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Wildland Fuel Characterization Across Space and Time

Susan J. Prichard[1], Eric Rowell[2], Robert E. Keane[3], Andrew T. Hudak[4], Duncan Lutes[3], and E. Louise Loudermilk[5]

ABSTRACT

Wildland fuels are foundational to smoke prediction and generally contribute to high uncertainty in smoke production and dispersion modeling. Until recently, wildland fuels and fuel consumption have been mapped using traditional methods to estimate the cover, height, and biomass (kg m^{-2}). Over the past decade, significant progress has been made in describing and quantifying fuels more accurately with 3D characterization and quantification across large spatial scales. This chapter introduces wildland fuels and approaches to mapping them at scales relevant to smoke management, smoke impacts to communities, and future research needs. Topics covered include (1) an introduction to wildland fuels, (2) traditional approaches to mapping wildland fuels. (3) next-generation approaches to wildland fuel mapping, and (4) research and development needs. Because source characterization of wildland fuels is critical to predicting smoke impacts, reviewing how to measure and map wildland fuel biomass and consumption provides important context for fire and fuels managers, smoke scientists, and policy makers. Although recent developments in 3D fuel mapping are promising, there are still many challenges associated in scaling-measured values to the scale of wildland fire events and assessing wildland fuels such as coarse wood and organic soils (duff, peat lands) that can contribute to long-duration smoke events.

4.1. INTRODUCTION

As smoke from wildland fires becomes an increasing concern to communities, improved predictions of smoke impacts to communities is essential (Rappold et al., 2011; Williamson et al., 2016; Liu et al., 2019; Holm et al., 2021). The amount, composition, and structure of fuels that burn in wildland fires play a central role in the type and amount of air pollutants emitted by wildland fire events, and how long they are produced (Byram, 1959; Ottmar et al., 2007, Weise & Wright, 2014). Wildland fuels are defined as the combustible biomass of live and dead vegetation (Keane, 2015). In their most basic expression, fuels are stored potential energy that when released by fire, generate heat and emit air pollutants. However, as we explore in this chapter, the structure, composition, and chemical composition of wildland fuels are highly variable and are anything but basic (Cruz et al., 2018). Along with weather and topography, the amount, type, structure, spatial continuity, and condition of fuels that

[1]*School of Environmental and Forest Sciences, University of Washington, Seattle, Washington, USA*
[2]*Tall Timbers Research Station, Tallahassee, Florida, USA*
[3]*Rocky Mountain Research Station, United States Forest Service, Missoula, Montana, USA*
[4]*Forestry Sciences Laboratory, Rocky Mountain Research Station, United States Forest Service, Moscow, Idaho, USA*
[5]*Southern Research Station, United States Forest Service, Athens, Georgia, USA*

Landscape Fire, Smoke, and Health: Linking Biomass Burning Emissions to Human Well-Being, Geophysical Monograph 280, First Edition.
Edited by Tatiana V. Loboda, Nancy H. F. French, and Robin C. Puett.

DOI: 10.1002/9781119757030.ch04

burn in a wildland fire event drive fire spread, energy release, fuel consumption, and smoke production (Fig. 4.1; Larkin et al., 2010).

Characterizing and mapping the structure and variability of wildland fuels are key elements of smoke modeling and can be difficult to accurately represent without site-specific information. Geography, climate, seasonality, and past disturbances all factor into the type and quantity of wildland fuels that are available for combustion and how much smoke is produced from wildland fire events. For example, a fully cured grassland at the end of a growing season generally burns as a fast-moving fire with short-duration smoke production

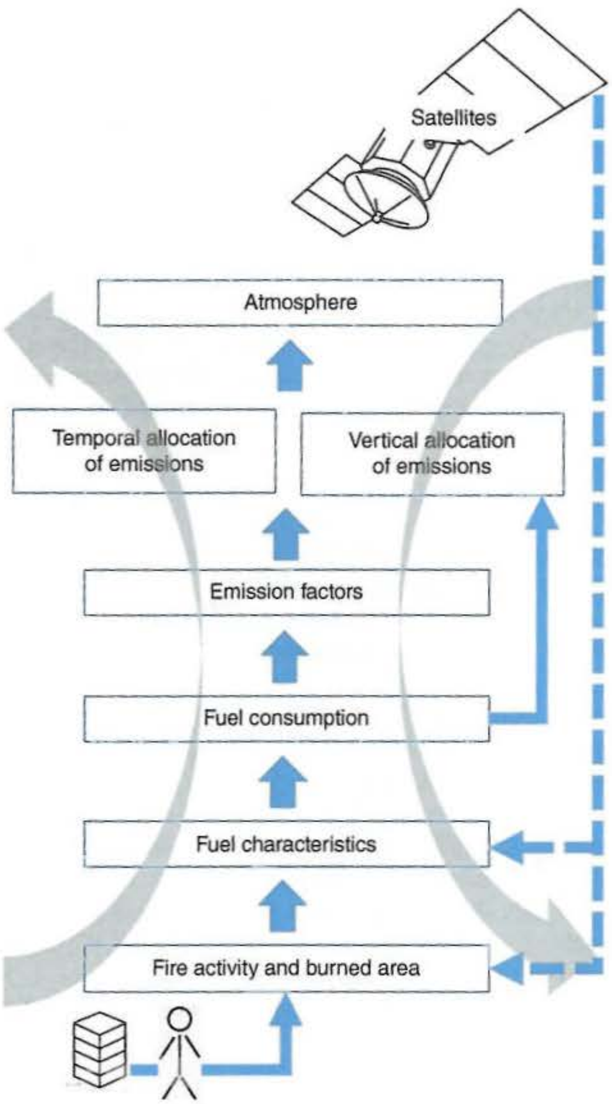

Figure 4.1 Interrelated steps to estimating wildland fire emissions from burned area, fuel characterization, and consumption to emissions and dispersion modeling (after Ottmar et al., 2009).

and relatively minimal $PM_{2.5}$ emissions compared with sites with higher available biomass for burning such as shrublands and forests (Cook et al., 2016). Following extensive fire exclusion, mixed-conifer forests generally have high biomass, accumulated understory fuels, and deep organic soils (Hessburg et al., 2019; Hagmann et al., 2021). In the absence of frequent fire, many mixed conifer forests have multilayered canopies that can support crown fires with large plume development and long-duration smoke emissions from the smoldering of coarse wood and organic soil layers (De Groot et al., 2007; Urbanski, 2014; Miller et al., 2019). However, forests that have been regularly prescribed burned often have light understory fuels that contribute to low-intensity surface fires that cannot reach the forest canopy; much like grasslands, these low-intensity surface fires can produce short-duration emissions compared with fire-excluded forests (Haikerwal et al., 2015; Liu et al., 2017; Jaffe et al., 2020).

Because the structure, continuity, and composition of wildland fuels matter so much for fire behavior and smoke prediction, wildland fuelbeds often need to be characterized into the types of fuels that are available for combustion, often organized in vertical layers, including tree canopies, dead tree boles (termed snags), shrub stems and leaves, grass and herbaceous vegetation, sound and rotten wood, needle and leaf litter, moss, lichen, and ground fuels, which are defined as partially to fully decomposed organic soils (Ottmar et al., 2007). Smoke emissions are then estimated based on type and mass of fuel consumed (g or kg), which is used to determine smoke composition by multiplying mass by emission factors for specific pollutants and fuel types (Urbanski, 2014; Prichard et al., 2020).

Of all variables involved in estimating smoke emissions, the amount of available fuel and proportion that is consumed often represent the greatest sources of uncertainty (Ottmar, 2014; Drury et al., 2014). Errors in estimates of pre-burn fuel biomass can contribute as much as 80% when calculating emissions, and errors in estimating fuel consumption can contribute another 30% (Peterson, 1987). Fuels, topography, and weather compose the classic fire environment triangle (Countryman, 1972). However, wildland fuels are the only one of the three variables that can be managed to influence fire behavior before an ignition occurs (see Box 4.1).

Although maps of wildland fuel biomass are widely available (e.g., LANDFIRE; Rollins, 2009), they generally have high uncertainty because they are derived from vegetation layers classified from remotely sensed imagery and are not based on direct observations. Reliable estimates of fuels generally require more detailed information

Box 4.1 Fuel Reduction Treatments and Emissions Scenarios

Fuel reduction treatments are used to reduce surface and canopy fuels and to mitigate future wildfire hazard (Omi, 2015; Kalies & Kent, 2016). In the following example, we evaluate potential consumption and emissions in managed dry, mixed conifer forests of the eastern Cascade Mountains (northwestern United States). The three fuelbeds represent an unmanaged forest dominated by Douglas fir (*Pseudotsuga menziesii*), ponderosa pine (*Pinus ponderosa*), and grand fir (*Abies grandis*) that have large accumulations of surface and canopy fuels from an extended period of fire exclusion. The Thin Rx scenario represents a restored forest that was thinned from below, removing midstory trees and thinning overstory trees. This treatment was followed by a prescribed understory burn, which reduced accumulated surface fuels. The thin-only scenario represents postthinning fuels that are elevated from the accumulated posttreatment logging slash and litter (see Table B4.1).

Consumption and $PM_{2.5}$ emissions scenarios were estimated in Consume (Prichard et al., 2007) under two scenarios. A summer wildfire scenario was evaluated to compare potential $PM_{2.5}$ emissions under dry fuels typical of summer wildfire seasons in dry mixed conifer forests of the eastern Cascade Mountains. Fuel moisture and other burn day inputs are listed in Table B4.2. Because thinned forests lack continuity between surface and canopy fuels, canopy consumption is often minimal. We therefore assumed 10% canopy consumption under the summer wildfire scenario and no consumption under the prescribed fire scenario.

Predicted $PM_{2.5}$ emissions differ markedly across scenarios. Under summer wildfires, the thinned and prescribed burn unit has sparse understory fuels that contribute little to $PM_{2.5}$ emissions. In contrast, downed woody debris and ground fuels in the thin only unit pose a substantial emissions potential. The unmanaged forest (control) has high crown fire potential, modeled at 75% canopy consumption. Although it might seem counterintuitive that thin-only treatments pose comparable risk to high $PM_{2.5}$ emissions as unmanaged forests, Figure B4.1 demonstrates that the majority of fuels that contribute to wildfire emissions are surface fuels. If thinning results in a rearrangement of canopy fuels to surface fuels, it would be expected that high emissions could result from a summer wildfire.

The prescribed burn scenario shows a similar contrast between treatments. Maintenance burning is common in restored dry forests, and, as presented in this scenario, actual $PM_{2.5}$ emissions can be quite low once fuels have been reduced from the first prescribed burn. In contrast, the thin-only unit has substantial emissions potential in ground fuels, litter, and especially downed wood. Where possible, additional biomass removal including whole-tree yarding and biomass utilization can reduce the emissions potential of recently thinned sites. In this case, the unmanaged control has less emissions potential than the thinned unit due to the elevated downed wood in the thin-only unit.

Table B4.1 Input fuel loadings (Mg/Ha)

	Canopy	Shrub	Herb	Wood	LLM	Ground	Total
Control	120.94	1.49	0.22	41.62	3.18	17.75	188.59
Thin only	62.55	1.31	1.12	87.96	10.41	17.75	232.45
Thin Rx	62.55	0	1.12	10.94	0.48	2.11	128.55

Note: Canopy, shrub, herb, downed wood (wood), litter-lichen-moss (LLM), and ground fuels (ground) of the three comparison fuelbeds including an unmanaged control, thin only and thin and prescribed underburn (Thin Rx)

Table B4.2 Environmental variable inputs to consume for summer wildfire and prescribed burn scenarios

	1,000 h FM (%)	Duff FM (%)	Litter FM (%)	Shrub consumption (%)	Canopy consumption (%)
Summer wildfire					
Control	10	10	6	100	75
Thin and thin Rx	10	10	6	100	10
Prescribed burn					
Control	20	40	15	100	10
Thin and thin Rx	20	40	15	100	0

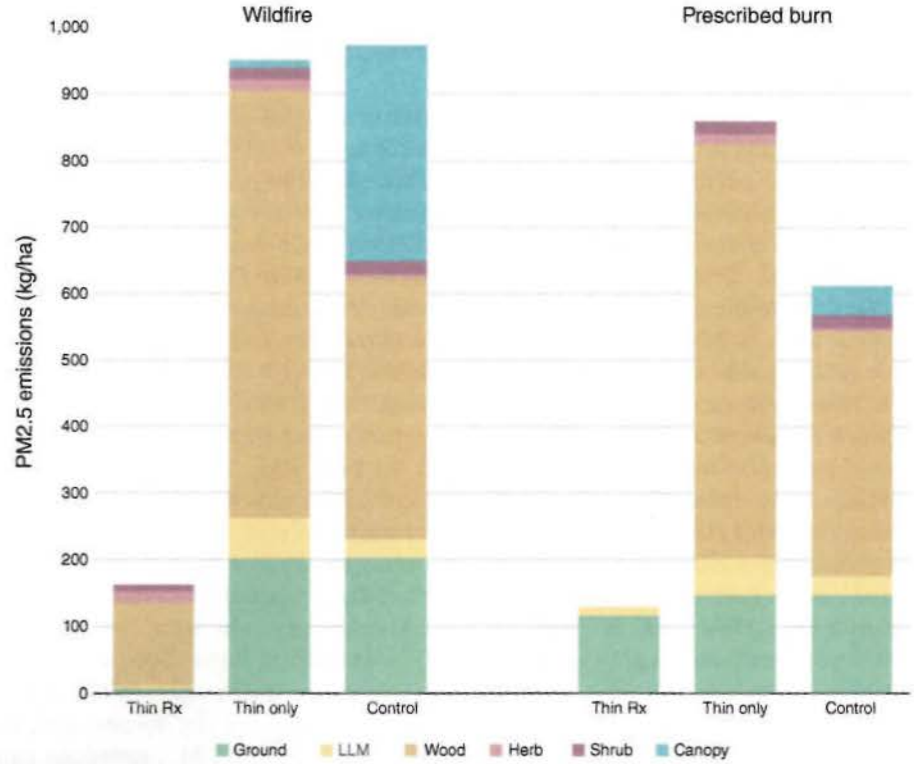

Figure B4.1 Comparison of predicted $PM_{2.5}$ emissions (kg/ha) under wildfire and prescribed fire scenarios for mixed conifer forests under three comparative management strategies including thinning and prescribed burning, thin only and prolonged fire exclusion (control).

than is provided by remotely sensed imagery and classified vegetation. For example, fuels that most often burn in a forest fire are obscured by forest canopies and are strongly dictated by past disturbances or management activities (Keane, 2015; Prichard et al., 2019). Passive remote sensing imagery may provide operational maps of forest vegetation type and cover but do not reflect the amount, structure, or condition of subcanopy fuels the drive fire behavior and consumption (Keane et al., 2001).

With increased availability of light detection and ranging (lidar) and structure-from-motion (SfM) photogrammetry, remotely sensed data sets are beginning to facilitate 3D fuel mapping (Loudermilk et al., 2009; Wang & Glenn, 2009; Hoff et al., 2019; Hudak et al., 2020). As such, methods for next-generation fuel characterization are being developed at scales and resolutions appropriate for physics-based computational fluid dynamics (CFD) models that are capable of resolving fire-atmosphere interactions, heat release, and smoke production (Linn et al., 2002; Mell et al., 2007; Loudermilk et al., 2009; Hudak et al., 2016a, 2020). However, even these new approaches to mapping fuels in 3D have limitations. In particular, distribution of downed logs and stumps may vary at fine spatial scales and be obscured from airborne remote sensing platforms (Brown, 1974; Keane, 2015), and there are currently no practical approaches for measuring forest floor layers (litter and duff depth, cover and bulk density) using remote sensing techniques. Reliable estimates of these fuel categories across burn units often are critical to anticipating long-term smoke impacts and residual smoldering following the flaming fire front.

This chapter introduces wildland fuels and approaches to mapping them at scales relevant to smoke management, smoke impacts to communities, and future research needs. Topics covered include (1) an introduction to wildland fuels, (2) traditional approaches to mapping wildland fuels, (3) next-generation approaches to wildland fuel mapping, and (4) research and development needs. Because source characterization of wildland fuels is critical to predicting smoke impacts, reviewing how to measure and map wildland fuel biomass and consumption provides important context for fire and fuels managers, smoke scientists, and policy makers. This chapter provides annotated content of a more detailed review recently published within the National Smoke Assessment with an emphasis on wildland fuel mapping applications relative to smoke modeling and forest health (Prichard et al., 2022).

4.2. WHAT ARE WILDLAND FUELS AND HOW DO THEY CONTRIBUTE TO SMOKE?

In wildland fire science and management, wildland fuels are often characterized in three vertical fuel layers: canopy, surface, and ground fuels (Keane, 2015; Gale et al., 2021). Canopy fuels are the biomass above the surface fuel layer (approximately >2 m). Surface fuels generally include biomass within 2 m above the ground surface. Ground fuels are all organic matter below the ground line, where the ground line is usually just below the litter (Oi soil horizon) and include the Oe and Oa soil horizons (collectively, "duff"), defined as partly to fully decomposed litter. Fuelbed layers are composed of finer-scale elements called *fuel strata* and *categories* (Fig. 4.2).

Fuel strata characterize the vertical profile of wildland fuels, and fuel categories are defined for specific applications, such as fire behavior prediction. For example, the downed wood stratum often contains fuel categories including fine wood (<8 cm diameter), coarse wood (>8 cm diameter), stumps, and piles (Riccardi et al., 2007). Fine wood is mostly consumed during the flaming phase of combustion (Ottmar, 2014) and is important for surface fire behavior prediction and flaming emissions, whereas coarse wood partially burns during the flaming phase of combustion and then often smolders long after the passage of the flaming front (Fig. 4.3), contributing to long-duration heat release and smoke (Albini, 1976; Hollis et al., 2010; Hyde et al., 2011).

Fuel strata and categories are also characterized by their physical and chemical properties, including bulk density, biomass (mass per area, kg m^{-2}), surface area (m^2), and heat content (J kg^{-1}), which are used as inputs to fire behavior and effects models (Keane, 2015). The finest scale of fuel description is the fuel particle, defined as a specific piece of fuel that is part of a fuel category (Gale et. al., 2021). A particle can be an intact or fragmented woody stick, grass blade, shrub leaf, or pine needle. Fuel particles have a broad range of physical properties, including density (kg m^{-3}), volume (m^3), and shape. The properties of fuel categories, strata, and fuelbeds are often quantified from statistical summaries of properties of the particles that compose them. For example, quadratic mean diameter and mean surface area-to-volume ratio (cm^2 cm^{-3}) are often applied to size classes of wood particles for fire and smoke modeling (e.g., Brown, 1974).

Because live and dead fuels generally have very different fuel moistures and availability for burning, wildland fuels are also defined by their status (live/dead) and condition (fuel moisture). Dead fuel is suspended or

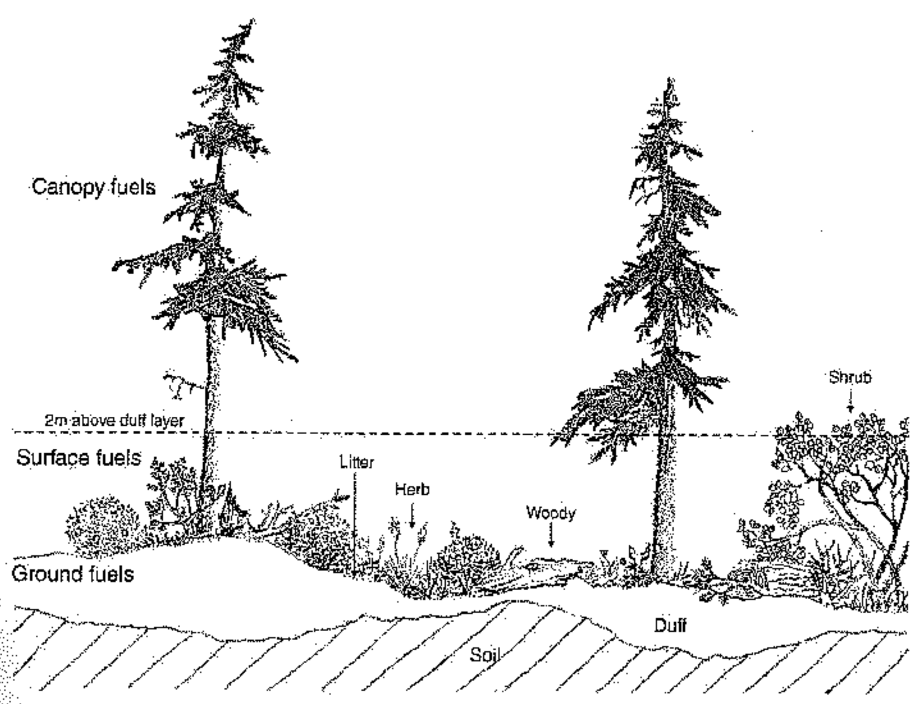

Figure 4.2 Vertical stratification of canopy fuels (>2 m aboveground fuels) and surface fuels.

Figure 4.3 Representative photos of (a) flaming, (b) short-term smoldering, and (c) long-term (residual) smoldering combustion (courtesy of Roger Ottmar).

downed dead biomass, and live fuel is the biomass of living organisms including vascular plants (trees, shrubs, herbs) and nonvascular plants (mosses, lichens, and liverworts). Live and dead fuel properties are both influenced by short-term variations in weather, but live fuel moistures are primarily controlled by chemical content (Fares et al., 2017) and plant physiology, including phenology, transpiration, evaporation, and soil moisture, which differ among taxa and across regional climate (Nelson, 2001; Jolly et al., 2014). In contrast, dead fuel moisture is dictated by the physical properties of the fuel (e.g., size, density, surface area) and their interaction with site climate, weather dynamics (wind, solar radiation, vapor pressure deficit), and available soil moisture (Fosberg et al., 1970; Viney, 1991; Banwell et al., 2013; Byram & Nelson, 2015). Live foliar moisture content influences when and where grasses, shrubs, and tree crowns are available to burn and can be highly variable across space and time. For example, green grass cover generally presents a barrier to fire spread whereas partially to fully cured grass facilitates rapid fire spread.

Because the type and condition of fuels vary over time, characterizing seasonality of wildland fuelbeds is critical for refining predictions of fire behavior and smoke productions. Differences in foliar moisture content between green and cured grasslands are well understood, but forests can also have marked differences in available fuels between growing and nongrowing seasons. For example, mixed pine and hardwood forests of southeastern North America are less available to burn during warm, humid, summer months with generally high monthly precipitation (Mitchell et al., 2009). However, dormant seasons are often marked by lower monthly precipitation with highly flammable litter fuelbeds that are generally composed of forest litter, grasses, and shrubs. Similarly, during the spring dip in boreal and subboreal landscapes, conifer tree species experience a pronounced decline in foliar moisture content prior to bud burst (Little, 1970; Chrosciewicz, 1986). During this short period of time, these forests can be particularly conducive to crown fires (Jolly et al., 2014).

The structure of wildland fuels is also an important characteristic that can strongly influence how fires spread and produce smoke. At fine spatial scales, the porosity of fuels influences how much available oxygen and air flow there is to support combustion (Fons, 1946). Complexes of dry fine wood, grass, and shrubs often burn efficiently and contribute most to flaming combustion. In contrast, duff is densely packed with low combustion efficiency and mostly contributes to smoldering combustion. Across coarser spatial scales, gaps in fuel structure influence fire spread, including whether a forest can support transitions from surface to crown fires (Weise et al., 2018) and how readily fires can spread from tree crown to tree crown (Parsons et al., 2017; Ziegler et al., 2017). For example, vertical gaps between understory fuels (shrubs, grasses, and litter) and canopy fuels can prevent surface fires from burning into forest canopies (Fig. 4.4). Similarly, the spatial continuity of surface fuels often strongly drives or constrains fire behavior (Atchley et al., 2021). Depending on fire intensity and wind speed, discontinuities in surface fuels such as patches of bare mineral soil or green vegetation with high foliar moisture content can create impediments to fire spread. Under mild weather and low wind speeds, surface fuel heterogeneity can strongly influence wildland fire behavior. However, vertical and horizontal gaps in fuel structure matter far less under more extreme fire weather and behavior. Desert ecosystems offer the most extreme example of fuel discontinuity; although desert vegetation is often dry enough to ignite a fire, fire spread is limited by the lack of continuity in sparse fuels (Gill & Allan, 2008; Swetnam et al., 2016).

Geospatial information on past fuel reduction treatments including thinning, prescribed burning, and past wildfires, is important for wildland fuel mapping because it can refine estimates of wildland fuel biomass and continuity. Fuel reduction treatments such as forest thinning and prescribed burning are generally designed to create gaps in fuel structure and, for a time, reduce the continuity and availability of fuels to burn in subsequent wildfire events (Kalies & Kent, 2016; Prichard et al., 2017). Following fuel reduction treatments or wildland fire events in fire-prone forests, understory fuels may either present barriers to fire spread through lack of continuity or support low intensity fire with concomitantly low emissions (Fulé et al., 2012; Omi, 2015). Specific information about the type of treatment and time since treatment are therefore critical to updating maps of wildland fuels and are used in wildland fuels mapping projects described in section 4.3.

Where organic soil layers including litter and ground fuels exist, they often comprise a substantial proportion of total available biomass and contribute disproportionately to smoke emissions including long-term smoldering events (Urbanski et al., 2014; Mickler et al., 2017). However, approaches to characterize peat land and forest floor layers have not advanced much in recent decades. To date, airborne remote sensing techniques are unable to

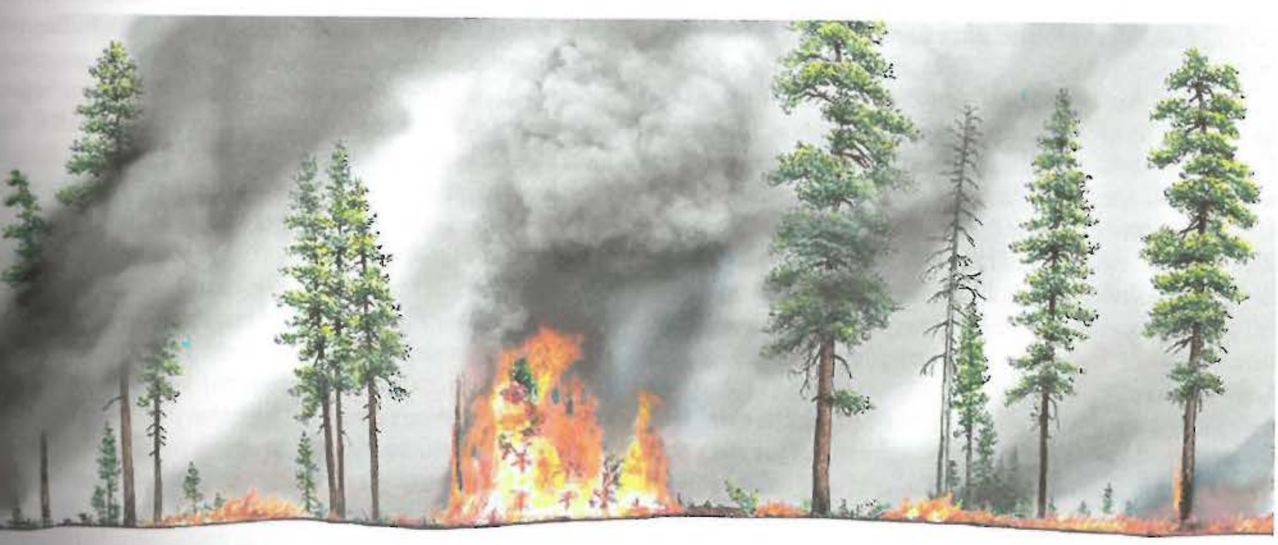

Figure 4.4 Conceptual diagram of mixed severity fire with a depiction of crown fire (middle) and surface fire (left and right) (courtesy of Bob Van Pelt).

penetrate organic soils and cannot resolve their density or depth. Instead, field observations in addition to models of organic soil accumulation (Zakem et al., 2021), decomposition, and changing moisture characteristics are needed to complement 3D fuel measurement techniques. Recent research on spatial distributions of ground fuel depth, biomass, and other characteristics in long-unburned forests of the southeastern United States emphasizes fine-scale spatial and temporal variability in ground fuels and the potential problems of sampling across forest stands or burn units (Kreye et al., 2014).

4.2.1. Temporal and Spatial Dynamics of Wildland Fuels

Much of the inherent complexity of wildland fuels is driven by how vegetation dynamics varies over space and time. Numerous ecological processes influence live and dead fuel dynamics, but the following four are particularly important in governing spatial and temporal distributions of wildland fuels (Keane, 2015).

1. Development. Wildland fuels accumulate from the establishment, growth, and mortality of vegetation (development). The rate of biomass accumulation, or productivity of vegetation, is dictated by interactions of the plant species available to occupy a site and the physical environment (climate, soils, and topography).

2. Deposition. Over time, portions of living biomass shed or die and are deposited on the ground to become dead surface fuels.

3. Decomposition. Belowground and aboveground dead organic matter is eventually decomposed by microbes and soil macrofauna.

4. Disturbance. Fire, insects, and disease and other disturbance agents act on living and dead biomass to change the magnitude, trend, and direction of fuel accumulation in space and time.

Wildland fuel properties and their distributions are a cumulative result of interactions of the above processes that create shifting mosaics of fuel conditions on fire-prone landscapes. The four processes listed above create such heterogeneous fuel distributions that any property of fuel often exhibits high variability. For example, the biomass per unit area, kg m^{-2} of fine woody debris, often termed *fine wood loading*, can vary by two to three times its mean over a small (<10 ha) prescribed burn unit (Keane et al., 2012a).

These four processes interact to influence fuel development, and the interactions depend on the ecosystem and corresponding climate and disturbance regimes. For example, live and dead vegetation characteristics often correlate to development and deposition, whereas climate drives decomposition and disturbance (Keane, 2008). Vegetation composition is sometimes used as a surrogate for fuels (Keane et al., 1998; Menakis et al., 2000), but often does not adequately represent the role of decomposition and disturbance on fuelbed development.

Understanding spatial and temporal variability of wildland fuels provides insight into how fuel consumption influences smoke emissions (Anderson, 1976) and how fuel management influences fuel properties. Processes that drive fuel dynamics also inform novel fire behaviors and effects (Parsons et al., 2010) and can contribute to new fuel classifications, sampling methods, and geospatial data sets (Keane, 2015). Spatial configuration of fuel characteristics is needed for next-generation fire effects and behavior models that rely on 3D fuel inputs and represent fire with CFD modeling (Linn et al., 2002; Mell et al., 2007; King et al., 2008; Parsons et al., 2010). It is this variability, combined with the inherent sampling error of various fuel sampling techniques, that makes estimating biomass for smoke prediction particularly challenging.

4.3. TRADITIONAL APPROACHES TO MAPPING WILDLAND FUELS FOR SMOKE MODELING AND EMISSIONS INVENTORIES

Traditional approaches to mapping wildland fuels fuel biomass (kg m^{-2}) and other characteristics (e.g., vegetation height and cover) are based on modeled relationships between classified vegetation and fuels (Keane, 2013). For example, LANDFIRE supports 30 m raster maps of wildland fuels and other data layers important to fire and smoke modeling. Wildland fuel characteristics are modeled from LANDSAT Thematic Mapper (TM) imagery, which is used to estimate vegetation cover and existing vegetation type (https://landfire.gov/evt.php), and airborne lidar data sets that inform vegetation height and cover metrics for 30 m pixels. Disturbances, including past fires, forest insects, windstorms, and forest management, are also used to update map layers and represent vegetation and fuel succession. Supported LANDFIRE fuel layers include surface fire behavior fuel models, canopy fuel, fuel loading models (Lutes et al., 2006), and fuelbeds for the Fuel Characteristics Classification System (Prichard et al., 2013).

Many biomass maps are also available at coarser spatial scales, based on remotely sensed optical, lidar, and radar data, and are used for global carbon modeling and emissions mapping. Examples include the U.S. Environmental Protection Agency's emission inventory (U.S. EPA, 2017), global carbon and biomass mapping (e.g., ESA Biomass Climate Change Initiative map by Santoro & Cartus, 2019), and wildland fuel maps based on major vegetation types (e.g., Pettinari & Chuvieco, 2016).

Although widely used, associating fuel characteristics with remotely sensed products has limitations due to imagery resolution and canopies that obscure surface and ground fuels (Keane et al., 2013). Because fuel categories vary independently of each other, high variability of fuel characteristics within a site may overwhelm unique fuelbed identification across sites (Prichard et al., 2019). A common approach to wildland fuel mapping is to assign fire behavior fuel models based on vegetation type and disturbance history for fire simulations (Burgan et al., 1998; Scott & Burgan, 2005). However, fuel models generally are too simplistic to represent the complexity of wildland fuels and do not support categories that are important to quantify for smoke modeling such as coarse wood and ground fuels (Sikkink & Keane, 2008; Keane, 2015).

Because mapping products are often unreliable at the scale of prescribed burning, field-based fuel characterization is required to further refine fuels for site-specific applications. Field surveys often include visual assessments, including use of photo load plots to assess live and dead surface fuels (Keane & Dickinson, 2007), photo series to visually estimate fuel loadings from similar sites (https://depts.washington.edu/nwfire/dps), and direct measurement (see Keane, 2015, for more detail on this topic). The most common direct measurement methods include planar intercept for sampling downed woody fuels and fixed-area plots for sampling the biomass per unit area of fuels (Brown, 1974; Catchpole & Wheeler 1992; Bate et al., 2004). Litter and ground fuel characterization generally involves destructive sampling and estimations based on depth measurements and has remained virtually unchanged over the last four decades (Brown et al., 1982; DeBano et al., 1998). For destructive sampling, plots are sampled to develop local bulk density values from dry-weight biomass measurements of a known volume (Keane, 2015). Some ecosystems may have patchy soil organic matter coverage (deserts, woodlands, sagebrush grasslands) making sampling difficult and often requiring a field measurement of ground fuel and litter cover. A common approach to estimate biomass (kg m^{-2}) of ground fuels is from measured depths of organic soil horizons (m), which are multiplied by bulk density (kg m^{-3}) to estimate biomass (kg m^{-2}; (Brown et al., 1982; Deluca & Boisvenue, 2012).

Until recently, a major gap in our understanding of wildland fuels has been a lack of spatial dimensionality in fuel characterization, which is necessary to reduce uncertainty and increase precision of inputs to fire behavior, fuel consumption, and smoke modeling. Due to the high spatial variability of wildland fuels and lack of correlation between fuel strata and categories, estimations based on traditional fuel measurement techniques often result in high variance and lack of precision (Brown et al., 1982). For example, planar intersect sampling of woody fuel biomass incorporates only one dimension of point intersections with a transect line (Brown, 1971). Given that fine and coarse wood can vary differently across space, linear sampling may not capture spatial variability of fine and coarse wood (Keane & Gray, 2013). Other conventional fuel inventory techniques, such as photo series, may also be inappropriate because fuels vary at spatial scales that might be different from the scales represented by the photo.

Whether collected in the field or through remote sensing, traditional wildland fuel mapping often provides a single estimate of biomass or depth for a given pixel. As such, the inherent uncertainty in wildland fuel estimation cannot be used to inform confidence intervals or probabilistic ranges of actual values. This is an important consideration for smoke modeling. With better knowledge of actual ranges in fuel distributions for mapped vegetation, we can provide better source characterization for wildland fire events and estimated uncertainty in smoke production. For example, in a recent study, Prichard et al. (2019) compiled biomass estimates by major fuel category based on plot data collected throughout the United States. They were able to estimate (based on the well-studied fuels, mostly forests) probability distributions of plot estimates. These values can be used to inform whether there are sufficient observations to fit distributions, and, if so, fitted distributions can be used to provide statistically derived estimates of means, ranges, and most likely values (e.g., 50th vs 95th quantile).

4.4. NEXT-GENERATION WILDLAND FUEL MAPPING

Advances in remote sensing techniques offer promising approaches to characterizing the structure and biomass of wildland fuels. These include airborne and ground-based lidar and structure-from-motion photogrammetry (SfM) (Loudermilk et al., 2009; Hudak et al., 2016a; Cooper et al., 2017). Airborne lidar scanning (ALS) is used operationally for precision forest inventory of tree stems and crowns and is useful for mapping vegetation height and cover and biomass (Hudak et al., 2008; García et al., 2011; Silva et al., 2016, 2017). However, its coarser resolution (3–5 m) limits its ability to adequately characterize understory and surface fuels, especially through an overstory forest canopy (Skowronski et al., 2011; Hudak et al., 2016a, b). Neither lidar nor other remote sensing systems can penetrate the forest floor to measure litter and ground fuel biomass, although recent work suggests that robust estimates of litter biomass may be possible in some forest types (Rowell et al., 2020).

Terrestrial laser scanning (TLS) is an emerging technology used to estimate the biomass and structure of surface, subcanopy, and canopy fuels (Loudermilk et al., 2009; Seielstad et al., 2011; Rowell et al., 2020). Mounted on a tripod or vehicle, TLS units obtain scan distances at sub-cm scales from the instrument location to vegetation, surface fuel, and other object surfaces and can penetrate through foliage layers. The lidar signal, which amounts to a 3D cloud of X, Y, and Z points, can then be related to biomass by constructing statistical models where destructively sampled bulk density for various categories is correlated to statistical metrics derived from the lidar point cloud data (Fig. 4.5). It can be difficult to differentiate between fuel categories using TLS in heterogeneous fuelbeds, and integration with multispectral imagery is sometimes necessary for image interpretation (e.g., Hudak et al., 2020).

Structure-from-motion (SfM) technology uses high-resolution images, often collected from cameras mounted on drones, to create 3D multispectral images of vegetation and fuels (Zarco-Tejada et al., 2014). Although photogrammetric point clouds have inferior vegetation penetration compared with lidar, the multispectral capabilities of digital cameras make assignment of plant functional type or live/dead status more feasible than from the single near-infrared or green channel data in most lidar sensors (Bright et al., 2016; Hudak et al., 2020). Integrating short-range SfM using digital cameras, mobile phones, or high definition (4K) digital video allows for fine-scale, 3D representations of wildland fuels in true color or multispectral images (Bright et al., 2016; Wallace et al., 2019). Once calibrated with field-based measurements (Fig. 4.6), these data sets can provide 3D mapping of live and dead canopy and surface fuel biomass and structure with applications for biomass mapping, fire behavior modeling, and fuel consumption measurements.

Because TLS and SfM images are sampled at high resolution, they can be merged into 3D point clouds for fine-scale mapping and quantification of live and dead surface and canopy fuels. Highly resolved spatial data from TLS and SfM expands sampling beyond the domains of traditional destructive plots and planar intersect fuel surveys. In particular, TLS excels at capturing detailed pre- and post-fire 3D data that represent continuous changes in estimates of bulk density at fine scales (Hudak et al., 2020). These technologies offer promising ways to characterize the vertical and horizontal distribution of wildland fuels with applications for fire behavior and smoke modeling (e.g., Rowell et al., 2016). High resolution 3D mapping is making pre- and post-burn fuel monitoring of spatially resolved fuel consumption possible. These advances have the potential to refine estimated fuel consumption and smoke emissions; they have implications for post-fire monitoring of vegetation response to fire.

Physics-based models of fire behavior and smoke production that rely on 3D fuel characterization are under evaluation for operational use (e.g., Linn et al., 2020). These rapid developments in fire behavior and smoke modeling (e.g., Atchley et al., 2021) are in close coordination with 3D fuel characterization and mapping approaches. When integrated with fire behavior monitoring (Moran et al., 2019), 3D consumption data can be used to evaluate fuel and fire interactions that produce smoke from a range of fire types and behavior.

Although recent developments in 3D fuel mapping are promising, there are still no established methods to scale 3D fuels data from fine-scale field measurements to the larger spatial scales (e.g., burn units or watersheds). Before such mapping applications can be developed, modelers need to identify how fuel metrics (e.g., biomass, bulk density, surface-area-to-volume ratio, and heat content) and characteristics (e.g., fuel type, status, and condition) can be assigned from sampled values to large spatial scales, across fire types (e.g., prescribed fire, wildfire, surface fire versus canopy fire) and across managed landscapes.

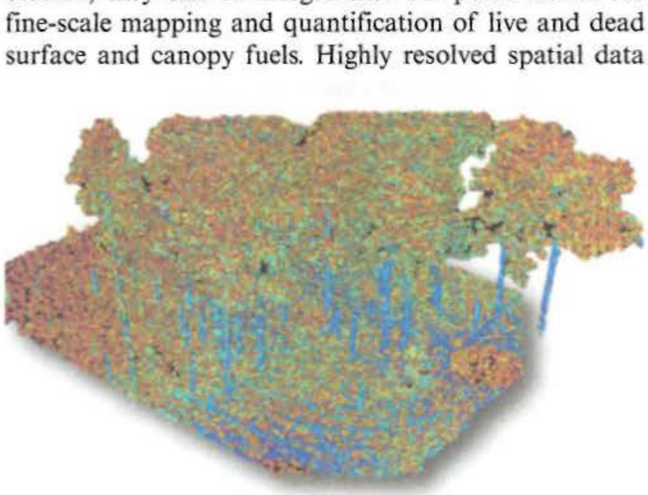

Figure 4.5 Example of a point cloud generated from terrestrial lidar scanning with denser fuels represented in blue and more porous fuels in red.

Figure 4.6 Example image of a forest understory generated from close-range structure-from-motion photogrammetry.

Appropriate scales for fuels mapping depend on the application and type of wildland fire event. For example, coarse-scale grid cells (e.g., 5 × 5 × 5 m) may be sufficient to represent crown fuels during extreme fire spread events, where fire weather and topography dominate fire behavior and smoke production patterns. In contrast, fine-scale fuel heterogeneity is often critical for accurate fire behavior predictions in a low-intensity surface fire such as a prescribed burn in light surface fuels. A forest that has been recently thinned and prescribed burned contains available fuels but in a structure that is unavailable to burn in most wildland fire events. However, column-driven fire spread combined with strong winds could exceed the threshold to burning for that site. Similarly, sites with high live fuel moisture in grass and shrub fuels may present barriers to fire spread under normal fire-weather conditions, but thresholds to burning can be exceeded by exceptional fire weather and spread events.

Mapping 3D fuels at the scale of wildland fire events, including wildfires and prescribed fires, presents several challenges to hierarchically scaled observations across spatial scales. Field and remote sensing measurements may be taken at similar scales but are inherently difficult to integrate due to intermixed fuels (e.g., complexes of live and dead shrubs, grasses, and leaf litter) and challenges in colocating and relating field and remote sensing measurements. However, the field of 3D fuel characterization is rapidly advancing with several promising approaches. Calibrated with field data sets, TLS and SfM photogrammetry point clouds offer a novel and scalable advancement in fuel characterization with highly resolved bulk density estimates for known volumes (Rowell et al., 2020). Robust coupling involves colocating techniques between individual 3D field plots and point-cloud data sets. For example, a recent approach to 3D field sampling (Hawley et al., 2018) was designed specifically to link 3D fuel types and fuel mass, collected within 10 × 10 × 10 cm cubes to the same resolution of volume TLS point clouds of vegetation structure. Additional work is needed to create machine-learning algorithms to classify 3D point-cloud data sets generated from TLS and/or SfM photogrammetry, then apply rule-based assignments of metrics such as bulk density, surface-area-to-volume ratios, and fuel moisture content to each classified object or volume for broader scale mapping applications.

4.5. RESEARCH NEEDS AND FUTURE DIRECTIONS

With rapid advancement in remote sensing and machine learning algorithms coupled with cloud computing, we anticipate that lidar and SfM photogrammetry will become readily accessible and provide highly resolved mapping of wildland fuels for fire behavior and smoke modeling. However, point-cloud imagery has its limitations, and future maps will likely involve an integration between remotely sensed and modeled fuel characterizations. In particular, research is needed to develop operational methods for coordinated image acquisition, interpretation, and mapping.

Given this reality, the largest gap in our knowledge of wildland fuels remains how to model fuel dynamics over space and time to create up-to-date and realistic characterizations for smoke modeling. Spatiotemporal interactions of living and dead vegetation are complex yet critical for providing temporally resolved estimates of fuel production and distribution. The 3D spatial complexity of fuels, and their dynamics over time, translates to similar complexity and variability in the availability of fuels to burn and their contribution to fire behavior and effects. However, the life cycle of fuels as it relates to vegetation dynamics and feedbacks with fire has not been fully defined. Furthermore, the temporal dynamics of fuels can be distinct between fine-scale changes in fine fuel moisture and the coarse-scale changes (e.g., vegetation structure, productivity, and climate).

Because long-duration smoke events create significant smoke impacts to communities, future research is needed to identify potential sources of smoldering consumption that can contribute to the severity and duration of smoke impacts to communities from prescribed burning. Organic soils can compose a substantial proportion of total site biomass and contribute disproportionately to smoke emissions including long-term smoldering events (Rappold et al., 2011; Urbanski, 2014). Because some fuels, including forest floor and peat-land soils, cannot be remotely sensed, future approaches to fuel characterization will involve a combination of traditional methods and new technologies that are currently under development. For example, in boreal ecosystems where the majority of biomass is stored in peat-land soils, Chasmer et al. (2017) showed that variation in forest floor depth could be quantified by differencing the ground-surface elevation models derived from separate pre- and post-fire lidar collections. However, in most fuelbeds, ground fuel layers are too shallow relative to the vertical precision of airborne lidar to detect changes in ground fuel depth due to consumption. Realistically, updating maps of wildland fuels will require linkages between remotely sensed data sets and ecological process models to account for the diversity of wildland fuels and challenges with remotely sensing forest floor layers. Ecological models that simulate development, deposition, decomposition, and disturbance can capture multiscaled fuel dynamics and translate them to fire behavior and smoke modeling at relevant spatial scales (Keane, 2015).

4.6. CONCLUSIONS

Wildland fuels are foundational to smoke prediction and generally contribute to high uncertainty in smoke production and dispersion modeling (Weise & Wright, 2014). Until recently, fuels and fuel consumption have been mapped using traditional methods to estimate the cover, height, and biomass (kg m^{-2}) of wildland fuels across dominant ecosystems of North America. Over the past decade, significant progress has been made in describing and quantifying fuels more accurately with 3D characterization and quantification across large spatial scales.

One of the biggest challenges in characterizing fuels is the high spatial and temporal variability that is present in wildland fuels in nearly all types of ecosystems. Most fuels managers do not have routine access to high-tech tools or high-resolution data (e.g., 3D characterization of fuels). Therefore, practical approaches are needed to improve field-based fuel characterization, fire behavior modeling, and consumption modeling, which will in turn inform the potential contribution of specific fuels (coarse wood, rotten stumps, basal accumulations, deep organic soil layers) to fire emissions and smoke dispersion.

Given the spatial and temporal complexity of wildland fuel dynamics, a better understanding is needed of the ecology of vegetation and fuels. In future decades, we anticipate that climate change will drive substantial changes in vegetation and fire dynamics, with concomitant changes in fuelbeds and their contribution to fuel consumption and emissions. Developing or revising ecological process models to ensure compatibility with next-generation fire behavior and smoke models will improve characterization of wildland fuel dynamics and both reduce and inform uncertainty in smoke predictions.

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