Chapter 7
Fuel Classifications

Science is the systematic classification of experience
Philosopher George Henry Lewes

7.1 Introduction

Wildland fire scientists and managers use classifications of fuelbeds for a number of reasons. Most importantly, classifications provide a means to easily enter fuelbed properties into fire management software. Fire managers often have insufficient resources to directly measure or sample fuel component characteristics in the field, so using a classification to quantify fuel characteristics is an appealing option. Second, many use classifications to communicate fuelbed characteristics to other professionals because most fuelbeds are highly complex and diverse (Chap. 2), and this complexity often limits effective technical exchange, especially in operational fire management planning and tactical firefighting. Third, the categories in some fuel classifications may be used as mapping units in the development of digital fuel maps over large areas (Chap. 9). Finally, some classifications can be used in the field as an alternative fuel inventory and monitoring protocol for assessing fuel loadings (Sikkink et al. 2009) (Chap. 8).

Classification is often defined as the process in which objects are recognized, differentiated, and understood. In this chapter, fuel classification is defined as the process of identifying unique fuelbeds and quantifying their component attributes. People differentiate fuelbeds in a number of ways. Some assume vegetation serves as an acceptable surrogate for differentiating fuelbeds, so they use vegetation classifications as de facto fuel classifications (Keane et al. 2013). Others classify fuelbeds by the way they might burn in a severe fire (Burgan 1987; Hornby 1935). While some subjectively evaluate the representativeness of a fuelbed through field reconnaissance (Ottmar et al. 2007), others use extensive field data to systematically classify fuelbeds using advanced statistical techniques (Lutes et al. 2009). Fuel classifications may use any number of variables to describe and quantify fuel component attributes, such as heat content, mineral content, and particle density, depending on the fire software application, but the most common variable used across fire management classifications is fuel loading (Weise and Wright 2014).

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7.2 Classification Approaches

Several fuel classifications are currently used by land management agencies across the globe, and most of these systems appear quite similar because they have comparable categories, components, and description variables (Anderson 1982; Keane 2013; Sandberg et al. 2001; Weise and Wright 2014). The main distinction between most existing fuel classification systems is in the approaches used to create them (Keane 2013). Although it would be much easier if there was only one fuel classification for all fire science and management applications, multiple fuel classification systems exist today because each fire modeling system requires a specific set of fuel inputs and its own unique classification input scheme. Fire behavior fuel classifications, for example, include fuel component attributes, such as fuel depth, that may not be needed in fire effects prediction systems.

Effective biological classifications are designed to be systematic (well organized), practical (easily identified using a key), singular (uniquely identifies a class), and comprehensive (the key can be used across a broad range of fuelbeds). This usually implies that the classes that comprise them are mutually exclusive, and a change in the value of an attribute of one class usually affects the values of the same attribute in other classes (Gauch and Whittaker 1981). However, many of today's fuel classifications were not created using systematic classification procedures that group fuelbeds based on statistical and ecological differences. Because of this, the fuel classifications in this chapter will be summarized by the four broad approaches used to create them: (1) association, (2) opportunistic, (3) classification, and (4) abstraction (Table 7.1). Of course, some of the fuel classifications presented as examples were created using a combination of approaches.

7.2.1 Association

Many have associated or linked fuel component information, such as loading, to the categories of other extant classifications commonly used in natural resource management (Keane 2013). This is often accomplished by summarizing field-collected fuels data by extant classification categories. For example, Reinhardt et al. (1997) average field-measured fuel loadings for eight fuel components across the vegetation-based categories of both the Eyre (1980) forest cover type classification and the Shiflet (1994) range cover type classification to facilitate input to the First-Order Fire Effects Model (FOFEM). In Canada, Hawkes et al. (1995) assigned fuel loadings to various categories of vegetation and timber type classifications, and the Canadian Fire Behavior Prediction System contains fuel input types that are associated with major forest vegetation types (FCFDG 1992). Poulos et al. (2007) created vegetation composition and structure layers from environmental gradients, satellite imagery, and forest inventory data, then scaled fuels information to the resultant biophysical classification for Texas fuelbeds. The fuel type group classification was created by summarized Forest Inventory and Analysis georeferenced fuels data by forest type groups (Keane et al. 2013).

Table 7.1 Comparison of the four approaches used to develop wildland fuel classifications for fire management

Approach	Description	Advantages	Disadvantages	Examples
Association	Fuels information is assigned to categories in extant classifications	Existing vegetation classifications and maps can be used to describe fuels; most existing classifications are widely used, well accepted, and used in all phase of land management; contain comprehensive keys to uniquely identify classes in the field	Fuel properties are often uncorrelated to vegetation categories; extant classifications are often too broad to describe subtle changes in fuels; fuel properties can be redundant across the classes; difficult to alter extant classifications to account for differences in fuel attributes	US: FOFEM SAF/SRM Cover types (Reinhardt et al. 1997), FCCS (Ottmar et al. 2007) Canada: FBP (Hawkes et al. 1995) China: Wu et al. (2011) Russia: Volokitina and Sofronov (2000)
Opportunistic	Unique fuelbeds are identified and sampled in the field and the fuelbed is added as another category in the classification	Represent real fuelbeds; designed for fine scales; easily add new fuel categories; easily add new fuel components	Data intensive; classes can be highly redundant; infinite number of classes makes it difficult to learn and use; many fuel types are missing because they are not yet sampled	US: FCCS (Ottmar et al. 2007), photo series (Vihnanek et al. 2009)
Classification	Fuel data are clustered into similar groups that are mutually exclusive using statistical techniques	Can control variation and limit redundancy across classes; comprehensive keys can be developed to identify classes in field; can design classification for any scale, area, or fuel type; easy to learn and use	Data intensive and many fuelbeds may not be represented in data; difficult to add new fuel types and new fuel components into the classification; classification is complex and difficult to understand	US: FLM (Lutes et al. 2009), Crown assessment (Fahnestock 1970) Greece: Dimitrakopoulos (2001) Australia: Gould et al. (2011)
Abstraction	Fuels inputs to fire models are adjusted to match observed fire behavior, and the adjusted fuel information becomes a category in the classification	Match the resolution of the fire models; widely used and accepted in fire management; training widely available for managers	Do not represent real fuel fuelbeds; can't directly use to estimate fuel loadings; difficult to create, use, and interpret; no keys are available to identify classes in the field; only useful for use in the fire behavior model for which they were developed	US: FBFMs: Anderson (1982), Scott and Burgan (2005) Greece: Dimitrakopoulos (2002)

There are many advantages to linking fuels to vegetation-based classifications that make this approach quite attractive to a number of researchers and managers (Bailey and Mickler 2007). Many vegetation and natural resource classifications are well known to fire managers and have a long history of use in land management because they are easy to learn and contain proven keys for quick and objective identification of vegetation categories in the field. Vegetation characteristics used in classification keys, such as composition, structure, and successional stage, are easily identified in the field with minimal training. Moreover, a vast array of ancillary land management analyses can be done by linking vegetation information with fuels data, such as predicting future fuel conditions using vegetation succession models (Davis et al. 2009), linking canopy fuels with surface fuels (Keane et al. 2006), creating fuel maps (Reeves et al. 2006), and prioritizing areas for fuel treatment (Hessburg et al. 2007). Finally, additional fuel components and characteristics can be added with little effort; canopy fuels, for example, can be summarized by vegetation type along with surface fuel loadings.

There are some major problems with the association method of linking fuel characteristics to existing classification categories that might limit the application of this approach in the future (Table 7.1). First and foremost, fuel characteristics are rarely correlated to vegetation attributes and categories, especially at fine scales, because they also depend on decomposition and disturbance (Chap. 6) (Keane et al. 2012b; Keane and Gray 2013). Brown and Bevins (1986) found that fuel loadings did not correlate with cover type or habitat type and speculated that stand disturbance history had more influence on fuelbed loadings than vegetation. One reason for this lack of relationship between fuels and vegetation might be that vegetation attributes, such as species cover and height, vary at coarser scales than wildland fuels (Chap. 6). Wildland fuel loadings are also highly variable across a vegetation type category (Chap. 6). As a result, many disparate fuelbeds may be represented within one vegetation type, and conversely, many vegetation types may have the same fuelbed description. This redundancy is also related to the fact that the resolutions of most vegetation classifications (e.g., species taxa) do not match the resolution of those fuelbed characteristics that foster unique fire behavior and effects (fine-scale fuel components) (Keane et al. 2012a). For these reasons, vegetation-based fuel classifications often have poor accuracies and low precisions (Keane et al. 2013). Accuracies of the vegetation classifications for which fuels are associated do not reflect the true accuracy of the fuel information. For example, a 90% accuracy of a vegetation map does not translate into 90% accuracy for the fuels data. The associated fuels information must be compared with field-collected fuel data to determine fuelbed accuracy, and often, these analyses show poor agreement (Keane et al. 2013). Moreover, since fuel component properties are independently averaged across somewhat broad vegetation categories, the resultant set of fuel component properties may represent a summarized fuelbed that may be rare.

Another problem with the association approach is that it is difficult to refine the fuel descriptions to improve classification accuracies. If classified fuel loading accuracies are low, as is often the case, there is little recourse to improve the accuracy without changing the original vegetation classifications by adding, modifying, or deleting categories, or by adding additional classifications to the already complex associative approach (e.g., combine a classification of stand structure with a cover type classification). The addition of new classifications or classes exponentially increases the amount of fuel data needed to cover all combinations of the merged classifications; so many combinations might be missing valuable fuel data to quantify fuel information.

7.2.2 Opportunistic

In the opportunistic approach to fuel classification, unique fuelbeds are subjectively identified in the field and selected as a new category to include in the classification based on their representativeness for a region, vegetation type, or fuel type. The newly identified fuelbed becomes a new class in the classification once the fuel component properties are measured and assigned to this fuelbed. Keane (2013) called this a "bottom-up" indirect classification approach where there are an infinite number of classes possible in this ever-expanding classification method.

Two fuel classifications provide excellent examples of this opportunistic approach: the photo series (Chap. 8) and the Fuel Characteristics Classification System (FCCS). In both, new and unique fuelbeds can be added as they are identified by managers, scientists, and resources specialists in the field for local, regional, or national applications (Berg 2007). When new fuelbeds are sampled, the resultant data become attributes of the new class in the classification (Riccardi et al. 2007b). The photo series is a set of photographs of fuelbeds where fuel component loadings have been measured (Fig. 7.1). These photographs are usually described and stratified by vegetation characteristics, such as cover type or species composition. Each photo in the series becomes a category in the classification and many have used photo series photos to describe and quantify fuel characteristics (Keyes 2002). The FCCS is a more formal adoption of an opportunistically derived fuel classification (Ottmar et al. 2007). In the FCCS, unique fuelbeds are identified, either in the field or office, and then directly or indirectly sampled to populate a database that links

Fig. 7.1 A picture from the Fischer (1980) photo series

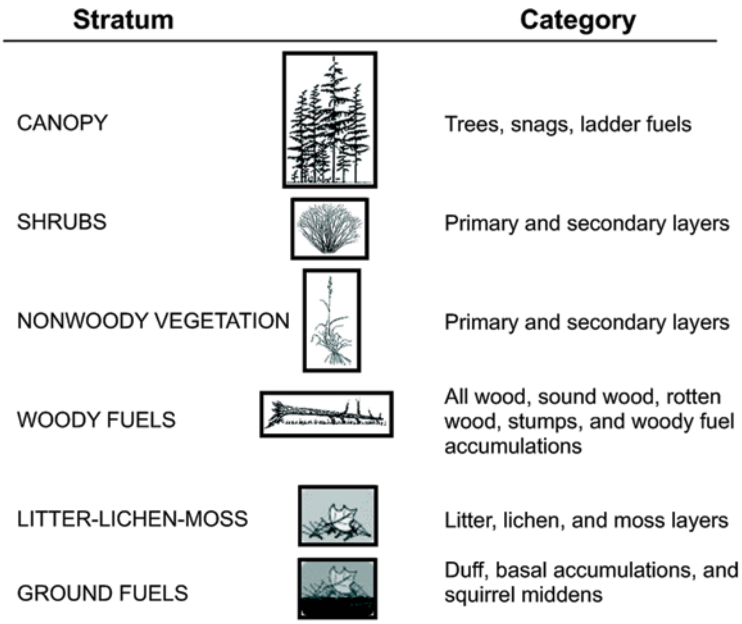

Fig. 7.2 A general description of the elements in the FCCS. (Ottmar et al. 2007)

fuel component properties with the identified FCCS "fuelbed." This fuelbed then becomes a category in the classification. The system uses ecoregion, stand structure, and site history classification variables to identify fuelbeds in the field (Riccardi et al. 2007a). FCCS is also somewhat special in that it also contains its own fire behavior model tuned for the FCCS fuel components (Sandberg et al. 2007).

The advantage of developing opportunistic classifications is that new fuel components and properties can be added to the classification with little effort. The FCCS has quantified over 20 fuel properties for several fuel components in each fuelbed in the classification (Fig. 7.2). Opportunistic classifications can be used to represent fuels at any scale; FCCS classifications have been developed for small areas, such as plots and treatment units, and for large regions, such as the entire USA (McKenzie et al. 2007). These classifications are also easy to understand and build, and they can be modified and revised by anyone with any level of experience. In addition, the classes represent actual fuelbeds that are extensively documented in the field.

There are some shortcomings in the opportunistic approach that may limit their application. Few opportunistic classifications are able to consistently and uniquely identify a fuelbed in the field (Ottmar et al. 2007). Most rely on the expertise of the fuel sampler to match the observed fuelbed conditions to the categories in the classification, or to identify a class based on the ancillary vegetation and site classification criteria used to describe the fuelbed (e.g., photo series). The FCCS, for example, does not contain a key to directly identify a fuelbed from fuelbed characteristics.

Instead, it uses a set of ecological descriptions mostly based on vegetation and stand history to aid in fuelbed identification (Ottmar et al. 2007). As a result, there is often redundancy across many fuel classification categories; the properties of one fuelbed may be quite similar to other fuelbeds sampled in another part of the country or for another vegetation type, especially for the fine woody debris components. Linking opportunistic classification categories to spatial data layer attributes is also problematic because it is difficult to consistently validate an assigned class in the field because there is no fuel classification key. Another problem is that since the variation across fuelbeds is not incorporated into the classification design, there can be an infinite number of possible categories (fuelbeds), and conversely, there can be many locally relevant fuelbeds that are missing in the final classification. Keane et al. (2006), for example, mapped FCCS categories across central Utah but found that over 30 % of the land area had vegetation attributes that did not match sampled FCCS classes. This issue makes opportunistic classifications somewhat difficult to learn because it is always changing and new classes are always being added.

7.2.3 Classification

Classification, as previously mentioned, is the process of systematically and comprehensively clustering items (fuelbeds) into unique groups based on selected attributes—mainly loading by fuel components. Usually, this involves numerical clustering and complex statistical techniques that attempt to directly identify unique groups based on the variation of the attributes selected to develop the classification (Gauch and Whittaker 1981; Orloci 1967). Once unique groups are identified, a comprehensive key based on the analysis variables (e.g., loading) can be devised to objectively identify the classification category for a field-assessed observation. This approach partitions the variation in the field data to reduce redundancy and produce a singular classification.

Few existing fuel classifications were built using this direct, top-down classification approach. In perhaps the first effort at directly classifying fuels, Fahnestock (1970) developed two keys that evaluated various fuel attributes, including particle size, compactness, vertical position, and horizontal continuity, to key to unique spread rate and crowning potential classes. Dimitrakopoulos (2001) created a fuels classification for Greece by clustering flammability variables, such as heat content, ash content, and particle density, into unique groups using hierarchical cluster analysis and canonical discriminant analysis for Mediterranean shrublands. The fuel loading models (FLMs) of Lutes et al. (2009) is distinctive in that field-collected fuel loading data were used to simulate smoke emissions and soil heating, and these simulation results, along with loading, were used to create unique classes using advanced clustering and then a unique key was created using regression tree analyses. As a result, this classification effectively integrated the resolution of the fire models for which the FLMs would eventually be used into the classification design (Fig. 7.3).

An advantage of the direct classification approach is that resultant classifications are fully supported by the data that were used to create them, and therefore,

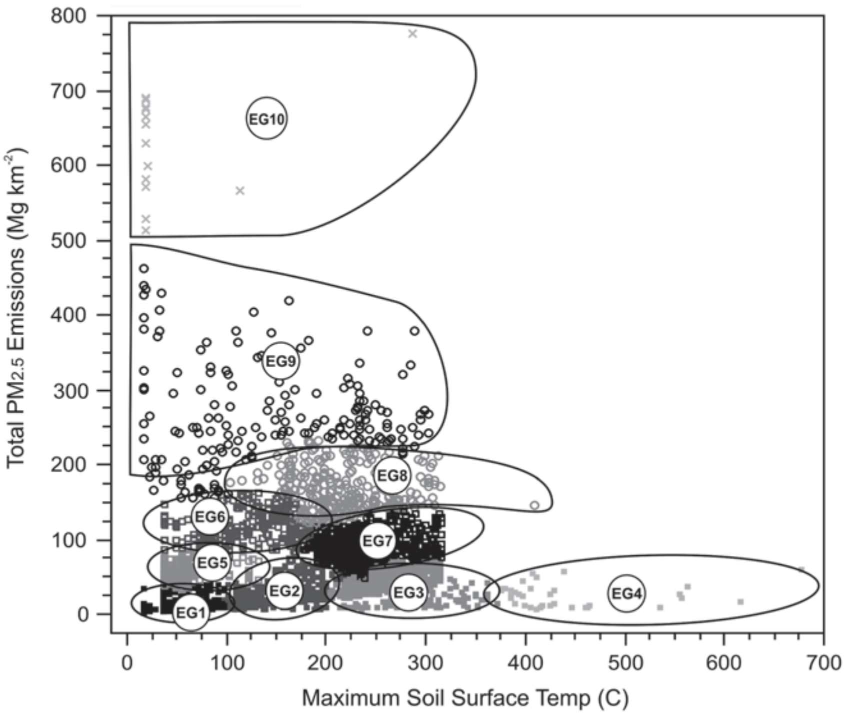

Fig. 7.3 The classification diagram showing the clustering of fire effects groups (e.g., EG1) on gradients of smoke emissions production and soil heating. These fire effects groups were then divided into finer groups to create the FLMs. (Lutes et al. 2006)

represent actual fuelbeds with measured loadings. As such, these classifications can be used as (1) inventory techniques to quantify fuel characteristics (Sikkink et al. 2009); (2) descriptors of unique fuel types to facilitate communication between managers, scientists, and other professionals (Sandberg et al. 2001); and (3) map units in fuel mapping efforts (Keane et al. 2001). Effective classified fuel systems contain dichotomous keys that can uniquely identify a class on the ground based on qualities of the fuelbed (Sikkink et al. 2009). The loading information for a classified category can be used in fire applications, such as simulating fire effects and validating fuel maps, and the variability of loadings within a category can be incorporated into the analyses. And since statistical classifications have low redundancy between classes, class attributes may be used for quantifying loading in fire models, as a field inventory technique (Chap. 7), and for identifying possible thresholds in fire behavior and effects modeling (Lutes et al. 2009).

Directly classified fuel classifications, such as FLMs, also have drawbacks. All fuel classifications, and especially those developed from direct classification techniques, require extensive data sets to fully represent the diversity of fuelbeds in the analysis. As a result, the depth, scope, and quality of the data sets used to create the classification system are rarely comprehensive enough to represent all possible fuelbeds that exist across the target area. While FLMs were developed using extensive data collected across the entire USA, the analysis data set was missing critical data from several major US fuelbeds that were unsampled at the time of FLM development, including many non-forest rangeland types, and therefore, these categories are missing in the classification (Lutes et al. 2009). Another limitation is that the parameters used in the clustering algorithms, such as the desired number of clusters, have a major influence on the classification, yet they are often subjectively estimated based on the objectives of the analysis. Finally, it is quite difficult to modify, add, or remove new categories or components as new data become available without completely redoing the entire classification.

7.2.4 Abstraction

Some fuel classifications were created using abstraction where the qualities of a fuelbed are related to abstract evaluations of fire behavior (Muraro 1965). Hornby (1936), for example, subjectively described western US fuelbeds using two fire behavior attributes: resistance to fire control and fire spread (Chap. 1). Most US fire behavior predictions systems were built using the Rothermel (1972) model, and the fuel classifications used as inputs to this model are often called fire behavior fuel models (FBFMs) that are essentially abstractions of expected fire behavior. Each FBFM is described by a set of fuel characteristics (e.g., loading, SAVR, mineral content, heat content) for each of the input fuel components required by the fire behavior modeling systems (Burgan and Rothermal 1984). However, the FBFM fuel characteristics are quantified to represent "expected" fire behavior and, as such, can't be used to describe actual fuel characteristics. To create FBFMs, fuel input parameters for each FBFM, including loading, are adjusted to reflect realistic fire behavior under known fuel moisture and weather conditions by comparing model results with observed fire behavior or expert opinion (Burgan 1987). This is because the inherent complexity of the quasi-mechanistic Rothermel (1972) fire behavior algorithm makes it difficult to predict realistic fire behavior from actual fuel loadings (Burgan 1987). As a result, a somewhat complicated procedure has been developed to create new FBFM models, called "custom" fuel models, where fuel loadings and other fuelbed characteristics need to be adjusted to achieve a realistic and believable fire simulations based on observations of fire behavior in the field. As a result, FBFMs are actually classifications of expected fire behavior. They were included in this chapter because they are perhaps the most used fuel classification in fire management. FBFMs have been used in the USA for over 30 years, and they have been broadly accepted by managers as a viable method of describing fuels for fire behavior modeling. The development and use of FBFMs are taught to fire managers in a wide variety of fire management courses throughout the world.

Most abstract fuel description systems today are FBFMs created for use in fire behavior applications that contain the Rothermel (1972) spread model as implemented in BEHAVE (Andrews 2008) and FARSITE (Finney 1998) systems. In the USA, the most commonly used FBFM classifications are the (1) 13 FBFMs described by Anderson (1982), (2) 40+ models of Scott and Burgan (2005), and (3) 20 fire danger fuel models used in the National Fire Danger Rating System (Deeming et al. 1977). Others have created new sets of custom FBFMs to these classifications. Reich et al. (2004), for example, created several new BEHAVE custom fuel models using field loading data that were then mapped to a South Dakota US landscape, and Cheyette et al. (2008) created custom fuel models for the wildland urban interface lands around Anchorage, Alaska, using a supervised vegetation-based classification of 13 cover types. In Greece, Dimitrakopoulos (2002) created seven FBFMs by synthesizing fuel data from 181 natural fuel complexes described by vegetation. In Corsica, Santoni et al. (2011) developed two fuel models for a spatially explicit fire model built to simulate fire behavior for maquis and juniper shrublands. To evaluate fire hazard in Portugal, Fernandes (2009) developed a suite of 19 fuel models based on the dominant vegetation structures and complexes in mainland Portuguese forests.

The main advantage in creating abstract fuel description systems is that, ideally, the resolution of fuel classes (FBFMs) match the resolution of the fire models for which the classes will be used as inputs. Another words, each FBFM represents a major change in predicted fire behavior in the Rothermel (1972) model. This means that the uncertainty and error in model predictions may be minimized from inaccurate and inappropriate fuel inputs because the fuel models were calibrated to actual fire behavior observations (Burgan 1987). Another advantage is that new custom fuel models can be developed for unique local situations or for broad use across large regions (Burgan and Hardy 1994).

The biggest drawback to the abstraction classification approach and their products, such as FBFMs, is that without prior knowledge of fire behavior in local fuel conditions, it is nearly impossible to accurately and consistently identify, use, and interpret most of the abstract classes. Identification of FBFMs in the field, for example, is highly subjective because it is based on an individual's perception of how fire will burn the fuelbed under severe weather conditions, rather than on actual measurements of fuel loadings. There are no standardized keys to consistently identify FBFMs for either the Anderson (1982) or Scott and Burgan (2005) FBFM classification systems. Because abstract classifications are inherently subjective and difficult to use, most fuel mapping efforts based on abstract classification products must rely on expert knowledge and past experience (Keane and Reeves 2011). FBFMs are also difficult to create because their development requires a delicate balance of parameter adjustments to match observed fire behavior with fire weather and fuel properties that should only be done by experienced analysts and fire managers (Burgan 1987). These limitations may preclude the use of FBFMs in the future as new fire behavior simulation models are developed, as novel fuelbeds are created from innovative fuel treatments, and as abundant fuel input data become available for describing fuelbeds.

Abstract fuel classifications can only be used for fire behavior prediction and are rarely used in other areas of fire and land management. FBFMs, for example, don't include loadings for some major fuel components, such as logs and duff, which are critical for computing smoke emissions, simulating post-frontal combustion, and evaluating wildlife habitat. FBFMs can only be used in the fire behavior model for which they were created; it is inappropriate to use existing fire behavior or danger fuel models in other fire simulation systems (Alexander 2013; Sandberg et al. 2007). Similar to opportunistic classification approaches, there can be an infinite number of abstractions to account for an infinite number of possible fire behaviors, making FBFMs that represent unique fire behaviors difficult to build, especially given the coarse resolution of the fire models. And because FBFMs indirectly represent the resolution of the fire behavior prediction systems, it is difficult to evaluate the effect that subtle changes in fuel characteristics brought about by fuel treatments have on fire behavior, especially if there are small changes in fuel loadings that are too fine for the resolution of the FBFM.

7.3 Challenges

Classifying wildland fuelbeds has always been difficult because of the highly variable composition, distribution, and arrangement of fuel particles in space and the dynamic changes in particle characteristics over time (Chaps. 2, 3, and 5). Spatial and temporal variability of fuel properties directly influences fire behavior (Parsons et al. 2010; Bachmann and Allgower 2002), controls fire effects (Reinhardt et al. 2001), confounds fuel sampling (Keane and Gray 2013), confuses mapping efforts (Keane et al. 2001), and complicates fuel classification (Keane 2013). Fuel properties are highly variable across space and can even be highly variable within individual fuel particles (Keane et al. 2012b). This variability is scale dependent with variability of smaller fuel particles distributed over smaller scales than large fuels (e.g., twigs vary at smaller scales than logs). Any fuel classification system that does not incorporate this variability into its design may be highly redundant and ineffective for some fire applications.

Fire managers and researchers are often frustrated by all these seemingly redundant classifications and may desire a single fuel description system that can be used across all software platforms and prediction systems. This would simplify fuel sampling, mapping, and input into the numerous fire management applications. This chapter presents several reasons why today's fuel classifications often have insufficient scope, quality, resolution, and accuracy to serve as the primary fuel classification in fire management. Several major advances in technology and research need to be made before a universal fuel description system can be created. It will be difficult to develop any new fuel description system without knowing what the new fire models need for fuels inputs. While the next generations of fire behavior and effects simulation models are being developed, it is critical that both new fuel classification systems be built to balance ecological understanding of fuel dynamics with both old and new input model requirements. It is also critical that future fire behavior models be implemented in three dimensions (3D) to account for the spatial distributions of fuel and its effect on fire behavior, especially those models used in fire research (Krivtsov et al. 2009). And, each of these characteristics must have an associated sampling method for accurate quantification, and these methods must account for the wide diversity of fuel particles comprising the fuelbed (Chap. 8). And last, the development of new comprehensive fuel classifications will need high quality data across large geographical areas, diverse ecosystems, and complex fuelbeds to ensure effective and robust applications (Conard et al. 2001).

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