Remote Sensing in Ecology and Conservation Open Access

REVIEW

Leveraging the next generation of spaceborne Earth observations for fuel monitoring and wildland fire management

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Keywords
Earth observation, fuel load, fuel management, fuel moisture, lidar, wildfire

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Editor: Prof. Mat Disney
Associate Editor: Prof. Jin Wu

Received: 15 January 2024; Revised: 6 June 2024; Accepted: 3 July 2024

doi: 10.1002/rse2.416

Abstract

Managing fuels is a key strategy for mitigating the negative impacts of wildfires on people and the environment. The use of satellite-based Earth observation data has become an important tool for managers to optimize fuel treatment planning at regional scales. Fortunately, several new sensors have been launched in the last few years, providing novel opportunities to enhance fuel characterization. Herein, we summarize the potential improvements in fuel characterization at large scale (i.e., hundreds to thousands of km^2) with high spatial and spectral resolution arising from the use of new spaceborne instruments with near-global, freely-available data. We identified sensors at spatial resolutions suitable for fuel treatment planning, featuring: lidar data for characterizing vegetation structure; hyperspectral sensors for retrieving chemical compounds and species composition; and dense time series derived from multispectral and synthetic aperture radar sensors for mapping phenology and moisture dynamics. We also highlight future hyperspectral and radar missions that will deliver valuable and complementary information for a new era of fuel load characterization from space. The data volume that is being generated may still challenge the usability by a diverse group of stakeholders. Seamless cyberinfrastructure and community engagement are paramount to guarantee the use of these cutting-edge datasets for fuel monitoring and wildland fire management across the world.

Introduction

Wildland fires are essential ecological processes significantly altered by anthropic activities (Bowman et al., 2013; Kelly et al., 2020; Pais et al., 2023). A direct consequence is a notable decline in global burned area that affects ecosystems that depend on fire (Andela et al., 2017) by leading to losses in biodiversity (Fidelis, 2020; Rosan et al., 2019) and ecosystem functioning (Bond et al., 2005; McLauchlan et al., 2020). On the other hand, the occurrence of extreme fire events, wherein large areas are severely burned, has escalated in the last decades (Adams et al., 2020; Fidelis et al., 2018; Lizundia-Loiola et al., 2020; Stavros et al., 2014), causing social, economical, and environmental damages (Tedim et al., 2018). Such events can become even more frequent with warming and drying from climate change and commensurate changes in fire season length and severity (Abatzoglou et al., 2019; Jain et al., 2022; Pausas & Keeley, 2021). Fire management has become a necessity to ensure that wildland fires occur in the appropriate frequency, intensity, and timing to maximize only their positive effects (Bowman et al., 2020).

Most of the strategies for fire control focus on fuel management, as other factors may be rather difficult to control (e.g., weather and topography) (Chuvieco et al., 2014; Duff et al., 2017; Pettinari & Chuvieco, 2020). Reference data for fuel characterization are traditionally dependent on field samples that may lack temporal and spatial representation. Alternatives based on remote sensing technologies are often necessary for spatially explicit fuel characterization used in management decisions (Gale et al., 2021). Fortunately, the increasing availability of resources that are coming from the remote sensing field can support fire managers worldwide in achieving this critical goal.

Remote sensing with spaceborne sensors is a prominent technique to characterize fuels over large areas. The associated costs to launch satellite systems can be on the order of millions of dollars ($U.S.) for large satellites (e.g., >1000 kg such as Landsat), but the information they provide far exceeds those costs (Craglia & Pogorzelska, 2020; Straub et al., 2019). This is particularly evident when data and products are made publicly available (Turner et al., 2015; Wulder & Coops, 2014). A successful example comes from NASA's Landsat program initiated in 1972. The long-term data archives from Landsat have been made freely available for users worldwide since 2008. Similarly, the European Copernicus program has adopted open policies for the Sentinel missions since 2013 (Jutz & Milagro-Pérez, 2020). The adoption of open data policy from these two major Earth observation programs resulted in a significant increase of users and insights to support advances in many science fields, including fire management (Masek et al., 2020; Wulder et al., 2022; Zhu et al., 2019).

There are several crucial topics to explore concerning the use of spaceborne remote sensing data for supporting fire management (Moore, 2019). In line with this, the impact of fires on the environment was ranked 1st among various biodiversity metrics to be measured from space (Skidmore et al., 2021). Furthermore, a significant part of research seems focused on Mediterranean and temperate forests (Gale et al., 2021), and fuel classification systems may not be available for many of the fire-prone ecosystems worldwide (Abdollahi & Yebra, 2023)—such as tropical savannas, which are essential for Earth's carbon budget and biodiversity (Abel et al., 2020; Abreu et al., 2017). Having globally available data for fuel characterization is a promising asset to support advances in fire research, management, and policy making.

Even with over 50 years of space-based Earth observations (Ustin & Middleton, 2021), we are in a new phase where freely available data from spaceborne sensors at finer spatial, spectral, and temporal resolutions are becoming available. The objective of this article is to identify the benefits arising from a new generation of spaceborne sensors that can be used for fuel characterization. We provide a summary of the needs and describe the key characteristics of spaceborne sensors launched in the last 5 years (2018–2022) to support advances in fuel characterization at large scales. We further discuss upcoming missions and tools to deal with the large data volumes from these spaceborne sensors.

Characterizing fuels in wildland fire science

Fuels are any combustible material which in the context of wildland fires includes the organic matter from both live and dead vegetation (Duff et al., 2017; McLauchlan et al., 2020). A wide range of fuel characteristics can be measured to determine the proportion of the total fuel data would burn under different environmental conditions. This is required as fire-prone ecosystems vary in vegetation structure, composition, and dynamics (Hollis et al., 2015). A common practical approach for describing fuel attributes in different ecosystems comes from classifying the attributes into homogeneous groups that have similar responses to fire. The groups are defined as "fuel types" or "fuel models" and are usually associated with specific applications (Abdollahi & Yebra, 2023; Aragoneses & Chuvieco, 2021; Arroyo et al., 2008; Keane, 2013; Riccardi et al., 2007). For instance, the McArthur (McArthur, 1966) system for Australia provides a straightforward way to monitor fire danger for two vegetation types: forest and grassland (Abdollahi & Yebra, 2023; McArthur, 1966). On the other hand, the Northern Forest Fire Laboratory (NFFL) system (Anderson, 1982) defines 13 classes that can be used for fire behavior modeling. The NFFL includes classes such as short grasses, hardwood litter, and logging slash. Scott and Burgan (2005) have also introduced 40 fuel models that may supplant NFFL in some applications. Overall, we see that the classification systems are practical but tend to be only locally applied. They are not presently available for all fire-prone ecosystems in the world and their transferability may be challenging (Abdollahi & Yebra, 2023).

Integrating field information into remote sensing approaches offers opportunities to incorporate additional variables for fuel characterization (Dickman et al., 2023; Gale et al., 2021). Since fire is a physical process, there are core biophysical and biochemical variables determining how fire will ignite and spread (Sullivan, 2017a, 2017b; Van Wagtendonk, 2006). Following Gale et al. (2021) these variables might be grouped as: (i) sub-fuel elements, such as biochemical compounds and water, (ii) fuel elements, such as particle size and shape, and (iii) fuel assemblages such as quantity and distribution.

Biochemical compounds are related to fuel's emissions and flammability (Weise & Wright, 2014). Flammability can be summarized as a combination of ignitability (how easy the fuel ignites), combustibility (how intense is the combustion), consumability (how much of the fuel can be entirely combusted), and sustainability (how long the fuel burns) (Anderson, 1970; Guerrero et al., 2021; Martin et al., 1993; Popović et al., 2021; White & Zipperer, 2010). In vegetation, chemical elements such as cellulose, lignin, and resins are involved in combustion and are highly variable depending on the species and ecosystem. Incombustible elements such as water also participate in the fuel's reactions to fire. The fuel moisture content (FMC) is a determinant component delaying fire ignition, spread rate (Chuvieco, 2009), and the partitioning of gasses that will be emitted from a fire. In dead vegetation, FMC is affected by variations in meteorological and microclimate conditions (Cawson et al., 2020; Matthews, 2014; Pickering et al., 2021; Rakhmatulina et al., 2021). In live vegetation, the FMC depends on plant physiology, adaptive traits, and soil water availability (Nolan et al., 2020, 2022; Scarff et al., 2021). Fuel particle size and shape are also related to fuel flammability (Van Wagtendonk, 2006). Finer particles are more susceptible to faster heat exchange and water removal (Andrews, 2018; Rothermel, 1972). The surface area-to-volume ratio of particles has been one of the main descriptors of fuel particle size incorporated into fire behavior models (Essaghi et al., 2016). Finally, the aggregation and arrangement of fuel components is a crucial determinant of fire ignition and spread (Gale et al., 2021). The amount of material available for burning, the fuel load, is directly related to the amount of energy released from a fire (Wooster et al., 2005) and the carbon emissions (Van Wagtendonk, 2006) when conditions are favorable for burning (e.g., low moisture). Fuels can be horizontally or vertically connected, facilitating fire spread. For example, the horizontal distribution of fuels can be determinant to fire final extent. Meanwhile, vertically connected fuels can facilitate canopy fires that are harder to control (Menning & Stephens, 2007; Reszka et al., 2020). Many species-specific traits are important for how all these fuel metrics are present and will affect fire behavior (Richter et al., 2019). For instance, traits such as leaf shape, bark thickness, and resin concentration can affect flammability (Varner et al., 2022). Furthermore, seasonal dynamics, physiological and phenological traits (e.g., leaf decay and decomposition) can affect how fuels accumulate (Sánchez-López et al., 2023). When remote sensing captures all these biochemical and biophysical aspects that control fire combustion and behavior, it offers a chance to move away from site-specific to transferable fuel characterization approaches.

Spaceborne remote sensing for large-scale fuel characterization

Several variables associated with vegetation traits can be retrieved from spaceborne remote sensors and associated with the fuel characteristics. The most common ones are summarized as the Remote Sensing Enabled Essential Biodiversity Variables (RSE-EBVs) (Skidmore et al., 2021) (Figure 1). RSE-EBVs can be retrieved either directly (e.g., canopy height) or derived through empirically and physically based approaches (e.g., using aboveground biomass models) (Duff et al., 2017; Franke et al., 2018; Keane et al., 2001; Lamelas-Gracia et al., 2019; Verrelst et al., 2019; Yebra et al., 2018). Biochemical components of fuels are often retrieved with passive sensors, whereas active sensors are more suitable for retrieving vertical structure and fuel load (Szpakowski & Jensen, 2019; Veraverbeke et al., 2018).

Detailed spectral information is crucial for assessing fuel biochemical compounds and FMC. For example, FMC is a commonly estimated fuel attribute using spaceborne sensors (García et al., 2020; Miller et al., 2023; Yebra et al., 2018). This is facilitated by the existence of known absorption features related to liquid water in the near-infrared (NIR, ~750–1100 nm) and short-wave infrared (SWIR, ~1100–2500 nm) spectral regions, typically centered at about 970, 1200, 1450, and 1940 nm (Knipling, 1970) (Figure 2). Furthermore, water's influence on transpiration affects surface temperature and the emitted energy from leaves (Gerhards et al., 2019). Sensors capable of capturing thermal infrared range (TIR, ~2500–14 000 nm) range of the spectrum (Neinavaz et al., 2021) have the potential to detect the temperature changes to help understand the effects related plant water stress. In addition, the plant water status impacts photosynthesis that can be linked to pigment content and the emission of solar induced fluorescence (Gerhards et al., 2019; Meroni et al., 2009). Similarly, structural carbon-based components (e.g., cellulose and lignin) and nutrients (e.g., N, P, and K) are responsible for part of the variability in the spectral response of vegetation in the NIR and SWIR regions (Kokaly et al., 2009; Ustin et al., 2004).

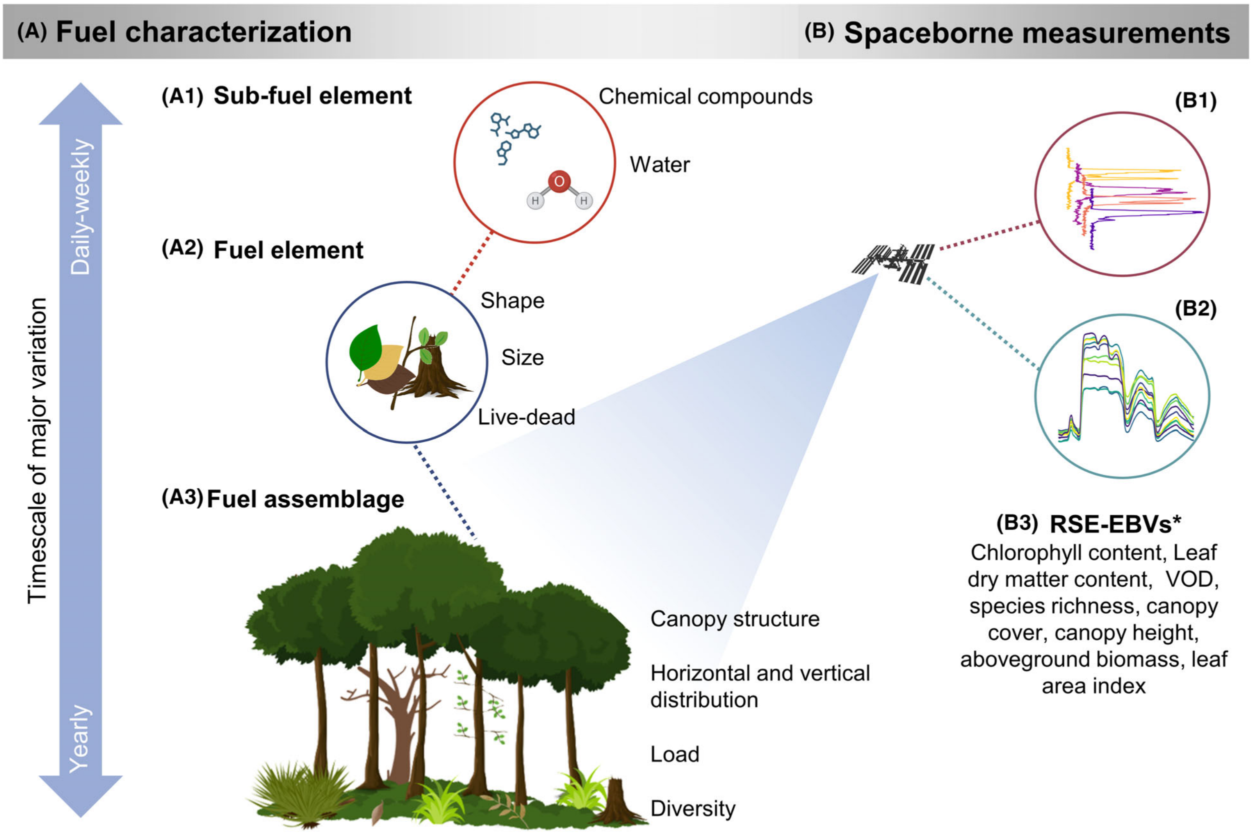

Figure 1. Conceptual framework relating (A) primary fuel characteristics retrieved with remote sensing data (Gale et al., 2021) and (B) spaceborne Earth observation measurements that allow the collection of linking metrics such as the (B3) Remote Sensing Enabled Biodiversity Variables (RSE-EBVs) (Skidmore et al., 2021). *RSE-EBVs list is not exhaustive. (B1) example of spaceborne large footprint lidar measurements, (B2) example of sectra from hyperspectral sensors.

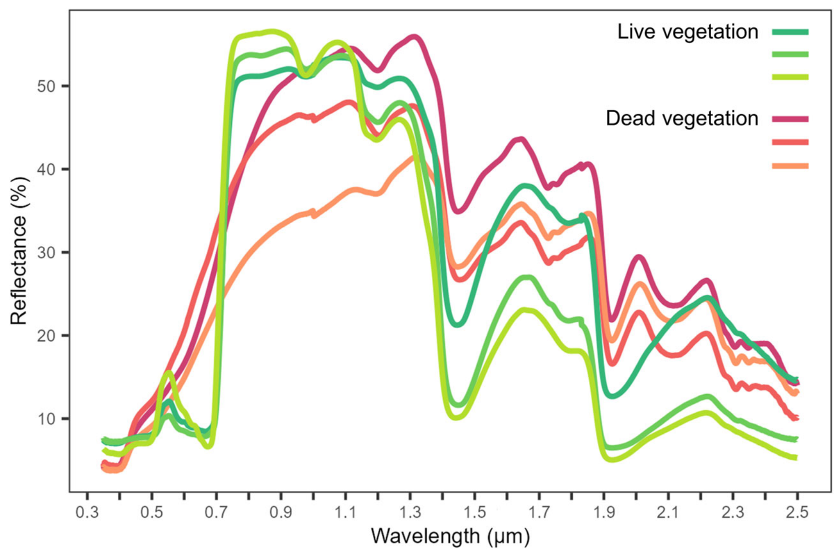

Figure 2. Example spectra collected with a field spectrometer of live and dead vegetation from visible to shortwave infrared. Spectra examples from the ECOSTRESS spectral library (Baldridge et al., 2009; Meerdink et al., 2019)—scripts for the library summarization and plotting the figures available in Appendix S1 and online repository (Leite, 2023).

Active sensors allow direct assessments of fuel vertical structure and canopy-related metrics. This advantage comes from the capability to generate 3D representations through range measurements and penetration into vegetation vertical layers of sensors such as radar and lidar. The signal tracking of synthetic aperture radar (SAR) sensors is sensitive to either structure or dielectric characteristics of vegetation (which includes vegetation moisture) (Konings et al., 2019) that can be assessed through polarimetry (Li & He, 2022; Rao et al., 2020; Saatchi et al., 2007), interferometry (Kumar et al., 2017; Zhou et al., 2009), or tomography (Aghababaei et al., 2020; Tong Minh et al., 2016) techniques. Lidar sensors often provide precise ranging measurements and have been widely used as the state-of-the-art for vegetation structure mapping using aerial and terrestrial platforms (Calders et al., 2020; Eitel et al., 2016). Recent advances in spaceborne lidar technology led to the launch of missions (see section "New sensors, new opportunities") to retrieve vegetation vertical profiles, canopy metrics, and fuels across vertical layers at finer spatial scale (Ashworth et al., 2010; García et al., 2012; Hoffrén et al., 2023).

The synergy between passive and active sensors offers the potential for their combined use in fuel characterization. Retrieving species diversity, for example, involves looking at both the biochemical and structure traits of vegetation (Rocchini et al., 2016). This is essential to support novel frameworks to fire behavior and effects modeling (Dickman et al., 2023; Nolan et al., 2022; Zylstra et al., 2016). Furthermore, many fuel components such as those from the surface (e.g., grasses and litter) can have greater temporal dynamics and be harder to directly measure with remote sensors (Costa et al., 2020; Leite et al., 2022; Oliveira et al., 2021). Improving the understanding of fuel dynamics could come from the integration of sensors that capture multiple structural and compositional components (Sánchez-López et al., 2023) or offering higher temporal resolutions (Bajocco et al., 2015; Verbesselt et al., 2007).

New sensors, new opportunities

The number of Earth Observation (EO) missions has exponentially increased in the last decades, bringing opportunities for fuel characterization (Figure S1) (Ustin & Middleton, 2021). We identified the EO missions launched in the last 5 years (2018–2022) offering freely available data (Table 1). We further restricted the sensors to those offering a level of spatial detail that can facilitate the relationship with field reference data for the needs of fuel managers. These needs might be hard to define as they can be based on specific applications, their relationship to a management unit, or even users familiarity with current EO data products (Meddens et al., 2022). The sensors we identified have a spatial resolution ranging from 2 to 70 m considering some of the requirements identified by (Meddens et al., 2022). Satellites carrying multispectral sensors are joining space with other long-term missions such as Landsat and Sentinel. Their combination can leverage higher temporal resolution to help in the understanding of fuel dynamics. Imaging spectrometers with bandwidths <13 nm measure the electromagnetic spectrum in higher spectral detail facilitating chemical composition retrieval. Finally, lidar sensors give unprecedented measures of vegetation vertical profiles that are well related to canopy structure and fuel load (Figure 3).

Multispectral sensors

Four multispectral missions with open data policies were launched in the last 5 years. The spatial resolution of the images from these sensors ranges from 2 to 70 m. The missions include (launch date in parenthesis): CBERS-4A (2019) (Oldoni et al., 2022; Vrabel et al., 2021), Amazonia-1 (2021) (Moutinho, 2021; Oldoni et al., 2022; Vrabel et al., 2021), Landsat-9 (2021) (Masek et al., 2020), and ECOSTRESS (2018) (Fisher et al., 2020).

CBERS-4A and Amazonia-1 were launched with the objective of reducing revisit time of multispectral remote sensors to track deforestation, especially in the Brazilian Amazon rainforest (Moutinho, 2021; Vrabel et al., 2022). They joined the previously launched CBERS-4 (Pinto et al., 2016) to form a constellation of satellites with similar characteristics to collectively provide near-daily data acquisitions. CBERS-4A/WPM panchromatic band spatial resolution of 2-m has helped on the differentiation of tree and shrub vegetation cover in an urban interface (Adorno et al., 2023). This highlights the importance of open satellite-based data at this spatial resolution for characterization of vegetation at a wildland-urban interface. Furthermore, the combination of CBERS-4A/WFI and Amazonia-1/WFI has allowed images of the same areas every 5 days (Maurano et al., 2023). The possibility of achieving a higher data frequency for an area by combining data from satellite constellations is a crucial step towards characterizing temporally dynamic fuel characteristics, such as moisture content (Quan et al., 2021; Yebra et al., 2018).

Landsat-9 was launched in 2021, continuing the Landsat program legacy (Masek et al., 2020). Landsat-9 sensors (OLI-2 and TIRS-2) have similar characteristics to Landsat 8 sensors (OLI-1 and TIRS-1) with bands in the VNIR, SWIR, and thermal ranges of the spectrum. Landsat-9 has an orbit that is 8 days out of phase from

Table 1. Description of spaceborne satellites and instruments launched in the last 5 years (2018–2022) with freely available data for research and spatial resolution of 2–70 m.

Type	Satellite/ instrument	Launch year	Description	References	Useful links
Multispectral	ISS/ECOSTRESS	2018	ECOSTRESS has 5 spectral bands covering the spectral range from 8000 to 12 500 nm, and has an additional band centered at 1600 nm for geolocation and cloud detection. The spatial resolution is ~38 × 69 m that is resampled to 70-m cells. Revisit time can be 1–5 days but is dependent on the ISS orbit.	(Fisher et al., 2020)	Data products/access: (ECOSTRESS, 2023) Tools/tutorials: (ECOSTRESS, 2023; ecostress-utils, 2023)
	CBERS-4A/WFI-MUX-WPM	2019	CBERS-4A system is composed of three sensors: Wide-Field Imager (WFI), Multispectral camera (MUX), and Wide-scan camera (WPM). The sensors collect data in 4 bands (blue, green, red, and NIR) with a spatial resolution of 55 m (WFI), 16.5 m (MUX) and 8 m (WPM). WPM has an additional panchromatic band with a spatial resolution of 2 m. Revisiting time is 31 days for MUX and WPM and 5 days for WFI.	(Oldoni et al., 2022; Pinto et al., 2016)	Data products/access: (CBERS on AWS, 2023; INPE, 2023) Tools/tutorials: –
	Amazonia-1/WFI	2021	Amazonia-1 satellite carries the WFI sensor to collect data in 4 bands (blue, green, red, and NIR) at a spatial resolution of ~60 m with revisit time of 5 days.	(Moutinho, 2021; Vrabel et al., 2022)	Data products/access: (AMAZONIA-1 on AWS, 2023) Tools/tutorials: –
	Landsat-9/OLI-2 – TIRS-2	2021	Landsat 9 sensors (OLI-2 and TIRS-2) have similar characteristics to Landsat 8 sensors (OLI-1 and TIRS-1) with bands in the VNIR, SWIR, and thermal ranges of the spectrum. The spatial resolution of panchromatic, VNIR/SWIR, and TIR bands is 15, 30, and 100 m, respectively. The instruments have a revisit time of 16 days.	(Masek et al., 2020)	Data products/access: (USGS, 2020; GEE data catalog, 2023a) Tools/tutorials: (Landsat Science, 2023a; USGS, 2022)
Hyperspectral	ISS/DESIS	2018	DESIS has 235 bands from 400 to 1000 nm. Bands in the VNIR region have bandwidths of 2.5 nm while in the SWIR region the bandwidth is 3.5 nm. The images have 30 m resolution. Revisiting time for data acquisition is dependent on the ISS orbit. Revisiting time following the ISS orbit can be ~3–5 days.	(Alonso et al., 2019)	Data products/access: (German Aerospace Center (DLR), 2019a, 2019b) Tools/tutorials: –
	PRISMA/HYC-PAN	2019	PRISMA's Hyperspectral Camera (HYC) records 241 bands: 66 in the VNIR (~400–1010 nm), 174 in the SWIR (~920–2500 nm), and one Panchromatic (PAN, 400–700 nm). Bandwidths are <13 nm in the VNIR and <14.5 nm in the SWIR regions of the electromagnetic spectrum. PRISMA/HYC provides images of ~30 m resolution. The PAN channel provides images of ~5 m for finer assessments. Revisiting time is 29 days at nadir and 7 days for off-nadir acquisitions.	(Cogliati et al., 2021)	Data products/access: (ASI PRISMA, 2023) Tools/tutorials: (Busetto & Ranghetti, 2020; prisma, 2023; rPRISMA, 2023)

(*Continued*)

Table 1. Continued.

Type	Satellite/ instrument	Launch year	Description	References	Useful links
	ISS/HISUI	2019	HISUI has 185 bands covering from 400 to 2500 nm with bandwidths of 10 nm in the VNIR and 12.5 nm in the SWIR regions of the electromagnetic spectrum. The spatial resolution in HISUI images is 30 m along track and 20 m cross track. Revisiting time follows ISS orbit.	(Matsunag et al., 2021; Matsunaga et al., 2020)	Data products/access: (HISUI, 2023; Japan Space Systems, 2023) Tools/tutorials: –
	EnMAP/HSI	2022	EnMAP's Hyperspectral Imager (HSI) carries a sensor that records information in 242 bands from 420 to 2500 nm with bandwidths of 6.5 nm in the VNIR and 10 nm in the SWIR regions of the electromagnetic spectrum. The spatial resolution of HSI images is 30 m. Revisit time is 4 days for acquisitions up to 30° off-nadir or 27 days for up to 5° off-nadir.	(Guanter et al., 2015)	Data products/access: (EnMAP, 2023a) Tools/tutorials: (EnMAP, 2023b; Scheffler et al., 2020)
	ISS/EMIT	2022	EMIT has 285 bands from 380 to 2500 nm with bandwidths of <13 nm. Surface reflectance products are delivered with spatial resolution of 60 m. Revisit time follows the ISS orbit.	(Green, 2022; Green et al., 2020)	Data products/access: (EMIT, 2023a; LP DAAC, 2023a) Tools/tutorials: (EMIT, 2023b, 2023c)
Lidar	ISS/GEDI	2018	GEDI is mounted on the International Space Station (ISS) and is the first spaceborne lidar system designed to map forests. It is a full-waveform lidar system composed of three lasers that together shoot 8 laser beams that illuminate the Earth's surface in ~25-m footprints separated 60 m along track and 600 m across track.	(Dubayah, Blair, et al., 2020; Dubayah, Armston, Healey, Bruening, et al., 2022)	Data products/access: (GEDI, 2023a, 2023b; GEE data catalog, 2023b; MAAP, 2023) Tools/tutorials: (LP DAAC, 2023b; ORNL, 2023; Silva et al., 2020)
	ICESat-2/ATLAS	2018	The ATLAS sensor on board ICESat-2 is a photon-counting lidar shooting 6 laser beams of green light (532 nm) to the Earth surface. The beams are organized in 3 pairs about 3 km apart and with a distance between paired beams of ~90 m. Each beam illuminates an area within a ~13 m footprint.	(Markus et al., 2017)	Data products/access: (IcePix, 2023; IceSat-2, 2023) Tools/tutorials: (IcePix, 2023; NSIDC, 2023) (Shean et al., 2023; SlideRule Earth, 2023)

Useful links include where to find or request the free products and examples of tools and tutorials available online. Detailed information on Tables S2 and S3 is presented in the Appendix S1.

Landsat-8 which means that it is possible to have images every 8 days while Landsat-8 and Landsat-9 are in orbit together. The long-term history and spatial coverage of the mission enable the generation of country-level monthly burned area products to help understand spatial temporal variability of fire (Neves et al., 2023). The higher radiometric resolution of Landsat-9 contributes to improved burned area mapping (Seydi & Sadegh, 2023). The Landsat sensors also share similarities with European Space Agency (ESA) Sentinel-2 images making it possible to generate products such as the Harmonized Landsat-Sentinel dataset (HLS) (Claverie et al., 2018) to potentially improve revisit frequency to ~3 days depending on latitude.

The ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS) represents a significant improvement in the use of thermal bands in spaceborne remote sensing to globally monitor plant evapotranspiration at finer spatial and temporal resolution (Fisher et al., 2020). Previous sensors were constrained from capturing plant diurnal cycles by always collecting data at the same time of the day (e.g., Landsat,

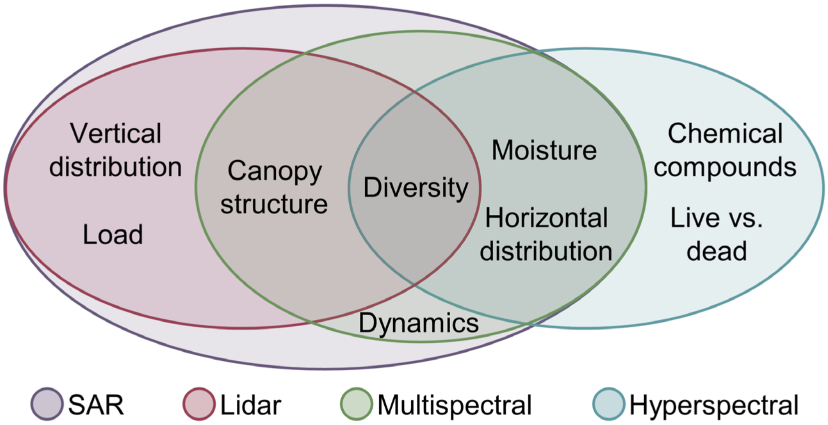

Figure 3. Summary of core fuel characteristics retrieved with spaceborne sensors for available spectral, temporal, and spatial resolution. SAR stands for synthetic aperture radar sensors; thermal sensors are included as part of multispectral.

MODIS, VIIRS, and Suomi-NPP) or by having coarser spatial resolution (e.g., GOES). ECOSTRESS deployment on the ISS allows data acquisition at different times of the day using 5 thermal bands at ~70 m spatial resolution and 1–5-day revisit time (higher latitudes are revisited more frequently). Changes in plants' evapotranspiration throughout the day can be captured and used to inform studies of plant water stress and its consequences (Xiao et al., 2021). Plant water stress derived from ECOSTRESS has been demonstrated to be a good predictor of fire severity (Masara et al., 2022; Pascolini-Campbell et al., 2022; Wilder & Kinoshita, 2022). Moreover, the ability to monitor evapotranspiration can contribute to the assessment of functional traits related to post-fire vegetation recovery (Poulos et al., 2021). By including ECOSTRESS into frameworks to assess post-fire effects with multiple sensors, we can gain a more comprehensive understanding of ecosystems' resistance and resilience to fire (Pérez-Cabello et al., 2021).

Hyperspectral sensors

Between 2018 and 2022, five missions were launched carrying imaging spectrometers with high spectral resolution (e.g., bands narrower than 13 nm), namely, German Aerospace Center (DLR) Earth Sensing Imaging Spectrometer DESIS (Alonso et al., 2019; Krutz et al., 2019), PRecursore IperSpecttrale della Missione Applicativa (PRISMA) (Cogliati et al., 2021), Hyperspectral Imager Suite (HISUI) (Matsunaga et al., 2020), Environmental Mapping and Analysis Program (EnMAP) (2022) (Guanter et al., 2015), and EMIT (Green, 2022; Green et al., 2020). The sensors collect hundreds of bands in the visible to SWIR regions in bandwidths lower than 13 nm at a spatial resolution of 30 m, except for EMIT's products (60 m) (Figure 4). High-level products from these sensors include geometrically and atmospherically corrected (L2) image products from DESIS, PRISMA, HISUI (for research purpose), (Matsunaga et al., 2020), EnMAP, and EMIT. EMIT's data coverage focused on specific sites on the Earth's surface (updated data coverage can be found at EMIT's open data portal (EMIT, 2023a).

DESIS, HISUI, and EMIT are deployed on the International Space Station (ISS) that has a non-sun-synchronous "shifting" orbit allowing data acquisition at different times of the day but having limitations related to data coverage. PRISMA has a nominal coverage specified between 70° N and S latitudes (Cogliati et al., 2021), whereas EnMAP collects data globally in near-nadir mode (view zenith angle $\leq 5°$) (Guanter et al., 2015). Data availability and information related to data access or request of the hyperspectral missions are available at the missions' websites (Table 1). Even though many of the new sensors do not have full Earth coverage or controlled revisit time, their use is helping pave the way for upcoming spaceborne image spectroradiometers.

The effectiveness of imaging spectroscopy for fire applications has been more widely demonstrated using data from airborne platforms (Veraverbeke et al., 2018), and the capabilities of the new hyperspectral sensors are just starting to be fully unveiled. For example, effectively deriving subpixel components for fuel map and fire severity classification has been demonstrated using PRISMA data (Quintano et al., 2023). Recent studies have also shown that species richness and diversity predictions based on DESIS data can outperform predictions based on multispectral data (Guo et al., 2023; Rossi & Gholizadeh, 2023). Nonetheless, the relationship between spaceborne spectroscopy-derived species richness to fire behavior and effects is yet to be fully understood.

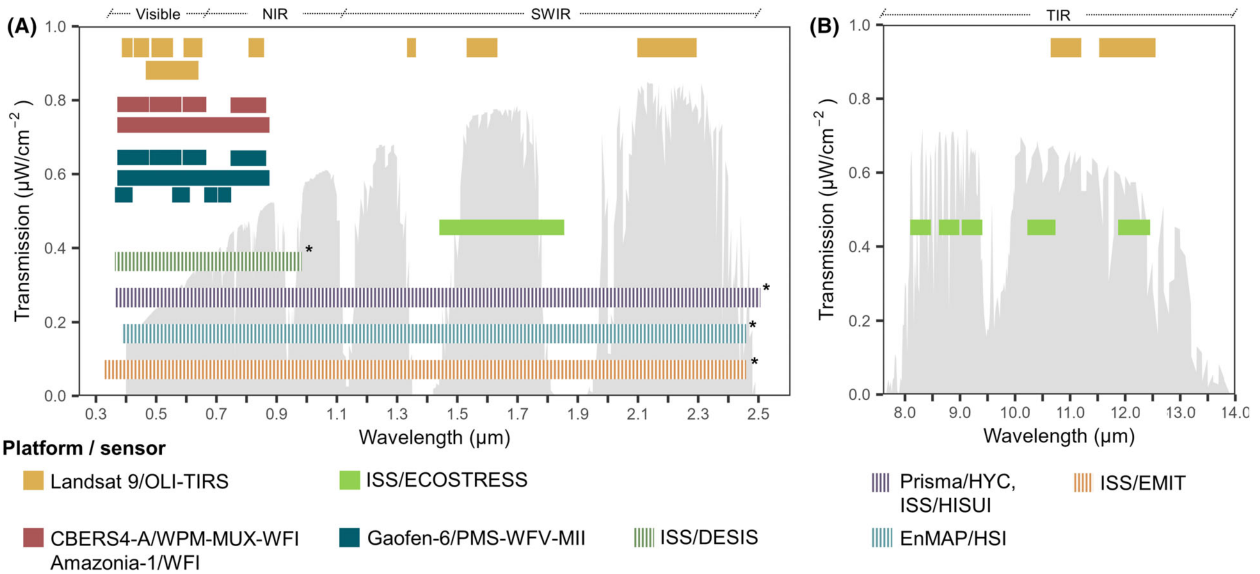

Figure 4. Spectral bands captured by spaceborne sensors in the (A) visible, near-infrared (NIR), shortwave-infrared (SWIR) and (B) thermal-infrared (TIR) regions of the spectra. *Figure scale constrained the complete visualization of the narrow spectral bands of hyperspectral systems. Number of bands (n) for the hyperspectral platform/instrument are: ISS/DESIS (n = 235), Prisma/HYC (n = 240), ISS/HISUI (n = 185), EnMAP/HSI (n = 242). 1 μm = 1000 nm.

Lidar sensors

The spaceborne lidar missions Ice, Cloud, and Land Elevation Satellite-2 (ICESat-2) (Markus et al., 2017) and Global Ecosystem Dynamics Investigation (GEDI) (Dubayah, Armston, Healey, Bruening, et al., 2022; Dubayah, Blair, et al., 2020) were launched in 2018, leveraging opportunities to improve fuel load and vertical structure retrieval at global scales. They are based on different lidar technologies. The ATLAS sensor on ICESat-2 is a photon-counting lidar (operating at 532 nm) meaning the receiver only needs the energy of a single returning photon to trigger a measurement. GEDI, on the other hand, onboard the (ISS) is a full-waveform lidar (1064 nm) that operates by recording all the returned energy as a function of time (Liu et al., 2021). Both systems operate in a sampling design with laser shots systematically spaced when they reach the Earth surface (Figure 5). The requirements for developing spaceborne lidar systems with global wall-to-wall coverage are yet to be reached (Hancock et al., 2021).

ICESat-2 was launched following the ICESat mission with most mission requirements related to measuring and monitoring ice sheet changes (Markus et al., 2017). Nevertheless, the utility of ICESat-2 data extends to vegetation applications (Duncanson et al., 2020; Narine et al., 2020; Neuenschwander & Pitts, 2019). Vegetation height and cover are available as ICESat-2 land, water, and vegetation elevation products (ATL08), and land/canopy gridded products (ATL18). GEDI, on the other hand, was the first spaceborne lidar sensor specifically designed to map Earth's vegetation with potential to fully penetrate vegetation with 95–98% of canopy cover (Dubayah, Blair, et al., 2020). GEDI provides high-level products at the footprint level: vegetation height (L2A, Dubayah, Hofton, et al., 2020), canopy cover and vertical profile metrics (L2B, Dubayah, Tang, et al., 2020), and aboveground biomass density (AGBD) (L4A, Dubayah, Armston, Kellner, Duncanson, et al., 2022; Duncanson et al., 2022; Kellner et al., 2023); and gridded at 1 km^2 cells: gridded level 2 metrics (L3, Dubayah et al., 2021), and gridded AGBD (L4B, Dubayah, Armston, Healey, Yang, et al., 2022). Studies have reported root mean square errors for canopy height metrics of ~1–4 m (Li et al., 2023; Liu et al., 2021). For AGBD products, the GEDI mission aims to achieve standard error <20% for cells where AGBD is larger than 100, and <20 Mg ha^{-1} standard error when AGBD is less than 100 Mg ha^{-1}(Dubayah, Armston, Healey, Bruening, et al., 2022). Currently, GEDI mission operations have been paused, and it will resume operations in 2024 (Smith, 2023).

The use of data from spaceborne lidar sensors has been essential in advancing the mapping and comprehension of vegetation structural characteristics in fire science. For example, ICESat-2 data has helped capture structural changes in vegetation due to fire (Konduri et al., 2023; Liu et al., 2019). ICESat-2 data capabilities for

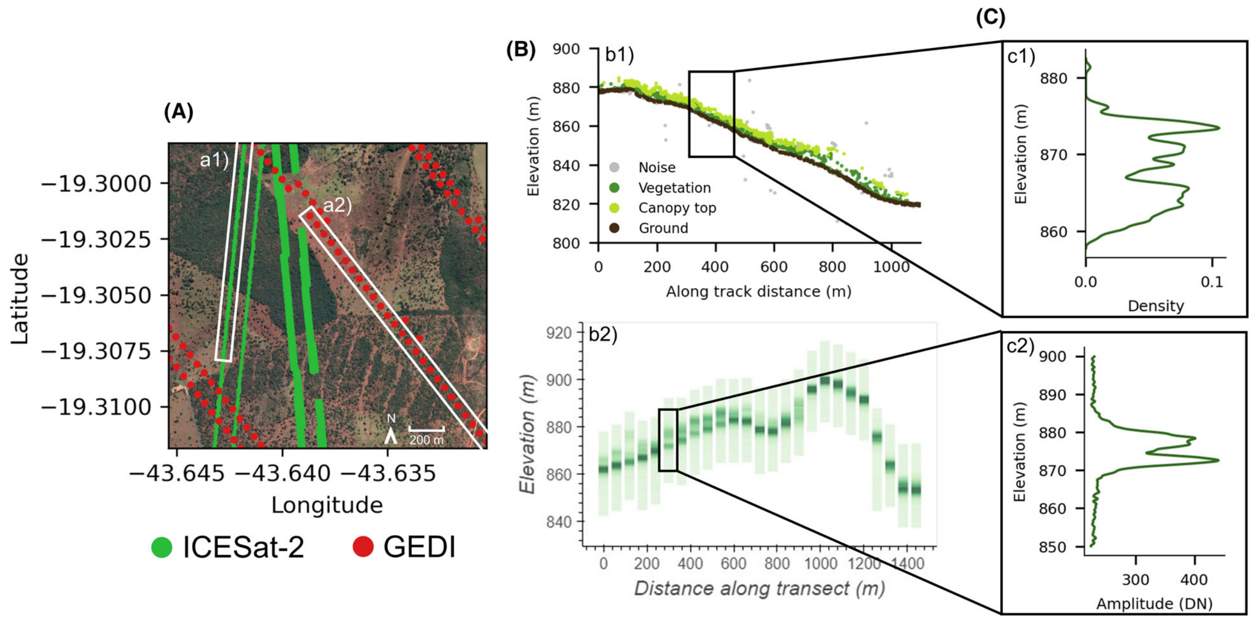

Figure 5. Figure exemplifying data collection over vegetation of spaceborne lidar sensors ICESat-2/ATLAS and GEDI. These sensors collect data in (A) a sampling pattern with footprints of ~13 m (ATLAS) and ~25 m (GEDI); (B1, B2) are subsets of the transects. The ICESat-2/ATLAS transect (B1) has the points classified for noise, vegetation, canopy top, and ground, available in the product ATL08. Figure (C1) is a density plot for a 250 m subset of the ICESat-2/ATLAS transect. Figure (C2) is the returned energy from a single GEDI footprint. Scripts to make the plots are available in the appendix (in Appendix S1) and on an online repository (Leite, 2023). GEDI and ICESat-2/ATLAS tracks extracted with SlideRule (Shean et al., 2023; SlideRule Earth, 2023).

characterizing fuels remains largely unexplored (Brown et al., 2023). The use of GEDI data has helped improve fuel classification (Hoffrén et al., 2023), predict fuel load across vegetation vertical layers (Leite et al., 2022), and also quantify fire-related structural changes in vegetation (Huettermann et al., 2023). The derivation of other structure-related fuel characteristics such as canopy base height and canopy bulk density still needs to be explored. GEDI and ICESat-2 are both sampling sensors, which means that the data is not collected "wall-to-wall" (Figure 4). This can be overcome with their integration with imaging sensors (Potapov et al., 2021). Joining these complementary capabilities can help to improve mapping fuel characteristics in space and time (Myroniuk et al., 2023). This is particularly important for fuels that are temporally dynamic such as those from lower vegetation layers (e.g., surface and ground fuels) (Leite et al., 2022).

Looking forward

Long-term Earth observation programs continuation

Long-term programs that have contributed to the advance of space-based EO are expected to develop new sensors in the decades ahead. The follow-on of the Landsat missions named Landsat-Next (Landsat Science, 2023b) will have improved spatial, temporal, and spectral resolutions featuring 26 bands, spatial resolutions of 10–60 m. The Landsat-next mission is designed as a constellation of three satellites, enabling a 6-day revisit time. Landsat Next satellites are expected to be launched in late 2030 and to collect data with its predecessor Landsat-9 (Wulder et al., 2022). The ESA is working to carry on the legacy of the Sentinel missions into the future. Soon, the upcoming Sentinel-1C and Sentinel-1D missions should replace Sentinel-1B (decommissioned in 2022) and Sentinel-1A for C-band SAR data acquisition every 6 days (Geudtner et al., 2021). Later this decade, the Sentinel-1 Next Generation mission will extend C-band data collection into the 2030s featuring improvements in data acquisition characteristics (Zonno & Matar, 2021). In the same time frame, ESA is also planning to introduce enhancements in the optical components of Sentinel-2 and Sentinel-3 in new missions (Löscher et al., 2020). Finally, we also note that there are references for data starting to be open for the Gaofen satellites that are part of the Chinese High-Resolution Earth Observation System program (Chen et al., 2022; Liu et al., 2023). Lower-level products may be available requiring additional processing before applying them to end uses (Chen et al., 2022; Zhong et al., 2021), but analysis ready data are also under development (Zhong et al., 2021). Similarly, the Sustainable Development Science Satellite-1 (SDGSAT-1), launched in 2021 and developed by the Chinese Academy of Sciences, is expected to provide freely available data (Ge et al., 2022).

Upcoming missions

Unprecedented SAR datasets are expected in the next few years. The SAR missions NISAR and BIOMASS are planned to be launched in 2024. NISAR will have global data collection using the L band and will be the first satellite to allow dual-frequency analysis by acquiring data using L and S bands on selected sites (Kellogg et al., 2020). NISAR will also have an exact repeat cycle of 12 days that will allow more frequent interferometric combinations and analysis. The mission will collect over 85 TB of data per day and plans to meet the requirements of yearly biomass disturbance mapping at 100 m spatial resolution, though lower-level products will be delivered at finer spatial resolutions (e.g., instrument nominal resolution of 7–48 m depending on acquisition mode) (Blumenfeld, 2017; NISAR, 2018). Meanwhile, BIOMASS is the first spaceborne sensor operating at the P-band, which is the SAR band with the highest penetration capability in dense vegetation and likely most effective to measure vegetation biomass (Quegan et al., 2019). BIOMASS acquisition parameters will further allow the production of vegetation profiles through tomographic analysis of the returning signal for the first three years of its life cycle. BIOMASS mission requirements include biomass and forest height maps at 200 m resolution and forest disturbance at 50 m resolution (Quegan et al., 2019). Note that there might be restrictions for BIOMASS operation that may limit data availability in some regions of the world (Quegan et al., 2019). Nevertheless, great opportunities arise from the integration of NISAR and BIOMASS with GEDI that are planned to operate together until the end of the decade. Their combination is boosted by their presence in the Multi-Mission Algorithm and Analysis Platform (MAAP, Albinet et al., 2019), a joint NASA-ESA collaborative cloud computing environment. Other SAR missions are also planned toward the end of the 2020–2030 decade such as TanDEM-L (Moreira et al., 2015; Schandri et al., 2022), ALOS-4 (Motohka et al., 2019, 2021), ROSE-L (Geudtner et al., 2021), and CBERS-6 (CLBRIEF, 2023; g1, 2023) to continue to support SAR-based vegetation analysis.

The current hyperspectral missions should lay ground for a future of imaging spectroscopy from space. The Surface Biology and Geology (SBG) mission (Schimel & Poulter, 2022; Stavros et al., 2023) and Copernicus Hyperspectral Imaging Mission for the Environment (CHIME) mission (Nieke & Rast, 2018) are the next generation of this type of sensor. SBG and CHIME will have global coverage, bandwidths <10-nm in the VSWIR, and spatial resolution of 30 m. Revisit time can be potentially less than 8-days by combining SBG and CHIME datasets (Poulter et al., 2023).

Finally, in the context of wildfire science, it is important to mention the first satellite with design planned for operational wildfire monitoring in Canada named WildFireSat (Johnston et al., 2020). This mission is under development and delivers images with coarser resolution than others cited in this article because the mission planning is focused on different objectives such as having near-real time data acquisitions, measuring wildfire behavior, and mapping smoke plumes. A key step toward the development of the sensors is the interaction with end-users to determine mission requirements including temporal resolution, data coverage, and latency (Crowley et al., 2023; Johnston et al., 2020; McFayden et al., 2023).

Maximizing EO data impact

The present and future EO sensors (Figure 6) are producing an increasing volume of data to meet the needs of a diverse group of users, which presents both opportunities and challenges. Making data open and easily accessible for the target users plays a critical role in the effective utilization of EO data. There has been a notable increase in the number of participating agencies operating and making satellite datasets available through several spatial data infrastructures. It is important to note, nonetheless, the significance of upholding standards for data validation and quality reporting to facilitate user's interoperability across multiple sensors (Niro et al., 2021). Not all the datasets are easily available yet. Many efforts are being made to deliver higher-level products, e.g., by building data cubes for specific countries (e.g., Ferreira et al., 2020; Giuliani et al., 2017; Lewis et al., 2017) and developing harmonized data products (e.g., Claverie et al., 2018). Additionally, following standardized structures and specifications such as the Spatio-Temporal Asset Catalog (STAC) (Simoes et al., 2021; STAC, 2021) can simplify data access by reducing the need to develop specific pipelines to access and process each available dataset.

Current trends to process the available datasets point to through data streaming and cloud computing, which reduce the need to download large amounts of data and in-house high-performance computing resources. Available cyberinfrastructures have facilitated this effort by combining data access and processing capabilities into a single platform (e.g., Google Earth Engine, Sentinel Hub, Open Data Cube, MAAP—Gomes et al., 2020). Improvements may be necessary to provide more levels of data

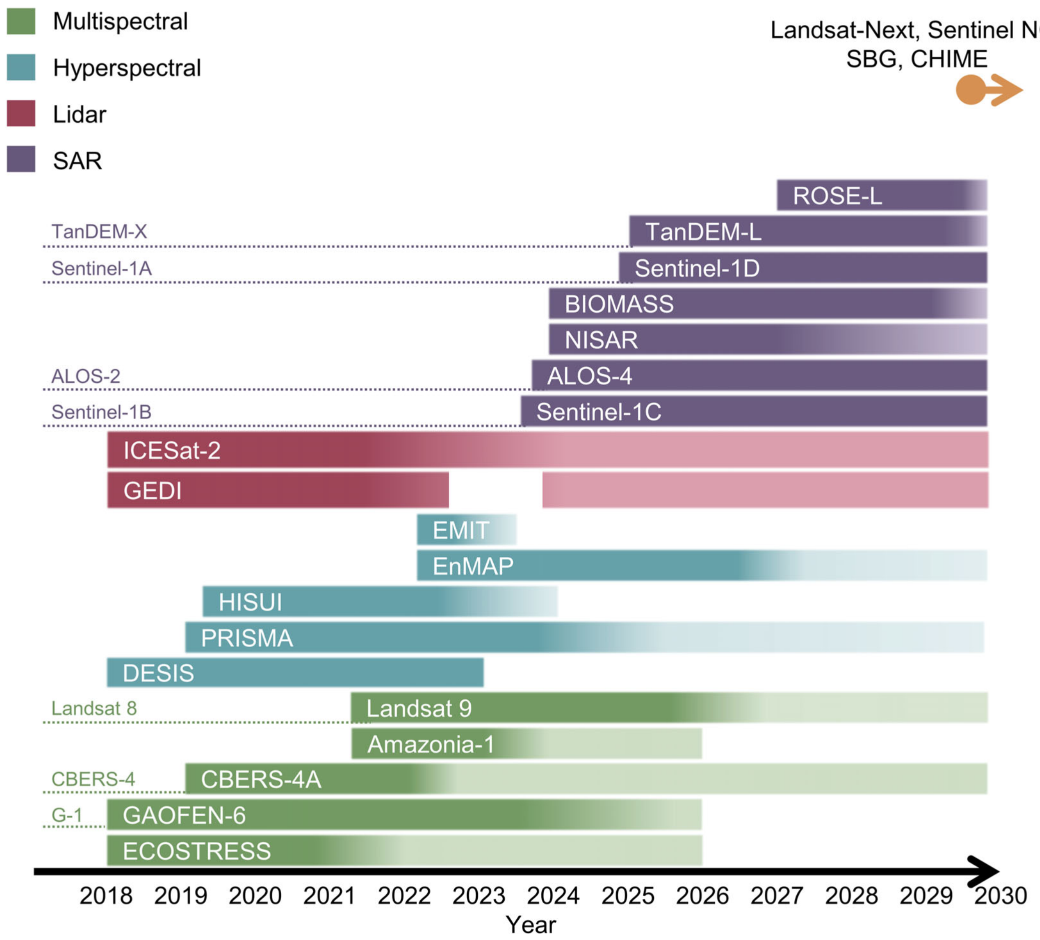

Figure 6. Timeline of data collection for the new satellites and instruments. Mission length is represented as a sum of both nominal (darker color) and potential (lighter color) mission lifetimes, which may depend on several factors. Names in the dotted lines represent previous missions to acknowledge the continuation of long-term Earth observation programs.

readiness to meet needs of users with a range of computing skills, improve communication with stakeholders, and allow the reproducibility of methods (Gomes et al., 2020). The deployment of public cloud cyberinfrastructure (e.g., NSF's Cyverse) is a prominent alternative to facilitate access to advanced computing resources to allow a range of users to process the data that is becoming available (McIntosh et al., 2023; Swetnam et al., 2024). The collaborative nature of these infrastructures aligns well with open science principles, which include making the approaches transparent and accessible (Vicente-Saez & Martinez-Fuentes, 2018). This accountability is essential to ensure that methods can be effectively transferred and adapted by different users.

In this sense, community engagement is an important factor for co-developing the next generation of spatial data infrastructure and products to increase and diversify the number of EO data users. Actively hearing a diverse range of users creates more inclusive and usable data products. Furthermore, the awareness of how the data could impact local communities in different ways has to be considered (de Lima et al., 2022; Walter et al., 2021). This collaborative approach is essential for leveraging the full potential of EO data ensuring that it contributes to cross-scale social and environmental sustainability.

Conclusion

Wildland fire management is essential to maintain the functionality of ecosystems and reduce the risks of extreme fire events. Leveraging the use of a new generation of spaceborne sensors can help managers to achieve these crucial goals. Fuel load and vertical structure can be obtained due to the penetration capacity of spaceborne active sensors, such as GEDI. New sensors collecting data in narrow bands of the electromagnetic spectrum can improve the retrieval of key biochemical constituents across large areas. Finally, data integration between lidar, hyperspectral, and constellations of multispectral and radar sensors may give the opportunity to scale up fuel characteristics in space and time to understand fuel dynamics. It is noteworthy that several missions are planned for this decade such as BIOMASS, NISAR, SBG, CHIME, and Landsat-Next to ensure the continuity of the use of EO systems for fuel characterization. The increasing availability of cross-mission data products, open-source tools, and seamless cloud-computing platforms is crucial for enabling the use of these cutting-edge datasets by multiple stakeholders across the world.

Acknowledgements

The research was supported by an appointment to the NASA Postdoctoral Programme at the Goddard Space Flight Centre, administered by Oak Ridge Associated Universities under contract with NASA. This research was supported in part by the USDA Forest Service, Rocky Mountain Research Station, and the NASA Earth Information System (EIS) Fire Project. This research was also supported by the Brazilian Coordination for the Improvement of Higher Education Personnel (CAPES) and the University of Colorado Boulder Grand Challenge, CIRES, Earth Lab. Co-author Silva was primarily funded through NASA's grants (ICESat-2, 80NSSC23K0941), Carbon Monitoring System (CMS, grant 80NSSC23K1257) and Commercial Smallsat Data Scientific Analysis (CSDSA, grant 80NSSC24K0055). The findings and conclusions in this publication are those of the authors and should not be construed to represent any official USDA or U.S. Government determination or policy.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table S2. Description of spaceborne satellites and passive instruments launched in the last 5 years (2018–2022) with freely available data for research and spatial resolution of 2–70 m.

Table S3. Description of spaceborne satellites and active instruments launched in the last 5 years (2018–2022) with freely available data for research and spatial resolution of 2–70 m.

Data S1. Leveraging the next generation of spaceborne Earth observations for fuel monitoring and wildland fire management.

Figure S1. Number of Earth Observation (EO) satellite missions launched between 1957 and 2022 – sources: NASA Space Science Data Coordinated Archive (NSSDCA) and Union of Concerned Scientists (UCS) filtered to Earth Observation or Earth Science applications missions only.

