# Mapping fuels at multiple scales: landscape application of the Fuel Characteristic Classification System[1]

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**Abstract:** Fuel mapping is a complex and often multidisciplinary process, involving remote sensing, ground-based validation, statistical modelling, and knowledge-based systems. The scale and resolution of fuel mapping depend both on objectives and availability of spatial data layers. We demonstrate use of the Fuel Characteristic Classification System (FCCS) for fuel mapping at two scales and resolutions: the conterminous USA (CONUS) at 1 km resolution and the Wenatchee National Forest, in Washington State, at 25 m resolution. We focus on the classification phase of mapping — assigning a unique *fuelbed* to each mapped cell in a spatial data layer. Using a rule-based method, we mapped 112 fuelbeds onto 7.8 million 1 km cells in the CONUS, and mapped 34 fuelbeds onto 18 million 25 m cells in the Wenatchee National Forest. These latter 34 fuelbeds will be further subdivided based on quantitative spatial data layers representing stand structure and disturbance history. The FCCS maps can be used for both modelling and management at commensurate scales. Dynamic fuel mapping is necessary as we move into the future with rapid climatic and land-use change, and possibly increasing disturbance extent and severity. The rule-based methods described here are well suited for updating with new spatial data, to keep local, regional, and continental scale fuel assessments current and inform both research and management.

**Résumé :** La cartographie des combustibles est un processus complexe et souvent multidisciplinaire, impliquant la détection, la validation sur le terrain, la modélisation statistique et les systèmes basés sur la connaissance. L'échelle et la résolution de la cartographie des combustibles dépendent à la fois des objectifs et de la disponibilité des couches de données à référence spatiale. Nous montrons comment utiliser le Système de classification des caractéristiques des combustibles pour cartographier les combustibles à deux échelles et deux résolutions : les zones limitrophes des États-Unis d'Amérique (É.-U.) (CONUS) avec une résolution d'un kilomètre et la Forêt nationale de Wenatchee, dans l'État de Washington aux É.-U., avec une résolution de 25 m. Nous mettons l'accent sur la phase de classification de la cartographie en assignant une couche de combustibles propre à chacune des cellules cartographiées dans une couche de données à référence spatiale. À l'aide d'une méthode à base de règles, nous avons cartographié 112 couches de combustibles dans 7,8 millions de cellules d'un km dans le cas de CONUS et 34 couches de combustibles dans 18 millions de cellules de 25 m dans la Forêt nationale de Wenatchee. Ces dernières 34 couches de combustibles seront encore subdivisées sur la base des couches de données à référence spatiale quantitatives représentant la structure du peuplement et l'historique des perturbations. Les cartes basées sur le Système de classification des caractéristiques des combustibles peuvent être utilisées aux mêmes échelles tant pour la modélisation que pour l'aménagement. La cartographie dynamique des combustibles est nécessaire parce que nous allons vers un avenir marqué par des changements rapides du climat et de l'utilisation du territoire et, possiblement, par une augmentation de l'étendue et de la sévérité des perturbations. Les méthodes basées sur des règles décrites ici sont bien adaptées à la mise à jour avec de nouvelles données à référence spatiale pour actualiser l'évaluation des combustibles à l'échelle locale, régionale et continentale et fournir des informations pour la recherche et l'aménagement.

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## Introduction

Recent large wildfires in western North America illustrate the need for accurate spatial information about the abundance and variability of vegetation and fuels. The Biscuit Fire (2002) in southwestern Oregon, the Hayman Fire (2002) on the Colorado Front Range, the Cerro Grande Fire (2000) in northern New Mexico, and the Cedar Fire (2003) in southern California all burned across multiple vegetation complexes and land ownerships. Fire severity ranged from extreme (Cerro Grande, Cedar) to mixed (Biscuit). In the latter, the mixed severity left a mosaic of patches whose residual structure reflected the pre-burn spatial pattern of fuels (Raymond and Peterson 2005). For each of these large fires, accurate estimates of canopy and surface fuel loads across the landscape, in conjunction with meteorological forecasts, would have helped firefighters anticipate extreme fire behavior in both space and time.

At regional to global scales, estimates of available fuel are typically the greatest source of uncertainty in modelling carbon dynamics in response to fire, because consumption and emissions are directly proportional to available fuel (Andreae and Merlet 2001; Battye and Battye 2002). Much of this uncertainty arises from the use of default fuel loads for broad classes of vegetation assigned by collapsing vegetation types into standard fuel models (Anderson 1982; Cohen and Deeming 1985). For example, fuel loads vary by a factor of 8 in the shrub layer of southwestern US chaparral (Ottmar et al. 2000), a factor of 4 in the forest floor in Alaskan black spruce (Ottmar and Vihnanek 1998), and a factor of 20 in the canopies of mixed-conifer forests of the Pacific Northwest (Ottmar et al. 1998). Consumption and emissions estimates in coarse-scale models propagate this uncertainty into predictions of regional air quality and apportionment of the global carbon budget (Duncan et al. 2003; Phuleria et al. 2005; McKenzie et al. 2006; Wiedinmyer et al. 2006).

Fuel mapping is a complex and often multidisciplinary process, potentially involving remote sensing, ground-based validation, statistical modelling, and knowledge-based systems (Huff et al. 1995; Burgan et al. 1998; Keane et al. 2000, 2001; Rollins et al. 2004). There are strengths and weaknesses of each technique, and a combination of methods is often the best strategy (Keane et al. 2001). The scale and resolution of fuel mapping depend both on objectives and availability of spatial data layers (Table 1). For example, input layers for mechanistic fire behavior and effects models must have as high resolution (≤30 m) as possible (Keane et al. 2000; Keane and Finney 2003). In contrast, continental-scale data for broad-scale assessment are usually no finer than 1 km, and often as coarse as 36 km, corresponding to the modelling domains for mesoscale meteorology (Grell et al. 1994) and air-quality assessment (Regional Modelling Center (RMC) 2004, Wiedinmyer et al. 2006).

Because of the time and effort required for ground-based measurements, and the intrinsic variability of fuel loads even at fine scales, estimation of fuel loads across broad extents must rely on indirect methods. For example, Ohmann and Gregory (2002) built stand-level models of vegetation, including fuel loads, from inventory plots, satellite imagery, and biophysical variables, and used nearest-neighbor imputation to assign them to unsampled plots (cells). Keane et al. (2000) used satellite imagery, terrain modelling, and simulation models to develop predictions of biophysical setting, vegetation cover, and structural stage, from which they assigned each cell a fire behavior fuel model (Anderson 1982). Both these efforts are *model-based* classifications.

At broader scales, or where no ground data are available, fuel mapping relies mainly on classifications of remotely sensed imagery and existing spatial data (e.g., Burgan et al. 1998). *Knowledge-based* classifications (Schmoldt and Rauscher 1996) are often more appropriate because of the multiple uncertainties associated with scaling predictive models (Rastetter et al. 1992, McKenzie et al. 1996 — but see Keane et al. 2006). *Rule-based* classifications are knowledge-based methods that invoke a *rule set*: a collection of inferences that can be qualitative, numerical, or both (Puccia and Levins 1985; Schmoldt and Rauscher 1996; Stockwell 2006).

The choice between rule-based and model-based classifications involves trade-offs. Model-based methods provide quantitative estimates of variance and uncertainty whereas rule-based methods only provide heuristic estimates. However, a poor quantitative model is generally less useful than a qualitative model (Puccia and Levins 1985; Schmoldt and Rauscher 1996; Schmoldt et al. 1999), so mapping efforts for which quantitative models perform poorly or cannot be validated are good candidates for rule-based methods.

Ecosystems are dynamic and fuel loads change with vegetation succession, in response to climatic variability, and after natural or anthropogenic disturbance. Quantitative fuel maps can therefore become obsolete rather quickly. To keep fuel maps current so that they will retain their value for users, methods are needed to update fuel layers efficiently as landscapes change. An advantage to rule-based mapping is that new data layers can be incorporated efficiently because rules only need to be built for new attributes. In contrast, bringing updated data layers into model-based mapping requires entirely new models because relationships between response and predictor variables will change.

In this paper, we demonstrate the use of the Fuel Characteristic Classification System (FCCS) for fuel mapping at two scales and resolutions: the conterminous USA (CONUS) at 1 km resolution and the Wenatchee National Forest, in Washington State, at 25 m resolution. We distinguish between a *classification* phase and a *quantification* phase of mapping, and focus on the classification phase — assigning a unique *fuelbed* (Riccardi et al. 2007*a*) to each mapped cell in a spatial data layer.

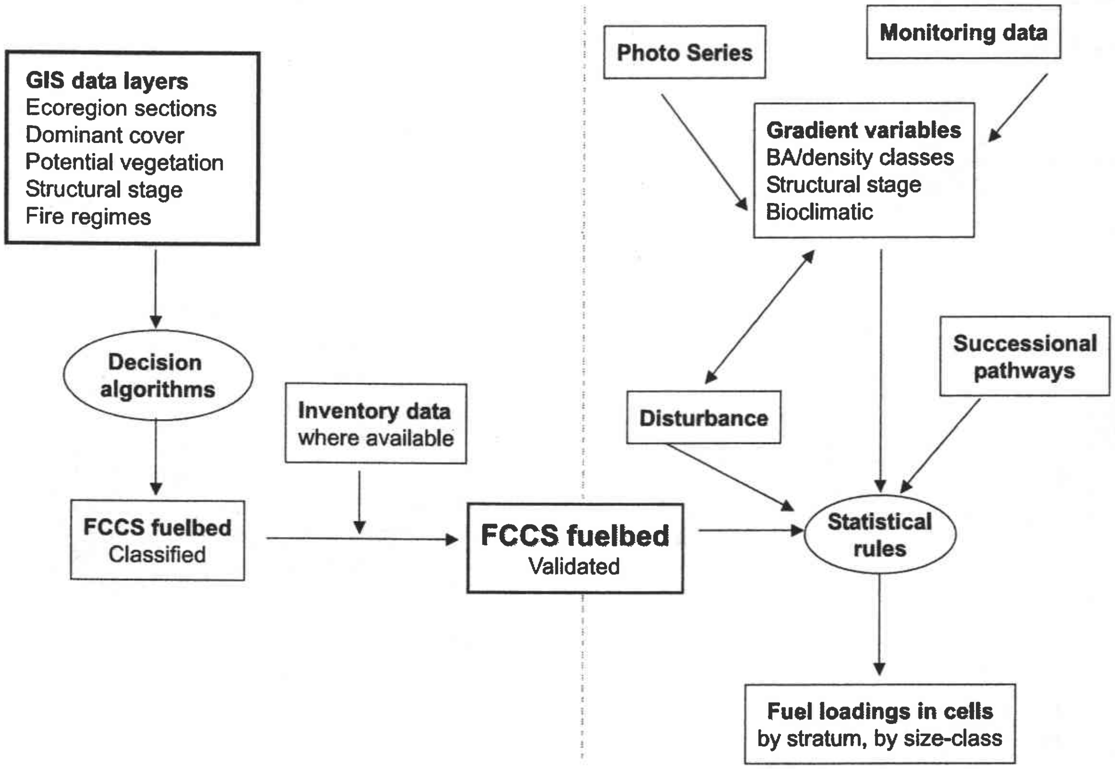
The classification phase of mapping names every cell in a geographic domain based on criteria established numerically (e.g., from models) or logically (Fig. 1). In a model-based classification, cell names (attributes) are inferred from predicted values of a model (e.g., Rollins et al. 2004), or from a post hoc cluster analysis (or a qualitative equivalent) that groups individual predicted values and requires a heuristic assignment of names (Burgan et al. 1998). In a rule-based classification, cell names can be assigned in one step (as we do here). This assignment arises from a qualitative probabilistic evaluation (what is the most likely choice?) or a deterministic logic (e.g., if A and B, then the only possible outcome is C).

**Table 1.** Overview of the range of potential scales and resolutions of fuel mapping, and examples of their respective applications.

| Scale | Resolution | Applications |
|---|---|---|
| Local | Point to 30 m | Plot- and project-level assessments, e.g., prescribed fire or local mechanical treatments |
| Regional | 30 m to 1 km | Landscape, watershed, or sub-basin scale mapping, spatial modelling of fire behavior or fire effects |
| Continental | 1–36 km | Carbon-cycle or air-quality modelling, national-scale fuel treatment planning |
| Global | 36 km to 10° | Global climatic change, especially carbon budgets affected by biomass burning |

**Note:** Resolutions at the regional scale and above correspond to the domains of commonly used simulation models.

**Fig. 1.** Elements of dynamic fuels mapping. Processes on the left belong to the classification phase; processes on the right to the quantification phase. See text for explanation.




The quantification phase assigns numerical attributes to a cell, based on its class. When fuel models are being mapped (Burgan et al. 1998; Keane et al. 2000, 2006; Rollins et al. 2004), the same fuel loads are assigned to every cell, substantially reducing the variability of the mapped layer compared to the landscapes it represents. In contrast, every FCCS fuelbed has not only a default value but also an associated minimum and maximum for each attribute (Riccardi et al. 2007*a*), with the further implication of a joint probability distribution of fuel loads across categories and strata. Although we present only the classification phase of FCCS mapping in this paper, we elaborate in the Discussion on the unique potential of FCCS-based maps for quantifying landscape variability of fuels.

We show how the classification scheme in the FCCS, based on ecosystem geography and dominant vegetation, facilitates the use of existing GIS layers in developing classification rules and ongoing updates of fuelbed maps as new GIS layers become available. We briefly discuss how the quantification phase — assigning actual fuel loads to cells — can proceed. Finally, we note the limitations and uncertainties associated with this modelling approach, and discuss applications of FCCS-based fuel maps for both modelling and management.

## Methods

### Continental-scale map (USA)

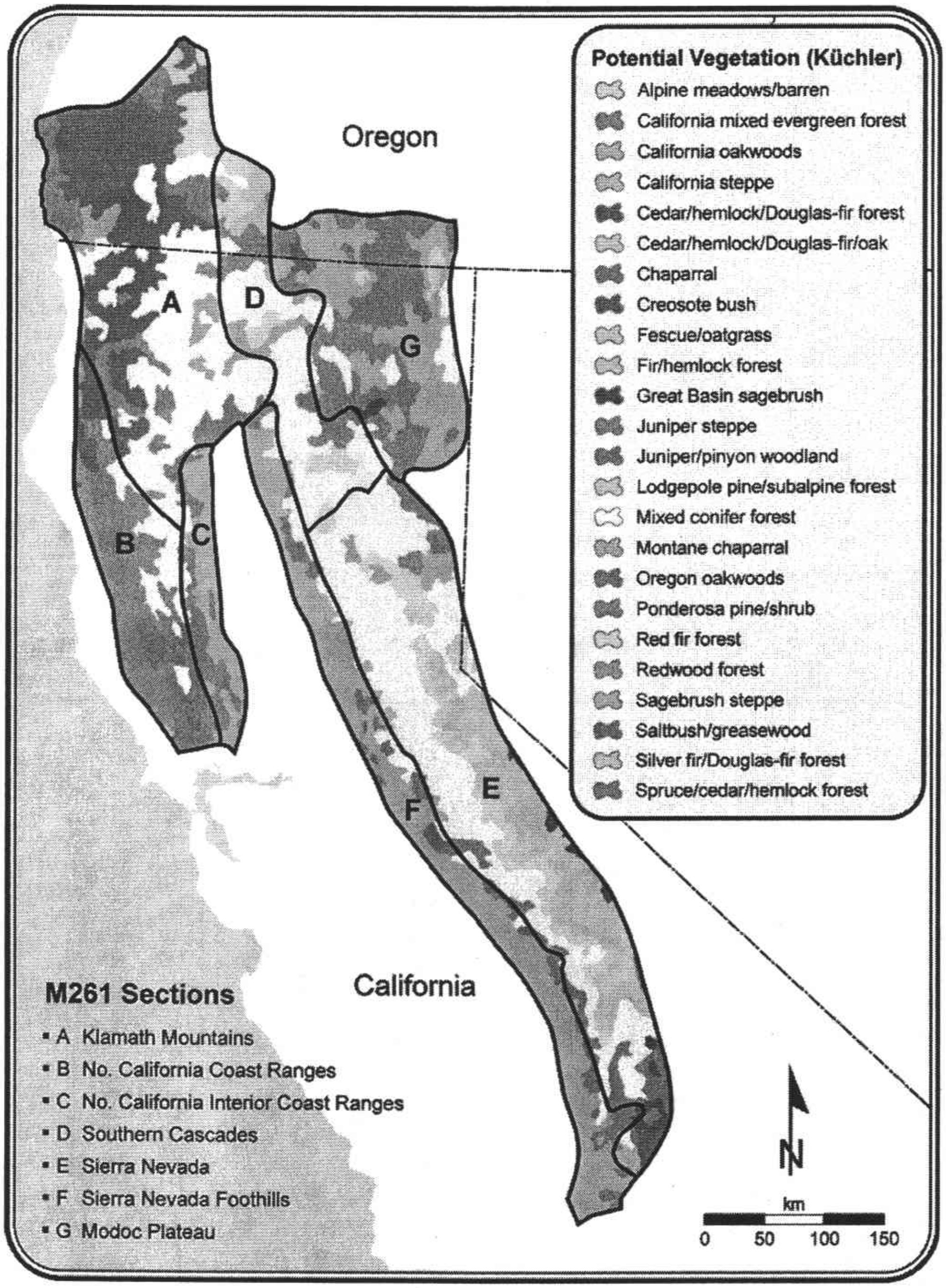
#### *Spatial data layers*

For coarse-scale modelling, we compiled GIS data from sources on the internet, US Forest Service archives, and databases developed in previous collaborative efforts. Current cover types were taken from Schmidt et al. (2002) (available from www.fs.fed.us/fire/fuelman/). Potential natural vegetation was taken from a polygon coverage of the Küchler (1964) classification, in the possession of the first author. Elevation data were taken from 1 km digital elevation models (DEM) provided by the US Geological Survey (available from edcdaac.usgs.gov/glcc/glcc.html).

#### *Fuelbed assignment*

Decision rules were developed separately within each

**Fig. 2.** Overlay of ecoregion sections (Bailey 1996) and potential vegetation polygons (Küchler 1964) for the Bailey ecoregion province M261: Sierran Steppe and mixed-conifer forest.




Bailey's section, within each province. Each section has multiple potential vegetation types (Fig. 2) and vegetation cover classes, but within a section, geographic characteristics are relatively homogeneous (Bailey 1996). All unique combinations of potential vegetation and current cover were entabulated and matched to FCCS fuelbeds, using vegetation associated with fuelbeds, gradient variables (elevation and climate), and geographic location as additional criteria. Where more than one fuelbed was possible the most likely was assigned to that cell. The following general rules were applied to establish candidate fuelbed(s) for a cell, after all cells designated urban, agriculture, or water by Schmidt et al. (2002) were eliminated:

(1) The fuelbed must have been associated with the specific Bailey's ecoprovince by the original fuelbed builder.
(2) Dominant vegetation type in the fuelbed should match the cover type from Schmidt et al. (2002) — 25 total possibilities.
(3) Dominant vegetation type in the fuelbed should be logically associated with the potential vegetation type from

**Fig. 3.** Example logic for identifying an FCCS fuelbed associated with potential vegetation (Küchler 1964) and vegetation cover (Schmidt et al. 2002) in the Sierra Nevada Mountains section (E) of ecoregion province M261.

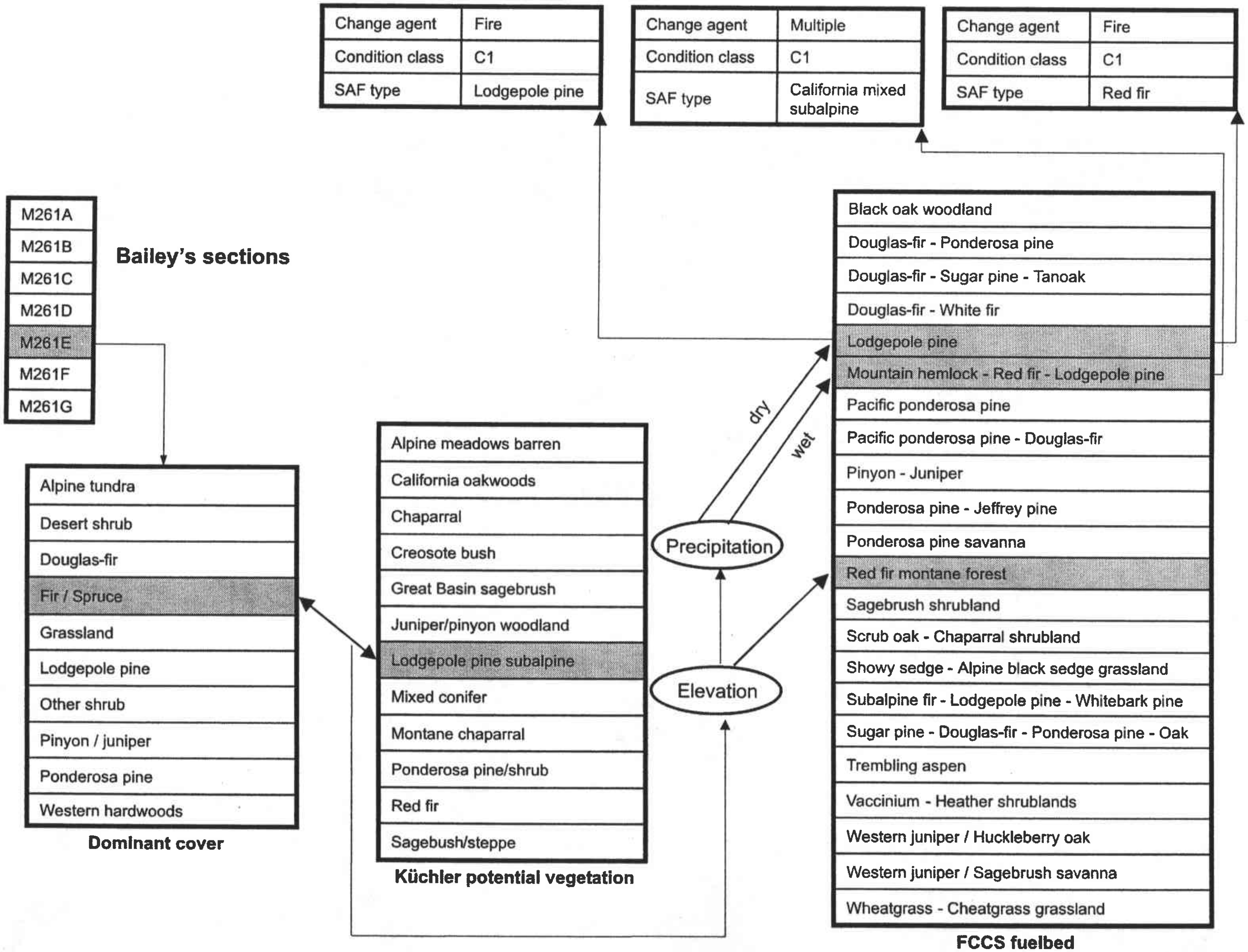
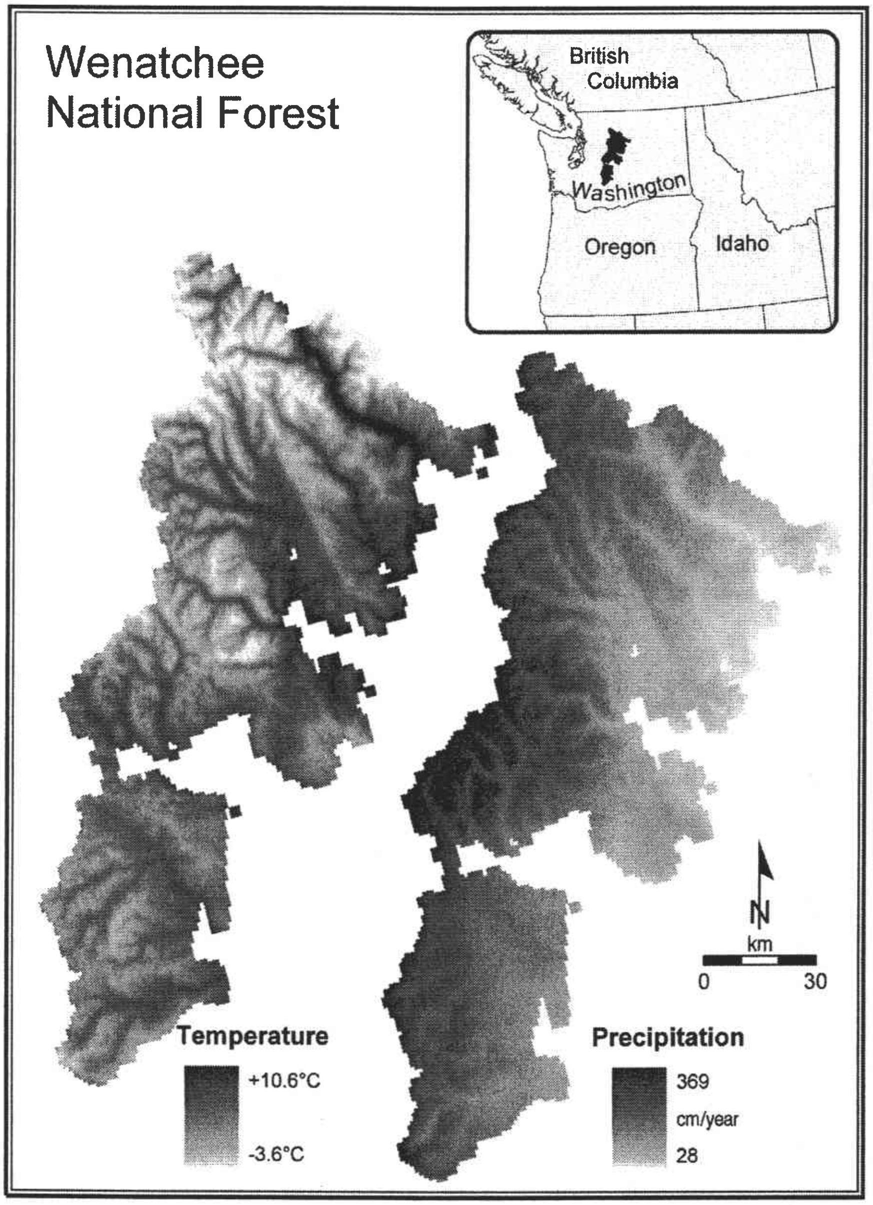


**Fig. 4.** Temperature and precipitation gradients on the Wenatchee National Forest. Data are from Thornton et al. (1997).




Küchler (1964) — 114 total possibilities. "Logically associated" included the possibility that dominant vegetation represented an earlier successional stage than the "potential" vegetation, but the Küchler (1964) layer included natural disturbance, so this was rarely invoked.

(4) Dominant vegetation type in the fuelbed should be likely at the median elevation of all cells associated with a particular combination.

(5) Rules had to be consistent across Bailey ecosections (the finest scale of the classification) within an ecoprovince (the next finest scale). Figure 3 illustrates the logic for two fuelbed assignments within the "Sierra Nevada Mountains" section of ecosystem province M261.

Initial rules were developed independently, for each ecoprovince, by the two authors with biogeographic expertise: (McKenzie and Kopper for the west and Andreu and McKenzie for the east). Fuelbed assignments were then compared within the pair of authors and differences reconciled. To maintain consistency across the CONUS, we elected not to solicit reviews of the rules from local or regional managers (unlike the fine-scale mapping — see the following).

Because the accuracy of this classification depends on the accuracy of the input GIS layers, no attempt was made to validate the map layer directly at the classification phase. For such accuracy assessments to be meaningful, validation data must exist at the appropriate spatial scale (Stehman and Czaplewski 1998; Foody 2002). Schmidt et al. (2002) had performed no validation on their vegetation layer, because of the inherent difficulties of ground-truthing 1 km cells (Kloditz et al. 1998), and we are using their vegetation classification as "truth".

**Table 2.** Subcategories of a generic fuelbed (Douglas-fir – moist grand fir) on the Wenatchee National Forest, Washington State, based on structure, age-class, and disturbance, and identified by experts on the forest.

| Age range (years) | Fuelbed ID | Structure and history |
|---|---|---|
| 0–30 | OW020 | Wildfire created opening |
| 30–60 | OW021 | Precommercial thin, seedlings and saplings |
| 30–60 | OW022 | No change agent, seedlings and saplings, high density and fuel load |
| 60–90 | OW023 | Selection cut and burn, poles |
| 60–90 | OW024 | No change agent, poles |
| 90–200 | OW025 | Selection cut and burn |
| 90–200 | OW026 | Multilayer, high density and load |
| Over 200 | OW027 | Layered mature, medium density and load |
| Over 200 | OW028 | Layered mature, high density and load |
| Over 200 | OW029 | Open parkland, low density and load |
| Over 200 | OW030 | Open parkland, medium density and load |

Coarse-scale classifications such as these need to rely on indirect methods to optimize accuracy in the context of the application, i.e., the least biased distribution of classes (fuelbeds) across broad landscapes (see Regional scale), or other aggregate statistics. This type of validation of coarse-scale data layers is a topic of active research, and will likely be more feasible with the next generation of satellite-based classification products (Morisette et al. 2002; Cohen et al. 2003; Turner et al. 2003).

At the quantification phase of mapping, when fuel loads are assigned to every cell, understanding the uncertainty associated with fuelbed assignments will be important, because estimates of biomass consumed and smoke emissions are directly proportional to available fuels. We therefore compared default values for percentage canopy cover in one or more canopy layers from the fuelbed database (Riccardi et al. 2007*b*) with those from the MODIS-derived vegetation continuous fields (VCF) 500 m resolution data layer for the CONUS (available from edcdaac.usgs.gov/modis/mod44b.asp). We focused on fuelbeds with a substantial representation in the CONUS map (>1000 cells assigned nationally to that fuelbed) and compared forest and nonforest fuelbeds with VCF tree cover and nontree cover, respectively.

## Regional-scale map (Wenatchee National Forest)

### *Study area*

The Wenatchee National Forest (USDA Forest Service) is in central Washington State, covering 890 000 ha from the crest of the Cascade Range eastward to savanna–steppe and agricultural lands. Topography is extremely rugged, with deep and steep-sided valleys. Climate is intermediate between the maritime climate west of the Cascade Crest and the continental climate east of the Rocky Mountains. East–west gradients in both temperature and precipitation correspond to the low–high elevational gradient (Fig. 4). Conifer species dominate, notably subalpine fir (*Abies lasiocarpa* (Hook.) Nutt.) and mountain hemlock (*Tsuga mertensiana* (Bong.) Carrière) at higher elevations and ponderosa pine (Pinus ponderosa Dougl. ex P. & C. Laws.) and Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco var. *menziesii*) at lower elevations.

### *Spatial data layers*

The classification phase used two GIS layers developed using a variety of sources and archived by the Wenatchee National Forest. A 25 km resolution raster layer (R6, named for USDA Forest Service region 6) comprises 13 cover types from a direct classification of LANDSAT TM imagery and 9 forested cover types from an interpretation of cover classes in terms of potential natural vegetation (Lillybridge et al. 1995; Bauer 2005). A polygon layer (WenVeg) distinguishes 26 forest types, each of which has one or more structural or age-classes associated with it. WenVeg polygons were classified from aerial photos, and range in size from <1 to 28 000 ha, but with only 18 polygons larger than 4000 ha. Many WenVeg polygons were validated either by site visits or by expert local knowledge of ecologists on individual forest districts.

The R6 raster layer was converted to polygons, then overlain with the WenVeg layer. Using the UNION operation in ArcGIS (Environmental Systems Research Institute (ESRI) 2005), we created a new coverage of the combined polygons whose attribute table retained the attributes of both the original layers. We created new ids for the combined polygons. ArcGIS 9.0 (ESRI 2005) was used for all GIS computations.

### *Fuelbed development*

Forest managers from the Okanogan and Wenatchee National Forest collaboratively designed 187 fuelbeds with distinct species composition, stand structure, and disturbance histories. We aggregated these into 35 general fuelbeds based on forest composition, within which one or more structural or age-classes could be distinguished, analogous to the WenVeg layer (Table 2). Additional spatial data on disturbance history, canopy cover, and stand structure can be used to distinguish the 187 specific fuelbeds (see Discussion).

We used 835 plots from the USDA Forest Service, Pacific Northwest Region, current vegetation survey (CVS) on the Wenatchee National Forest to determine if the designated fuelbeds adequately represented the likely species combinations. Some species and species combinations in the spatial data layers were not represented by the original 35 general fuelbeds, so we added four general fuelbeds to the list. Conversely, some species combinations known by managers to be present were not represented in the spatial layers. For example, the initial list included fuelbeds dominated by both whitebark pine (*Pinus albicaulis* Engelm.) and subalpine larch (*Larix lyallii* Parl.), but the GIS layers lumped these species into one high-elevation parkland classification, so

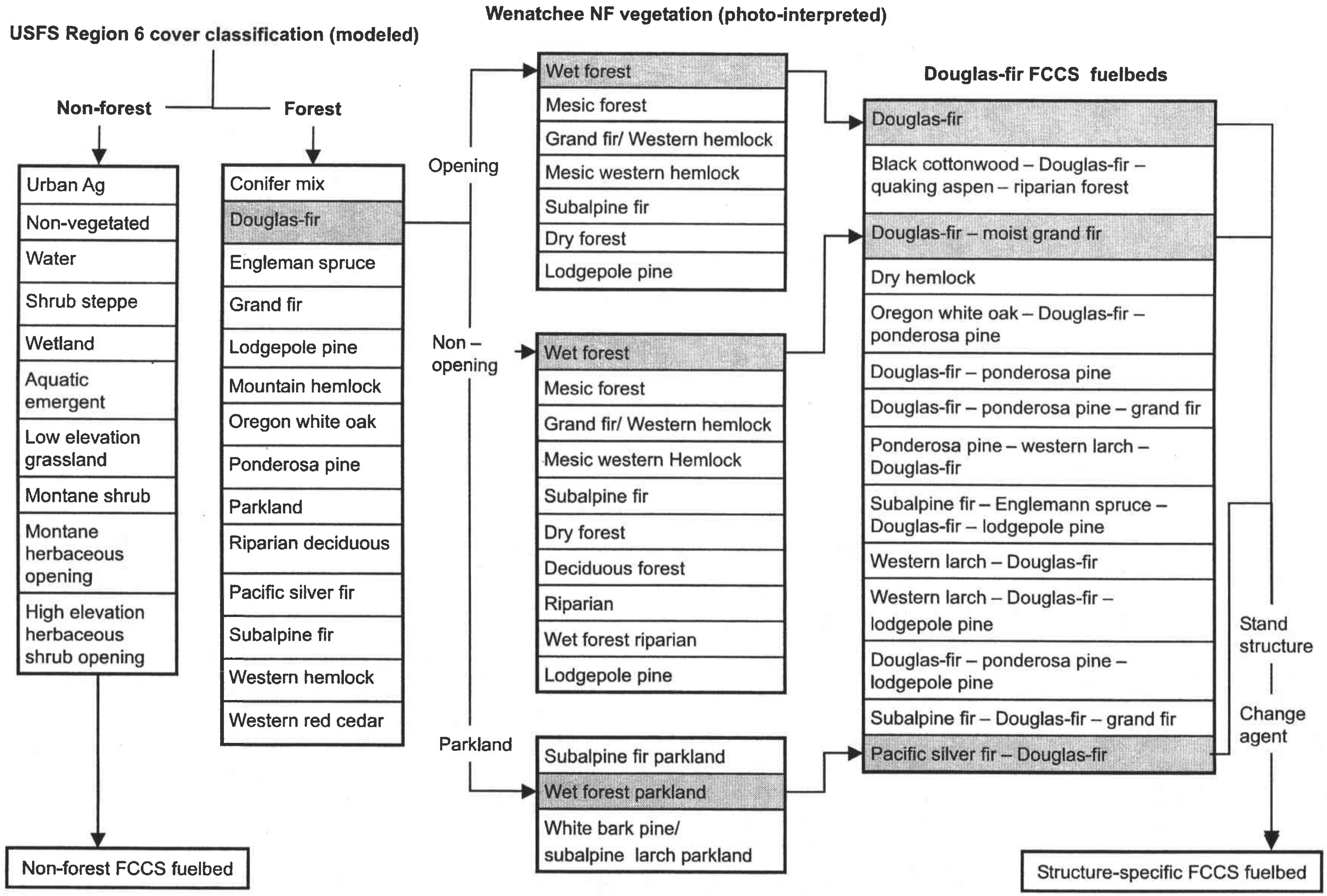



**Fig. 5.** Example logic for identifying a general FCCS fuelbed for combinations of satellite-mapped vegetation and photointerpreted vegetation on the Wenatchee National Forest. "Structure-specific" fuelbeds are identified using additional quantitative data layers.

**Fig. 6.** FCCS classification for the conterminous United States at 1 km resolution. A larger version of the map and the data (as a GIS layer) are available at www.fs.fed.us/pnw/fera/fccs/maps.shtml. Figure appears on the following page.

we added one corresponding high-elevation parkland fuelbed, bringing the final count of fuelbeds available for mapping to 40.

### *Fuelbed assignment*

We assigned fuelbeds using a rule-based approach similar to that for the national-scale map. The overarching criterion was that the fuelbed assignment first had to be consistent with the WenVeg layer, because this was the one in whose accuracy local managers had the most confidence. Because WenVeg does not distinguish species composition as finely as the general fuelbeds, we used the R6 layer to narrow possibilities for dominant species. For each R6 cell within each WenVeg polygon, the most likely fuelbed was assigned by authors McKenzie and Raymond, using the same technique as did the other pairs of authors for the national map. Figure 5 illustrates the logic for three distinct fuelbed assignments within the cover class "Douglas-fir" in the R6 layer, depending on the WenVeg polygon within which they fall.

### *Model evaluation*

We used the CVS plots to evaluate how the fuelbed assignments based on the remotely sensed data corresponded to their likely proportions on the ground. The objective of this exercise was to compare the frequency distribution of fuelbeds represented in the spatial data layer with that of fuelbeds represented by the CVS plots, not to match individual cells to individual plots. We assigned a fuelbed to each of the CVS plots based on the relative tree species composition by basal area, giving weight to the most dominant species and the presence of rare species. Each CVS plot is a cluster of five subplots in which trees were sampled in a 15.6 m radius circular plot (0.076 ha). To compare fuelbeds at a commensurate scale, only data from the center subplot were used, which corresponded to one 25 m grid cell.

We also had an all-day review session with fire managers on the Wenatchee National Forest, during which we exhaustively zoomed in on subsections of the draft fuels map and compiled observations about inconsistencies with local knowledge. These observations were systematized, where possible, and integrated with the draft rules to develop the final rule set.

## Results

### Continental-scale map

Across 35 ecoprovinces, each with between one and seven sections (Bailey 1996), 112 fuelbeds were assigned (Fig. 6), based on 5840 unique rules similar to those depicted in Fig. 3. A complete set of rule tables is available from the first author. Of the ca. 7.8 million 1 km cells in the CONUS GIS layer, 35% were assigned to "urban, agriculture, or barren". Of the 112 fuelbeds, 14 were very common (>100 000 cells), and 14 were rare (<500 cells) (Table 3). Commonness reflects not only the wide range of some vegetation types and their associated fuelbeds (e.g., sagebrush shrubland, wheatgrass, and pinyon-juniper), but also the range of possible choices. For example, there is only one FCCS fuelbed dominated by sagebrush, but six dominated by Douglas-fir and five by ponderosa pine. The most homogeneous areas within the CONUS were agricultural lands of the Plains states and upper Midwest and the grasslands and shrublands of the interior West (Fig. 6). In contrast, the greatest spatial heterogeneity was found in western mountains, reflecting the patchiness of vegetation types associated with mountainous topography.

Comparison of MODIS VCF percentage cover with default values from FCCS fuelbeds suggested a slight bias toward underestimation of tree cover in the FCCS when applied nationally via our mapping procedure. For example, the sum of cover in canopy layers for fuelbeds was often, though not always, slightly below the *projected* cover estimated from MODIS (Fig. 7). These discrepancies may arise from misclassification of some cells, inaccuracy in the FCCS default values, or both. The quantification phase of mapping needs to adjust for discrepancies to ensure the best possible representation of fuel loads over the domain (see Discussion).

### Regional-scale map

The combination of nine modeled (R6) vegetation types and 13 LANDSAT-based cover types with 26 classes from the photointerpreted WenVeg layer assigned 34 of the 40 general fuelbeds across the domain (Fig. 8), including six common (>1 000 000 cells) and five rare (<10 000 cells) fuelbeds (Table 4). "Western hemlock, Pacific silver fir, mountain hemlock" was most prevalent, accounting for 14% of the mapped area (2 233 445 cells). As with the national map, the commonest fuelbeds were those whose dominant vegetation type was widespread across the domain and those that were quite distinct from other possible fuelbed choices. For example, fuelbed choices for the Wenatchee National Forest included only two dominated by western hemlock and only one dominated by mountain hemlock, but five dominated by Douglas-fir.

The rarest fuelbeds reflect the species with more restricted ranges in the study area: Oregon white oak (*Quercus garryana* Dougl.) and Engelmann spruce (*Picea Engelmannii* Parry ex Engelm.). The Wenatchee map showed areas of greater homogeneity in the middle elevations on the west side of the forest where "western hemlock, Pacific silver fir, and mountain hemlock" and "mountain hemlock, Pacific silver fir, and subalpine fir" occur in large patches. In contrast, patterns in the lower elevations on the east side of the forest were more heterogeneous, a consequence of both more fuelbed options and a more patchy disturbance regime creating finer-scale spatial variability.

Five fuelbeds with western larch or western white pine as a significant component were not mapped on the Wenatchee because of the limited resolution of the original GIS layers. These species are problematic for the rule-based logic of assigning fuelbeds, because even when present, they rarely dominate stands or represent the climax species.

### *Model evaluation*

The evaluation indicated a bias towards fuelbeds com-

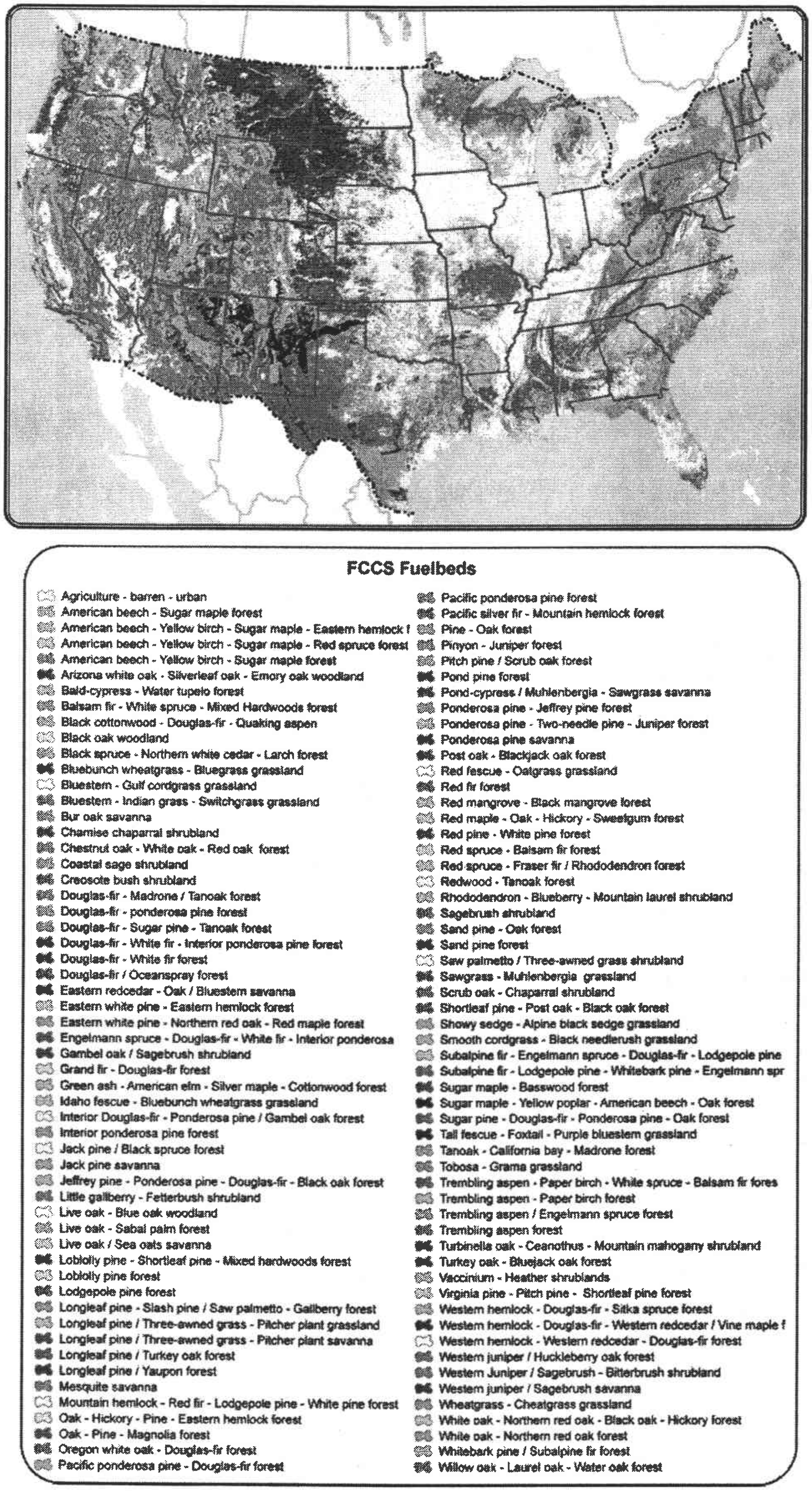

FCCS Fuelbeds
Agriculture - barren - urban
American beech - Sugar maple forest
American beech - Yellow birch - Sugar maple - Eastern hemlock f
American beech - Yellow birch - Sugar maple - Red spruce forest
American beech - Yellow birch - Sugar maple forest
Arizona white oak - Silverleaf oak - Emory oak woodland
Bald-cypress - Water tupelo forest
Balsam fir - White spruce - Mixed Hardwoods forest
Black cottonwood - Douglas-fir - Quaking aspen
Black oak woodland
Black spruce - Northern white cedar - Larch forest
Bluebunch wheatgrass - Bluegrass grassland
Bluestem - Gulf cordgrass grassland
Bluestem - Indian grass - Switchgrass grassland
Bur oak savanna
Chamise chaparral shrubland
Chestnut oak - White oak - Red oak forest
Coastal sage shrubland
Creosote bush shrubland
Douglas-fir - Madrone / Tanoak forest
Douglas-fir - ponderosa pine forest
Douglas-fir - Sugar pine - Tanoak forest
Douglas-fir - White fir - Interior ponderosa pine forest
Douglas-fir - White fir forest
Douglas-fir / Oceanspray forest
Eastern redcedar - Oak / Bluestem savanna
Eastern white pine - Eastern hemlock forest
Eastern white pine - Northern red oak - Red maple forest
Engelmann spruce - Douglas-fir - White fir - Interior ponderosa
Gambel oak / Sagebrush shrubland
Grand fir - Douglas-fir forest
Green ash - American elm - Silver maple - Cottonwood forest
Idaho fescue - Bluebunch wheatgrass grassland
Interior Douglas-fir - Ponderosa pine / Gambel oak forest
Interior ponderosa pine forest
Jack pine / Black spruce forest
Jack pine savanna
Jeffrey pine - Ponderosa pine - Douglas-fir - Black oak forest
Little gallberry - Fetterbush shrubland
Live oak - Blue oak woodland
Live oak - Sabal palm forest
Live oak / Sea oats savanna
Loblolly pine - Shortleaf pine - Mixed hardwoods forest
Loblolly pine forest
Lodgepole pine forest
Longleaf pine - Slash pine / Saw palmetto - Gallberry forest
Longleaf pine / Three-awned grass - Pitcher plant grassland
Longleaf pine / Three-awned grass - Pitcher plant savanna
Longleaf pine / Turkey oak forest
Longleaf pine / Yaupon forest
Mesquite savanna
Mountain hemlock - Red fir - Lodgepole pine - White pine forest
Oak - Hickory - Pine - Eastern hemlock forest
Oak - Pine - Magnolia forest
Oregon white oak - Douglas-fir forest
Pacific ponderosa pine - Douglas-fir forest
Pacific ponderosa pine forest
Pacific silver fir - Mountain hemlock forest
Pine - Oak forest
Pinyon - Juniper forest
Pitch pine / Scrub oak forest
Pond pine forest
Pond-cypress / Muhlenbergia - Sawgrass savanna
Ponderosa pine - Jeffrey pine forest
Ponderosa pine - Two-needle pine - Juniper forest
Ponderosa pine savanna
Post oak - Blackjack oak forest
Red fescue - Oatgrass grassland
Red fir forest
Red mangrove - Black mangrove forest
Red maple - Oak - Hickory - Sweetgum forest
Red pine - White pine forest
Red spruce - Balsam fir forest
Red spruce - Fraser fir / Rhododendron forest
Redwood - Tanoak forest
Rhododendron - Blueberry - Mountain laurel shrubland
Sagebrush shrubland
Sand pine - Oak forest
Sand pine forest
Saw palmetto / Three-awned grass shrubland
Sawgrass - Muhlenbergia grassland
Scrub oak - Chaparral shrubland
Shortleaf pine - Post oak - Black oak forest
Showy sedge - Alpine black sedge grassland
Smooth cordgrass - Black needlerush grassland
Subalpine fir - Engelmann spruce - Douglas-fir - Lodgepole pine
Subalpine fir - Lodgepole pine - Whitebark pine - Engelmann spr
Sugar maple - Basswood forest
Sugar maple - Yellow poplar - American beech - Oak forest
Sugar pine - Douglas-fir - Ponderosa pine - Oak forest
Tall fescue - Foxtail - Purple bluestem grassland
Tanoak - California bay - Madrone forest
Tobosa - Grama grassland
Trembling aspen - Paper birch - White spruce - Balsam fir fores
Trembling aspen - Paper birch forest
Trembling aspen / Engelmann spruce forest
Trembling aspen forest
Turbinella oak - Ceanothus - Mountain mahogany shrubland
Turkey oak - Bluejack oak forest
Vaccinium - Heather shrublands
Virginia pine - Pitch pine - Shortleaf pine forest
Western hemlock - Douglas-fir - Sitka spruce forest
Western hemlock - Douglas-fir - Western redcedar / Vine maple f
Western hemlock - Western redcedar - Douglas-fir forest
Western juniper / Huckleberry oak forest
Western Juniper / Sagebrush - Bitterbrush shrubland
Western juniper / Sagebrush savanna
Wheatgrass - Cheatgrass grassland
White oak - Northern red oak - Black oak - Hickory forest
White oak - Northern red oak forest
Whitebark pine / Subalpine fir forest
Willow oak - Laurel oak - Water oak forest

**Table 3.** The most common (>100 000 cells) and rarest (<500 cells) fuelbeds in the national map.

| | No. of cells |
|---|---|
| **Common fuelbeds** | |
| Sagebrush shrubland | 577 816 |
| Bluebunch wheatgrass – bluegrass grassland | 500 424 |
| Creosote bush shrubland | 465 776 |
| Pinyon – juniper forest | 201 629 |
| White oak – northern red oak – black oak – hickory forest | 192 597 |
| Chestnut oak – white oak – red oak forest | 182 210 |
| Loblolly pine – shortleaf pine – mixed hardwoods forest | 176 482 |
| American beech – yellow birch – sugar maple forest | 157 268 |
| Western juniper – sagebrush savanna | 139 384 |
| Loblolly pine forest | 134 102 |
| Bluestem – Indian grass – switchgrass grassland | 127 495 |
| Lodgepole pine forest | 122 624 |
| Post oak – blackjack oak forest | 109 933 |
| Wheatgrass – cheatgrass grassland | 109 419 |
| **Rare fuelbeds** | |
| Rhododendron – blueberry – mountain laurel shrubland | 16 |
| Douglas-fir – white fir – Interior ponderosa pine forest | 23 |
| Longleaf pine – three-awned grass – Pitcher plant grassland | 37 |
| Sand pine – oak forest | 50 |
| Saw palmetto – three-awned grass shrubland | 64 |
| Pitch pine – scrub oak forest | 67 |
| Little gallberry – fetterbush shrubland | 111 |
| Whitebark pine – Subalpine fir forest | 157 |
| Eastern redcedar – Oak – Bluestem savanna | 221 |
| Pond pine forest | 242 |
| Live oak – Sabal palm forest | 338 |
| Jack pine savanna | 375 |
| Turkey oak – Blackjack oak forest | 389 |
| Sand pine forest | 484 |

posed of late seral species (e.g., western hemlock – Pacific silver fir – mountain hemlock) and dry forest fuelbeds were under-represented (e.g., Douglas-fir – ponderosa pine – grand fir). This was not entirely unexpected because one of the spatial data layers was partially developed from modeled potential vegetation, which generally represents later successional stages rather than existing cover types affected by periodic disturbance. To adjust for this bias, we revisited each classification rule for the combined spatial data layers, under the assumption that a systematic shift towards the early seral species in the R6 plant associations would correct the bias. However, the only rules amenable to this adjustment represented a small enough number of cells that the distributions changed only slightly toward lesser bias. The most common fuelbeds (Table 4) were not affected.

## Discussion

We completed classification of FCCS fuelbeds at two spatial scales, using a rule-based method that takes advantage of spatial data layers for vegetation and biophysical environment and the biogeographically based hierarchical structure of the FCCS. To be useful for management and modelling applications, these classes must be translated into fuel types (e.g., canopy, live-surface fuels, dead-surface fuels, litter, and duff) and fuel loads for each type. The FCCS has default values, as do other classifications, so the simplest implementation of the quantification phase (see the preceding) of mapping would be to assign each cell its default value for each fuel category. Fuels are highly variable in space and time, however, so although this approach might produce unbiased estimates of mean fuel loads, it clearly underestimates the variability of fuels across a landscape, region, or continent.

We identified two spatial scales for mapping based on both the availability of spatial data layers and the expected applications of each map. The quantification phase can also take advantage of existing spatial layers if they are either at the same resolution as the classification layer or can be resampled to that resolution with minimal error. Because the FCCS is based on ecosystem geography and vegetation, rather than being specifically designed to inform fire-behavior modelling as are other fuel classifications, we can draw from a wealth of satellite-based classifications to map the variability in fuel loads. For example, we used the MODIS VCF for a first pass at validating FCCS-based cover estimates across the CONUS. Tree canopy and shrub biomass are highly variable within many FCCS fuelbeds (as recognized by the min. and max. values; Riccardi et al. 2007*b*). They are also critical for determining fire behavior and fire effects. Using the VCF, the CONUS map, and the FCCS calculator (Ottmar et al. 2007), we can assign every cell in the map a unique cover value associated with the VCF value (see Fig. 7), greatly increasing the precision of the map and reproducing the spatial variability of canopy fuels across the CONUS.

Similarly, we can use high-resolution quantitative GIS layers that cover the Wenatchee National Forest. The Interagency Vegetation Mapping Project (IVMP) (available from www.or.blm.gov/gis/projects/vegetation/) estimated both canopy cover and quadratic mean diameter (QMD) at 30 m resolution across the forest from LANDSAT TM imagery. The canopy cover layer is analogous, at the regional scale, to the MODIS VCF at the continental scale. The QMD layer provides structural information that can be linked to specific fuelbeds (e.g., Table 2), thereby refining estimates of fuel loads for each cell to the more precise default values associated with the specific fuelbeds. This will be particularly valuable for quantifying fuels below the canopy layer — a problematic task in mapping fuels and vegetation in general (Keane et al. 2001).

Fuels are also highly variable over time because of vegetation succession, disturbance, and land use. The FCCS includes a facility for incorporating change agents (Ottmar et al. 2007) to account for modification of fuelbeds by disturbance and management. This feature, along with the FCCS' basis in vegetation, enables straightforward updates of the mapped layers as new vegetation layers become available and disturbances are identified and mapped. The Wenatchee National Forest maps fire areas, insect disturbances, and logging activities. The base map we developed can be updated to implement a change agent for fuelbeds assigned to cells affected by disturbance, or in some cases a change to a new general fuelbed. For example, a lodgepole pine fuelbed infested by mountain pine beetle (*Dendroctonus ponderosae* Hopkins, 1902) might first become a stand mainly of snags, and within 10–15 years succeed to open-canopy Douglas-fir saplings.

**Fig. 7.** Distribution of canopy cover from MODIS vegetation continuous fields (VCF) for (*a*) fuelbed 24 (Pacific ponderosa pine – Douglas-fir forest), and (*b*) fuelbed 267 (American beech – yellow birch – sugar maple – red spruce forest). The vertical dotted lines mark the default values in FCCS for the overstory and midstory canopy layers.

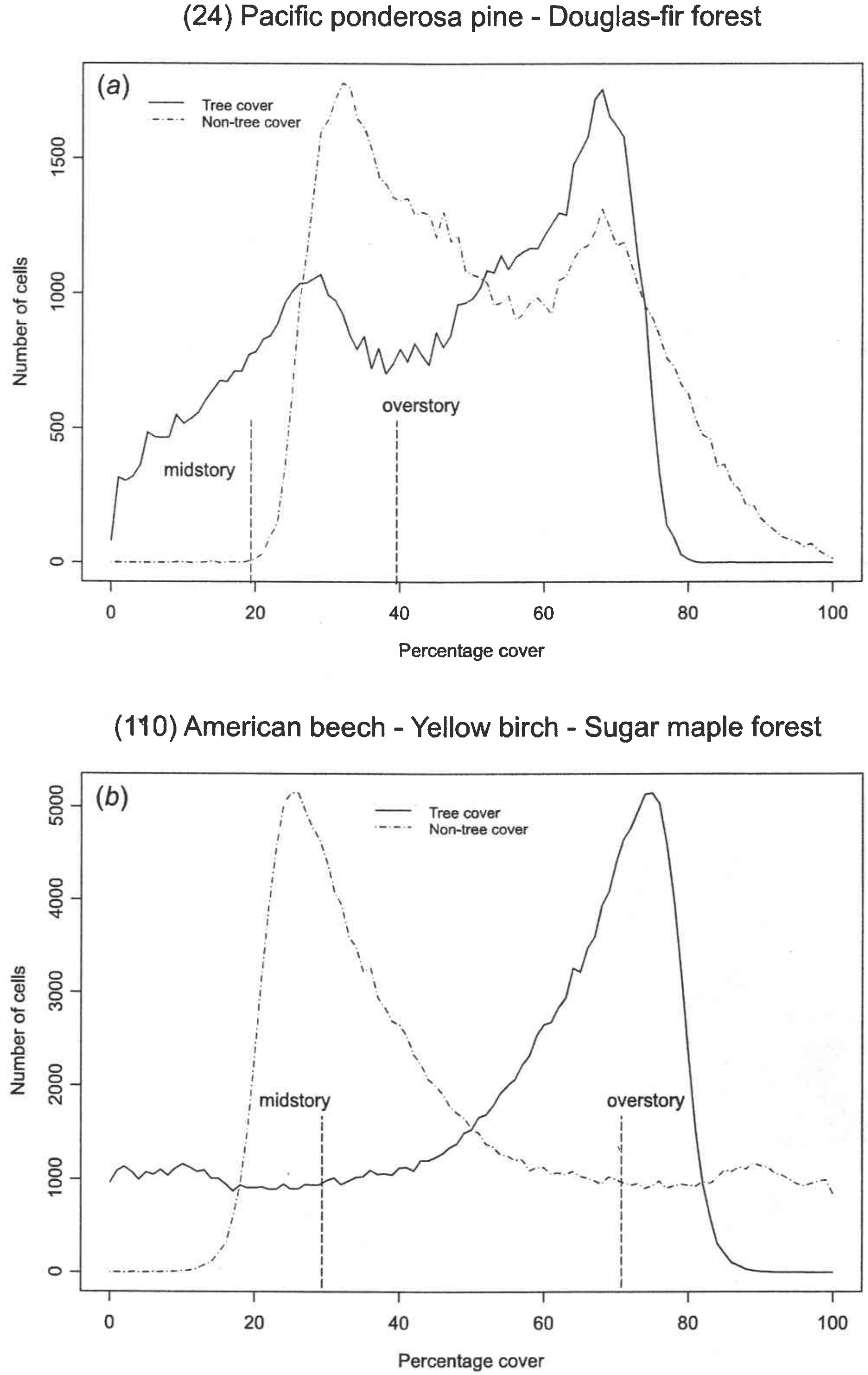


**Fig. 8.** FCCS classification for the Wenatchee National Forest, Washington State, at 25 m resolution. The 37 classes on the map include (the last) three that do not represent an actual fuelbed.

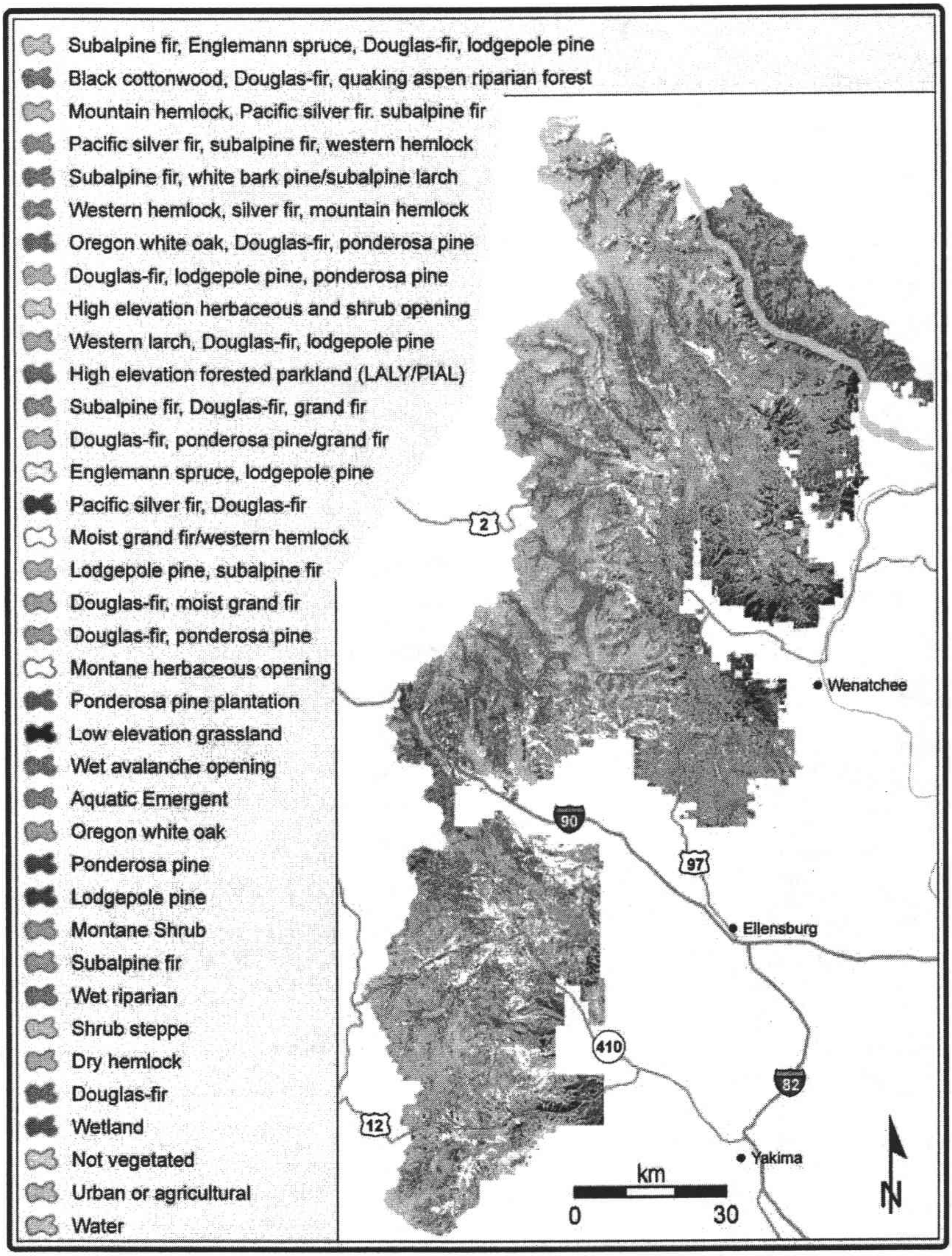


**Table 4.** The most common (>1 000 000 cells) and rarest (<10 000 cells) fuelbeds on the Wenatchee National Forest map.

| | No. of cells |
|---|---|
| **Common fuelbeds** | |
| Western hemlock, Pacific silver fir, subalpine fir | 2 233 445 |
| Mountain hemlock, Pacific silver fir, subalpine fir | 1 558 847 |
| Douglas-fir, ponderosa pine | 1 463 399 |
| Moist grand fir, western hemlock | 1 366 236 |
| Nonvegetated | 1 301 893 |
| Montane herbaceous opening | 1 146 366 |
| **Rare fuelbeds** | |
| Oregon white oak | 229 |
| Wet avalanche opening | 278 |
| Engelmann spruce, lodgepole pine | 1 732 |
| Oregon white oak, Douglas-fir, ponderosa pine | 5 098 |
| Dry hemlock | 6 083 |

### Limitations

The mapping rules were based on qualitative reasoning, which would be more problematic to replicate than if there were clear quantitative guidelines, even though a generic framework was adopted to ensure consistency. We found that the generic rules often allowed for several possibilities for fuelbeds; often two or more appeared to be nearly equally likely. A potential solution to this would be to introduce a fuzzy classification scheme (Krishnaswamy et al. 2004; Tapia et al. 2005), which would assign partial membership in two or more fuzzy sets (in this case, fuelbeds) to any cell whose combination of classes from the vegetation layers suggested more than one possible fuelbed.

Fuzzy classification would enable one to represent subcell heterogeneity, at least indirectly, a significant issue when cells are 1 $km^2$ and fuels are known to vary at scales of tens of meters. This of course would be only a proxy for real subcell heterogeneity, unless the vegetation base layers, also at 1 $km^2$, were fuzzy classifications. If the cover-type layer (Schmidt et al. 2002) or the future vegetation layers were the result of a fuzzy classification, then derivative layers such as our fuelbed classification could take full advantage of fuzzy methods.

Maps can be deceptive in that they give a false sense of accuracy, particularly if they are drawn at much coarser resolution than the processes with which they are associated, e.g., fuel succession. Applying mapped data at inappropriate scales almost guarantees misleading inferences. For example, our 1 km map is appropriate for national-scale air-quality modelling (see the following), but not for local assessments of fuel heterogeneity, let alone stand-level fire-behavior modelling. Conversely, as we note above, traditional accuracy assessments that use fine-scale data to validate a coarse-scale classification are similarly misleading.

### Applications to modelling and management

Any attribute associated with a class (fuelbed) can be mapped at the same resolution as the class. FCCS maps are particularly rich in attributes. Not only can the default fuel loads for each of 16 categories of fuels be mapped, but also any output from the FCCS calculator (Riccardi et al. 2007*b*) can be similarly mapped. For example, total available fuel, associated with the FCCS fire potentials (Sandberg et al. 2007), can be estimated across the CONUS via a lookup table produced by the FCCS calculator (Fig. 9).

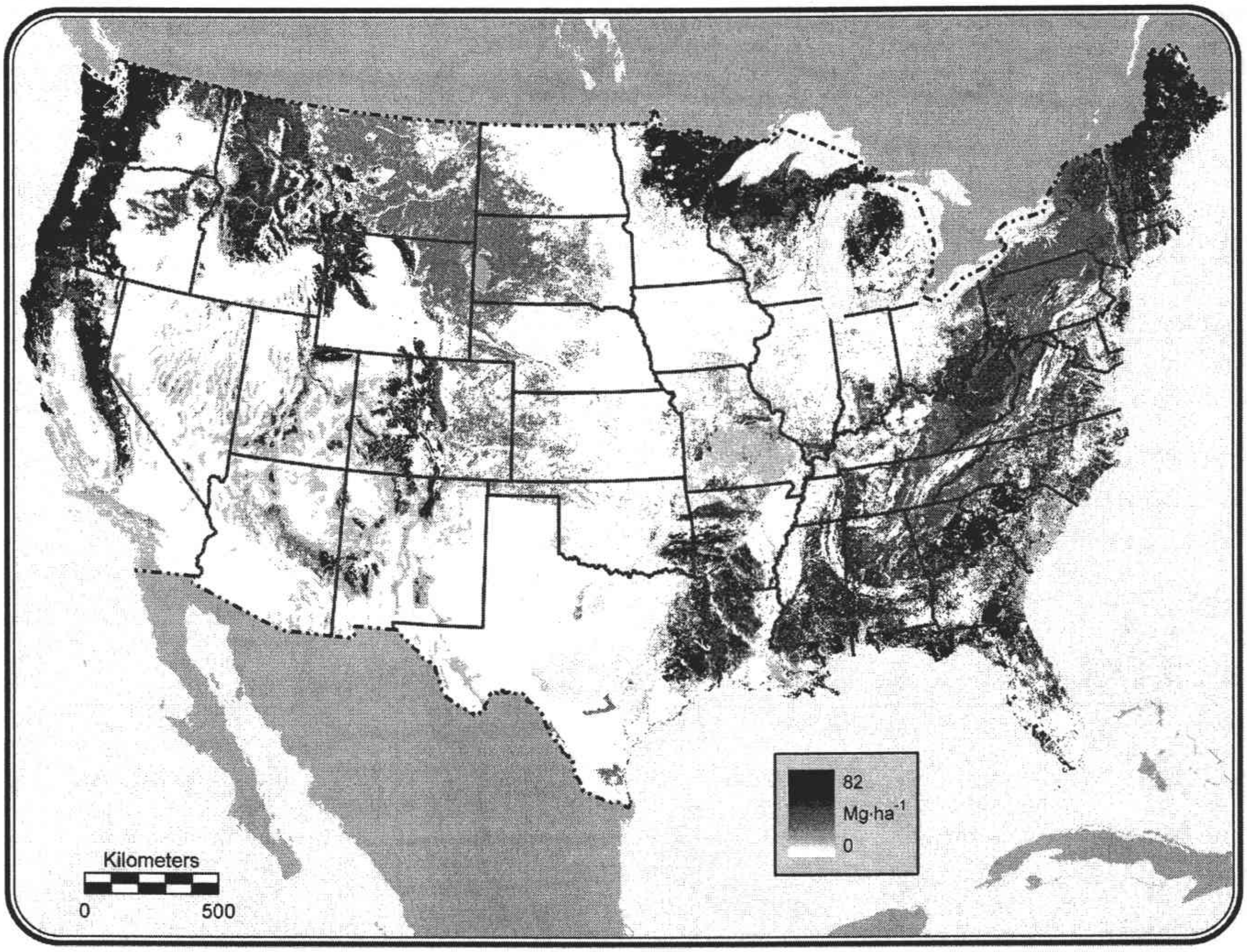
Mapped FCCS attributes can provide input layers for current and future modelling efforts at multiple scales. The US Environmental Protection Agency (US EPA) is using the CONUS FCCS map, in conjunction with the BlueSky-EM modelling framework (available from www.airfire.org/projects/bluesky.html), to develop a national emissions inventory for air-quality modelling. From the FCCS map, we extract a lookup table for default fuel loads in categories used by the BlueSky emissions module. Similarly, the Western Regional Air Partnership (WRAP) (available from www.wrapair.org) is using the CONUS map both for input to modelling and for estimating real-time consumption from fires in their regional fire-tracking system. McKenzie et al. (2006) and Wiedinmyer et al. (2006) used the FCCS map layer within an integrated framework to estimate emissions and air quality in the Pacific Northwest at 12 km resolution and North America at 36 km resolution, respectively.

Over the next century, land-use change is expected to intensify (Walker and Steffen 1997), and wildfire extent and severity are expected to increase (Flannigan et al. 1998; Lenihan et al. 1998; McKenzie et al. 2004; Gedalof et al. 2005). Modelling of carbon dynamics in response to climatic change and disturbance will require ground-based estimates of fuels at broad scales to complement satellite-based estimates. Maps like the FCCS layer that can be updated efficiently and regularly can contribute a key ingredient to continental- and even global-scale models.

On the Wenatchee National Forest, the 25 km resolution fuelbed map provides an input layer for landscape fire modelling that captures the spatial variability of fuels better than standard fuel models. Not only can the values for some fuel categories in individual cells be tuned using quantitative vegetation layers such as developed by the IVMP (see the previous section), but all categories of fuels, including those opaque to remote sensing, can be represented stochastically in a model based on an underlying probability distribution associated with each category in each fuelbed. For example, in our evaluation exercise we assigned 59 CVS plots to the general Douglas-fir – moist grand fir fuelbed (Table 2) and 68 to the general subalpine fir, Engelmann spruce, Douglas-fir, lodgepole pine fuelbed. Distributions of fuels within the CVS plots can be used to generate landscape distributions of fuels in each category, either independently or using a procedure such as a Gibbs sampler (Casella and George 1992), which samples from joint probability distributions where the covariates (fuel categories) are correlated. The ensuing landscape distributions of fuel loads provide both unbiased estimates of total abundance and a realistic representation of their variability. Furthermore, such sampling can be repeated, enabling *ensemble* simulations of landscape fire rather than single realizations with no variability and thus no estimates of uncertainty.

US national fire policy prescribes fuel-reduction treatments across the CONUS, focusing on ecosystems considered to have departed from their historical condition (Fulé et al. 1997; Landres et al. 1999). Fire regime condition class (FRCC) (Schmidt et al. 2002; Hann and Strohm 2003) pro-

**Fig. 9.** Total available fuel for the conterminous USA, based on default values from FCCS fuelbeds.




vides a simple ordinal scale (1–3) for assessing departures, and Schmidt et al. (2002) assigned FRCCs across the CONUS at 1 km resolution using an aggregated version of the Küchler (1964) map of potential natural vegetation. The FCCS national map provides a quantitative alternative to FRCCs via the fire potentials (Sandberg et al. 2007), while maintaining FRCC as a fuelbed attribute (Ottmar et al. 2007) that can be mapped across the same domain.

At the regional scale, on US national forests and districts within forests, managers can use FCCS-based maps as planning tools because their forest-wide coverage with fine resolution matches the scale of forest plans (R. Harrod, personal communication, 2006). The ability to create *custom fuelbeds* within the FCCS (Ottmar et al. 2007), facilitates the quantitative evaluation of fuel-treatment scenarios across the landscape. For example, one might concentrate thinning operations in high-density young forests with ladder fuels, such as represented by the Douglas-fir, grand fir fuelbed OW022 (Table 2). The FCCS map could easily be modified, via the FCCS editor and the custom fuelbed option, to reduce understory live fuels in 5% of the cells assigned to this fuelbed, potentially rearranging the spatial pattern (as represented by the map) of high fuel loads in the Douglas-fir, grand fir forest type. Attributes of this new configuration related to fire effects or fire hazard can be computed and their aggregate properties across the domain compared to output from other scenarios.

The hierarchical scheme of the FCCS enables a crosswalk to existing and future spatial data layers using straightforward decision rules. Fuelbed attributes such as vegetation cover and fuel loads can likewise be matched to quantitative spatial data layers. Dynamic fuel mapping is necessary as we move into the future with rapid climatic and land-use change, and possibly increasing disturbance extent and severity. The rule-based methods described here are well suited for updating with new spatial data, to keep local, regional, and continental scale fuel assessments current and inform both research and management.

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