Chapter 9
Fuel Mapping

> *Knowing where things are, and why, is essential to rational decision making*
> Jack Dangermond, ESRI

9.1 Introduction

Since 1990, major advances in computer software and hardware have enabled development of spatially explicit fire growth models, thereby revolutionizing fire management decision support systems (Xiao-rui et al. 2005; Ball and Guertin 1992; Keane et al. 1998b). However, these complex spatial models demand detailed, high-resolution digital maps of surface and crown fuel characteristics to generate accurate and consistent fire behavior predictions (Pala et al. 1990). The commonly used FARSITE fire growth model, for example, requires five fuel layers to simulate surface and crown fire growth and intensity (Finney 1998). Early efforts at mapping fuels did not describe the physical aspects of the fuelbed, but rather interpreted resultant fire behavior if the fuels burned and how difficult it would be to suppress that fire, then mapped those attributes (Hornby 1936). With advancing computer technology, most fuel maps were developed to meet the input requirements of fire models (Keane et al. 1998a).

Fuel maps are now used in nearly all phases of fire management from planning to operational analysis at multiple organizational and spatial scales (Rollins 2009). Coarse scale fuel maps are integral to global, national, and regional fire danger assessment to more effectively plan, allocate, and mobilize suppression resources at weekly, monthly, and yearly evaluation intervals (Burgan et al. 1998; De Vasconcelos et al. 1998). Regional fuel maps are also useful as inputs for simulating regional carbon dynamics, smoke scenarios, and biogeochemical cycles (Kasischke et al. 1998; Leenhouts 1998; McKenzie et al. 2007), while finer scale subregional fuel layers are critically needed to rate ecosystem health (Keane et al. 2007), identifying fuel treatment locations (Agee and Skinner 2005), evaluating fire hazard and risk for land management planning (Hessburg et al. 2010), and aiding in environmental assessments and fire danger programs (Chuvieco and Salas 1996). However,

R. E. Keane, *Wildland Fuel Fundamentals and Applications*,
DOI 10.1007/978-3-319-09015-3_9

most fuel maps are used at finer scales, primarily for landscape assessments, because this is the scale at which most fires can effectively be simulated and managed (Heyerdahl et al. 2001). Landscape fuel maps are used to predict future spread of wildfires (Finney 2005), describe fire hazard and risk (Finney 2006), and portray fire severity (Karau and Keane 2010).

Creating wildland fuels maps is quite difficult, especially at landscape to regional scales, for a number of reasons (Arroyo et al. 2008; Keane et al. 2001). The lack of critical resources, such as limited geo-referenced fuel data and inadequate fuel classifications, coupled with a variety of ecological concerns, such as fuelbeds being hidden by the canopy and scale mismatches in field data, imagery, and analysis techniques, often complicate fuel-mapping efforts. Accurate fuels layers are costly to build because they require abundant field data, extensive expertise in a wide variety of spatial fields (remote sensing, geographic information system (GIS), fire and fuel modeling, image processing, vegetation mapping), and of course, a comprehensive knowledge of fuels (Keane et al. 2001). But most importantly, fuels are notoriously difficult to map because of their high variability and disparate spatial distributions across components (Chap. 6). This chapter first summarizes some critical mapping resources needed for nearly all mapping projects and then presents some general approaches used to map fuels for fire management at multiple scales. The challenges of fuel mapping are presented last to explain why most of today's fuel maps have some major limitations.

9.2 Fuel-Mapping Resources

9.2.1 Field Data

Field data are the most critical resource for mapping fuels, and collecting enough appropriate field data is often the most costly and time-consuming part of any mapping effort (see Chap. 8). Ground-based fuel sampling is literally the only way to realistically, accurately, and consistently describe the fuel characteristics being mapped (Keane et al. 2013) and it would be imprudent to attempt to map fuels without extensive field sampling. Geo-referenced field data are important for many reasons. First, field data provide important references for the mapped fuels classes because the data provide the only detailed descriptions of fuels (loading, classification category). Field plot data can also be used to describe polygons that can then be used as training areas in supervised classifications, or they can be used to describe unique clusters in unsupervised classifications (Verbyla 1995). More importantly, field data allow the development of statistical models for predicting fuel characteristics over space using ancillary biophysical spatial layers. Field data also provide a means for quantifying accuracy and precision of not only the fuel map but also the classification whose categories are being used as mapping units (Keane et al. 2013; Burgan and Hardy 1994). Plot data can be used to design and improve keys for the vegetation and fuels classifications being mapped. And most importantly, field data provide a means for interpreting fuel maps; inaccuracies or inconsistencies in mapping results can be explored using detailed plot data. A mapped shrub–herb category, for example, might be poorly mapped because the sampled cover of bare soil and rock was high on field plots.

9.2.2 Ancillary Spatial Data Layers

Fuel maps can be dramatically improved if supplementary spatial data are integrated into the mapping process (Keane et al. 2001). These ancillary spatial data often describe the biophysical environment to provide ecological context to the mapping process and to represent those processes that control fuel dynamics to increase predictive potential (Chap. 6). The most important ancillary GIS layer is the digital elevation model (DEM) that is used to describe the topography (e.g., slope, aspect, position) and indirectly represent the biophysical environment (e.g., climate). Many important topographic products can be derived from the DEM, such as slope position, stream corridors, and drainage basins (Skidmore 1989), to use as independent variables in statistical predictive models that create fuel maps. Moreover, it is possible to use the DEM as input to simulation models to create other biophysical layers, such as radiation, exposure, and microsite temperatures, and these new biophysical layers can be used to developed predictive relationships for mapping fuels (see Sect. 9.3.4). The DEM also is useful in delineating broad biophysical settings that can be used to stratify statistical modeling and fuel-mapping processes.

Perhaps the next most used ancillary data layers are digital maps of potential and existing vegetation classification systems, such as cover type, potential vegetation type, and structural stage maps (Menakis et al. 2000). Even though fuel loadings are rarely correlated to vegetation (Chap. 6), these maps are be important because they provide valuable context for assigning fuels to known settings, information on biophysical environment, and important linkages to other land management concerns. Vegetation layers are most useful if they were created across multiple scales using standardized, hierarchical classifications so that categories can be merged or split based on the ability of remote sensing to discriminate differences (Loveland et al. 1993; McKenzie et al. 2007). The most commonly used vegetation maps are ones that describe species composition (cover type), structure (vertical canopy layers), and some expression of potential vegetation (i.e., biophysical site; Menakis et al. 2000) because these three maps can be used to simulate vegetation development and therefore possibly fuel succession (Keane et al. 2006b).

Many other existing data layers have been used to map fuels. Spatial chronosequences of ecosystem characteristics, such as leaf area index (LAI), created from updated satellite imagery (e.g., MODIS), can be integrated in map development to quantify available biomass, represent fuel models, and correlate to many other fuel attributes (Rollins et al. 2004). Climate layers that integrate long-term weather into quantitative summaries that relate to fuel dynamics are also valuable ancillary layers

(Keane et al. 2001). Spatial soils data can also be used to describe the biophysical environment that can then be statistically related to fuel loadings or used in simulation models to create ancillary biophysical layers. Digital maps that describe social context (population density), transportation routes (roads, trails), utilities (power lines, gas lines), political (land ownership, management units), and ecological (stand maps, values at risk) resources can be used as references to characterize local to regional fuel differences and to stratify fuel assignments (Krasnow 2007).

The last set of ancillary data layers are those that are created from simulation modeling (Rollins et al. 2004; Keane et al. 2006a). Simulation modeling provides a platform to integrate disparate ancillary biophysical variables, such as climate, topography, and soils, into one comprehensive, integrated variable that may be more related to fuel attributes than the other variables separately. A potential evapotranspiration (PET) layer, computed from soils and climate data layers using an ecosystem model, may have a better relationship to fuel loading than the soils or climate data alone or together (Rollins et al. 2004). This simulation approach is discussed extensively in Sect. 9.3.4.

9.2.3 Fuel Classifications

A comprehensive fuel classification system is indispensable in fuel mapping because the classification's categories can serve as mapping units in the fuel map (Chap. 7). It is difficult to map loading, or any other fuel property, for each of the fuel components because of the high number of components and the fact that most components are difficult to map remotely, such as duff and litter, because they are hidden by higher fuel strata such as the forest canopy (see Sect. 9.4). Fuel classifications simplify the mapping process by providing a means to map all fuel components at once. Since most classifications were developed for specific fire applications, creating a map using a classification ensures that it will be useful in fire management. Finally, most fire managers are somewhat familiar with most existing fuel classifications, so mapping existing classifications eliminates the need for additional training to learn newly developed map units.

An ideal fuel classification for mapping should quantify a myriad of fuel characteristics (e.g., loading, size, bulk densities) for all fuel components at the appropriate mapping scale and resolution (Chap. 7). Fuel classification categories should be easily, accurately, and consistently identified in the field with comprehensive keys, and the classification should be related to other standardized vegetation and biophysical classifications (Keane 2013). The fuel classification should uniquely identify fuel types based on fuelbed characteristics, not on vegetation attributes or environmental descriptions, because the mapped categories must be easily validated in the field or using existing fuel data (Keane et al. 2013). Moreover, the classification structure should allow hierarchical aggregation and division so fuel categories can be tailored to match the strengths of the mapping approach, attributes of the remotely sensed products, resolution of available field data and imagery, and scale of eventual fire application. A link to other historical and current land-use maps is also desirable. Another desirable trait of useful fuel-mapping classifications is that the categories in the classification are easily and effectively discriminated by the diverse approaches used to map fuels (see Sect. 9.3).

Nearly all the fuel classifications mentioned in Chap. 7 have been used in fuel-mapping efforts. Perhaps the most mapped classifications are the fire behavior fuel models (FBFMs) which are needed to simulate wildfire in the USA. Reeves et al. (2009) created fine-scale (30 m) FBFM maps for both the Scott and Burgan (2005) and Anderson (1982) classifications for the contiguous USA. Root et al. (1985) mapped FBFMs for North Cascades in the US Pacific Northwest, while Peterson et al. (2012) produced FBFM maps for Yosemite National Park and Falkowski et al. (2005) for northern Idaho. McKenzie et al. (2007) mapped FCCS fuelbeds at 1 km for a national US scale and at 30 m for the Wenatchee National Forest, Washington, USA. Hawkes et al. (1995) mapped the fuel types in the Canadian Fire Behavior Prediction system for landscapes in British Columbia, Canada. The National Fire Danger Rating System (NFDRS) fuel types were mapped at a coarse scale by Burgan et al. (1998) for the USA and by Chuvieco and Salas (1996) for Spain.

There is a fundamental problem with using FBFMs as mapping units. The identification of FBFMs in the field is entirely subjective because it is based on an individual's perception of fire behavior under assumed weather rather than on actual measurements of fuel loadings (Chap. 7). Many field technicians find it difficult to consistently identify FBFMs on the ground because it requires knowledge of the fuel characteristics important to fire behavior, expertise in forecasting fire behavior in the field, and familiarity with the FBFMs. Even more important is that it is impossible to uniquely identify a FBFM from extant or legacy field data because a visual inspection of the fuelbed is absolutely essential for evaluating potential fire behavior (Anderson 1982). The FuelCalc program (Reinhardt et al. 2006) contains a routine that attempts to assign a FBFM from fuel loading data, but the routine has never been evaluated for accuracy and consistency. As a result, it is impossible to assess map accuracy for any of the FBFM classifications; one would have to observe fire behavior at a burning pixel to properly evaluate FBFM map accuracy. Reeves et al. (2009) addressed this subjectivity by holding calibration workshops attended by fire behavior specialists to evaluate fuel maps and adjust values where needed (Keane and Reeves 2011). And since most FBFMs quantify only a fraction of all dead and live biomass pools, they are rarely useful for most other fire applications such as smoke estimation and carbon cycling simulation.

9.3 Fuel-Mapping Approaches

Today's fuel maps are created by a complex merging of technologies and integration of analysis techniques (Arroyo et al. 2008). In general, there are four general approaches used to map fuels at multiple scales: field assessment, association, remote sensing, and biophysical modeling (Table 9.1). Early attempts at mapping fuels often used only one or two of these approaches, but as computing resources

Table 9.1 Summary of the approaches used to map fuels for fire management

Approach	Description	Advantages	Disadvantages
Field assessment	Using ground-based surveys and field reconnaissance to assign fuel attributes across an area	Mapping actual observations; no introduced modeling or analysis error; limited number of steps; easily modified and refined; easily augmented with field sampling	Costly and time-consuming; inconsistency between mappers; somewhat subjective; bias toward mountainous terrain
Association	Assigning fuel attributes to categories in extant classifications, often vegetation classifications	Simple, direct, and easy; no need for additional mapping; most extant classifications are well known and easily understood; can assign many fuel attributes to one category; can use many classifications to fine-tune fuel assignments; create robust maps useful for other natural resource applications	Fuels are often unrelated to vegetation categories; scale and resolution of extant classification does not match scale of fuel data or subsequent application; high redundancy in fuel attributes across extant classification categories
Remote sensing	Correlating remotely sensed imagery with fuel characteristics	Readily available; provides snapshot of existing conditions; well accepted and long history of resource mapping using remote sensing products; many products available at different resolutions and detail	Fuels often are uncorrelated to imagery signals; scale of imagery may not match scale of fuel distribution; requires extensive expertise in remote sensing, GIS, statistical modeling, and wildland fuel science; difficult to understand reasons for mapping successes or failures
Biophysical modeling	Calculating or simulating biophysical gradients to correlate to fuel attributes	Relating those processes that control fuel dynamics to fuel mapping; provides context for interpreting fuel maps; can often simulate environmental gradients at multiple time and space scales; can be used to map many other ecological characteristics to augment fuel mapping	Best describes potential rather than existing fuel conditions; fuel attributes often are uncorrelated to biophysical variables; difficult to decide the type, detail, and scale of the biophysical gradient that best represents fuel dynamics; scale of simulated gradient may not match scale of fuel distribution or fuel processes; requires extensive expertise in ecosystem modeling, GIS, statistical modeling, and wildland fuel science; demands extensive data for initialization and parameterization

improved, mapping expertise increased, and extensive spatial ecological data sets became available, most of today's fuel-mapping efforts integrate these multiple technologies to get the best possible fuel maps (Keane et al. 2001). Therefore, these approaches should not be considered methods *per se*, but rather a set of general strategies to map fuels.

Several analysis methods were not included as approaches in this chapter because they are used across most of the four mapping approaches. The most important and most commonly used analysis method is statistical modeling, where advanced statistical techniques, such as multiple regression analysis, generalized linear modeling, and regression trees, are used with field and spatial data to create empirical models that are then employed to build fuels maps (Miller et al. 2003). Another exciting branch of spatial analysis is the integration of expert knowledge into numerical analysis to develop fuel maps (Keane and Reeves 2011); the vast knowledge and expertise of fire professionals can be used to develop and test fuel maps using a wide variety of computing technology, such as expert systems, neural networks, and artificial intelligence (Krivtsov et al. 2009).

9.3.1 Field Assessment

Field assessments involve traversing a landscape on the ground and recording fuel conditions using data recorders, notebooks, or paper maps (Arroyo et al. 2008). Conditions in the field are assessed using a diversity of methods that include actual sampling of the fuel (Chap. 8), recording a category in a fuel classification category (Chap. 7), or describing the fuel type using vegetation, disturbance, and site characteristics. The observed conditions are then assigned to polygons on a photo or map. Few fuel maps were created using this approach, and of those that were, they were mostly for fine-scale, small-area projects. The exception was Hornby (1936), who remarkably mapped more than 6 million ha in the northern Rocky Mountains using more than 90 Civilian Conservation Corps (CCC) workers. These crews walked, rode, or drove through national forests in Montana and Idaho of the USA and described fuel conditions by coloring polygons on maps. But, instead of actually recording fuels loadings, the CCC crews mapped two categorical fire behavior descriptors that were inferred from the fuel conditions: resistance to control and rate of fire spread. The fuel classification used by Hornby (1936) was only useful for one fire management purpose, suppressing wildfires. Many employed the Hornby (1935) methods to other parts of the country (Abell 1937; Banks and Frayer 1966; New Jersey Department of Conservation and Development 1942) (Chap. 1).

The primary advantage of the field survey strategy is that fuels are mapped from actual conditions observed on the ground (Table 9.1). Mapping error is limited to erroneous fuel-type assessments or improper stand delineations on paper maps and no error is introduced from inappropriate statistical modeling or data analysis. Fuel assignments can be subjectively adjusted based on the observers' knowledge of the fuel complex, of how fire burns the fuel complex, and of how fire behavior models simulate burning in the fuel complex. Observers are easily able to visually assess highly variable fuel conditions across large areas to estimate an average or representative value providing there is extensive training. Any special conditions that arise in the field, such as the identification of a new fuel type or the elimination of a rare fuel type, can be easily integrated into the mapping scheme. And this approach can easily be augmented with field sampling to increase accuracies and map detail. It can also be scaled to specific projects creating anywhere from high-resolution maps for small areas to coarse-resolution maps for large regions.

The great amount of effort involved in a successful field approach would probably preclude its use in most large-scale operational fuel-mapping projects today. The majority of time and money spent on any fuel-mapping effort is usually in field assessments of fuel conditions so assessing the entire map area would be impractical. Another drawback is that there are always inconsistencies between field observers because of differences in their expertise and knowledge of fuels and fire (Sikkink and Keane 2008). And there is a sampling bias toward mountainous terrain since most of the reconnaissance mapping efforts are done from observation points on high, burned-over vistas, so locations not directly seen from these observation areas were probably mapped with less accuracy (Brown and Davis 1973). This approach would be more valuable if it were integrated with field sampling to create the field reference datasets to augment with other fuel-mapping approaches.

9.3.2 Association

In the association approach, fuel maps are developed by assigning fuel attributes to the categories or mapping units of maps of other land classifications, similar to the associative fuel classification (Chap. 7) and associative fuel-sampling (Chap. 8) approaches. There are a number of readily available, well-known spatial data layers of vegetation, topography, and land use that can be used either alone or in combination to associate fuel characteristics to each classification category or combination (McKenzie et al. 2007). In the association process, fuel attributes are usually quantified or selected from a synthesis of field data across extant classification categories. These fuel attributes are then assigned to that category to create the fuel map from the existing map. Satellite imagery and other remotely sensed products are better suited for differentiating between vegetation types than fuel types (Keane et al. 2001). Keane et al. (1998a), for example, overlaid maps of vegetation and topography classifications with plot-level geo-referenced FBFM assessments and, for each vegetation and topography class combination, they assigned the modal FBFM of all field plots within that combination. A fuel type group map was created by averaging fuel loadings for each of eight fuel components for all USFS Forest Inventory and Analysis plots in each forest-type group category (Keane et al. 2013). This approach may also be used with expert knowledge techniques that assign fuel-classification categories to other map categories using the experiences of fire professionals (Keane and Reeves 2011) or statistical analysis of field data to build empirical models that assign fuel characteristics to other classification categories

(Reeves et al. 2009). The associative approach is easily the most commonly used approach for developing fuel maps.

Examples of this approach can be presented by spatial scale. Coarse-scale imagery is often used to discriminate broad vegetation types or land cover classes, and these classes sometimes correlate with fuels because vegetation categories are so broad they generally have unique fuel characteristics. Burgan et al. (1998) used Omernik (1987) ecoregions and the Loveland et al. (1991) AVHRR land-cover classification to develop an NFDRS fuel model map of the conterminous USA. Landsat imagery was used to map vegetation on 100 million ha in Alaska, and then fuel models were assigned to each vegetation category (Willis 1985). McKenzie et al. (2007) mapped FCCS fuelbeds to vegetation and disturbance classification categories, and the FCCS fuelbeds of Ottmar et al. (1994) were assigned to combinations of vegetation cover and structure types for the Interior Columbia Basin Ecosystem Management Project (Quigley et al. 1996). Menakis et al. (2000) expounded on the "vegetation triplet" approach where fuel models or classes are assigned to categories in three classifications: potential vegetation, vegetation composition, and vegetation structure. Jain et al. (1996) intensively sampled fuels for all categories of a forest-type map created from Linear Image Self Scanning (LISS II) imagery to create a fuel map for Rajaji National Park in India. In Canada, the Canadian Forest Fire Behaviour Prediction System (FBP, Forestry Canada Fire Danger Group 1992) fuel types were assigned to vegetation categories on maps created from Landsat Multi-Spectral Scanner (MSS) data for Wood Buffalo National Park (Wilson et al. 1994), Quebec (Kourtz 1977), British Columbia (Hawkes et al. 1995), and Manitoba (Dixon et al. 1985).

The association approach is used for many reasons. The most common reason is that it is relatively easy, quick, and economical to create fuel maps from other maps because they can be done by anybody for any location where there is an associative map. There are many vegetation classification maps available to associate fuel characteristics (Anderson et al. 1998; Grossman et al. 1998), and most people can easily identify the vegetation-type categories of these classifications in the field. There are also many field data sets that contain assessments of these extant classification categories at the plot level that can augment fuel mapping. Since extant classification maps are used extensively in resource management, the assignment of fuel attributes are easily understood by managers, and the resultant fuel maps can be linked to other resource concerns. Many fuel attributes can be assigned to an extant category allowing the creation of many types of fuel maps, such as surface fuel maps and canopy fuel maps (Keane et al. 2000). Finally, associative maps often provide a context for interpreting fuel distributions across a landscape. For example, it is helpful to know that a polygon was assigned a needle and litter FBFM because it was a ponderosa pine stand.

The major disadvantage of association in fuel mapping is that fuels are not always correlated with vegetation characteristics or land-use categories so statistical relationships between fuel and the associated layers may be too weak to develop useful predictive models (Chap. 6). An example of this lack of relationship is the redundancy of fuel classes across the associated mapped classification classes. For example, there were as many as four different FBFMs found in the many of the combinations of vegetation structure, species composition, and topographic settings classes for maps of the Selway-Bitterroot Wilderness Area, USA. (Keane et al. 1998a). Stand disturbance history, biophysical setting, and vegetation structure are significant factors governing fuel characteristics so they should be incorporated into the fuel model assignment protocols. Also, the scales of the base classifications may not match the scale of the fuels being mapped or the sample design of the field data used in the mapping (Keane et al. 2006a). The vegetation categories in the Society of American Foresters (SAF) cover-type classification used in the FOFEM model, for example, are so broad for some cover types that they encompass a wide variety of fuelbed conditions that overwhelm important local differences (Schmidt et al. 2002). Other disadvantages are compounding errors occurring when the error inherent in the original base classifications is combined with errors in the fuels classifications and errors in fuel class assignment (Keane et al. 2013).

9.3.3 Remote Sensing

Remote sensing approaches attempt to correlate remotely sensed imagery with fuel characteristics using statistical modeling to create a fuel map (Keane et al. 2001; Lanorte et al. 2011). The imagery can be from any number of passive and active sensors. Passive sensors include digital aerial photography (Oswald et al. 1999), Landsat Thematic Mapper (TM; Brandis and Jacobson 2003), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER; Falkowski et al. 2005), and hyperspectral (Jia et al. 2006), while active sensors are usually LiDAR (Andersen et al. 2005) and radar (Bergen and Dobson 1999). These sensors can be mounted on any number of platforms including fixed wing aircraft, helicopters, and satellites to obtain a wide range of resolutions and detail (Xiao-rui et al. 2005). Passive sensors usually measure the reflectance of light in a narrow band of the electromagnetic spectrum, and some of these sensors, such as Landsat's TM with a 30 m pixel size, create multiple data layers that represent the reflectance from multiple spectral bands. Hyperspectral imagery, such as Airborne Visible InfraRed Imaging Spectrometer (AVIRIS), Hyperion, and HYDICE, may have more than 50 different spectral reflectance layers. Active sensors, such as LiDAR, consist of a cloud of point measurements of return times and signal strengths that are then used to statistically model height and loading (Riaño et al. 2003).

The central assumption of the remote sensing approach is that there is a correlation between fuel characteristics and the remotely sensed data signal. Fuel attributes, such as loading, canopy bulk density (*CBD*), or classification categories, either computed from legacy plot data or measured directly on geo-referenced plots, are related to the reflectance values of the plot location using simple to complex statistical modeling. Two general statistical methods are used to create fuel maps. In the supervised classification technique, statistical models that directly predict fuels information are built from the reflectance values of the imagery and the field data. Then, fuel maps are then created by employing the developed predictive relationships across all pixels. In the unsupervised classification technique, the reflectance values of all pixels are used in advanced statistical clustering methods to create unique spectral "signatures" and then various statistical techniques are used to assign the geo-referenced plot information to the mapped spectral signatures. Numerous other data layers and spatial information can be augmented with the spectral imagery to improve both the unsupervised and supervised statistical analyses (see Sect. 9.3.2).

Many types of fuel maps have been created using passive satellite imagery, mainly from Landsat satellite sensors. The majority of fuel-mapping efforts used from Landsat MSS and TM imagery to map surface fuel classification categories. Kourtz (1977) used Landsat MSS data to map fuel models in Canada. Salas and Chuvieco (1994) classified Landsat TM imagery directly to 11 of Anderson's (1982) fuel models, then assigned vegetation categories to each fuel model to compute fire risk on a large landscape in Spain. An Anderson (1982) FBFM map was classified directly from TM imagery of Camp Lejeune, North Carolina, for simulating prescribed fires with FARSITE (Campbell et al. 1995). However, the highest successes are when total living and dead biomass were directly mapped to spectral signatures. Direct biomass imagery mapping is more accurate for grasslands and shrublands (Chladil and Nunez 1995; Millington et al. 1994; Friedl et al. 1994), but less certain when assessing surface fuels in forested ecosystems because of the canopy obstruction problem (Elvidge 1988; see Sect. 9.4). Merrill et al. (1993) estimated living grassland biomass in Yellowstone National Park using regression models on bands 4, 6, and 7 from Landsat MSS) imagery. Using TM imagery, Peterson et al. (2012) directly mapped 1-, 10-, and 100-h loadings in Yosemite National Park USA and Brandis and Jacobson (2003) mapped total fuel loads in Australia. Large-scale aerial photography and aerial sketch mapping have been used successfully to estimate natural and slash fuel distributions in a variety of forested settings in Canada (Belfort 1988; Morris 1970; Muraro 1970).

Other imagery has been successfully used in fuel-mapping efforts. At fine scales, Lasaponara and Lanorte (2007a) used QuickBird high-resolution imagery (2.9 m) to map fuel types in Italy. ASTER imagery, having higher spectral (15 bands) and spatial (15 m) resolution than Landsat TM (7 spectral plus a panchromatic band, 30 m spatial resolution), was used to map Mediterranean fuel types in southern Italy (Lasaponara and Lanorte 2007b) and the 13 Anderson (1982) FBFMs in Idaho, USA (Falkowski et al. 2005). Root and Wagtendonk (1999) used hyperspectral imagery to map fuels in Yosemite National Park, USA, while Jia et al. (2006) used AVIRIS hyperspectral imagery to map canopy fuels. Active remote sensors such as Synthetic Aperture Radar (SAR) that propagate pulses of electromagnetic radiation and detect the reflective backscatter have shown promise for mapping stand biomass (Rignot et al. 1994) so they may be useful for estimating surface fuel models, crown bulk densities, and canopy dimensions. In Yellowstone National Park in the USA, Saatchi et al. (2007) mapped canopy fuel characteristics and Huang et al. (2009) mapped CWD using SAR and other ancillary data layers. Keramitsoglou et al. (2008) fused hyperspectral imagery with ASTER to map fuel types in Greece.

Airborne LiDAR appears to be the most promising remotely sensed product for the mapping of fuel properties, especially canopy fuel attributes, because it describes the vertical profile of the fuelbed. LiDAR estimates distance to an object by measuring the time delay between the transmission of a pulse of light and the detection of the reflected light from a target. This process, in a vegetative setting, can result in millions of points in an area that describe the fuel strata. The point distances can be used to calculate elevations to map a fuelbed in three dimensions if the spatial density of laser measurements is high. The distribution of elevations can be used as a signal to map fuels and the strength of the return signal is also useful for determining the surface condition that may be related to certain fuel types. Some have used LiDAR to map surface FBFMs with some success (Mutlu et al. 2008), but the real strength of LiDAR is in the mapping of canopy fuels (Andersen et al. 2005; Erdody and Moskal 2010) because the number of LiDAR distance measurements within the canopy profile is often correlated to CBD and canopy base height (CBH; Riaño et al. 2003). However, LiDAR also has its problems. While it can accurately produce a canopy height profile, it has limited ability in differentiating the material that reflected the laser intercept; it is difficult to tell if the piece of biomass hit by the laser was a leaf, twig, or log. The canopy obstruction problem is also a factor in that upper canopies obscure lower canopy strata and thereby collect a disproportionate number of LiDAR hits. Loadings for those fuel components that contain the majority of dead biomass, logs, litter, and duff are also difficult to sense from LiDAR because their size or depth is nearly impossible to measure using LiDAR.

There are advantages to using a remote sensing approach (Arroyo et al. 2008). First, unlike all other approaches, remotely sensed data provide a spatial description of existing landscape conditions and act as a snapshot of the landscape. As such, these data can be useful for the detection of changes in fuel conditions through time and space. Most imagery products are easy to obtain but their cost is highly variable ranging from free to quite expensive. Remotely sensed imagery can be obtained for a wide variety of resolutions allowing appropriate scaling of the imagery to fuel component distributions.

Logistical concerns, however, may limit many remotely sensed fuel-mapping projects. Expertise in image processing, GIS analysis, and statistical modeling is rare and expensive, and combined with expertise in fuel science and fire behavior modeling, the number of people qualified for fuel-mapping projects are scarce. Absolutely critical to remotely sensed fuel-mapping projects are surface and canopy fuel data which are often limiting in most areas. The analysis of the imagery also demands high computing resources which may be restrictive for many fire managers. Finally, many of the remotely sensed products, such as LiDAR, ASTER, and SAR, may be too expensive for operational fuel mapping across large domains and require specialized expertise in data processing.

There are also important ecological limitations of remote sensing approaches for fuel mapping. As mentioned, some fuel component attributes, such as CBH, FWD, and herbs, are obscured by the canopy in most forest and some shrubland ecosystems (Keane et al. 2001). Even if the fuel components were visible from above, the remotely sensed imagery probably would probably have low correlation to many attributes that are being mapped, such as loading, because of the mismatch in scales. Logs and FWD are too small to be sensed by most imagery products with 30-m pixel resolution, yet they comprise the majority of loading in some environments. Duff and litter loading, as another example, depends on their depth on the ground, and this depth is rarely correlated to imagery signals (Asner 1998). Most imaging sensors were designed to differentiate vegetation characteristics, so vegetation conditions may often overwhelm any fuel signal, and most fuel components, such as woody fuels, have similar reflective properties making it difficult for their differentiation.

Another limitation is that it is often difficult to quantify fuelbed characteristics for each component with only one unique spectral signature, unless, of course, a fuel classification is being mapped, but then few fuel classifications are highly correlated to imagery (Keane et al. 2013). Conversely, if fuel components are mapped separately, there is a good chance that each component map will be spatially incongruent or inconsistent, and impossible combinations may result. And, since fuel components are spatially distributed at different scales, using only one imagery product with one resolution ensures some fuels may always be mapped at an inappropriate scale (Keane et al. 2012a; Chap. 6); fine fuels important for fire spread are too small to be detected accurately by most passive imagery products. It is also difficult to detect the vertical distribution of fuels with passive imagery; the sensed FWD might actually be suspended above the ground.

9.3.4 Biophysical Modeling

This last approach relates fuel attributes to measured or simulated biophysical gradients using statistical modeling. Biophysical gradients describe those ecological phenomena that may directly or indirectly influence fuel dynamics (Chap. 6), such as climate, productivity, and disturbance. Spatial data representing these gradients can be (1) measured directly, such as climate, soils, and topography, (2) measured indirectly by correlating with imagery, or (3) simulated using biophysical models. The direct and indirect gradients are often used as inputs into biophysical models to create additional gradients.

Ecosystem models have vastly improved over the past two decades and there are a wide variety of models for application at coarse (e.g., MAPPS, Lenihan et al. 1998), regional (e.g., BIOME-BGC, Thornton et al. 2002), and fine scales (e.g., FireBGCv2, Keane et al. 2011). These models simulate those ecosystem processes known to govern fuel dynamics and these simulated processes can then be mapped and used to predict fuel characteristics across space. Relationships between biophysical processes and organic matter accumulation and decomposition, for example, can be used to predict fuel characteristics (Gosz 1992; Ohmann and Spies 1998). Rollins et al. (2004) developed a prototype system to link remote sensing, gradient modeling, and ecosystem simulation into a package for mapping those characteristics important to land management, and then used the system to map FBFMs (Keane et al. 2006a). Biophysical layers can be topographical (e.g., elevation, aspect, slope), biological (e.g., successional stages), geological (e.g., soils, landform), or biogeochemical (i.e., evapotranspiration, productivity, nutrient availability). Kessell (1976) used seven biophysical gradients based on topography and vegetation to spatially predict fuel models and loadings in Glacier National Park, Montana. Habeck (1976) sampled fuels and vegetation in the Selway-Bitterroot Wilderness Area of Idaho and related fuel loadings to stand age and moisture–temperature gradients. Keane et al. (1997) developed a protocol for mapping surface fuels from several biogeochemical and biophysical variables using an extensive network of field plots, and later used those techniques for mapping canopy fuels (Keane et al. 2006a).

The value of this approach is that simulated environmental gradients provide an ecological context in which to understand, explore, and finally, predict fuel dynamics. Low fuel loadings in a stand, for example, may be explained by low precipitation, high evapotranspiration, and low productivity. Furthermore, environmental gradients can quantify those important ecosystem processes that correlate with fuels, such as decomposition, to provide a temporal and spatial framework for creating dynamic fuels maps. Climate change effects on spatial fuel loadings can be easily computed by evaluating changes in environmental gradients under the new climate (Keane et al. 1996). Most environmental gradients are scale-independent, meaning the same gradients might be useful to predict fuel characteristics across many spatial scales, but the range, distributions, and strengths of the relationships might change. These models can also be used to update fuel maps by simulating deposition and decomposition processes to see how the fuels have changed over the life of the map. And once biophysical layers are developed, they may be used by land management agencies for many management applications (Keane et al. 2002).

One major problem with this approach is that biophysical gradients do not provide a comprehensive description of existing biotic conditions so remotely sensed data are often needed to spatially portray the current fuel conditions. Another disadvantage is that this approach requires abundant field data, complex ecosystem models, and intensive statistical analyses requiring extensive expertise in ecological sampling, simulation modeling, and statistical examination. Ecosystem models demand comprehensive initialization, parameterization, calibration, and validation to be useful, and this often requires extensive data, time, expertise, and computing resources. Biophysical settings are inherently difficult to map because they represent the complex integration of long-term climatic interactions with vegetation, soils, fauna, and disturbance (Barrett and Arno 1991; Habeck 1976; Keane et al. 1996b). Moreover, identification of those biophysical processes critical to fuel dynamics is difficult because most are unknown or unquantifiable, and they are difficult to identify in the field because of their temporal aspect. Many biophysical layers may have limited value for mapping fuels because of interacting factors and they are often correlated with other biophysical processes. And last, all biophysical gradients affect fuel processes at different scales so it is important that the biophysical layers are created at the most appropriate scales that influence fuel properties.

9.3.5 Integrating Approaches

Most mapping projects integrate all approaches to create state-of-the-art fuel maps. Peterson et al. (2012) statistically modeled live and dead woody fuel component loadings using regression classification procedures with a suite of climate, topography, imagery, and fire history-independent variables. Varga and Asner (2008) merged LiDAR with hyperspectral imagery to map surface fuels in Hawaii. A knowledge-based system of neural networks was used to search for unique fuel patterns on a large landscape in Portugal from land-use, vegetation, satellite imagery, and elevation information (Vasconcelos et al. 1998). Pierce et al. (2012) used intensive field sampling to describe surface fuels for spectral clusters in an unsupervised approach and correlated canopy fuel characteristics to topography (elevation, slope, aspect) and Landsat TM imagery using Random Forests statistical modeling. And, in the most extensive fuel-mapping effort in the USA, Reeves et al. (2009) mapped canopy fuel attributes (*CBD, CBH*) for the contiguous USA by creating regression models from Landsat TM reflectance imagery, biophysical gradients simulated by an ecosystem process model, and topographic variables calculated from the DEM. They also mapped four surface fuel classifications using an associative approach where categories were assigned to combinations of vegetation cover, structure, and biophysical classifications using statistical modeling and expert opinion. The merging of multiple approaches has resulted in some of the most useful and accurate fuel maps.

9.4 Challenges

The accuracy of fuels maps varies widely, but generally, most fuel maps have low accuracies. When accuracy assessments were reported, they usually ranged between 5 and 85% correct, regardless of fuel-mapping approach or integrative strategy (Keane et al. 2013). Fuel map accuracies often reflect the approaches used to create the maps; maps created with the associative approach, for example, tend to have the same accuracies as the core maps used to associate fuel attributes. Low map accuracies, however, don't always mean the fuel map is worthless, especially considering the high variability and complexity of fuels. Alternative management strategies can be effectively compared by assessing the relative differences in fuel conditions between sites in fuel maps with precision. Low fuel map accuracies may be a result of a number of inherent sampling and analysis errors that are out of the mapper's control, such as (1) scale differences in field data and mapped elements, (2) improper geo-registration, (3) erroneous field identification or measurement of a mapped attribute, (4) improper use of vegetation or fuels classifications, (5) mistakes in field data entry, (6) differences in sampling error across fuel components, and (7) inappropriate fuel-sampling methods and designs. However, the main reason for low fuel map accuracies probably lies in the ecology of fuels rather than in the limitations of the approaches and data used to map them.

Several ecological reasons are to blame for the low accuracies in most fuel maps. As with other fuel applications, the high variability of fuel characteristics in space and time across the diversity of components compromises most fuel-mapping efforts (Chap. 6). In a validation of the LANDFIRE fuel maps, Keane et al. (2013) found that the inability of a fuel classifications' category to uniquely quantify fuel loadings was the biggest reason for poor mapping results. This inability to predict fuel loadings was mainly because of the high variability of loadings across components within a classification category (Chap. 6). High variability of loadings across classification categories is often because fuel components vary at different scales and are uncorrelated with each other (Keane et al. 2012b). Keane et al. (2000) hierarchically assessed accuracy of vegetation and fuel maps by quantifying error in the field data, vegetation and fuel classifications, and found more than 20 % of map error resulted from the inherent variability of fuel components attributes sampled at the stand-level. This high loading variability is also because fuel components are spatially distributed at different scales and accumulate at different rates (Chap. 6). In summary, the high variability of fuel attributes, especially loading, often overwhelms any spectral or biophysical signal used for mapping, resulting in inadequate discrimination of fuel classification categories and attributes.

Stand disturbance history, expressed as time since last fire for an example, is perhaps the single most important factor dictating fuel bed characteristics (Chap. 6) yet there are few ancillary spatial data sources that describe stand history that can be used in fuel mapping. Vogelmann et al. (2011) use fire severity maps to update the LANDFIRE vegetation and fuels data layers, but there are few comprehensive maps of other disturbances. Past fires both reduce fuel component loadings by consumption and increase loadings by causing plant mortality (Chap. 6). Insects, diseases, and wind often increase fuel loadings disproportionately across components. Without a spatial description of the timing, severity, and extent of past disturbances, it will always be difficult to map fuels.

There may be other logistical reasons for poor map accuracies. The biggest limitation in most fuels mapping is the lack of timely, dependable, geo-referenced field data describing existing fuels conditions. Few comprehensive standardized fuel-sampling efforts have created the databases needed for fuel-mapping efforts. For those projects where fuels were actually measured, inadequate training in fuel model assessment and fuel measurement techniques resulted in questionable field estimates (Keane et al. 1998b). Fuel characteristics (e.g., surface fuel model, crown fuels, stand height) should not be mapped independently or illogical combinations will inevitably result. All fuel layers must be developed and mapped in parallel so they are spatially congruent and consistent.

Low fuel map accuracies may be improved by employing newer methods and better technology, but there are more fundamental challenges in fuel mapping that need to be addressed first before accurate fuel maps are possible. As mentioned, we need to view fuels as biomass and understand those ecological processes and conditions that influence biomass properties over time and space. Once we understand fuel dynamics, we can then develop standardized sampling methods that describe fuels at their appropriate scales for quantifying reference conditions and select biophysical layers that represent those ecological processes that most influence fuel dynamics (Chap. 8). Spatial fuels databases containing all collected geo-referenced field data that is appropriately scaled to each fuel component can then be created so that spatially explicit fuels data can be accessible to everyone. Comprehensive, robust, and flexible fuel classifications can then be developed from these data (Chap. 7) that incorporate and account for the high variability in their design (Keane 2013). Categories in these new classifications can then be mapped using a fusion of the technologies mentioned here and any new technologies developed in the future. A new approach to fuels mapping is needed for enlightened fire management.

References

Abell CA (1937) Rate of spread and resistance to control data for Region 7 fuel types and their application to determine strength and speed of attack needed. Preliminary Report. U.S. Department of Agriculture, Forest Service, Asheville, pp 7

Agee JK, Skinner CN (2005) Basic principles of forest fuel reduction treatments. For Ecol Manage 211:83–96

Andersen H-E, McGaughey RJ, Reutebuch SE (2005) Estimating forest canopy fuel parameters using LIDAR data. Remote Sens Environ 94(4):441–449

Anderson HE (1982) Aids to determining fuel models for estimating fire behavior. USDA Forest Service Intermountain Research Station, General Technical Report INT-122 Ogden, Utah, USA, pp 22

Anderson M, Bourgeron P, Bryer MT, Crawford R, Engelking L, Faber-Langendoen D, Gallyoun M, Goodin K, Grossman DH, Landaal S, Metzler K, Patterson KD, Pyne M, Reid M, Sneddon L, Weakley AS (1998) International classification of ecological communities: terrestrial vegetation of the United States. The National Vegetation Classification System: list of types, vol. 2. The Nature Conservancy, Arlington, Virginia, pp 445

Arroyo LA, Pascual C, Manzanera JA (2008) Fire models and methods to map fuel types: the role of remote sensing. For Ecol Manage 256:1239–1252

Asner GP (1998) Biophysical and biochemical sources of variability in canopy reflectance. Remote Sens Environ 64(3):234–253

Ball GL, Guertin DP (1992) Advances in fire spread simulation. In: Proceedings on the third forest service remote sensing applications conference—Protecting natural resources with remote sensing. Tucson, Arizona USA, April 9–13 1992. American Society of Photogrammery and Remote Sensing, 5410 Grosvenor lane, Bethesda, Maryland USA, pp 241–249

Banks WG, Frayer HC (1966) Rate of forest fire spread and resistance to control in the fuel types of the eastern region. U.S. Department of Agriculture, Forest Service, Washington, DC. Fire Control Notes 27(2):10–13.

Barrett SW, Arno SF (1991) Classifying fire regimes and defining their topographic controls in the Selway-Bitterroot Wilderness. In: 11th Conference on Fire and Forest Meteorology, Missoula, MT, 1991, pp 233–245

Belfort W (1988) Controlled-scale aerial sampling photography: development and implications for multiresource inventory. J For 86(11):21–28

Bergen KM, Dobson MC (1999) Integration of remotely sensed radar imagery in modeling and mapping of forest biomass and net primary production. Ecol Model 122:257–274

Brandis K, Jacobson C (2003) Estimation of vegetative fuel loads using Landsat TM imagery in New South Wales, Australia. Internat J Wildland Fire 12:185–194

Brown AA, Davis K (1973) Forest fire control and use second edition. McGraw-Hill, New York

Burgan RE, Hardy CC (1994) Ground truthing a national AVHRR based vegetation fuels map. Proceedings of the 12th conference on fire and forest meteorology. Society of American Foresters, Bethesda, Maryland, pp 428–436

Burgan RE, Klaver RW, Klaver JM (1998) Fuel models and fire potential from satellite and surface observations. Int J Wildland Fire 8(3):159–170

Campbell J, Weinstein D, Finney M (1995) Forest fire behavior modeling integrating GIS and BEHAVE. USDA Forest Service, Washington

Chladil MA, Nunez M (1995) Assessing grassland moisture and biomass in Tasmania—The application of remote sensing and empirical models for a cloudy environment. Int J Wildland Fire 5(3):165–171

Chuvieco E, Salas J (1996) Mapping of spatial distribution of forest fire danger using GIS. Int J Geogr Inf Syst 10(3):333–345

De Vasconcelos MJP, Paul JCU, Silva S, Pereira JMC, Caetano MS, Catry FX, Oliveira TM (1998) Regional fuel mapping using a knowledge based system approach. 3rd International conference on forest fire research 14th Conference on fire and forest meteorology, November 1998, pp 2111–2123

Dixon R, Shipley W, Briggs A (1985) Landsat—a tool for mapping fuel types in the boreal forest of Manitoba: a pilot study. In: Proceedings of the Pecora X symposium, 1985. American Society for Photogrammetry and Remote Sensing, Falls Church, Virginia, pp 392–393

Elvidge CD (1988) Thermal infrared reflectance of dry plant materials: 2.5–20.0 micrometers. Remote Sens Environ 26:265–285

Erdody TL, Moskal LM (2010) Fusion of LiDAR and imagery for estimating forest canopy fuels. Remote Sens Environ 114(4):725–737. http://dx.doi.org/10.1016/j.rse.2009.11.002

Falkowski MJ, Gessler PE, Morgan P, Hudak AT, Smith AMS (2005) Characterizing and mapping forest fire fues using ASTER imagery and remote sensing. For Ecol Manage 217:129–146

Finney MA (1998) FARSITE: fire area simulator—model development and evaluation. United States Department of Agriculture, Forest Service Rocky Mountain Research Station, Research Paper RMRS-RP-4. Fort Collins, CO USA, pp 47

Finney MA (2005) The challenge of quantitative risk analysis for wildland fire. For Ecol Manage 211:97–108

Finney MA (2006) An overview of FlamMap fire modeling capabilities. In: Andrews PL, Butler BW (eds) Fuels management—how to measure success, Portland, OR, 28–30 March 2006. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Proceedings RMRS-P-41 Fort Collins, CO USA, pp 213–220

Friedl MA, Michaelsen J, Davis FW, Walker H, Schimel DS (1994) Estimating grassland biomass and leaf area index using ground and satellite data. Int J Remote Sens 15(7):1401–1420

Gosz JR (1992) Gradient analysis of ecological change in time and space: implications for forest management. Ecol Appl 2(3):248–261

Grossman DH, Faber-Langendoen D, Weakley AS, Anderson M, Bourgeron P, Crawford R, Goodin K, Landaal S, Metzler K, Patterson K, Pyne M, Reid M, Sneddon L (1998) International classification of ecological communities: terrestrial vegetation of the United States Volume I. The National Vegetation Classification System: development, status, and applications., vol I. The Nature Conservancy, Arlington VA., USA

Habeck JR (1976) Forest, fuels and fire in the Selway-Bitterroot Wilderness, Idaho. 14th Tall timbers fire ecology conference 14:305–353

Hawkes B, Niemann O, Goodenough D, Lawson B, Thomson A, Sahle W, Fuglem P, Beck J, Bell B, Symingto P (1995) Forest fire fuel type mapping using GIS and remote sensing in British Columbia. In: Heit M, Parker HD, Shortreid A (eds) Proceedings of the symposium GIS applications in natural resources 2 – the 9th symposium on geographic information systems, Vancouver, British Columbia, Canada, pp 290–299

Hessburg PF, Reynolds K, Keane RE, James K, Salter RB (2010) Evaluating wildland fire danger and prioritizing vegetation and fuels treatments. In: Pye JM, Rauscher HM, Sands Y, Lee DC, Beatty JS (eds) Advances in threat assessment and their application to forest and rangeland management, Portland, OR, 2010. Gen. Tech. Rep. PNW-GTR-802. U.S. Department of Agriculture, Forest Service, Pacific Northwest and Southern Research Stations, pp 329–353

Heyerdahl EK, Brubaker LB, Agee JK (2001) Spatial controls of historical fire regimes: a multiscale example from the Interior West, USA. Ecology 82(3):660–678

Hornby LG (1935) Fuel type mapping in region one. J For 33(1):67–72

Hornby LG (1936) Fuel type mapping, its relation to forest fire control plannig. Northwest Sci 4:3–7

Huang S, Crabtree RL, Potter C, Gross P (2009) Estimating the quantity and quality of coarse woody debris in Yellowstone post-fire forest ecosystem from fusion of SAR and optical data. Remote Sens Environ 113(9):1926–1938. doi:10.1016/j.rse.2009.05.001

Jain A, Ravan SA, Singh RK, Das KK, Roy PS (1996) Forest fire risk modelling using remote sensing and geographic information systems. Curr Sci India 70(10):928–933

Jia GJ, Burke IC, Kaufmann MR, Goetz AFH, Kindel BC, Pu Y (2006) Estimates of forest canopy fuel attributes using hyperspectral data. For Ecol Manage 229:27–38

Karau EC, Keane RE (2010) Burn severity mapping using simulation modelling and satellite imagery. Int J Wildland Fire 19(6):710–724

Kasischke ES, French NFH, Bourgeau-Chavez LL, Ustin SL, Christensen NL (1998) Estimating the release of carbon from forest fires in Alaska using satellite remote sensing data. http://cstars.ucdavis.edu/papers/sustin/carbon/paper.html

Keane RE (2013) Describing wildland surface fuel loading for fire management: a review of approaches, methods and systems. Int J Wildland Fire 22(1):51–62

Keane RE, Reeves MC (2011) Use of expert knowledge to develop fuel maps for wildland fire management. In: Perera A, Drew A (eds) Expert knowledge and its application in landscape ecology. Island Press, New York, pp 211–228

Keane RE, Kevin CR, Running SW (1996) Simulating effects of fire on northern Rocky Mountain landscapes with the ecological process model Fire-BGC. Tree Physiol 16:319–331

Keane RE, McNicoll CH, Schmidt KM, Garner JL (1997) Spatially explicit ecological inventories for ecosystem management planning using gradient modeling and remote sensing. In: Proceedings of the sixth forest service remote sensing applications conference—remote sensing; people in partnership with technology. American Society of Photogrammetry and Remote Sensing. Bethesda, MD., USA, pp 135–146

Keane RE, Garner JL, Schmidt KM, Long DG, Menakis JP, Finney MA (1998a) Development of input spatial data layers for the FARSITE fire growth model for the Selway-Bitterroot Wilderness complex, USA. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-3 Fort Collins, CO USA, pp 66

Keane RE, Long DG, Schmidt KM, Mincemoyer SA, Garner JL (1998b) Mapping fuels for spatial fire simulations using remote sensing and biophysical modeling. Natural resource management using remote sensing and GIS: proceedings of the seventh forest service remote sensing applications conference, Nassau Bay, Texas, April 6–10, 1998. American Society for Photogrammetry and Remote Sensing c1998, Bethesda

Keane RE, Mincemoyer SA, Schmidt KM, Menakis JP, Long DG, Garner JL (2000) Mapping vegetation and fuels for fire management on the Gila National Forest Complex. USDA Forest Service, Rocky Mountain Research Station General Technical Report RMRS-GTR-46-CD Fort Collins, CO USA, pp 67

Keane RE, Burgan RE, Wagtendonk JV (2001) Mapping wildland fuels for fire management across multiple scales: integrating remote sensing, GIS, and biophysical modeling. Int J Wildland Fire 10:301–319

Keane RE, Cecilia McNicoll, Rollins MG (2002) Integrating ecosystem sampling, gradient modeling, remote sensing, and ecosystem simulation to create spatially explicit landscape inventories. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-92 Fort Collins, CO USA, pp 61

Keane RE, Frescino TL, Reeves MC, Long J (2006) Mapping wildland fuels across large regions for the LANDFIRE prototype project. In: Rollins MG, Frame C (eds) The LANDFIRE prototype project: nationally consistent and locally relevant geospatial data for wildland fire management, 2006. USDA Forest Service Rocky Mountain Research Station, General Technical Report RMRS-GTR-175 Ogden, UT USA, pp 367–396

Keane RE, Holsinger L, Pratt S (2006b) Simulating historical landscape dynamics using the landscape fire succession model LANDSUM version 4.0. USDA Forest Service Rocky Mountain Research Station, General Technical Report RMRS-GTR-171CD Fort Collins, CO USA, pp 73

Keane RE, Rollins M, Zhu ZL (2007) Using simulated historical time series to prioritize fuel treatments on landscapes across the United States: the LANDFIRE prototype project. Ecol Model 204(3–4):485–502. doi:10.1016/j.ecolmodel.2007.2.005

Keane RE, Loehman RA, Holsinger LM (2011) The FireBGCv2 landscape fire and succession model: a research simulation platform for exploring fire and vegetation dynamics. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-255 Fort Collins, CO USA, pp 137

Keane R, Gray K, Bacciu V, Leirfallom S (2012a) Spatial scaling of wildland fuels for six forest and rangeland ecosystems of the northern Rocky Mountains, USA. Landsc Ecol 27(8):1213–1234. doi:10.1007/s10980-012-9773–9

Keane RE, Gray K, Bacciu V (2012b) Spatial variability of wildland fuel characteristics in northern Rocky Mountain ecosystems. USDA Forest Service Rocky Mountain Research Station, Research Paper RMRS-RP-98 Fort Collins, Colorado USA, pp 58

Keane RE, Herynk JM, Toney C, Urbanski SP, Lutes DC, Ottmar RD (2013) Evaluating the performance and mapping of three fuel classification systems using forest inventory and analysis surface fuel measurements. For Ecol Manage 305:248–263. http://dx.doi.org/10.1016/j.foreco.2013.06.001

Keramitsoglou I, Kontoes C, Sykioti O, Sifakis N, Xofis P (2008) Reliable, accurate, and timely forest mapping for wildfire management using ASTER and Hyperion satellite imagery. For Ecol Manage 255:3556–3562

Kessell SR (1976) Gradient modeling: a new approach to fire modeling and wilderness resource management. Environ Manage 1(1):39–48

Kourtz PH (1977) An application of Landsat digital technology to forest fire fuel mapping. In: Dube DE (ed) Fire ecology in resource mangement: a workshop. Northern Forest Research Centre, Information Report NOR-X-210 Edmonton, Alberta, pp 79–81

Krasnow K (2007) Forest fuel mapping and strategic wildfire mitigation in the Montane zone of Boulder County, Colorado. Graduate Thesis, University of Colorado, Boulder, CO USA, pp 55

Krivtsov V, Vigy O, Legg C, Curt T, Rigolot E, Lecomte I, Jappiot M, Lampin-Maillet C, Fernandes P, Pezzatti GB (2009) Fuel modelling in terrestrial ecosystems: an overview in the context of the development of an object-orientated database for wild fire analysis. Ecol Model 220(21):2915–2926

Lanorte A, Lasaponara R, Murgante B, Gervasi O, Iglesias A, Taniar D, Apduhan B (2011) On the use of satellite remote sensing data to characterize and map fuel types. In: Computational science and its applications—ICCSA 2011, vol 6783. Lecture Notes in Computer Science. Springer Berlin/Heidelberg, pp 344–353. doi:10.1007/978-3-642-21887-3_27

Lasaponara R, Lanorte A (2007a) On the capability of satellite VHR Quickbird data for fuel type characterization in fragmented landscapes. Ecol Model 204:79–84

Lasaponara R, Lanorte A (2007b) Remotely sensed characterization of forest fuel types by using satellite ASTER data. Int J Appl Earth Obs Geoinf 9(3):225–234. http://dx.doi.org/10.1016/j.jag.2006.08.001

Leenhouts B (1998) Assessment of biomass burning in the conterminous United States. Conserv Ecol 2(1):1–23

Lenihan JM, Daly C, Bachelet D, Neilson RP (1998) Simulating broad scale fire severity in a dynamic global vegetation model. Northwest Sci 72:91–103

Loveland TR, Merchant JM, Ohlen DO, Brown JF (1991) Development of a land-cover characteristics database for the conterminous U.S. Photogramm Eng Remote Sens 57(11):1453–1463

Loveland TR, Ohlen DO, Brown JF, Reed BC, Merchant JW (1993) Prototype 1990 conterminous United States land cover characteristics data set EROS Data Center, US Geological Survey, CD-ROM 9307 Souix Falls, SD USA

McKenzie D, Raymond CL, Kellogg L-KB, Norheim RA, Andreu A, Bayard AC, Kopper KE, Elman E (2007) Mapping fuels at multiple scales: landscape application of the fuel characteristic classification system. Can J For Res 37:2421–2437. doi:10.1139/x07-056

Menakis JP, Keane RE., Long DG (2000) Mapping ecological attributes using an integrated vegetation classification system approach. J Sustain For 11(1–2):245–265

Merrill EH, Bramble-Brodahl MK, Marrs RW, Boyce MS (1993) Estimation of green herbaceous phytomass from Landsat MSS data in Yellowstone National Park. J Rang Manage 46:151–157

Miller JD, Danzer SR, Watts JM, Stone S, Yool SR (2003) Cluster analysis of structural stage classes to map wildland fuels in a Madrean ecosystem. J Environ Manage 68(3):239–252

Millington AC, Critchley RW, Douglas TD, Ryan P (1994) Estimating woody biomass in sub-Saharan Africa. The World Bank, Washington, DC

Morris WG (1970) Photo inventory of fine logging slash. Photogramm Eng Remote Sens 36:1252–1256

Muraro SJ (1970) Slash fuel inventories from 70 mm low-level photography. Canadian Forest Service, Information Report 1268, Ottawa, Ontario, Canada, pp 63

Mutlu M, Popescu SC, Stripling C, Spencer T (2008) Mapping surface fuel models using lidar and multispectral data fusion for fire behavior. Remote Sens Environ 112(1):274–285. http://dx.doi.org/10.1016/j.rse.2007.5.005

New Jersey Department of Conservation and Development U.S. Department of Agriculture FS (1942) Forest fuel types of New Jersey. New Jersey Department of Conservation and Development, Trenton, NJ

Ohmann JL, Spies TA (1998) Regional gradient analysis and spatial pattern of woody plant communities of Oregon forests. Ecol Monogr 68(2):151–182

Omernik JM (1987) Ecoregions of the conterminous United States. Annu Assoc Am Geogr 77(1):118–125

Oswald BP, Fancher JT, Kulhavy DL, Reeves HC (1999) Classifying fuels with aerial photography in East Texas. Int J Wildland Fire 9(2):109–113

Ottmar RD, Vihnanek R, Alvarado E (1994) Forest health assessment: air quality tradeoffs. In: Proceedings of the 12th international conference on fire and forest meterology, Jekyll Island, Georgia, USA, October 26–28, 1993. Society of American Foresters, Bethesda, MD, USA, pp 47–62

Pala S, Taylor D, Holder G (1990) Integrating satellite-derived forest fuel data into fire management decision support models. In: Proceedings, second national GIS conference, Ottawa, Canada, March 5–8, 1990

Peterson SH, Franklin J, Roberts DA, van Wagtendonk JW (2012) Mapping fuels in Yosemite National Park. Can J For Res 43(1):7–17. doi:10.1139/cjfr-2012-0213

Pierce AD, Farris CA, Taylor AH (2012) Use of random forests for modeling and mapping forest canopy fuels for fire behavior analysis in Lassen Volcanic National Park, California, USA. For Ecol Manage 279:77–89. doi:http://dx.doi.org/10.1016/j.foreco.2012.05.010

Quigley TM, Graham RT, Haynes RW (1996) An integrated scientific assessment for ecosystem management in the Interior Columbia River Basin and portions of the Klamath and Great Basins. US Department of Agriculture, Forest Service, Pacific Northwest Research Station, PNW-GTR-382 Portland, OR., USA, pp 126

Reeves MC, Ryan KC, Rollins MC, Thompson TG (2009) Spatial fuel data products of the LANDFIRE project. Int J Wildland Fire 18:250–267

Reinhardt E, Lutes D, Scott J (2006) FuelCalc: a method for estimating fuel characteristics. In: Andrews PL, Butler BW (eds) Fuels management—how to measure success, Portland, OR, 2006a. I U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Proceedings RMRS-P-41 Fort Collins, CO, pp 273–287

Riaño D, Meier E, Allgöwer B, Chuvieco E, Ustin SL (2003) Modeling airborne laser scanning data for the spatial generation of critical forest parameters in fire behavior modeling. Remote Sens Environ 86(2):177–186

Rignot E, Way J, Williams C, Viereck L (1994) Radar estimates of aboveground biomass in boreal forests of interior Alaska. IEEE Trans Geosci Remote Sens 32(5):1117–1124

Rollins MG (2009) LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment. Int J Wildland Fire 18(3):235–249. doi:10.1071/WF08088

Rollins MG, Keane RE, Parsons R (2004) Mapping ecological attributes using gradient analysis and remote sensing. Ecol Appl 14(1):75–95

Root RR, Wagtendonk J (1999) Hyperspectral analysis of multi-temporal Landsat TM data for mapping fuels in Yosemite National Park. In: Annual ASPRS Conference, Portland, OR., USA, May 17–21, 1999. Society of American Photogrammeters, Bethesda, MD., USA, pp 399–408

Root RR, Stitt SCF, Nyquist MO, Waggoner GS, Agee JK (1985) Vegetation and fire fuel models mapping of North Cascades National Park. In: The tenth William T. Pecora remote sensing symposium, Fort Collins, CO, 1985, pp 287–294

Saatchi S, Halligan K, Despain DG, Crabtree RL (2007) Estimation of forest fuel load from radar remote sensing. Geosci Remote Sens, IEEE Trans 45(6):1726–1740. doi:10.1109/tgrs.2006.887002

Salas J, Chuvieco E (1994) Geographic information systems for wildland fire risk mapping. Wildfire 3(2):7–13

Schmidt KM, Menakis JP, Hardy CC, Hann WJ, Bunnell DL (2002) Development of coarse-scale spatial data for wildland fire and fuel management. USDA Forest Service Rocky Mountain Research Station, General Technical Report RMRS-GTR-87 Fort Collins, CO, USA, pp 41

Scott J, Burgan RE (2005) A new set of standard fire behavior fuel models for use with Rothermel's surface fire spread model. USDA Forest Service Rocky Mountain Research Station, General Technical Report RMRS-GTR-153. Fort Collins, CO USA, pp 66

Sikkink PG, Keane RE (2008) A comparison of five sampling techniques to estimate surface fuel loading in montane forests. Int J Wildland Fire 17(3):363–379. doi:Doi 10.1071/Wf07003

Skidmore AK (1989) A comparison of techniques for calculating gradient and aspect from a gridded digital elevation model. Int J Geogr Info Sys 3(4):323–334

Thornton PE, Law BE, Gholz HL, Clark KL, Falge E, Ellsworth DS, Goldstein AH, Monson RK, Hollinger DY, Falk M, Chen J, Sparks JP (2002) Modeling and measuring the effects of disturbance history and climate on carbon and water budgets in evergreen needleleaf forests. Agric For Meteorol 113:185–222

Varga TA, Asner GP (2008) Hyperspectral and LiDAR remote sensing of fire fuels in Hawaii Volcanoes National Park. Ecol Appl 18(3):613–623. doi:10.1890/07-1280.1

Vasconcelos JJPd, Paul JCU, Silva S, Pereira JMC, Caetono MS, Catry FX, Oliveira TM (1998) Regional fuel mapping using a knowledge based system approach. In: Proceedings: III international conference on forest fire research and 14th conference on fire and forest meterology, vol. II, 1998. pp 2111–2123

Verbyla DL (1995) Satellite remote sensing of natural resources. Lewis Publishers, CRC Press Valley Stream, New York

Vogelmann JE, Kost JR, Tolk B, Howard S, Short K, Xuexia C, Chengquan H, Pabst K, Rollins MG (2011) Monitoring landscape change for LANDFIRE using multi-temporal satellite imagery and Ancillary data. Selected topics in applied earth observations and remote sensing. IEEE J 4(2):252–264. doi:10.1109/jstars.2010.2044478

Willis JM (1985) Applications of Landsat imagery for fire fuels mapping projects covering large geographic areas. In: Proceedings of the Pecora X symposium, 1985. American Society for Photogrammetry and Remote Sensing, Falls Church, Virginia, USA, pp 394–395

Wilson BA, Ow CFY, Heathcott M, Milne D, McCaffrey TM, Ghitter G, Franklin SE (1994) Landsat MSS classification of fire fuel types in Wood Buffalo National Park, Northern Canada. Glob Ecol Biogeogr Lett 4:33–39

Xiao-rui T, McRae D, Li-fu S, Ming-yu W (2005) Fuel classification and mapping from satellite imagines. J For Res 16(4):311–316. doi:10.1007/bf02858198