Final Report to the Governing Board, Joint Fire Science Program

Project 01-1-4-09

A Novel Approach to Regional Fuel Mapping: Linking Inventory Plots with Satellite Imagery and GIS Databases Using the Gradient Nearest Neighbor Method

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Introduction

This report summarizes accomplishments, key findings, and final products from Project 01-1-4-09 funded by the Joint Fire Science Program, "A novel approach to regional fuel mapping: linking inventory plots with satellite imagery and GIS databases using the Gradient Nearest Neighbor method" (also referred to as the 'GNNFire' project). This report is accompanied by DVDs containing all project deliverables in electronic format (see Appendix 4). This report and final products also can be viewed and downloaded from our website, *http://www.fsl.orst.edu/lemma/gnnfire*. LEMMA is the Landscape Ecology, Modeling, Mapping, and Analysis research team responsible for GNNFire and several other projects.

Project Description

This project investigated use of the Gradient Nearest Neighbor (GNN) method for mapping vegetation and fuels in three contrasting ecoregions in the Western US. The GNN method uses multivariate direct gradient analysis to link field plot data, satellite imagery, and maps of environmental variables in a raster GIS database. Individual pixels are associated with forest inventory plots that have the most similar spectral and environmental characteristics. A suite of detailed plot variables is then imputed to each pixel, allowing simultaneous and consistent predicting of a wide range of vegetation attributes. Because the plot-level variables are attached to the GIS database, a wide array of summary variables and classifications can be portrayed to meet different objectives.

At the time of our proposal, GNN had been successfully used to generate forest vegetation maps suitable for detailed, stand-level modeling across a large multi-ownership province in coastal Oregon. However, the method had not been tested in other ecoregions, nor specifically for mapping fuels. Accurate regional maps of vegetation and fuels are increasingly needed for assessing fire hazard, planning fuel management, and modeling the behavior and effects of prescribed burns and wildfires. In order for such maps to be useful to land managers, they must accurately predict a large number of vegetation and fuel attributes across heterogeneous, multi-ownership landscapes. We hypothesized that the flexibility of GNN, combined with its capacity for multivariate spatial predictions, would make it particularly useful for developing regional fuels maps.

This study examined the utility of GNN for predicting fuel patterns in three prototype landscapes in coastal Oregon, northeastern Washington, and the California Sierra Nevada, which encompass vegetation from dense forests to rangelands in a mosaic of natural and human-dominated environments. Our two primary objectives were: (1) Develop a methodology for using multivariate statistical models and imputation to simultaneously map fuel characteristics, species composition, and forest structure as continuous variables across environmentally heterogeneous, multi-ownership landscapes using inventory plot data, remote sensing imagery, and environmental GIS data layers; and (2) apply this methodology to generate vegetation and fuel maps for pilot landscapes located in three distinctive ecoregion divisions in the western US.

<u>Success in Meeting Original Project Objectives</u>

We met both of our primary study objectives. We developed a viable methodology for using GNN to successfully map both vegetation and fuels. The major new elements of this methodology include:

1. Procedures for developing consistent estimates of dead fuel loadings, surface fuel models, and crown fuels variables for large plot databases incorporating data from multiple inventories.

2. Methods for integrating plot inventories and remote sensing imagery from multiple dates into a consistent modeling framework.

3. New methods of accuracy assessment that are specific to imputation methods.

4. Use of GNN for mapping gradients in species composition and environment, which may prove useful to regional assessments of potential vegetation, fire regime, and fire regime condition class.

We applied these methods to map fuels and vegetation in forested landscapes of our three study areas using GNN, and integrated the GNN maps with ancillary maps of nonforest and chaparral (California only) to develop complete spatial coverages. This report summarizes our key research findings and our research products and deliverables.

A secondary objective in our proposal was to link our GNN databases and maps to the Fuel Characteristic Classification System (FCCS) (*http://www.fs.fed.us/pnw/fera/fccs/*). While this deliverable is close to completion, it is not final at the expiration of our grant period. We are behind schedule because the FCCS was well behind their own production schedule, and because the FCCS system does not contain the user functionality we were told to expect at the time the proposal was written and additional development efforts were required on our part. The batch mode for calculating FCCS fuelbeds and fire potentials requires that data adhere to the FCCS XML schema. This required that we develop a translator for converting standard inventory data to the XML schema used by FCCS for their fuelbeds. We are close to completing this work and hope that it will be readily transferable to other field plot databases.

Key Findings

- <u>GNN models can be 'tuned' to increase map accuracy for different types of plot attributes.</u> The use of multivariate statistics and imputation by GNN results in unique spatial modeling properties. As with most predictive models, alternative model forms can be specified to optimize for different objectives and outcomes. Indeed, this flexibility is a strength of GNN relative to other approaches of vegetation mapping. In our GNN modeling, we learned that we can greatly influence the accuracy and appearance (spatial patterning) of the final maps by changing the response variables used in model development, and the spatial resolution of the independent variables – particularly those derived from Landsat TM imagery. Different

GNN models can be specified based on study objectives and intended map applications. Rather than provide one GNN map for each study area, we have developed four models that illustrate major variations in model form: (1) species model, (2) species-size model, (3) structure model of fine grain, (4) structure model of coarse grain. Short descriptions of these four kinds of GNN models are included in the summary of deliverables. We expect that each model has advantages for certain applications, and seek feedback from map users as they exercise the maps.

- The major factor limiting site-level map accuracy is the capability of Landsat TM imagery for characterizing forest structure. We assessed GNN map accuracy through cross-validation, in which map predictions were compared to ground measurements at plot locations. This local-scale prediction accuracy was better overall for measures of forest structure in Oregon than in Washington or California, but differences varied among forest attributes. The potential for accurately modeling fine-scale variability appears to be greatest in closed-canopy, even-aged, conifer-dominated forests like those characteristic of coastal Oregon. We attribute this primarily to the reduced capabilities of Landsat TM data in discriminating many forest attributes within sparse-canopy forests, due to mixed reflectance signals within pixels of soil and other ground surfaces with vegetation. In future mapping efforts, incorporating other sources of remotely sensed imagery with high spatial and/or spectral resolution (e.g., ASTER or LIDAR imagery), as well as multi-date Landsat imagery, may be particularly important for mapping forest structure and fuels in drier, open-canopied forest types.

- The GNN method is very effective at maintaining the range of variability of individual variables at the regional scale, as well as the covariance structure of multiple variables at the local scale. As an imputation method, GNN does not truncate the range of variability in the response variables like multiple regression and other parametric methods. Additionally, within-stand covariance structure is maintained when a single nearest-neighbor plot is imputed to each pixel. Therefore, GNN maps are well suited to applications where these map characteristics are important. In regional fire risk assessments, for example, it is most important to identify sites with extreme values of multiple variables (e.g., high surface fuel accumulations, high canopy bulk density, and low height to canopy base). These advantages of GNN imputation maps may come at the cost of prediction accuracy for local sites.

- Environmental variation strongly influences the form and accuracy of GNN models. In areas where environmental gradients are long and strong, the environmental component of the GNN model (which is more strongly correlated with species composition) plays a stronger role in imputation (i.e., selection of nearest-neighbor plots) than does the Landsat component (which is more strongly correlated with forest structure). Environmental gradients in the Washington and California study areas were longer and stronger than in Oregon. Consequently, accuracy of our species predictions (presence/absence) was better in California and Washington than in Oregon, whereas prediction accuracy for measures of forest structure was better in Oregon.

- We developed new methods of accuracy assessment that are specific to imputation methods. The ranking of candidate plots for imputation by their separation distance in multivariate

space provides for several innovative accuracy assessment products. Using the interplot distributions of distances, we can quantify the number of plots within a similarity threshold. We can use those similar plots to assess the amount of natural variability exhibited by individual attributes for a particular environmental envelope, thus providing a map of natural variability. We also can assess the number of inventory plots that bear similarity to a target mapping location and thus the degree to which the data inform predictions about that location. We refer to this product as the sampling sufficiency map. Because we are still evaluating the properties of these measures and their potential usefulness, they are not included in our final report.

- Challenges are ongoing in communicating map accuracy in ways that are relevant to users, and that can help clarify appropriate applications of various maps. The quantification and visualization of map accuracy is complex and multi-dimensional. We continue to seek ways to communicate map accuracy that resonate with users. As developers of regional map products, we frequently encounter skepticism about map usefulness when local or pixel-scale accuracy is poor. Our maps are not appropriate for site-level, operational decisions, but in general should be used to guide planning and policy decisions at broader scales. We expect our ability to characterize GNN map quality in useful ways will evolve as we continue dialogue with map users over time. We are adding a feature on the GNNFire website to register GNN map users so we can follow up and seek feedback on their experiences.

- GNN-Fire vegetation and fuels maps can be applied to carry out regional fire risk assessment using FLAMMAP and FARSITE. The raster GIS datasets produced for the three GNNFire study areas include all of the fuel and vegetation layers that are required for input into the FLAMMAP and FARSITE models (Anderson fuel model, canopy bulk density, height to base of live canopy, canopy cover, and stand height). To assess the potential for using these datasets with FLAMMAP, we split the Oregon Coast Range study area into six subregions and developed a FARSITE/FLAMMAP landscape file for each subregion. FLAMMAP runs were carried out for a range of wind and fuel moisture conditions. Results indicated that the potential for large areas of continuous crown fire was relatively low, mainly because of landscape fragmentation by young hardwood-dominated stands, clearcuts, and non-forested areas. However, several regional 'hotspots' of potential active crown fire behavior under extreme weather conditions were identified.

- We have linked the GNN plot databases to the Fuel Characteristic Classification System (FCCS), but additional work is needed to evaluate reasonableness of the resulting GNN maps. The interface for FCCS (*http://www.fs.fed.us/pnw/fera/fccs/*) is designed to guide users to a default fuelbed, analogous to a stylized fuel model, and allow them to edit that fuelbed for their specific location before calculation of fire potentials. Subjecting inventory data to this editing scheme is excessively time-consuming as each inventory plot could take an hour or more to enter through the appropriate menus. Alternatively, the FCCS system has the capability of calculating fire potentials very rapidly, using a batch mode, if fuelbed files exist in the proper XML data format. We have developed a two step process that converts inventory data to a standard comma delimited format, derivable from any database- or spreadsheet-based data, followed by a translator to convert that data into FCCS fuelbeds in

their XML data format. We are close to completing this work and hope that it will be readily transferable to other field plot databases. We are behind schedule on linking to the FCCS because the FCCS was well behind their own production schedule, and because we were not aware that the FCCS batch mode required conversion of standard inventory data to an XML schema used by FCCS for their fuelbeds.

Key findings related to data limitations

- Nonforest and shrub cover types currently cannot be mapped using GNN due to limitations of regional plot data. The quality of GNN results are limited by the quality of data used in model development. While this is true for any modeling approach, it is especially true for imputation. There are no systematic, field-based samples of nonforest and shrub land cover types across all land ownerships available for any of our study areas. FIA does not install plots in areas classified as nonforest or shrubland. Although we apply GNN wall-to-wall, our data and models are only valid for the forested portions of our study areas. We used maps from ancillary sources to 'mask out' other land cover classes. The quality of available land cover data is mixed, and strongly influences the overall quality and usefulness of the GNN maps for applications to modeling fire hazard and behavior. This is especially true in heterogenous landscapes containing mixtures of nonforest, chaparral, woodland, and forest, such as in our California study area. All of the land cover maps we've examined consistently overestimate the area of nonforest, as determined by comparison with forest/nonforest calls for field plot locations. Examination of the area distributions in our accuracy assessment products (vegclass_error_matrix*.pdf) shows that most confusion in the GNN imputation maps is between nonforest areas and forested areas with sparse canopies. Looking ahead to future applications of GNN, development of more robust methods for mapping nonforest and shrublands for integration with GNN maps is an important research need. Such methods and data may result from LANDFIRE, the next version of NLCD, or other regional mapping projects, but were not available at the time of our study.

- Plot database development remains the single greatest challenge and cost in implementing GNN. Despite progress that has been made towards standardized, regional forest inventories, considerable effort is still required to compile multiple inventories into a single, consistent database that spans all ownerships for regional mapping and analysis. This is particularly true for vegetation components other than live trees, such as understory vegetation, snags, down wood. Many of these vegetation attributes are important to assessing fuel conditions, fire hazard, and fire behavior. For example, we are distributing very few core variables for down wood (Appendix 3) because of inconsistencies across our six component plot databases in minimum size criteria and decay class methodology. At the time of our study, the FIA Annual Inventory had not been fully implemented, but when available these data will represent another positive step towards regional (even national) standardization of vegetation data elements. However, the temporal distribution of Annual plots (spread over 10-15 years within a given geographic location) will present a new challenge for mapping applications that rely on satellite imagery.

- Plot-level data for many fuels variables are insufficient for accuracy assessment using cross-validation. Although it appears that prediction accuracy is poor for fuels variables that are below the forest canopy, and indeed one might expect low accuracy based on models that rely on Landsat data that senses the upper canopy, we have good reason to suspect the validity of our cross-validation for these variables. The cross-validation component of our map accuracy assessment is based on the assumption that the observed (plot) values are 'truth.' In reality, this is not the case for several forest and fuel variables measured on the regional inventory plots. In particular, plot-based measurements of coarse and fine dead fuels are insufficient to characterize the plot or stand. For example, the sample of down wood on individual FIA plots was intended to be combined with other plots to characterize the down wood population within a forest stratum. Transect length is insufficient to reliably estimate down wood present within an individual plot area. Our cross-validation results for these variables therefore should be interpreted with caution.

- There remains much variation and subjectivity in how fuels variables are measured or assigned in the field, including stylized fuel models. We derived our fuel variables and models from field-measured data using the most widely accepted and published methods. However, assigning these variables is still to some extent an art (e.g., assigning fuel models), and empirical approaches such as ours may yield very different results from those assigned via expert opinion. More research is needed to assess the sensitivity of follow-on analyses, such as with FARSITE, to variation in fuel variable calculation method.

- GNN can potentially be applied to any landscape or ecoregion, but map reliability strongly depends on availability of relevant plot and spatial data. In particular, GNN will not yield acceptable map products for undersampled areas. In our study, we initially planned to include Sequoia and Kings Canyon National Parks in our California study area. However, after considerable effort and experimentation, we ultimately concluded that available plot data graciously provided by Park staff was unsuitable for GNN modeling. The provided data had been collected only along highway corridors in the western, low-elevation parts of the Parks, and key variables required for the GNN models, such as understory vegetation and stand age, were not collected. While the Park has an abundance of data on fuels, vegetation and trees, these data lie within different inventories. Our imputation method requires simultaneously sampled attributes within a single inventory (on the same plots). We revised our study area boundary to omit these parks, rather than distribute a map of poor quality. Our experience underscores the value of regional, systematic inventories that sample all ownerships. FIA Annual Inventory plots will soon be available for all National Parks, but were not yet available at the time of our study.

Deliverables

We produced all deliverables listed in our proposal, plus several additional products. Copies of all final products except our website and draft manuscript are provided in electronic format on the enclosed DVDs. The directory structure and file names for final products on the DVDs are in Appendix 4. All products on the DVDs are suitable for distribution and posting to websites. The

final maps and accuracy assessments produced for each of our three study areas using the GNN method also are available for download from our website (*http://www.fsl.orst.edu/lemma/gnnfire*), or will be provided upon request on DVD. Our manuscript is still in preparation, and is expected to be ready for submission to a refereed publication by the end of November 2005. We will provide JFSP a copy of the submitted manuscript at that time.

GNN models and map products

We are providing four alternative GNN models with associated products for each study area, for a total of 12 models. For each model we are providing the gradient (statistical) model, the resulting GNN imputation map, a map of nearest-neighbor distance, and a suite of accuracy assessment products, which are described below.

The four kinds of GNN models are described in more detail in Appendix 1. Briefly, the models vary in their emphasis on species composition vs. forest structure, and in their degree of spatial filtering, which affects fine-scale heterogeneity in the imputation maps. We expect that each kind of model has advantages for certain applications, and we seek feedback from map users as they exercise our maps. The four kinds of GNN models are: (1) species model: emphasizes species composition, and does not use Landsat imagery; (2) species-size model, filtered: a 'hybrid' between the species and structure models, uses Landsat imagery that is median-filtered to reduce fine-scale heterogeneity; (3) structure model, filtered: emphasizes forest structure, uses Landsat imagery that is median-filtered to reduce fine-scale heterogeneity; (4) structure model, unfiltered: same as (3) but uses unfiltered satellite imagery, resulting in more fine-scale heterogeneity. Median filtering consists of moving a nine-pixel window across the image and assigning the median value for the nine pixels to the center pixel.

   Gradient models (CANOCO files).– Documentation of the gradient (statistical) model used in GNN imputation. The documentation consists of the output (*.out) and solution (*.sol) files from canonical correspondence analysis (CCA) from the CANOCO software (version 4.5). The files list the explanatory variables used in the models and their coefficients.

   GNN imputation maps.– Digital GNN imputation map, provided as 30-m-resolution ArcGIS grid, where the grid value is a unique plot number that links to the plot database. Selected fuels and vegetation variables from the plot database are joined as items in the grid to facilitate viewing and exploratory spatial analysis (e.g., in ArcMap or ArcView). Metadata for the fuels and vegetation variables are found in the plot databases. More detailed documentation of methods used in developing the fuels variables as part of this project are in Appendix 2. Descriptions of the core fuels and vegetation variables are in Appendix 3. With the GNN approach, map dates are determined by the vintage of the satellite imagery used to construct them. For the species-size and structure models, which rely heavily on Landsat data, map dates are 2000 (Washington and California) and 1996 (Oregon).

We are distributing 'masked' versions of the GNN maps, where areas of nonforest land cover (and chaparral in California) developed from ancillary data sources have been embedded in the

GNN grids. The GNN models in this study apply only to forest land (areas currently or with the potential to support at least 10% tree cover), because a consistent regional plot sample of nonforest areas is unavailable. For our masks in Oregon and Washington we used 1992 National Land Cover Data (NLCD). In California, the nonforest mask was developed primarily from CALVEG (Classification and Assessment with Landsat of Visible Ecological Groupings) (*http://www.fs.fed.us/r5/rsl/projects/classification/*) data, with small areas of missing CALVEG data filled in with NLCD data. Unmasked versions of the GNN maps are available upon request, for users who would like to apply a nonforest mask of their own choosing.

GNN nearest-neighbor-distance maps.– Digital map where the grid value is the distance to the nearest-neighbor plot that was imputed to the pixel. Distance is unit-less Euclidean distance in eight-dimensional gradient space for the first eight CCA axes, with axes weighted by their explanatory power in the model (eigenvalues), and converted to integer grids.

GNN map accuracy assessments.– Accuracy for the Gradient Nearest Neighbor (GNN) maps has been assessed in several ways in order to reflect various standards. We are providing all of the following accuracy assessment products for GNN imputation maps from the species-size and structure models. For the species models, we are providing kappa statistics for presence/absence of common tree species ((2) below), and the histograms of inter-plot distances ((5) below). The accuracy assessment methods are described in Ohmann and Gregory (2002) and Ohmann et al. (in press).

(1) Confusion matrix for vegetation classes defined by canopy cover, species composition (hardwood/conifer), and average tree size, from cross-validation. Rows in the tables represent observed (plot) values and columns represent GNN-predicted values for plot locations. Table values are numbers of plots.

(2) Kappa statistics for vegetation classes, from cross-validation.

(3) Kappa statistics for presence/absence of common tree species, from cross-validation, for species models only.

(4) Scatterplots and correlations between GNN-predicted vs. ground-observed values for selected continuous vegetation and fuel variables, from cross-validation.

(5) Distribution of forest area among vegetation classes, as predicted from the GNN models and as estimated from the systematic sample of grid plots. The histograms provide a regional view of overall accuracy.

(6) Distribution of forest area among fuel models, as predicted from the GNN model and as estimated from the systematic sample of grid plots. The histograms provide a regional view of overall accuracy.

(7) Histogram of all inter-plot distances in eight-dimensional gradient space, as a companion to the nearest-neighbor-distance grid.

Plot databases with metadata

Relational database for each study area, provided as Microsoft Access files. The three plot databases contain all plot data used in GNN model development and mapping. Our primary original source of data was the Integrated Database (IDB) compiled by the Pacific Northwest Research Station's Forest Inventory and Analysis Program. The IDB contains plot data from regional forest inventories conducted by PNW-FIA (periodic inventories on nonfederal lands), the USDA Forest Service (Current Vegetation Survey on National Forests in Region 6 and the periodic forest inventory in Region 5), and the Bureau of Land Management (BLM) on BLM lands in western Oregon. We acquired additional plot data for the North Cascades National Park in Washington and the Yosemite, Sequoia, and Kings Canyon National Parks in California, which were not sampled in the periodic FIA or National Forest System inventories.

We derived summary variables from the source tree data at the forest class level, which are contained in the provided plot databases. In many cases this required the application of models to 'dub in' values where data were missing, which are documented in the plot metadata. All GNN modeling was conducted at the forest class level. A forest class consists of all portions of a plot that sample forest land, including multiple forest condition classes where they are present. Condition classes are defined by contrasting areas of forest composition, size, density, and ownership, e.g., old growth adjacent to a young plantation (see FIA field manuals for more detail).

Because of federal law concerning the confidentiality of plot ownership and FIA policy concerning the confidentiality of plot locations (X and Y coordinates), coordinates are not included. Values for explanatory variables associated with the plots also cannot be distributed because of the possibility of reverse-engineering to determine plot locations. Each database contains tables with descriptions and codes for all fuel and vegetation variables.

Spatial data with metadata

Rasters for all spatial variables used as explanatory variables (predictors) in the GNN models, and selected ancillary data layers are provided. Ancillary data layers include: study area boundaries, nonforest (Boolean) mask, and NLCD grids from which our masks were developed, and ownership class. All spatial data are provided as 30-m-resolution ArcGIS grids except the study area boundaries, which are ArcGIS polygon coverages. FGDC-compliant metadata accompanies each of these grids. All grids are co-registered and clipped to the study area boundaries. Projections are UTM zone 10 (Oregon and California) and UTM zone 11 (Washington), datum NAD 1927, and map units are meters.

Link to the Fuel Characteristic Classification System (FCCS)

Our link to the FCCS system consists of two parts. The first part is a comma-delimited data format for inventory data, which can be exported from any database or spreadsheet program and should be readily transferable to other field plot databases. The second part is a 'translator' program written in PERL that will convert the comma-delimited plot data into a series of

separate files, one for each plot, in the XML format for FCCS fuelbeds. These files can be processed in batch mode by the FCCS system. Both the data format and the translator will be made available on our website. As the data format is subject to change, web distribution will ensure the availability of the most current version. While this deliverable is close to completion, it is not final at the expiration of our grant period. We are behind schedule because the FCCS was well behind their own production schedule, and because the FCCS system does not contain the user functionality we were told to expect at the time the proposal was written, and additional development efforts were required on our part (i.e., developing a translator to XML schema).

GNN software

The software for running GNN (program GNNRUN) allows other scientists and managers to apply the GNN method to other geographic areas and data. The software runs in MS-Windows 2000/XP. To run the software, users must have their spatial data in the format of ESRI ArcGIS grids or Erdas Imagine files, and output files from gradient analysis conducted using either PC-ORD or CANOCO software. The software is a work-in-progress, and we seek feedback from users on how we might improve it. A version with a graphical user interface (GUI) is currently under development.

Websites

The GNNFire project website provides information about our project and access to final products for download: http://*www.fsl.orst.edu/lemma/gnnfire*. At the time of this writing, most products are posted to the site, but we will continue to develop and populate the site with more information over the next few of months.

Our project also is in the FIREHouse database and website (*http://www.fs.fed.us/pnw/fera/firehouse*), which links to the GNNFire website above.

Our project is referenced from the PNW Research Station's 'Fire Tools and Databases' page (*http://www.fs.fed.us/pnw/publications/firetools.shtml*), under 'Improved Programs for Hazardous Fuels Reduction.'

Publications (GNNFire-specific)

Pierce, KB, Jr, JL Ohmann, MC Wimberly, MJ Gregory, and JS Fried. In prep. Mapping wildland fuels and forest structure to support management and simulation modeling. *Ecological Applications*.

Wimberly, MC, JL Ohmann, KB Pierce, MJ Gregory, and JS Fried. 2003. A multivariate approach to mapping forest vegetation and fuels using GIS databases, satellite imagery, and forest inventory plots. Proceedings of the Second International Wildland Fire Ecology and Fire Management Congress. Orlando, FL; 16-20 November 2003. American Meteorological Society. On the web (*http://www.ams.confex.com/ams/FIRE2003/techprogram/paper_65758.htm*) and CD-ROM.

Publications (related projects)

Ohmann, JL, and MJ Gregory. 2002. Predictive mapping of forest composition and structure with direct gradient analysis and nearest neighbor imputation in coastal Oregon, USA. Canadian Journal of Forest Research 32:725-741.

Ohmann, JL, MJ Gregory, and TA Spies. In press. Influence of environment, disturbance, and ownership on forest composition and structure of coastal Oregon. Ecological Applications.

Wimberly, MC, and JL Ohmann. 2004. A multi-scale assessment of human and environmental constraints on forest land cover change on the Oregon (USA) coast range. Landscape Ecology 19:631-646.

Presentations and workshops

"Predictive vegetation mapping and current vegetation biodiversity in coastal Oregon." Guest lecture, graduate-level course in remote sensing, Forest Resources Dept., OSU; Corvallis, OR; November 2002. (invited) (presented by Ohmann)

"Predictive mapping of forest composition and structure with direct gradient analysis and nearest-neighbor imputation (the Gradient Nearest Neighbor method)." Focus session at the Joint Meeting of Fourth Annual Forest Inventory and Analysis Science Symposium and the Southern Forest Mensurationists; New Orleans, LA, November 2002. (invited) (presented by Ohmann)

"Modeling and mapping vegetation composition and structure at broad spatial scales." Science information-sharing seminar day, Pacific Northwest Region, Portland, OR, January 2003. (invited) (presented by Ohmann)

"Predictive vegetation mapping and current vegetation biodiversity in coastal Oregon." Botany and Plant Pathology Departmental seminar, OSU; Corvallis, OR; February 2003. (invited) (presented by Ohmann)

"A novel approach to regional fuel mapping: linking inventory plots with satellite imagery and GIS database using the Gradient Nearest Neighbor method." Joint Fire Science Program Principal Investigator Workshop; Phoenix, AZ; March 2003. (presented by Pierce)

"Mapping live and dead forest fuels at the ecoregion scale in coastal Oregon with Landsat imagery and forest inventory plots." Annual Symposium of the U.S. Regional Association of the International Association of Landscape Ecology; Banff, Alberta, Canada; April 2003. (presented by Ohmann)

"Regional variation in Pacific Northwest forests: finding pattern in a messy world." American Statistical Association, Oregon Chapter; Corvallis, OR; October 2003. (invited) (presented by Ohmann)

"Integrating plot and spatial data to assess vegetation biodiversity in a large, multi-ownership region." Annual meeting of the Society of American Foresters, Buffalo, NY, October 2003. (invited) (presented by Ohmann)

"A multivariate approach to mapping forest vegetation and fuels using GIS databases, satellite imagery, and forest inventory plots. 5th Symposium on Fire and Forest Meteorology and 2nd International Wildland Fire Ecology and Fire Management Congress; Orlando, FL; November 2003. (presented by Wimberly)

"A novel approach to regional fuel mapping: linking inventory plots with satellite imagery and GIS database using the Gradient Nearest Neighbor method." Joint Fire Science Program Principal Investigator Workshop; Phoenix, AZ; April 2004. (presented by Ohmann)

"Assessing spatial uncertainty in landscape vegetation maps created with imputation procedures." Annual Symposium of the U.S. Regional Association of the International Association of Landscape Ecology; Las Vegas, NV; April 2004. (presented by Pierce)

"Influences of landscape structure, drought, and wind on crown fire spread in forest landscapes." Annual Symposium of the U.S. Regional Association of the International Association of Landscape Ecology; Las Vegas, NV; April 2004. (presented by Wimberly)

"Spatial modeling of regional vegetation using field plots and geospatial information: a software framework for the Gradient Nearest Neighbor method." Booth and poster presented at the Software and Modeling Demonstration and Swap Meet, spanning a full day at the Annual Symposium of the US Regional Association of the International Association of Landscape Ecology; Las Vegas, NV; April 2004. (presented by Gregory and Ohmann)

"Regional-scale mapping of fuels: integrating Gradient Nearest Neighbor (GNN) and Fuels Characteristics Classification System (FCCS)." Workshop on hazardous fuel and vegetation treatment; PNW Station and Region 6, USDA Forest Service; Bend, OR; May 2004. (invited) (presented by Don McKenzie)

"Landscape connectivity and the potential for catastrophic fire in forested landscapes." Annual Ecological Society of America Meeting. Portland, OR, August 2004. (presented by Wimberly)

"Mapping forests of the Pacific Northwest: structure, species and uncertainty." Annual Ecological Society of America Meeting; Portland, OR; August 2004. (presented by Pierce)

"Scaling plot inventories for regional assessments." Annual Symposium of the U.S. Regional Association of the International Association of Landscape Ecology; Syracuse, NY; March 2005. (presented by Pierce)

"Detailed forest vegetation maps for monitoring landscape-scale habitat and riparian conditions: CLAMS and beyond." 1st annual remote sensing workshop, Pacific Northwest Aquatic Monitoring Partnership; Portland, OR; May 2005. (invited) (presented by Ohmann)

"Creating wall-to-wall forest vegetation maps for the Pacific Northwest: lessons learned and future plans." Region 10 FIA Users Forum; Juneau, AK; June 2005. (invited) (presented by Ohmann)

"Gradient Nearest Neighbor imputation mapping in support of risk assessment." Workshop for evaluating quantitative techniques for deriving national scale data for assessing and mapping risk; organized by Forest Health Technology Enterprise Team, Forest Health Protection, USDA Forest Service; Ft. Collins, CO; July 2005. (invited) (presented by Pierce)

"Predictive mapping of forest composition and structure with direct gradient analysis and nearest-neighbor imputation for regional policy analysis and ecological research." Annual meeting of American Statistical Assoc.; Minneapolis, MN; August 2005. (invited) (presented by Ohmann)

"Regional vegetation mapping in support of risk assessment." Workshop on regional risk assessment methodologies." Organized by Western Wildlands Environmental Threat Assessment Center, USDA Forest Service; Portland, OR; September 2005.(invited) (presented by Pierce)

"Gradient Nearest Neighbor imputation based on FIA plots – useful tool or lying with maps?" Seminar at Forestry Sciences Lab; Portland, OR; August 2005. (invited) (presented by Ohmann)

"What is the probability that I-30 runs through Fort Worth? Incorporating uncertainty into map use." Annual meeting of the Society of American Foresters; Ft. Worth, TX; October 2005. (invited) (presented by Pierce)

"Healthcare and forestry - Half-Life 2: meet serious games modding." Serious Games Summit: Interactive Solutions for Shared Challenges; Washington, DC; October 2005. (invited) (presented by Tim Holt)

"A mid-scale approach to mapping forest fuel and fire hazards at the wildland-urban interface by imputation and modeling of inventory plot data." Seventh Annual Forest Inventory and Analysis Science Symposium; Portland, ME, October 2005. (presented by Fried)

"Gradient Nearest Neighbor imputation for local scale basal area mapping: FIA 2005 Symposium interpolation contest." Seventh Annual Forest Inventory and Analysis Science Symposium; Portland, ME, October 2005. (presented by Gregory)

"A novel approach to regional fuel mapping: linking inventory plots with satellite imagery and GIS databases using the Gradient Nearest Neighbor method." Joint Fire Science Program

Principal Investigator Workshop, San Diego, CA, November, 2005. (presented by Ohmann) (poster)

Site visits to our Washington and California study areas

Our research team conducted two site visits to our study areas: Washington in summer 2003 and California in summer 2004. Most of our team members were already familiar with the Oregon study area from previous studies and due to its close proximity, so no formal site visit was conducted. In addition, GNN vegetation maps were already available for coastal Oregon, and conversations with numerous forest and fire managers in this region revealed limited interest in fuels- and fire-related maps.

We spent a week in each of the other two study areas meeting with potential clients for our map products, experts in local forest and fire ecology, and other scientists and managers interested in developing their own GNN models. We conducted extensive field tours of the study areas to familiarize ourselves with local forest and landscape conditions and management issues, in many cases accompanied by local experts and potential clients. The Washington site visit led to a request for us to expand our study area to encompass all National Forest lands in eastern Washington, for use analyses in support of National Forest Plan revision.

Follow-on grants, projects, and use of GNN maps by agencies

Based on successes with GNNFire and previous projects, the LEMMA research team has taken on several new studies involving spatial modeling of forest vegetation across the Pacific Coast States. All projects are being conducted with an eye towards interfacing with and complementing related work by LANDFIRE.

In 2004 we began research as part of the Central Oregon Landscape Analysis (COLA) pilot study to test data and methods for landscape characterization and modeling for use in the Oregon Department of Forestry's (ODF's) Assessment of Forest Sustainability in Oregon. The LEMMA team used GNN to develop gradient models and maps of existing forest vegetation. The maps interface with state-and-transition models for analysis of future landscape dynamics based on assumptions about natural and human disturbances.

In fall 2005, LEMMA will begin a new program to model, map, and monitor forest vegetation and land cover of the Pacific Coast States (Oregon, California, and Washington) on a continuing basis on a five-year remeasurement cycle. This program of mapping and research is coordinated with ongoing FIA inventories, other agency programs for vegetation mapping and landscape analysis, the ODF's Assessment, and the Pacific Northwest Landscape Analysis (PNLA) study. The PNLA builds on COLA methods, which have been adopted by the USDA Forest Service, Region 6, as their standard for landscape analysis in support of National Forest Plan revision. Several research objectives of the new mapping program derived from lessons learned during the GNNFire project. The PNLA effort represents the first time in history that the Forest Service, BLM, and ODF have collaborated on a single, statewide effort to consistently map and model the dynamics of vegetation and land cover.

Also in fall 2005, LEMMA will begin a study to model and map Ecological Systems of eastern Oregon and Washington as part of the national Gap Analysis Program. The project will develop detailed maps of forest composition and structure using GNN, and integrate them with maps of nonforest habitats developed by OSU Institute of Natural Resources and Oregon Natural Heritage Program.

In an innovative approach to technology transfer of our GNN maps, we are beginning a JFSP-funded study to integrate computer gaming and GIS technology. These tools will allow researchers, map developers, and map users to better visualize the regional maps, and interact with each other real-time within a virtual map environment.

Funding for these and other related projects is from a variety of sources, as listed here:

2004. Extension of the GNNFire study area to encompass all lands administered by the Wenatchee NF; eastern Washington National Forest Plan revision team; $10,000.

2004. Mapping forest vegetation using Gradient Nearest Neighbor imputation for the Central Oregon Landscape Analysis (COLA) pilot study, as part of a larger effort to develop data and analysis methods in support of the Oregon Forest Assessment; Oregon Department of Forestry and PNW Focused Science Delivery Program; $15,400.

2005. How does spatial resolution affect Gradient Nearest Neighbor vegetation maps and models of wildlife habitat capability? Competitive grant for Ecosystem Processes Program, PNW Station; $25,000.

2005. Proposal to map Ecological Systems of mapping zones 8&9 with GNN imputation and regional inventory plots. With Oregon State University and Oregon Natural Heritage Program. Funded by national Gap Analysis Program, US Geological Survey; $93,000.

2005. A program to map forest vegetation and land cover in the Pacific Coast States (Oregon, California, and Washington) on a five-year cycle with GNN imputation and FIA plots. PNW FIA Program and Western Wildlands Environmental Threats Assessment Center (WWETAC). Estimated total cost is $2.2 million over the first five years.

2005. Innovative, 3-D, interactive, and immersive techniques for visualizing, querying, and understanding regional maps of forest vegetation, fuels, and fire risk. Joint Fire Science Program; $254,489.

2005. Pacific Northwest Landscape Analysis (PNLA), in support of the Oregon Department of Forestry's statewide Oregon Assessment, and as the official analytical process to be used by Region 6 in National Forest Plan Revision. The interagency PNLA is budgeted for > $3.3 million over four years, divided among Region 6, PNW, BLM, and ODF. The map of forest vegetation for this project will be developed using GNN.

2005. Region 6, USDA Forest Service, has incorporated GNN as part of its strategy for Providing Existing Vegetation Maps (see link to Existing Vegetation Mapping Strategy at *http://www.reo.gov/ecoshare*).

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Appendix 1 – Documentation of Gradient Nearest Neighbor (GNN) models distributed as JFSP final products.

This appendix describes the four kinds of models (Table 1) distributed as JFSP final products, and summarizes the plot data (Table 2) and satellite imagery (Table 3) used in model development.

Four kinds of GNN models

The use of multivariate statistics and imputation by GNN results in unique spatial modeling properties. As with most predictive models, alternative model forms can be specified to optimize for different objectives and outcomes. Rather than provide one GNN model and map for each study area, we've developed four GNN models that illustrate major variations in model form as a function of spatial pattern and emphasis on species composition vs. forest structure. We expect each kind of model to have advantages for certain applications, and we seek feedback from map users on the alternative model forms as they exercise the maps (e.g., via feedback received on the web site and from follow-up surveys of users who download or request GNN data). The four kinds of models are summarized in Table 1 and described below.

Table 1.– Summary of four kinds of GNN models, as determined by spatial filtering of Landsat-derived explanatory variables and specification of response variables that emphasize species composition vs. forest structure.

Spatial filtering of Landsat-derived explanatory variables	Response variables Species <=====> Structure		
Median-filtered	Species model (no imagery in model)	Species-size model, median-filtered	Structure model, median-filtered
Unfiltered		--	Structure model, unfiltered

The appearance (spatial patterning) of the final GNN maps are strongly influenced by tuning the spatial resolution of the independent variables – particularly those derived from Landsat TM imagery. Median-filtering of the raw Landsat imagery has the effect of reducing the fine-scale heterogeneity, or salt-and-peppering, in the final map, while maintaining boundaries between contrasting vegetation conditions (e.g., of clearcuts or stand-replacing fires). The median filtering consists of moving a nine-pixel window across the image, and assigning the median value of nine pixels to the center pixel. Grids for individual bands, ratios, and transformations are filtered independently. In general, overall accuracy in resulting GNN predictions appears to be little affected by the filtering, so decisions on which model to use are largely subjective based

on appearance – at least until more experience is gained on the sensitivity of map applications to different spatial grains.

Species model: Response variables used in model development are basal area by tree species. Landsat TM, disturbance, and ownership variables are not included as explanatory variables. This model provides the most accurate spatial predictions of distributions of individual species and of community types that are defined based on species composition. Stand structure variables are not attached to this grid.

Species-size model: Response variables used in model development are basal area by species and size-class (but not all size-classes were recognized for all species). Explanatory variables derived from Landsat TM imagery are median-filtered, which reduces fine-scale heterogeneity or 'salt-and-peppering' in the GNN map. This model is a 'hybrid' between the species and structure models, and may be a good compromise model for applications where elements of both species composition and stand structure are needed, and covariance among these elements must be maintained (e.g., if tree lists are to be input into simulation models such as the Forest Vegetation Simulator). Accuracy for species variables in this model was intermediate between the species and structure models. Accuracy for structure variables was comparable or slightly worse than the structure model.

Structure model, median-filtered: Response variables are basal area by species group (conifer or hardwood) and size-class, total canopy cover, snag density by size class, and total down wood volume. This model provides slightly better overall accuracy of structure and fuels variables compared to the species-size model, but less accurate depiction of species distributions compared to the species and species-size models. We are distributing structure models developed at both coarse (median-filtered) and fine (unfiltered imagery) resolutions. Maps developed from median-filtered imagery contain less fine-scale variability than the unfiltered versions.

Structure model, unfiltered: Same as above but developed from unfiltered satellite imagery, which results in a map with much more fine-scale heterogeneity or 'salt-and-pepper' effect.

Plot data used in GNN models

Table 2.– Summary of plot data used in GNN models.

Study area	Data source	Ownerships sampled	Years measured	Number of plots	
				Species model	Species-size and structure models
California	FIACA	Nonfederal	1993-1994	306	200
	R5	National Forest	1995-2000	1,407	1,288
	YOSE	Yosemite National Park	1988-1989	236	347
	All plots			1,949	1,835
Oregon	FIAWO	Nonfederal	1995-1997	572	385
	BLMWO	BLM	1997	115	99
	R6 (CVS)	National Forest	1993-1996	316	279
	All plots			1,003	763
Washington	FIAEW	Nonfederal	1991	475	468
	R6 (CVS)	National Forest	1993-1997	1,856	1,808
	NCNP	North Cascades National Park	2000	43	49
	All plots			2,374	2,325

Satellite imagery used in the GNN models

Table 3.– Satellite imagery used in GNN models.

Study area	Model	Landsat imagery used
California	ca_spp	no imagery
	ca_sppsz_fil	2000 Landsat ETM+, median-filtered, tasseled cap transformations
	ca_struct_fil	1992 Landsat TM and 2000 Landsat ETM+, median-filtered, raw bands
	ca_struct_unf	1992 Landsat TM and 2000 Landsat ETM+, unfiltered, raw bands
Washington	wa_spp	no imagery
	wa_sppsz_fil	2000 Landsat ETM+, median-filtered, raw bands
	wa_struct_fil	1992 Landsat TM and 2000 Landsat ETM+, median-filtered, raw bands
	wa_struct_unf	1992 Landsat TM and 2000 Landsat ETM+, unfiltered, raw bands
Oregon	or_spp	no imagery
	or_sppsz_fil	1996 Landsat TM, median-filtered, tasseled cap
	or_struct_fil	1996 Landsat TM, median-filtered, raw bands
	or_struct_unf	1996 Landsat TM, unfiltered, raw bands

Appendix 2.-- Methods for Deriving Fuel Loadings from Forest Inventory Plot Data to Support Regional Mapping of Forest Vegetation and Fuels

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Table of Contents

1   Canopy Fuels

Canopy bulk density characterizes the mass of canopy fuels per unit volume and is a key input to indices of crown fire risk (Scott and Reinhardt 2001) and spatial models of fire behavior (Finney 1998). Forest inventories do not include direct measurements of canopy fuels. Instead the weights of various canopy fuel components (foliage, live branches, and dead branches) are modeled at the tree level, usually as a function of DBH. Canopy volume per unit area and height to the base of the live canopy can also be estimated based on tree height and crown ratio measurements. This section outlines the procedures used in the GNN-Fire project to model canopy fuels and canopy structure based on forest inventory plot data.

1.1   Tree-Level Calculations

Published equations were used to predict the total live and dead crown weights of individual trees as a function of their DBH. Crown fraction equations were also used to subdivide the live crown weight into a foliage component and several branch-size components (Table 1.1). These crown fraction variables were used in subsequent steps to compute available canopy fuels, which included the mass of live conifer foliage plus one-half the mass of live and dead conifer branches in the 0-0.25 inch size class (Reinhardt and Crookston 2003).

Table 1.1: Individual-tree variables included in the Livetree database table.

Variable Name*	Description
LCMASS	Total mass of live foliage and branches (kg)
DCMASS	Total mass of dead branches (kg)
LCFRAC1	Proportion of live crown mass comprised of foliage
LCFRAC2	Proportion of live crown mass comprised of foliage plus branches < 0.25 inches
DCFRAC1	Proportion of dead crown mass comprised of branches < 0.25 inches

* In the GNN-Fire databases, variables names preceded with an "R" (e.g. "RLCMASS") indicate variables that were computed based on the Brown (1978) crown weight equations. See the sections describing individual study areas for more details.

Height to crown base was computed for each tree as a function of crown ratio and tree height. One problem with this method is that field crews estimate a "compacted" crown ratio, in which the height to the lowest live branch is shifted upward to compensate for asymmetrical crowns. This estimate results in biased estimate of height to crown base. Therefore, an "uncompacted" crown ratio was also computed for each tree using equations developed by Monleon et al. (2004).

1.2   Plot-Level Calculations

1.2.1   Canopy Bulk Density

Two methods were used to compute canopy bulk density (Table 1.2). The first method, similar to that used by Cruz et al. (2003) and Keane et al. (1998), computed canopy bulk density as

CBD1 = CANFWT/CL

where CANFWT was the total weight of available canopy fuels weight expressed as kg/m^2 and CL was the average canopy depth in m computed as STNDHGT - HCB. The units of CBD1 were kg/m^3 (mass per unit volume).

Table 1.2: Plot/condition class/forest class canopy fuels and canopy structure variables.

Variable Name*	Description
CBD1	Canopy bulk density computed with plot average method and "compacted" crowns (kg/m^3)
CBD2	Canopy bulk density computed with vertical layering method and "compacted" crowns (kg/m^3)
CBDU1	Canopy bulk density computed with plot average method and "uncompacted" crowns (kg/m^3)
CBDU2	Canopy bulk density computed with plot vertical layering method and "uncompacted" crowns (kg/m^3)
HCB	Weighted mean height to crown base of all trees in the plot (m)
HTCB2	Height to canopy base computed with vertical layering method and "compacted" crowns (m)
HTCBU2	Height to canopy base computed with vertical layering method and "uncompacted" (m) crowns
CANMASS	Total crown weight of all conifers (kg/ha)
CANFWT	Total weight of all available canopy fuels (kg/ha)

* Variables names preceded with an "R" (e.g. "RLCMASS") indicate variables that were computed based on the Brown (1978) crown weight equations. See the sections describing individual study areas for more details.

The second method of computing canopy bulk density involved vertically partitioning the canopy into a series of 0.3 m thick layers. (Sando and Wick 1972, Kilgore and Sando 1975, Scott and Reinhardt 2001). The proportion of each tree's crown mass that fell within each vertical layers was computed by assuming a uniform distribution of crown mass between the crown base and the top of each tree. Canopy bulk density was then computed for each layer as

$$CBD_l = CFW_l/CL_l$$

where CBD_l was the total canopy fuel weight in layer l and CL_l was the depth of layer l. The vertical canopy bulk density profile was then smoothed using a 4.5 m running mean, and CBD2 was computed as the maximum value of this running mean.

Two versions of each of each canopy bulk density variable were generated (Table 1.2). The first version was based on the original "compacted" crown ratio estimates, whereas the second version was based on the "uncompacted" crown ratio estimates.

1.2.2   Height to Base of Live Canopy

Two methods were used to compute height to the base of the live canopy for each inventory plot (Table 1.2). The first method used a weighted mean of height to crown base for all trees on the plot, with each tree weighted by its expansion factor (Cruz et al. 2003). The second method involved vertically partitioning the forest canopy into 0.3-m thick layers and computing canopy bulk density for each layer as described in the previous section. The vertical canopy bulk density profile was then smoothed using a 1 m running mean and height to base of live canopy was

4

defined as the lowest height at which at least 0.011 kg/m^3 of available canopy fuels was present (Scott and Reinhardt 2001). Two versions of the layered canopy base height variable were computed: the first based on the original "compacted" crown ratio estimates, and the second based on the "uncompacted" crown ratio estimates (Table 1.2).

1.2.3   Other Canopy Variables

Two additional canopy fuels variables were computed for each inventory plot (Table 1.2). CANMASS was computed as the total weight of all conifer trees crowns on the plot, including foliage and all live and dead branches. CANFWT was computed as the total weight of available fuels, which included the mass of live conifer foliage plus one-half the mass of live and dead conifer branches in the 0-0.25 inch size class

1.3   Details for Individual Study Areas

1.3.1   Oregon Coast

Two sets of canopy fuels and canopy structure variables were computed for the Oregon Coast study area. The first set of variables was based on crown weight and crown fraction equations developed specifically for the coastal Pacific Northwest. Live crown weight estimates for coastal Douglas-fir and western hemlock were based on the equations of Snell and Anholt (1981). Live crown weights for other coastal conifer species were computed using the approach of Snell and Brown (1980). In this approach, equations developed for the northern Rocky Mountains by Brown (1978) were used to predict live crown weight for trees smaller than 40 inches DBH. Live crown weight was predicted as a ratio of the crown weight of coastal Douglas-fir for trees larger than 40 inches (Snell and Brown 1980).

Dead crown weights for coastal lodgepole pine, western white pine, western redcedar, western hemlock, and grand fir were computed using the equations of Snell and Brown (1980). Dead crown weights for other conifer species were computed using the equations provided by Brown (1978).Live crown fractions for coastal Douglas-fir were computed using equations from Snell and Anholt (1981). Live crown fractions for other conifer species were computed using equations from Brown (1978). Dead crown fractions for all conifer species were computed using equations from Brown (1978).

Brown (1978) developed separate equations to predict live crown weight for dominant/ codominant trees, intermediate/ suppressed trees, and trees < 2 inches dbh. When using the Brown (1978) equations to predict crown weights of conifers smaller than 40 inches DBH in coastal forests, the dominant/codominant equations equations were used for all trees. This decision was made for consistency with Snell and Anholt (1981), who did not break down their equations for coastal Douglas-fir and western hemlock by tree size or crown class. It is not clear whether the distinctions between dominant/ codominant and intermediate/ suppressed crown morphology would be the same in coastal forests as in inland forests. Furthermore, Brown (1978) only included intermediate/suppressed tree equations for ponderosa pine, Douglas-fir, grand fir, and western red cedar.

A second set of canopy fuels and canopy structure variables was computed based entirely on the northern Rocky Mountain equations developed by Brown (1978). In the GNN-Fire database, this second set of variables is distinguished by an "R" preceding each variable (e.g. "CBD1" was

computed using the coastal Pacific Northwest equations, whereas "RCBD1" was computed using the northern Rocky Mountain equations). This second set of variables was computed primarily to assess how sensitive the derived canopy variables were to crown weight equations from different geographic regions.

Crown weight equations were not available for all tree species in the Coast Range. Species for which no equations were available were assigned a surrogate species to link them with the available equations. Most of the species that required surrogates were relatively uncommon. A major exception was Sitka spruce, for which Douglas-fir was used as a surrogate species.

1.3.2   Eastern Washington

Canopy fuels and canopy structure variables for the Eastern Washington study area were based entirely upon the crown weight and crown fraction equations developed by Brown (1978) for the northern Rocky Mountains. The geographic distribution of the samples used to develop these equations (the Rocky Mountains of Northern Idaho and Northwestern Montana) was adjacent to our eastern Washington study area, and had environmental conditions that were similar to the interior Pacific Northwest. Equations were available for all of the major tree species within the study area. Species for which no equations were available were assigned a surrogate species to link them with the available equations. For consistency with the Oregon Coast Range study area, the names of all crown weight and canopy fuels variables in the Eastern Washington database were prefaced by an "R" (e.g. "RCBD1") to indicate that they were computed using the Brown (1978) equations.

1.3.3   Sierra Nevada

Canopy fuels and canopy structure variables for the Sierra Nevada study area were based entirely upon the crown weight and crown fraction equations developed by Brown (1978) for the northern Rocky Mountains. Despite the many physical and ecological differences between the Sierra Nevada and the northern Rocky Mountains, we decided to use the Brown (1978) equations for several reasons. First, they encompassed most of the major tree species within the Sierra Nevada study area. Furthermore, there was no comparable set of published crown weight equations available for the Sierra Nevada. Although there were other published allometric equations for some species developed specifically for Sierra Nevada (e.g. Westman (1987)), these studies did not include the crown fractions estimates that are required to estimate the proportion of total crown weight that is available canopy fuel. Therefore, we decided it would be better to use a consistent set of crown weight and crown fraction equations than to combine multiple equations from a variety of different sources. Species for which no equations were available were assigned a surrogate species to link them with the available equations. As with the Eastern Washington database, the names of all crown weight and canopy fuels variables in the Sierra Nevada database were prefaced by an "R" (e.g. "RCBD1") to indicate that they were computed using the Brown (1978) equations.

2   Crown Ratio Models

Crown ratio and height to crown base measurements were not available for the National Park Service inventory plots from Yosemite and King's Canyon National Parks. Previous studies have found that these attributes can be modeled based on tree size, stand competition, and site characteristics (Hasenauer and Monserud 1996, Temesgen et al. 2005). Using data from Region

5 and FIA plots that did have crown ratio measurements, we developed regression equations to predict crown ratio and height to crown base for trees on the Park Service plots.

2.1 Methods

Data from the Region 5 and FIA inventories were randomly split into two subsets for fitting and validating crown ratio models. Models were developed for the following species: *Abies concolor* (ABCO), *Abies magnifica* (ABMA), *Calocedrus decurrens* (CADE), *Pinus albicaulis* (PIAL), *Pinus contorta* (PICO), *Pinus jeffreyi* (PIJE), *Pinus lambertiana* (PILA), *Pinus ponderosa* (PIPO), *Psuedotsuga mensizeii* (PSME), and *Tsuga mertensiana* (TSME). Crown ratios were transformed to constrain model outputs between 0 and 1 where TRANS.CR= ln[1/(cr-1)]. Linear models were developed for each species to predict transformed crown ratio using several variables. Diameter at breast height (DBH) was used as a measure of tree size. Variables characterizing stand competition included density in trees per hectare (TPH), basal area of all trees per hectare (BAA), tree diameter diversity index (DDI), and basal area of trees larger than the subject tree (BAL). Percent slope (SLP), elevation (DEM), and aspect (ASP) were included a site variables. All variables with skewed distributions were transformed with a square root transformation. Linear models were initially fit with all variables. All non-significant variables ($p \leq 0.01$) were eliminated using backward stepwise regression. Highly correlated variables were also eliminated from the models to prevent multicolinearity.

Once all significant variables for predicting the transformed crown ratio were determined we used non-linear regression to refit the logistic model for crown ratio. All variables identified as significant from the linear models were included and coefficients from the linear models were used as starting values for the nonlinear models. Nonlinear models for each species were then fit to the validation data set. Accuracy of the non-linear models was assessed by applying them to the validation datasets, and then using linear regression to compare observed versus predicted values by species. Both crown ratio and height to canopy base were examined in the validation exercise

2.2 Results

Linear models differed considerably in the number of significant variables, the variables that were significant, and the fit of the model (Table 1). Final models for the nonlinear models can be seen in Table 2. Coefficients for the final nonlinear models are in Table 3. Estimates of height to crown base ranged from $r^2=0.83$ to $r^2=0.48$ and were much better than estimates of crown ratio which ranged from $r^2=0.31$ to $r^2=0.0016$ (Table 4).

Table 2.1: Coefficients and r^2 values of linear crown ratio models.

Species	Intrcpt.	DBH	SLP	ASP	TPH	BAA	BAL	DDI	DEM	r2
ABCO	0.0047	-0.043	ns	ns	ns	0.1568	0.004	ns	-0.0005	0.2
ABMA	0.6011	0.071	-0.0072	-0.0802	0.0098	ns	0.1853	ns	-0.0009	0.21
CADE	-1.0901	0.0053	ns	0.1151	0.0161	ns	0.1603	ns	-0.0002	0.138
PIAL	2.1755	-0.2494	ns	-0.628	ns	ns	-0.1695	ns	ns	0.423
PICO	0.0309	ns	ns	ns	ns	0.0638	0.0636	ns	-0.0004	0.076
PIJE	-0.7506	ns	0.0116	-0.0278	0.0278	ns	ns	0.1696	-0.0005	0.3
PILA	-0.682	ns	0.0051	ns	ns	0.1928	ns	ns	-0.0005	0.212
PIPO	-0.3692	-0.0724	0.0034	ns	-0.005	ns	0.1189	ns	-0.0006	0.383
PSME	-0.7776	-0.0872	0.003	ns	ns	0.2061	ns	ns	ns	0.158
TSME	2.085	ns	ns	ns	ns	ns	ns	ns	-0.001	0.051

Table 2.2: Crown ratio model formulas.

Species	Formula
ABCO	CR = 1/(1 + exp(b0 + b1 * sqrt(DBH) + b2 * sqrt(BAA) + b3 * DEM + b4 * BAL))
ABMA	CR = 1/(1 + exp(b0 + b1 * DBH + b2 * sqrt(TPH) + b3 * ASP + b4 * SLP + b5 * DEM + b6 * sqrt(BAL)))
CADE	CR = 1/(1 + exp(b0 + b1 * DBH + b2 * sqrt(TPH) + b3 * ASP + b4 * DEM + b5 * sqrt(BAL)))
PIAL	CR = 1/(1 + exp(b0 + b1 * sqrt(DBH) + b2 * ASP + b3 * sqrt(BAL)))
PICO	CR = 1/(1 + exp(b0 + b1 * sqrt(BAA) + b2 * DEM + b3 * sqrt(BAL)))
PIJE	CR = 1/(1 + exp(b0 + b1 * sqrt(TPH) + b2 * ASP + b3 * SLP + b4 * DEM + b5 * DDI))
PILA	CR = 1/(1 + exp(b0 + b1 * sqrt(BAA) + b2 * SLP + b3 * DEM))
PIPO	CR = 1/(1 + exp(b0 + b1 * sqrt(DBH) + b2 * sqrt(TPH) + b3 * SLP + b4 * DEM + b5 * sqrt(BAL)))
PSME	CR = 1/(1 + exp(b0 + b1 * sqrt(DBH) + b2 * sqrt(BAA) + b3 * SLP))
TSME	CR = 1/(1 + exp(b0 + b1 * DEM))

Table 2.3: Coefficients of nonlinear crown ratio models

Species	Intrcpt.	DBH	SLP	ASP	TPH	BAA	BAL	DDI	DEM
ABCO	-0.01191	-0.03360	ns	ns	ns	0.13516	0.00417	ns	-0.00044
ABMA	0.61781	0.00602	-0.00717	-0.06765	0.00802	ns	0.16097	ns	-0.00078
CADE	-0.97163	0.00470	ns	0.10257	0.01443	ns	0.13515	ns	-0.00017
PIAL	2.05578	-0.23473	ns	-0.55285	ns	ns	-0.16350	ns	ns
PICO	0.06948	ns	ns	ns	ns	0.05340	0.06128	ns	-0.00036
PIJE	-0.68546	ns	0.01095	-0.18274	0.02717	ns	ns	0.15183	0.00043
PILA	-0.61664	ns	0.00413	ns	ns	0.17303	ns	ns	-0.00040
PIPO	-0.66867	0.05500	0.00096	ns	0.00798	ns	0.23817	ns	-0.00052
PSME	-0.68382	-0.07782	0.00251	ns	ns	0.18387	ns	ns	ns
TSME	1.73104	ns	ns	ns	ns	ns	ns	ns	-0.00085

Table 2.4: Crown ratio and height to crown base r^2 for validation of model estimates.

Species	Crown Ratio r^2	Height to Crown Base r^2
ABCO	0.1805	0.7607
ABMA	0.1569	0.7973
CADE	0.1046	0.7785
PICO	0.1589	0.7097
PIJE	0.2989	0.7714
PILA	0.1468	0.8299
PIPO	0.309	0.8272
TSME	0.0047	0.5152
PSME	0.2856	0.7871
PIAL	0.0016	0.4782

3   Fuel Model Crosswalks

3.1   Oregon Coast Range

The rules used to establish the relationships between forest structure and fuel models in the Oregon Coast Range were derived from the FVS-FFE documentation (Reinhardt and Crookston 2003; Reinhardt and Crookston 2004) (Reinhardt and Crookston 2003, 2004), but were modified to reflect the fuels and forest structure variables that are available in the GNN-Fire database. Unless otherwise specified, variable names are identical to those used in the GNN-Fire Coast Range database.

The general procedure for the fuel model crosswalk is as follows. Individual steps are described in more detail in subsequent sections.

Step 1: Categorize each plot as either a "high fuel" plot or a "low fuel" plot based on the loadings of small down fuels (< 3") and large down fuels (> 3").

Step 2: If the plot is categorized as having high fuels, assign one of the "high fuel models" (either 10 or 12) based on the loadings of small and large down fuels. Otherwise, go to step 3.

Step 3: If the plot is categorized as having low fuels, choose a set of classification rules based on the species group that comprise the majority of stand basal area.

Step 4: Using the classification rules chosen in step 3, assign one of the "low fuel models" (usually 5, 8, or 9) based on canopy cover and quadratic mean diameter.

3.1.1   Step 1 – High Versus Low Fuel Classification

Plots were assigned to the high fuel model category if either the fine fuels loadings (< 3 inches) *or* the large fuels loadings (> 3 inches) were above threshold levels specified in the FVS-FFE documentation (Reinhardt and Crookston 2003, page 39). The fine fuel loading threshold for assigning a high fuel model was 6 tons/acre (13,450 kg/ha), and the large fuel loading threshold for assigning a high fuel model was 15 tons/acre (33,625 kg/ha).

Estimates of large fuels loadings were available for all plots in the GNN-Fire database. A new LGFUEL variable (total loading of all down fuels > 3 inches) was created by summing the DDF_1000 and the DDF_1000P variables.

Fine fuels loadings were only available for plots from the CVS and BLM inventories. Even for these plots, fine fuels measurements did not include the smallest (< 0.25 inch) size class. A logistic regression model was developed to classify plots as falling either above or below the fine fuels threshold. Plots from the CVS and BLM inventories were classified as being above the threshold if their total fine fuel loadings were greater than 4.2 tons/acre (9,415 kg/ha). These cutoff values were selected based on the assumption that the 0.25 – 3 inch fuels recorded in these databases accounted for 70% of the total loading of fuels < 3 inches. This assumption was derived from the relative amounts of these sizes classes in fuel model 10. The following logistic regression equation used to predict whether fine fuels were above this threshold based on stand structure variables.

logit (p) = 0.7341693 – 4.29528 * SDBA + 0.05879063 * sqrt(TPHTOL_GE_3) – 0.1014303 * sqrt(TPH_GE_3) – 1.15949 * sqrt(BAH_PROP) + 0.0002815691 * CANCOV^2

The probability that a stand was above the fine fuels threshold was then computed as

p = 1/(1 + exp(- logit(p)))

A new variable, SMFUEL, was created to indicate whether each plot was above or below the fine fuels threshold as predicted by the logistic regression equation. Plots were considered to be above the fine fuels threshold (SMFUEL = 1) if p > 0.42 and below the fine fuels threshold

(SMFUEL = 0) otherwise. This cutoff value correctly classified 67% of the plots while maintaining the same proportion of high and low fuels plots as in the original data.

The logistic regression equation was used to compute SMFUEL for all of the stands in the GNN-Fire database. The following rule was then used to classify plots into the "high fuels" and "low fuels" categories.

If SMFUEL = 1 **or** LGFUEL > 33,625
      Select a "high fuel" model (go to step 2)
Otherwise
      Select a "low fuel" model (go to step 3)

3.1.2 *Step 2 – High Fuel Model Assignment*

Fuel models were selected for plots in the "high fuels" category using the variables computed in Step 1 (SMFUEL and LGFUEL). The following rules were adapted from the FVS-FFE documentation (Reinhardt and Crookston 2003, page 39).

If SMFUEL = 1 **and** LGFUEL > 44,833
      Assign fuel model 12
Otherwise
      Assign fuel model 10

3.1.3 *Step 3 – Low Fuel Model Species Grouping*

Plot basal area was summed by species, and then species basal areas were summed to compute basal area within each of several species groups. Plots in the "low fuels" category were assigned to a species group based on total basal area within each species group (Reinhardt and Crookston 2004, page 81).

BAPISIGRP = BAPISI + BATSHE + BATHPL
BAPSMEGRP = BAPSME + BAABGRC
BAALRUGRP = BAALRU + BAACMA3
BAPICOGRP = BAPICO
BALIDEGRP = BAQUGA4 + BALIDE3

The species group with the highest basal area was assigned to the plot. For plots with no trees present, the default species group was assumed to be PSME.

3.1.4 *Step 4 – Low Fuel Model Assignment*

The following sets of decision results was used to select fuel models depending on the species group assigned in step 3 (Reinhardt and Crookston 2004, page 83).

For plots belonging to the Sitka spruce group or the Douglas-fir group
If QMDA_GE3 > 10.16 cm
      If CANCOV > 80
            Assign fuel model 8
      Otherwise
            Assign fuel model 5

Otherwise
      Assign fuel model 5

For plots belonging to the red alder group
      If CANCOV > 50
            Assign fuel model 9
      Otherwise
            Assign fuel model 5

For plots belonging to the lodgepole pine group
      If CANCOV > 50
            Assign fuel model 8
      Otherwise
            Assign fuel model 5

For plots belonging to the tanoak group
      If CANCOV > 50
            Assign fuel model 5
      Otherwise
            Assign fuel model 2

3.2   Eastern Washington

The rules used to establish the relationships between forest structure and fuel models in the Oregon Coast Range were derived from the FVS-FFE documentation (Reinhardt and Crookston 2003), but were modified to reflect the fuels and forest structure variables that were available in the GNN-Fire database. Unless otherwise specified, variable names are identical to those used in the GNN-Fire Eastern Washington database.

The general procedure for the fuel model crosswalk is as follows. Individual steps are described in more detail in subsequent sections.

Step 1: Categorize each plot as either a "high fuel" plot or a "low fuel" plot based on the loadings of small down fuels (< 3") and large down fuels (> 3").

Step 2: If the plot is categorized as having high fuels, assign one of the "high fuel models" (either 10 or 12) based on the loadings of small and large down fuels. Otherwise, go to step 3.

Step 3: If the plot is categorized as having low fuels, determine whether the plot falls within the Northern Idaho or the East Cascades variant as described in the FVS-FFE documentation. Then choose a set of classification rules based on the species group that comprise the majority of stand basal area.

Step 4: Using the classification rules chosen in step 3, assign one of the "low fuel models" based on canopy cover, quadratic mean diameter, and whether the canopy is composed of a single stratum or is multistoried.

3.2.1 Step 1 – High Versus Low Fuel Model Classification

Plots were assigned to the high fuel model category if either the fine fuels loadings (< 3") *or* the large fuels loadings (> 3") were above threshold levels specified in the FVS-FFE documentation (Reinhardt and Crookston 2003, page 39). The fine fuel loading threshold for assigning a high fuel model was 6 tons/acre (13,450 kg/ha), and the large fuel loading threshold for assigning a high fuel model was 15 tons/acre (33,625 kg/ha).

Estimates of small and large fuels loadings were available for all plots in the GNN-Fire database. A new LGFUEL variable (total loading of all down fuels > 3") was created by summing the DMPH_3_9P, DMPH_9_20C and DMPH_GT_20C variables after converting each to tons/acre by dividing by 2241.702308. A small fuel variable (DMPH_0_3) was created by converting DVPH_0_3P (volume) to mass using a wood density of 0.44 g/cm^3.

3.2.2 Step 2 – High Fuel Model Assignment

Fuel models were selected for plots in the "high fuels" category using the variables computed in Step 1 (SMFUEL and LGFUEL). The following rules were adapted from the FVS-FFE documentation (Reinhardt and Crookston 2003, page 39):

If SMFUEL > 6 *and* LGFUEL > 20
  Assign fuel model 12
Otherwise
  Assign fuel model 10

3.2.3 Step 3 – Low Fuel Model Species Grouping

Plots in the "low fuels" category were determined, by geographic location, to be either in the Northern Idaho (p. 95) or the East Cascades variant (p.159) as described in the FVS-FFE documentation. Second, plots were assigned to a species group based on total basal area within each species group using the following procedure:

1) Basal area by size class (in the SPECIESUDB table in the database) was totaled for each species. For example:

PSME1 + PSME2 + PSME3 + PSME4 = PSME

2) Species were then grouped so that plots fell within species groups described in Reinhardt and Crookston (2003).

PSMEGRP = PSME + THPL
PIPOGRP = PIPO
PICOGRP = PICO + PIMO3 + PIEN2 + PIAL + LALY
ABLAGRP = ABLA
TSMEGRP = TSME + TSHE + ABAM + ABGR
LAOCGRP = LAOC
MOISTGRP = BEPAC + POTR5 + POBAT

The species group with the highest basal area was assigned to the plot. For plots with no trees present, the default species group was assumed to be PSME.

3.2.4   Step 4 – Low Fuel Model Assignment

The following sets of decision were are used to select fuel models depending on the species group assigned in step 3:

For the Northern Idaho variant (Reinhardt and Crookston, page 103):

If the plot was dominated be either PSMEGRP or PIPOGRP, then

       If CANCOV < 30%
             Assign fuel model 1
       If 30% CANCOV < 50%
             Assign fuel model 8
       If CANCOV > 50%
             Assign fuel model 9

If the plot was dominated by a species group other than PSMEGRP or PIPOGRP, then
       Assign fuel model 8

For the East Cascades variant (Reinhardt and Crookston, page 169):

**In order to use the rules for this variant, it had to be determined whether the canopy was single storied or multistoried. The following equation was developed:

Stratum = (STNDHGT – HCB) / (STNDHGT)

If stratum < 0.5 or if STNDHGT = 0, the canopy was ruled single storied. Otherwise, the canopy was ruled multistoried.

If the plot is dominated by the Douglas-fir group (**PSMEGRP)** or if all species groups have a value of 0, then

If CANCOV < 20%, then
       If the canopy is single storied, then
             Assign fuel model 1
       Otherwise
             Assign fuel model 5
If 20% < CANCOV < 50%, then
       If the canopy is single storied, then
             Assign fuel model 5
       Otherwise
             Assign fuel model 8
If 50% <CANCOV < 80%, then
       If the quadratic mean diameter (QMDA_DOM1) < 3", then
             Assign fuel model 5
       Otherwise
             Assign fuel model 8
If CANCOV > 80%, then
       Assign fuel model 8

If the plot is dominated by the Ponderosa pine group (**PIPOGRP)**, then

If CANCOV < 20%, then
        If the canopy is single storied, then
                Assign fuel model 2
        Otherwise
                Assign fuel model 6
If 20% < CANCOV < 50%, then
        If the canopy is single storied, then
                Assign fuel model 6
        Otherwise
                Assign fuel model 9
If 50% < CANCOV < 80%, then
        If QMDA_DOM1 < 3", then
                Assign fuel model 6
        Otherwise
                Assign fuel model 9
If CANCOV > 80%, then
        Assign fuel model 9

If the plot is dominated by the lodgepole pine group (**PICOGRP)**, then

If CANCOV < 20%, then
        If the canopy is single storied, then
                Assign fuel model 1
        Otherwise
                Assign fuel model 5
If 20% < CANCOV < 50, then
        If the QMDA_DOM1 < 3", then
                Assign fuel model 1
        Otherwise
                If the canopy is single storied, then
                        Assign fuel model 8
                Otherwise
                        Assign fuel model 5
If 50% < CANCOV < 80%, then
        If the QMDA_DOM1 < 3", then
                Assign fuel model 5
        Otherwise
                Assign fuel model 8
If CANCOV > 80%, then
        If the canopy is single storied, then
                If QMDA_DOM1 < 3", then
                        Assign fuel model 5
                Otherwise

Assign fuel model 8
        Otherwise
                Assign fuel model 8

If the plot is dominated by the subalpine fir group (**ABLAGRP**), then

If CANCOV < 20%, then
        If the canopy is single storied, then
                Assign fuel model 1
        Otherwise
                Assign fuel model 5
If 20% < CANCOV < 50%, then
        If the canopy is single storied, then
                If the QMDA_DOM1 < 3", then
                        Assign fuel model 5
                Otherwise
                        Assign fuel model 8
        Otherwise
                Assign fuel model 8
If 50% < CANCOV < 80%, then
        If the QMDA_DOM1 < 3", then
                Assign fuel model 5
        Otherwise
                Assign fuel model 8
If CANCOV > 80%, then
        Assign fuel model 8

If the plot is dominated by the mountain hemlock group (**TSMEGRP**), then

If CANCOV < 20%, then
        If the canopy is single storied, then
                Assign fuel model 1
        Otherwise
                Assign fuel model 5
If 20% < CANCOV < 50%, then
        If the canopy is single storied, then
                If the QMDA_DOM1 < 3", then
                        Assign fuel model 5
                Otherwise
                        If QMDA_DOM1 < 20", then
                                Assign fuel model 8
                        Otherwise
                                Assign fuel model 5
        Otherwise
                Assign fuel model 8
If 50% < CANCOV < 80%, then

If the quadratic mean diameter (QMDA_DOM1) < 3", then
  Assign fuel model 5
Otherwise
  Assign fuel model 8
If CANCOV > 80%, then
 Assign fuel model 8

If the plot is dominated by the western larch group (**LAOCGRP**), then

If the quadratic mean diameter (QMDA_DOM1) < 3", then
 If CANCOV < 20%, then
  Assign fuel model 1
 Otherwise
  If CANCOV < 80%, then
   Assign fuel model 5
  Otherwise
   Assign fuel model 8
If 3" < QMDA_DOM1 < 8", then
 If CANCOV < 20%, then
  If the canopy is single storied, then
   Assign fuel model 1
  Otherwise
   Assign fuel model 5
 Otherwise
  Assign fuel model 8
If 8" < QMDA_DOM1 < 20", then
 If the canopy is single storied, then
  If CANCOV < 20%, then
   Assign fuel model 5
  Otherwise
   Assign fuel model 8
 Otherwise
  Assign fuel model 8
If QMDA_DOM1 > 20%, then
 If CANCOV < 20%, then
  If the canopy is single storied, then
   Assign fuel model 1
  Otherwise
   Assign fuel model 5
 Otherwise
  Assign fuel model 8

If the plot is dominated by the moist habitat group (**MOISTGRP**), then

If CANCOV < 20%, then
 If the canopy is single storied, then

If QMDA_DOM1 < 8", then
    Assign fuel model 1
Otherwise
    If QMDA_DOM1 < 20", then
        Assign fuel model 5
    Otherwise
        Assign fuel model 1
Otherwise
    Assign fuel model 5
If 20% < CANCOV <50%, then
    If the canopy is single storied, then
        If QMDA_DOM1 < 3", then
            Assign fuel model 5
        Otherwise
            If QMDA_DOM1 < 20", then
                Assign fuel model 8
            Otherwise
                Assign fuel model 5
    Otherwise
        Assign fuel model 8
If 50% < CANCOV < 80%, then
    If QMDA_DOM < 3", then
        Assign fuel model 5
    Otherwise
        Assign fuel model 8
If CANCOV > 80%, then
    Assign fuel model 8

3.3   Sierra Nevada

The methods for assigning fuel models to each plot were adapted from the description of the Western Sierra variant of FFE-FVS in (Reinhardt and Crookston 2003), but have been modified to reflect the fuels and forest structure variables that are available in the GNN-Fire database, and to incorporate recommendations from Dave Sapsis of the California Department of Forestry.

The general procedure for the fuel model crosswalk is as follows. Individual steps are described in more detail in subsequent sections.

Step 1: Classify each plot into a forest cover type based on the California Wildlife Habitat Relationships System (Mayer and Laudenslayer 1988).

Step 2: Classify each plot into canopy cover and size classes based on the California Wildlife Habitat Relationships System (Mayer and Laudenslayer 1988).

Step 3: Assign a fuel model to each plot based on its dominant species class, canopy cover class, and size class.

3.3.1   Step 1: Forest Cover Type

Forested plots were assigned cover types based on the proportion of their basal area falling within various species groups. The algorithm for classifying each plot consisted of the following steps:

1. If the quadratic mean diameter of trees on the plot was less than 2.54 cm or the canopy cover of the plot was less than 10%, then the plot was classified as either a **Nonstocked** or **Montane chaparral** class.

> 1a. If total shrub cover was greater than 50%, the plot was classified as **Montane chaparral**.

> 1b. Otherwise, the plot was classified as **Nonstocked**.

2. Otherwise, if hardwoods comprised more than 50% of the total plot basal area, the plot was classified as **Hardwood**.

3. Otherwise, if Ponderosa pine comprised more than 80% of the total plot basal area, the plot was classified as **Ponderosa pine**.

4. Otherwise, if Red fir plus Shasta red fir comprised more than 80% of the total plot basal area, the plot was classified as **Red fir**.

5. Otherwise, if White fir comprised more than 80% of the total plot basal area, the plot was classified as **White fir**.

6. Otherwise, if Douglas-fir comprised more than 80% of the total plot basal area, the plot was classified as **Douglas-fir**.

7. Otherwise, if Giant sequoia comprised more than 80% of the total plot basal area, the plot was classified as **Giant sequoia**.

8. Otherwise, if Jeffery pine comprised more than 80% of the total plot basal area, the plot was classified as **Jeffery pine**.

9. Otherwise, if Lodgepole pine comprised more than 80% of the total plot basal area, the plot was classified as **Lodgepole pine**.

10. Otherwise, if the total basal area of *Pinus spp*. comprised more than 50% of the total conifer basal area, the plot was classified as **Pine mixed-conifer**.

11. Otherwise, if the total basal area of *Abies spp*. comprised more than 50% of the total conifer basal area, the plot was classified as **Fir mixed-conifer**.

12. Otherwise, if the total basal area of all conifers except *Abies spp*. and *Pinus spp*. comprised more than 50% of the total conifer basal area, the plot was classified as **Other conifer**.

13. Otherwise, the plot was classified as **Fir mixed-conifer** (the default class)

Note that plots that fall through to the end of the algorithm and are assigned the default class are actually labeled NCL (for nonclassified) in the database. These plots are still treated as if they belong to the **Fir mixed conifer** class when fuel models are assigned in Step 3. The NCL label was included to easily distinguish between plots that are assigned to the **Fir-mixed conifer** class based on the 50% of total conifer basal area threshold (these are assigned an FMC label) versus those that are assigned to the **Fir-mixed conifer** as the default class (these get the NCL label).

3.3.2   Step 2: Structural Classification

Non-stocked plots (with quadratic mean diameter < 2.54 cm or canopy cover < 10%) were not assigned a size or density class. For other plots, tree size and tree density classes were assigned based on the quadratic mean diameter of dominant and co-dominant trees (QMDA_DOM1 in the GNN-Fire plot database) and overstory canopy cover (CANCOV in the GNN-Fire plot database). The cutoffs used for assigning these classes are listed in Table 3.1.

Table 3.1: Forested plots are assigned to a CWHR size and density classes using the following criteria.

Tree Size (DBH cm)[1]	Canopy Cover (%)	CWHR tree size class	CWHR tree density class
Any	< 10	1	NA
2.54	>=10	1	NA
2.54-15.24	10-24	2	S
2.54-15.24	25-39	2	P
2.54-15.24	40-59	2	M
2.54-15.24	>= 60	2	D
15.24-27.94	10-24	3	S
15.24-27.94	25-39	3	P
15.24-27.94	40-59	3	M
15.24-27.94	>= 60	3	D
27.94-60.96	10-24	4	S
27.94-60.96	25-39	4	P
27.94-60.96	40-59	4	M
27.94-60.96	>= 60	4	D
> 60.96	10-24	5	S
> 60.96	25-39	5	P
> 60.96	40-59	5	M
> 60.96	>= 60	5	D
> 60.96	>= 60% total *and* > 1 canopy layer	6	NA

[1]QMD of dominant and codominant trees

Size class 6 from the California Wildlife Habitat Relationships system was a multi-layered stand class. In addition to the size and canopy cover criteria, plots belonging to this class were also required to have more than one distinctive canopy layer. The number of canopy layers was obtained from the COLA_LAYERS field in the GNN-Fire plot database.

3.3.3 Step 3: Fuel Model Assignment

All plots classified as Nonstocked were assigned a fuel model 5.

All plots classified as Montane chaparral were assigned a fuel model 26 (Modified chaparral, see Appendix A).

Otherwise, a fuel model is assigned to each plot based on its forest cover type, size class, and density class (Table 3.2). This look-up table is based on recommendations from Dave Sapsis of the California Department of Forestry. Although it is based on the same format as the look-up table in Reinhardt and Crookston (2003), the fuel model assignments are different.

Table 3.2: Fuel model assignments for forested habitats

Size class	1	2				3				4				5				6
Density class		S	P	D	M	S	P	D	M	S	P	D	M	S	P	D	M	
Cover type																		
Pine	5	5	5	9	9	26	26	10	10	26	26	10	10	26	26	10	10	10
Red fir	5	5	5	8	8	11	11	8	8	8	8	8	8	8	8	8	8	10
White fir	5	5	5	8	8	11	11	8	8	9	9	11	11	9	9	11	11	10
Douglas-fir	5	5	5	9	9	5	5	8	8	11	11	10	10	11	11	10	10	10
Giant sequoia	5	5	5	9	9	9	9	9	9	9	9	9	10	9	9	9	10	10
Jeffrey pine	5	5	5	9	9	2	2	9	11	2	9	11	9	2	2	9	11	10
Hardwoods	5	5	5	9	9	5	9	8	8	5	9	9	8	9	9	9	8	9
Lodgepole pine	5	5	5	8	8	8	8	8	8	5	8	8	8	5	8	8	8	10
Pine mixed con	5	5	5	9	9	26	11	10	10	26	10	10	10	26	10	10	10	10
Fir mixed conifer	5	9	5	8	8	26	11	10	8	5	5	9	10	5	10	9	10	10
Other conifers	5	8	5	9	10	6	10	10	10	26	10	10	10	26	10	10	10	10

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Appendix 3 – Core vegetation and fuels variables joined to GNN imputation maps and used in accuracy assessments for species-size and structure models. All variables are at the at the forest class level (summary of all portions of a plot that are forest). All variables are in metric units; updated versions of our plot databases with English-unit-versions of the variables will be made available for download from our website.

Category	Variable name	Description
Plot identification	*PLTID*	Unique plot identification number.
	FCID	Unique forest class identification number.
	DATA_SOURCE	Source of the plot data: BLMWO = BLM in western Oregon, FIACA = FIA in California, FIAEW = FIA in eastern Washington, FIAWO = FIA in western Oregon, NCNP = North Cascades National Park, R5 = Forest Service Region 5, R6 = Forest Service Region 6, SEKI = Sequoia-Kings Canyon National Park, YOSE = Yosemite National Park.
Live tree	*BAA_GE_3*	Basal area (m^2/ha) of all live trees >=2.54 cm dbh
	BAC_GE_3	Basal area (m^2/ha) of all live conifers >=2.54 cm dbh
	BAH_GE_3	Basal area (m^2/ha) of all live hardwoods >=2.54 cm dbh
	BAH_PROP	Proportion of total live tree basal area that is hardwood.
	QMDA_DOM	Quadratic mean diameter (QMD) (cm) of all dominant and codominant trees.
	QMDC_DOM	QMD (cm) of all dominant and codominant conifers.
	QMDH_DOM	QMD (cm) of all dominant and codominant hardwoods.
	CANCOV	Canopy cover (percent) of all live trees, calculated using methods in the Forest Vegetation Simulator (Crookston and Stage 1999).
	CANCOV_CON	Canopy cover (percent) of all conifers, calculated using methods in the Forest Vegetation Simulator (Crookston and Stage 1999).
	CANCOV_HDW	Canopy cover (percent) of all hardwoods, calculated using methods in the Forest Vegetation Simulator (Crookston and Stage 1999).
	STNDHGT	Average height (m) of dominant and codominant trees.
	FORTYPBA	Forest type (alpha code comprised of one or two species codes). Assigned based on plurality of species basal area, as follows. If *CANCOV* <10 then *FORTYPBA* = 'remnant.' If *BAH_PROP* >=0.65 and >=80% of the hardwood basal area is in one species, a single hardwood species is assigned; otherwise *FORTYPBA* is named for the two predominant hardwood species. If *BAH_PROP* 0.20-0.64, *FORTYPBA* is named by the dominant hardwood species and the dominant conifer species, shown in order of most basal area. If *BAHPROP* <0.20 and >=80% of total conifer basal areas is in one species, *FORTYPBA* is that single (conifer) species; otherwise, *FORTYPBA* is named for the two predominant conifer species. Species codes are defined in the plot database.

	VEGCLASS	Vegetation class from Johnson and O'Neil (2001) 1 Sparse (*CANCOV* <10) 2 Open (*CANCOV* 10-39) 3 Broadleaf, sap/pole, mod/closed (*CANCOV* >=40, *BAH_PROP* >=0.65, *QMDA_DOM* <25 cm) 4 Broadleaf, sm/med/lg, mod/closed (*CANCOV* >=40, *BAH_PROP* >=0.65, *QMDA_DOM* >25 cm) 5 Mixed, sap/pole, mod/closed (*CANCOV* >=40, *BAH_PROP* 0.20-0.64, *QMDA_DOM* <25 cm) 6 Mixed, sm/med, mod/closed (*CANCOV* >=40, *BAH_PROP* 0.20-0.64, *QMDA_DOM* 25-50 cm) 7 Mixed, large+giant, mod/closed (*CANCOV* >=40, *BAH_PROP* 0.20-0.64, *QMDA_DOM* >50 cm) 8 Conifer, sap/pole, mod/closed (*CANCOV* >=40, *BAH_PROP* <0.20, *QMDA_DOM* <25 cm) 9 Conifer, sm/med, mod/closed (*CANCOV* >=40, *BAH_PROP* <0.20, *QMDA_DOM* 25-50 cm) 10 Conifer, large, mod/closed (*CANCOV* >=40, *BAH_PROP* <0.20, *QMDA_DOM* 50-75 cm) 11 Conifer, giant, mod/closed (*CANCOV* >=40, *BAH_PROP* <0.20, *QMDA_DOM* >75 cm)
	SIZECL	Size class from Johnson and O'Neil (2001, p. 116-119) 1 Shrub/seedling (*QMDA_DOM* <2.5 or *CANCOV* <10) 2 Sapling/pole (*QMDA_DOM* >=2.5 and <25.0) 3 Small tree (*QMDA_DOM* >=25.0 and <37.5) 4 Medium tree (*QMDA_DOM* >=37.5 and <50.0) 5 Large tree (*QMDA_DOM* >=50.0 and <75) 6 Giant tree (*QMDA_DOM* >=75.0)
	COVCL	Cover class from Johnson and O'Neil (2001, p. 116-119) 1 Sparse/remnant (*CANCOV* <10) 2 Open (*CANCOV* >=10 and <40) 3 Moderate (*CANCOV* >=40 and <70) 4 Closed (*CANCOV* >=70)
	CWHR_SIZE	Size class from California Wildlife Habitat Relationships Program (Mayer and Laudenslayer 1988) (California only) 1 Seedling tree (*CANCOV* < 10) 2 Sapling tree (*CANCOV* >= 10 and *QMDA_DOM* 2.54-15.24) 3 Pole tree (*CANCOV* >= 10 and *QMDA_DOM* 15.24-27.94) 4 Small tree (*CANCOV* >= 10 and *QMDA_DOM* 27.94-60.96) 5 Medium/large tree (*CANCOV* >= 10 and *QMDA_DOM* > 60.96) 6 Multi-layered tree (*CANCOV* >= 60 and at least two canopy layers present)

	CWHR_DENSITY	Canopy closure class from CWHR (Mayer and Laudenslayer 1988) (California only) NA (not applicable – *CANCOV* <10) S (sparse, *CANCOV* 10-24) P (open, *CANCOV* 25-39) M (moderate, *CANCOV* 40-59) D (dense, *CANCOV* 60-100)
Understory	*SHRCOV*	Cumulative cover (percent) of all shrubs (may be >100%). [Not available for Oregon.]
Snag	*STPH_GE_25*	Density (trees/ha) of snags >=25.0 cm dbh and >=2.0 m tall.
	STPH_GE_50	Density (trees/ha) of snags >=50.0 cm dbh and >=2.0 m tall.
	SVPH_GE_25	Volume (m^3/ha) of snags >=25.0 cm dbh and >=2.0 m tall.
	SVPH_GE_50	Volume (m^3/ha) of snags >=50.0 cm dbh and >=2.0 m tall.
	SBPH_5_9	Biomass (kg/ha) of snags 5-9 inches (12.7-22.9 cm) dbh and >=2.0 m tall.
	SBPH_9_20	Biomass (kg/ha) of snags 9-20 inches (22.9-50.8 cm) dbh and >=2.0 m tall.
	SBPH_GE_20	Biomass (kg/ha) of snags >=20 inches (50.8 cm) dbh and >=2.0 m tall.
Down wood	*DVPH_GE_25*	Volume (m^3/ha) of down wood >=25.4 cm diameter at intercept and >=1 m long. [R5 plots limited to pieces >=3.0 m long. FIA plots do not include decay class 5 logs.]
	DVPH_GE_50	Volume (m^3/ha) of down wood >=50.0 cm diameter at intercept and >=1 m long. [R5 plots limited to pieces >=3.0 m long. FIA plots do not include decay class 5 logs.]
	DBPH_9_20	Biomass (kg/ha) of down wood 9-20 inches (22.9-50.8 cm) diameter at large end and >=1 m long. [R5 plots limited to >=10 in (25.4 cm) diameter and >=3.0 m long. FIA plots do not include decay class 5 logs. Missing decay class set=3 for YOSE.]
	DBPH_GE_20	Biomass (kg/ha) of down wood >=20 inches (50.8 cm) diameter at intercept and >=1 m long. [R5 plots limited to >=3.0 m long. FIA plots do not include decay class 5 logs. Missing decay class set=3 for YOSE.]

Canopy and surface fuels	PCANFWT	Total weight of all available canopy fuels (kg/ha), which includes the mass of live conifer foliage plus one-half the mass of live and dead conifer branches in the 0-0.25 inch size class (see Appendix 2). Based on equations for the coastal Pacific Northwest (used for Oregon).
	RCANFWT	Total weight of all available canopy fuels (kg/ha), which includes the mass of live conifer foliage plus one-half the mass of live and dead conifer branches in the 0-0.25 inch size class (see Appendix 2). Based on equations for the northern Rocky Mountains (used for California and Washington).
	PHTCBU2	Height to crown base (m) computed with vertical layering method, 'uncompacted' crowns, and equations for the coastal Pacific Northwest (see Appendix 2) (used for Oregon). Code '999' is assigned where there is minimal crown.
	RHTCBU2	Height to crown base (m) computed with vertical layering method, 'uncompacted' crowns, and equations for the northern Rocky Mountains (see Appendix 2) (used for California and Washington). Code '999' is assigned where there is minimal crown.
	PCBDU2	Canopy bulk density (kg/m^3) computed with vertical layering method, 'uncompacted' crowns, and equations for the coastal Pacific Northwest (see Appendix 2) (used for Oregon).
	RCBDU2	Canopy bulk density (kg/m^3) computed with vertical layering method, 'uncompacted' crowns, and using equations for the northern Rocky Mountains (see Appendix 2) (used for California and Washington).
	FUEL_MODEL	Fire behavior fuel model. For all study areas, classification rules were modified slightly from those in documentation for the appropriate variant of FVS-FFE and to reflect the fuels and vegetation variables available in the GNNFire database (see Appendix 2) and local expert knowledge. 1 short grass 2 timber (grass and understory) 5 brush 6 dormant brush, hardwood slash 8 closed timber litter 9 hardwood litter 10 timber (litter and understory) 11 light logging slash 12 medium logging slash 26 modified chaparral (California)

Literature Cited

Crookston, NL, and AR Stage. 1999. Percent canopy cover and stand structure statistics from the Forest Vegetation Simulator. RMRS-GTR-24. 8 pp.

Johnson, DH, and TA O'Neil. 2001, eds. Wildlife-habitat relationships in Oregon and Washington. Oregon State University Press; Corvallis, OR; 736 p.

Mayer, KE, and WF Laudenslayer, eds. 1988. A guide to wildlife habitats of California. California Department of Forestry and Fire Protection; Sacramento, CA; 166 p.

Monleon, VJ, D Azuma, and D Gedney. 2004. Equations for predicting uncompacted crown ratio based on compacted crown ratio and tree attributes. Western Journal of Applied Forestry 19:260-267.

Appendix 4 – Directory structure and file names for final products on enclosed DVDs.

Filename	File type	Description
Publications and other products		
\pubs_and_reports\final_report_01-1-4-09.pdf	Adobe pdf	JFSP final report
\pubs_and_reports\pierce_etal_in-prep_EcoApp.pdf	Adobe pdf	draft GNNFire manuscript to be submitted to Ecological Applications (do not distribute)
\pubs_and_reports\ohmann_etal_inpress_EcoApp.pdf	Adobe pdf	Ohmann et al. (in press)
\pubs_and_reports\ohmann_gregory_2002_CJFR.pdf	Adobe pdf	Ohmann and Gregory (2002)
\pubs_and_reports\pierce_etal_2004_esa_poster.pdf	Adobe pdf	poster from ESA (2004)
\pubs_and_reports\wimberly_etal_2003_fireconf.pdf	Adobe pdf	Wimberly et al. (2003)
\pubs_and_reports\wimberly_Ohmann_2004_LandEco.pdf	Adobe pdf	Wimberly et al. (2004)
\pubs_and_reports\gregory_ohmann_2004_GNNrun_poster.pdf	Adobe pdf	poster from US-IALE software swap meet (2004)
All study areas		
\all_study_areas\documentation\plot_database_documentation.mdb	Access database	code definitions and data dictionary for plot data
\all_study_areas\gnnrun_software\gnnrun.exe	Windows executable	software for running GNN
\all_study_areas\gnnrun_software\gnnrun_users_guide.pdf	Adobe pdf	users guide for running GNN
California		
\california\models\accuracy_assessment\interplots_ca.pdf	Adobe pdf	Histogram of inter-plot distances in gradient space to accompany NNDIST grid (all models)
\california\models\accuracy_assessment\spp_kappa_ca.pdf	Adobe pdf	Kappa statistics for species presence/absence (spp model)
\california\models\accuracy_assessment\vegclass_error_matrix_ca.pdf	Adobe pdf	Two-way error matrix for vegetation class (sppsz and struct models)

\california\models\accuracy_assessment\vegclass_kappa_ca.pdf	Adobe pdf	Kappa statistics for vegetation class (sppsz and struct models)
\california\models\accuracy_assessment\vegclass_area_histograms_ca.xls	Adobe pdf	Distribution of forest area among vegetation classes predicted from GNN and estimated from grid plots (sppsz and struct models)
\california\models\accuracy_assessment\fuelmod_area_histograms_ca.pdf	Adobe pdf	Distribution of forest area among fuel models predicted from GNN and estimated from grid plots
\california\models\accuracy_assessment\scatters_ca_sppsz_fil.pdf	Adobe pdf	Scatterplots and correlations between GNN-predicted vs. plot-observed values for selected vegetation and fuels variables
\california\models\accuracy_assessment\scatters_ca_struct_fil.pdf	Adobe pdf	Scatterplots and correlations between GNN-predicted vs. plot-observed values for selected vegetation and fuels variables
\california\models\accuracy_assessment\scatters_ca_struct_unf.pdf	Adobe pdf	Scatterplots and correlations between GNN-predicted vs. plot-observed values for selected vegetation and fuels variables
\california\models\ca_spp\canoco.out	text	output file from Canoco software
\california\models\ca_spp\canoco.sol	text	solution file from Canoco software
\california\models\ca_spp\ca_spp	ArcGIS grid	GNN imputation map
\california\models\ca_spp\nndist	ArcGIS grid	GNN nearest-neighbor-distance map, converted to integer (NNDIST * 100)
\california\models\ca_sppsz_fil\canoco.out	text	output file from Canoco software
\california\models\ca_sppsz_fil\canoco.sol	text	solution file from Canoco software
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\california\models\ca_sppsz_fil\nndist	ArcGIS grid	GNN nearest-neighbor-distance map, converted to integer (NNDIST * 100)

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\california\models\ca_struct_fil\canoco.sol	text	solution file from Canoco software
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\california\spatial\climate\annvp30	ArcGIS grid	Annual vapor pressure (scaled * 10 and converted to integer)
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\california\spatial\climate\contpre30	ArcGIS grid	Percentage of annual precipitation falling in June-August (scaled * 1000 and converted to integer)
\california\spatial\climate\decmint30	ArcGIS grid	Mean December minimum temperature (degrees C) (scaled * 1000 and converted to integer)
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\california\spatial\disturbance\fire200030	ArcGIS grid	Fire perimeters and years since burn (up to 2000) (from CDF)

Oregon		
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\oregon\models\accuracy_assessment\spp_kappa_or.pdf	Adobe pdf	Kappa statistics for species presence/absence (spp model)
\oregon\models\accuracy_assessment\vegclass_error_matrix_or.pdf	Adobe pdf	Two-way error matrix for vegetation class (sppsz and struct models)
\oregon\models\accuracy_assessment\vegclass_kappa_or.pdf	Adobe pdf	Kappa statistics for vegetation class (sppsz and struct models)
\oregon\models\accuracy_assessment\fuelmod_area_histograms_or.pdf	Adobe pdf	Distribution of forest area among fuel models predicted from GNN and estimated from grid plots (sppsz and struct models)
\oregon\models\accuracy_assessment\vegclass_area_histograms_or.xls	Adobe pdf	Distribution of forest area among vegetation classes predicted from GNN and estimated from grid plots (sppsz and struct models)
\oregon\models\accuracy_assessment\scatters_or_sppsz_fil.pdf	Adobe pdf	Scatterplots and correlations between GNN-predicted vs. plot-observed values for selected vegetation and fuels variables
\oregon\models\accuracy_assessment\scatters_or_struct_fil.pdf	Adobe pdf	Scatterplots and correlations between GNN-predicted vs. plot-observed values for selected vegetation and fuels variables
\oregon\models\accuracy_assessment\scatters_or_struct_unf.pdf	Adobe pdf	Scatterplots and correlations between GNN-predicted vs. plot-observed values for selected vegetation and fuels variables
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\oregon\models\or_spp\canoco.sol	text	solution file from Canoco software
\oregon\models\or_spp\or_spp	ArcGIS grid	GNN imputation map

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\oregon\spatial\climate\smrtp30	ArcGIS grid	Growing season moisture stress (ratio of temperature to precipitation from May-September) (scaled * 1000 and converted to integer)
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Washington		
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\washington\models\accuracy_assessment\vegclass_kappa_wa.p df	Adobe pdf	Kappa statistics for vegetation class (sppsz and struct models)
\washington\models\accuracy_assessment\fuelmod_area_histogr ams_wa.pdf	Adobe pdf	Distribution of forest area among fuel models predicted from GNN and estimated from grid plots (sppsz and struct models)
\washington\models\accuracy_assessment\vegclass_area_histogr ams_wa.xls	Adobe pdf	Distribution of forest area among vegetation classes predicted from GNN and estimated from grid plots (sppsz and struct models)
\washington\models\accuracy_assessment\scatters_wa_sppsz_fil. pdf	Adobe pdf	Scatterplots and correlations between GNN-predicted vs. plot-observed values for selected vegetation and fuels variables
\washington\models\accuracy_assessment\scatters_wa_struct_fil .pdf	Adobe pdf	Scatterplots and correlations between GNN-predicted vs. plot-observed values for selected vegetation and fuels variables
\washington\models\accuracy_assessment\scatters_wa_struct_un f.pdf	Adobe pdf	Scatterplots and correlations between GNN-predicted vs. plot-observed values for selected vegetation and fuels variables
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\washington\models\wa_spp\canoco.sol	text	solution file from Canoco software
\washington\models\wa_spp\wa_spp	ArcGIS grid	GNN imputation map

\washington\models\wa_spp\nndist	ArcGIS grid	GNN nearest-neighbor-distance map, converted to integer (NNDIST * 100)
\washington\models\wa_sppsz_fil\canoco.out	text	output file from Canoco software
\washington\models\wa_sppsz_fil\canoco.sol	text	solution file from Canoco software
\washington\models\wa_sppsz_fil\wa_sppsz_fil	ArcGIS grid	GNN imputation map
\washington\models\wa_sppsz_fil\nndist	ArcGIS grid	GNN nearest-neighbor-distance map, converted to integer (NNDIST * 100)
\washington\models\wa_struct_fil\canoco.out	text	output file from Canoco software
\washington\models\wa_struct_fil\canoco.sol	text	solution file from Canoco software
\washington\models\wa_struct_fil\wa_struct_fil	ArcGIS grid	GNN imputation map
\washington\models\wa_struct_fil\nndist	ArcGIS grid	GNN nearest-neighbor-distance map, converted to integer (NNDIST * 100)
\washington\models\wa_struct_unf\canoco.out	text	output file from Canoco software
\washington\models\wa_struct_unf\canoco.sol	text	output file from Canoco software
\washington\models\wa_struct_unf\wa_struct_unf	ArcGIS grid	GNN imputation map
\washington\models\wa_struct_unf\nndist	ArcGIS grid	GNN nearest-neighbor-distance map, converted to integer (NNDIST * 100)
\washington\plot\wa_plots.mdb	Access database	Plot data used in GNN model development and mapping
\washington\spatial\warefbnd_po	ArcGIS polygon	Study area boundary
\washington\spatial\wamask30	ArcGIS grid	Nonforest mask
\washington\spatial\ancillary\nlcdorig30	ArcGIS grid	Original NLCD grid
\washington\spatial\ancillary\owner30	ArcGIS grid	Ownership classes
\washington\spatial\predictors\landsat\tm19230	ArcGIS grid	Landsat ETM band 1, 1992

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\washington\spatial\predictors\landsat\tm39230	ArcGIS grid	Landsat ETM band 3, 1992
\washington\spatial\predictors\landsat\tm49230	ArcGIS grid	Landsat ETM band 4, 1992
\washington\spatial\predictors\landsat\tm59230	ArcGIS grid	Landsat ETM band 5, 1992
\washington\spatial\predictors\landsat\tm79230	ArcGIS grid	Landsat ETM band 7, 1992
\washington\spatial\predictors\landsat\tm10030	ArcGIS grid	Landsat ETM band 1, 2000
\washington\spatial\predictors\landsat\tm20030	ArcGIS grid	Landsat ETM band 2, 2000
\washington\spatial\predictors\landsat\tm30030	ArcGIS grid	Landsat ETM band 3, 2000
\washington\spatial\predictors\landsat\tm40030	ArcGIS grid	Landsat ETM band 4, 2000
\washington\spatial\predictors\landsat\tm50030	ArcGIS grid	Landsat ETM band 5, 2000
\washington\spatial\predictors\landsat\tm70030	ArcGIS grid	Landsat ETM band 7, 2000
\washington\spatial\climate\annfrost30	ArcGIS grid	Mean number of days/yr when daily minimum temperature <=0.0 degrees C (scaled * 10 and converted to integer)
\washington\spatial\climate\annpre30	ArcGIS grid	Annual precipitation (natural logarithm, mm) (scaled * 1000 and converted to integer)
\washington\spatial\climate\annsw30	ArcGIS grid	Annual sum of total daily incident shortwave radiative flux (MJ^{-2} day^{-1}) (scaled * 10 and converted to integer)
\washington\spatial\climate\annvp30	ArcGIS grid	Annual vapor pressure (scaled * 10 and converted to integer)
\washington\spatial\climate\augmaxt30	ArcGIS grid	Mean August maximum temperature (degrees C) (scaled * 100 and converted to integer)
\washington\spatial\climate\contpre30	ArcGIS grid	Percentage of annual precipitation falling in June-August (scaled * 100 and converted to integer)

\washington\spatial\climate\decmint30	ArcGIS grid	Mean December minimum temperature (degrees C) (scaled * 100 and converted to integer)
\washington\spatial\climate\smrpre30	ArcGIS grid	Mean precipitation from May-September (natural logarithm, mm) (scaled * 1000 and converted to integer)
\washington\spatial\climate\smrtp30	ArcGIS grid	Growing season moisture stress (ratio of temperature to precipitation from May-September) (scaled * 1000 and converted to integer)
\washington\spatial\location\xutm30	ArcGIS grid	UTM X coordinate (m)
\washington\spatial\location\yutm30	ArcGIS grid	UTM Y coordinate (m)
\washington\spatial\topography\dem30	ArcGIS grid	Elevation (m)
\washington\spatial\topography\prr30	ArcGIS grid	Potential relative radiation
\washington\spatial\topography\slppct30	ArcGIS grid	Slope (percent) (rounded to nearest integer)
\washington\spatial\topography\tpi45030	ArcGIS grid	Topographic position index, calculated as difference between cell's elevation and mean elevation of cells within a 450-m-radius window
\washington\spatial\ownership\usfsblm30	ArcGIS grid	Forest Service and BLM ownerships

he Joint Fire Science Program (JFSP)1 has funded over 300 projects examining wildfire, prescribed fire, and fuel management activities. Many of these projects, or portions of them, are examining or have examined fire effects on soils. The topics considered by these studies are as varied as the services provided by soils. All share the common goal of increased understanding of both short- and long-term responses of soil to fire by building on previous knowledge and providing specific information from forests and other ecosystems where detailed information is lacking. Although erosion rates were low, the researchers did find that ero-sion was related to the amount of area with bare ground, in particular where elk (Cervus elaphus) and small mammals disturbed the soil.8. Assessment. Final report. 01.0(~. Vanessa O'Connor, P.Eng., NHC. ca::E=. Geo, NHC. CITY OF VANCOUVER 453 West lih Avenue Vancouver, BC, VSY 1V4. ~ - -rGhV\. ._. """ L)'. A continuous simulation (joint probability) approach was taken to establish the ocean levels affected by meteorological and oceanographic conditions corresponding to the selected return periods for each scenario. The approach is statistically defensible and reduces the conservatism inherent in the method presented in the 2011 Provincial Guidelines. Project final report. Grant Agreement number: 308645. Project acronym: P-REX. 4.1 Final publishable summary report. 4.1.1 Executive summary. The P-REX project built on the outputs of previous European research projects and performed the first holistic large scale evaluation of innovative and available phosphorus recovery technologies using municipal sewage sludge or ashes from mono-incineration in comparison with traditional phosphorus recycling by land application of sewage sludge. As one of the key results of the project, the proof of feasibility of novel technical options for phosphorus recovery and recycling from the wastewater stream are given and factors for market success or failure were assessed.