Identifying Primary Fuel Attributes Known to Influence the Fire Behavior Processes

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Abstract

This report delves into the complex nature of bushfire fuels, encompassing both living and dead vegetation, and their profound influence on fire dynamics. Examining critical attributes such as vegetation type, moisture content, fuel shape and size, fuel load, chemical composition, and arrangement (whether horizontal or vertically oriented), we explore their collective impact on fire behavior. In the subsequent sections, we present a concise overview of these primary fuel attributes, comprehensively detailing each aspect and exploring their ramifications on fire danger through the lens of remote sensing techniques. The study aims to unravel the intricate relationships between these fuel characteristics and the overarching danger posed by bushfires. Additionally, the conclusion offers a summary of diverse remote sensing methods employed for mapping various fuel attributes in the unique Australian context. Utilizing advanced remote sensing techniques enhances our understanding of spatial and temporal dynamics, contributing to a holistic approach in fire management and mitigation. The diverse range of remote sensing methods highlighted in the report underscores their significance in mapping and monitoring various fuel attributes, offering valuable insights for predicting, managing, and responding to bushfires.

Keywords: Fire behavior; fuel attributes; forest fuel monitoring and mapping; remote sensing;

Contents

1. Fuel moisture content (FMC)

The moisture content within the fuel, known as Fuel Moisture Content (FMC), stands out as a pivotal factor significantly influencing both the initiation and propagation of bushfires (Yebra et al., 2013). FMC, expressed as a percentage, represents the water content within a given fuel. Forest fuels are broadly categorized as live and dead fuels, leading to the division of FMC into Live FMC (LFMC) and Dead FMC (DFMC). Both LFMC and DFMC play crucial roles in shaping the occurrence and behavior of forest fires. However, obtaining precise and frequent estimates of FMC across spatial and temporal scales poses challenges. Local accuracy is achievable through field sampling and gravimetric methods, albeit at a high cost. However, extrapolating such measurements to broader landscape, regional, or global scales proves impractical. Alternatively, meteorological data has been explored for FMC estimation, presenting two primary challenges. Firstly, the spatial extent of meteorological data is limited, and secondly, the distribution of meteorological stations may be inadequate for FMC predictions, particularly in urban areas. Consequently, calculating FMC relies on interpolation methods, often leading to significant errors. To overcome these hurdles, remote sensing (RS) data emerges as a valuable tool for assessing FMC across extensive areas, offering fine spatial and temporal resolutions. However, it is crucial to note that the utilization of RS data for FMC assessment requires careful calibration and validation, as highlighted in this review (Yebra et al., 2013). Below, we present some of the prior studies focused on FMC estimation using remote sensing data. Subsequently, we compile a summary outlining the strengths and limitations of each remote sensing technique employed for this specific task in Table 1.

1.1. LFMC estimation using satellite products

The prevalent options for estimating LFMC from remote sensing (RS) data often involve globally accessible coarse spatial resolution datasets, such as Advanced Very High-Resolution Radiometer (AVHRR) or Moderate Resolution Imaging Spectrometer (MODIS) data. These datasets offer a combination of high temporal resolution, making them particularly suitable for operational applications. The extended time series and cost-effectiveness of AVHRR images position it as a favorable choice for operational applications, given its ability to provide valuable data with high temporal frequency. For example, García et al. (2008) conducted LFMC estimation for two vegetation types, grasslands and shrublands, in Cabañeros National Park, Spain, utilizing Advanced Very High-Resolution Radiometer (AVHRR) data along with meteorological information. However, AVHRR data presents significant limitations for Fuel Moisture Content (FMC) calculations due to the absence of Shortwave Infrared (SWIR) bands, low radiometric stability, and suboptimal spatial resolution. The deficiency in SWIR bands is particularly notable as they directly contribute to plant water absorption, offering a more direct means of estimating FMC. In a different approach, Yebra et al. (2018) employed a physically-based retrieval model to estimate LFMC from MODIS reflectance data for continental Australia. This methodology sought to enhance the accuracy of LFMC estimation by incorporating a model grounded in physical principles.

LFMC has also been estimated using medium-spatial-resolution products such as Landsat sensors. For example, Chuvieco et al. (2002) applied the Landsat Thematic Mapper (TM) sensor to estimate LFMC in Mediterranean grassland and shrubland. Their study also involved predicting fire danger using defined indices and reflectance measurements. Despite the slightly higher correlations observed with Landsat TM data, the combination of cloud cover and a temporal resolution of every 16 days might pose limitations for LFMC monitoring applications. These factors can potentially restrict the use of this type of data, even though it offers valuable insights into LFMC estimation and fire danger prediction.

WorldView-2, IKONOS, QuickBird, and GeoEye-1 represent high spatial resolution sensors that, to date, haven't been extensively utilized for Live Fuel Moisture Content (LFMC) estimation. While simple Vegetation Indices (VI) based on visible and near-infrared reflectance may offer some utility, the limited spectral range of these sensors (typically 4–8 bands covering the visible and near-infrared) hinders a comprehensive assessment of spectral characteristics, including liquid water absorption. For more effective high-resolution LFMC analysis, the upcoming WorldView-3 mission is cited as a potentially more valuable resource. This mission incorporates a 3.7 m spatial resolution Shortwave Infrared (SWIR) band, providing enhanced capabilities for LFMC estimation by offering a broader spectral range and improved sensitivity to water absorption characteristics.

The use of active microwave data is advantageous for studying Live Fuel Moisture Content (LFMC) in regions with persistent cloud cover. The wavelengths associated with active microwave data are not impeded by cloud cover, enabling researchers to gather information on LFMC even in areas where traditional optical sensors may be hindered by cloudiness. This capability makes active microwave data a valuable tool for LFMC investigations in regions prone to frequent cloud cover. In the study conducted by Fan et al. (2018), monitoring of LFMC was carried out using microwave remote sensing data. The findings of the study suggest that optical remote sensing indices are highly effective for LFMC monitoring. Looking ahead, future research is expected to explore data-fusion approaches or the integration of satellite-derived indices from both optical and microwave data to enhance global LFMC monitoring capabilities. This approach aims to leverage the strengths of different remote sensing modalities for a more comprehensive and accurate assessment of LFMC on a global scale.

The utilization of airborne hyperspectral products for estimating LFMC has demonstrated notable benefits when compared to satellite observations. This approach, involving high-resolution hyperspectral data collected from airborne platforms, enhances the precision and detail of LFMC estimation. The increased spatial and spectral resolution afforded by airborne hyperspectral products contributes to a more refined and accurate assessment of LFMC, showcasing the advantages of this method over satellite-based observations. For instance, in a semi-natural upland region dominated by Calluna vulgaris in the United Kingdom, Al-Moustafa et al. (2012) investigated the use of airborne hyperspectral data for predicting Live Fuel Moisture Content (LFMC). The study indicated that while airborne data may lack the required temporal resolution for direct LFMC estimation, it can be acquired on demand. The Hyperspectral Infrared Imager (HyspIRI) mission, designed for space-borne imaging spectroscopy, is slated to have a 19-day repeat coverage, which may be insufficient for real-time LFMC tracking. Nevertheless, this data could prove valuable for calibrating and validating LFMC estimates derived from sensors with higher temporal resolution. The combination of coarse and fine spatial resolution sensors is proposed as a strategy to provide complementary spatial information for practical LFMC assessment.

1.2. Estimation of DFMC from satellite data

For operational estimations of Dead Fuel Moisture Content (DFMC), remote sensing (RS) data emerges as a viable option. Unlike meteorological observations, RS data provides geographically comprehensive products across various scales, both spatially and temporally, depending on the sensor used. To date, the majority of studies utilizing remotely sensed data for Fuel Moisture Content (FMC) calculations have primarily focused on Live Fuel Moisture Content (LFMC), with relatively fewer studies dedicated to DFMC. Among the remotely sensed data, MODIS (Moderate Resolution Imaging Spectroradiometer) and MSG-SEVIRI (Meteosat Second Generation - Spinning Enhanced Visible and Infrared Imager) data are the most commonly employed for DFMC retrieval. MSG-SEVIRI data offers high temporal resolution, while MODIS data provides varying levels of spatial resolution. This dual utilization caters to different aspects of DFMC monitoring, considering both temporal dynamics and spatial granularity.

In a study conducted by Zormpas et al. (2017) within a complex Mediterranean ecosystem, the objective was to evaluate Landsat 8's capability to retrieve Dead Fuel Moisture Content (DFMC). The study correlated the 10-hour fuel moisture content and surface temperature reported by Remote Automatic Weather Stations (RAWS) with the Normalized Difference Vegetation Index (NDVI) and top-of-atmospheric brightness temperature. Training data were collected for the year 2015, and validation data were applied for the year 2016. Initially, DFMC was associated with the NDVI/LST ratio, but the results were deemed unsatisfactory, showing low R^2 coefficients. However, enhanced models based on DFMC and brightness temperature (BT) were developed, yielding satisfactory R^2 values. The validation using new data suggested that top-of-atmosphere brightness temperature derived from Landsat 8 could be employed to predict the spatial distribution of DFMC. Beyond Landsat 8, the study also acknowledged the potential of new sensors with high spatial, spectral, and temporal resolutions, such as Sentinel-2, for deriving water content-sensitive indices. Additionally, commonly used indices like the Normalized Difference Infrared Index (NDII) and the Normalized Difference Water Index (NDWI) were highlighted for measuring the Equivalent Water Thickness (EWT) of leaves and canopies remotely. These findings emphasize the importance of exploring a range of sensors and indices to enhance the accuracy of DFMC predictions in diverse ecosystems.

Table 1. Different remote sensing data are applied to fuel moisture content mapping (FMC).

Sensor	Country/Scale	Advantages	Disadvantages	Reference
AVHRR	Spain/Regional	• Provide high enough temporal resolution • Low cost	• Low radiometric stability • Poor spatial resolution • Lack of SWIR bands	(García et al., 2008)
Modis	Australia/National	• Time series imagery is available • Low cost • Global coverage	• Limited to canopy • Poor spatial resolution	(Yebra et al., 2018)
Landsat Thematic Mapper	Spain/Regional	• Low cost • Easy access	• Low spatial resolution • Limited to canopy • Cloud cover may limit the use of this type of data	(Chuvieco et al., 2002)
Microwave Images	France/Regional	• Not interfered by cloud cover • Penetrate into the canopy • Can capture vegetation water dynamics better than lower wavelength optical metrics (sensitive to dielectric properties)	• Spatial resolution varies and is usually low, except for TerraSAR-X • Restricted access to data (a certain number of the scene; also, some data not sharable with certain developing countries)	(Fan et al., 2018)
Airborne Hyperspectral Data	UK/Regional	• Provide detailed information • Have a fine spectral resolution	• They are unlikely to have the temporal resolution • Costly and complex	(Al-Moustafa et al., 2012)

2. Fuel types classification

A fuel type has been defined as ‘‘an identifiable association of fuel elements of distinctive species, form, size arrangement, and continuity that will exhibit characteristic fire behavior under defined burning conditions’’(Merrill and Alexander, 1987).

Identifying and mapping fuel types presents a considerable challenge, underscoring the importance of selecting an appropriate mapping method. Traditional approaches, such as field surveys, have been conventionally employed for this purpose. The primary advantage of field measurements lies in the direct interaction with the fuel, allowing for mapping based on genuine ground conditions. Consequently, field observations remain indispensable for accurately mapping fuel types. However, the significant time and financial investments required for field surveys pose challenges, making their implementation impractical for many land managers. Moreover, the necessity for regular updates to fuel type maps further compounds the difficulty of maintaining accuracy through this method. As a result, the quest for alternative and more efficient mapping approaches is imperative in order to address the limitations associated with traditional field surveys (Falkowski et al., 2005). In response to the limitations of field surveys, alternative approaches for operational fuel type mapping have emerged, with remote sensing technologies playing a key role. These technologies leverage images to discern and classify fuel types, offering solutions to the cost and spatial coverage constraints associated with traditional field surveys. Remote sensing provides a valuable tool for efficiently mapping fuel types over large areas, allowing for broader coverage and cost-effective data collection. This shift towards remote sensing addresses the challenges posed by the traditional field survey method and contributes to more effective and scalable fuel type mapping for land management purposes.

2.1. Fuel types mapping using remote sensing techniques

Remote sensing offers a versatile array of sensors and techniques to facilitate fuel type mapping. In this section, the techniques employed for fuel type mapping through remote sensing are categorized based on the type of sensor used. Table 2 succinctly outlines the advantages and limitations of each approach, providing a comprehensive overview of the diverse methods available for effective fuel type mapping (Abdollahi and Yebra, 2023).

2.1.1. Passive sensors

Multispectral remote sensing data, including sources like Modis, Landsat, SPOT, ASTER, Sentinel-2, and high-resolution data such as QuickBird and IKONOS, have been effectively utilized for mapping fuel types. However, a notable constraint of these optical data sources is their limited ability to penetrate forest canopies. This limitation becomes particularly pronounced in areas with multiple canopy layers, where these sensors may struggle to identify surface fuels effectively. Additionally, in regions with open-crowned stands where sensors can observe the ground, conventional image processing methods encounter challenges in distinguishing between surface fuel sizes and groups. Furthermore, the reflectance captured by these sensors is not directly linked to vegetation height, a crucial factor in determining fuel types. Despite their advantages, the mentioned optical data sources exhibit limitations in scenarios involving complex vegetation structures, emphasizing the need for complementary approaches and alternative sensors for comprehensive fuel type mapping (Lasaponara and Lanorte, 2006).

Hyperspectral remote sensing technologies leverage numerous continuous spectral bands to measure reflected electromagnetic radiation. This wealth of spectral information has proven to be highly beneficial for both spatial and spectral differentiation of various fire-related vegetation properties. Hyperspectral data facilitates the assessment of factors such as the distribution of bare ground, the ratio of dead-to-living plant material, vegetation moisture content, and green canopy closure. The detailed and extensive spectral bands provided by hyperspectral sensors enhance the capacity to discern and characterize diverse vegetation features related to fire behavior and fuel properties (Jia et al., 2006). The primary limitation of airborne hyperspectral images, such as those from sensors like MIVIS and AVIRIS, is their restricted spatial coverage. In contrast, satellite-based hyperspectral sensors present a more promising alternative due to their broader coverage, greater constancy, and cost-effectiveness in monitoring. Notably, sensors like Hyperion have demonstrated effective applications in mapping forest types and assessing fire risk. The utilization of satellite-based hyperspectral data offers the advantage of consistent and widespread monitoring, making it a valuable resource for large-scale assessments and long-term monitoring of vegetation properties related to fire behavior and fuel types (Keramitsoglou et al., 2008). The key aspects of the hyperspectral sensors are presented in Table 2.

2.1.2. Active sensors

LiDAR (Light Detection and Ranging) is emerging as a viable alternative to address the primary challenges posed by passive optical data in mapping fuel types. It proves particularly useful when the forest canopy obstructs the observation of surface fuels, as LiDAR can penetrate the canopy and provide valuable information about these fuels. Moreover, LiDAR can be employed to determine fuel heights, a critical factor for distinguishing between various fuel types and assessing fuel loads accurately. Beyond surface fuel mapping, LiDAR data can be leveraged to obtain additional metrics crucial for fire behavior modeling. These metrics include crown bulk density and canopy-based height, demonstrating the versatility of LiDAR in capturing detailed information about vegetation structure and characteristics relevant to fire dynamics and fuel properties (Chuvieco and Kasischke, 2007).

Active sensors, such as RADAR data, offer valuable supplementation to optically detected fuel type properties. Various experiments have been conducted to determine critical forest properties for fuel type mapping, including canopy closure, tree height, tree volume, and foliar biomass, using satellite RADAR data (Garestier et al., 2007; Smith-Jonforsen et al., 2007). Despite the satisfactory outcomes and expectations from these investigations, relatively few studies delve into the utilization of satellite RADAR data specifically for fuel type mapping. Nonetheless, RADAR data can serve as an ideal complement to LiDAR measurements. It allows for the analysis of broader areas and is generally less expensive to acquire. The combination of active sensors, such as RADAR, with other remote sensing techniques presents a comprehensive approach to effectively capture a wide range of vegetation properties relevant to fuel type mapping.

2.2. Integrated methods for fuel types mapping

In the realm of remote sensing, employing a combination of multiple fuel mapping methods and/or data sources represents a promising and innovative strategy. This approach holds potential not only for fuel mapping but also for a variety of diverse applications. One avenue involves integrating remote sensing technology with conventional techniques, proposing an inclusive methodology that combines extensive field sampling, biophysical gradient modeling, and categorization of vegetation characteristics. This integrated approach capitalizes on the strengths of each method, leveraging the spatial and spectral capabilities of remote sensing alongside the detailed insights provided by conventional techniques. By synergizing these methodologies, researchers and land managers can attain a more comprehensive and accurate understanding of fuel types and related vegetation properties. This strategy exemplifies the growing trend in remote sensing towards holistic and synergistic approaches for a wide range of environmental applications (Falkowski et al., 2005).

Relying solely on remote sensing technology, the integration of multiple sensors has proven to be a highly effective strategy. Particularly, the combination of spectrum data, often derived from Very High-Resolution (VHR) or hyperspectral sensors, with LiDAR has demonstrated significant effectiveness. This synergistic approach serves as a viable alternative for addressing the intricate nature of fuels. By merging spectrum data and LiDAR information, researchers gain the advantage of both detailed spectral information and accurate three-dimensional structural data. This combined dataset enhances the ability to discern and classify different fuel types and provides a more comprehensive understanding of vegetation structure relevant to fire behavior. The integration of diverse remote sensing technologies underscores the capacity to exploit the complementary strengths of various sensors for more robust and accurate fuel type mapping (Mutlu et al., 2008).

In Australia, particularly outlined in studies by Cruz et al. (2018) and Hollis et al. (2015), the Australian Fire Danger Rating System (AFDRS) has developed a static fuel classification and map based on the National Vegetation Information System (NVIS) and Australian Land Use Management Classification (ALUM). While this provides a foundational understanding, dynamic maps can significantly enhance the accuracy and utility of fuel classifications. Dynamic maps, facilitated by various temporal remote sensing (RS) data, involve observing and analyzing fuel types at different times. This approach allows for the identification of changes in the state of fuel types over time, providing valuable insights for bushfire modeling and aiding policymakers in informed decision-making processes. The dynamic mapping approach offers a more nuanced and up-to-date perspective on fuel conditions, contributing to a better understanding of the evolving fire risk landscape (Matthews S, 2019).

Table 2. 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

3. Fuel load estimation

Fuel load, defined as the amount of combustible material in a defined space and fuel layer, is a critical parameter in forest ecosystems, influencing fire behavior, flame length, fireline intensity, and the rate of spread (Keane, 2012). Improved predictions of fire behavior, risk assessments, and control strategies can be achieved by regularly obtaining accurate fuel load distributions across various vegetation types and scales. Two primary approaches are typically employed to obtain fuel load data. The first method involves using site-specific fuel characteristics calculated for the landscape to simulate wildfires (Elia et al., 2015). The second method adopts standard fuel parameters, such as fuel models and associated studies (Keane, 2012; Wu et al., 2011). While estimating fuel characteristics for a specific area has been identified as the optimal strategy for accurate site-specific fire simulation, field surveys pose challenges due to their high cost and time commitment, limiting their replication across diverse locations and on a regular basis (Hermosilla et al., 2013). Although the second technique is considered more cost-effective and time-efficient for obtaining fuel characteristics, it is recognized that fire simulations may be influenced by various biases when using non-site-specific input data. Striking a balance between accuracy and practicality remains a challenge in the quest for robust fuel load data for effective fire management strategies.

Indeed, the need for regularly estimating fuel parameters across various vegetation types and scales has prompted the development of novel techniques. The growing availability of advanced sensors and remote sensing technology has played a crucial role in addressing this need by providing data for modeling fuel load estimates (Abdollahi and Yebra, 2023). Researchers have actively explored a variety of remote sensing techniques to assess vegetation fuel loads, acknowledging the limitations and challenges associated with traditional methods discussed earlier. These efforts contribute to the advancement of more efficient and scalable approaches for regularly monitoring fuel parameters, ultimately enhancing our understanding of fire behavior and supporting effective fire management strategies.

For instance, in the USA, researchers have utilized various remote sensing technologies to estimate fuel loads. For example, in New Mexico, aerial photographs were employed to develop fuel load snapshots for specific areas (Scott et al., 2002). Similarly, Landsat imagery was utilized in South Dakota to create fuel load models (Reich et al., 2004), while multifrequency polarimetric synthetic aperture radar was employed in Yellowstone National Park (Saatchi et al., 2007). The first two studies noted that although the high spatial resolution fuel load models were generally good, they exhibited high errors in one of the study areas and some degree of skewed distribution. In the third study, it was found that estimates of three key fuel load characteristics provided over 70% accuracy when compared to plot measurements. However, the use of these fuel load models was limited to regions with similar climates, terrain, and soil conditions. In China, a recent study utilized a high-resolution satellite image from QuickBird and Landsat imagery to construct a fuel load model for a region in the northeast of the country. The researchers found that both QuickBird and Landsat models better estimated fine fuel loads but were less accurate for coarse fuel loads (Jin and Chen, 2012). In northeastern Spain, Arellano-Pérez et al. (2018) employed two machine learning algorithms (Random Forest and Multivariate Adaptive Regression Splines) and Sentinel-2 data to estimate the surface fuel load of pinewood. However, the model's performance was poor, possibly due to the authors' reliance solely on Sentinel-2A products as remote sensing parameters, neglecting the potential benefits of incorporating multi-source data.

D’Este et al. (2021) used multi-source remote sensing products such as Light Detection and Ranging (LIDAR), optical (Sentinel-2), and Synthetic Aperture Radar (SAR, Sentinel-1) data along with machine learning techniques for fine dead fuel load estimation for the Apulia region (southern Italy). The LIDAR factors were shown to have a higher predictive ability than the NDVI and vertical transmit/horizontal receive (VH) polarization. The most essential variables for fuel load estimation are the canopy height model (CHM), followed by canopy and vegetation cover. It is most probably linked to the fact that if the canopy's degree of height and coverage increases, the biomass of small branches, twigs, and leaves will also increase. These findings are consistent with those of (Chen et al., 2017), who used airborne/terrestrial LIDAR and multiple regression analysis for surface fuel load estimation in Australia's open eucalyptus forests. When canopy layers are stratified and dense, NDVI is unable to identify the undergrowth. Furthermore, NDVI does not provide information on vegetation structure, unlike LIDAR variables. The findings also indicate that VH polarization played a lesser role in fuel estimation. A more reasonable reason, derived from the findings of similar research, is that the Sentinel-1 satellite data have a short wavelength, resulting in minimal canopy penetration (Patel et al., 2006). For instance, Kumar et al. (2019) discovered that VH polarization acquired by Sentinel-1A and above-ground biomass assessed in the field had a negligible association. In contrast, the researchers showed a link between VH polarization collected by ALOS PALSAR and biomass. This is because the L-Band is more sensitive to backscatter values and has a higher canopy penetration as opposed to Sentinel 1-A's C-band.

In a study conducted by D’Este et al. (2021) in the Apulia region of southern Italy, multi-source remote sensing products, including Light Detection and Ranging (LiDAR), optical data from Sentinel-2, and Synthetic Aperture Radar (SAR) data from Sentinel-1, were employed in conjunction with machine learning techniques for fine dead fuel load estimation. The research found that LiDAR factors exhibited higher predictive ability compared to the Normalized Difference Vegetation Index (NDVI) and vertical transmit/horizontal receive (VH) polarization from Sentinel-1. The most crucial variables for fuel load estimation were identified as the canopy height model (CHM), followed by canopy and vegetation cover. This association is likely attributed to the fact that an increase in canopy height and coverage corresponds to an increase in biomass of small branches, twigs, and leaves. These results align with the findings of Chen et al. (2017), who used airborne/terrestrial LiDAR and multiple regression analysis for surface fuel load estimation in Australia's open eucalyptus forests. In dense and stratified canopy layers, NDVI struggles to identify undergrowth, and it does not offer information on vegetation structure as effectively as LiDAR variables. The study also indicated that VH polarization played a lesser role in fuel estimation. This observation is consistent with similar research, suggesting that Sentinel-1's short-wavelength data leads to minimal canopy penetration. For example, Patel et al. (2006) found that VH polarization acquired by Sentinel-1A had a negligible association with above-ground biomass assessed in the field. In contrast, research by Kumar et al. (2019) demonstrated a link between VH polarization collected by ALOS PALSAR (L-Band) and biomass, emphasizing the importance of wavelength sensitivity and canopy penetration in remote sensing applications for fuel load estimation.

In Australia, a study conducted in Popran National Park, New South Wales, utilized observed data and Landsat imagery for fuel load estimation. Two methods were tested: the first employed classification techniques to derive current fuel loads from predicted vegetation types and fire history, while the second relied on litterfall estimation from biomass. The results indicated that the classification method tended to overestimate fuel loads, while the biomass method exhibited less uncertainty (Brandis and Jacobson, 2003). Another study focused on wildfire risk modeling in the Mojave Desert, Nevada, using lower spatial but higher temporal resolution satellite products. This research incorporated NDVI into the fuel load prediction model, along with other climate and topography parameters (Van Linn et al., 2013). Additionally, Chaivaranont (2018) concentrated on monitoring grassland degree of curing (DOC) and fuel load across Australia using satellite observations. New methods were developed for estimating grassland DOC and fuel load by leveraging recently developed microwave-based satellite data (VOD) and the Moderate Resolution Imaging Spectroradiometer (MODIS). Table 3 summarizes the advantages and limitations of different remote sensing data for fuel load mapping. According to the table, integrating multiple sources of remote sensors can enhance the success and effectiveness of fuel load estimation, representing a promising tool for such assessments.

Table 3. Different remote sensing data are applied to fuel load mapping.

Sensor	Country/Scale	Advantages	Disadvantages	Reference
Aerial Photographs		• Exhibited a high degree of relative accuracy	• Limited to certain regions that have similar climate, terrain, and soil conditions • Restrictive area coverage	(Scott et al., 2002)

Landsat Imagery	USA/Regional	• Easy access	• Limited spatial resolution • Limited to canopy	(Reich et al., 2004)
Multifrequency Polarimetric Synthetic Aperture Radar (SAR) Imagery		• Have the potential to predict canopy fuel parameters with accuracy suitable for forest fire models • Able to penetrate through clouds and collect data at night • Longer wavelengths are able to penetrate the forest canopy.	• Limited to certain regions that have similar climate, terrain, and soil conditions	(Saatchi et al., 2007)
QuickBird and Landsat Imagery	China/Regional	• Estimates from the QuickBird data outperformed those from the Thermatic Mapper with a lower spatial resolution. • QuickBird images with the high spatial resolution are still useful for measuring fine fuels	• Coarse fuel loads were not estimated as well using both satellite images • High-resolution images are expensive • Limited to canopy	(Jin and Chen, 2012)
Sentinel-2		• Add useful information regarding fuel variables on the surface and canopy	• Does not give information on the structure of the vegetation • Unable to discern undergrowth	(D’Este et al., 2021)
Synthetic Aperture Radar (SAR, Sentinel-1)	Italy/Regional	• Independence from cloud cover and solar illumination • Good spatial/temporal resolution	• C-band images of Sentinel-1 are less sensitive to fine fuel load	(D’Este et al., 2021)
LIDAR		• LIDAR variables showed a higher predictive power than the NDVI and vertical transmit/horizontal receive (VH) polarization	• Expensive to run • Not all areas are covered unless extensive field campaign efforts are deployed	(D’Este et al., 2021)

Airborne and Terrestrial LIDAR	Australia/ Regional	• LiDAR-derived independent variables improved the efficiency and the accuracy in developing the predictive model of surface fuel load for eucalypt forests with high a spatial resolution	• Surface fuel load estimations are limited to the open eucalyptus forests	(Chen et al., 2017)
LANDSAT		• Easy access • Freely available	• The method overestimated fuel loads • Saturation of the optical signal at high biomass density and cloud cover	(Brandis and Jacobson, 2003)
Microwave-based Satellite Data (VOD) and MODIS	Australia/National	• Include greater repeat frequency • The availability of a suite of products • Global coverage	• Limited to surface fuel load estimations • Limited to Grassland • Modis cannot observe the surface when cloud cover is present	(Chaivaranont, 2018)

4. Fuel continuity

Fuel continuity, concerning ladder and surface fuels, denotes the extent to which fuel particles are distributed in a fuel bed in an uninterrupted manner, influencing the fire's capacity for sustained spread and combustion (NWCG, 2018). Fuels are dispersed both horizontally and vertically, and fuel continuity encompasses the distribution of fuels in both dimensions. Continuous fuels are indispensable for the fire to propagate from the forest floor to the canopy or across the landscape (Keane et al., 2001). Horizontal fuel continuity elucidates how fuels are spatially interconnected across landscapes, occurring on various geographical scales, spanning from meters to kilometers. The potential for fire to move from one area of the landscape to another is largely dictated by the continuous connection of fuels on the ground, such as litter fuel beds or grass. Vertical fuel continuity delineates how effectively biomass fuels are linked from the soil/duff interface to the tree tops' needles. Ladder and aerial fuels are those connecting the forest floor (litter and duff) to the upper reaches of canopy trees, encompassing the lower branches of canopy trees, small trees, shrubs, and grasses. These continuous fuel ladders between the surface and canopy fuels facilitate the spread of fire into the canopy (Cooper, 1960).

Instead of relying solely on field personnel, remote sensing techniques, particularly LiDAR, prove to be effective methods for obtaining precise forest structural data across diverse scales (Andersen et al., 2005). LiDAR data enables the provision of vertical and horizontal information with high accuracy and spatial resolutions (Lim et al., 2003). The literature contains studies exploring the utility of remote sensing data, specifically LiDAR, for characterizing forest structures (Andersen et al., 2006; Andresen et al., 2019). For instance, Aragoneses and Chuvieco (2021) implemented a methodology to map fuel types on a regional-continental scale (e.g., Balearic Islands, Spain) using Sentinel-3 images, horizontal vegetation continuity, biogeographic regions, and biomass data. In determining horizontal fuel continuity, they utilized the 2019 global MODIS vegetation continuous field collection 6 version 1 (Townshend et al., 2011), which provides the percentage of tree and non-tree vegetation cover (0–100%) at a resolution of 250 meters. However, the optical remote sensing data employed in this study was confined to a few species and tended to lack sensitivity to variations in forest structure.

Olszewski and Bailey (2022) employed LiDAR acquisitions captured before and after a substantial forest restoration project in the Malheur National Forest, located in eastern Oregon, USA. Their objective was to evaluate changes in vertical fuel continuity. Although the primary focus of their study centered on using LiDAR data to gauge vertical fuel continuity in a dry forest landscape, further research could lead to methodologies for assessing additional hazard fuel features through LiDAR data. Examples of such features include tree distribution by size class or horizontal fuel continuity. These approaches need not be limited to airborne LiDAR; terrestrial LiDAR stands as an alternative that could provide more accurate data on below-canopy conditions (Donager et al., 2018). Additionally, the exploration of drone-acquired photogrammetry and structure-from-motion is worth considering (Cunliffe et al., 2016). Skowronski et al. (2007) quantified forest structure and ladder fuels, defined as vertical fuel continuity between the understory and canopy, in the New Jersey Pinelands, USA. They utilized Forest Inventory and Analysis (FIA) data, intensive biometric measurements in plots, and a single-beam, first-return profiling LiDAR measurements of canopy height. However, when specific regions were examined independently, correlations for Oak/Pine and Pine/Scrub Oak stands were found to be low. Novo et al. (2020) introduced a technique for identifying vegetation continuity (both horizontal and vertical) within two distinct groups, such as shrubs and trees, using aerial LiDAR point clouds. They applied point cloud processing techniques in conjunction with LiDAR data to assess areas around roads in the northwest region of Spain. Their focus was specifically on the buffer distance between road vegetation, aligning with the fire regulations in Galicia. In a separate study, González-Ferreiro et al. (2017) utilized data from low-density airborne laser scanning (ALS) and the Spanish national forest inventory to construct a framework for modeling the vertical profile of accessible canopy fuel in pine stands, encompassing two species. The National Forest Inventory (NFI) in Spain currently stands as the sole source of information on canopy fuel complex properties at both national and regional scales. However, this inventory method can be time-consuming, taking several years to complete, and lacks complete spatial coverage (Boudreau et al., 2008). Recognizing ALS's ability to estimate the three-dimensional structure of vegetation and other forest features at various scales, it proves to be a valuable supplementary data source for defining the canopy fuel stratum.

In Australia, the significance of fuel structural characteristics in influencing fire behavior and suppression ease was underscored by the Australian bushfire study, Project Vesta (Gould et al., 2008). Fuel structure in this context is categorized into five layers based on their horizontal arrangement and vertical position within the forest profile, encompassing canopy fuels, shrubby elevated fuels, near-surface fuels, litter fuels (surface fuels), and bark fuels (Gould et al., 2008). Presently, guidelines for measuring fuel structure through visual assessment have been developed for south-eastern Australia and Western Australia, facilitated by the Overall Victorian Fuel Hazard Assessment Guide and Project Vesta, respectively. Visual assessments involve the rapid evaluation of fuel structural characteristics such as depth, height, percentage cover, horizontal continuity, and vertical arrangement at distinct fuel layers. While visual assessments are quick, they may be subjective, inconsistent, and constrained by the complexity of local terrain. Consequently, the development of an efficient and accurate method for assessing fuel structural characteristics holds significance in bushfire-related studies and forest fuel resource management (Andersen et al., 2005).

Due to its capability for highly accurate three-dimensional (3D) measurements, LiDAR proves invaluable in reconstructing the vertical layout of both the understory and overstory vegetation (Andersen et al., 2005). A notable example is the work of Chen et al. (2016), who developed a methodology utilizing a geographic information system and terrestrial LiDAR data to automatically assess forest fuel structural properties. This includes the vertical and horizontal arrangement of fuel strata. However, LiDAR encounters challenges when estimating bark fuels due to the complexity of describing texture and assessing the impact of bark on suppression challenges, requiring more sophisticated empirical knowledge. Various limitations, such as scale (both vertical and horizontal), scanning angle, and position, constrain the use of Terrestrial Laser Scanning (TLS) in estimating and monitoring forest fuels. A more comprehensive evaluation of forest fuel hazards, along with overcoming these limitations, can be achieved by combining terrestrial and airborne LiDAR measurements. Table 4 provides a summary of the advantages and drawbacks associated with different remote sensing data for mapping fuel continuity.

Table 4. Pros-cons of different remote sensing data applied to fuel continuity mapping.

Fuel Continuity	Sensor	Country/Scale	Challenges	Opportunities	Reference
Horizontal	Landsat Thematic Mapper Modis	Spain/ Regional	• Restricted to a few species and small sites • Optical data tend to lose sensitivity to forest structure variation	• Integration of multispectral/hyperspectral and LiDAR data	(Aragoneses and Chuvieco, 2021)
	Airborne LiDAR	Spain/Regional	• Only considered the buffer distance between road vegetation	• Terrestrial LiDAR is an option and may be able to gather more accurate below-canopy data	(Novo et al., 2020)

			• Limited to two groups		
	Terrestrial LiDAR	Australia/Regional	• Difficulty in assessing bark fuels • The application of TLS is restricted by scanning angle, scale (vertical and horizontal), and position	• Terrestrial/airborne LiDAR and hyperspectral observations can be integrated to provide a more complete forest fuel hazard assessment	(Chen et al., 2016)
Vertical	Airborne LiDAR	USA/Regional	• Applied only across a dry forest landscape • Limited coverage • Don’t consider below-canopy data	• Terrestrial LiDAR and drone-acquired photogrammetry and structure-from-motion are options and may be able to gather more accurate below-canopy data	(Olszewski and Bailey, 2022)
	Forest Inventory data Low-density airborne laser scanning (ALS)	Spain/Regional	• Costly/time-consuming • Does not yield full spatial coverage • Less effective in denser areas • Limited to two species	• Terrestrial LiDAR, drone-acquired photogrammetry and ALS can be integrated to provide complete information	(Novo et al., 2020) (González-Ferreiro et al., 2017)
	Terrestrial LiDAR	Australia/Regional	• Difficulty in assessing bark fuels • The application of TLS is restricted by scanning angle, scale (vertical and horizontal), and position	• Terrestrial and airborne LiDAR observations can be integrated to provide a more complete forest fuel hazard assessment	(Chen et al., 2016)

5. Fuel chemical content

The heat yield of combustible volatiles and the ignition temperature of fuel are determined by the chemical composition of the fuel. Specific elements within the fuel's chemical content, such as volatile oils and waxes, contribute to the spread of fire even in the presence of high moisture content. On the other hand, elements like mineral content may diminish fire intensity when moisture content is low (Gale et al., 2021). Traditionally, these measurements have been conducted through time-consuming field data collection, providing information on a very limited scale. The integration of remote sensing with ecosystem models presents an alternative method for estimating forest ecosystem function on a regional scale. Fuel chemical composition stands out as a crucial forest characteristic, offering insights into ecosystem processes, and it can be remotely sensed (Wessman et al., 1988). Numerous studies have explored the relationships between canopy chemistry and remotely sensed data across various forest ecosystems (Johnson et al., 1994; Peterson et al., 1988). This approach provides a broader understanding of forest characteristics and contributes to the efficient estimation of forest ecosystem function at a regional level.

In these investigations, near-infrared (NIR) spectral data within the range of 1100–2500 nm have been correlated with field-measured foliar chemistry parameters, including cellulose, nitrogen, and lignin. The data for these studies were collected using the Airborne Imaging Spectrometer (AIS) and the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS). While these studies have showcased the potential utility of remote sensing in estimating foliar chemistry, the remote sensing of chemical attributes relevant to fuel heat content and flammability faces current limitations. The challenge lies in the difficulty of measuring such attributes in the field or laboratory (Varner et al., 2015), coupled with ongoing debates about their significance in full-scale fire behavior and their exclusion from many fire behavior models (Fernandes and Cruz, 2012). Therefore, the fusion of airborne full-waveform systems, hyperspectral, and lidar techniques emerges as a promising approach to mitigate uncertainty in retrieving fuel chemical properties. This integrated methodology holds the potential to advance the remote sensing of chemical fuel attributes and contribute to a more comprehensive understanding of their role in fire behavior.

6. Fuel shape

Fuel shape plays a crucial role in determining the effectiveness of heat transfer to fuel molecules, the residence time of combustion, and the susceptibility of fuel elements to drying. The dimensions of flames, combustion sustainability, and the aerodynamics of firebrands are all influenced by the shape of the fuel. Fire propagation relies on the transfer of heat generated by reactions, such as pyrolysis reactions, to neighboring fuel. The importance of a specific heat transmission mechanism in fire spread is primarily dictated by the burning conditions (Albini, 1985). In the context of wildfires, the conductivity of fuel is typically low (Luke and McArthur, 1978). Consequently, heat transfer is most efficient for fuels with a large surface area relative to volume, such as leaves and small twigs. Fine fuel elements, often thinner than 4–6 mm, experience radiative pre-heating and maximal combustive heat release as a single phase (Barboni et al., 2017). Additionally, finer fuel elements exhibit higher sensitivity to short-term atmospheric moisture fluctuations, resulting in increased flammability during dry weather (Rothermel, 1986). Fuel shape influences fuel ignition time, combustion duration, and flame length by determining the surface area-to-volume ratio

(Zylstra et al., 2016). Furthermore, fuel shape dictates fuel element aerodynamics, influencing firebrand behavior and spotting, which can be a major mechanism of fire spread under certain conditions (Cruz et al., 2012). Factors such as curvature, length-to-width ratio, and size of firebrands have been identified as key elements affecting their behavior (Almeida et al., 2011; Ellis, 2011). Understanding the intricate interplay between fuel shape and fire behavior is crucial for developing effective wildfire management strategies.

However, in the literature on remote sensing studies, there is a notable lack of detailed presentation on fuel element size and shape, likely stemming from the inherent complexity of describing these features, particularly given the relatively coarse resolution of many existing remote sensing techniques. Despite this limitation, the importance of identifying fine fuel in forests is underscored by the emphasis placed on it in both the understanding and modeling of fire behavior. This focus is distinct from considerations of above-ground biomass, coarse woody debris, or total fuel load. The observed shortcomings in these studies may indicate a mismatch between the fuel attributes that significantly influence fire behavior and the current capabilities of remote sensing technologies and field sampling procedures (Gale et al., 2021). Bridging this gap is essential to enhance our understanding of fire behavior and improve the effectiveness of remote sensing applications in the context of fine fuel identification and assessment.

After conducting a detailed review and explanation of the application of remote sensing techniques for individual fuel attributes, a concise overview of the various types of remote sensing data utilized for mapping different fuel attributes in Australia was provided in Table 5. The summary encapsulates the diverse methods employed to capture crucial information about fuel characteristics across the country. Additionally, opportunities and methods for addressing the challenges and limitations inherent in existing approaches for mapping fuel attributes were presented. This information aims to contribute to the improvement of methodologies, offering insights on how to overcome obstacles and enhance the accuracy and scalability of fuel attribute mapping across Australia. The goal is to facilitate the acquisition of up-to-date information on a large scale, thereby advancing the understanding of fuel dynamics in the context of fire management and ecology.

Table 5. Challenges-opportunities of various remote sensing data used for different fuel attribute mapping for Australia.

Fuel Attribute	Remote Sensing Data	Country/ Scale	Limitations	Opportunities	Reference
Fuel Moisture Content	Optical data (e.g., Modis, Sentinel-2)	Australia/ National	• Limited to canopy • Cloud cover may limit the use of this data	• Improve accuracy • Merge with different RS • Use active microwave images • Use airborne hyperspectral data for local/regional studies	(Yebra et al., 2018)
Fuel Type Classification	Doesn't exist	Australia/ National	• Based on inventory data • Static map	• Improve the map • Make dynamic map • Combine various temporal RS data	(Matthews S, 2019)

				• Spatial resolution can be improved •	
Fuel Quantity	Microwave-based satellite data (VOD) and MODIS Airborne and terrestrial LIDAR	Australia/ National Australia/ Regional	• limited to Grassland • Cloud cover may limit the use of this data • Surface fuel load estimations are limited to the open eucalyptus forests	• The integration of multiple sources of remote sensors can be more successful and represents a promising tool for estimating fuel loads • Extend to large-scale and various fuel types	(Chaivaranont, 2018) (Chen et al., 2017)
Fuel arrangement (vertical and horizontal continuity)	Optical data (e.g., Modis) Terrestrial LiDAR	Australia/ Regional	• Restricted to a few species and small sites • Optical data tend to lose sensitivity to forest structure variation • Difficulty in assessing bark fuels • The application of TLS is restricted by scanning angle, scale (vertical and horizontal), and position	• Integration of multispectral/hyperspectral and LiDAR data • Terrestrial and airborne LiDAR observations can be integrated to provide a more complete forest fuel hazard assessment	(Chen et al., 2016)
Fuel Shape	________	Local	• The difficulty of characterizing these attributes • Given the relatively coarser resolution of most current remote sensing systems	• The recent development of airborne full-waveform systems/Multispectral LiDAR/Hyperspectral techniques has resulted in the increased recent application of this technology for the estimation of fuel attributes	________

Fuel Chemical Content	Airborne Imaging Spectrometer (AIS) and the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS)	Local	• The remote sensing of this sub–fuel element is currently limited • The difficulty of measuring such attributes in the field or laboratory	• Fusion of airborne full-waveform systems, hyperspectral and lidar techniques can reduce uncertainty in the retrieval of fuel chemical properties.	(Johnson et al., 1994)

7. Field measurements

Obtaining spatially extensive and temporally frequent estimations of fuel characteristics poses significant challenges. Localized methods such as field sampling and gravimetric approaches are effective but come with high costs. Additionally, field sampling lacks the capacity to generalize measurements to regional or global scales. In contrast, remote sensing (RS) data offers the potential to estimate fuel properties with fine spatial and temporal resolution over large areas. However, this data must undergo calibration and validation processes, as highlighted in this review. For the effective calibration and validation of satellite-based techniques used to estimate various fuel attributes, field measurements are indispensable. Yet, creating these field measurements presents challenges, particularly in ensuring their spatial equivalence to RS data. The fundamental constraint lies in the spatial scale of sampling. Therefore, to enable a meaningful comparison with satellite-based measurements, field measurement of fuel attributes necessitates careful considerations (Yebra et al., 2013):

(1) Maintaining detailed site metadata, including sampling locations and dates, is crucial for comprehensive data documentation. While the center coordinates of the sampling site are typically adequate, providing a polygon around the perimeter of the sampling site proves even more valuable. Consistently sampling the same site whenever possible is essential for establishing a long-term record of fuel properties at that location. This approach ensures continuity and facilitates meaningful time-series comparisons. It's important to note that even slight alterations in sampling due to different slopes or aspects can introduce variability, making it more challenging to compare time-series data. Therefore, efforts should be made to minimize such variations and maintain consistency in sampling procedures to enhance the reliability and comparability of the collected data over time.

(2) To facilitate practical comparisons between fuel attributes and remote sensing (RS) data, it is essential to ensure that the area surrounding fuel sample locations is as homogeneous as possible in terms of vegetation and topography. This homogeneity reduces the potential for confounding factors that could introduce variability in the data and allows for more meaningful and accurate comparisons between ground-based measurements and remote sensing observations. A consistent and well-defined sampling environment enhances the reliability of the results and helps establish robust relationships between field data and RS-derived information.

(3) When selecting sites for fuel attribute sampling, it is advisable to avoid mixed vegetation locations and, instead, prefer sites that are predominantly dominated by a single vegetation type. This approach helps ensure homogeneity in the sampled areas, reducing the complexity introduced by multiple vegetation types. Sites dominated by a single vegetation type provide a more focused and clear representation of the characteristics of that particular vegetation, enhancing the accuracy and reliability of the collected fuel attribute data. This targeted sampling strategy contributes to more effective comparisons with remote sensing data and improves the overall quality of the dataset.

A comprehensive and standard sampling protocol should address several key aspects to ensure consistency and reliability in data collection (Yebra et al., 2013). These elements include:

(i) **Plot size:** Clearly define the size of the sampling plot to ensure uniformity across measurements.

(ii) **Best time to collect samples:** Specify the optimal time for collecting samples to minimize variations due to seasonal or diurnal changes.

(iii) **Handling rain:** Provide guidelines on what to do if rain falls during the sampling process to mitigate potential impacts on the collected material.

(iv) **Type of material to harvest:** Clearly outline the specific types of vegetation or fuel material to be harvested in line with the objectives of the study.

(v) **Quantity and number of samples:** Define how much material and how many samples per plot should be collected to ensure representative and statistically meaningful data.

(vi) **Details on the weighting process:** Specify the procedures for weighing collected material to maintain consistency and accuracy in measurements.

(vii) **Drying procedure:** Provide information on the drying process, including duration and conditions, to standardize moisture content measurements.

(viii) **Material for sample transfer:** Outline the material or method to seal the samples for transfer to the laboratory, ensuring their integrity during transportation.

A well-defined sampling protocol ensures that data collected from different locations and times are comparable, contributing to the overall reliability and quality of the study.

8. Implications and Future Directions

This report presents a thorough overview of the identification of primary fuel attributes known to influence fire behavior modeling. Various remote sensing techniques have been employed in recent years to evaluate key fuel properties, including moisture content, fuel type, fuel load, fuel continuity, fuel chemical content, and fuel shape. The primary focus of the report is on elucidating the remote sensing technologies used to quantify diverse fuel attributes across distinct categories and layers, exploring their implications for understanding fire behavior processes. The report covers the predominant techniques employed in each study and provides examples of ongoing research. Limitations identified in the scrutinized studies largely stem from the inherent constraints of existing remote sensing technologies. Accurately estimating fuel properties, especially across different layers, presents challenges, and relying solely on a single remote sensing data source may not always provide a comprehensive approach to characterizing fuel attributes. The exploration of innovative approaches for fuel properties estimation, aligned with contemporary technology's capabilities and limitations, is conceivable with continuously advancing remote sensing techniques. As a result, significant strides in the utilization of remote sensing technology and anticipated advancements in sensor technology offer promising prospects for the evolution of fuels assessment. Future research endeavors are expected to enhance existing methodologies while integrating emerging technologies such as photogrammetry and unmanned aerial vehicles (UAVs) for precise fuels mapping at sub-meter scales. Furthermore, the integration of advanced machine learning algorithms is poised to play a crucial role in ensuring accurate analysis and prediction of fuel dynamics.

Author Contributions

Conceptualization, A.A. and M.Y.; conduction of primary literature review, summarization of relevant research studies, and identification of key themes and findings, A.A.; writing—original draft preparation and editing, A.A.; supervision, M.Y.

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Conflicts of Interest

The authors declare no conflict of interest.

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