Equations for Predicting Uncompacted Crown Ratio Based on Compacted Crown Ratio and Tree Attributes

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ABSTRACT: *Equations to predict uncompacted crown ratio as a function of compacted crown ratio, tree diameter, and tree height are developed for the main tree species in Oregon, Washington, and California using data from the Forest Health Monitoring Program, USDA Forest Service. The uncompacted crown ratio was modeled with a logistic function and fitted using weighted, nonlinear regression. The models were evaluated using cross-validation. Mean squared error of predicted uncompacted crown ratio was between 0.1 and 0.15, overall bias was negligible, and correlation between the predicted and observed uncompacted crown ratio was high for most species. The sensitivity of crown fire risk to crown ratio estimation method was evaluated using the Fire and Fuels Extension of the Forest Vegetation Simulator. Torching index, an estimate of the wind speed needed for a crown fire to develop, was significantly greater when compacted crown ratio was used instead of uncompacted crown ratio. The close agreement in torching indices simulated using predicted and observed uncompacted crown ratio provides further evidence of the utility of the models developed in this study. West. J. Appl. For. 19(4):260–267.*

Key Words: Crown fire risk, crown base height, cross-validation.

The crown ratio of a tree is defined as the portion of the tree height supporting live foliage. Thus, a crown ratio of 1 would indicate that the foliage reaches the ground, and a crown ratio close to 0 would indicate a very small crown. Although crown ratio is frequently estimated in forest inventories, what is actually measured depends on the protocol used and the objective of the inventory. Trees often have asymmetric crowns, so determining the base of the crown tends to be subjective, and crown ratio depends on the criteria used to define the base of the crown (Maguire and Hann 1987).

Many forest inventories, including the Forest Inventory and Analysis (FIA) and Forest Health Monitoring (FHM), conducted by the USDA Forest Service, measure the "compacted crown ratio" (CCR). Crown base height is determined by mentally transferring lower live branches to fill in large holes in the upper portion of the crown, until a full crown is generated. Then, the ratio of the tree height covered by this compacted crown to its total height is estimated visually and recorded as CCR. The rationale behind the CCR approach is that crown ratio is a surrogate for the total amount of foliage and tree photosynthetic potential. Thus, it is directly related to a tree's growth potential (Hanus et al. 2000). As such, it is often included in forest growth models such as ORGANON (Hann et al. 1997) and FVS (Wykoff et al. 1982).

Crown ratio measurements also are relied on by a variety of forest models, including stand visualization, wildlife habitat potential, and fire behavior models, for which CCR may not be best crown ratio. For example, fire behavior models assume that the risk of crown fire is greater if there is vertical continuity of fuels from the ground to the crown, a concept often described as a "fire ladder." Therefore, the greater the crown ratio, the greater the likelihood that a crown fire will occur. In this context, the main interest is not in the CCR, where the lower branches of trees with asymmetric crowns have been "lifted," but in the uncompacted crown ratio (UCR). Fortunately, both compacted and uncompacted crown ratio were measured on 341 FHM plots in California, Oregon, and Washington during the 2000 and 2001 field seasons. The objective of this study was to use

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this data to develop prediction equations to estimate UCR as a function of CCR, tree diameter, and tree height.

Materials and Methods

Data Description

A complete description of the data collection protocols can be found in the West Coast Forest Health Monitoring Field Guide FY2000 (on file at the Pacific Northwest Research Station). Plots were systematically located on a 16-mi grid across California, Oregon, and Washington, covering all land ownerships and forest types. Only plots located in forestlands, defined as areas with at least 10% potential tree cover, were measured. Each plot consisted of a cluster of four fixed-radius, circular, 1/24-ac subplots, systematically distributed within a 1-ha circle. The plots measured during the 2000 and 2001 inventory years are a spatially balanced sample of about two-fifths of the total number of plots. A total of 341 plots and 7,578 live trees with diameter $\geq$5 in. were measured.

For each tree included in the sample, the diameter at breast height (dbh) was measured using a diameter tape to the closest tenth of an inch. The actual height of most trees was measured with a laser rangefinder to the closest foot, but that of 786 (10%) was visually estimated. A total of 342 (4.5%) trees had a broken top and were excluded from the analysis.

Compacted crown ratio was determined by visually transferring lower live branches to fill in large holes in the upper portion of the tree until a full, even crown was visualized (p. 61, West Coast Forest Health Monitoring Field Guide, Apr. 2000). Uncompacted crown ratio was measured as the ratio of the live crown height to the total height of the tree. The base of the crown was an imaginary horizontal line drawn across the trunk from the bottom of the lowest live foliage of the "obvious live crown," defined as the point of the tree where most live branches are continuous and typical for a tree species and site. Any branch >1 in. in diameter and within 5 ft of the "obvious live crown" was considered part of the live crown, and thus a new horizontal line was established. This evaluation process continued until no live branches of the required size were found (West Coast Forest Health Monitoring Field Guide, Apr. 2000, p. 168). Both crown ratios were measured in 5% increments.

The sample of trees modeled was reduced further according to two additional criteria. First, only species with trees present in at least 10 plots and with at least 50 trees measured were included. This restriction was imposed to ensure a minimum sample size and a degree of spatial variation in the sample. In addition to individual equations by species, equations at the genus level were developed for *Pinus* and *Quercus*. These equations also included trees from species that not meet the sample size criteria. Second, only trees with CCR $\leq$90% were included. This reduced the total sample size by an additional 164 trees. Although this restriction may seem arbitrary, there are important practical as well as statistical reasons to do so. Note that the UCR cannot be smaller than the CCR. Therefore, the UCR must fall between the CCR and 1. So, if the CCR of a tree is 0.95, the UCR has to be between 0.95 and 1. From a practical point of view, once the UCR is estimated to be greater than 0.9, the exact value may not matter and will certainly be within measurement error. Furthermore, the data used to develop these models measure crown ratio in 5% increments, as do most other forest inventories. Once the CCR is greater than 0.9, it is in the highest possible class, and the UCR is known with total certainty. From a statistical point of view, the restriction of the possible values of the UCR to a very small range results in a very small variance for those trees and therefore in a nonconstant variance of the residuals from the prediction equations. Although we used weighted regression, the weights may assign too much influence to observations with UCR greater than 0.9, an undesirable result given that the predicted values for those observations are known.

A list of the tree species included in the analysis, together with summary statistics, is presented in Table 1.

Analysis

General Approach

The goal of the analysis was to develop equations to predict UCR from CCR and tree diameter and height. Because most inventories do not measure the height of all the trees in the sample, we developed two equations for each species: one including CCR, dbh, and height, and another including only CCR and dbh.

UCR is a proportion, and therefore it does not follow a normal distribution, is usually not linear in the explanatory variables, has nonconstant variance, and is bounded between CCR and 1. If using linear regression, proportions are typically modeled after a log-odds (logit) or arcsine square root transformation (Ramsey and Schafer 1996). The logit transformation is equivalent to a linearized logistic function and has been used to model crown ratio (or equivalently, bole ratio) by Ritchie and Hann (1987) and Zumrawi and Hann (1989). Another approach, also used by those authors and Hasenauer and Monserud (1996), is to fit the logistic function directly using nonlinear regression.

In this study, we tried nonlinear logistic regression as well as the logit and arcsine square root transformation of the UCR in the context of simple linear and linear mixed-effects regression. Examination of residual plots and the results of the validation techniques described below indicated that nonlinear regression performed better than the linear regression options and therefore was used to model UCR.

An important concern is the relative paucity of the data for some species, especially the low number of plots sampled. The small sample size may raise concerns about the validity of these equations to predict new observations. To address these concerns, we used several cross-validation techniques to assess the predictive performance of the models.

Table 1. Number of sample plots and trees, and median and range (in parenthesis) of tree variables, by species.

Scientific name	Common name	No. of plots	No. of trees	UCR (%)	CCR (%)	Dbh (in.)	Height (ft)
Abies amabilis	Pacific silver fir	19	182	70 (15–99)	50 (10–90)	8.8 (5–49.8)	49 (17–180)
Abies concolor	White fir	49	452	80 (20–99)	60 (10–90)	9.4 (5–46.8)	44 (12–135)
Abies grandis	Grand fir	27	138	70 (5–99)	47.5 (1–90)	8.0 (5–38)	50 (15–160)
Abies lasiocarpa	Subalpine fir	10	155	90 (45–99)	70 (30–90)	8.2 (5–33.1)	39 (17–101)
Abies magnifica	Red fir[a]	13	111	85 (35–99)	65 (25–90)	9.5 (5–39.2)	39 (15–130)
Abies procera	Noble fir	12	64	55 (15–99)	45 (15–90)	12.6 (5–29.2)	81 (16–133)
Juniperus occidentalis	Western juniper	30	157	85 (10–99)	65 (10–90)	7.8 (5–28.6)	26 (8–57)
Larix occidentalis	Western larch	13	54	57.5 (15–99)	47.5 (10–85)	9.4 (5.1–29.3)	60 (23–130)
Librocedrus decurrens	Incense cedar	31	165	70 (5–99)	50 (5–90)	8.4 (5–45.8)	35 (15–120)
Picea engelmannii	Engelmann spruce	17	80	85 (20–99)	60 (20–90)	9.5 (5–33.2)	57 (20–120)
Pinus spp.	Pines[b]	158	1422	70 (10–99)	50 (5–90)	8.5 (5–48.1)	45 (9–157)
Pinus jeffreyi	Jeffrey pine	19	146	80 (45–99)	65 (25–90)	8.9 (5–48.1)	29 (13–146)
Pinus lambertiana	Sugar pine	23	71	70 (25–95)	50 (20–90)	10.1 (5.2–44.8)	55 (13–157)
Pinus monticola	Western white pine	10	59	90 (15–99)	60 (10–90)	8.5 (5–39.4)	28 (12–124)
Pinus ponderosa	Ponderosa pine	81	572	70 (15–99)	50 (10–90)	8.8 (5–41.7)	45 (13–154)
Pseudotsuga menziesii	Douglas-fir	153	1722	65 (5–99)	50 (5–90)	10.3 (5–69.1)	63 (17–214)
Thuja plicata	Western redcedar	17	95	80 (10–99)	50 (10–90)	10.0 (5–63.1)	52 (19–169)
Tsuga heterophylla	Western hemlock	43	519	60 (5–99)	45 (5–90)	9.8 (5–57.3)	68 (12–173)
Tsuga mertensiana	Mountain hemlock	14	122	85 (10–99)	55 (10–90)	10.9 (5–25.5)	45 (12–114)
Acer macrophyllum	Bigleaf maple	18	73	40 (20–99)	40 (15–90)	11.8 (5–23.4)	72 (19–145)
Alnus rubra	Red alder	27	153	45 (10–95)	40 (10–90)	9.8 (5–27.0)	68 (25–126)
Abutus menziesii	Pacific madrone	22	86	45 (15–95)	30 (10–75)	7.6 (5–23.8)	40 (11–93)
Lithocarpus densiflorus	Tanoak	17	377	55 (15–99)	40 (10–80)	7.0 (5–31.1)	45 (10–109)
Quercus spp.	Oaks[c]	73	768	65 (10–99)	40 (5–90)	7.3 (5–42.5)	32 (8–98)
Quercus chysolepsis	Canyon live oak	21	236	67.5 (10–99)	45 (10–90)	6.8 (5.1–29.0)	28 (10–67)
Quercus douglasii	Blue oak	21	143	80 (25–99)	45 (15–90)	7.6 (5–27.5)	29 (14–49)
Quercus garryana	OR white oak	13	120	55 (10–99)	40 (10–80)	8.5 (5–27.8)	36 (13–85)
Quercus kelloggii	CA black oak	26	155	45 (15–99)	30 (5–90)	7.2 (5.2–32.1)	39 (8–98)
Quercus wislizenii	Interior live oak	10	72	70 (25–99)	45 (20–90)	6.7 (5–19.8)	25 (8–51)

[a] Includes California red fir (*Abies magnifica*) and Shasta red fir (*A. magnifica* var. *shastensis*).
[b] Includes the species in the table, plus whitebark pine (*Pinus albicaulis*), knobcone pine (*P. attenuata*), Coulter pine (*P. coulteri*), and gray pine (*P. sabiniana*).
[c] Includes the species in the table, plus coast live oak (*Quercus agrifolia*), white oak (*Q. alba*), California white oak (*Q. lobata*), and chinkapin oak (*Q. muehlenbergii*).

Model Equations and Model Fitting

The general equation fitted to the data was a logistic equation:

$$UCR = \frac{1}{1 + e^{-x\beta}}$$

where $x\beta$ is a linear combination of the explanatory variables.

The explanatory variables considered were CCR, dbh (in.) and tree height (ft). The distributions of both dbh and height tended to be very skewed: most trees had relatively low values, but a few of them had very large values. To minimize the problem of observations with high leverage and influence, the natural logarithm of dbh and height was taken. The height-diameter ratio (H/D, measured as ft/in.), also was included in the models because it is usually important in modeling crown or bole ratio (Hanus et al. 2000, Hasenauer and Monserud 1996, Ritchie and Hann 1987). We used UCR as the response variable because this is the variable that was measured by FHM and by most inventories. Several authors model the height to crown base using a logistic function (Hann and Hanus 2002, Ritchie and Hann 1987, Zumrawi and Hann 1989). However, after weighting by the inverse of the square of the height to stabilize the variance, they actually fit a logistic model of bole ratio on tree attributes.

The following rich models were considered, depending on whether tree height is available (Equation 1) or not (Equation 2):

$$x\beta = \beta_0 + \beta_1\,\mathrm{CCR} + \beta_2 \ln(\mathrm{dbh}) + \beta_3 \ln(\mathrm{height}) + \beta_4\,(\mathrm{H/D}) \quad (1)$$

$$x\beta = \beta_0 + \beta_1\,\mathrm{CCR} + \beta_2 \ln(\mathrm{dbh}) \quad (2)$$

where β_i is the regression coefficient; CCR the compacted crown ratio, measured as a proportion; ln(dbh) and ln(height) are the natural logarithm of the dbh and tree height, respectively; and H/D the ratio of tree height to tree dbh.

The models were fitted using weighted nonlinear regression. Because the response variable is a proportion, there was a tendency for the variance to be greater when the UCR or CCR was around 0.5 than when it was close to 0 or 1. Thus, the regression was weighted by the inverse of UCR*(1 – UCR), which is proportional to the inverse of the variance of a binomial distribution. All the models were fitted using S-PLUS' "nle" function (MathSoft Inc. 1999). To select a parsimonious subset of variables from those included in Equations 1 and 2, we used stepwise regression. The models were compared using a F-test with α set to 0.05 (Venables and Ripley 1999).

Assessment of the Fit of the Models

The fit of the models was assessed by examining residual plots, and a decision to use weighted regression was made based on them. In addition, we used two internal validation techniques. The first method is the leave-one-out jackknife method (Stone 1974). For each species, one observation was excluded from the dataset and the selected model fitted to the rest of the observations. Then, that model was used to predict the left-out observation. The same process was repeated for all the observations in the dataset. Because the model was fitted without the observation that was later predicted, the prediction is not biased by that observation and we can assess how well the model will behave when predicting a new observation.

The second method, leave-one-plot-out, is similar. Instead of excluding a single observation, all the observations from one entire plot are excluded for each iteration. Then, the model is fitted with the remaining observations, and used to predict the observations from the excluded plot. The process is repeated over all of the plots in the dataset. The rationale behind this method is that observations from the same plot tend to be correlated. Then, excluding an individual observation may not properly assess the performance of the model if UCR predictions for trees from a different stand are desired. The traditional leave-one-out method seems to be better suited for evaluating the predictive performance for a new observation from one of the plots included in the dataset.

The cross-validation statistics used to evaluate the performance of the models are (Cressie 1991):

$$CRV_1 = \left[(1/n \sum_{i=1}^{n} (Y_i - \hat{Y}_{-i})^2 \right]^{1/2}$$

(Estimate of the root mean squared error)

$$CRV_2 = (1/n) \sum_{i=1}^{n} [(Y_i - \hat{Y}_{-i})/\sigma_{-i}]$$

(Estimate of the bias factor)

where n is the number of observations for the species being evaluated; Y_i is the true UCR for tree i; $\hat{Y}_{-i}$ is the predicted UCR for tree i obtained from the cross-validation − excluding tree i; and σ^2_{-i} is the mean squared prediction error from the cross-validation. CRV_1 is an estimate of the mean squared error and measures the accuracy of the prediction. Smaller values of CRV_1 indicate that the predicted values are close to the actual values. It is measured in the same units as UCR. CRV_2 is an estimate of the bias ratio and provides a check of the unbiasedness of the prediction. It should be approximately 0.

The coefficient of determination is not a meaningful statistic for nonlinear regression because, in general, the regression and error sum of squares do not add up to the total sum of squares (Neter et al., 1996, p.547). In linear regression, the coefficient of determination also measures the square of the correlation between the predicted and the observed values. This statistic would provide a measure of the fit of the model in nonlinear regression, equivalent to R^2, and has a very direct interpretation. In the calculations of this estimate of R^2, we used the UCR predicted using the leave-one-out method, thus providing a more realistic estimate. The statistic is:

$$CRV_3 = [Corr(Y, \hat{Y}_{-})]^2$$

(Estimate of the coefficient of determination)

where Y is the vector of true UCR and $\hat{Y}_{-}$ is vector of predicted UCR from the cross-validation.

In addition, we compared the predicted UCR with the CCR. The logistic model used in this study allows for the predicted UCR to be smaller than the CCR, an unreasonable result. This check will evaluate the extent of this problem.

Results and Discussion

Tables 2-5 show the coefficients from the nonlinear regression of UCR on CCR, the natural logarithms of dbh and height, and H/D ratio, and the results from the cross-validation analysis for those models. The coefficients from the nonlinear regression of UCR on CCR and ln(dbh) only are shown in Table 4. UCR can be predicted as follows:

1. If CCR > 0.9, set UCR = CCR.
2. Otherwise, multiply the coefficients from the appropriate row in Table 2 or 4 by the corresponding explanatory variables. Blank cells imply that the coefficient is 0. For example, for a 20-in. diameter, 120-ft tall Douglas-fir with 0.60 CCR, calculate:

$$Y = -0.4480 + 4.9065*0.60 + 0.3090*\ln(20) - 0.4776*\ln(120) = 1.0951$$

3. Calculate the uncompacted crown ratio as:

$$UCR = 1/(1 + \exp(-Y))$$

For the previous example, UCR = 1/(1 + exp(−1.0951)) = 0.75

Compacted crown ratio was the variable that provided most of the information for predicting UCR, while the addition of the tree size variables improved the fit only slightly. For most species, adding the tree size variables to CCR only increased the cross-validation estimate of the coefficient of determination between 0.01 and 0.06.

When only one tree size variable, such as dbh or height, was included in the model, the sign of its coefficient was almost always negative. This indicates that, given two trees with the same CCR, the larger the tree, the lower the UCR. Therefore, larger trees tend to have more symmetric crown than smaller trees of similar CCR. The only exceptions to this general rule were subalpine fir, western juniper and interior live oak, possibly reflecting the open-growth habit of those species.

Assessment of the Fit of the Models

The leave-one-plot-out cross-validation method should be a more accurate measure of the predictive performance of the models for new observations because the observation

Table 2. Estimated coefficients of the regression of UCR on CCR, the natural logs of dbh and height, and the height to diameter ratio (H/D) (Equation 1). Standard errors in parentheses.

Species	Intercept	CCR	ln(dbh) (in.)	ln(height) (ft)	H/D (ft/in.)
Abies amabilis	−0.3826 (0.3736)	5.8437 (0.3298)		−0.2002 (0.0894)	−0.1300 (0.0389)
Abies concolor	2.3632 (0.5447)	4.6270 (0.1881)	2.5099 (0.7399)	−2.9255 (0.7481)	0.3706 (0.1503)
Abies grandis	−1.7252 (0.1602)	5.3703 (0.3980)			
Abies lasiocarpa[a]	−2.1221 (0.4331)	4.6659 (0.3896)	0.4243 (0.1551)		
Abies magnifica[a]	0.8979 (0.3856)	3.0106 (0.3943)			−0.2783 (0.0735)
Abies procera	−0.3174 (0.4240)	5.1141 (0.3697)		−0.3892 (0.0914)	
Juniperus occidentalis[a]	−0.7538 (0.2167)	4.7236 (0.3895)			−0.1356 (0.0387)
Larix occidentalis[a]	−0.7934 (0.4929)	4.6197 (0.3078)		−0.2624 (0.1068)	
Librocedrus decurrens	−1.1817 (0.2316)	5.0975 (0.2798)	−0.2235 (0.1059)		
Picea engelmannii	−1.7708 (0.2165)	5.3623 (0.4248)			
Pinus spp.	0.2071 (0.1376)	4.1248 (0.0998)		−0.2914 (0.0366)	−0.0767 (0.0088)
Pinus contorta	0.9674 (0.2881)	4.8052 (0.1759)		−0.5528 (0.0813)	−0.0657 (0.0134)
Pinus jeffreyi	−0.4129 (0.1306)	2.6760 (0.2082)			
Pinus lambertiana	−1.5360 (0.1833)	4.5971 (0.4089)			
Pinus monticola	0.0736 (0.4031)	4.8448 (0.4882)			−0.2554 (0.0734)
Pinus ponderosa	0.0042 (0.2334)	3.7274 (0.1526)		−0.2193 (0.0535)	−0.0599 (0.0196)
Pseudotsuga menziesii	−0.4880 (0.1656)	4.9065 (0.0805)	0.3090 (0.0452)	−0.4776 (0.0560)	
Thuja plicata	−2.2138 (0.2722)	5.4231 (0.4682)			0.0936 (0.0425)
Tsuga heterophylla	−1.0495 (0.2145)	5.7329 (0.1634)		−0.2615 (0.0518)	
Tsuga mertensiana	1.3446 (0.5427)	5.6170 (0.4186)		−0.7973 (0.1453)	
Acer macrophyllum[a]	2.8400 (0.7081)	4.2944 (0.5515)		−1.0567 (0.1591)	
Alnus rubra	−2.3245 (0.0867)	5.5445 (0.2132)			
Abutus menziesii	0.3110 (0.6093)	4.0012 (0.4463)		−0.4740 (0.1588)	
Lithocarpus densiflorus	−2.0265 (0.0842)	5.9318 (0.2277)			
Quercus spp.	−0.1455 (0.2408)	5.2591 (0.1866)		−0.3223 (0.0694)	−0.0949 (0.0183)
Quercus chysolepsis	0.4076 (0.4401)	5.8761 (0.3381)	2.6528 (0.5804)	−2.9754 (0.5804)	0.5893 (0.1471)
Quercus douglasii[a]	0.7690 (0.9159)	4.5209 (0.5575)		−0.5383 (0.2546)	
Quercus garryana	−1.2372 (0.2092)	5.0814 (0.3974)			−0.1250 (0.0366)
Quercus kelloggii	0.5300 (0.5953)	5.3119 (0.4198)	0.5424 (0.1436)	−0.9444 (0.1886)	
Quercus wislizenii	−3.5355 (0.7228)	5.4086 (0.6252)	0.9413 (0.3497)		

[a] Based on the cross-validation results, we do not recommend the use of these models.

used to fit the model are always from a different plot. However, because the number of observations used to fit the cross-validation models is less than the total number of observations used in the full model, the actual performance from the full model should be better than that inferred from the cross-validation results (Harrell et al. 1996). The root mean squared error, an estimate of the accuracy of the prediction, is between 10 and 15% live crown. Except for a few species, the estimate of the bias factor is very close to 0, suggesting that the predictions are virtually unbiased. The bias factor is the ratio of the bias to an estimate of the mean squared prediction error. Because the mean squared error is 0.10–0.15, the actual bias is approximately one-tenth the bias factor—much less that 0.5% for most species. The estimate of the coefficient of determination ranged between 0.19 and 0.87, but it was above 0.70 for those species with a reasonable sample size. As expected, the cross-validation statistics are slightly better for the leave-one-out method.

A better assessment of the validity of the models can be derived from the comparison of the two cross-validation methods. A discrepancy would suggest a lack of model stability and, therefore, a recommendation that the model not be relied on. For most species, there was very little discrepancy, but for subalpine fir, California red fir, noble fir, western juniper, western larch, bigleaf maple and, to a lesser degree, western white pine, western redcedar, and some of the oak species, the discrepancies were more troubling. For those species, the sample size and the number of plots visited were relatively low, and therefore there was not enough information to develop reliable models. Subalpine fir and California red fir proved particularly challenging because most of the trees had a relatively large UCR. Median UCR were 90 and 85% for subalpine fir and California red fir, respectively. The limited range of UCR for these species in the dataset is partially responsible for the poor fit of the models. These models had the lowest estimated coefficients of determination.

The logistic regression model does not limit the predicted UCR to be greater than the measured CCR. However, only bigleaf maple and Jeffrey pine showed predicted UCR values greater than the CCR. This confirms the conclusion that the bigleaf maple model is not very reliable. In the case of Jeffrey pine, the underprediction was only about 1% and only happened in trees with a relatively large CCR.

Implications for Crown Fire Risk Assessment

The number of trees that had a symmetric crown was surprisingly small. Out of 7,069 trees that had a dbh ≥5-in., an unbroken top, and a crown ratio less than or equal to 0.9, only 549 (7.8%) had the same value of compacted and uncompacted crown ratio. The mean difference between CCR and UCR was 0.16 (range from 0 to 0.84). Thus, using the CCR when the variable of interest is the full height of the crown may lead to an important underestimation.

We used the Fire and Fuels Extension (FFE; Reinhardt and Crookston 2003) of the Forest Vegetation Simulator (FVS; stage 1973, Wykoff et al. 1982) to assess the effect of using CCR instead of UCR on crown fire potential. We also

Table 3. Cross-validation analysis of the regressions from Table 2. CRV_1 is an estimate of the root mean squared error, CRV_2 is an estimate of the bias ratio, and CRV_3 is an estimate of the coefficient of determination. For the "leave-one-out" method, one observation is excluded, the regression fit to the rest of the observations, and the excluded observation predicted. The "leave-one-plot-out" method is similar, but all the observations from one plot are excluded at a time.

	Leave-one-out method			Leave-one-plot-out method		
Species	CRV_1	CRV_2	CRV_3	CRV_1	CRV_2	CRV_3
Abies amabilis	0.115	0.025	0.71	0.117	0.023	0.70
Abies concolor	0.112	0.014	0.68	0.113	0.021	0.67
Abies grandis	0.150	–0.008	0.53	0.154	0.008	0.50
Abies lasiocarpa	0.092	0.018	0.44	0.127	–0.276	0.25
Abies magnifica	0.104	0.015	0.30	0.113	0.114	0.19
Abies procera	0.087	–0.020	0.82	0.103	–0.017	0.74
Juniperus occidentalis	0.126	0.016	0.46	0.133	0.104	0.39
Larix occidentalis	0.076	–0.016	0.86	0.099	0.319	0.78
Librocedrus decurrens	0.108	0.013	0.69	0.108	0.012	0.69
Picea engelmannii	0.093	–0.008	0.71	0.093	0.012	0.71
Pinus spp.	0.108	0.008	0.73	0.109	0.015	0.72
Pinus contorta	0.100	0.012	0.83	0.101	0.043	0.83
Pinus jeffreyi	0.081	0.024	0.45	0.082	0.010	0.44
Pinus lambertiana	0.102	0.002	0.67	0.107	0.012	0.65
Pinus monticola	0.112	0.038	0.63	0.120	0.007	0.58
Pinus ponderosa	0.107	0.007	0.64	0.107	0.010	0.63
Pseudotsuga menziesii	0.094	–0.004	0.81	0.094	–0.003	0.81
Thuja plicata	0.133	0.026	0.67	0.139	0.089	0.64
Tsuga heterophylla	0.098	–0.006	0.79	0.100	0.014	0.78
Tsuga mertensiana	0.101	0.035	0.65	0.106	–0.018	0.62
Acer macrophyllum	0.125	–0.035	0.72	0.132	0.075	0.69
Alnus rubra	0.075	–0.005	0.87	0.076	–0.001	0.87
Abutus menziesii	0.122	–0.007	0.54	0.124	–0.009	0.53
Lithocarpus densiflorus	0.112	0.016	0.71	0.113	0.023	0.70
Quercus spp.	0.129	0.017	0.69	0.129	0.025	0.69
Quercus chysolepsis	0.123	0.035	0.71	0.125	0.093	0.70
Quercus douglasii	0.143	0.023	0.34	0.154	0.061	0.25
Quercus garryana	0.118	–0.010	0.68	0.125	0.081	0.65
Quercus kelloggii	0.128	0.009	0.69	0.132	0.032	0.68
Quercus wislizenii	0.139	0.013	0.60	0.139	0.034	0.59

Table 4. Estimated coefficients of the regression of UCR on CCR and ln(dbh) (Equation 2). Standard errors in parentheses.

Species	Intercept	CCR	ln(dbh) (in.)
Abies amabilis	–1.9067 (0.148)	5.8008 (0.3369)	
Abies concolor	–1.1015 (0.1762)	4.9546 (0.1977)	–0.1653 (0.0723)
Abies magnifica[a]	–0.2956 (0.2394)	3.1074 (0.4043)	
Abies procera[a]	–1.2483 (0.3086)	5.3161 (0.4001)	–0.3164 (0.1059)
Juniperus occidentalis[a]	–2.1474 (0.4793)	4.6581 (0.3944)	0.4613 (0.1914)
Larix occidentalis	–1.4555 (0.2870)	4.8989 (0.3113)	–0.2366 (0.1188)
Pinus spp.	–1.4072 (0.0847)	4.7545 (0.1011)	–0.0911 (0.0378)
Pinus contorta	–1.9751 (0.0762)	5.5608 (0.1904)	
Pinus monticola	–1.2625 (0.2317)	5.7554 (0.6248)	
Pinus ponderosa	–0.9894 (0.1169)	4.0365 (0.1434)	–0.1345 (0.0513)
Pseudotsuga menziesii	–1.8901 (0.0332)	5.1949 (0.0753)	
Thuja plicata	–1.2125 (0.3451)	5.5236 (0.4716)	–0.2416 (0.1099)
Tsuga heterophylla	–1.7810 (0.1111)	5.8122 (0.1760)	–0.1732 (0.0494)
Tsuga mertensiana	–0.4421 (0.4168)	5.4142 (0.4483)	–0.4748 (0.1684)
Acer macrophyllum[a]	–0.0446 (0.4986)	5.0942 (0.6354)	–0.7906 (0.1911)
Abutus menziesii	–1.4784 (0.1570)	4.1007 (0.4606)	
Quercus spp.	–1.9238 (0.0731)	5.9070 (0.1928)	
Quercus chysolepsis	–1.9831 (0.1309)	6.0840 (0.3301)	
Quercus douglasii[a]	–1.0937 (0.2295)	4.6366 (0.5572)	
Quercus garryana	–1.7613 (0.1612)	5.0864 (0.4102)	
Quercus kelloggii	–2.0640 (0.1485)	6.0504 (0.4578)	

[a] Based on the cross-validation results, we do not recommend the use of these models.

used the predicted UCR from the models developed in this study to evaluate the practical relevance of the predictions. A total of 71 plots that fell within the range of application of the Eastern Cascades (EC) and Southern Oregon and Northeastern California (SORNEC) variants of FVS were selected. Several plots were partially forested, had only a few trees measured, and were excluded from the analysis. Each plot was run with all the input variables identical,

Table 5. Cross-validation analysis of the regressions from Table 4. Refer to the Table 3 caption for an explanation of the cross-validation statistics.

Species	Leave-one-out method			Leave-one-plot-out method		
	CRV_1	CRV_2	CRV_3	CRV_1	CRV_2	CRV_3
Abies amabilis	0.122	0.022	0.68	0.125	0.017	0.66
Abies concolor	0.121	0.012	0.62	0.122	0.011	0.62
Abies magnifica	0.108	-0.018	0.24	0.112	0.031	0.20
Abies procera	0.093	−0.025	0.79	0.109	−0.070	0.71
Juniperus occidentalis	0.130	0.024	0.42	0.134	0.043	0.39
Larix occidentalis	0.077	−0.031	0.86	0.080	0.040	0.85
Pinus spp.	0.118	0.003	0.68	0.120	0.010	0.67
Pinus contorta	0.118	0.002	0.76	0.123	0.030	0.74
Pinus monticola	0.124	0.098	0.56	0.144	−0.011	0.43
Pinus ponderosa	0.109	0.006	0.63	0.110	0.010	0.62
Pseudotsuga menziesii	0.096	−0.002	0.81	0.096	−0.002	0.80
Thuja plicata	0.132	0.030	0.67	0.138	0.056	0.64
Tsuga heterophylla	0.100	−0.004	0.78	0.103	0.036	0.77
Tsuga mertensiana	0.113	0.032	0.56	0.129	−0.075	0.46
Acer macrophyllum	0.139	−0.021	0.65	0.163	0.191	0.55
Abutus menziesii	0.125	−0.016	0.52	0.127	−0.023	0.51
Quercus spp.	0.133	0.012	0.67	0.134	0.020	0.66
Quercus chysolepsis	0.122	−0.006	0.71	0.125	0.057	0.70
Quercus douglasii	0.144	0.014	0.33	0.153	0.038	0.25
Quercus garryana	0.124	−0.010	0.65	0.132	0.031	0.60
Quercus kelloggii	0.133	0.005	0.67	0.135	0.036	0.66

except that CCR, UCR, or predicted UCR were used as the input value for the crown ratio. The torching index, an estimate of the 20-ft wind speed at which a surface fire is expected to ignite the crown, was used to compare the results. The value of the torching index was 0 for a substantial number of plots, regardless of the crown ratio value, indicating that a crown fire would always happen. These plots are not included in the following tables and calculations, reducing the total number of plots to 28.

Using CCR instead of UCR or the predicted UCR had a significant effect on the torching index (Table 6). The median torching index for CCR, UCR, and predicted UCR was 7.8, 1.6, and 1.6 mph, respectively. Therefore, using CCR instead of UCR increases the estimated wind speed

Table 6. Estimated torching index using the Forest Vegetation Simulator, for the observed CCR and UCR, and for the predicted UCR. Each entry represents one FHM plot.

County	Torching index (mph)			Forest type
	CCR	UCR	Predicted UCR	
Yakima (WA)	17	2.8	10.7	Grand fir
Wasco (OR)	9.8	0	0	Noble fir
Lassen (CA)	13.8	9.3	9.3	Red fir
Okanogan (WA)	48.1	13.4	17.5	Subalpine fir
Modoc (CA)	1.4	0	0	White fir
Klamath (OR)	1.7	0.1	0.1	White fir
Hood River (OR)	216.2	171	166.1	Douglas-fir
Kittitas (WA)	40.9	18.5	4.3	Douglas-fir
Okanogan (WA)	1.9	1.9	1.9	Douglas-fir
Okanogan (WA)	68	52.7	54.9	Douglas-fir
Yakima (WA)	8.9	0	0	Douglas-fir
Okanogan (WA)	20.7	13	13	Engelmann spruce
Klamath (OR)	0.6	0	0	Mountain hemlock
Klamath (OR)	4	0.5	0.5	Lodgepole pine
Lake (OR)	8.7	5.1	5.6	Lodgepole pine
Okanogan (WA)	16	0	0	Lodgepole pine
Yakima (WA)	21.6	2.9	2.9	Lodgepole pine
Deschutes (OR)	6.4	3	3	Ponderosa pine
Klamath (OR)	0.3	0	0	Ponderosa pine
Klamath (OR)	0.5	0	0	Ponderosa pine
Klamath (OR)	1.6	0	0.5	Ponderosa pine
Chelan (WA)	47.5	15.4	26.1	Ponderosa pine
Yakima (WA)	43.3	9.9	24.5	Ponderosa pine
Lassen (CA)	2.5	1.2	1.2	Jeffrey/Coulter pines/Bigcone Douglas-fir
Plumas (CA)	6.9	5	2.8	Jeffrey/Coulter pines/Bigcone Douglas-fir
Lassen (CA)	2.4	0	0	California mixed conifer
Modoc (CA)	1.8	0	0.3	California mixed conifer
Modoc (CA)	2.9	0.7	0.7	California mixed conifer

that would result in a crown fire approximately fivefold. The estimated median torching index obtained with the predicted UCR was identical to that obtained with the observed UCR, and it was very close in most stands, thus providing a practical validation of the models developed in this study.

The decrease in the wind speed required to start a crown fire suggests that if a primary objective of an inventory were to evaluate fire hazard, it would be very desirable to measure the height to the base of the live crown, as opposed to an estimate of the CCR. Given the importance of fire in western forest, and the little additional time that it may take, we would suggest that UCR or height to the base of the crown should be a standard measurement in all inventories.

Regional inventories, such as FIA and FHM, provide a unique opportunity to develop prediction equations for tree characteristics. Usually, a large number of trees and plots are sampled, providing a very rich dataset. More importantly, the plots are sampled in a systematic fashion covering the range of the species. Therefore, there is no selection bias, and all the environments in which the species appears are represented.

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