Estimating Canopy Cover from Standard Forest Inventory Measurements in Western Oregon

Anne C.S. McIntosh, Andrew N. Gray, and Steven L. Garman

Abstract: Reliable measures of canopy cover are important in the management of public and private forests. However, direct sampling of canopy cover is both labor- and time-intensive. More efficient methods for estimating percent canopy cover could be empirically derived relationships between more readily measured stand attributes and canopy cover or, alternatively, the use of aerial photos. In this study, we compared field-based measures of percent canopy cover with estimates from aerial photography, with equations of individual tree crown width and crown overlap used in the US Forest Service Forest Vegetation Simulator (FVS) equations and with models we developed from standard stand-level forest mensuration estimates. Standard inventory estimates of cover using 1:40,000 scale aerial photos were poorly correlated with field-measured cover, especially in wet hardwood ($r = 0.60$) and dry hardwood ($r = 0.51$) stands. FVS equations underestimated cover by 17% on average at high cover levels (>70%) in wet conifer and wet hardwood stands. We also developed predictive models of canopy cover for three forest groups sampled on 884 plots by the Forest Inventory and Analysis program in western Oregon: wet conifer, wet hardwood, and dry hardwood. Predictions by the models were within 15% of measured cover for >82% of the observations. Compared with previous studies modeling canopy cover, our best predictive models included species-specific stocking equations, whereas species-invariant basal area was not an important predictor for most forest types. Accuracies of these new predictive models may be adequate for some purposes, reducing the need for direct measures of canopy cover in the field. FOR. SCI. 58(2):154–167.

Keywords: crown closure, aerial photos, forest inventory and analysis, forest simulator, stocking equations

Measures of canopy cover, the percentage of the horizontal forest area occupied by vertical projection of tree crowns, are used to assess forest conditions and wildlife habitat. Cover levels and the vertical structure of forest canopies influence disease and insect susceptibility (Mathiasen 1996, Winchester and Ring 1996), fire hazard (Latham et al. 1998), atmospheric interactions (Rose 1996), microclimate (Yang et al. 1999), and habitat structure (Maguire and Bennett 1996). The canopy is also an important habitat feature for numerous wildlife species (e.g., MacArthur and MacArthur 1961, Thomas and Verner 1986, Mayer and Laudenslayer 1988, Hayes et al. 1997, North et al. 1999, Johnson and O'Neil 2001). Cover data have been used for predicting tree volume and potential forage production and for the evaluation of forest pest damage (O'Brien 1989).

Although canopy cover is an important forest attribute that provides many ecosystem services, because field-based measurements of canopy cover are labor- and time-intensive, remotely sensed data have been used to estimate this forest attribute. Aerial photography is often used to estimate tree cover, but in multilayered or high foliage density forests measuring the outer or upper canopy surface may underestimate forest canopy cover (Van Pelt and North 1996). Lund et al. (1981) found that combining measures from aerial photography with stocking density improved estimates of canopy cover.

Allometric equations have also been used to estimate canopy cover, albeit with limited success. Bentley (1996) explored relationships between tree growth and stand parameters associated with canopy cover (i.e., basal area and canopy cover, tree diameter and crown diameter, tree diameter and crown area, and stand age and canopy cover) in northern Ontario white pine (*Pinus strobus* L.) forests and found basal area to be a poor predictor of canopy cover. In ponderosa pine (*Pinus ponderosa* P. & C. Lawson) stands in the southern Rockies, Mitchell and Popovich (1997) evaluated the ability of multiple stand- and tree-level biotic and abiotic variables, including basal area, stand density, and tree height, to estimate canopy cover. They found that only basal area was correlated with canopy cover whenever cover was ≤60%. Cade (1997) estimated tree composition and cover from basal area and stand density in multiple subalpine forest types. Buckley et al. (1999) investigated relationships of canopy cover and basal area and found a strong relationship between them in Michigan oak and pine stands. Multiple studies have calculated crown radii using predictive equations based on tree diameter (e.g., Paine and Hann 1982, Gill et al. 2000).

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Forest managers and researchers in the United States commonly rely on the Forest Vegetation Simulator (FVS) to compare potential outcomes of management on stand development, including the development of canopy cover (e.g., Christensen et al. 2002, Hummel et al. 2002). Equations in FVS predict canopy cover by calculating crown width from tree diameter with species-specific equations, summing individual (circular) tree crown areas, and then correcting for overlap (Moeur 1985, Crookston and Stage 1999).

There has been little work to evaluate how well these predictive models and aerial photos can estimate canopy cover, including that among conifer- and hardwood-dominated forests in the Pacific Northwest. It is unclear whether the same variable(s) should be expected to predict canopy cover across multiple forest types. Basal area is a variable that is found in many predictive models, and yet it assumes all species have the same relationship of crown area to dbh, whereas we know that there is variation in the relationship between crown structure and dbh among species (e.g., Monserud and Marshall 1999). Therefore, we expect that mensuration variables that capture differences among species may better predict canopy cover. The main objectives of this study were threefold: to compare both aerial photography and FVS-modeled cover with field-based cover measurements; to develop new models to predict canopy cover using standard forest inventory measurements, including both species-specific and species-invariant variables; and to evaluate the efficacy of our models for measuring canopy cover in place of ground-based canopy data collection.

Methods

Study Site

We used data collected by the US Forest Service Forest Inventory and Analysis (FIA) program for the inventory of western Oregon from 1994 to 1997 (Azuma et al. 2004). Study sites are a permanent grid of plots located throughout western Oregon (Fig. 1). Western Oregon is defined as the

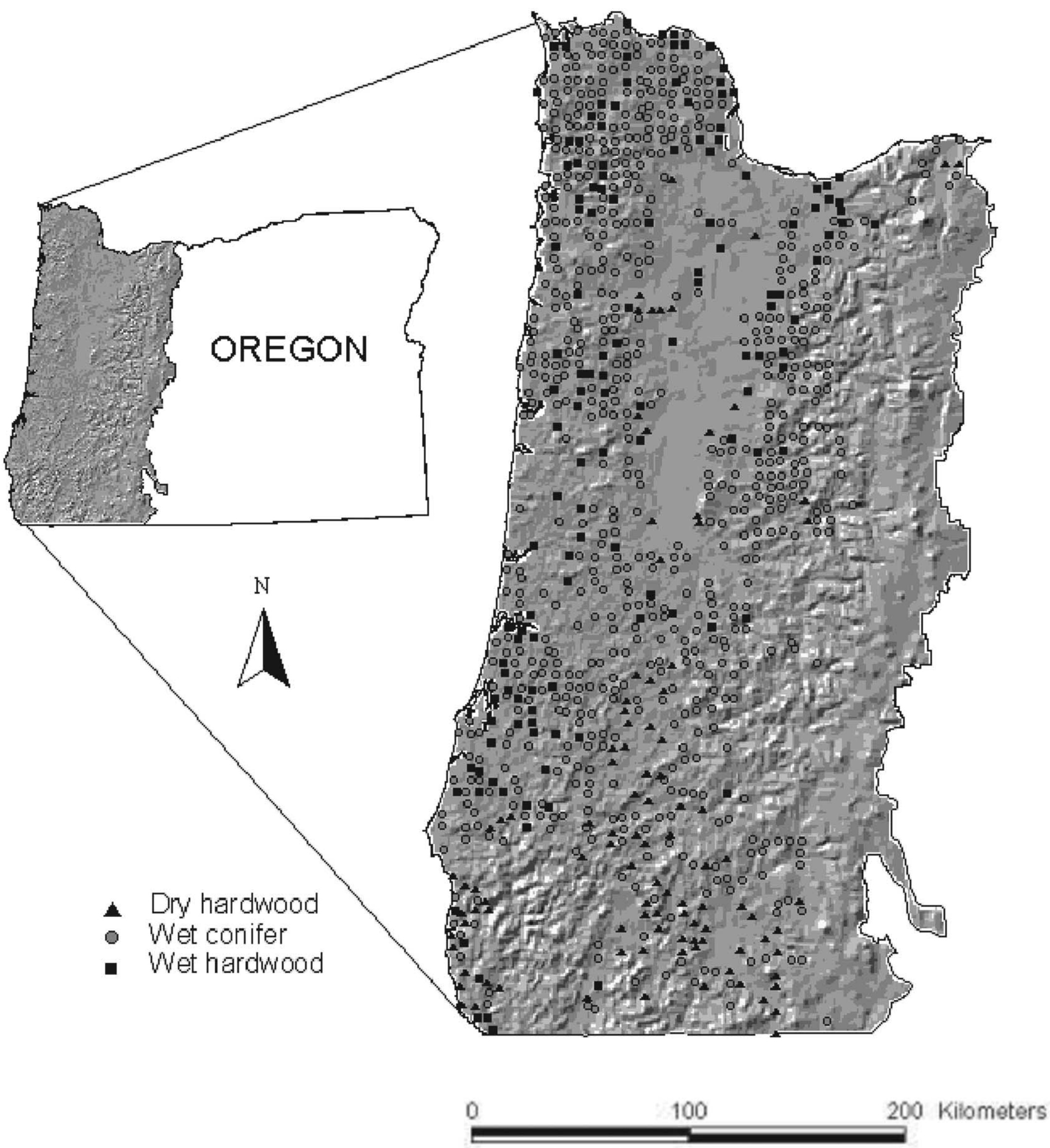

Figure 1. Approximate locations of the 884 forested FIA 1995–1997 inventory plots analyzed in this study.

area west of the crest of the Cascade Mountain Range, delimited by county boundary lines. In this inventory FIA plots were measured at all grid-points on private lands and public forested lands excluding those administered by the Bureau of Land Management and the US Forest Service. A separate inventory system that did not collect comparable canopy structure data was used on these federal lands in the 1990s. A nationally consistent measurement protocol was implemented on all forested lands starting in 2001 but excludes field measurements of canopy cover.

The study sites encompassed five physiographic provinces: Oregon Coast Range, Willamette Valley, Oregon Western Cascades, Klamath Mountains, and High Cascades (Franklin and Dyrness 1973). Forest zones included in the FIA inventory included *Picea sitchensis*, *Tsuga heterophylla*, *Abies amabilis*, *Tsuga mertensiana*, *Quercus* woodland, interior valley, mixed-evergreen, mixed-conifer, *Abies concolor*, and *Abies magnifica shastensis* (Franklin and Dyrness 1973).

Study Design

The FIA inventory design was based on a double sample for stratification (Cochran 1977). This design consists of permanently established primary photo-interpreted points and secondary field plots. In the first phase of sampling, estimates of land use type, successional stage, and canopy cover were made with 1:40,000 scale black and white aerial photos from 1994 at photo-points distributed on a 1.36-km grid. The second phase, completed from 1995 to 1997, consisted of field plot measurements of every 16th photo-point, with a grid density of 5.4 km.

To estimate cover in the aerial photos, the percentage of live, visible tree cover present within its land class polygon within the photo plot area was recorded (to the nearest 5%, with trace recorded as 01). Visible tree cover was either the distinguishable crowns of individual trees or vegetative cover that by its texture, tint, or other visual clues appeared to be tree cover. Cover estimates were based on a 4-mm circle on a photo through a stereoscope.

Field plots were a systematically arranged cluster of five 0.09-ha subplots across a 2.5-ha area, regardless of stand boundaries or forest types. Subplots were ascribed to a "condition" class to identify differences in forest type, stand size class, management intensity, or presence of nonforest land use. We only used plot information for forested condition classes sampled by at least 0.27 ha (three subplots) to ensure an adequate sample of stand characteristics. Hereafter we use the term "stand" to refer to this experimental unit.

In each stand, trees were measured to a fixed-distance of 17 m from each subplot center in variable-radius plots, using a 7-m^2/ha basal area factor prism. Collected tree data included age, dbh, compacted crown ratio, and height.

Field-based canopy cover estimates were collected using the line-intercept method (Canfield 1941, O'Brien 1989, Fiala et al. 2006). Trees were assigned to a maximum of three canopy layers, with discrete layers differing by a minimum of 5 m in mean height. Canopy layers were classified as upper, middle, and lower based on relative stature. Layer heights varied among stands, because canopy layers were relative to stand conditions. The height of the upper layer was used as an estimate of stand height in the predictive models (below). For every tree species within a canopy layer, crown boundaries were vertically projected onto transects. The distance along a transect line that the crown intercepted was recorded. Canopy cover was measured on three 17-m long horizontal transects originating at each subplot center and radiating out at 0, 135, and 225° (153–255 m of line intercept sampled per stand). The proportion of transect lengths intercepted by the crowns was the field-based estimate of canopy cover. Cover by species by layer was vertically collapsed to calculate total cover; therefore. cover did not exceed 100%.

Standard inventory procedures were used to calculate stand age and forest type. Stands were grouped into 10-year age classes up to age 200 and lumped into a 100-year age class for ages 200–300, and stands >300 years were all combined into a single age class (which we arbitrarily labeled as age 400). Forest type was derived by determining whether hardwood or softwood trees dominated the stand, and then the forest type was assigned on the basis of the dominant tree species within the hardwood or softwood group.

We derived independent variables that we thought could be potentially important for quantifying canopy cover. Stocking density, the contribution of measured trees to a fully stocked stand based on normal yield tables, was calculated from multiple equations (MacLean 1979) (Table 1). Following FIA convention, raw stocking values were then adjusted for tree social position. Stocking values for trees <12.8 cm dbh with crown ratios >40, 21–40, and <21% were multiplied by 1.1, 0.7, and 0.4, respectively; stocking values for dominant and codominant trees >12.8 cm dbh with crown ratios >21 and <21 were multiplied by 1.1 and 0.7, respectively; and stocking values for trees >12.8 cm dbh in intermediate and suppressed crown positions were multiplied by 0.7 and 0.4, respectively. For the stocking variable used in this study, the final adjustment ensured that the summed stocking of trees in a stand position on a subplot did not exceed 100% (referred to as "unadjusted proportioned stocking" in data and documentation in Waddell and Hiserote (2005)). Mean annual increment at culmination (mai) was calculated from species-specific site

Table 1. Contribution of each tree to normal stand stocking.

Equation no.	Primary species	*A*	*B*
1	*Acer macrophyllum*	0.0010742	1.53
2	*Alnus rubra*	0.001834	1.4057
3	*Fraxinus latifolia*	0.003101	1.13
4	*Pinus contorta*	0.00035	1.7
5	*Pinus ponderosa*	0.0003659	1.73
6	*Pinus monticola*	0.0002689	1.734
7	*Populus* spp.	0.0015724	1.39
8	*Pseudotsuga menziesii*	0.0007372	1.54385
9	*Quercus* spp.	0.000991	1.63
10	*Sequoia sempervirens*	0.0002828	1.6757
11	*Tsuga heterophylla*	0.0003656	1.67

Contribution of each tree to normal stand stocking was calculated with the equation $\text{tph} \cdot A \cdot \text{dbh}^B$ where tph is trees/ha contribution from each tree and coefficients *A* and *B* are shown in the table, by species.

index and growth and yield equations (Hanson et al. 2002). Stem density (tph), basal area per hectare (ba), and quadratic mean diameter (qmd) were calculated from tree measurements. We calculated stem densities by three dbh classes (≤30, 30–50, and >50 cm), four crown ratio classes (≤ 10, 10–40, 40–60, and > 60%), and four tree height classes (≤5, 5–20, 20–30, and >30 m). Compacted crown ratio classes only included dominant and codominant trees, as these were the trees expected to contribute most to total cover.

We examined stands from three general forest groups: wet conifer, wet hardwood, and dry hardwood (Table 2). The fourth general forest group in western Oregon, dry conifer, had too few samples (n = 33 plots) and was not analyzed. Douglas-fir (*Pseudotsuga menziesii* [Mirb.] Franco) was the predominant species in the wet conifer group, red alder (*Alnus rubra* Bong) was the dominant species in the majority of wet hardwood stands, and Oregon white oak (*Quercus garryana* Dougl. ex Hook) and Pacific madrone (*Arbutus menziesii* Pursh) dominated in most dry hardwood stands. The transition between wet and dry forest groups was approximately 1.5 m estimated annual precipitation (PRISM climate model) (Daly et al. 1994).

Comparison of Aerial and Line-Intercept Canopy Cover

Line-intercept cover measurements and aerial photo-interpreted (1:40,000 scale black and white) cover estimates were compared for stands within each forest group. Because tree cutting or other disturbance between the time the photos were taken (1994) and the plots were measured (1995–1997) could lead to differences in cover measurements, stands with evidence of disturbance within this time period were excluded from analysis. Aerial cover estimates were plotted against field-based estimates. We used Pearson correlation coefficients and the number of aerial cover observations within 10 and 15 percentage points of the measured cover to evaluate accuracy of the aerial estimates.

Comparison of FVS and Line-Intercept Cover

The Pacific Northwest Regional Variant of the FVS (Donnelly and Johnson 1997) models stand-level percent canopy cover by summing individual tree crown areas, using tree species crown radii formulas specific to the region (Crookston and Stage 1999). We calculated overlap-corrected cover predictions (Crookston and Stage 1999) using the FVS Region 6 Variant crown radii formulas for each stand (Donnelly 1997). FVS cover estimates were plotted against field-based estimates for each of the forest groups. We used Pearson correlation coefficients and the number of FVS cover observations within 10 and 15 percentage points of the measured cover to evaluate FVS accuracy.

Prediction of Cover from Forest Inventory Measurements

We used an information-theoretic approach (Anderson et al. 2000) to examine the ability of FIA stand inventory measurements to predict canopy cover for each of the three forest groups. Rather than try to fit all possible standard forest mensuration variables and combinations of them, which would have resulted in hundreds of potential models, we considered the ability of mensuration variables to predict canopy cover on the basis of our own knowledge of canopy cover-mensuration relationships, along with insights from previous studies that modeled canopy structure features in other regions of North America (e.g., Paine and Hann 1982, Moeur 1986, Bentley 1996, Cade 1997, Mitchell and Popovich 1997, Buckley et al. 1999, Crookston and Stage 1999, Gill et al. 2000). Hypothesized relationships resulted in 44 a priori models using one to four variables (Tables 3 and 4). In all models, canopy cover was logit transformed (0.5 was added to all cover values before transformation as a correction factor so that cover values of 0 could be logit transformed). We also evaluated a null model for each forest group, for which only an intercept term was included. With the exception of the null model, all models were fit using a

Table 2. Three general forest groups included in the 1995–1997 FIA ground inventory that met the criteria for inclusion in this study.

Forest group	n	Age range (yr)	Dominant tree species in the stand[1]
Wet conifer	645	5–400	*Pseudotsuga menziesii* (n = 558, Equation 8), *Tsuga heterophylla* (n = 57, Equation 11), *Picea sitchensis* (n = 15, Equation 11), *Thuja plicata* (n = 7, Equation 11), *Abies procera* Rehd. (n = 4, Equation 11), *Abies amabilis* (n = 2, Equation 11), *Chamaecyparis lawsoniana* (A. Murr.) Parl. (n = 2, Equation 11)
Wet hardwood	137	5–250	*Alnus rubra* (n = 99, Equation 2), *Acer macrophyllum* Pursh. (n = 25, Equation 1), *Populus balsamifera* L. ssp. trichocarpa (Torr. & Gray) Brayshaw (Salicaceae) (n = 5, Equation 7), *Salix* spp. (n = 3, Equation 2), *Umbellularia californica* (Hook. & Arn.) Nutt. (n = 3, Equation 9), *Fraxinus latifolia* Benth. Oregon ash (n = 2, Equation 3)
Dry hardwood	102	5–165	*Quercus garryana* (n = 42, Equation 9), *Arbutus menziesii* (n = 32, Equation 2), *Lithocarpus densiflora* (Hook. & Arn.) Rehd. (n = 18, Equation 9), *Quercus kelloggii* Newb. (n = 6, Equation 9), *Quercus chrysolepis* Liebm. (n = 3, Equation 9), *Castanopsis chrysophylla* (Dougl.) DC. (n = 1, Equation 2)

Stands were grouped by hardwood and conifer type and mean precipitation levels.
[1] The number of plots in which a species was dominant is shown in parentheses, followed by the stocking equation number used to calculate stocking from Table 1 for dominant species.

Table 3. Descriptions of variables measured or calculated in the western Oregon FIA plots that were used in predictive models of canopy cover.

Variable	Abbreviation	Units	Expected relationship[1]	Transformation
Aerial photo estimated cover	photocov	%	Logit	log(photocov)
Basal area	ba	m^2/ha	Linear or square root	$\sqrt{ba}$
Elevation	elev	m	Linear	
Forest Vegetation Simulator cover	FVScov	%	Logit	log(FVScov)
Mean annual increment	mai	ft^3/acre/yr	Linear or quadratic	mai + mai^2
No. of tree species in a plot	nspecies	n/a	Linear	
Precipitation[2]	precip	cm	Linear	
Quadratic mean diameter	qmd	cm	Linear or quadratic	qmd + qmd^2
Stand age	age	years	Linear or inverse	1/age
Stand height	height	m	Linear	
Stocking density	stock	%	Linear or square root	$\sqrt{stock}$
Total trees per ha	tph	trees/ha	Linear or quadratic	tph + tph^2
Trees per ha in crown class 1 (<10% compacted crown)	tphcrn1	trees/ha	Linear	
Trees per ha in crown class 2 (10–40%)	tphcrn2	trees/ha	Linear	
Trees per ha in crown class 3 (40–60%)	tphcrn3	trees/ha	Linear	
Trees per ha in crown class 4 (>60%)	tphcrn4	trees/ha	Linear	
Trees per ha in dbh class 1 (tree dbh < 30 cm)	tphdbh1	trees/ha	Linear	
Trees per ha in dbh class 2 (30–50 cm)	tphdbh2	trees/ha	Linear	
Trees per ha in dbh class 3 (>50 cm)	tphdbh3	trees/ha	Linear	
Trees per ha in height class 1 (tree height < 5 m)	tphht1	trees/ha	Linear	
Trees per ha in height class 2 (5–20 m)	tphht2	trees/ha	Linear	
Trees per ha in height class 3 (20–30 m)	tphht3	trees/ha	Linear	
Trees per ha in height class 4 (>30 m)	tphht4	trees/ha	Linear	

[1] Expected relationships with logit-transformed percent canopy cover.
[2] Mean annual precipitation from the PRISM climate model (Daly et al. 1994) measured for years 1961–1990.

mixed-effects design (PROC MIXED) (SAS Institute, Inc. 1999). We then ranked models using the Akaike information criterion for small sample sizes (AICc) (Burnham and Anderson 1998). ΔAICc values, Akaike weights, and importance weights were used as evidence that models and model variables were important (Burnham and Anderson 1998). The best approximating model (best model) had ΔAICc = 0 (Burnham and Anderson 1998). The good model set consisted of all models with Akaike weights >0.01 to ensure that we did not exclude potentially biologically important models or variables.

Stands within each forest group were divided into two sets. Seventy-five percent of the data were randomly selected for model generation (model data set). The remaining 25% were set aside to evaluate model fit (test data set). Values for the explanatory variables were similar in range for the model and test data sets. The predicted cover estimate for each stand in the test data set was back-transformed for comparison with the line-intercept value. The back-transformed cover value was derived by

$$\text{Canopy Cover (\%)} = \left(\frac{1.005}{1 + \exp(-\beta_0 - \beta_1 \text{ (Variable 1)} \cdots - \beta_x(\text{Variable } X))}\right) * 100. \quad (1)$$

where β_0 is the intercept value, β_1 is the coefficient for variable 1, β_x is the coefficient for variable X, and x is the number of variables included in a given model.

The good model sets were corroborated using the test data sets within each forest group. The predicted mean square errors (predMSEs) from the test data set were compared with the mean square errors (MSEs) of the model data set. Similar predMSEs and MSEs suggested that the predictive model was not spurious. Graphs of predicted versus measured cover used the SE of the estimate to provide upper and lower confidence limits. Accuracies of prediction quantified the number of observations that were predicted within 10 and 15 percentage points of the measured cover.

In general, model assumptions were satisfied. Residual plots showed constant variance and errors were normally distributed. There was high correlation among several of the variables (Pearson correlation coefficients >0.60): stocking and basal area ($r = 0.91$) and basal area and qmd ($r = 0.65$). Therefore, these variables were not simultaneously included in a model. Repetition of the Akaike information criterion model selection process with three randomly selected subsets of high-cover stands confirmed that full data regression results were not affected by the skewed distribution of cover values.

Results

Comparison of Aerial and Line-Intercept Canopy Cover

Correspondence between field-based and photo-interpreted cover estimates differed among the three general forest groups (Fig. 2; Table 5). The strongest correlation between the two methods occurred in wet conifer forests. For the wet conifer and wet hardwood groups, a consistent bias was not apparent. However, for dry hardwood stands with <60% cover (line-intercept), aerial photo cover measures tended to be higher.

Table 4. A priori models and their ranking for predicting total canopy cover for three forest groups in western Oregon.

Model	Model structure	Wet conifer ΔAICc	Wet conifer w	Wet hardwood ΔAICc	Wet hardwood w	Dry hardwood ΔAICc	Dry hardwood w
28	$\beta_0 + \beta_1(\sqrt{\text{stock}}) + \beta_2\ (\text{mai})$	**0**	**0.73**	**5.25**	**0.05**	**2.01**	**0.16**
29	$\beta_0+\beta_1(\sqrt{\text{stock}})+\beta_2(\text{height})+\beta_3(\text{mai})$	**2.04**	**0.27**	**6.03**	**0.04**	**3.33**	**0.08**
9	$\beta_0 + \beta_1(\sqrt{\text{stock}})$	13.58	<0.001	**4.29**	**0.09**	**6.45**	**0.02**
27	$\beta_0 + \beta_1(\sqrt{\text{stock}}) + \beta_2(\text{height})$	15.6	<0.001	**4.85**	**0.07**	**6**	**0.02**
8	$\beta_0 + \beta_1(\text{stocking})$	186.36	0	**0**	**0.75**	18.68	0
31	$\beta_0 + \beta_1(\sqrt{\text{ba}}) + \beta_2(1/\text{age})$	61.94	0	14.37	<0.01	**0.72**	**0.3**
11	$\beta_0 + \beta_1(\sqrt{\text{ba}})$	137.32	0	12.63	<0.01	10.61	0
30	$\beta_0 + \beta_1(\sqrt{\text{ba}}) + \beta_2(\text{height})$	134.78	0	14.78	<0.01	12.79	0
32	$\beta_0 + \beta_1(\sqrt{\text{ba}}) + \beta_2(\text{mai})$	133.5	0	14.24	<0.01	12.44	0
33	$\beta_0 + \beta_1(\sqrt{\text{ba}}) + \beta_2(\text{height}) + \beta_3(\text{mai})$	131.41	0	16.44	<0.01	14.61	0
44	$\beta_0 + \beta 1(\sqrt{\beta\alpha}) + \beta 2(\text{mai}) + \beta 3(\text{stand height}) + \beta 4(1/\text{age})$	37.43	0	18.09	0	0	**0.43**
40	$\beta_0 + \beta_1(\text{tph}) + \beta_2(\text{tph}^2) + \beta_3(\sqrt{\text{ba}}) + \beta_4(\text{tph} \cdot \text{ba})$	113.27	0	18.71	0	16.37	0
45	$\beta_0 + \beta_1(\log(\text{FVScov}))$	151.9	0	44.47	0	41.23	0
6	$\beta_0 + \beta_1(1/\text{age})$	301.47	0	71.23	0	68.51	0
36	$\beta_0 + \beta_1(\text{qmd}) + \beta_2(\text{qmd}^2) + \beta_3(\text{height}) + \beta_4(\text{mai})$	314.2	0	53.04	0	65.4	0
34	$\beta_0 + \beta_1(\text{qmd}) + \beta_2(\text{qmd}^2) + \beta_3(\text{height})$	316.98	0	51.82	0	70.87	0
35	$\beta_0 + \beta_1(\text{qmd}) + \beta_2(\text{qmd}^2) + \beta_3(\text{mai})$	327.53	0	52.19	0	63.18	0
13	$\beta_0 + \beta_1(\text{qmd}) + \beta_2(\text{qmd}^2)$	328.74	0	51.29	0	71.43	0
10	$\beta_0 + \beta_1(\text{ba})$	351.56	0	26.78	0	35.87	0
42	$\beta_0+\beta_1(\text{tphht1})+\beta_2(\text{tphht2})+\beta_3(\text{tphht3})+\beta_4(\text{tphht4})$	357.06	0	34.64	0	68.62	0
41	$\beta_0 + \beta_1(\text{tphdbh1})+\beta_2(\text{tphdbh2})+\beta_3(\text{tphdbh3})$	478.75	0	57.72	0	76.73	0
39	$\beta_0 + \beta_1(\text{tph}) + \beta_2(\text{tph}^2) + \beta_3(\text{height}) + \beta_4(\text{mai})$	502.82	0	93.75	0	87.91	0
37	$\beta_0 + \beta_1(\text{tph}) + \beta_2(\text{tph}^2) + \beta_3(\text{height})$	512.05	0	92.17	0	85.79	0
12	$\beta_0 + \beta_1(\text{qmd})$	536.51	0	77.47	0	86.03	0
7	$\beta_0 + \beta_1(\text{height})$	542.92	0	88.34	0	89.65	0
24	$\beta_0 + \beta_1(\log(\text{photocov}))$	546.5	0	89.39	0	97.79	0
20	$\beta_0 + \beta_1(\text{tphdbh2})$	547.4	0	58.68	0	85.76	0
18	$\beta_0 + \beta_1(\text{tphht3})$	616.23	0	51.41	0	98.05	0
16	$\beta_0 + \beta_1(\text{tphht1})$	623	0	85.34	0	113.85	0
43	$\beta_0 + \beta_1(\text{tphcrn1}) + \beta_2(\text{tphcrn2}) + \beta_3(\text{tphcrn3}) + \beta_4(\text{tphcrn4})$	646.29	0	89.63	0	100.04	0
21	$\beta_0 + \beta_1(\text{tphdbh3})$	682.05	0	88.5	0	104.23	0
5	$\beta_0 + \beta_1(\text{age})$	686.05	0	88.82	0	102.6	0
19	$\beta_0 + \beta_1(\text{tphht4})$	690.85	0	92.56	0	110.68	0
4	$\beta_0 + \beta_1(\text{nspecies})$	718.46	0	101.88	0	121.54	0
17	$\beta_0 + \beta_1(\text{tphht2})$	722.85	0	105.06	0	93.16	0
3	$\beta_0 + \beta_1(\text{mai})$ - $\beta_2(\text{mai}^2)$	752.12	0	105.49	0	118.33	0
22	$\beta_0 + \beta_1(\text{tphcrn2})$	759.37	0	101.43	0	119.38	0
2	$\beta_0 + \beta_1(\text{mai})$	762.95	0	103.86	0	119.2	0
38	$\beta_0 + \beta_1(\text{tph}) + \beta_2(\text{tph}^2) + \beta_3(\text{mai})$	763.48	0	107.07	0	121.97	0
26	$\beta_0 + \beta_1(\text{precipitation}) + \beta_3(\text{mai})$	763.87	0	98.34	0	119.32	0
14	$\beta_0 + \beta_1(\text{tph})$	765.38	0	104.03	0	120.63	0
1	β_0	765.55	0	103.02	0	120.79	0
25	$\beta_0 + \beta_1(\text{precip})$ - $\beta_3(\text{elev})$	766.49	0	96.92	0	107.08	0
15	$\beta_0 + \beta_1(\text{tph}) + \beta_2(\text{tph}^2)$	767.01	0	106.19	0	121.86	0
23	$\beta_0 + \beta_1(\text{tphcrn3})$	767.53	0	95.16	0	118.62	0

Abbreviated variables are described in Table 3. Ranking is based on AICc values. w values are Akaike weights. Good models ($w > 0.01$) are highlighted in bold.

Comparison of FVS and Line-Intercept Cover

Correspondence between FVS-modeled cover and field-based line-intercept measures varied among the three general forest groups (Fig. 3; Table 5). The FVS equations tended to underestimate canopy cover in the wet conifer and wet hardwood stands but not in the dry hardwood stands. In the latter stands, prediction accuracy was about equal to or greater than the accuracy with aerial photos (Table 5).

Prediction of Cover from Forest Inventory Measurements

The very high ΔAICc score of our null models within each of the forest groups (Table 4) suggested that at least one of the independent variables had explanatory capacity.

Our best predictive model of canopy cover for the wet conifer forest group was based on stocking and mai (model 28, Table 4). The only other wet conifer model in the good

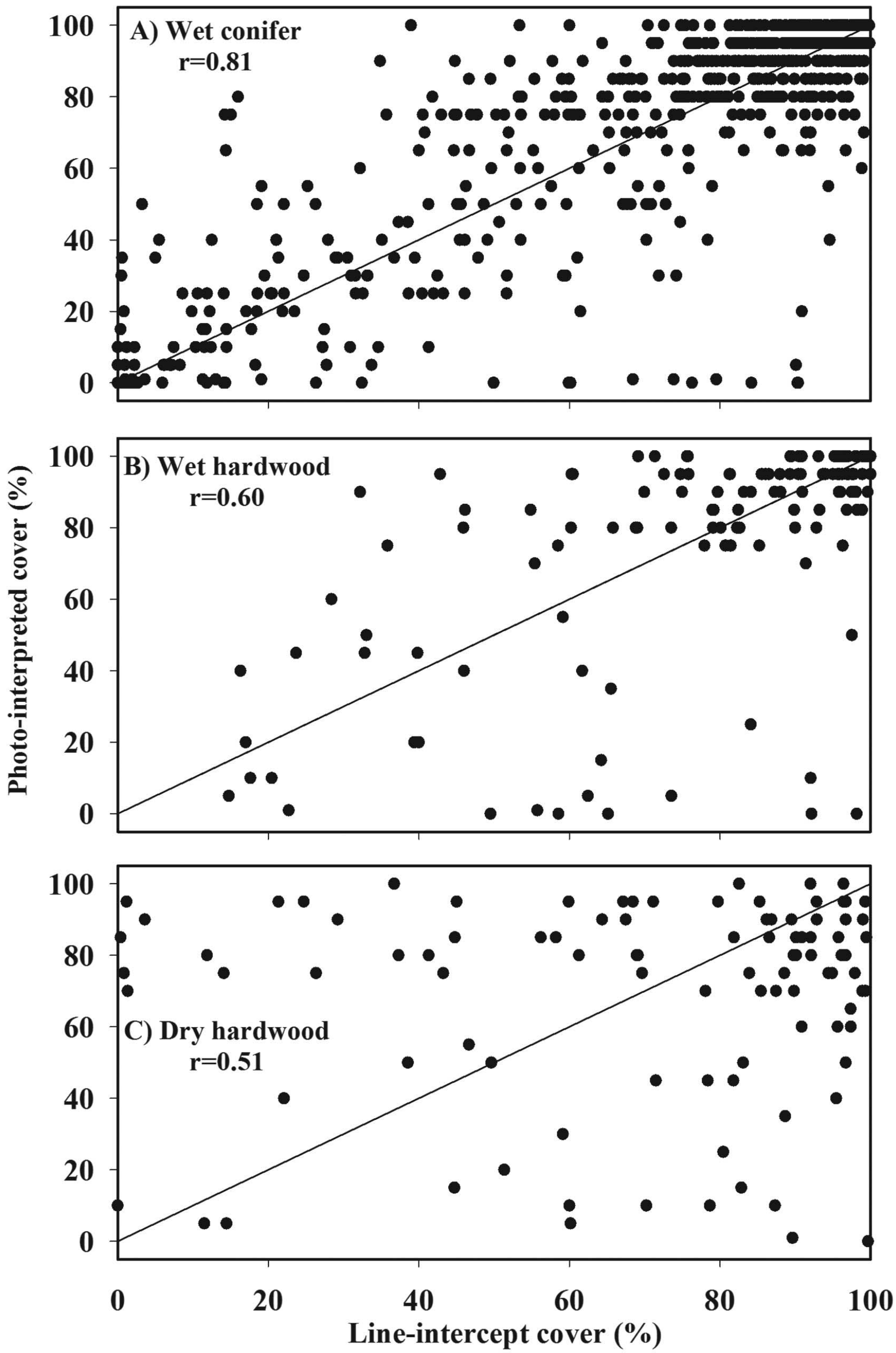

Figure 2. Comparison of 1:40,000 aerial photo-interpreted canopy cover with ground-based line-intercept cover measures for three general forest groups (Table 2). The diagonal line represents a 1:1 relationship between the two cover estimates. The *r* value is the Pearson correlation coefficient.

set (with Akaike weight >0.01) was based on the same variables plus stand height (model 29). The best model of canopy cover for the wet hardwood forest group was based on stocking alone (model 8), and all other good models used combinations of stocking, mai, and height (models 9 and 27–29). Although the models based on stocking were also in

Table 5. **Percentage of predicted values within 10 and 15 percentage points of observed values by predictive method for the three forest groups.**

Prediction method	Wet conifer		Wet hardwood		Dry hardwood	
	10pp	15pp	10pp	15pp	10pp	15pp
Aerial photo	59	74	56	68	52	58
FVS equation	34	49	40	58	50	63
Best model(s)[1]	73	86	59	82	58, 58	65, 85

Best model and model number refer to regression models listed in Table 4. pp, percentage points.
[1] Best models are as follows: for wet conifer, 28, for wet hardwood, 8, and for dry hardwood, 44 and 29, respectively.

the good set for dry hardwood stands, the best models for these stands included age and basal area as independent variables (models 31 and 44, Table 4). As suggested by the best models for each forest group, stocking (stock or $\sqrt{\text{stock}}$) was the most important variable for the wet conifer and hardwood groups, whereas stand age and basal area (age and $\sqrt{\text{ba}}$) were most important for the dry hardwood group (Table 6). mai and stand height (height) were also important variables, particularly for the wet conifer and dry hardwood models. Parameter estimates are provided for each good cover model (Table 7).

Within each forest group, goodness-of-fit statistics for the good models were comparable (Table 8). The similarity in error estimates between the model and test data sets suggests that the results of the analysis were not spurious. However, the errors for the test data set for the dry hardwood stands were almost half as large as those for the model based on stocking and mai (model 29) than for the model selected as best (model 44), suggesting that the latter model may have overfit the data. Differences in predMSE may be due to the low sample size ($n = 102$). However, results for the dry hardwood stands indicate that models based on stocking could be used without significant loss of precision.

Correspondence between field-measured cover and predictions of best models differed among forest groups. Prediction accuracy for the best model for the wet conifer forest group was higher than that for other forest groups (Fig. 4; Table 5). Confidence intervals were larger for the best model for the wet hardwood forest group than those for the wet conifer forest group, with 95% confidence intervals >40% cover over most of the cover levels (Fig. 5; Table 5). As indicated by the fit statistics for the dry hardwood forest group, the 95% confidence intervals for model 44 (based on age, basal area, mai, and stand height) were greater than those for model 29 (based on stocking, mai, and stand height) (Fig. 6; Table 5). Results suggest that model 29 had better predictive ability than model 44 at the stand level. For all three general forest groups, 95% confidence intervals were tighter at the two extreme levels of cover (0 and 100%) and much wider at intermediate cover levels. This pattern is a direct consequence of the logit transformation that was used during the model selection process. Prediction accuracy of the best models for all three forest groups exceeded accuracy with aerial photos and the FVS equations (Table 5).

Discussion

Comparison of Aerial and Line-Intercept Canopy Cover

Although there was a correspondence between line-intercept measurements of tree cover and cover estimated from aerial photography, the correlation coefficients were not very high. Inaccuracies in plot coordinates and in transferring those coordinates to photos could have resulted in differences in cover measurements for some plots (i.e., mismatches). The scale (1:40,000) of the black and white aerial photos is adequate for classifying land use and estimating volume class (the primary variables for poststratification of inventory data), but because of the coarse scale may have led to misclassification of shrubs as trees in young stands and vice versa. This probably led to the lower correlation of the two cover measures for the hardwood forest groups compared with the wet conifer group. Finally, aerial photos do not always show the full extent of cover in the middle and lower layers because photos only show crowns illuminated by sunlight and the portion of crowns that extend above the intersection with their neighbors (Gill et al. 2000). Although more detailed photos may enhance the accuracy of cover estimates, shrub and tree misclassification and the inability to clearly discern vertical layering suggests that estimates of tree canopy cover from aerial photography will usually have substantial errors. In contrast, ground-based line intercept sampling directly measures all of the trees along the transects, ensuring a more accurate measurement of canopy cover than with the aerial estimates at the stand level. Using ground-based measurements, such as line-intercept sampling, we expect some variation at the subplot level due to the spatial clumpiness of cover. However, aggregation of cover data at the stand level should minimize the overall variation in cover levels compared with aerial estimates of cover.

Comparison of FVS and Line-Intercept Cover

Estimates from the crown width and crown overlap equations of the Pacific Northwest Variant of FVS (Donnelly 1997, Crookston and Stage 1999) consistently underestimated observed line-intercept cover values in the wet hardwood and wet conifer stands. Similar results were found for another FVS variant used in Montana Douglas-fir/western larch forests. Applegate (2000) compared cover predictions from the Northern Idaho variant of FVS with densitometer and moosehorn measures and found that FVS equations underpredicted cover in multiple forest types including stands dominated by Douglas-fir, western larch (*Larix occidentalis* Nutt.), ponderosa pine, and lodgepole pine (*Pinus contorta* Douglas ex louden). It is possible that the random overlap correction (Crookston and Stage 1999) overcompensates for overlap in productive stands where light may be the most limiting resource and trees occupy crown space efficiently. For dry hardwood stands, canopy overlap may be less of an issue, which may explain why FVS equation

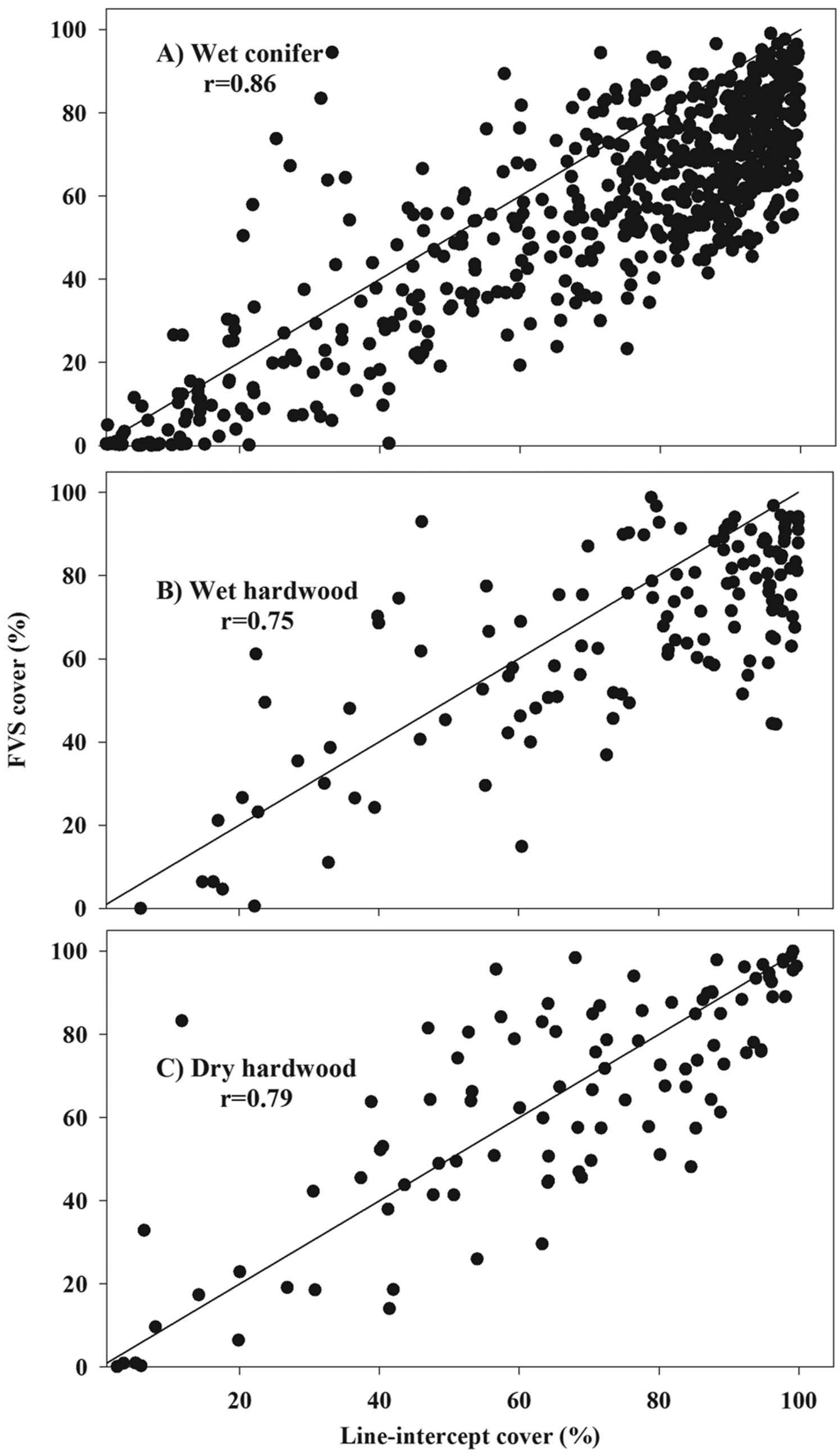

Figure 3. Comparison of cover predicted by FVS equations and ground-measured line-intercept cover for three general forest groups in western Oregon. The diagonal line represents a 1:1 relationship between the two cover estimates. The *r* value is the Pearson correlation coefficient.

estimates did not exhibit bias compared with observed line-intercept measures. Although the FVS model is probably appropriate for comparing the relative effects of different prescriptions on canopy cover, reliance on the absolute FVS cover estimates for wet hardwood and wet conifer stands in western Oregon could lead to erroneous conclusions.

Table 6. Importance weights for the variables included in the good model set ($w > 0.01$) for each of the three forest groups.

Forest group	Variable	Weight
Wet conifer ($n = 484$)	$\sqrt{stock}$	1.0
	mai	1.0
	height	0.27
Wet hardwood ($n = 103$)	stock	0.75
	$\sqrt{stock}$	0.25
	height	0.10
	mai	0.09
Dry hardwood ($n = 76$)	1/age	0.73
	$\sqrt{ba}$	0.73
	mai	0.67
	height	0.53
	$\sqrt{stock}$	0.28

Table 7. Coefficients (1 SE) for the best predictive models of total canopy cover ($w > 0.01$) for the three forest groups.

Group	Model[1]	Variable	Coefficient estimate
Wet conifer	28	intercept	−3.6161 (0.1635)
		$\sqrt{stock}$	0.6200 (0.0144)
		mai	0.0032 (0.0008)
	29	intercept	−3.6145 (0.1649)
		$\sqrt{stock}$	0.6211 (0.0199)
		mai	0.0032 (0.0008)
		height	−0.0004 (0.0051)
Wet hardwood	8	intercept	−1.3934 (0.2516)
		stock	0.0493 (0.0037)
	9	intercept	−2.9729 (0.3744)
		$\sqrt{stock}$	0.6138 (0.0474)
	27	intercept	−3.2261 (0.4245)
		$\sqrt{stock}$	0.5877 (0.0516)
		height	0.0173 (0.0138)
	28	intercept	−3.3151 (0.4888)
		$\sqrt{stock}$	0.6108 (0.0474)
		mai	0.0022 (0.0021)
	29	intercept	−3.5244 (0.5195)
		$\sqrt{stock}$	0.5866 (0.0516)
		height	0.01625 (0.0139)
		mai	0.0021 (0.0021)
Dry hardwood	44	intercept	−1.9002 (0.3449)
		1/age	−7.2584 (2.0069)
		$\sqrt{ba}$	0.6613 (0.0796)
		mai	0.0031 (0.0018)
		height	−0.0014 (0.0151)
	31	intercept	−1.8872 (0.3443)
		1/age	−6.1006 (1.9047)
		$\sqrt{ba}$	0.6981 (0.0613)
	28	intercept	−3.4753 (0.2663)
		$\sqrt{stock}$	0.5427 (0.0309)
		mai	0.0043 (0.0017)
	29	intercept	−3.4969 (0.2675)
		$\sqrt{stock}$	0.5190 (0.0399)
		mai	0.0039 (0.0017)
		height	0.0132 (0.0140)
	27	intercept	−3.2548 (0.2524)
		$\sqrt{stock}$	0.5093 (0.0408)
		height	0.0215 (0.0139)
	9	intercept	−3.1707 (0.2488)
		$\sqrt{stock}$	0.5491 (0.0320)

Canopy cover is estimated using Equation 1.
[1] Model numbers correspond to those in Table 4.

Table 8. Comparison of model statistics for the model data set and the test dataset for each of the forest groups.

Forest group	Model[1]	MSE	Adj. R^2	predMSE
Wet conifer	28	0.827	0.80	0.760
	29	0.828	0.79	0.760
Wet hardwood	8	1.065	0.64	1.229
	9	1.110	0.62	1.086
	27	1.104	0.62	1.056
	28	1.108	0.62	0.975
	29	1.104	0.62	0.958
Dry hardwood	44	0.597	0.81	0.802
	31	0.605	0.81	0.798
	28	0.590	0.81	0.438
	29	0.591	0.81	0.420
	27	0.625	0.80	0.466
	9	0.636	0.80	0.512

The fitted MSE and adjusted R^2 (Adj. R^2) were calculated for the stands used to fit the models ($n = 484$, 103, 76 for wet conifer, wet hardwood, and dry hardwood, respectively). predMSE was derived from the test data set and the best model predictions for each forest group to test the fit of the model ($n = 161$, 34, and 26, respectively). Only models with $w > 0.01$ were examined (ΔAICc < 7).
[1] Model numbers correspond to those in Table 4.

Prediction of Cover from Forest Inventory Measurements

The good model sets for predicting canopy cover from other forest measurements differed among the three general forest groups, but stocking was a common variable among them. The best cover prediction model for wet conifer stands included stocking and mean annual increment, whereas the best model for wet hardwood stands only included stocking. The best model for dry hardwood stands included basal area, mean annual increment, stand height, and stand age. The selection of stand age was surprising, because distinct patterns in canopy cover across a stand age gradient in this forest type were not evident (Fiala 2003, McIntosh et al. 2009). The dry hardwood model with the best fit for the test data set included stocking, mean annual increment, and stand height.

Our findings suggest that models based on the same variables can be expected to work across forest types. However, our model selection results differ from previous studies that predominately selected basal area as the best predictor of cover. Mitchell and Popovich (1997) included stand density as a potential predictor but found that cover in ponderosa pine stands was best predicted by basal area, and only for stands with canopy cover <60%. Buckley et al. (1999) demonstrated that regression of the square root of basal area could potentially be used to estimate canopy cover levels in Michigan oak and pine stands ($R^2 \geq 0.95$). Basal area, dbh, and stem density together were used as the best predictors of canopy cover in northern California stands ($R^2 = 0.75$ and 0.66 for test and model data sets) (Gill et al. 2000). Cade (1997) recommended use of basal area to estimate cover when emphasis of larger diameter uncommon trees was desired, such as in wildlife studies.

There are several potential reasons why stocking density was preferentially selected over basal area among most forest groups in our study. One potential reason is that, except for the study conducted by Mitchell and Popovich

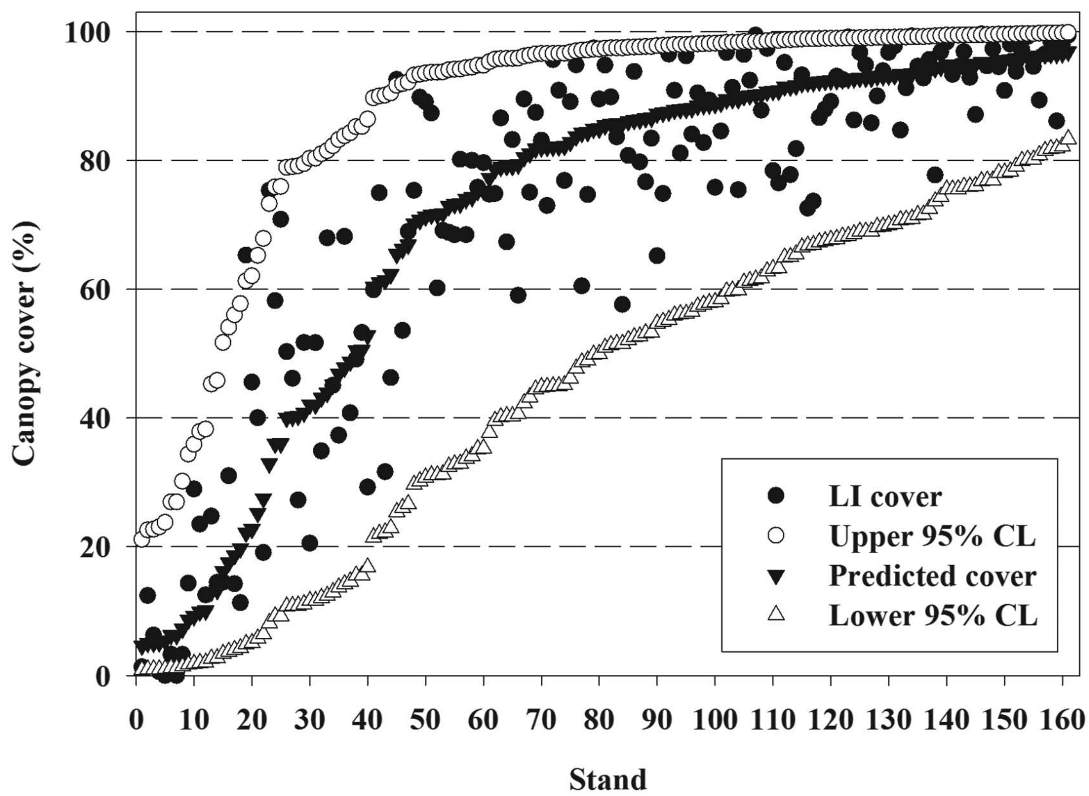

Figure 4. Predicted canopy cover for the wet conifer forest group using model 28 (stocking and mai) compared with measured line-intercept (LI) cover from the test data set. Individual stands are in ascending order by predicted cover. The 95% upper and lower confidence limits (CL) used the SE of the estimates.

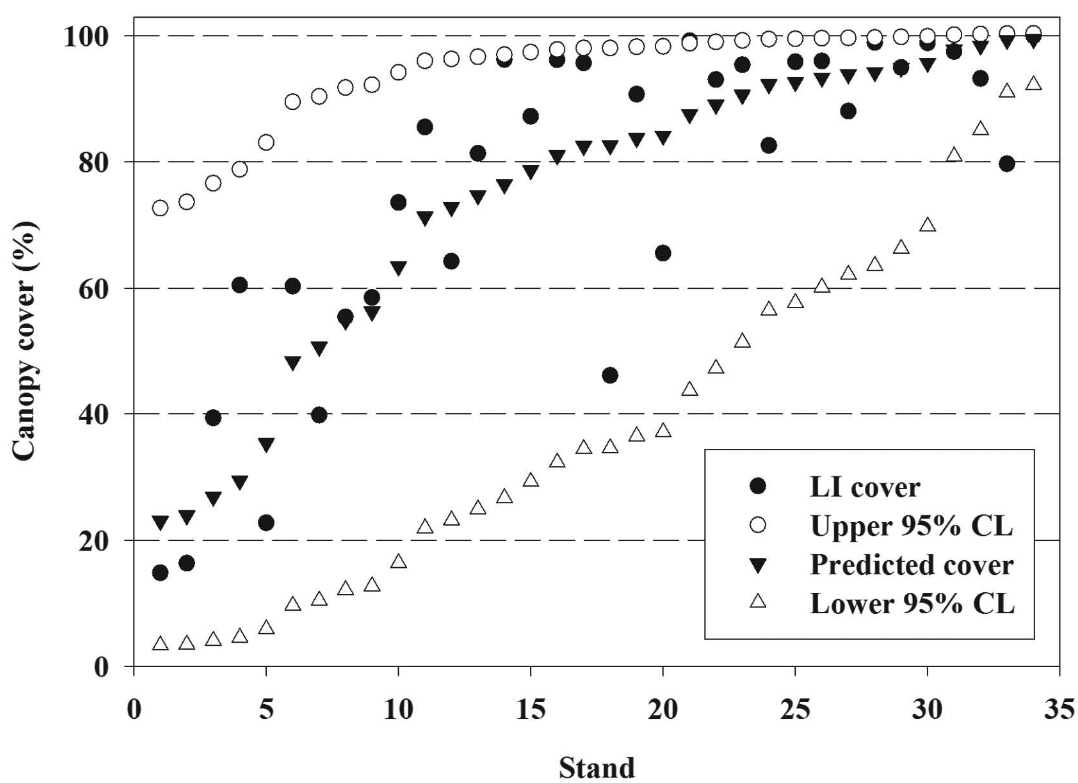

Figure 5. Predicted canopy cover for the wet hardwood forest group using model 8 (stocking) compared with measured line-intercept (LI) cover from the test data set. Individual stands are in ascending order by predicted cover. The 95% upper and lower confidence limits (CL) used the SE of the estimates.

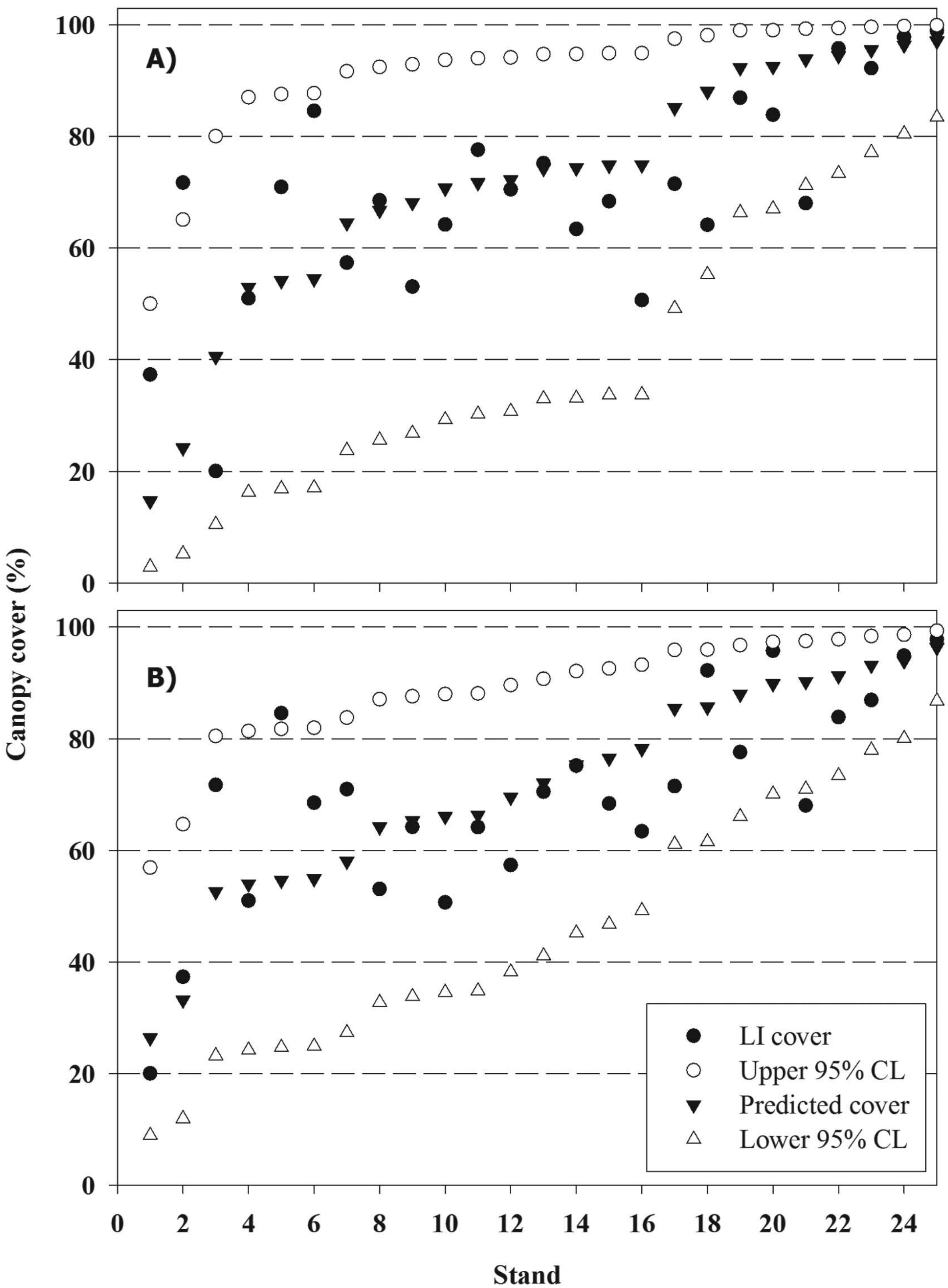

Figure 6. Predicted canopy cover for the dry hardwood conifer forest group using (A) model 44 (age, basal area, mai, and stand height) and (B) model 29 (stocking, mai, and stand height) compared with measured line-intercept (LI) cover from the test data set. Individual stands are in ascending order by predicted cover. The 95% upper and lower confidence limits (CL) used the SE of the estimates.

(1997), previous studies did not consider a measure of stocking. In addition, previous studies did not have the regional scope and range of stand variation of this one. Stocking density, calculated as the contribution of each measured tree to a fully stocked stand based on normal yield tables, is an estimate of proportional site occupancy. In contrast, basal area is an absolute, species-invariant measure with no inherent bounds. Stocking equations are also species-specific and may therefore reflect species differences in maximum attainable density better than basal area.

The utility of the predictive models we generated in this study is dependent on the desired accuracy. If predicting cover within a range of 15% is acceptable, the best models for each of the forest groups are useful. However, if accuracy of 10% cover is needed, we recommend use of only the best model for the wet conifer forest group (Table 5). If greater stand-level predictive accuracy is desired than those the models provide, we recommend use of field-based cover measurements with the line intercept or the moosehorn technique (Fiala et al. 2006).

Data used to derive predictive models in this study have both strengths and limitations. Data spanned a range of stand attributes across western Oregon; thus, predictive models have a relatively high degree of generality. These attributes included variable species composition, gradients of precipitation and elevation, multiple ownership types with different intensities of management, a wide range of stand ages, and varying site productivities. We did not use subsets of the data to develop models for specific stand conditions (e.g., species composition or elevation) and geographically localized areas to provide a wide scope of inference; however, such models could be derived if required. An important limitation of our data was the paucity of older stands. Given the population of nonfederal lands sampled by this FIA inventory and the land use history of western Oregon, few forests older than 80 years of age were available (Fiala 2003). Detailed canopy measurements were not available for inventories of federal lands, where the majority of older stands in this region are located (Campbell et al. 2002). Older forests in the region tend to have greater canopy layering and clumped tree distributions than younger forests (Stewart 1986, Van Pelt and Nadkarni 2004), and this may or may not affect the relationships between canopy cover and the independent variables selected in our models.

Overall, our study demonstrated that use of predictive models incorporating species-specific variables can have a lot more value than use of a species-invariant measure such as basal area. We recommend that researchers use the good set of predictive models we developed for western Oregon as a template for exploring the relationships between canopy cover and species-specific attributes such as stocking density and mean annual increment in other forest types. These predictive models have the potential to act as substitutes for ground-based canopy measurements, depending on the level of accuracy needed.

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