Chapter 8
Fuel Sampling

Not everything that can be counted counts, and not everything that counts can be counted
Albert Einstein

8.1 Background

Directly measuring fuel properties in the field is the most accurate and consistent method for fire managers and scientists to collect the inputs needed for fuel description and fire behavior and effects simulation, especially when compared to fuel classification approaches (Chap. 7). Quantification of these properties is generally accomplished by *field sampling*; measuring fuel characteristics *in situ* to estimate fuel properties. And since there is a great diversity of fuel components (Chap. 3), coupled with a large number of fuel characteristics (Chap. 2), there are numerous sampling designs to estimate fuel properties at the particle, component, and fuelbed scale. Here, field sampling is a general term used to describe the wide range of approaches for measuring fuel properties for fuel components, including designing sample projects, conducting measurements in the field, and creating databases from measured information. Sampling design is easily the most important aspect of field sampling and it includes deciding on the sampling intensity (e.g., number plots), sample locations (e.g., random, stratified random), methods (e.g., planar intercept, fixed area plots), protocols (e.g., size classes, plot sizes), and techniques (e.g., caliper measurements). And since the majority of operational and research fuel sampling methods were designed to estimate loading, this chapter will focus on those sampling methods that estimate loading for a variety of surface fuel components. Methods, protocols, and techniques for estimating other fuel properties, such as mineral contents and particle densities, were mostly developed for research so they are difficult and costly to employ under operational sampling efforts and therefore, are not discussed here. This chapter also includes a general description of the common methods used to measure canopy fuel characteristics in the field.

R. E. Keane, *Wildland Fuel Fundamentals and Applications*,
DOI 10.1007/978-3-319-09015-3_8

Sampling designs can be stratified into two broad categories—inventory and monitoring. Inventory techniques are used to quantify fuel characteristics for one point in time, usually for planning and designing fuel treatments and describing fuel hazard and fire risk (Sampson and Sampson 2005). Monitoring involves sampling to estimate current status and detect change over time, such as that resulting from fuel treatments or fuel accumulation. There are usually two or more measurements at the same exact place but at different times (e.g., pretreatment, 1 year post-treatment, and at 5 year intervals after treatment). Monitoring protocols are often quite rigorous because they must detect subtle changes over time, sometimes across multiple spatial scales, so more plots and more detailed measurements are sometimes necessary. Both inventory and monitoring are critical tasks for fire management, yet there are few standardized efforts to collect field data on fuel properties across nearly all fire management agencies. To implement effective fuel treatment programs, which cost millions of dollars, and to assess the efficacy of these treatments, a comprehensive, standardized fuel sampling program is a critical tool to facilitate enlightened and adaptive fire and fuel management.

Inventory and monitoring fuel sampling methods are often designed for one of two broad objectives—research or management. Research sampling techniques are usually uniquely specialized to quantify some set of fuel properties with high precision and accuracy to satisfy research objectives. They are often tailored to answer a specific research question, and because of this, these methods are usually quite intense (large samples, many plots), highly localized, time-consuming, costly, and often requiringe highly skilled personnel and specialized equipment. Since most research sampling techniques were designed around specific study objectives and study areas, they are often difficult to apply in broader situations, such as operational fire management. There are many physical fuel properties measured in research studies, such as heat content and specific gravity, which change little across fuel particles relative to particle abundance, so these research results are often used IN many management applications (Nalder et al. 1999).

Management-oriented or operational sampling is often done to facilitate the planning, design, and eventual implementation of a fire management project. Often, these sampling designs do not require the same degree of accuracy as research sampling, so they are often less intensive, not as costly, and easier to implement (Lutes et al. 2006). Management sampling efforts are often designed to be applied across large areas by field technicians with little to high levels of training in fuel sampling. Sampling techniques designed for managers are also often highly generalized so that they can be applied across diverse areas and situations. This may result in the application of sampling techniques or protocols that may be inappropriate for a particular ecosystem or treatment area. Logs, for example, may be sampled using an insufficient number of transects to meet a desired level of accuracy, especially in those ecosystems where logs are scarce (Sikkink and Keane 2008). The main topic of this chapter is how to sample fuel biomass for each fuel component. However, knowledge of the basics of fuel sampling is first needed to fully understand the use of the methods presented here.

8.2 Sampling Basics

The first and most important step in any fuel sampling effort is to clearly articulate a sampling objective. Many fuel sampling efforts were unsuccessful because there never was a comprehensive statement of the purpose for the sampling. A well-written sampling objective will guide all other decisions involved in designing sampling projects (Lutes et al. 2006). Sampling objectives should follow the S.M.A.R.T. guidelines: Specific, Measureable, Achievable, Relevant, and Time-based (Lutes et al. 2006). Many people make the mistakes of (1) using goals instead of defining objectives (not specific), (2) failing to mention what is being sampled (hard to measure), (3) specifying too many objectives for a sampling effort (not achievable), (4) including aspects that are unrelated to the sampling effort (irrelevant), and (5) forgetting to add deadlines and scheduling concerns (not time-based). Without doubt, a well-stated objective is the keystone of a successful sampling design.

Many fuel loading sampling efforts estimate loadings for a defined area (target population) using a set of opportunistically, randomly, or systematically located sampling units. Sampling units, such as fixed-area plots (FAPs) or planar intercept (PI) transects, are used to sample the target area. Measurements taken within the sampling units that are distributed across the sample area are then summarized to compute an estimate of loading for the sample area. The first step in fuel sampling is delineating the sample area and then deciding on a sampling unit (Catchpole and Wheeler 1992). Sampling unit selection is important because it will dictate the logistics of sampling design. The sample unit can be FAPs, transects, planes, or points. FAP sampling units, for example, can vary in size from macroplots (generally 100–1000 m^2) to microplots (~1–100 m^2) to nanoplots (~0.1–1 m^2) to dimensionless points, depending on the fuel component sampled, available resources, and the stated objective. Each sampling effort employs a unique design developed specifically to meet sampling objectives while considering important sampling constraints, such as time, cost, and available expertise.

All ecological sampling projects, but especially wildland fuel loading sampling efforts, are designed using a delicate balance between ecological, logistical, and resource concerns. The most important factor in operational management fuel inventory and monitoring projects is the amount of resources available for sampling. In the end, most field fuel sampling efforts reflect a compromise in some resource limitation. The most important resource is funding because with adequate funding, most of the other resource limitations can be mitigated (e.g., hire more people, buy more equipment). The next valuable resource is time. Many sampling efforts were unsuccessful because it was impossible to both collect and report the critical data in the time frame allowed. The number of qualified people available to assist in the sampling effort may also dictate sampling designs. And last, transportation, safety, and equipment resources are also important to consider in sampling designs. Vehicles to get crews to remote locations on rough gravel roads may be a limiting factor, as is the lack of sampling equipment required for fuel measurement, including the critical gear that ensures crew safety such as radios, first aid kits, and cell phones.

Expertise of the field crew and the people that will ultimately analyze and interpret the data is important in fuel sampling. Inexperienced field crews will require intensive training that may reduce the time available for sampling. And similarly, inexperienced analysts may produce inappropriate statistical summaries and come to the wrong conclusions, while inexperienced managers may use completed analysis results in inappropriate contexts that don't fit sampling objectives or sampling designs. Fuel sampling personnel may be highly experienced, who can easily adapt to any challenge in the field without significant changes in productivity and quality, to novice student summer temporary hires, who have difficulty navigating in the field let alone accurately measure fuel characteristics. Effective training is the only remedy for inexperienced sampling crews.

The last important factor is the level of statistical rigor demanded by the sampling project, which should always be determined in the context of the sampling objective. One of the most important parameters in the sample design is the number of sample units (n) to establish in the sample area to obtain a statistically credible loading estimate, often called the sampling intensity. This is done using the following formula:

$$n = \left[\frac{z\sigma}{E} \right]^2, \tag{8.1}$$

where E is the difference between the sampled mean value (i.e., loading) and the population mean loading value, σ is the population variance, and z is the z value for tail of the t distribution for a selected probability value α often selected as $\alpha = 0.05$ for most sampling projects. E is estimated by how close the sampler wants to be to the population mean (e.g., 20 % of the population mean). To calculate n, most sampling projects need an *a priori* (beforehand) estimation of the loading variability (σ) and the population mean to compute the number of sampling units needed for a statistically credible estimate. The problem is that the statistical parameters (E, σ) for fuel loading depend on the fuel component, and the variability of each fuel component loading is highly localized and is different by region, ecosystem, topographic setting, and time since disturbance (Keane et al. 2012a). Therefore, a priori population mean variabilities by component are difficult to estimate from past projects. Moreover, the factors mentioned above (resources, expertise) may often overwhelm requirements for statistical rigor in some sampling projects. Requiring an unachievable number of sample units given resource limitations to satisfy a statistical requirement may be counterproductive. Likewise, executing a sampling program that cannot hope to address the project's objectives because of inadequate precision also makes poor use of available resources. Statistical rigor must be balanced with the other factors to construct a successful sampling design.

In summary, there are usually several tasks that must be done to design an effective sampling projects: (1) identify the number of people available and assess their expertise, (2) estimate the time allowed to conduct the sampling, (3) delineate and describe the sample area(s) that need sampling, (4) select an appropriate sampling unit to get the project done on time and with the people and resources available, and (5) decide on the equipment required for sampling. This information can then be used to design a sampling approach using the following example. Assume there is a 100-ac treatment unit that will be monitored for changes in fuel loading and potential smoke emissions and there is only 1 month (20 working days) to accomplish the initial measurements of the monitoring project. By selecting the First Order Fire Effects Model (FOFEM) program to estimate emissions (Reinhardt et al. 1997), the set of surface fuel components that need loading estimates are identified as litter, duff, 1, 10, 100, 1000 h, shrub, and herb (Table 3.1). A 0.1 ac circular macroplot is selected as the sampling unit because protocols for measuring all eight surface components and canopy fuels are easily nested in this FAP. Assuming a two-person crew and a 1-h sampling time to measure loading for all eight components including travel to the next plot, and assuming 1 h in each 8-h day is used for transportation to and from the site, we can then estimate the potential number of plots for this project as 140 (seven plots per day, 20 working days). This means that approximately 14 % of the project area may be sampled for those fuel components (140 plots × 0.1 ac = 14 ac of 100 ac). Estimates of variability for each fuel components obtained from other projects or from the literature (see Keane et al. 2012b) can be used to compute the number of plots needed for a statistically credible sample (see Eq. (8.1) or Lutes et al. 2006). The statistical estimate can be compared with the 140 plots to adjust the design criteria to create a successful sample design, such as adding more people, increasing sampling time (work 10 h days, add 10 days), reducing number of fuel components measured, or modifying the sample design (e.g., distribute plots systematically or among strata). The last important sampling item to be selected is the surface or canopy fuel sampling technique to use at each of the plots. The next two sections detail the diverse methods often employed by fuel specialists to sample fuel characteristics.

8.3 Surface Fuel Loading Sampling

Numerous techniques and methods have been developed to estimate surface fuel loading for both research and management to allow for greater flexibility in matching available resources with sampling objectives and constraints (Catchpole and Wheeler 1992). These techniques are arranged below in order from easiest to most difficult with a corresponding gradient from most to least uncertain (Table 8.1). The first set of indirect methods is not recommended, but many fire managers have used these methods in the past to estimate fuel loadings when no other information is available and there aren't resources for other alternatives.

Table 8.1 Comparison of possible surface fuel sampling methods and techniques to estimate fuel loading for forest and rangelands. In general, the techniques are arranged in the order of easiest with most variability and uncertainty to the most difficult but more accurate and precise. Abbreviations and codes are as follows: Fuel component are the fuel components in Table 3.1 that can be sampled with this method; sampling time is the time it takes to get estimates (1: fast, 10: slow), level of uncertainty is the amount of uncertainty in fuel loading estimates (1: highly certain to 10: highly uncertain), cost is the relative cost of implementing technique (1: inexpensive to 10: costly), and training needed is how much training is needed to get acceptable estimates of fuel attributes (1: low to 10: high)

Technique	Description	Advantages	Disadvantages	Fuel components	Sampling time	Level of uncertainty	Cost	Training needed
Indirect methods—association techniques								
Existing data	Use existing data from other areas to extrapolate to the project area	Many fuel attributes may be available	Fuel conditions are highly variable across sites depending on disturbance history	All	1	8	3	2
Vegetation	Existing data are summarized by vegetation type and these summaries are assigned to project area based on vegetation type	Most people can identify vegetation types	Vegetation not related to fuels	All	3	7	4	2
Map value	Use mapped values as fuel estimates	Represents local area	Fuel maps have low accuracies	All	1	9	2	1
Indirect methods—visual techniques								
Eye estimate	Estimating loading from visual inspection	Integrates local knowledge	Highly inaccurate with high user bias. Requires extensive training	All	3	7	3	8
Photo series	Use a local photo series publication to visually assess fuel loadings at the project area	Many series available; quantify many fuel comp. and attributes	Requires training; rarely assessed for accuracy	All	4	6	3	6
Photoload	Use a series of photographs that show fuelbeds with gradually increasing loading	One set of photos good for most woody fuelbeds	Doesn't include all fuel components; requires training	1, 10, 100, and 1000 h, shrub, herb	5	5	3	7

Table 8.1 (continued)

Technique	Description	Advantages	Disadvantages	Fuel components	Sampling time	Level of uncertainty	Cost	Training needed
Fuel classification	Use a field-keyed fuel classification category to obtain the fuel estimates	Direct link to fuel map entities and sampling estimates	Few classifications key fuelbed characteristics	All	4	6	3	5
Fuel hazard assessments	Rate hazard for various fuel layers and components on an ordinal scale and correlate to loadings	Links hazard assessment to fuel loadings; easy to teach and use	Must be developed for each ecosystem; specific to Australian fuel components	Litter, Fine Woody Debris (FWD), shrub, herb	5	5	3	6
Visual cover-volume	Use canopy cover and height to estimate volume, and then use volume and bulk density to estimate loading for some fuel components	Often the only efficient technique for measuring shrub, herb, duff, and litter loadings	High variability in cover estimates coupled with high variability in height (depth) measurements	Litter, duff, shrub, herb	4	5	3	5
Indirect methods—imagery techniques								
Image processing	Analyze imagery to measure fuel conditions	Visual record of fuelbed	Imagery not correlated to some fuel attributes	Depends on imagery	4	5	8	9
Terrestrial LiDAR	Use scanning LiDAR to obtain a profile of the fuelbed to estimate fuel attributes	Locations of all fuel particles are measured	Can't relate LiDAR strikes to material that reflected the strike	Depends on the analysis	7	4	10	9
Direct methods								
Planar intercepts	Estimate fuel attributes along a vertically oriented sampling plane	Readily available and standardized methods available	Only useful for woody fuels	1, 10, 100, 1000 h	7	7	7	6
Fixed-area microplots	Estimate fuel attributes within a plot frame	Adjust plot size to fuel component distributions	High variability across microplots; may require many microplots	All	8	8	8	7

Table 8.1 (continued)

Technique	Description	Advantages	Disadvantages	Fuel components	Sampling time	Level of uncertainty	Cost	Training needed
Perpendicular distance sample (PDS)	Use PDS methods to estimate fuel loading by measuring distances or using a prism or other similar device	Relatively quick and easy	Training required; only used for one component	Coarse woody debris (CWD)	3	7	5	8
Measured cover-volume	Measure cover using standard ecological sampling protocols, then measure component heights to get volume and multiply by bulk density to get loading	Useful for novel fuelbeds, best method for litter and duff	Not useful for woody fuels, cover poorly correlated to fuels	Litter, duff, shrub, herb	7	4	6	5
Destructive	Collect fuel within a defined area, bring it back to lab and dry it, then weigh it to get loading	Highest accuracy in measuring loadings	Too costly and time-consuming for operational applications	All	9	2	9	4

8.3.1 Indirect Methods

These methods involve quantifying fuel loadings using techniques that do not directly involve measuring the fuel property, but rather, use other references or sources to quantify loadings. This usually involves subjectively assigning loadings by comparing with existing data (association), inspecting fuel conditions and visually comparing to reference conditions (visual), or correlating with remotely sensed imagery (imagery).

8.3.1.1 Associative Techniques

The most common associative technique involves using *existing data* or information, often collected by someone else from somewhere else, to estimate loading values for the area of concern or project area. Fuel loading data collected for another area, for example, may be assigned to the area in question if the two areas are deemed similar, perhaps based on vegetation composition, disturbance histories, and biophysical site conditions. Catchpole and Wheeler (1992) call this approach the comparative yield method and mention that they could be improved by using statistics, photos, and expertise to aid in the data assignment. The problem with this technique is that each site and project area is ecologically unique and the extrapolation of loadings from one site to another might ignore those important but subtle factors that have influenced component loadings, such as differences in basal area, tree density, disturbance history, topographic setting, and stand structure.

Another commonly used associative technique is to assign fuel loadings to a sample area based on the sampled area’s *vegetation* characteristics, similar to association approach used in fuel classification (Chap. 7), except, in this case, it is used to assess actual loadings in the field. Several fuel classifications were built by summarizing plot-based fuel component loadings across categories in vegetation and related classifications such as structural stage, cover type, and potential vegetation type. The FOFEM program, for example, includes loading defaults as a summary of fuel loadings across legacy plots within SAF (Society of American Foresters) and SRM (Society of Range Management) cover type categories (Reinhardt et al. 1997). Many people have used these defaults as a fuels inventory when conducting various analyses. The Fuel Characteristics Classification System (FCCS) (Ottmar et al. 2007) was specifically designed so that fuel loading data collected for one area could be used for other areas based on a set of seven vegetation and disturbance-related stratifications. This indirect method assumes that fuel component loading values, either individually or as a collective group, correlate to vegetation characteristics. However, as in fuel classification development (Chap. 7), studies have found that fuel loadings correlate poorly to vegetation types, especially at the fine spatial scales of project and treatment areas (Brown and Bevins 1986; Keane et al. 2012b, 2013). Vegetation classification categories may correlate to fuels at coarser scales (e.g., lifeforms, large regions), but the high variability of fuels at fine scales often overwhelms differences across broad vegetation types (Keane et al. 2012b). Disturbance history (e.g., time since disturbance, severity) is more important than vegetation to predict fuel loadings (Brown and Bevins 1986), but few studies have explored this relationship. Some have found that a variation of this vegetation associative technique is useful to create predictive loading equations from measured vegetation characteristics using statistical methods (Catchpole and Wheeler 1992). Fuel loadings can be correlated to various stand-related characteristics, such as basal area, Leaf Area Index (LAI), and stand height. Keane et al. (2012b) found that stand attributes were poorly correlated to surface fuel loadings but were highly correlated to canopy fuel variables.

Another associative method is using mapped loading values from readily available *digital geospatial products* as fuel loading estimates (Chap. 9). The LANDFIRE National Project, for example, mapped four fuel classifications across the United States using satellite imagery (Reeves et al. 2006) and many have used the loading values from these classifications to quantify loadings for a specific project area. However, Keane et al. (2013) found low accuracies for fuel loadings from LANDFIRE fuel maps. Therefore, this practice, while inexpensive, quick, and easy, is not recommended for fine scale, project-level applications until existing fuel maps are much improved. Locally created fuel maps may have sufficient quality, but regional and national maps should only be used for fuel analyses at broad scales, not at the project level. Depending on the resolution, fuel maps could still be useful for stratifying the sample area (or target population) into more homogeneous subunits to make sampling efforts more efficient.

8.3.1.2 Visual Techniques

Visual techniques involve assessing the loading of fuel components from ocular estimates. Some fuel specialists feel they can accurately estimate loadings by *eye* without any guides or references. This level of resolution and accuracy may be acceptable for some fuel applications, such as describing fuels to other professionals. However, it is rare that anyone can accurately and consistently estimate the loadings of all fuel components by eye, especially for FWD, duff, and litter. One reason for this is that fuel loadings have high spatial variability over small areas (Chap. 6) and the ocular estimate is often biased toward smaller portions of the project area; it is difficult to evaluate a large, heterogeneous area to obtain a truly integrated visual fuel loading estimate (Sikkink and Keane 2008). While visual estimation by eye is preferable to some of the associative methods presented above providing there is a high expertise and confidence in the sampler, it is rare that a person can accurately estimate fuel component loadings across diverse fuelbeds at the same detail. Therefore, many have resorted to using pictures as guides and references for comparing loading estimations.

Perhaps the most popular comparative visual technique is the *photo series,* which is both a classification (Chap. 7) and a fuel assessment technique. Using photo series sampling methods, surface fuel loadings are ocularly estimated using a set of photos that present stand conditions for various vegetation types and site conditions (Fig. 7.1). Photos were taken of representative fuel types in a particular geographical region, and then fuel component loadings were measured for the photo footprint and the summary of those loadings is reported next to the photo in the photo series publication. These photo series publications are taken to the field and the observed conditions in the field are visually matched to the best photo and the loading measured for the photographed stand are used for the loadings of the matched stand. A different photo can be used to estimate each of the various fuel components. Often, photo series fuel types are stratified by vegetation conditions (cover type, structural stage).

The photo series was introduced by Maxwell (1976), improved upon by Koski and Fischer (1979) and Fischer (1981), and then extrapolated across the USA (http://www.fs.fed.us/pnw/fera/research/fuels/photo_series/). Many have taken the photo series concept and applied it to areas that have been treated (Koski and Fischer 1979), experienced severe disturbances (Vihnanek et al. 2009), contain special vegetation types (Ottmar and Vihnanek 2000), and found in other countries (Morfin-Ríos et al. 2007). Others have adapted the photo series concept to use three-dimensional stereoscopic photos (Vihnanek et al. 2009). Photo series data comprise the majority of the national fuelbeds in the FCCS database that have been mapped across the USA by McKenzie et al. (2007) and Reeves et al. (2009). A list of completed photo series for the US Rocky Mountains is presented in Baker (2009).

And most importantly, photo series have been developed for many local settings to be applied at fine scales within a small geographical region. One highly valuable aspect of the photo series is that the fire behavior fuel model (FBFM, Chap. 7) is often documented along with fuel loadings so that FBFMs can be more easily assessed in the field.

Despite its huge popularity, the photo series sampling technique has yet to be comprehensively evaluated across many vegetation types or environmental conditions. Sikkink and Keane (2008) found loading estimated using photo series approaches were often inaccurate and difficult to repeat across observers, albeit there were some limitations in the training of the crews. Many photo series photos emphasize stand-level differences with oblique photos, and, as a result, some fine fuel components, such as FWD, litter, and duff, may be hidden by the vegetation in the photo or are undetectable because of their small size. Additionally, the photo series cannot be used to assess the loading of duff or litter because the photos do not show their profile depth. While photo series may give loading estimates to the resolution needed for management decisions, other uses of loading estimates, such as predicting smoke emissions and carbon inventories, may demand a more accurate and repeatable method of loading estimate.

A new method of visually assessing fuel loading has been developed to improve on photo series techniques and to compete with other direct sampling methods (Sect. 8.3.3). The *photoload* method uses calibrated, downward-looking photographs of known fuel loads for woody, shrub, and herbaceous fuels to compare with conditions in the field (Keane and Dickinson 2007a, b). These ocular estimates can then be adjusted for diameter, rot level, and fuelbed height. There are different photoload methods for logs, FWD, shrubs, and herbaceous material, but there are no photoload methods for measuring duff and litter loading. The photoload technique differs from photo series in that assessments are made by comparing field fuel conditions to smaller-scale downward-pointing photographs of graduated fuel loadings. Photoload methods are much faster and easier than more complicated techniques (Sect. 8.3.2) with comparable accuracies (Sikkink and Keane 2008), and they can be used in multistage sampling strategies where a fraction of the total plots are also destructively sampled and correlated to photoload samples to develop a means for correcting all photoload estimates (Keane et al. 2012b). However, Keane and Gray (2013) found the photoload technique requires extensive training to be used effectively; inexperienced users often could not consistently and accurately estimate high fuel loads.

Fuel classifications can also be used as an inventory and monitoring method (Chap. 7). In this technique, a fuel classification class is visually identified in the field, and the loadings assigned for that class are used as the sampled loadings. Those fuel classifications that use vegetation to classify fuelbeds are probably the most suspect, while classifications that contain dichotomous keys for identifying classes based on fuelbed properties, such as the Fuel Loading Model (FLM) classification (Lutes et al. 2009b), are best for fuel assessment because they can be used in the field by inexperienced crews to estimate fuel loadings with moderate accuracies (Keane et al. 2013).

Another effective visual fuel sampling method uses fuel hazard assessments across different fuel strata to obtain loading estimates for various components in the fuelbed. Originally developed by Gould et al. (2008) for Australia, this method involves making hazard assessments for the overstory and intermediate canopy layers, and then elevated, high, and low surface fuel layers. Each layer is given a score from 0 to 4 based on a variety of fuelbed attributes including percent canopy cover, presence of stringy bark, and suspended dead material. These scores are then summarized and the summaries are correlated to actual fuel loadings using statistical techniques (Gould et al. 2011). This rapid technique produced moderately accurate loadings with minimal training. Techniques that successfully link visually distinctive signatures, such as canopy cover, with fuel component loadings might be effective for operational fuel sampling in the future because it balances and integrates the elements of hazard assessment into the sampling design.

One last visual technique involves using *cover-volume methods* to calculate loadings from visually estimated canopy cover and height. In this technique, canopy cover is estimated by eye for those components with small and variable fuel particles that are grouped together into one component, such as shrubs, herbs, and trees, and an estimate of measured or ocularly estimated height is also made in a fixed-area sample unit for those components. Some fuel sampling packages, such as FIREMON (Lutes et al. 2006), describe how to estimate canopy cover in 10% classes (e.g., 1–5, 5–15, 15–25%, and so on) and how to visually estimate height. Volumes of the assessed components (volume includes air pockets) are then calculated by multiplying the proportion cover (percentage cover divided by 100) by height (m) and sampling area (m^2). Fuel loadings are then estimated by multiplying volume (m^{-3}) by bulk density estimates (kg m^{-3}) for the sample unit. Bulk densities for litter, duff, shrub, and herb components can be found in the literature (Brown 1981; Keane et al. 2012b) or destructively sampled for a small proportion of the plots. This is often the only operational method for estimating fuel loadings for these complex fuel components. Sneeuwjagt (1973) used a variation of this approach when he developed equations that predicted loading from height for both litter and shrubs. While canopy cover is used extensively in plant ecology studies (Mueller-Dombois and Ellenberg 1974), it requires extensive training to visually estimate cover of multiple, overlapping fuel components to the accuracy and precision needed for fuel sampling.

8.3.1.3 Imagery Techniques

Imagery techniques involve using advanced statistical analysis to correlate fuel loadings to the digital signatures in the digital imagery. This imagery is taken in the field and is different from the airborne or satellite imagery used for fuel mapping (Chap. 9). A potentially useful imagery technique is the quantification of fuel loads using *image processing* techniques or software. Many years ago, Fahnestock (1971) calculated loading for several fuel components using a dot grid projected on color photographs of a cross-section of bayberry shrub fuel layer. Today, there are more sophisticated image processing approaches that use computer software. The stereoscopic vision technique (SVT), for example, involves taking stereoscopic photos of the fuelbed in the field then inputting the digital photos into computer-image recognition software to identify woody fuels and then compute loading volume (Arcos et al. 1998; Sandberg et al. 2001). Others have taken pictures of the fuelbed and then attempted to quantify loading using advanced image processing techniques (Jin 2004). Photographic methods are still under development and there needs to be major gains in image processing to discriminate between fuel components and compute volumes. Its primary use is in quantifying CWD loading (Arcos et al. 1998), but it may find some eventual use for measuring FWD, shrub, and grass loading.

Another emerging technology is the use of *ground-based LiDAR* to estimate fuel loads for some fuelbeds (Loudermilk et al. 2009). Here, a terrestrial scanning LiDAR (TSL) unit is mounted on a truck or some other vehicle to obtain scan distances for ground fuels at subcentimeter scales. The LiDAR signal can then be related to loading by constructing statistical models where destructively sampled loadings for various components are correlated to the LiDAR imagery scan distances. It is sometimes difficult to differentiate between fuel components using TSL in heterogeneous fuelbeds, but it is still possible. This technique may only be possible for research purposes in the near future because the TSL instrument is rather expensive (> $ 40,000), demands a high level of expertise to use and analyze, and it is also difficult to transport and use in complex terrain.

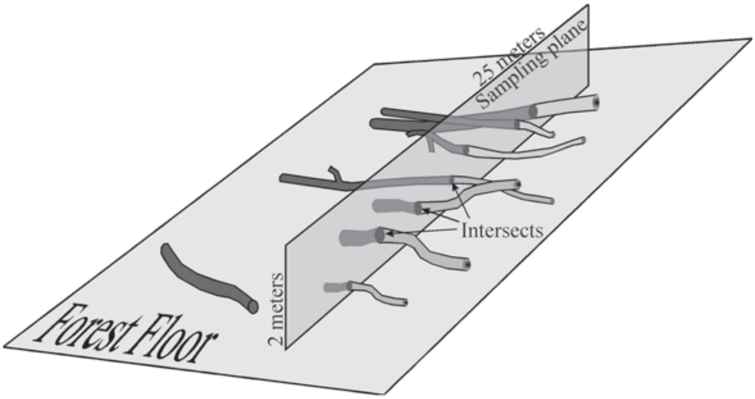

Fig. 8.1 Illustration showing the sampling of fuel particles using the planar intercept method

8.3.2 Direct Methods

These methods involve directly sampling or measuring characteristics of fuel particles to calculate loading. This usually involves direct contact with the fuel, such as measuring dimensions of particles using calipers, estimating depths of duff and litter using rulers, or collecting particles for drying and weighing in the lab.

8.3.2.1 Planar Intercept (PI)

PI techniques are the most commonly used sampling methods for sampling downed woody fuels for both management and research (Catchpole and Wheeler 1992; Dibble and Rees 2005) and both inventory and monitoring projects (Busing et al. 2000; Waddell 2001). PI sampling involves counting woody fuel particles by diameter size classes, or by directly measuring individual particle diameters, as they intercept a vertical sampling plane that is of a fixed length and height (Brown 1970, 1974; Fig. 8.1). These intercepts are then converted to loadings using standard formulae (Brown 1974). There are correction factors for the slope of the sampling plane and orientation of the fuel particles. One major parameter for computing loading is the particle density (specific gravity) of the particles (Table 2.1; Chap. 2).

PI is the operational version of the line transect method originally introduced by Warren and Olsen (1964) and made applicable for measuring CWD by Van Wagner (1968). The line transect method is founded in the probability-proportional-to-size concepts and several variations of it have been developed since 1968, including those that vary the transect arrangements and directions, and those that apply the technique using different technologies (Hansen 1985; Nemec-Linnell and Davis 2002; Vries 1974). Brown (1971) modified the line transect method so that particle intercepts are measured in a two-dimensional plane rather than a one-dimensional line for operational sampling of FWD and CWD in forests (Brown 1974; Brown et al. 1982). Many still locate the bottom of the plane using a line transect that is often represented by a cloth tape.

The advantages of the PI method are that it is easy to use and easy to teach (Lutes et al. 2006, 2009a). Novice field technicians can be taught this method in a short time (1 h) to achieve moderately repeatable measurements. The method can also be easily modified to adjust for local conditions, available expertise, and sampling conflicts, such as long plot times, scattered woody fuels, and slash. The sampling plane can be any size, shape, or orientation in space and samples can be taken anywhere within the limits set for the plane (Brown 1971). It also requires few specialized equipment; often a plastic ruler and cloth tape are the only gear needed.

However, there are some problems to the PI method. First, it only can be used for estimating downed dead woody loading; loadings for other fuel components, such as canopy fuels, litter, and duff, must be estimated with entirely different methods. This is somewhat problematic because the sampling unit for PI (transect) does not always scale to the FAP methods used for sampling other components or used in other forest and range inventories (Keane and Gray 2013). The CWD transects, for example, are usually too long to fit within the area of standard fixed area plots. PI sampling designs are also difficult to merge with other sampling designs because the PI was designed to sample entire stands, not FAPs. PI methods also require a large number of transects under highly variable fuel conditions, which may be time- and cost-prohibitive for operational sampling efforts. Keane and Gray (2013) found that over 200 m of transect were needed on a 0.05 ha plot to sample FWD within 20 % of the mean. Moreover, some feel that it is difficult to repeat particle intercept counts with any degree of reliability (Sikkink and Keane 2008). Particles are often hidden by other fuels often partially buried in the litter and duff making repeatability across and within observers difficult.

8.3.2.2 Fixed-Area Plots (FAP)

In contrast to unequal probability strategies (e.g., PI), FAP are based on equal probability sampling methods and have been adapted from vegetation composition and structure studies to sample fuels (Mueller-Dombois and Ellenberg 1974). In FAP sampling, a plot of any geometric shape, often round or square, is used as a sampling unit and all fuels within the plot boundary are measured using any number of fuel measurement methods including destructive collection (cut, dry, and weigh fuels; see Sect. 8.3.3.5), volumetric measurements (measure diameter, length to compute volume, then use density to estimate weight), vertical depths of duff and litter layers (measure thickness of duff and litter layer), and particle counts by size class (count particles, assume standard length, diameter, then compute weight) (Keane et al. 2012b). FAPs can be any size, and the most effective sampling efforts scale the size of the FAP to the fuel being measured. Because FAP approaches require significant investments of time and money, they are more commonly used to answer research questions rather than to monitor or inventory fuels for management planning. However, new methods have been designed to use FAP in operational sampling projects (Keane and Gray 2013).

The FAP method may be a preferable and more appropriate method for obtaining accurate fuel loading estimates for many surface fuel components. Most importantly, FAP techniques tend to give a better representation of the actual variation observed in the field for surface fuel components (Keane and Gray 2013). FAP sizes and number can be adjusted to reduce sampling times but may result in reduced precision of fuel loading estimates. FAP size can also be adjusted to account for the spatial scaling of loading by fuel size. Larger fuels (CWD), for example, can be sampled with larger plots to fully account for spatial distributions in sample estimates. Moreover, FAP sampling is easily adapted or merged with other protocols that are commonly used to sample other fuel components or other ecosystem attributes. Microplots used to sample FWD, for example, can also be used to sample tree seedling densities, herbaceous biomass, and duff depths. Large macroplots (~400 m^2) can be used to sample both logs to compute CWD loading and trees to compute canopy fuels. Sampling times can be shortened by employing an easier technique for estimating loading; the photoload method, for example, can be used to estimate loadings rather than actually measuring particle dimensions or destructively collecting fuels for weighing. Or, PI techniques can be used to estimate FWD on transects within a macroplot. And last, it may be more practical to sample fuels using FAP methods because many fuel components can be linked together in the same sampling unit.

The main limitation of the FAP sampling method is that there has yet to be a set of standardized operational FAP protocols for surface fuel sampling. Many fuel professionals are unfamiliar with the FAP technique and do not have the knowledge and expertise to create their own FAP methods. Moreover, FAP estimates tend to be unbiased but imprecise; variabilities of the loading estimates are often quite high. While sampled high variability often reflects realistic field conditions, it makes the detection of change across time or difference between areas using statistical techniques difficult, especially when compared against PI methods. Another limitation is that many fuel particles may extend to outside microplot boundaries making it difficult to cut particles without disrupting other fuel particles. And, unlike PI, it may take a high number of FAP microplots to obtain a reliable measure of loading (Keane and Gray 2013).

8.3.2.3 Distance Sampling

Another new method is *perpendicular distance sampling* (PDS) which samples logs using probability proportional to volume concepts (Ducey et al. 2013; Gove et al. 2012; Williams and Gove 2003). With PDS, the total volume of the logs on a landscape can be estimated from counts of logs at various sample points. Loading can then be estimated by multiplying volume by particle density (kg m^{-3}) estimates. PDS is named because a log is selected to the sample if a line from a sample point intersects the central axis of the log at a right angle and the length of this line is less than some limiting distance that changes along the log length in a manner that is based on the sampling design. There are many variants of PDS including the distance-limited protocol for PDS, which uses a fixed distance from the perpendicular line to estimate volume then loading (Ducey et al. 2013). Transect relascope, point relascope, and prism sweep sampling use angle gauge theory to expand on the PDS and line-transect method for sampling CWD (Bebber and Thomas 2003; Gove et al. 2005; Stahl 1998).

This method is most effective for measuring only one fuel component, CWD (Gove et al. 2012), but Ducey et al. (2008) demonstrated how PDS can be used to estimate other ecological attributes, perhaps finding a future use in FWD loading estimation. Several studies have compared traditional sampling techniques and PDS methods and variants to evaluate their performance, accuracy, and bias in measuring CWD (Bate et al. 2004; Delisle et al. 1988; Lutes 1999; Jordan et al. 2004; Woldendorp et al. 2004). Gove et al. (2013) compared PDS variants using simulation modeling and found unbiased estimators of CWD using all variants and the differences in variances were small across all variants so selection of the most appropriate variant depends on field conditions. Affleck (2008) merged PDS with PI sampling to create line intercept distance sampling to improve fuel sampling and got similar performances to PDS. Ståhl et al. (2010) merged critical length methods with PDS which appears to have improved CWD sampling. However, few studies have yet examined the performance of various sampling techniques for measuring across multiple fuelbed components, such as combinations of FWD and CWD, live and dead shrubs, and herbs on the forest. Because of this, there are few operational protocols that use PDS methods or variants for fuel inventory and monitoring.

8.3.2.4 Cover and Volume Sampling

An alternative to the above direct methods that measure fuel particle dimensions is applying the abundant methods that directly measure *canopy cover* in vegetation sampling efforts to fuel sampling, as opposed to visually estimating canopy cover as presented in Sect. 8.3.1.2. Canopy cover is directly measured using a suite of methods, techniques, and protocols for ecological inventories and research efforts (Krebs 1999; Mueller-Dombois and Ellenberg 1974), and some of these may potentially be applied to measuring fuel loading. Point sampling, for example, involves using a vertically placed rod of a small diameter to determine the particle that it contacts, and the number of contacts per particle type (i.e., fuel component) is then used to estimate cover. If applied to fuel sampling, the number of contacts can be correlated with the destructive sampling estimates of biomass. Measures of the height of each contact can be augmented with number of contacts to associate both cover and average height with loading (Catchpole and Wheeler 1992). Axelson et al. (2009), for example, used point and height methods to estimate shrub biomass for the western Australian karri forest. Line intercept techniques, where the length of intercept of plant parts are used to estimate cover, can also be used to estimate fuel loading.

Many other cover sampling techniques, such as relative frequency, could be modified for certain sampling environments to quantify loading (Lutes et al. 2006).

The problem with the modification of cover methods to estimate loadings is that canopy cover, regardless of how it's measured, may be poorly correlated with fuel loadings (Catchpole and Wheeler 1992). The depth of the litter layer, for example, is more correlated with loading than litter ground cover. Woody particle diameters, especially log diameters, are more important for computing loading than their projected cover. Many of these cover methods provide repeatable estimates with low bias compared to visual techniques. However, the use of cover methods to assess all fuel component loadings would not be recommended.

The volume method involves sampling the dimensions of a fuel particle or component to compute volume then multiplying volume by particle density or bulk density to get loading. An advantage of the volume method is that it can be used at particle, component, and fuelbed scale. Fuel component volume can indirectly calculated as discussed in Sect. 8.3.1.2 where the proportion measured cover (percentage cover divided by 100) is multiplied by height (m), sampling area (m^2), and bulk density (kg m^{-3}). Hood and Wu (2006) used the cover-volume approach to calculate loadings of masticated fuelbeds. Fuel component or particle dimensions can also be measured to directly estimate volume. Litter loading, for example, can be estimated by (1) measuring litter depths within a 1 m^2 microplot, (2) computing an average depth (m), (3) multiplying by sample unit FAP area (1 m^2) to calculate volume, and (4) calculating loading by multiplying volume (m^3) by bulk density (kg m^{-3}) and dividing by area of microplot (m^2). However, volume can also be used to estimate the mass of a fuel particle by (1) measuring particle dimensions (length, width, and depth), (2) estimating a volume by multiplying length, width, and depth, and then (3) multiplying particle volume by particle density to get dry weight. Loading can then be calculated by summing all particle dry weights over sample unit (FAP) area. As mentioned, bulk and particle density estimates for many fuel components can be found in the literature (Brown 1981; Keane et al. 2012b) or it can be estimated by destructively sampling a small proportion of the plots.

8.3.2.5 Destructive Sampling

As mentioned, *destructive sampling* involves removing fuel by clipping and collecting, drying the material, and weighing the dry mass of material. An alternative is to (1) collect and weigh the wet fuel in the field; (2) subsample that fuel to dry and weigh to estimate a moisture content, and then (3) use the subsampled moisture content to adjust the wet field weight to dry weight. Destructive sampling can be scaled for any sampling design or objective. Fuel particles can be collected individually, as a group (shrub or tree), or on FAPs. Destructive sampling almost always involves subsampling a fuel component or fuelbed so statistical methods are often required to summarize subsampled estimates to describe the sampling area. Often, destructive sampling is used to create predictive biomass equations for a fuel component or entity, such as a tree or shrub. This predictive equation can then be applied to inventory data to compute loading. Most destructive sampling is done for research rather than operational management inventory and monitoring.

8.3.3 Integrated Surface Fuel Sampling

Sampling projects are rarely designed using only one sampling approach or technique. The diversity of surface fuel components coupled with the constraints of limited resources always result in project-level sampling designs that compromise statistical rigor to ensure success by integrating the above techniques and approaches. Conventional standardized surface fuel sampling protocols nearly always recommend using PI techniques for woody fuel loading and volume approaches for litter, duff, shrub, and herb (Lutes et al. 2006). The photoload approach has been augmented with PI, fixed-area log sampling, and volume estimates for duff and litter (Keane et al. 2012b). Catchpole and Wheeler (1992) mention a sampling technique called "double sampling" where destructive techniques are used on a subsample of FAPs to calibrate loading estimates from visual techniques. Keane et al. (2012b) used double sampling for another reason—to adjust visual estimates using statistical regression. This melding of approaches, techniques, and intensities may aid in successful sampling designs, but the resultant loading estimates have different error distributions, variability, and usefulness for each fuel component. This makes evaluating fire model performance difficult when the uncertainties of loading estimates are different across fuel components.

8.4 Canopy Fuel Sampling

The five canopy fuel characteristics (*canopy base height* (*CBH*)*, canopy height* (*CH*)*, canopy bulk density* (*CBD*)*, canopy fuel load* (*CFL*), and *canopy cover* (*CC*) in Chap. 4) can be estimated using any of four approaches. The first approach involves the destructive sampling of the canopy in vertical layers within a FAP (*destructive canopy methods*). Here, all canopy biomass is cut, dried, and weighed within a canopy layer for the plot area. This usually involves climbing or cutting trees, clipping their branches within a given canopy layer, clipping and sorting branch material into fuel components (needles, wood by diameter size class), and then drying and weighing the fuels in a laboratory. Reinhardt et al. (2006b), for example, sampled five forested stands in the western USA using this technique to describe CBD and CFL vertical distributions. This is obviously a time-consuming and costly method and is only done for research studies.

The second approach involves using various instruments or sampling schemes to indirectly measure canopy fuel variables (*indirect canopy methods*). In this approach, various specialized equipment or protocols are used to measure stand characteristics, such as gap fraction (percent of vertically projected canopy cover not containing canopy biomass), LAI, and canopy cover, and these simple measurements are then correlated to canopy fuel variables. Keane et al. (2005), for example, measured gap fraction using five different instruments for the destructively sampled plots of Reinhardt et al. (2006b) and then developed statistical models that predicted CBD from gap fraction for each instrument. These predictive relationships were then used by Poulos et al. (2007) to estimate CBD for stands in Texas, USA. Another alternative to this approach is using simple stand-level measurements to estimate canopy fuel variables. Alexander and Cruz (2014) created tables that show values for the five canopy fuel variables for various stand basal area and tree density classes for four western US forest types. These indirect techniques are relatively quick and cheap, but the instruments may be expensive, especially a terrestrial scanning LiDAR. However, the statistical models that predict canopy fuel characteristics from indirect measurement are generally not robust and are most accurate for stand types that are similar to the ones destructively sampled (Keane et al. 2005).

The most commonly used canopy sampling approach is estimating the canopy fuel variables using stand inventory data and modeling canopy biomass using allometric relationships (*allometric methods*). This technique uses an inventory of trees in a stand to compute the five canopy fuels variables. The inventory is often represented by a "tree list," which is a list of tree cohorts in the stand on a per area basis. Six attributes are usually measured for each tree cohort in most stand inventory protocols: tree density (trees per unit area), species, condition (live vs. dead), diameter breast height (DBH), height, and height to live crown base. There can be any number of tree cohorts in the tree list. The tree list is then used to compute the amount of canopy material in vertical canopy layers of specified thicknesses. This is often done by first computing burnable canopy biomass from the empirically derived allometric biomass equations for each crown fuel component (Brown 1978). This burnable canopy biomass is then distributed across the vertical crown length for each tree by assuming a crown shape and then using tree height and live crown base height to allocate biomass into each layer based on geometric analysis. The biomass is then summed across all trees for each layer and this sum is then divided by the volume of that layer (plot area multiplied by layer thickness) to calculate *CBD*. *CBH* and *CH* are calculated as the layer height at which the CBD exceeds or goes below a threshold value (Chap. 4). *CFL* is simply the sum of all burnable biomass over all layers divided by plot area. This technique is programmed into a computer application called FuelCalc (Reinhardt et al. 2006a).

One great advantage of the allometric method is that it can be used with any of the diverse stand inventories commonly conducted by natural resource management agencies. Moreover, the sampling techniques and methods for measuring trees using timber inventory techniques are widely known and many field crews are familiar with the protocols so training may be minimal. There are also many databases that contain tree lists that can be used to quantify canopy fuels characteristics; the US Forest Service's Forest Inventory and Analysis program has tree lists for thousands of plots across the USA. However, while this technique has been used for many fuel projects (Keane et al. 2006; Reeves et al. 2006) and is easily the most popular for sampling canopy fuels, there are some limitations. First, there are precious few studies that developed biomass equations for each of the crown fuel components (burnable canopy fuels; <3 mm), and most canopy biomass equations are for mostly western US forest species. Second, many of the assumptions in the method, such as crown shape and crown fuel distribution, may not be appropriate for some ecosystems and stand conditions. Third, some tree lists were created using stand inventory techniques that may be at an inappropriate scale. Plot-less sampling, for example, uses a prism or limiting distance sampling to determine which trees to sample, and these trees are usually above a certain breakpoint diameter resulting in few of the understory trees being sampled. The resultant tree list typically underrepresents the understory canopy biomass important to crown fire transition (Chap. 2). This means that overstory conditions will be summarized independently of understory conditions at stand level which ignores the importance of spatial autocorrelation in canopy fuel characteristics at smaller scales (Keane et al. 2012a). Sampling trees inside a FAP to create a tree list, and then using this plot-level tree list to compute canopy fuels provides for a better representation of canopy fuels than computing canopy fuels from averaged stand conditions.

The last canopy fuel sampling approach involves using a set of photos to visually estimate canopy fuel variables (*visual canopy methods*). Scott and Reinhardt (2005) developed a set of stereo photos of canopies from five western US sites in four different stand densities and calculated canopy fuel variables from destructive sampling at each site. These photos can then be compared to canopy conditions observed in the field to estimate the five canopy fuel variables along with other stand variables (basal area, tree density). Many of the newer photo series publications mentioned in Sect. 8.3.1.2 now have canopy fuel characteristics as attributes to the photos that are used to match with field conditions.

Estimating canopy fuel variables using field methods poses a dilemma to the fuels manager. The coarse resolution of crown fire modeling (Chap. 4) is often at odds with detailed sampling of canopy fuel characteristics. The coarser methods of indirect and visual canopy fuel sampling may provide sufficient resolution for the canopy fuel variables, and the more accurate and precise measurements gathered from the destructive and allometric methods may not match the coarse resolution of the canopy biomass in fire models. In fact, Reeves et al. (2006) created canopy fuels maps by quantifying canopy fuel variables from the allometric approach using the FuelCalc model but then had to adjust these precise measurements to use in the spatial fire prediction packages.

8.5 Challenges

The main challenge in fuel sampling is obtaining precise estimates of loading for each fuel component given the enormous spatial and structural variability across the different surface fuel components. With limited resources, it is simply impossible to sample to the same level of precision for all fuel components, and for some fuel components, it is incredibly difficult to obtain a precise estimate of loading without extensive sampling. The problem is that fuel component properties have unique spatial distributions that dictates the size and shape of the sampling unit. Small woody fuels (FWD) vary at scales that are much smaller than logs (CWD) (Keane et al. 2012a). Therefore, sampling designs must accommodate these spatial distributions along with the properties of the fuel component by using hierarchically nested sampling unit designs (e.g., nanoplots nested within microplots nested within macroplots).

Some fuel types are often ignored in most sampling projects for logistical, cost, and time reasons. Conifer seedling loading, for example, may comprise a significant portion of the fuelbed and contribute to fire ignition and spread (Fig. 3.4), yet few sampling designs include effective methods for sampling seedlings (Riccardi et al. 2007). Squirrel middens, animal scat, and pollen cones (Chap. 3) are other examples of fuel types that have few sampling methods and are rarely tied to fuel components (Ottmar et al. 2007).

Woody fuel loading should be stratified in statistically and ecologically appropriate size classes that still provide value in predicting fire behavior. Keane and Gray (2013) found the highest sampling uncertainty occurred when FWD were stratified by the conventional, nonuniform time-lag moisture sizes (e.g., 1, 10, 100, and 1000 h) rather than actually measuring particle diameters or measuring diameters to 1 cm size classes. As mentioned in Chap 3, the unbalanced Fosberg et al. (1970) size classes that get wider with larger particle diameters ignore subtle but important differences between species, degree of rot, and stand structure. Moreover, aggregating loadings of all log sizes into one class makes accurate decomposition predictions nearly impossible because of the great ecological importance of log size in various ecosystem processes (Harmon et al. 1986).

Four major biological factors are responsible for high levels of uncertainty in most sampling methods. First, wood density is highly variable both within and across the fuel particles, so the assumption of a constant density across all particles may be flawed. An assessment of density during sampling might improve loading estimates, but it would be difficult at this time to expect sampling crews to estimate particle density because there isn't any technology or standardized method as yet. Keane et al. (2012b) found high variability in wood density within a woody fuel component and an even higher variability within a sample site. Some woody fuel sampling protocols use the decay classes of Maser et al. (1979) to key to different wood densities (Lutes et al. 2009a; Lutes et al. 2006), but rarely are estimates of wood density actually measured in the field along with loading and rarely is the Maser et al. (1979) key applied to FWD. Second, woody fuel particles are not cylinders, but rather complicated volumes of highly variable cross-sections and contorted lengths (Chap. 3). Therefore, assumptions that woody fuel particle shapes can be approximated by frustums or cylinders using diameters and lengths may be oversimplified and techniques for measuring fuel diameters using rulers and gauges may be too coarse. Next, the high variability in fuel properties, specifically loading, within an area may often overwhelm targeted sampling precision. Often it is difficult to estimate fuel loading for coarser woody fuels to within reasonable targets without an impractical number of sample units. And last, fuelbeds are constantly changing over time; live fuels are constantly growing and depositing dead biomass on the decomposing necromass on ground (Chap. 6). The rates of biomass production, deposition, and decomposition change throughout the year because of plant phenology, climate, and disturbance. Sampling live fuels before the growing season, for example, may result in an underestimation of fuels that will burn during the fire season. Moreover, dead woody diameters are not static and change with weather conditions, often becoming thicker when wet, and cracked when dry, making diameter measurements difficult and further complicating the geometry used to estimate volume.

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