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Editorial

Preface: Special Issue on Advances in the Measurement of Fuels and Fuel Properties

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1. Introduction

Increasing global temperatures and variability in the timing, quantity, and intensity of precipitation and wind have led to longer fire season lengths, greater fuel availability, and more intense and severe wildfires [1]. These broad-scale shifts have increased the emphasis on understanding wildland fuel dynamics through fine-scale laboratory experiments [2], refined fuel sampling strategies [3,4], the characterization of fuel hazards and treatment longevity [5,6], and operational fuel mapping [7,8]. Many of these efforts seek to enhance fuel estimation precision, along with the spatial and temporal resolutions of fuel products available for management decision making. Recent research has emphasized the need to advance fuel knowledge and management through (1) improving the speed and accuracy of techniques for characterizing fuel properties, such as fuel moisture and arrangement; (2) evaluating how fuel properties respond to management and disturbance events; and (3) integrating these techniques to improve the mapping of fuel characteristics and hazards across space and time. This Special Issue represents a collection of papers that highlight the diversity in fuel dynamics, characterization approaches, and mapping strategies from around the world.

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2. Highlights

Recent years have seen an increased emphasis in the fuel management and research community on improving the speed and reliability of fuel sampling techniques used to inform fuel hazard assessments [9] and three-dimensional (3D) fire behavior modeling [10]. This collection highlights papers that test both traditional and terrestrial laser scanning (TLS) methods of fuel sampling for describing 3D fuel loading and arrangement [11,12], along with a study modeling fuel hazard development [13]. Full parameterization of 3D fire behavior models can integrate more detailed observations of fuels than classic Rothermel-based fire models. Although the application of 3D point data for characterizing fuels for fire behavior modeling is not a new concept [14], a considerable lag was apparent prior to the widespread assessment of operational studies [15], in part due to a lack of access to data and analysis tools [16–19]. Advances in data access and tools have improved and led to the widespread availability of 3D point data for use in mapping fuels and aboveground biomass over a range of scales [20–22]; however, fully parameterizing and validating these 3D models still requires new ways of sampling fuels. To meet this need, Hiers et al. [11] demonstrate a 3D quadrat sampling strategy for gathering and modeling vertical gradients of herbaceous and woody litter fuel bulk density. Via testing rapid TLS characterization of fuel arrangement, Wallace et al. [12] found the technology was able to reliably describe the 3D fuel arrangement and that sensors across different price points provided consistent results. Other strategies are being developed to understand coarser-scale fuel dynamics. Marsden-Smedley et al. [13] were able to use time since the previous fire to predict fuel loading within different surface and ladder fuel strata, with their model providing the best prediction of fuel hazard when weighing the strata based on their influence on fire behavior.

Fuel stratum and particle-level fuel chemistry attributes that drive the ignition and propagation of fire have also received recent attention due to their importance in describing changes in fuel hazard. Bowman et al. [23] developed a fuel moisture index for fine fuels in Tasmanian forests from inexpensive humidity and temperature sensors, finding that 1-hour fuel moisture could reliably be predicted but was sensitive to *Eucalyptus* forest type, time since disturbance, and understory cover [23]. Working in the grasslands of Brazil, dos Santos et al. [24] found that species-specific parameterization of fuel moisture content models provided significant improvements over the existing general Grass Fuel Moisture Code that is in operational use. Building on these types of field studies, Zhang [25] used a laboratory experiment to better quantify the impacts of wind velocity and fuel bed compaction on the drying rates of different litter types. Using a controlled lab setting, the study was able to quantify the effects of wind and compaction on litter drying and establish predictive models for both fuel types [25]. Advances in these fields have the potential to inform the next generation of fuel hazard systems.

Parallel efforts have investigated fuel particle ignition and energy release dynamics and the potential for different ember sources to ignite fuel beds. New methods of describing live fuel energy release potential were evaluated by Melnick et al. [26] through "in flame" testing of fuel interacting with a fire front. Testing of the new method showed improved sensitivity to moisture content and a reduction in energy release in the oxygen-limited combustion zone compared to standard methods [26]. Burton et al. [27] compared litter bed ignitability between laboratory and field tests for successful and sustained ignitions. Although the results varied between the test sets, their conclusions highlight that laboratory trials are an effective substitute for field experiments [27]. Other studies have focused on how ignition sources interact with fuel beds. Recent emphasis on mastication as a fuel management strategy [28] has raised questions about the ignition potential of masticated fuel. Matvienko et al. [29] evaluated the potential of using firebrands to ignite wood chips, finding that increased wind speed was the predominant driver of greater ignition potential. Similarly, Viegas et al. [30] examined the potential of using cigarettes as ignition sources, demonstrating that fuel bed and cigarette moisture content, along with wind speed, were the driving factors behind the probability of and time to ignition. Collective research efforts into the controls of fuel moisture and ignition potential are refining the ability of managers to interpret and communicate the hazards of wildfire to the public [31].

While some fuel dynamics can be assessed in a laboratory, others require extended time periods in natural environments to understand their more complex interactions. Brown et al. [32] investigated the influence of various forest structures in Australia on dead fuel moisture content, showing positive and negative feedback of forest structure (i.e., light penetration index) on moisture content that was best accounted for through an autoregressive model with time-lagged weather inputs. To understand the cycling and recovery of shrub fuels following mastication, Pickering et al. [33] tracked 63 treatments over a 9-year period. This extended study revealed that fine woody fuel loading declined over time and shrub cover remained low following treatment, but that coarse fuel load remained high, posing a trade-off where coarse fuels might increase soil heating and smoke emissions while reduced shrub cover should moderate fire behavior [33]. Others have been able to draw management implications by integrating treatment data with postfire observations. Gannon et al. [34] evaluated the drivers of fuel break effectiveness in California, the United States, showing that fire breaks that were supported with direct attack efforts and experienced increased relative humidity had a greater chance of stopping fire progression, while fuel breaks in fires experiencing a greater daily area burned had reduced effectiveness.

Operationalizing the knowledge developed through research on fuel properties and their spatial and temporal dynamics often comes in the form of fuel mapping efforts. Ongoing advances in machine learning capabilities are making fuel mapping increasingly reliable. Sabrabadi and Innocente [35] were able to integrate hyper-parameter tuning along with Bayesian optimization into machine learning algorithms to achieve forest type classifications with 97% accuracy across the topographically driven landscape of the Colorado Front Range. Although remote sensing has long been integrated into fuel mapping [36], continuous advances in sensor resolution and data processing algorithms will further improve mapping capabilities. Aragoneses and Chuvieco [37] integrated Sentinel-3 Synergy imagery into a support vector machine algorithm to conduct a supervised classification of 45 vegetation types across the Iberian Peninsula with 85% overall accuracy. Among the hardest fuel strata to map are surface fuel conditions; Alipour et al. [38] employed a multimodal data fusion strategy with a neural network ensemble to predict 27 surface fuel models across California, the United States. By integrating neural networks with multispectral reflectance, high-resolution imagery, and biophysical climate and terrain data, they were able to achieve classification accuracies as high as 75% when ignoring the most minor fuel models (<5%) across the landscape [38].

3. Future Direction

Although considerable progress has been made in advancing the characterization of fuels using 3D point data for incorporation in fire behavior models, much work remains. Continued advancements in remote sensing resolution and processing, along with data assimilation strategies capable of incorporating a variety of data structures and relationships, hold the potential to unlock the next generation of fuel maps to support the operationalization of 3D fire behavior modeling and fuel hazard assessment. One of the most widely used fuel maps in the United States is the LANDFIRE project, which is now more than 20 years old, but provides 30 m resolution fuel predictions for landscape fire simulation. Recently, there have been calls to update the LANDFIRE program to provide predictions of 3D fuel mapping by combining the existing protocol with advances in machine learning, geostatistics, and remote sensing [39] to provide discrete predictions of forest structures capable of populating 3D fire behavior models. Additionally, there have been proposals to allow local management organizations to "on-ramp" standardized fuels and forest structure observations to these national modeling efforts to improve local model accuracy. Although 3D airborne laser altimetry has been widely used to assess individual tree characteristics, such as heights, stem and crown diameters, and biomass [40–43], other avenues of data collection need to be considered. Advances in terrestrial and handheld laser scanning [44,45] and drone-based structure-from-motion photogrammetry [46–48] are making it possible to infer metrics important for fire behavior models, such as the height of branches, quantity and type of ladder fuels, fuel strata loads, the distinction between live and dead fuels, the rates of downed woody debris accumulation and decomposition, and the assessment of live and dead fuel moisture content [49–51]. Cross-platform integration of these different data collection strategies may be able to unlock the resolution and accuracy needed to reliably operationalize the next generation of fire behavior models. Finally, while not a new concept [52], further research is still needed that improves the mechanistic integration of remotely sensed and field data that describe the pre-fire fuel data with both active fire processes (e.g., consumption and emissions) and the myriad of postfire ecosystem responses [53].

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