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Review

## Hyperspectral remote sensing of fire: State-of-the-art and future perspectives

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### ABSTRACT

Fire is a widespread Earth system process with important carbon and climate feedbacks. Multispectral remote sensing has enabled mapping of global spatiotemporal patterns of fire and fire effects, which has significantly improved our understanding of interactions between ecosystems, climate, humans and fire. With several upcoming spaceborne hyperspectral missions like the Environmental Mapping And Analysis Program (EnMAP), the Hyperspectral Infrared Imager (HyspIRI) and the Precursore Iperspettrale Della Missione Applicativa (PRISMA), we provide a review of the state-of-the-art and perspectives of hyperspectral remote sensing of fire. Hyperspectral remote sensing leverages information in many (often more than 100) narrow (smaller than 20 nm) spectrally contiguous bands, in contrast to multispectral remote sensing of few (up to 15) non-contiguous wider (greater than 20 nm) bands.

To date, hyperspectral fire applications have primarily used airborne data in the visible to short-wave infrared region (VSWIR, 0.4 to 2.5 µm). This has resulted in detailed and accurate discrimination and quantification of fuel types and condition, fire temperatures and emissions, fire severity and vegetation recovery. Many of these applications use processing techniques that take advantage of the high spectral resolution and dimensionality such as advanced spectral mixture analysis. So far, hyperspectral VSWIR fire applications are based on a limited number of airborne acquisitions, yet techniques will approach maturity for larger scale application when spaceborne imagery becomes available. Recent innovations in airborne hyperspectral thermal (8 to 12 µm) remote sensing show potential to improve retrievals of temperature and emissions from active fires, yet these applications need more investigation over more fires to verify consistency over space and time, and overcome sensor saturation issues. Furthermore, hyperspectral information and structural data from, for example, light detection and ranging (LiDAR) sensors are highly complementary. Their combined use has demonstrated advantages for fuel mapping, yet its potential for post-fire severity and combustion retrievals remains largely unexplored.

#### 1. Introduction

Fire is a ubiquitous disturbance agent in the terrestrial biosphere and fire occurs in ecosystems that range from tropical rainforest to deserts and boreal forests (Bond and Keeley, 2005; Bowman et al., 2009). Fire occurs in a variety of forms including high intensity crown fires to long-duration ground fires in organic soils with relatively low intensity (van der Werf et al., 2017). Ecosystems and fire regimes are

rapidly changing at historically unprecedented rates (Dennison et al., 2014; Gillett et al., 2004; Stavros et al., 2014; Westerling, 2006). For example, fire activity has significantly increased in boreal forest ecosystems (Gillett et al., 2004; Turetsky et al., 2011; Veraverbeke et al., 2017) and declined in savannas (Andela et al., 2017; Andela and van der Werf, 2014).

The fire disturbance continuum discriminates between discrete temporal phases during which fire processes occur (Jain et al., 2004).

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Fig. 1. Temporal phases in the fire disturbance continuum (after Jain et al., 2004).

The fire disturbance continuum includes pre-fire, active, and post-fire environments (Fig. 1). The pre-fire environment refers to the type, and condition of fuels as influenced by climate, weather and land management. The active fire environment is the phase during which fires spread over the landscape. Topography, fuels and fire weather influence active fire behavior and intensity. Fire intensity describes the physical combustion process of energy release from organic matter (Keeley, 2009) and is directly related to fire emissions (Wooster et al., 2005). Finally, the post-fire environment is what is left after the fire is extinguished. The post-fire environment is often described interchangeably with the terms fire and burn severity (Boer et al., 2008; Keeley, 2009). Here, we define fire severity as the degree of environmental change caused by a fire as evidenced immediately after the fire without recovery effects (Lentile et al., 2006; Morgan et al., 2014; Veraverbeke et al., 2010). Conversely, burn severity gauges both the immediate fire-induced change and vegetation recovery. Fire and burn severity include fire effects on vegetation and soil (Key and Benson, 2006; Morgan et al., 2014; Parsons et al., 2010).

Remote sensing has been successfully applied in all stages of the fire disturbance continuum for several decades. Success stories include fuel type mapping (Marino et al., 2016; Mitri and Gitas, 2006; Peterson et al., 2013; Roberts et al., 2003), fire risk assessments (Chuvieco et al., 2004; Meng et al., 2017; Yu et al., 2017), active fire detection (Giglio et al., 2003; Schroeder et al., 2014), burned area mapping (Barbosa et al., 1999; Giglio et al., 2009; Gitas et al., 2008; Katagis et al., 2014; Koutsias and Karteris, 2000; Pereira, 2003; Roy et al., 2005), fire/burn severity assessments (Eidenshink et al., 2007; Meng et al., 2017; Veraverbeke et al., 2010), and vegetation recovery mapping (Lewis et al., 2017; Riaño et al., 2002; van Leeuwen et al., 2010; Veraverbeke et al., 2012a). These applications have primarily capitalized upon broadband multispectral remote sensing data. Broadband multispectral remote sensing is the simultaneous acquisition of calibrated radiance units in a limited number (generally in the order between three and 15) of non-contiguous broad (generally wider than 20 nm) spectral bands. In contrast, narrowband hyperspectral remote sensing is the simultaneous acquisition of calibrated radiance in many (generally more than 100) narrow (generally 20 nm or smaller) spectrally contiguous bands. Hyperspectral imaging, or imaging spectroscopy, refers to the acquisition of coregistered images over contiguous narrow spectral bands (Schaepman et al., 2009). Hyperspectral remote sensing has proven its utility in a wide range of Earth system science domains including fire applications (e.g. Dennison and Roberts, 2009; Schepers et al., 2014; Veraverbeke et al., 2014). Prior hyperspectral fire studies were mostly conducted based on airborne imagery, often from the Airborne Visible/ Infrared Imaging Spectrometer (AVIRIS, Green et al., 1998), or the Airborne Prism Experiment (APEX, Itten et al., 2008). To date, Hyperion on the Earth-Observing One (EO-1) platform acquiring data between 2000 and 2017 has been the only spaceborne hyperspectral imager that acquired data in the visible to short-wave infrared spectral range (approximately between 0.4 and 2.5 µm) (Pearlman et al., 2003). In the next few years several spaceborne hyperspectral sensors may be launched: Environmental Mapping And Analysis Program (EnMAP, Stuffler et al., 2007), Hyperspectral Imager Suite (HISUI, Iwasaki et al., 2011), Hyperspectral Infrared Imager (HyspIRI, Lee et al., 2015), Precursore Iperspettrale Della Missione Applicativa (PRISMA, Labate et al., 2009), and the Space-borne Hyperspectral Applicative Land and Ocean Mission (SHALOM, Feingersh and Ben Dor, 2016). These missions will greatly increase the availability and application of hyperspectral data. Furthermore, a global hyperspectral mapping mission was recently recommended by the Decadal Survey for Earth Science and Applications from Space from the National Academy of Sciences from the USA (National Academies of Sciences, 2018).

With upcoming spaceborne hyperspectral missions and the proven utility of hyperspectral data in fire applications, we provide a review of the current state-of-the-art in hyperspectral remote sensing of fire. We therefore review developments in the pre-fire, active fire, and post-fire stages of the fire disturbance continuum. Benefits from hyperspectral retrievals may result from the characterization of narrow spectral features (e.g. water or gaseous absorption, Kuai et al. (2016), Yebra et al. (2013)) because of the high spectral resolution and/or detailed spectral signatures because of higher spectral data dimensionality (Veraverbeke et al., 2014).

The primary focus of this review is on applications where hyperspectral data provides a clear improvement over multispectral data, or on novel opportunities that arise from hyperspectral data that are not possible based on multispectral data. We also propose avenues for further research.

#### 2. Hyperspectral fire applications

### 2.1. Pre-fire applications

The pre-fire environment refers to fuel type and condition (Chuvieco et al., 2003a, 2003b) and how these change through time as a function of climate, weather, land management, and land use. First, fuel type represents an association of fuel elements of vegetation species, form, size arrangement and continuity that results in a characteristic fire behavior (Merrill and Alexander, 1987). Fuel type affects the chemical composition and thus available energy content that then affects fire intensity, the physical combustion process of energy release from organic matter (Agee, 1993; Keeley, 2009). Second, fuel condition refers to the moisture content and the live or dead fuel status. These parameters influence fuel drying and combustion (Pickett et al., 2010). Moisture content affects the flammability of fuels and thus fire behavior such as ignition probability and fire spread rate and consequent smoke impacts (Anderson, 1970; Forkel et al., 2012).

Multispectral remote sensing of fuel type by mapping plant functional types has capitalized upon classification and vegetation index approaches (Bartholomé and Belward, 2005; Friedl et al., 2002; Hansen and Reed, 2000; Loveland et al., 2000; Nelson et al., 2013; Rollins et al., 2006; Ryan and Opperman, 2013). Similarly, retrieving fuel moisture and photosynthetic, i.e. live, versus non-photosynthetic, i.e. dead, vegetation from multispectral data is often based on spectral indices (Anderson et al., 2004; Gao, 1995; Jackson et al., 2004; Liu and Kogan, 1996); sometimes augmented with land surface temperature data from thermal bands (Chuvieco et al., 2003a, 2003b; Verbesselt et al., 2002). Empirical relationships between spectral indices and fuel moisture are regionally specific (Jurdao et al., 2013; Riano et al., 2005; Yebra et al., 2013). Physically based radiative transfer models (RTMs) have been used to overcome site-specificity of empirical fuel moisture estimation methods (Yebra et al., 2013). These models estimate fuel moisture content as the ratio between equivalent water thickness and dry matter

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