Fuels Characterization Techniques

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Synonyms

Fuel measurement and fuel estimation

Definition

Fuel characterization is defined as the qualitative and quantitative measurement and characterization of combustible material in the wildland environment excluding materials of anthropogenic origin.

Introduction

The measurement and characterization of wildland fuel matrices in ways that are relevant to both fire managers and scientists remains challenging. Wildland fuel characterization differs markedly from the characterization of fuels in the built environment, as these fuels are comprised of the components of dynamic ecosystems where change is a constant. This problem is confounded by the spatial and temporal extents and resolutions at which fuels are to be measured. Additionally, the number of variables that must be considered can make fuel characterization efforts seem intractable. However, the importance of the fuels in the wildland environment is amplified because they are the one variable that fire managers are able to alter prior to a fire event.

A definition of wildland fuels may consider them to be all things available for combustion; however, in a more broad sense, we must consider the characterization of components that are not directly fuel for fires because of their influence on flow, radiative energy transfer, and their ecophysiological influence on the fire environment (Keane 2015). In the literature, fuels are typically described by variables that can lead to their classification, such as the sizing of fuel particles, growth form of vegetation, and geographic locale of the area of interest, to name a few.

In order to simplify the characterization of fuels in practice, fuel matrices have been typically classified by their attributes into functional groups. These groupings are described in a hierarchical manner with the simplest level of arrangement splitting fuelbeds into four basic categories of grasses, brush, timber, and slash (Anderson 1982). Eleven fuel models were defined by Rothermel (1972) and developed to provide greater detail for a "complete set of

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[fuel] inputs for the mathematical fire spread model." These were later refined to 13 models by Albini (1976) and later to 40 models by Scott and Burgan (2005). These models are useful for the prediction of fire behavior attributes such as rate of spread, flame length, fire intensity under specific terrain (slope, aspect) and weather (moisture content, wind, humidity) conditions.

Due to the recent development of computational fluid dynamics (CFD) models for wildland fire such as WFDS (Mell et al. 2007) and FIRETEC (Linn et al. 2002), there is a growing need for more detailed, spatially explicit, fuel inputs. Additionally, more detailed studies that incorporate measurements of fire dynamics in situ have required these same types of data in order to make sense of high-resolution measurements of the fire environment (Mueller et al. 2016; Peterson and Hardy 2016; Hudak et al. 2017).

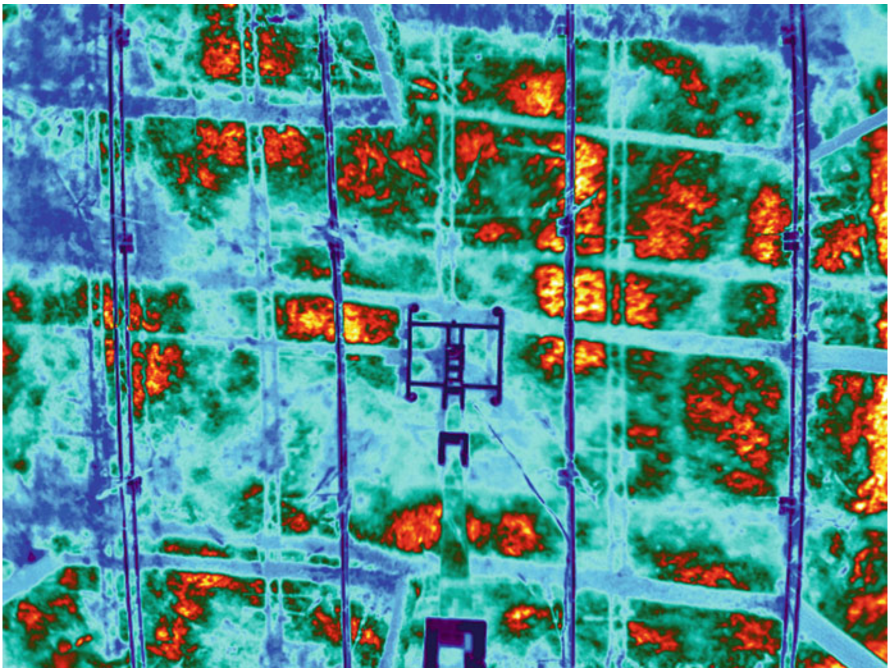
This section is intended to give a broad explanation of fuels measurement techniques ranging from traditional brute-force sampling techniques, spanning into the cutting edge of fuels measurement using high resolution photogrammetry and point cloud data to construct three-dimensional fuel beds. In practice, a manager or scientist will have to bound their sampling to what is relevant to their problem and also feasible. This section is not meant to act as a comprehensive guide for these fuels sampling theories or techniques, nor is it intended to serve as a complete bibliography of the literature that is available on this very broad topic.

Characteristics of Fuels

When considering fuels, we typically think in terms of a fuel "bed" that consists of any number of different or similar fuel particles which occur in one or more vegetation layers called strata. For instance, a grassland has only one stratum (herbs and grasses) and may be comprised of very few different types of fuel particles. A multiaged forest, however, may have an herb and grass stratum, but also other strata relating to other vegetation leading up to the canopy. Strata can be classified in many ways but are typically divided into an over-story, mid-story, understory, and forest floor. Strata may contain similar vegetative components that may be in different growth form or life cycle stages (seedlings, saplings, trees, shrubs, and detritus) and consist of different components (live and dead foliage, several size classes of stems, etc.). There are various physical attributes that may remain nearly identical for fuels of similar plant species, but their combustion properties, driven by their chemical and moisture compositions, can be very different. In general, the variables that we consider for the various components of the fuel bed are their three-dimensional structure, loading, size, arrangement, composition, moisture, and flammability (e.g., the ease of ignition and heat-release rate of a fuel).

Fuels are not static and they change in both space and time. It is important to be cognizant of the dynamic environment and that the local ecology of the system has a great deal of influence on the characteristics of the fuel bed. The heterogeneity of fuel components varies in both two- and three-dimensions. Temporal and spatial variability exist over many scales and can have very subtle impacts on fuels. Fuel moisture and fuel temperature can vary over very fine spatial scales and are dependent on a variety of factors. Figure 1, for instance, illustrates a 40 °C variability in fuel temperature in a 10 × 10 m fuel plot that has only fuels on the forest floor beneath an overstory of tall conifers. Even this plot, without the added complicity of a mid-story or understory, shows a tremendous amount of spatial variability. The models currently used for fire management are not able to deal with these issues.

Because we cannot account for, or measure, all variables, a set of specific objectives must be defined in designing a sampling scheme. For instance, the measurements needed to define inputs for a 10 × 10 m plot for a CFD model are much different from those needed for a fuel loading study at the regional scale. It is impossible to measure every variable in a plot even ignoring the likely need for replication or some sort of spatial sampling design. Given all of these factors, the design and installation of the sampling scheme is an



Fuels Characterization Techniques, Fig. 1 The temperature variability of an instrumented fuel plot with only needles on the forest floor and overstory conifers as fuels after O'Brien et al. (2016). The plot is 10 × 10 m and the instrument was a FLIR A655sc infra-red camera mounted at 10 m above the plot which resulted in approx. 20 × 20 cm pixel sizes and temperatures ranging from −20 °C to 22 °C (cool to warm color scale). The horizontal lines (up and down) are trusses that bear instruments 2 m above the ground. Tree stems and foliage create obvious variability on the forest floor through shading

important portion of fuels sampling. If the design is substandard, then all of the data collected could be questioned and could be potentially useless. Statistical design and sampling protocols will not be discussed here, but an understanding of these basic principles is vital in developing a meaningful dataset (Sokal and Rohlf 1995). Again, the "question" is the determining factor for this type of work.

Standard Fuel Characterization Techniques

Here, we will describe methodologies for the characterization of fuels using standard, field-based, sampling methods. These techniques can be used both before and after a fire to provide estimates of all of the characteristics that are described above. It is important to note that many of these measures are aggregated within some unit of area (e.g., a plot, subplot, stand) and are reported in two dimensions. As such, some amount of their spatial characteristics is often lost when information is aggregated across an area, such as a plot. We divide these techniques into two sections. The first, surface fuel sampling, will encompass the sampling of woody material, duff, litter, grasses, and forbs. Second, we will discuss sampling the mid-story, which consists of shrubs and small trees, and the over-story, which consists of mature trees.

Surface Fuel Sampling

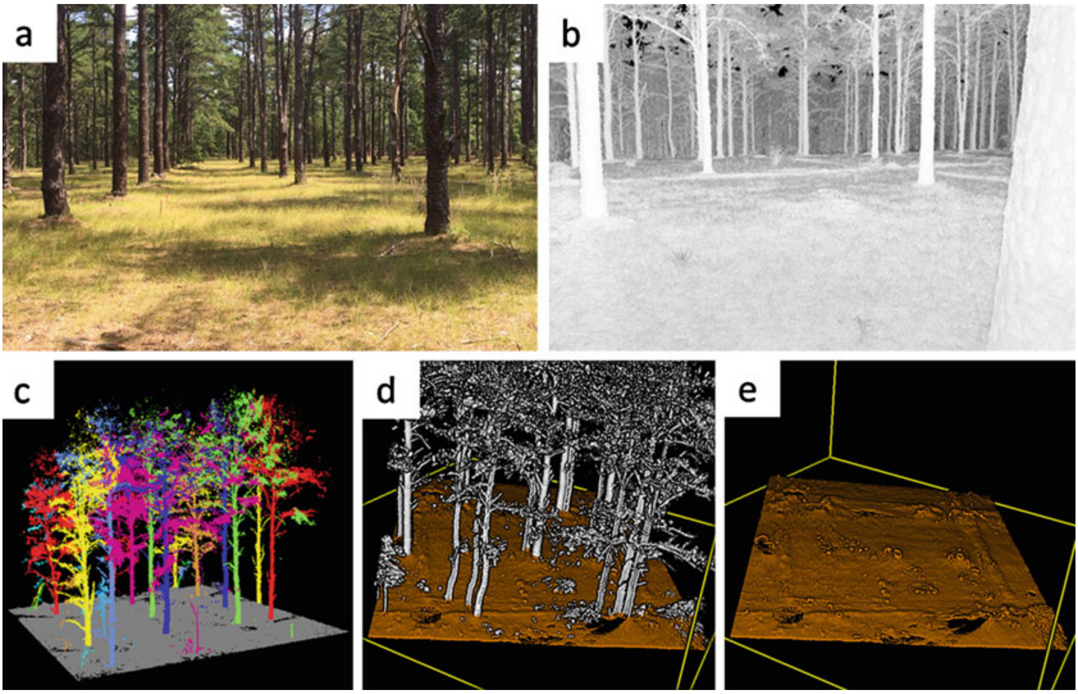
Surface fuels are typically sampled with the purposes of acquiring data inputs for fire spread models, estimating fuel hazard, or estimating fuel reduction from treatments. Surface fuels, as a complex matrix of many different components, are characterized by both their composition and characteristics of loading such as mass, depth, and bulk density. The desired use of surface fuels data should ultimately dictate how many of these characteristics are necessary to be measured. For instance, for estimating fuel consumption, estimates of mass are sufficient, while bulk density measurements may be required inputs for fire spread models, and moisture content may be important to a research experiment aimed at explaining variations in fire behavior.

Surface fuels are often subdivided into duff, litter, grasses, forbs, and woody material. Probably the most well-known sampling technique is a planar intercept technique developed by Brown et al. (1982). This technique uses statistical sampling to estimate the size-class distribution of fuel elements and also the composition of fuel components along transects. Grid frames of a fixed area typically 1 m^2 can also be used to sample various fuel components and to help to estimate a species or component composition of an area and provide an estimate of variability if enough samples are taken.

For fuel loading, this same type of area-based technique can be used. All forest floor components within a given area can be collected, returned to the lab, and dried to estimate loading of a fixed area on a unit dry mass per area basis. Additional sorting, in either the field or the lab, allows for the estimation of fuel loading by each type of fuel component. Moisture content can be estimated by weighing these samples both before and after they are dried. Although destructive sampling of fuels may be the only way to provide direct measurements of crucial fuel characteristics, it is important to consider two shortcomings to destructive sampling methods. First, this approach to measurement inherently alters the object that is being measured, and subsequently, there is no way to return to take additional measurements once the material has been harvested. For instance, one cannot come back and directly measure fuel consumption after a fire at the exact location it was harvested prior to the fire. Another disadvantage with these techniques is that they are not spatially explicit. This means that they do not describe spatial distributions or boundaries of the characteristics across the landscape, thus making it difficult to link them back to any localized fire dynamics or effects that might be observed. Trampling of the understory fuel bed is also a very large concern.

Coarse woody debris (CWD) consists of fallen trees and large branches on the forest floor, which are often distributed more sparsely or sporadically across the forest floor and are best captured using transect intercept methods, rather than small plots. With this approach, lengths and diameters of coarse woody debris are measured when they cross a transect line. These fuels are often grouped into diameter-based classes which relate to their dryness and availability to burn. These classes are based on theoretical response times of these fuels to atmospheric moisture gradients and they are called 1-h, 10-h, 100-h, and 1000-h fuels (Albini 1976). As an example, a fine fuel, such as a pine needle, would be considered a 1-h fuel because it would equilibrate with the atmosphere moisture in a short time and will readily burn with little energy input, while a downed tree bole would be a 1000-h fuel because it would take a much longer time to equilibrate and more energy to combust. In this way, these classifications are common for approximating the receptiveness of a fuelbed to fire and the fire behavior that could be expected under a certain set of conditions.

The condition of CWD, often described as its decay class, is a factor commonly recorded while conducting CWD transect assessments. Decay is important because it relates to the combustion properties of a log, which change substantially as it decomposes. Recently fallen material with little decay is typically less combustible and less important as a fuel source than seasoned decaying wood. Numerous transects can be measured across a forest to determine the amount of CWD in the forest. Although CWD does not often contribute to fire spread (Anderson 1969), due to its sparse distribution, it may represent the greatest amount of fuel in the forest and contribute to high fire intensities and smoke emissions (Albini and Reinhardt 1995). This may be especially relevant in areas of insect-damaged trees or blowdown (Keane and Gray 2013).



Fuels Characterization Techniques, Fig. 2 Perspectives of fuels in a research plantation at the Silas Little Experimental Forest using LiDAR. Visual comparison of the color photograph (**a**) and raw LiDAR data (**b**) illustrate the level detail and coverage that can be obtained using laser-based approaches. These data can be resolved using algorithms to identify the material described biometrics of individual trees (**c**), differential surface fuels from areal fuels (**d**), and facilitate the removal of fuels for simulation purposes (**e**)

Mid- and Overstory Fuel Sampling

Overstory fuels characteristics are important inputs for models that estimate fuel hazard and predict crown fire scenarios. Overstory fuels typically focus on live and dead forest canopy material but can also include the boles of trees. The primary canopy characteristics used in models include the canopy height profile (CHP), canopy bulk density (CBD), canopy base height (CBH), canopy height (CH), and canopy fuel load (CFL; Keane et al. 2005). Refinements of these characteristics are sometimes used as well, but these are the most common. The canopy height profile describes vertical distribution of fuel in the forest and is useful for estimating the potential for transition to crowning as well as for a sustained crown fire. Canopy bulk density represents the density of fuel within the canopy and relates to fire intensity, rate of spread, and potential for sustained crown fire and represents the canopy fuel load divided by the crown height over a given area. Canopy base height is primarily used to estimate the potential of surface fires to transition to crown fires, while canopy height is used to predict crown fire intensity. Canopy fuel load represents the fuel available for consumption (e.g., trunks are often too dense to burn) and is used primarily for predictions of smoke emissions, lost biomass, or lost carbon (Fig. 2).

Allometric relationships, or the patterns in the proportions of plant components, are useful when assessing mid- and overstory characteristics and allow us to make many useful inferences about overstory fuel characteristics from a few basic tree dimensions. Some such useful inferences include total fuel, canopy height profiles, and canopy bulk density (Reinhardt et al. 2006). At the most basic level, species and tree diameter data can be used to estimate canopy fuel load. Although inferences from diameter data alone are rough and can vary in accuracy with species, they are sometimes used alone. However, incorporating tree height data into the equation can greatly improve the accuracy of these estimates and also allows for the calculation of canopy bulk density and fire intensity in the event of a crown fire.

The data required to generate the commonly used canopy fuel characteristics can be easily determined by sampling the forest with plots of a given area. This is common practice in forestry, for monitoring stand health and productivity, and therefore these data are often available from existing forest monitoring or inventorying efforts. If not, however, collecting these measurements it can be accomplished by technicians with limited equipment. Diameter is measured with a "diameter tape," which is stretched around a tree at a standard height of 4.5 ft, while height data can be measured using numerous types of mechanical, laser, or sonic clinometer or hypsometer devices. These represent the two key tools with which the primary field data are gathered.

Advanced Plot-Based Techniques

Technological developments have recently added several tools useful for the estimation of fuels at the scale of individual plots. These tools consist of active sensors and also spectral reflectance datasets with very small grain sizes and high spectral resolution which, when properly reduced, are intrinsically well-suited for use in CFD models. These techniques are also adept at helping to develop models to estimate variables over the landscape using larger-scale remote sensing data. Specifically, several types of instruments can collect point clouds of three-dimensional plot attributes allowing for a much more thorough handling of the structural attributes in these plots. Additionally, the use of fine scale photogrammetry is becoming a modern way of measuring these small-scale fuels plots. In order to make use of these three-dimensional datasets, new fuel sampling techniques are under development that record the three-dimensional aspects of fuels that the typical sampling strategies, as above, have ignored.

There are various techniques to collect small-scale point cloud datasets, at the plot scale. These techniques make use of various forms of point cloud data collected from fixed-point terrestrial laser scanners, hand-held laser scanners, and multiple (overlapping) image photogrammetry. The collection of this type of data is often used in many other fields, ranging from crime scene investigation to archeological surveys, and provides unparalleled spatial information describing three-dimensional attributes as individual x,y,z points, of which there are potentially millions per scene. The challenge of using these data is to reduce it in a repeatable and transferrable way to provide either a wireframe depiction of the plot or variables described for individual voxels (a three-dimensional volume) within a plot and then to link these variables with physically measured fuel variables. Using standard fuel estimation techniques, the dimensionality of these point cloud datasets is vastly underutilized because of the limitations of the data we have to build models from. As such, these new technologies have necessitated the development of enhanced plot-based sampling protocols that allow for the measurement of various fuel attributed in the plot while respecting the need for the data to be linked to point clouds in three-dimensions (Hudak et al. 2017). In these cases, estimation of canopy bulk density in two dimensions is not adequate for building models with the point cloud datasets (Clark et al. 2013). As a result, several research groups have been working on new methods to quantify these fuel attributes using a voxel approach where fuels are sampled in a cubic volume with the location of the sampling recorded with high accuracy and precision spatially so that they can be linked back to the various point cloud and spectral reflectance datasets in the computing environment. Models are then developed using these plot measured three-dimensional data as the dependent variable and the various, spatially coincident, variables from the instrument as the independent dataset (Rowell 2017). These models are then applied to the voxelized point cloud variables (e.g., density of returns in each voxel) to provide a three-dimensional output of the variable of interest for the entire plot.

Small-scale work using spectral reflectance data has also proven an alternative to destructive harvest in field plots, particularly for the estimation of fuel bed composition. Several studies have illustrated methods of using visual estimation using spectral reflectance data. The Photoload technique is an example of this type of work that uses nondestructive techniques for the estimation of fuels (Keane and Dickinson 2007). A guide has also been developed for the implementation of this type of technique (Holley and Keane 2010), as well as a comparative study that compares it to other, destructive, techniques (Sikkink and Keane 2008). The nondestructive nature of this sampling has a great deal of utility because of the expediency of the process and also because the fuel-bed is left in place allowing for observation of fire dynamics and postburn assessment of the fuels in the identical spatial location.

Remote Sensing Techniques

Remotely sensed data have provided a way to move from plot-based measurements to wall-to-wall estimates of fuels at the scale of landscapes, regions, and even nationally (Rollins 2009). These datasets can generally be divided into spectral reflectance datasets from satellite-based sensors such as MODIS, LANDSAT, or WorldView-3 or from aircraft or drone-borne sensors. There are also active sensors such as spaceborne or airborne LiDAR and RADAR systems that sense forest structure and can be used to estimate spatial positioning and loading of these fuels. It is important to note here, however, that all of these remotely sensed datasets need adequate field data in order to develop models or classification trees to translate their properties into meaningful and accurate fuels data.

Spectral reflectance datasets are typically best suited for determining the fuel type and are often linked to the various fuel models that have been introduced earlier. These data are dependent on the individual sensor as sensor data vary both spatially, in pixel size and extent, spectrally in wavelengths measured, the number of bands, and the width of these bands, and in the periodicity of the remeasurement. Much like field sampling, the selection of the appropriate spatial reflectance data is determined by the objective of the work. For example, MODIS data have a high periodicity with remeasurement on the scale of days but have a very coarse pixel size (Justice et al. 2002). Conversely, LANDSAT ETM has a longer remeasurement window, weeks, but has higher resolution and a very long, consistent, history of measurement (Markham and Helder 2012). WorldView-3 has been shown to be consistent spectrally with LANDSAT ETM estimates of fire severity with a 4× improvement in spatial resolution but is not freely available and must be specifically tasked (Warner et al. 2017). These data are typically linked with ground-measured training data, such as forest type or fuel model, and a classification routine is used to train the spectral reflectance data and develop wall to wall maps of the variable of interest, which are then validated using a subset of the ground-measured dataset (Arroyo et al. 2008). A multitude of studies (Van Wagtendonk and Root 2003; Mallinis et al. 2014) have made use of this practice and it has also been applied on the ground for operational decision making. Spectral reflectance has been used to develop continuous estimates of fuel temperature (Vlassova et al. 2014) and fuel moisture across landscapes as well (Yebra et al. 2013).

Active remote sensing has also been used to estimate fuel loading across landscapes and regions. Typically, because of availability, airborne laser scanning (ALS) data are typically used for this work. These data sets can be used to estimate typical canopy parameters such as average height, canopy base height, and canopy bulk density across landscapes (Andersen et al. 2005). Additionally, ALS has been validated with field data to describe the three-dimensional distribution of canopy fuels in 30 × 30 × 1 m voxels across a county in the New Jersey Pinelands (Skowronski et al. 2011). Data on this scale are useful for the assessment of management practices and also for guiding future land management work, such as prescribed burning or thinning. Additionally, ALS derived fuel parameters data have been used to parameterize CFD models and to estimate fuel consumption from experimental fires (Mueller et al. 2017).

The combination of active and passive remote sensing datasets has also been shown to improve the accuracy of estimates of fuel loading and classification. For example, Mutlu et al. (2008) were able to map and describe the uncertainty of mapping surface floor fuels using a combination of ALS and spectral remote sensing data. Erdody and Moskal (2010) evaluated the accuracy of spectral reflectance data, ALS, or a fusion of the two, for estimating various canopy fuel variables to be used as inputs into FARSITE or other models. They found that fusing LiDAR with imagery and/or LiDAR intensity led to small increases in estimation accuracy over LiDAR alone. More recently, Marino et al. (2016) took an approach using spectral reflectance data, LANDSAT 8 in this case, to develop a map of fuel classifications and then ALS data to derive fuel structure and loading data. As we advance our ability to fuse these two types of data, it is likely that our landscape-scale estimates of fuel classifications and of fuel loading will continue to improve.

Additional Resources

There are a wide variety of additional resources available to assist in the selection of methods for fuels characterization. Many of these present detailed field sampling protocols that have been put together over the years that give a more thorough treatment of specific techniques than we do here. Keane (2015) presents perhaps the most comprehensive discussion and treatment of fuels. For techniques focused more in the realm of carbon accounting, Hoover (2008) provides a good resource. Several US Government Agencies present specific guides for fuels measurement and monitoring. For example, the National Park Service has published the "Fire Monitoring Handbook" (NPS 2003) which serves as a nearly comprehensive guide for traditional fire and fuels monitoring protocols. The Fire Effects Monitoring and Inventory Protocol, or FIREMON, is another resource available through the USDA Forest Service that provides standardized methodologies and reporting strategies for various types of fire monitoring (Lutes et al. 2006).

Summary

Here, we have provided a broad overview of various fuel measurement techniques that are used both for current management practices and ongoing research efforts. The traditional techniques for measuring fuel will remain the standard into the foreseeable future. However, there is a need for higher fidelity measurements of fuels in three-dimensional space and through many scales of time. Recent and future technological advances in the realms of unmanned airborne systems, active and passive remote sensing technologies, and computational advances will result in the advancement of these traditional methods.

Terminology

Wildland fuel refers to the flammable, nonanthropogenic materials of the forest.

A wildland fuel matrix is the arrangement of wildland fuels in three dimensional space comprised of fuel particles, such as individual leaves, twigs, and stems, all occupying unique space.

A fuel particle is a single plant structure, such an individual leaf, twig, bark flake, pine cone. These vary by shape, moisture content, combustibility, and prominence within the wildland fuel matrix.

A fuel bed refers to surface fuels, which may or may not include fuels in all strata of vegetation present. Most often fuel bed refers specifically to of detritus, herb and grass, and shrub fuels.

Fuel load refers to the amount of fuel, often per unit area.

Fuel model refers to a set of conditions often used as inputs for other models in describing a standard fuelbed for a given vegetation type.

Surface fuels are a fuel types specific to the lower vegetation strata, including detritus, herbs and grasses, and shrubs that would fuel a surface fire. The differences between surface fuels and fuel bed are nuanced, mainly stemming from the context which they are used.

A crown fire is a fire that spreads across the forest canopy.

Cross-References

- ▶ Firebrands and Embers
- ▶ Fuel Moisture
- ▶ Ground Fuel
- ▶ Physics-based Modeling
- ▶ Size Classes
- ▶ Surface to Crown Transition
- ▶ Wildland Fuel Treatments

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