Probability models for individually segmented tree crown images in a sampling context

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Abstract

Individually segmented tree crowns are an increasingly common intermediate product for forest inventories using ALS and/or high resolution digital photography. Empirical models are often used to predict the species and sizes of the individual trees associated with each individually delineated tree crown (ITC). Data for such models can come from purposive sampling or from design-based probability sampling. In either case, the empirical predictions will have errors, both with respect to tree size and species. Furthermore, the data used for modeling will often have incorrect matches between ITCs and sample trees. Probability models are well suited to deal with the problem of incorrect matches, false positives and omissions. Examples of such models are shown for a forest in the southern U.S., consisting of pine plantations and naturally regenerated pine stands, with various amounts of natural fill-in of both pine and hardwood. The probability models, coupled with design-based probability sampling, can be unbiased for selected measures of yield by species at the stratum level.

Keywords: remote sensing, sampling, tree crowns, matching.

1. Introduction

Forest inventories involving extensive remotely sensed data such as that from LiDAR, coupled with ground sampling, are in increasingly common use. The analysis of the remotely sensed data can be on an area basis (Næsset, 2004), or may be based on segmentation of individual tree crowns (ITCs). The latter approach may have the greater intuitive appeal. Næsset et al. (2004) and Maltamo et al. (2007) give overviews of recent experiences with the various methods. Gougeon and Leckie (2003) summarize research in individual crown segmentation going back over twenty years. Many different sources of remotely sensed data, singularly or combined, can be used to delineate individual tree crowns (ITCs). Reports of crown delineation based on LiDAR include Hyyppä et al. (2001a), and Persson et al. (2002).

Aside from the need for calibration, there are several basic problems which hinder the accuracy of predictions based on ITC. These include incorrect segmentation, undetected dominant trees, hidden trees (Mehtatalo, 2006), incorrect species predictions, and the likelihood that allometric relationships used to predict diameter as a function of height and crown area will vary with stand history and other factors. Though species identification is improving over the 50% error rate reported by Hyyppä et al. (2001b), correct species identification of all or most ITCs has been an elusive goal. Progress in species identification has been reported by Gougeon and Leckie (2003) and Holmgren and Persson (2004),

The data used to fit ITC to tree prediction relationships are often selected without benefit of a rigorous sampling methodology. The ITCs are the entities upon which the predictions are based; however they are seldom used to construct a sample frame. Furthermore, the linkages between the sample ITCs and the trees they correspond to are often very subjective or incomplete. The inventory study that is the subject of this paper utilizes the full set of ITCs to form a rigorous sample frame. The linkage between sample ITCs and sample trees uses methodology which is almost free of subjectivity. The theory is reported in Flewelling (2006) and Flewelling (2008). Section 2 of the present paper has a brief description of the study material, and all the processing steps prior to the development of the probability models.

2. Study Material and Preliminary Processing

The forest being inventoried consisted of two blocks in the coastal plain of Texas, USA. The majority of the stands were either plantations of slash pine or loblolly pine. Others were naturally regenerated pine. Significant amounts of hardwood were in the natural stands, and in the planted stands in one of the two blocks. An inventory was available showing past management practices including age of establishment and thinning history. Stand boundaries were in a geographic information system (GIS). The inventory described here excludes stands of age 12 and younger, and excludes stands which had been classified as hardwoods; those stands were inventoried using different methods. The inventory presented here is comprised of 1573 stands with a total area of 14,800 ha.

2.1 Remotely Sensed Data and Processing

Two types of remotely sensed data were available: LiDAR and color-infrared (CIR) digital photography (red, green and near infrared channels). The LiDAR data were acquired using an Optech Altm 3100 sensor. Specifications were for a minimum of five postings per square meter. Only the first and last returns from each LiDAR pulse were retained. The LiDAR data were used to create a digital elevation map; the first returns were converted to values of height above ground, and further converted to 0.5 by 0.5 m pixels. Pixel heights were set to the highest return in each pixel; pixels without returns had heights imputed from neighbouring pixels. The CIR data were fused with the pixelized LiDAR data.

Individually delineated tree crowns (ITCs) were identified over the entire forest by applying a semi-automatic valley-following technique (Kelle et al., 2007) with similarities to that of Hyyppä et al. (2001a). Each ITC is represented by a contiguous set of whole pixels. ITC height was determined as the greatest of the pixel heights; ITC area was determined as the sum of the areas of the pixels; ITC location was determined as the geometric mean of the pixel locations. ITC color was determined as the average of the color values of the pixels.

All ITCs were assigned a species group (SPG). The two species groups were pine and hardwood. The assignments were made through a operator-guided training process, which was calibrated separately by stand type and block. The assignment methodology used a neural network approach, based mainly on the color data. This approach allows a species-group probability to be assigned to each ITC. Subsequently each ITC was assigned a putative species group: the species group with the higher probability. Every stand had species cover assessed ocularly. The putative species group assignments for the ITCs within each stand were adjusted to match the overall assessment for the stand.

2.2 Sampling

Stands were grouped into twenty-two sampling strata based upon block, species planted, thinning history, origin, and age. Within each stratum several stands were selected without replacement for sampling; the probability of selection was proportional to stand area; most strata had six stands selected; one strata had four stands selected. Within the GIS representation of each selected sample stand, two points were randomly selected to become plot centers.

A field crew was given the coordinates of each preselected plot center. They used survey-grade GPS equipment to travel to the preselected locations in the forest, and monumented plot centers at those locations. Fixed-area circular field plots, of size 0.04858 ha, were established at each location. Field measurements included the species, location, and diameter (DBH) of each tree whose diameter exceeded a threshold (D_{min}) of 7.493 cm. Location data (horizontal distance and azimuth) were sufficient to allow for the calculation of the breast-height location of each tree relative to the plot center. A sample of heights was recorded for each species on each field plot. The height data were used to fit height-diameter curves by species for each plot; unmeasured tree heights were imputed from the curves. Sample weights, which are required for unbiased estimation, were computed for each ITC. Further details are as described in Flewelling (2008).

2.2 Plot Registration

The field plots are not assumed to have been located perfectly. The determination of the location of the field plot on the crown map is accomplished with a computer-assisted system that overlays the field-determined stem map on a representation of the remotely sensed data After the registration is completed, the location of the field plot's center on the ITC map becomes the accepted location for the sample.

2.3 ITC and Tree Matching

A statistically valid procedure was required to identify the tree or trees to be associated with each ITC. Such a procedure is described by Flewelling (2008); that procedure was applied here to all the ITCs whose centers were within crown analysis plots of size 0.03644 ha, centered about each of the corrected plot centers. The procedure used was similar to that described by Persson at al. (2002). Each ITC was expanded by up to 1 m in each direction to form Veroni tessellations. Field sample trees whose coordinates were within a particular ITC's expanded area were tentatively matched to that ITC. Infrequently, trees not falling within any of the ITC tessellations were matched to the nearest ITC if the match appeared to be physically correct. The trees which are matched to particular ITCs can be referred to as directly associated trees.

3. Methods

Probability models were developed to predict the number and species of trees associated with each ITC. For trees predicted by these probability models, conditional regression equations were required to predict tree diameter. The resultant regression predictions of DBH were further modified using a common "tripling" technique which increases the dispersion of predicted diameters and heights, but which does not alter the predicted yield. Heights are predicted as a function of DBH and the LiDAR-based height of the ITC. A separate simpler model accounts for trees not associated with ITCs.

3.1 Species and Count Predictions

For each stand there are two components of the overall prediction: trees inferred directly from ITCs and an unseen component. The unseen stand component contains relatively few trees, which are usually smaller than the other trees. The unseen component is addressed in section 3.5. This section deals only with the directly associated trees.

There are many possible combinations of matched trees for a single ITC. A notation system was devised to track the possible outcomes for an ITC match. The notation allows for a count (C) of the trees to be associated with a particular ITC, allows for identifying the species group of the associated trees, and tracks the trees by comparative DBH. The largest tree associated with an ITC is referred to as a primary tree; any smaller trees associated with an ITC could be referred to as secondary trees. Secondary trees which are not the second-largest are also referred to as tertiary trees.

The independent data for the ITCs includes stratum, and:

SPG_{ITC}	Assigned species group: P=pine, H=hardwood
A	Crown area (m^2).
H_{ITC}	Height of the ITC (m)

All the ITC heights are 4 m or greater. The variables being predicted are:

SPG_{TREE}	Species group for a tree: P for pine, H for hardwood.
DBH	Diameter at breast height. (cm.),
HT	Total tree height (m)
EC	Expected tree count; also expressed as E(C).
TRS	Tree-record sequence, a code used to track predicted trees.

The first of the probability equations for ITCs classified as pine is:

$$\Pr\{C \geq 1\} = \text{logit}^{-1}(L) = \exp(L)/[\ 1 + \exp(L)] \qquad (1)$$

where L is a linear function of A, H_{ITC}, and their cross product. Other equations for the pine ITCs have the same form, but different coefficients. There are two more "count equations" ; these predict $\Pr\{C \geq 2 \mid C \geq 1\}$ and $\Pr\{C \geq 3 \mid C \geq 2\}$. The unconditional probabilities for counts 0, 1, 2, and ≥ 3 can be computed by combining the foregoing empirical equations according to standard rules for probability expressions.

The above equations deal with tree count. Tree species are predicted separately by the size order of the directly associated trees. Subscripts 1, 2 and 3 refer to the largest-DBH tree associated with an ITC, the second largest, and all others. Species probabilities are predicted for the pine ITCs as:

$$\Pr\{SPG_1 = P \mid C = 1] = \text{logit}^{-1}(c_0 + c_1 \times A + c_2 \times H_{ITC} + c_3 \times A \times H_{ITC}) \qquad (2)$$

where the inverse logit function is as defined in Eqn. 1. Coefficients c_0 through c_3 for a representative stratum are (-2.43, -0.455, 0.1667, -0.01553). Other equations of the same form predict $\Pr\{(SPG_1= P) \mid C \geq 2)\}$, $\Pr\{(SPG_2 =P) \mid C \geq 2, SPG_1 = P)\}$, $\Pr\{(SPG_2 = P) \mid C \geq 2, SPG_1 = P)\}$, $\Pr\{(SPG_2 = P) \mid C \geq 2, SPG_1 = H)\}$. The latter equations are sufficient to calculate probabilities that the species of the largest and second largest trees are (P, P), (P, H), (H, P) or (H, H). The conditional expected count of tertiary trees for the pine ITCs, E{C of tertiary Conifers | C ≥ 3} and E{C of tertiary Hardwoods | C ≥ 3} are estimated as constants.

This completes all of the empirical computations for E(C) on possible realizations of the probability models for pine ITC's. Table 1 shows all the realizations, and their expected counts. The tree-record sequences (TRS) are arbitrary labels. Each ITC that had been classified as a pine produces twelve tree records with the expected counts shown in Table 1. The ITCs classified as hardwoods have a similar, but simpler set of prediction equations; these are not shown.

3.2 DBH Predictions

DBH is predicted as a function of crown area and ITC height, using the following model for all primary trees and second-position trees associated with pine ITCs:

$$DBH = a_0 + a_1 \times \{ 1 - \exp[a_3 \times (A)^{a_4} \times (H_{ITC})^{a_5}] \}^{a_2} \qquad (3)$$

Most coefficients are constant across all strata, but do vary with TRS. An all-strata weighted regression is used to estimate the coefficients. Coefficient a_3 is subsequently revised by stratum such that the weighted sum of predicted basal areas associated with the sample ITCs is exactly equal to the weighted sum of the basal area of the ground sample trees for that TRS and stratum.

The tertiary trees associated with pine ITCs use a different equation for DBH. The predicted values are always between D_{min} and the predicted diameter of the second-largest associated tree. As with the previous equation, the fit is constrained so as to have unbiased predictions for basal area by stratum.

3.3 Tripling

Tripling is a commonly used mechanism to increase variance of model predictions. Each original predicted tree record is split into three, each representing one-third the original E(C). The DBHs for the three new records (i = 1,3) are:

$$DBH_i = SQRT\{ (D_{min})^2 + (1 + f_i \times k) [DBH^2 - (D_{min})^2]\} \qquad (4)$$

where $(f_1, f_2, f_3) = (-1, 0, 1)$, and k is set so that the variance of the predicted DBHs are similar to the variance of the observed DBHs.

3.4 Tree Height Predictions

There are two sources of height predictions: one based on a commonly used height-DBH relationship, and the other based on the LiDAR derived height of the ITC. The first of these is referred to as the allometric height prediction:

$$HT_A = BH + a_1 \times \exp(a_2 / DBH) \qquad (5)$$

where BH is breast height, 1.37 m. Coefficients are fit separately by stratum and the species group of the tree.

The above prediction of height is used as an independent variable in the final regression, which incorporates both sources of information:

$$HT = BH + a_1 \times (HT_A - BH) + a_2 \times (HT_{ITC} - BH) \qquad (6)$$

Fitting is done separately for the planted strata and the natural strata. Coefficients vary with tree species group, and with match position. The coefficients are constrained such that the weighted sum of the product of basal areas and heights is unbiased.

3.5 Unseen Trees

Some trees are not detected at all in the ITC generation process, or fail to be linked to an ITC. For each sampling stratum, all such trees are put into a per-hectare listing of trees, showing species group, DBH and the count per ha. represented by each entry.

4. Results

False positives, ITCs with no matching trees, were 9.9% of the total; for such ITCs which had been identified as pine or hardwood respectively, the false-positive rates were 9.1% and 16.4% The crown area of these false ITC's was 4.0% of the total area of all ITC's. Unseen trees were 2.5% of the total, representing 1.4% of the basal area. Results for all the matched ITCs and trees are in Table 2. Each such ITC is matched, on average, to 2.06 trees. The primary trees represent 48% of the total number of matched trees and 74% of the total matched basal area.

The forest-wide average stand tables for pine and hardwood are shown in Figure 1. The observed and predicted stand tables are in good accord. The two most notable errors are that the hardwood trees in the lowest DBH class (8 cm) are underestimated, and the peak prediction for pine at DBH class 12 cm does not exactly match the field data.

Table 1: Predicted species and counts for trees associated with ITCs classified as pine.

TRS	Description	SPG_{TREE}	E(C)
1	Single Tree	P	$Pr\{C = 1\} \times Pr\{SPG_1 = P \mid C=1\}$
2	Single Tree	H	$Pr\{C = 1\} \times [1 - Pr\{SPG_1 = P \mid C=1\}]$
3	Larger of (P,P)	P	$Pr\{C \geq 2\} \times Pr\{$ species=(P,P) $\mid C \geq 2\}$
4	Smaller of (P,P)	P	$Pr\{C \geq 2\} \times Pr\{$ species=(P,P) $\mid C \geq 2\}$
5	Larger of (P,H)	P	$Pr\{C \geq 2\} \times Pr\{$ species=(P,H) $\mid C \geq 2\}$
6	Smaller of (P,H)	H	$Pr\{C \geq 2\} \times Pr\{$ species=(P,H) $\mid C \geq 2\}$
7	Larger of (H,P)	H	$Pr\{C \geq 2\} \times Pr\{$ species=(H,P) $\mid C \geq 2\}$
8	Smaller of (H,P)	P	$Pr\{C \geq 2\} \times Pr\{$ species=(H,P) $\mid C \geq 2\}$
9	Larger of (H,H)	H	$Pr\{C \geq 2\} \times Pr\{$ species=(H,H) $\mid C \geq 2\}$
10	Smaller of H,H)	H	$Pr\{C \geq 2\} \times Pr\{$ species=(H,H) $\mid C \geq 2\}$
11	Tertiary pine	P	$Pr\{C \geq 3\} \times E\{$C of tertiary Conifers $\mid C \geq 3\}$
12	Tertiary Hdwd	H	$Pr\{C \geq 3\} \times E\{$C of tertiary Hardwoods $\mid C \geq 3\}$

Table 2: Summary of matched ITCs and trees. Forest-wide estimates from 0.0364 ha analysis plots.

		Trees per ha			Basal area (m²/ha)			
	Tree	ITC species			ITC Species			Basal
Match	Species	Pine	Hdwd	All	Pine	Hdwd	All	Area (%)
Primary	Pine	308	13	321	13.1	0.4	13.5	68
	Hdwd	35	25	60	0.7	0.6	1.3	6
	All	343	38	381	13.7	1.0	14.8	74
Secondary	Pine	216	6	222	3.4	0.1	3.4	17
	Hdwd	151	32	183	1.3	0.3	1.7	9
	All	368	38	405	4.7	0.4	5.1	26
All	Pine	524	19	543	16.5	0.5	17.0	85
	Hdwd	186	57	243	2.0	0.9	2.9	15
	All	711	76	787	18.5	1.4	19.9	100

5. Discussion

The modeling and sampling approach presented here produces unbiased results at the stratuma level. Most other methods of using remote sensing in forest inventory estimation either are unbiased, or could be made unbiased through a strategy of adjustments based upon randomly located sample plots. For example, consider a system based on individual crown delineation coupled with empirical relationships to predict DBH and height as functions of crown characteristics. The regressions could be based on non-representative data and, as a consequence, could not be directly used for unbiased estimation. However, if the regression results were subsequently adjusted, perhaps with a ratio estimator, the adjusted results would be unbiased by stratum.

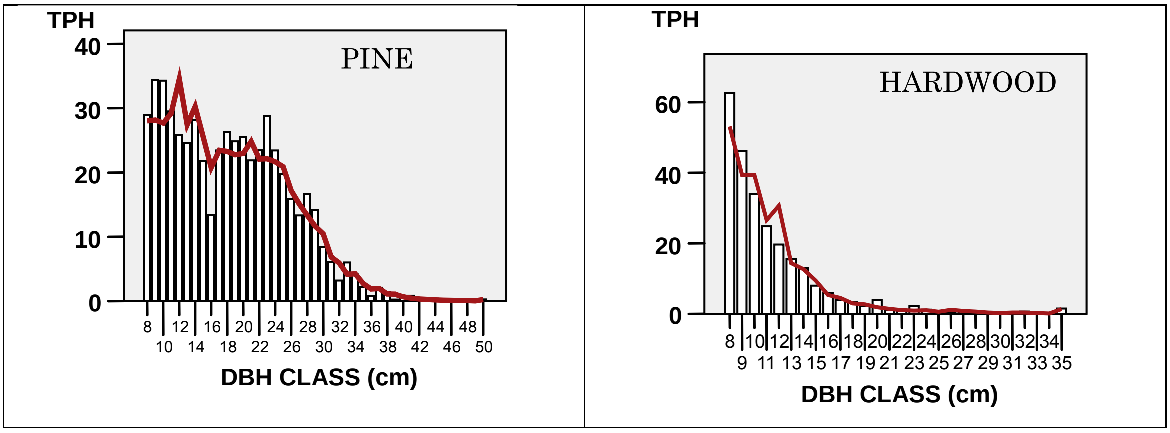

Figure 1. Trees per hectare by 1 cm diameter classes for pine (left) and hardwood (right). Histograms represent observed ground plot data; the overlaid line are the predictions.

The approach presented here has an added advantage of statistical efficiency due to an almost-exact matching between the remotely sensed sample and the ground sampling. Plot registration error is minimized, and correlations between the remotely sensed data and the corresponding ground data are maximized. Consider that a perfectly registered plot may have several crowns whose centers are near the plot boundary. Without crown and tree matching, it is just a matter of chance whether the trees actually associated with these ITCs will be inside the ground plot or outside the ground plot. With good matching, that uncertainty is removed, making each plot more valuable for the purpose of ratio adjustment. The benefit of highly correlated tree and crown data also accrues to the present method, even though there is no explicit ratio adjustment based on yields of sample plots.

A goal that is hinted at in various papers and presentations is that data obtained from crown segmentation, together with good allometric relationships, may lessen or eliminate the need for on-the-ground sampling. That goal is unlikely to be realized while the non-primary trees associated with the ITC's constitute over a quarter of the total basal area (Table 2). Mehtatalo (2006) reviewed the literature on unseen trees; such trees would often include what I have referred to as secondary trees. He concluded that the problem of unseen trees won't be eliminated through direct analysis of remotely sensed data. He proposed using distributional models to correct for censoring. However, it should not be assumed that tree size distributions will always be regular. The probability models presented here have the potential to account for unseen or secondary trees in most situations where the desired one-to-one correspondence between ITCs and trees is lacking. And the predicted DBH distributions appear to be reasonable.

Apart from the modeling, there remains a lot of uncertainty about how best to associate sample ITCs and sample trees. The method described here is a type of cluster sampling. To be valid, the matches must be invariant to the random positioning of the plots. Though not a statistical requirement, the best methods will have matches which closely correspond to the apparent physical reality. Tree-top matching as shown by Korpela et al (2007) is probably better than matching based on ground projections. Another promising method could model the entire crown in three dimensions as proposed by Andersen et al. (2002), and then search for intersections of boles and crowns at some intermediate height.

Reliable estimates of mean square error (MSE) for the estimators of basal area and volume by stand could not be obtained due to the small number of sample stands in each stratum. Flewelling (2008) reported on a different study with similar methodology but with fewer strata and more samples per stratum than in the present study. The reported root mean square error for stand basal area in that inventory was 9.7%. The less-than-trustworthy pooled-variance result for the present study corresponds to a root mean square error for merchantable basal area of 21.3%; the corresponding figure for merchantable volume is 24.3%. Merchantable trees are those with DBH $\geq$ 11.4 cm; outside-bark cubic volumes are from stump height (15.2 cm) to a 7.6 cm small-end outside-bark top diameter. As should be expected in a studies utilizing LiDAR to predict diameter distributions and heights, the stand-level errors in volume are only slightly greater than the stand level errors in basal error, for errors measured as percentages. If there had been more samples per stratum, the estimated variances would be expected to be lower, and the estimates of the variances would be expected to be much more reliable.

One of the shortcomings in the present analysis is the forced binary decision on species group for each ITC. Estimates of species probabilities are potentially more useful than discrete estimates. The proprietary neural network approach to species classification did provide a means to estimate species probabilities for ITCs. Those probabilities were not used because of concerns as to whether the computations were correct. Without regard to that particular concern, most methods of assigning species should be able to also assign probability estimates for the species. For example, a discriminant analysis based on the three color channels and the separate mean profiles for pine and hardwood would produce species probability estimates for each ITC. The mean profiles for the two species groups could be from subjectively selected ITCs or they could be a random subset of the sample data. A different approach used in agriculture (Foody et al., 2006) focuses on the species of most interest, which would be pine in this case. The color values from the training set for pine could be used to describe a multivariate distribution. Relative probabilities of being pine would be assigned to the ITCs based upon probability density values computed from that multivariate distribution. There is no need for a similar multivariate distribution for hardwoods. The methods used in the present study, and the suggested alternatives, all share a common feature of keeping the computations on the CIR data separate from the other probability computations. Hence the analyses are simplified, at a cost being unable to fully explore interactions of the CIR data and the LiDAR derived characteristics of the ITCs.

If probability estimates of species for the ITCs had been directly used, there would have been no need to make up separate sets of equations for pine-classified ITCs and hardwood-classified ITCs. Instead, a single set of probability equations could have been fit, using as one of the independent variables a logit transformation of the initially predicted pine probability. Such an approach would have retained more information on the species inference than was possible with the binary approach to species estimation. If ocular estimates of crown cover percentages were available for each stand, these could easily be brought into this estimation process by adding a stand-dependent constant to each logit-transformed probability such that the resultant ITC-area-weighted mean pine probability for a stand matched the ocular estimate.

Regardless of whether the models presented here or some other models are used, the statistical characteristics of errors for predictions based on ITCs will be substantially different from those seen in traditional stand-level inventories. Traditional inventories can be unbiased by stand for all major attributes, including the diameter distributions. Models based upon remotely sensed data, without ground sample data in every stand, are not unbiased by stand. At best, unbiasedness holds at the stratum level, usually for a small set of attributes. For the models presented here, unbiasedness at the stratum level holds for numbers of trees, basal area, and the basal area- height product, overall and by species.

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