and Burgan 40” (Scott and Burgan, 2005a) models. Anderson’s fuel model extends an original set of 11 fuel models developed by Rothermel (Andrews, 2018), later refined to 13 categories by Albini (1976). Anderson (1982) described these models along with representative images. The Anderson 13 fuel models are developed based on observed inherent characteristics of certain fuel types—e.g., bulk density, packing ratio, surface area to volume (SAV) ratio—and are designed for Rothermel’s rate-of-spread model. Anderson’s model classifies fuel into four main categories: Grass, Shrub, Timber, and Slash, with each class further refined into different fuel types, resulting in a total of 13 fuel types.

Focused on overcoming the limitations of Anderson’s fuel model, the Scott and Burgan fuel model was developed using the *Natural Fuels Photo Series* project (Ottmar, 2005), fire behavior simulations, and feedback from fire science researchers (Scott and Burgan, 2005a) on Rothermel’s rate-of-spread model and this fuel model comprises 40 distinct fuel types. The main categories in the Scott and Burgan model consist of Nonburnable, Grass, Grass-Shrub, Shrub, Timber-Understory, Timber Litter, and Slash-Blowdown.

The most commonly used fuel model in Canada is the Canadian Fire Behavior Prediction (FBP) System, developed from a database of over 400 experimental, prescribed burn, and wildfire observations. The fuel types in this system are categorized into four broad categories: coniferous, mixed-wood, deciduous, open, and slash, and then further divided into 16 discrete fuel types (Forestry Canada Fire Danger Group, M. A., 1992). These fuel types describe fire behavior characteristics under various burning conditions, incorporating surface and ladder fuels, stand structure and composition, and specific forest floor cover and organic (duff) layer present.

Prometheus fuel classification was developed for Europe by simplifying the Northern Forest Fire Laboratory (NFFL) (Hoffrén et al., 2023) fuel models and adapting them to Mediterranean conditions and ecosystems (Arroyo et al., 2006). This classification is based on the type and height of the fuel growth (Riaño et al., 2002b), divided into three major groups: grass, shrub, and trees. Several European countries, such as Switzerland, the U.K., and Portugal, have also developed fuel classification systems based on the Prometheus system (Arroyo et al., 2008).

Nonetheless, it is worth mentioning that not all ecoregions utilize fuel models to describe surface fuels. For instance, Australia does not have fuel models like those developed in the U.S. or Europe. Instead, they employ various fire behavior models specifically designed for the Australian ecoregion, which take fuel parameters such as fuel load, fuel moisture content, and drought factor as input, like parameters used in other locations’ fuel models. The most widely used fire behavior models in Australia are the McArthur Forest Fire Danger Rating System and the McArthur Grassland Fire Danger Rating System, developed by Alan McArthur (1966, 1967). Originally presented in tabular form, these systems have been transformed into equations to enable computerized fire behavior prediction and danger rating (Sirakoff, 1985; Noble et al., 1980). They were developed based on experimental fires and observations of wildfires, considering weather parameters and fuels unique to the Australian ecosystem (Cruz et al., 2015).

2.3. Review of fuel mapping approaches

This section reviews different fuel mapping approaches from the literature. The four major approaches in this area are (i) Field

Table 2
Summary of selected literature on surface and canopy fuels.

Inputs	Region of interest	Method	Surface Fuels	Canopy Fuels	Reference
Spectral indices, topography, climate	400 km ² area in British Columbia, Canada	Artificial Neural Network (ANN)	Nine classes of Canadian Forest Fire Behavior System	N/A	(Pickell et al., 2021)
LIDAR and AVIRIS data	395.45 km ² area of 2014 King Fire, California, USA	K-means clustering	Anderson 13 fuel model	N/A	(Stavros et al., 2018)
ASTER imagery	212 km ² area in the Canary Islands, Spain	Maximum Likelihood (ML), Support Vector Machine (SVM), ANN, and Object-based Image Analysis	Scott and Burgan 40 fuel model	N/A	(Alonso-Benito et al., 2013)
Airborne Laser Scanning and Indian Remote Sensing imagery	Two 165 km ² and 487 km ² areas in Sicily, Italy	Classification and Regression Tree (CART), Random Forest (RF), and CART Stochastic Gradient Boosting	Nine classes of NFFL fuel model	N/A	(Chirici et al., 2013)
LIDAR data	A 410 km ² national park in Spain	Spectral Mixture Analysis, Spectral Angle Mapper, and Multiple Endmember Spectral Mixture Analysis	Prometheus fuel model	N/A	(Huesca et al., 2019)
LIDAR and Quickbird	47.15 km ² area in east Texas, USA	Maximum Likelihood	Seven classes of Anderson 13 fuel model	Canopy cover	(Mutlu et al., 2008)
ASTER imagery	64 km ² region in the south of Italy	Maximum Likelihood	Modified seven Prometheus fuel model	N/A	(Lasaponara and Lanorte, 2007)
LIDAR data and red, green, blue, and NIR bands of NAIP imagery	99.5 km ² of northern Sierra Nevada, California, USA	K-means, RF, CART, and Sequential Minimal Optimization	Scott and Burgan 40 fuel model	N/A	(Marek K. Jakubowski et al., 2013)
LIDAR and Airborne Thematic Mapper data	2.3 km ² of a natural park in Spain	SVM and Decision Tree (DT)	Prometheus fuel model	N/A	(García et al., 2017)
ALS data, LANDSAT-8 imagery, and Digital Terrain Model	3678 km ² area in the Canary Islands, Spain	RF and Decision Rules	NFFL and Canary Islands Fuel Model	N/A	(Marino et al., 2016)
LANDSAT-TM imagery and Digital Elevation Model	A 410 km ² national park in Spain	Maximum Likelihood	Modified Prometheus fuel model	N/A	(Riaño et al., 2002a)
LIDAR data and WorldView-2 imagery	A 15 km ² island in the Canary Islands, Spain	Object-Based Image Analysis with Image Stack, Principal Component Analysis, and Minimum Noise Fraction fusion	Prometheus fuel model	N/A	(Alonso-Benito et al., 2016)
Airborne Laser Scanner and Sentinel 2 data	2023 km ² forest in Spain	Spearman's rank correlation coefficient, all subset selection, and SVM	Prometheus fuel model	N/A	(Domingo et al., 2020)
U.S. Forest Service's Integrated Resource Inventory data	715.67 km ² area in Boulder, Colorado	CART and Experts' opinion	Scott and Burgan 40 fuel model	N/A	(Krasnow et al., 2009)
ASTER imagery	250 km ² area in Idaho, USA	Maximum Likelihood and DT	NFFL fuel model	N/A	(Falkowski et al., 2005)
Quickbird, LANDSAT-TM, and EO-1 Hyperion imagery	60 km ² area in Greece	SVM	Own-developed six classes	N/A	(Mallinis et al., 2014)
Spectral Indices and LiDAR	New England, USA	3D CNN	N/A	Forest Attributes such as aboveground biomass, total biomass, and basal area	(Ayrey et al., 2021)
LANDSAT and LiDAR	14,000 km ² in Minnesota, USA	RF and k-NN	N/A	Canopy bulk density, canopy base height, and stand age	(Aragonese et al., 2025; Engelstad et al., 2019)
RapidEye bands and topography	0.52 km ² in Kelowna, British Columbia, Canada	k-NN	N/A	Forest Attributes such as canopy base height and large and coarse woody debris coverage	(Ferster and Coops, 2016)
LANDSAT and LiDAR	1040 km ² area of the 2013 Rim Fire, California, USA	SVM	N/A	Canopy bulk density, canopy fuel load, and canopy cover	(García et al., 2011)
Spectral indices and ALS	Southern Spain	Linear Regression	N/A	Canopy fuel load, canopy live fuel moisture content, and canopy live-to-dead ratio	(Romero Ramirez et al., 2018)
LANDSAT	Western USA	Gradient Boosting	N/A	Canopy bulk density, canopy base height, canopy height, and canopy cover	(Moran et al., 2020)
LANDSAT and LiDAR	Eglin Air Force Base, Florida, USA	RF	N/A	Tree density, basal area, and dominant vegetation type	(Hudak et al., 2016)
SAR imagery	Yellowstone National Park, Wyoming, USA	Semi-empirical equation with Least Square parameter fitting	N/A	Canopy bulk density, canopy fuel load, and foliage moisture content	(Saatchi et al., 2007)

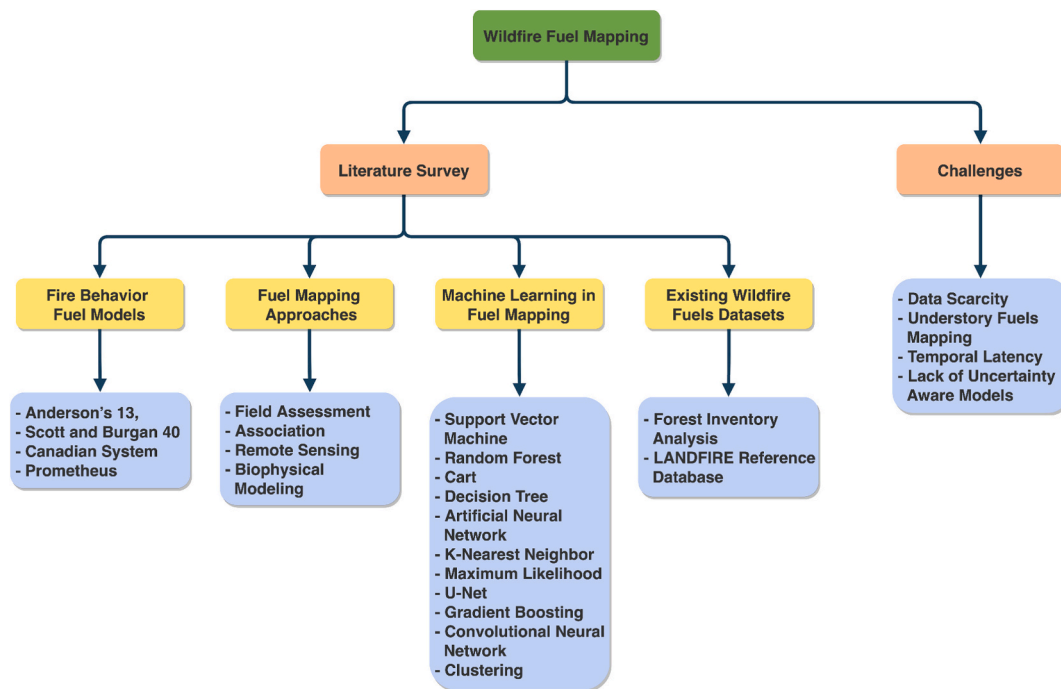


Fig. 6. Research tracks, methods employed, and present challenges in wildfire fuel mapping.

assessment, (ii) Association, (iii) Remote Sensing, and (iv) Biophysical modeling (Keane, 2015b; Keane, 2015a). Table 3 gives an overview of these approaches with advantages and disadvantages. In recent years, researchers have been using an integration of one or more of these approaches with AI to obtain state-of-the-art fuel maps (Alipour et al., 2023; Pickell et al., 2021; Shaik et al., 2022).

2.4. Machine Learning in fuel mapping

The primary objective of this section is to offer an overview of the ML methods employed in fire fuel mapping and to demonstrate how AI can

address the challenges in this field. ML has been broadly defined as a set of methods that can detect patterns in data to predict future data or other outcomes of interest (Murphy, 2012). Thus, ML can be viewed as a branch of AI that focuses on building descriptive, predictive, or actionable models for specific problems using incoming or collected data. ML models learn their mapping directly from the data, which is particularly advantageous when dealing with multi-variable relationships and complex patterns between inputs and outputs. Nevertheless, it should be noted that the performance of ML models heavily relies on the characteristics of existing data, such as accuracy and quantity.

In general, ML methods are categorized into one of three groups: (1)

Table 3
Overview of approaches used in fuel mapping.

Approach	Description	Advantages	Disadvantages
Field Assessment	Employing ground-based surveys and field reconnaissance to ascribe fuel attributes throughout a designated area.	Employs real observations; devoid of introduced modeling or analysis errors; utilizes a limited number of steps; easily adaptable and extendable; and amenable to integration with field sampling. Effortless and straightforward, requiring no extra mapping; most extant classifications are widely recognized and easily understandable; can enable the assignment of multiple fuel attributes to a single category; can use various classifications allowing for precise fuel assignments; create robust maps useful for other natural resource applications.	Expensive and time-intensive; somewhat subjective; bias toward mountainous landscapes.
Association	Assigning fuel attributes to categories of vegetation classifications.	Easily accessible; offers a snapshot of current conditions; widely acknowledged with a longstanding tradition of resource mapping through remote sensing products; numerous products available at varying resolutions and levels of detail.	Fuels and vegetation categories are frequently dissimilar; the extant classification's scale and resolution do not align with the fuel data or its application; significant redundancy in fuel attributes within the current classification categories.
Remote Sensing	Correlating remotely sensed imagery with fuel characteristics.	Connects fuel dynamics control processes to fuel mapping; offers context for interpreting fuel maps; frequently simulates environmental gradients at various temporal and spatial scales; can be extended to map multiple other ecological characteristics alongside fuel mapping.	Fuels frequently show no correlation with imagery signals; the scale of imagery might not align with the scale of fuel distribution; expertise in remote sensing, GIS, statistical modeling, and wildland fuel science is essential for accurate analysis; reasons behind mapping successes or failures can be challenging to comprehend. Emphasizes potential rather than current fuel conditions; fuel attributes often show no correlation with biophysical variables; difficulty in determining the ideal type, detail, and scale of the biophysical gradient that accurately reflects fuel dynamics; simulated gradient scale may not align with the scale of fuel distribution or processes; requires significant expertise in ecosystem modeling, GIS, statistical modeling, and wildland fuel science; demands extensive data for initialization and parameterization.
Biophysical Modeling	Deriving bio-physical gradients for correlating fuel attributes.		

supervised learning, (2) unsupervised learning, and (3) agent-based learning methods (Carbonell et al., 1983; Kotsiantis et al., 2006; Murphy, 2012). Supervised learning involves a parameterized function, often called a “model,” that maps known inputs (predictor variables) to known outputs (target variables). Most ML methods fall into this category. When the outputs (target variables) are unknown, the problem is considered unsupervised learning with established tasks such as clustering and dimensionality reduction. Pattern extraction in unsupervised learning is achieved by identifying similarities or relationships without guidance from the target variables. The third category of ML methods involves learning by simulating the behaviors and interactions of one or more autonomous agents. An example of agent-based models is reinforcement learning, which is used for modeling decision-making problems and is based on observing critical features of the environment interactively through trial and error (Carbonell et al., 1983; Murphy, 2012).

Methods from the aforementioned ML algorithm categories have been utilized for fuel mapping in literature, with a higher focus on supervised learning. Fig. 7 presents a histogram of fuel mapping literature based on the utilized ML approaches from our bibliometric analysis, which shows that Random Forest is the most utilized model. Brief descriptions of these models are provided in Fig. 8.

2.5. Existing wildfire fuels datasets

While there is an abundance of earth observation data collected using a variety of remote sensing modalities and equipment, this section specifically focuses on datasets that include information on wildfire fuels. In other words, the focus here is on databases where expert knowledge of fuels is utilized to provide qualitative or quantitative fuel labels, which are essential for fuel modeling and are the key components in successfully applying ML techniques to fuel mapping.

2.5.1. Forest inventory and analysis (FIA)

The United States Department of Agriculture (USDA) Forest Service's Forest Inventory and Analysis (FIA) program was started in response to a strategic plan set forth by the Agricultural Act of 2014 (Edgar et al., 2021). The inventory was designed to provide credible and timely assessments of U.S. forests, aiming to provide information to various agencies, resource managers, and policymakers. The FIA program data collection consists of three phases. Phase 1 aims to classify land into forest and non-forest classes and to take spatial measurements. Phase 2 involves field sampling to collect basic forest characteristics from plots across regions with at least one plot for every 6000 acres. The collected characteristics aim to provide data for distinct aspects of the forest, including trees, vegetation, and down (fine and coarse) woody materials. By revisiting the plots from Phase 2 during the growing season, Phase 3 seeks a complete picture of the ecological data, such as soil

indicators, and vegetation diversity and structure. FIA database is restricted for public use due to federal law (Burrill et al., 2022; Tinkham et al., 2018; US Forest Services, 2022) and requires special access permissions for research.

2.5.2. LANDFIRE reference database (LFRDB)

The Landscape Fire and Resource Management Planning Tools (LANDFIRE) is a joint program between the wildland fire management programs of the U.S. Department of Agriculture Forest Service and the Department of the Interior (Ryan and Opperman, 2013). LANDFIRE aims to provide consistent “all-land” vegetation and fuel data suitable for strategic planning and analysis. The base layer of this program is created in a 7-year cycle, with national products released for the Continental U.S. (CONUS) and Alaska/Hawaii in 2005 and 2009, respectively. The product has been periodically updated in response to anthropogenic and natural disturbances, with updates conducted in 2012 and 2014. In 2016, LANDFIRE performed a complete remap of their base product to represent circa-2016 ground conditions. LANDFIRE introduced “capable fuel” products in this remapping effort, which consider the effects of time on disturbances to create representative fuel maps for specific years. The LANDFIRE products are created using a series of GIS data layers known as the LANDFIRE Reference Database (LFRDB), which includes Landsat-TM images and terrain, soils, and meteorology data to model and map biophysical gradients and wildland fuel layers, including both surface and canopy fuels, at 30-m resolution (Rollins, 2009; Ryan and Opperman, 2013). While the complete version of LFRDB is not publicly available, a version containing the vegetation and fuel data used for the 2016 remap can be freely accessed. This public version of LFRDB has been used as reference data for training ML/DL models related to remote sensing data (Alipour et al., 2023).

3. Challenges in fuel mapping and proposed solutions

A variety of ML and remote sensing data have been used to generate models that identify and characterize surface and canopy fuels throughout the landscape. A review of the performance of the models in the literature indicates that the fuel identification problem remains challenging due to the complex relationships and extensive variability of fuels and biophysical conditions. However, AI-based approaches have been demonstrated to offer accurate and regionally scalable fuel mapping methods in a number of recent efforts (Alipour et al., 2023; Pickell et al., 2021). Nevertheless, an analysis of this literature reveals that a series of major challenges remain that have not been fully addressed. At the same time, several yet-to-be-explored opportunities also exist that can yield potentially significant advances. This section of the manuscript summarizes the major challenges in wildfire fuel mapping identified through our literature review. It also offers a presentation of the corresponding opportunities, proposed solutions, and future work.

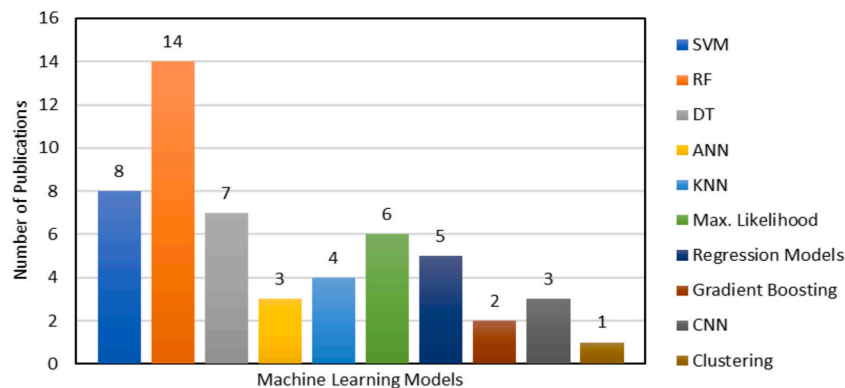


Fig. 7. Publications per machine learning model for fuel mapping (SVM: Support Vector Machine, RF: Random Forest, DT: Decision Tree, ANN: Artificial Neural Network, KNN: K Nearest Neighbor, and CNN: Convolutional Neural Network).

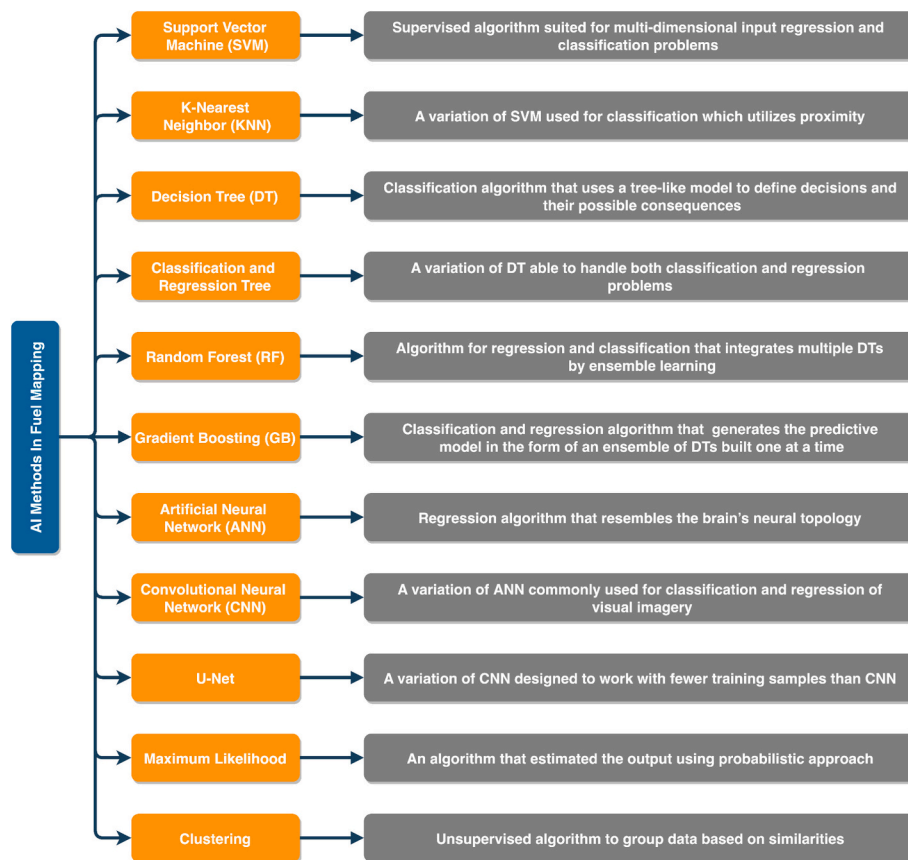


Fig. 8. Brief descriptions of AI methods employed in fuel mapping literature.

3.1. Challenge 1: scarcity of ground truth data

As mentioned above, supervised learning approaches to the fuel mapping problem rely on the availability of copious amounts of annotated data where existing fuels are determined/labeled through human expert supervision. While shallow learning models can be trained on comparably small datasets, DL methods need large-scale datasets to achieve the desired generalization performance, (Zhang and Sabuncu, 2018)—namely, accuracy in classifying fuels unseen in the training dataset. Large-scale general image databases, such as ImageNet (Deng et al., 2009), have been created in the past decade for computer vision research and applications, becoming the backbone of many recent advances in ML. However, the collection of annotated remote sensing data is more complicated due to the extensive need for human expertise required for annotation and the wide variety of target applications. As our review of existing datasets revealed, in the field of wildfire fuel mapping, there is still no single go-to dataset that could serve the purpose of transparent benchmarking and standardized pre-training (Alipour et al., 2023; Shaik et al., 2021). Suggested solutions to this problem are described next.

3.1.1. Proposed solution 1: transfer learning

Transfer learning refers to the process of transferring knowledge from one domain or task to improve the learning process in another, usually related, domain. It has been shown that knowledge transfer can improve the performance of learners built using limited training data (Babbar and Schölkopf, 2019; Bansal et al., 2022). Such techniques can alleviate data scarcity by transferring knowledge from other domains. For example, deep-learning-based classifiers that usually have many features to be trained can be first “pre-trained” on large-scale generic datasets (e.g., ImageNet) and then repurposed for fuel mapping tasks. Fig. 9 illustrates this concept, where effective features learned via pre-

training on ImageNet are transferred to the new task and fine-tuned on the limited fuel data.

Transfer learning has shown improved performance in various applications, such as human activity classification (Fix et al., 2022), computer vision for dry bean classification (Taspinar et al., 2022), software defect classification (Fix et al., 2022), and multi-language text classification (Iqbal et al., 2018). In the field of remote sensing, transfer learning has also been applied in diverse applications, including scene classification (Li et al., 2021; Zeng et al., 2021), crop yield production (A. X. Wang et al., 2018), airplane detection (Chen et al., 2018), Land Use Land Cover (Alem and Kumar, 2022), roads extraction (Senthilnath et al., 2020), and rice seedling analysis (Tseng et al., 2022). Alipour et al., 2023 utilized transfer learning for fuel mapping using multimodal data (Landsat-8 and NAIP imagery) and LANDFIRE samples as ground truth. Weiss et al. (2016) conducted a comprehensive survey on transfer learning, covering both homogeneous and heterogeneous transfer learning methodologies.

3.1.2. Proposed solution 2: label propagation

A different approach to address the scarcity of target labels is to use semi-supervised learning through which labels can be expanded by exploiting the patterns in the available data guided by expert knowledge. Two main approaches in this realm are label propagation techniques and data augmentation. These approaches leverage expert-driven reasoning with embedded patterns and similarities within the data and utilize feasible data transformations to augment and complement the limited labels.

Label propagation identifies and exploits the hidden patterns and relationships embedded within the data to predict the labels of unlabeled observations. Fig. 10 depicts one of the label propagation methods based on *local descent*, which labels its nearest neighbors and repeats training until it converges. Cui et al. (2018) developed a semi-supervised

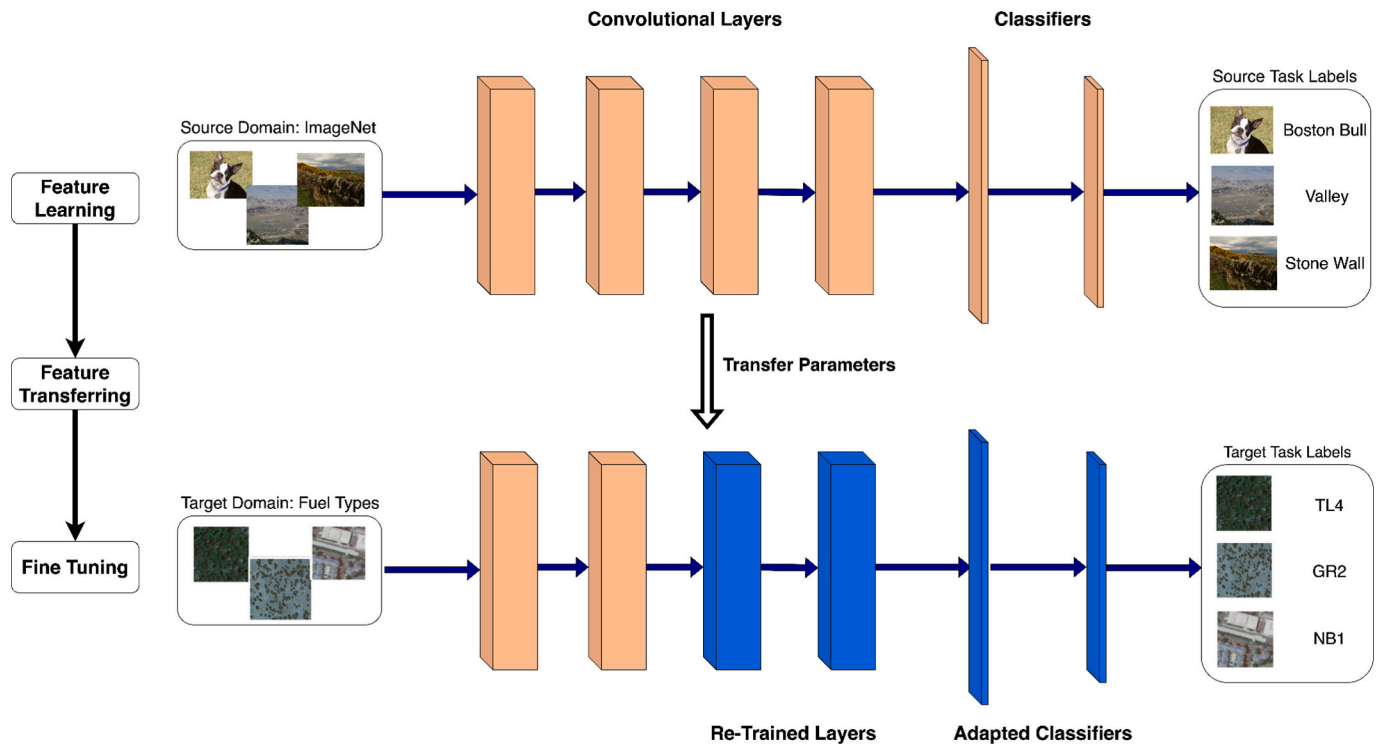


Fig. 9. Transfer learning by fine-tuning deep learning networks pre-trained on ImageNet. Transfer learning uses a pre-trained network on a certain task for a different problem to improve accuracy and reduce the training data.

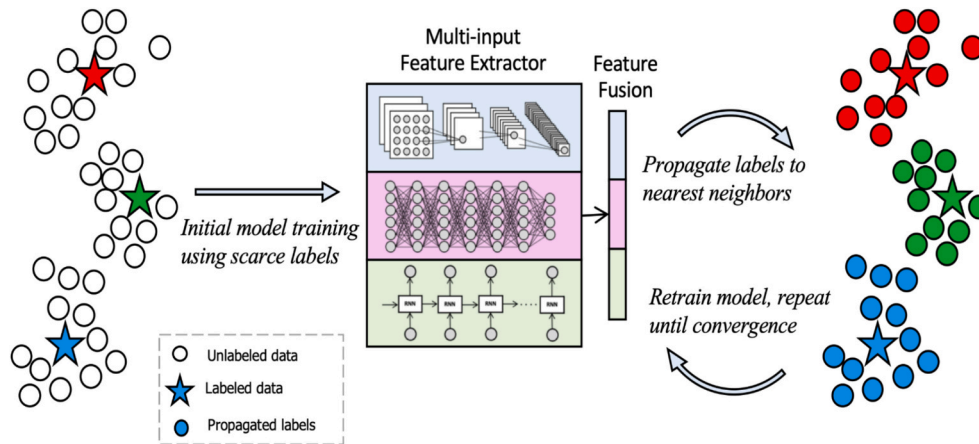


Fig. 10. Label propagation through local descent.

classification approach based on rolling guidance filtering. Zhang et al. (2019) propagated labels using an ensemble method that uses Euclidean distance as a similarity metric and a random subspace method to partition the high-dimensional features. Wang et al. (2014) proposed an approach for semi-supervised hyperspectral data classification, which uses spatial-spectral graphs to update the training set. While label propagation techniques are broadly applied elsewhere, specifically in wildfire fuel mapping are extremely scarce. A recent exception is the study by Shaik et al. (2022), who proposed a pseudo-labeling method for fuel mapping using the Jeffries-Matusita spectral angle mapper combined with k -means clustering to address hyperspectral data scarcity.

3.1.3. Proposed solution 3: data augmentation

Data augmentation is the process of artificially expanding the size of a dataset used for training ML models by transforming the available datasets in various ways (Yu et al., 2017). Earlier augmentation methods

have been domain-specific, and only recently, advances in photo editing have made this approach applicable to various data modalities, making it a valuable tool in model training (Lv et al., 2021). The literature review reveals a wide variety of methods for data augmentation, including geometric and color transformations, feature space augmentation, and adversarial augmentation (Maharana et al., 2022). In fuel mapping, for example, Alipour et al., 2023 used random horizontal and vertical flipping and rotations of high-resolution NAIP imagery to increase the training set's size, yielding a more effective fuel mapper.

3.2. Challenge 2: understory fuel mapping

Understory vegetation and fuels play a significant role in forest ecosystems and their accurate characterization are essential for wildfire simulations. Therefore, understanding the spatio-temporal dynamics of understory vegetation and fuels is crucial for effective wildfire

management. Obtaining detailed information on the distribution of understory fuel types is challenging due to the interference of the overstory canopy. Despite efforts by the fire science community to overcome this challenge (Prichard et al., 2020), large-scale mapping of understory fuels is still limited because the developed methods lack generality, and the required remotely sensed data is often not readily available. Additionally, identifying understory vegetation types through field surveying is costly and laborious (Eskelson et al., 2006). A review of the literature reveals two current approaches to solving these problems—namely, terrestrial and regressive mapping techniques.

3.2.1. Proposed solution 1: multivariate mapping

This approach focuses on extracting implicit and indirect relationships between biophysical variables, understory and overstory characteristics, soil properties, topographic factors, disturbances, herbivory, and bioclimatic conditions. It leverages the easier-to-measure biophysical and overstory variables to infer hard-to-reach understory variables. Some of the primary explanatory variables used in the multivariate mapping to predict understory vegetation cover include (1) overstory-derived variables (e.g., trees per hectare, leaf area index (LAI), basal area (BA), and canopy cover), and (2) topographic-derived variables (e.g., aspect, slope, digital terrain synthesis (DTS)) (Eskelson et al., 2006; Kerns and Ohmann, 2004; Russell et al., 2017; Suchar and Crookston, 2010; Venier and Pearce, 2007).

Researchers have observed that the understory composition in Europe's beech and temperate oak forests correlates well with precipitation and temperature gradients (Bertrand et al., 2011; De Frenne et al., 2013; Van Der Veken et al., 2004). Furthermore, climate change has been shown to cause shifts in local forest understory communities, primarily due to increased thermophile species locally (De Frenne et al., 2013; Reczyńska and Świerkosz, 2017). Novel understory communities emerge as migration potentials and climatic niche breadth vary for individual species (Bertrand et al., 2011; Bruielheide et al., 2018; Weigel et al., 2019). In their study, Weigel et al. (2019) concluded that understory vegetation is highly dependent not only on climatic conditions but also on soil parameters.

Suchar and Crookston (2010) developed a regression model considering vegetation, climatic parameters, geographic variables, disturbance, herbivory, and soil characteristics. Their vegetation category considered the crown cover, and climatic variables included annual temperatures (mean, median, maximum, and minimum) and precipitation. Geographic variables consisted of elevation and slope. Disturbances over time and due to fire and exploited plots were also considered. Regarding herbivory, the presence and absence of animal use were considered. The model was concluded to have only a weak predictive power ($R^2 < 0.20$) but was deemed improvable by using robust models for predicting sub-canopy characteristics. Similarly, Aragonese and Chuvieco (2021) conducted a study to map the understory shrublands and grasslands for the entire Europe using mean annual precipitation (MAP) and a linear model that related shrubland and MAP for California (Bohlman et al., 2018). This choice was based on the similarity between European arid/semi-arid regions and Californian bioclimatic conditions (Zepner et al., 2021). Interestingly, Arellano-Pérez et al. (2018) conducted a study focusing on the spatial mapping of understory fuels in relation to canopy fuels and their implications for crown fire potential. Their research was carried out in stands of *Pinus radiata* and *Pinus pinaster* located in northwest Spain, a region prone to wildfires. The study utilized advanced remote sensing techniques and field data to establish a detailed relationship between understory vegetation characteristics and overstory canopy attributes. By successfully linking these layers, the researchers provided valuable insights into how understory fuels contribute to the overall fire behavior and potential crown fire risks in these forest ecosystems.

3.2.2. Proposed solution 2: terrestrial mapping

There have been efforts to map understory vegetation using

terrestrial LiDAR measurements. LiDAR has demonstrated its ability to directly measure the three-dimensional structure of ecosystems across large areas (Barber et al., 2016). This type of data produces three-dimensional characterizations of objects in the form of point clouds defined by spatial coordinates. These attributes serve as the basis for forest inventory and characterization because, theoretically, every object in a forest can be detected with a vertical dimension if adequate LiDAR point densities are collected within the forest canopy layers (e.g., understory) (Pesonen et al., 2008).

While the use of lidar to measure understory fuels in densely forested areas is limited due to obstructions from the canopy layer, there are a few examples of its application in cases with partial canopy cover. Martinuzzi et al. (2009) studied the presence of understory shrub cover (i.e., cover >25 %) on pixels in an area of 20 m² by using airborne discrete return LiDAR. The presence of shrubs was validated with an accuracy of 83 %. Hill and Broughton (2009) reported their work on predicting the presence of understory vegetation using two separate airborne discrete-return LiDAR datasets in leaf-on and leaf-off conditions. They achieved 72 % and 77 % validation accuracies for leaf-off LiDAR and a combination of both LiDAR datasets, respectively.

Moreover, Morsdorf et al. (2010) utilized airborne discrete return LiDAR height and intensity information to identify individual vegetation strata on 5 m × 5 m pixels in various forest conditions with relative success in detecting the presence of understory vegetation strata. Additionally, Pesonen et al. (2008) and Carl and Seielstad (2003) reported studies on coarse woody debris detection using LiDAR, yielding promising results. Alonso-Rego et al. (2021) demonstrated an innovative approach to forest fuel characterization by integrating airborne laser scanning (ALS) and terrestrial laser scanning (TLS) data. Using advanced machine learning models, they effectively estimated key parameters critical to fire behavior modeling and forest management. These parameters included fuel strata gap, which represents vertical discontinuities in fuel layers; fuel load by layers, providing a detailed quantification of biomass distribution across vertical strata; surface fuel height, essential for understanding ground-level fire propagation; stand mean height, indicative of the overall vertical structure of the forest; canopy base height, which helps predict crown fire initiation; canopy bulk density, a critical factor in assessing crown fire spread potential; and canopy fuel load, representing the total available fuel in the canopy.

3.2.3. Proposed solution 3: multimodal data fusion and learning

It is widely known that different remote sensing modalities provide information about vegetation and fuel variables with different trade-offs regarding sensitivity, resolution, and penetration. For example, spectral signatures within multispectral imagery effectively distinguish vegetation types and conditions, and high-resolution RGB imagery provides information on the composition. Still, they cannot penetrate through the overstory layer and provide vertical information through the depth of the forest. Synthetic Aperture Radar (SAR) L-band can penetrate the overstory and provide understory information (Huang et al., 2009). In contrast, LiDAR measurements can directly measure the 3D structure of fuels but cannot penetrate through obstacles. This heterogeneity of the sensing capabilities results in the need to use multimodal data in a complementary setting. In our analysis of the fuel mapping articles reviewed, only 14 studies used multimodal data and much of the work was carried out using multispectral data. Also, in most of the fuel mapping works with multimodal data, outputs from different modalities of data were combined only in the end. A potentially more effective solution is to create a training dataset that combines multimodal data at the beginning to train AI models. For example, in a study conducted by Shaik et al. (2024; 2025) estimated the understory fuels leveraging ensemble of machine learning models and training with multimodalities of data. Fig. 11 illustrates the four primary options for multimodal data fusion: *early* fusion (combining raw modalities prior to feature extraction), *slow* fusion (concatenating modality-specific features before classification), *late* fusion (combining modality-wise classification results),

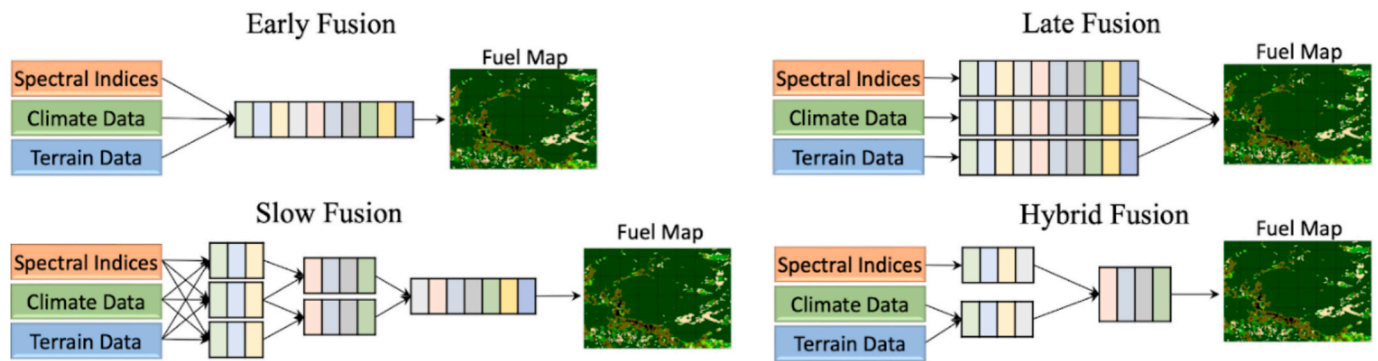


Fig. 11. Schematic representation of four different types of data fusion.

and *hybrid* fusion (combination of one or more of the other fusion).

3.3. Challenge 3: temporal latency

Large and high-intensity fire events are unplanned and occur eventually in forested environments. Key factors are often the high quantity and complex structure of forest fuels. Fuel type maps are the primary input for fire behavior calculations and simulation studies, so compiling spatially comprehensive, accurate, and real-time fuel information is essential to support various aspects of land and risk management in forested environments. However, thematic maps are not easily produced at the scale and speed needed to assess and mitigate wildfire threats. Moreover, real-time fuel mapping appears impossible to achieve through traditional site-based approaches.

3.3.1. Proposed solution 1: AI-based fuel mapping algorithms

AI techniques applied to remotely sensed regional scale data can potentially address the temporal latency problem. Given the need for effective algorithms for predicting real-time fuels at the required scales, the research community has started focusing on AI-based techniques. For instance, Pickell et al. (2021) explored how AI methods can be applied to remote-sensed data to map and update fuel types annually. Their ANN was trained and applied over forty thousand square kilometers of landscape in British Columbia, Canada, which was affected by a mega-fire in 2017. Their algorithm generated fuel maps and attained an overall accuracy of ~60 % based on independent validation. The authors resolved that the lack of forest inventory to train their ANN model was the primary reason for the relatively low accuracy.

More recently, Shaik et al. (2022) have developed an automatic algorithm using PRISMA hyperspectral data and an ML model, which uses the CORINE landcover map provided by EU Copernicus as input. Their study concluded that their algorithm could map fuel types available in any part of Europe using CLC as input with an overall accuracy of 80 %. Also, E-GEOS SpA in Italy has developed an ML-based fuel mapping algorithm, which could be used to map fuel types in Europe with an accuracy of 75 %. In the most recent effort, Alipour et al., 2023 have developed a regional-scale AI-based fuel mapping algorithm. Their study produced a fuel map for California with an accuracy of ~70 %. Many similar studies are anticipated from the research community that will explore a variety of algorithmic and data processing options to attain ever more accurate fuel maps for a large variety of wildfire-prone regions.

3.4. Challenge 4: lack of uncertainty-aware fuel mapping

Modeling complex environmental phenomena is fraught with uncertainties (Beven and Binley, 1992), and fire behavior is no exception. Uncertainty is intrinsically associated with (1) model applicability, scope, and inherent limitations, (2) inherent accuracy of model structure, (3) natural variability, (4) parametric uncertainty, (5) skill and

knowledge of the user, and (6) input data reliability (Alexander and Cruz, 2013; Bachmann and Allgöwer, 2002; Beven and Binley, 1992; Cruz et al., 2017; Scott and Burgan, 2005a; Yuan et al., 2015). Alexander and Cruz (2013) reported that among these causes of uncertainty, input data reliability can be the dominant source of error in fire spread predictions. Shamsaei et al. (2023) investigated wind, ignition location, and fuel data as sources of error. Errors associated with fuel classification and parameterization (Keane et al., 2013) across large spatial fuel variability and heterogeneity profoundly impact predicted fire behavior (Albini, 1976; Salazar, 1985). If uncertainties in the input data (fuel types) are not well quantified, then the knowledge of fuel models and fire behavior will be impeded. Therefore, understanding and quantifying the impacts of uncertainties in fuel maps is essential, and integrating uncertainty into fire spread models/simulations is key to fire risk management.

3.4.1. Proposed solution 1: ML-based uncertainty quantification

There has been a sharp increase in interest in machine-learning-based uncertainty quantification (UQ) methods. We have observed that over the last decade, more than 2500 papers addressing the implementation of UQ in AI were published across various fields, such as image processing, signal processing, computer vision, etc. (Freimane and Wei, 2022). Uncertainty can arise in the selected ML/DL model and/or in the dataset. Furthermore, uncertainties fall into two types: epistemic (EU) and aleatoric (AU), respectively. Therefore, predictive uncertainty (PU) is calculated as the sum of EU and AU.

Several effective methods for uncertainty quantification in DL are available, including Monte Carlo dropout (Neal, 1995; Askari and Mahsuli, 2020), Markov chain Monte Carlo (Kupinski et al., 2003), Variational Inference (Swiatkowski et al., 2020), Bayesian Active Learning (Hossain et al., 2017; Neal, 2012), Bayes by Backprop (Blundell et al., 2015), Variational autoencoders (Kingma and Welling, 2013), and Laplacian approximations (Yang, 2005). Bayesian approaches were also applied for uncertainty parameterization, as reviewed by (Ghavamzadeh et al., 2015). Additionally, ensemble-type UQ methods have been used to predict both epistemic and aleatoric uncertainties. Among these ensemble methods, techniques such as deep ensemble (Hu et al., 2019), deep ensemble Bayesian/Bayesian deep ensemble (Fersini et al., 2014), and Uncertainty in Dirichlet deep networks (Tsiligkaridis, 2021) have proven their capability in the past. Many more techniques were not mentioned here but can be referenced from the cited sources. Our proposed solution is to utilize these techniques for fuel mapping, which can also provide a measure of uncertainty.

4. Future of fuel mapping

Current fuel mapping efforts, as discussed earlier, utilize label-based fuel mapping using various standard fuel models—see, e.g., Anderson. (1982), Scott and Burgan (2005a), or Tymstra et al. (2010). However, these fuel models are designed to characterize a broad spectrum of fuel

properties using various assumptions that oversimplify the fuel bed representation (Hiers et al., 2009; Rowell et al., 2020). This oversimplification, in turn, can lead to inaccurate simulations from fire behavior models due to their critical role in fire behavior (Loudermilk et al., 2017; Hiers et al., 2009; Loudermilk et al., 2012; O'Brien et al., 2018). Furthermore, the standard fuel models assume a two-dimensional fuel bed, which limits their applicability to three-dimensional Computational Fluid Dynamic-based fire behavior models—e.g., WFDS and HIGRAD/FIRETEC (Dupuy et al., 2011).

Physics-based fuel mapping can address the limitations by directly mapping fuel characteristics—such as fuel load (Abdollahi and Yebra, 2025; Martin-Ducup et al., 2025), height, and surface area-to-volume ratio—instead of only mapping fuels as standardized fuel labels. Various tools such as Terrestrial Laser Scanner (TLS) and data sources such as FIA can provide measurements of fuel characteristics. TLS has been widely used for fine-scale fuel characteristics estimation (Newnham et al., 2015), including fuel biomass (Greaves et al., 2015; Loudermilk et al., 2009; Olsoy et al., 2014) and fuel height (Rowell et al., 2016). FIA data provide field plot measurements of the fuel characteristics, such as fuel biomass and height. These two data sources, however, suffer from limited spatial coverage (i.e., they provide measurements of only small patches of the ground). While several studies investigated coupling TLS data with other data sources for landscape-scale fuel biomass mapping (Greaves et al., 2017; Rowell et al., 2016), the applications of TLS and FIA for different fuel beds and nationwide physics-based mapping remain challenging. AI/DL techniques can serve as powerful tools to fuse various data sources for nationwide physics-based fuel mapping. Rapid developments for characterizing canopy fuel properties using AI/DL approaches have been used to generate estimates of crown bulk density, surface area to volume ratio, and foliar moisture content that are attributed to a 3D voxel lattice for national-scale three-dimensional fuels data used in fire modeling, for example in BurnPro3D (Prichard and Rowell, 2023).

5. Conclusions

This paper thoroughly reviewed previous research papers on fire fuel mapping to examine state-of-the-art fire fuel models, fuel mapping methods, remote sensing data, existing datasets/reference maps, and AI techniques. Some of the main findings are as follows:

- a. Research on fire fuel mapping is steadily increasing year-by-year in all wildfire-affected countries, particularly in the U.S. and the Mediterranean countries of Europe.
- b. Most studies utilized multispectral imagery for fuel mapping due to its easy accessibility and cost-effectiveness.
- c. Among the various ML models, the Random Forest classifier was highly preferred for its ability to learn from limited data.
- d. Many studies focused on predicting fuels over regions where only a limited number of fuel types are present.

The survey also elucidated major challenges in fuel mapping at present, and possible solutions were identified, which can be summarized as follows.

- i. A significant challenge in fuel mapping is ground truth data scarcity. Possible solutions for this problem are to use transfer learning, label propagation, and data augmentation techniques. Only a few very recent studies have explored these pathways at present, and significant advances are anticipated.
- ii. Understory vegetation plays a crucial role in fire management, but mapping it accurately is challenging due to the interference of the overstory canopy, making remote detection of understory vegetation difficult. Possible solutions to this challenge include using TLS data for direct mapping, employing multivariate mapping (by correlating bioclimatic conditions, topographic

variables, disturbance, and biophysical parameters), or applying multimodal data fusion through AI techniques.

- iii. Temporal latency in the development of fuel maps is a barrier to simulating fire behavior at the required time. This problem can be addressed by developing AI-based algorithms for on-demand mapping of fuel types wherever and whenever necessary.
- iv. The lack of uncertainty-aware models for fuel mapping can significantly and adversely affect the utility of fire behavior simulations. Therefore, it is necessary to employ Uncertainty Quantification (UQ) techniques to bound prediction errors. In this paper, the UQ techniques available for ML/DL models that have been deployed in wildfire fuel mapping were examined.

In conclusion, it appears that fuel mapping research can make significant leaps by utilizing the available state-of-the-art AI techniques to address the many issues and challenges that impeded progress to date.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests.

Ertugrul Taciroglu reports financial support was provided by National Science Foundation. Ertugrul Taciroglu reports financial support was provided by Amazon. Ertugrul Taciroglu reports financial support was provided by Edison International. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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