Mapping Fuels on the Okanogan and Wenatchee National Forests

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***Abstract**—Resource managers need spatially explicit fuels data to manage fire hazard and evaluate the ecological effects of wildland fires and fuel treatments. For this study, fuels were mapped on the Okanogan and Wenatchee National Forests (OWNF) using a rule-based method and the Fuels Characteristic Classification System (FCCS). The FCCS classifies fuels based on their combustion properties, producing unique "fuel beds," each of which represents a distinct fire environment. Managers on the OWNF identified 187 fuel beds which were consolidated into 40 general fuel beds representing the major vegetation forms (forest vs. non-forest) and species groups. Fuel beds were assigned to each 25-m cell in the forest domain (27,353,425 cells) using decision rules based on a combination of spatial data layers. General fuel beds can then be subdivided into specific structural types using spatial data on canopy cover, quadratic mean diameter, and past disturbances (fires, insects, and management). This rule-based approach allows for the incorporation of more specific data if available or a more general classification if they are unavailable, and for reclassification when new data become available. Key uses of the fuels map include spatially explicit modeling of fire effects and assessment of spatial patterns of fire hazard under different management strategies.*

Introduction

Fuel mapping is a complex and often multi-disciplinary process, potentially involving remote sensing, ground-based validation, statistical modeling, 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 efforts depend both on objectives and availability of spatial data layers. For example, input layers for mechanistic fire behavior and effects models must have as high resolution (≤ 30 m) as possible (Keane and Finney 2003).

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 loadings 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 modeling, 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.

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

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 qualitative estimates. 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 loadings change with succession, in response to climatic variability, or after disturbance. Quantitative fuel maps can become obsolete rather quickly. In order 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 FCCS for fuel mapping on the Okanogan (ONF) and Wenatchee National Forests (WNF) at 25-m resolution. We focus on the process of assigning a unique *fuel bed* (Riccardi et al., in review) to each mapped cell in a spatial data layer and show how the classification scheme in FCCS, based on dominant vegetation, facilitates the use of existing GIS layers in developing classification rules and ongoing updates of fuel bed maps as new GIS layers become available. We briefly discuss how assigning actual fuel loads to cells can proceed. Finally, we discuss applications of FCCS-based fuel maps for both modeling and management.

Methods

Study Area

The Okanogan (690,400 ha.) and Wenatchee National Forests (890,000 ha.) are in north central Washington State extending from the crest of the Cascade Range eastward to savanna-steppe and agricultural lands. Near the crest 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. The Okanogan highlands portion of the ONF lies further east and topography there differs from the western portion by having more moderate slopes and broad rounded summits. Conifer species dominate, notably subalpine fir (*Abies lasiocarpa*) and mountain hemlock (*Tsuga mertensiana*), at higher elevations and ponderosa pine (*Pinus ponderosa*) and Douglas-fir (*Pseudotsuga menziesii*) at lower elevations.

Spatial Data Layers

We used GIS layers developed from a variety of sources and archived by the ONF and WNF. We selected the best available (highest level of local manager confidence) spatial data layers for each forest so techniques and methods differed based on the layers chosen. ArcGIS 9.0 (ESRI 2005) was used for all GIS computations.

For the WNF we used a 25-m raster layer (R6) and a photo-interpreted polygon layer (WenVeg) of cover type. The R6 layer comprises 6 cover types from a direct classification of LANDSAT TM imagery and 9 forested cover types from an interpretation of the cover classes in terms of potential natural vegetation (Lillybridge et al. 1995). The WenVeg layer 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 less than 1 ha to 28,000 ha, but with only 18 polygons larger than 4,000 ha. Many polygons were validated by site visits or expert local knowledge of ecologists on individual forest districts. The R6 layer was converted to polygons, then overlain with the WenVeg layer. We created a new coverage of the combined polygons whose attribute table retained the attributes of the original layers.

For the ONF we used a 30-m resolution raster layer of modeled hierarchical potential vegetation consisting of 10 vegetation zones (VZ) subdivided into 42 plant association groups (PAG), and a 25-m resolution raster layer of 36 cover types classified from LANDSAT TM imagery (USU 1997). Forest managers on the ONF conducted an accuracy assessment of the USU LANDSAT TM imagery and reclassifications were done when necessary (K. Davis, personal communication, 2006). The 30-m resolution PAG layer was resampled to 25-m and the resampled PAG layer and the USU layer were overlain and combined to create a new raster layer of all possible combinations of PAG and USU cover types.

Fuel Bed Development

Forest managers from the ONF and WNF collaboratively designed 187 fuel beds with distinct species composition, stand structure, and disturbance histories. We aggregated these into 35 general fuel beds based on forest composition, within which one or more structural or age classes could be distinguished (for example, table 1). Additional spatial data on disturbance history, canopy cover, and stand structure can be used to distinguish the 187 specific fuel beds (see Discussion).

Table 1—Sub-categories of a generic fuel bed (Douglas-fir, moist grand fir) on the Okanogan and Wenatchee National Forests based on structure, age class, and disturbance.

Fuel bed ID	Age range (yrs)	Structure	Change agent
OW020	0-30	Created opening	Wildfire
OW021	30-60	Seedlings & saplings	Pre-commercial thin
OW022	30-60	Seedlings & saplings, high density & load.	None
OW023	60-90	Poles	Selection cut and burn
OW024	60-90	Poles	None
OW025	90-200	Multi-layer	Selection cut & burn
OW026	90-200	Multi-layer, high density & load.	None
OW027	Over 200	Layered mature, medium density & load.	None
OW028	Over 200	Layered mature, high density & load.	None
OW029	Over 200	Open parkland, low density & load.	None
OW030	Over 200	Open parkland, medium density & load.	None

We used 1,490 plots from the USFS Pacific Northwest Region Current Vegetation Survey (CVS) on ONF and WNF to determine if the designated fuel beds adequately represented the likely species combinations. Some species and species combinations were poorly represented by the original 35 general fuel beds, so we added 5 general fuel beds. A limiting factor of using available spatial data is that some species are difficult to map due to the resolution of the data layers. For example, the initial list included fuel beds dominated by both whitebark pine (*Pinus albicaulis*) and subalpine larch (*Larix lyallii*), but the spatial layers lumped these species into one high-elevation parkland classification, so we added a corresponding high-elevation parkland fuel bed.

Fuel Bed Assignment

We assigned a fuel bed to each 25-m cell in the forest layers using a rule-based approach that incorporated the GIS layers for each national forest. The overarching criterion for the WNF was that the fuel bed 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 fuel beds, however, we used the R6 layer to narrow possibilities for dominant species. For each R6 cell within each WenVeg polygon, the most likely fuel bed was assigned. Figure 1 illustrates the logic for three distinct fuel bed assignments within

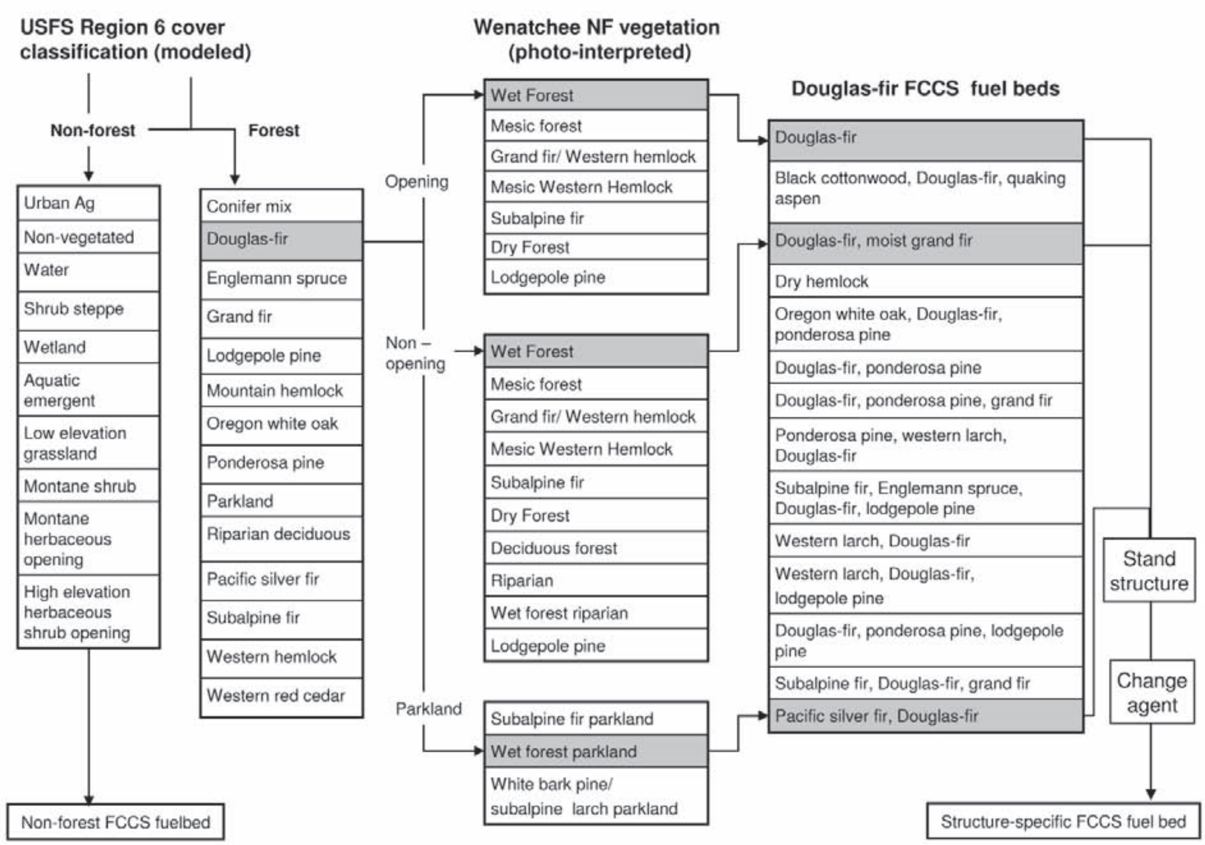

Figure 1—Example of logic for identifying a generic FCCS fuel bed for combinations of satellite-mapped vegetation and photo-interpreted vegetation on the Wenatchee National Forest.

the cover class "Douglas-fir" in the R6 layer, depending on the WenVeg polygon within which they fall. The LANDSAT-based cover type classification was the primary GIS layer used to assign fuel beds on the ONF because it was a measure of current vegetation for which an accuracy assessment was completed. If the cover type was not specific, it was further refined using the VZ, and if the cover type classification was common and coincided with many PAG, the PAG were also used to assign the most likely fuel bed. Figure 2 illustrates the logic for assigning fuel beds to the "Douglas-fir" LANDSAT-based cover type in the USU layer.

We used the CVS plots to validate the fuel bed assignments based on the remotely sensed data. The objective of this validation was to compare the frequency distribution of fuel beds represented in the spatial data layer with that of fuel beds represented by the CVS plots, not to match individual cells to individual plots. First we assigned a fuel bed 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 hectares). To compare fuel beds at a commensurate scale, only data from the center plot were used, which corresponded to one 25-m grid cell.

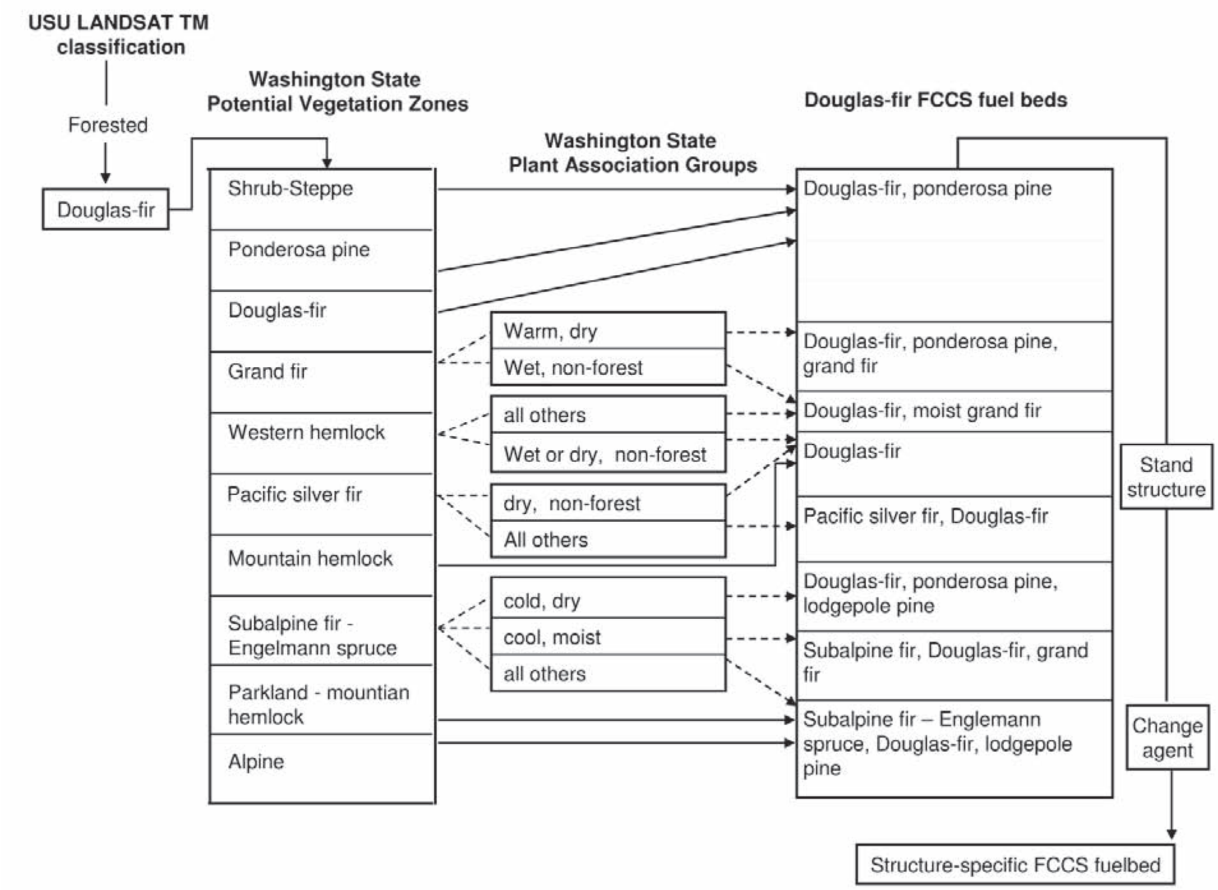

Figure 2—Example of logic for identifying a generic FCCS fuel bed for combinations of satellite-mapped vegetation and modeled potential vegetation on the Okanogan National Forest.

Results

The combination of 9 R6 modeled vegetation types and 6 LANDSAT-based cover types with 26 classes from the photo-interpreted WenVeg layer yielded 34 general fuel beds (figure 3) including 6 common (greater than 1,000,000 cells) and 5 rare (less than 10,000 cells) fuel beds (table 2). "Western hemlock, Pacific silver fir, mountain hemlock" was most prevalent, accounting for 14 percent of the mapped area (2,233,445 cells). The commonness reflects both the range of vegetation and the range of possible fuel bed choices. For example, fuel bed choices for the WNF included only two dominated by western hemlock and only one dominated by mountain hemlock, but five dominated by Douglas-fir. Five fuel beds with western larch or western white pine as a significant component were not mapped on the WNF due to the limited resolution of the original GIS layers. These species are problematic for the rule-based logic of assigning fuel beds on the WNF, because even when present, they rarely dominate stands or represent the climax species.

As would be expected, the rarest fuel beds reflect the species with more restricted ranges in the study area: Oregon white oak (*Quercus garryana*) and Engelmann spruce (*Picea Engelmannii*). The WNF map showed areas of greater homogeneity in the middle elevations on the west side of the forest where "Western hemlock, Pacific silver fir, mountain hemlock" and "Mountain hemlock, Pacific silver fir, 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 fuel bed options and a more patchy disturbance regime creating finer-scale spatial variability.

The combination of PAG and LANDSAT-based cover types yielded 36 fuel beds on the ONF (fig. 4)including 4 common (greater than 1,000,000 cells) and 6 rare (less than 10,000 cells) fuel beds (table 3). The most frequently occurring fuel bed was "Subalpine fir, Engelmann spruce, Douglas-fir, lodgepole pine" covering 16 percent of the area (1,776,623 cells). All fuel beds were mapped except the two Oregon white oak fuel beds because the area is beyond its range. The greater specificity of the LANDSAT-based cover type layer on the ONF better captured rare species such as Engelmann spruce, white bark pine, western larch, and western white pine. The greater frequency of these fuel beds reflects both the higher number of categories in the USU LANDSAT layer and the greater abundance of these species on the ONF. The pattern of fuel beds across the ONF domain distinguishes four general areas: (1) the western portion of the forest along the Cascade crest and west of the crest is dominated by the Mountain hemlock, silver fir, subalpine fir" fuel bed, (2) the north east is dominated my lodgepole pine fuel beds, (3) the south east is dominated by Douglas-fir and ponderosa pine fuel beds and (4) the Okanogan highlands is highly variable with the greatest fuel bed heterogeneity.

Validation

Validation of fuel beds on the WNF indicated a bias towards fuel beds composed of late seral species (for example, western hemlock, Pacific silver fir, mountain hemlock) and dry forest fuel beds were under-represented (for example, Douglas-fir, ponderosa pine, grand fir) (figure 5). This was not entirely unexpected as one of the spatial data layers was partially developed from modeled potential vegetation. To adjust for this bias, we revisited each classification rule, under the assumption that a systematic shift towards the early seral species in the R6 plant associations would correct the bias. However,

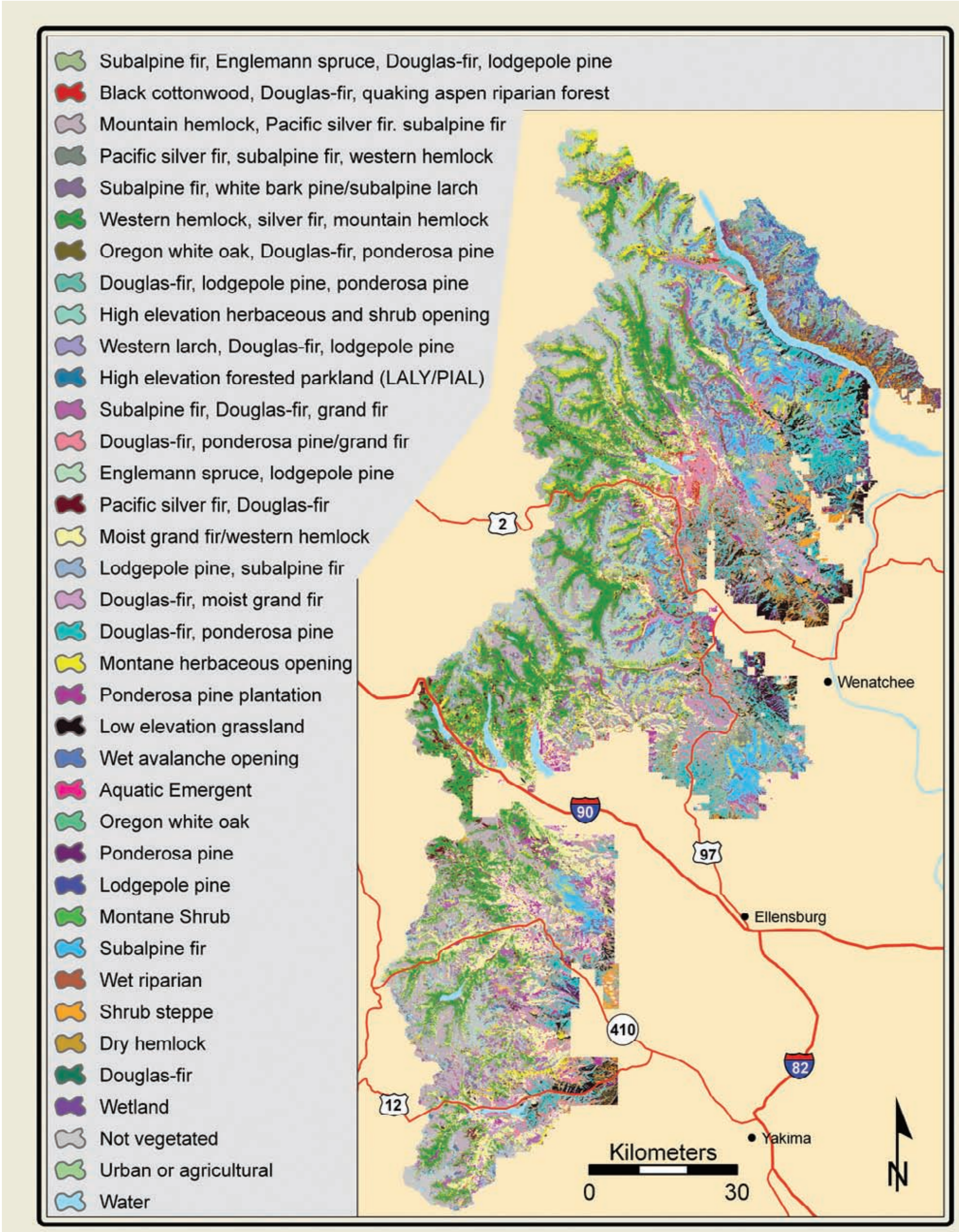

Figure 3—Fuel bed classification for the Wenatchee National Forest, Washington state, at 25-m resolution.

Table 2—Percentage area of the common (> 1,000,000 cells) and rarest (< 10,000 cells) fuel beds in the Wenatchee National Forest map.

Common fuel beds	Area (%)
Western hemlock, Pacific silver fir, mountain hemlock	13.84
Mountain hemlock, Pacific silver fir, subalpine fir	9.66
Douglas-fir, ponderosa pine	9.07
Moist grand fir, western hemlock	8.47
Non-vegetated	8.07
Montane herbaceous opening	7.10
Rare fuel beds	
Dry hemlock	0.038
Oregon white oak, Douglas-fir, ponderosa pine	0.032
Engelmann spruce, lodgepole pine	0.011
Wet avalanche opening	0.002
Oregon white oak	< 0.001

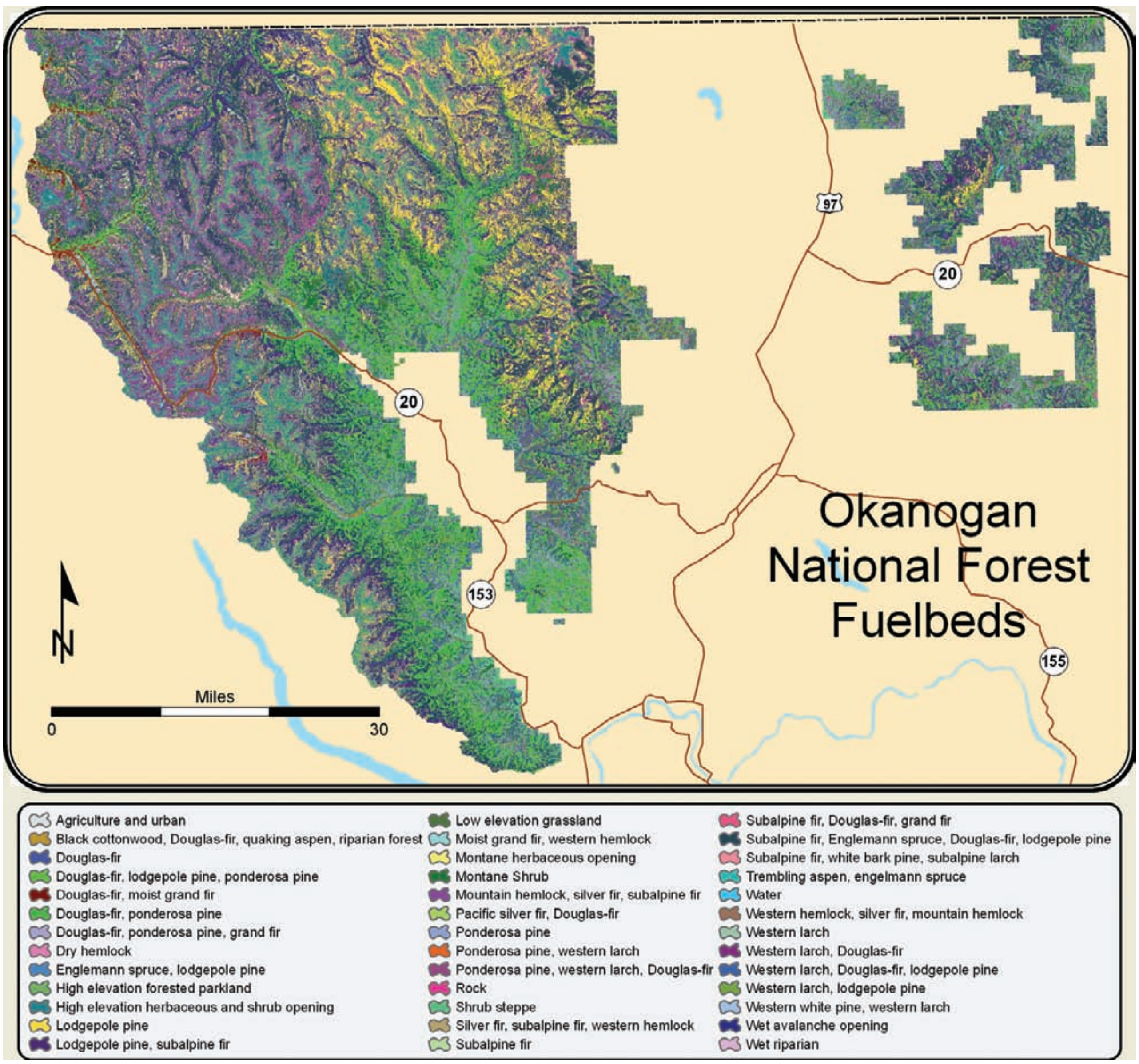

Figure 4—Fuel bed classification for the Okanogan National Forest, Washington state, at 25-m resolution.

Table 3—Percentage area of the most common (> 1,000,000) and rarest (< 10,000) fuel beds in the Okanogan National Forest map.

Common fuel beds	Area %
Subalpine fir, Engelmann spruce, Douglas-fir, lodgepole pine	15.84
Douglas-fir, ponderosa pine	14.29
Lodgepole pine	9.92
Lodgepole pine, subalpine fir	9.10
Rare fuel beds	
Low elevation grassland	0.079
Dry hemlock	0.054
Western larch	0.031
Western larch, lodgepole pine	0.024
Wet riparian	0.016
Ponderosa pine, western larch	0.006

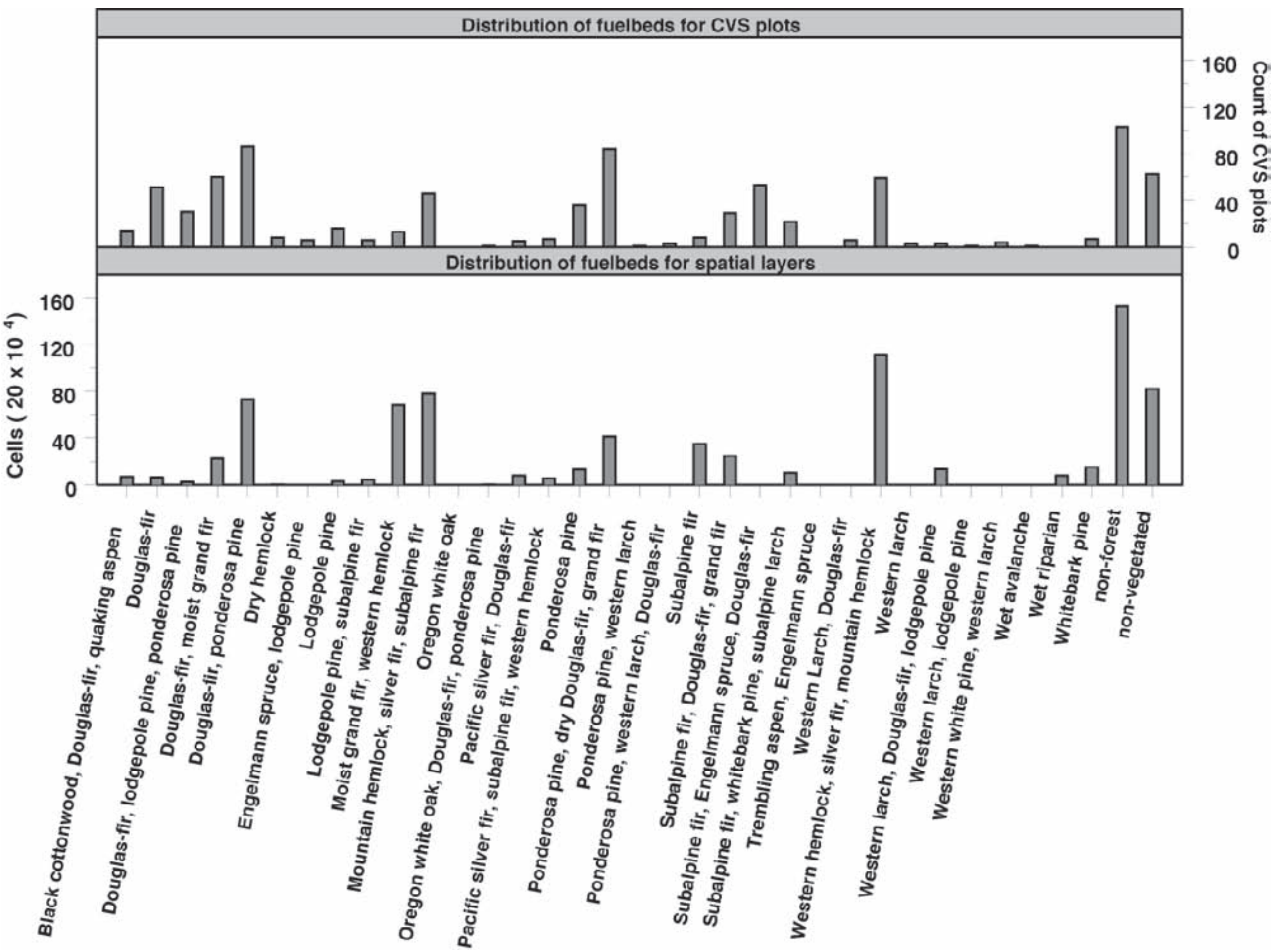

Figure 5—A comparison of fuel bed distributions from two sources on the Wenatchee National Forest, 835 CVS plots and remotely-sensed data.

the only rules amenable to this adjustment represented a small enough number of cells that the distributions changed only slightly toward lesser bias.

Validation with the CVS plots on the ONF indicated that the fuel bed classification process better captured the spatial distribution of fuel beds on the ONF than on the WNF. The distribution of fuel beds represented by the spatial data layers on the ONF was remarkably similar to that of the CVS plots with a few exceptions (figure 6). Classification of the spatial data layers over represented the "lodgepole pine" and "lodgepole pine, subalpine fir" fuel beds. Conversely two Douglas-fir fuel beds, "pure Douglas-fir" and "Western larch, Douglas-fir," occurred with much greater frequency in the CVS plots than in the classification of the combined spatial data layers.

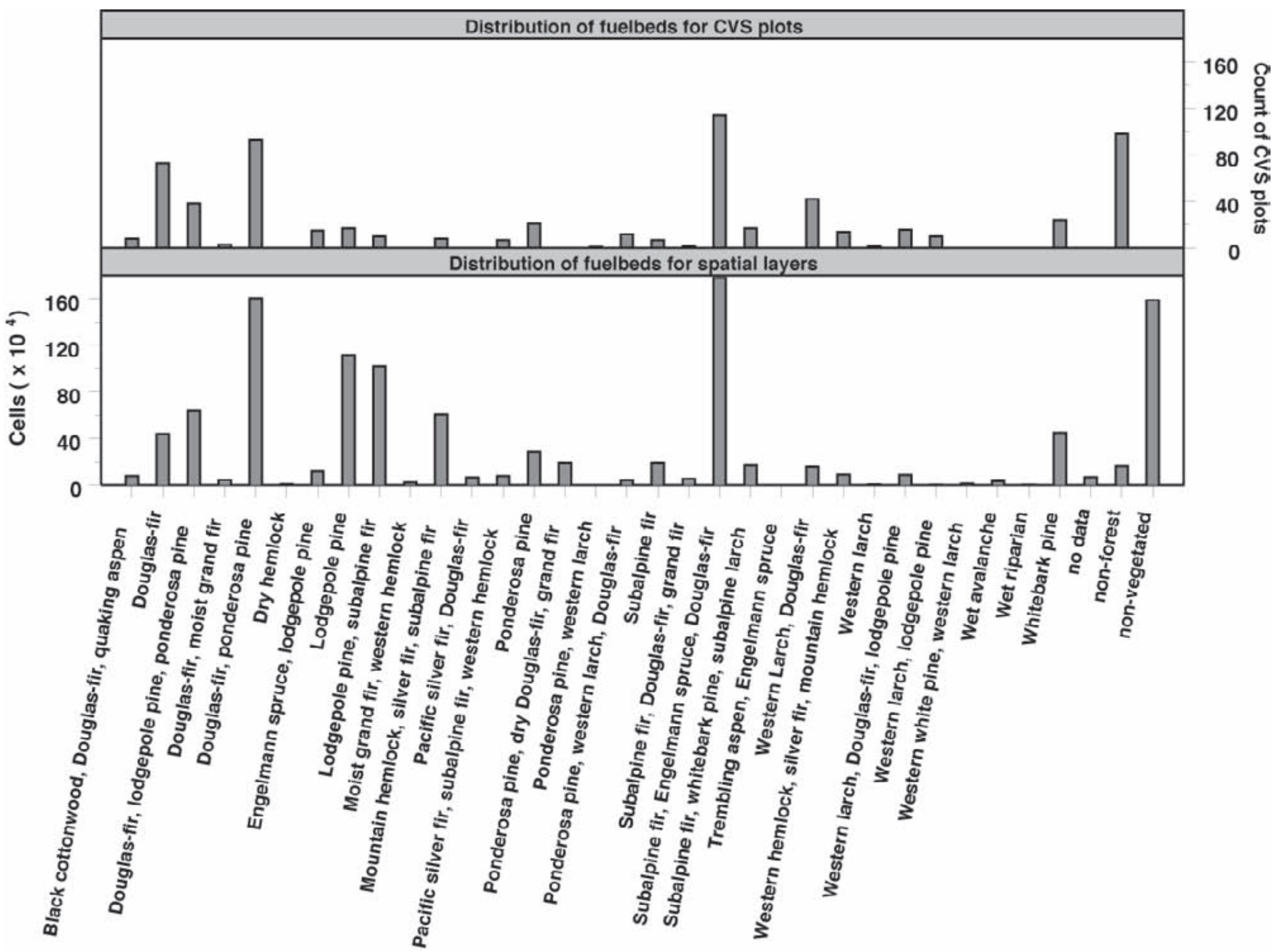

Figure 6—A comparison of fuel bed distributions from two sources on the Okanogan National Forest, 655 CVS plots and remotely-sensed data.

Discussion

We completed classification of FCCS fuel beds on two national forests using a rule-based method that takes advantage of spatial data layers of current and potential vegetation. In order to be useful for management and modeling applications, these fuel beds must be translated into fuel loads by fuel type (for example, canopy, live surface fuels, dead surface fuels, litter and duff). The FCCS has default values so the implementation of mapping fuel loads can proceed by assigning 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 loadings, it clearly underestimates the variability of fuels across a region.

We can use high-resolution quantitative GIS layers that cover the WNF and ONF to quantify the attributes of each fuel bed. The Interagency Vegetation Mapping Project estimated both canopy cover and quadratic mean diameter (QMD) at 30-m resolution across the forest from LANDSAT TM imagery. The USU LANDSAT TM imagery included layers of canopy cover and stand size (d.b.h class) at 30-m resolution across the ONF. These layers provide structural information that can be linked to specific fuel beds (for example, table 1), thereby refining estimates of fuel loadings for each cell to the more precise default values associated with the specific fuel beds. 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., in review) to account for modification of fuel beds 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 base maps we developed can be updated to implement a change agent for fuel beds assigned to cells affected by disturbance, or in some cases changed to a new general fuel bed, by incorporating spatial data layers on fire and insect disturbances and logging activities

Applications to Modeling and Management

Any attribute associated with a fuel bed can be mapped at the same resolution as the fuel bed. Not only can the default fuel loads for each of 16 categories of fuels be mapped, but also any output from the FCCS calculator can be similarly mapped. Mapped FCCS attributes can provide input layers for current and future modeling efforts at multiple scales. Managers can use these FCCS-based maps as planning tools for the national forest, because their forest-wide coverage with fine resolution matches the scale of forest plans (R. Harrod, personal communication, 2006). The ability to customize fuel beds within FCCS facilitates the quantitative evaluation of fuel-treatment scenarios across the landscape.

The hierarchical scheme of FCCS enables a crosswalk to existing and future spatial data layers using straightforward decision rules. Fuel bed 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 we describe here are well suited for updating with new spatial data, to keep local and regional scale fuel assessments current and inform both research and management.

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