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Assessing forestland area based on canopy cover in a semi-arid region: a case study

J. W. COULSTON[1]*, S. N. OSWALT[1], A. B. CARRAWAY[2] AND W. B. SMITH[3]

[1]USDA Forest Service, Southern Research Station, Knoxville, TN 37919, USA
[2]Texas Forest Service, College Station, TX 77840, USA
[3]USDA Forest Service, Washington Office, Arlington, VA 22209, USA
*Corresponding author. E-mail: jcoulston@fs.fed.us

Summary

Forestland area estimates are the first principle of most ecological assessments across spatial scales. The definition of forest used by the United Nations Food and Agriculture Organization is based on a 10 per cent canopy cover threshold while the definition of forest used by the US Forest Service Forest Inventory and Analysis programme in western woodlands is based on a 5 per cent canopy cover threshold. Most of the eastern US forests have the ability to reach 10 per cent cover; however, in semi-arid areas such as western Texas, there is considerable area of forestland with less than 10 per cent canopy cover. The main objective of this research was to provide an estimate of forestland area in west Texas based on a 10 per cent canopy cover threshold. To accomplish this, we developed and compared three classification models that discriminate between inventory plots with less than 10 per cent cover and those with at least 10 per cent cover. We found that ~3.9 million ha (17 per cent) of forestland area (based on 5 per cent cover) did not meet the 10 per cent canopy cover threshold.

Introduction

Quantifying and reporting the extent of forest resources is one of the primary objectives of forest resource assessments across geopolitical scales (e.g. local, regional, national and international). While there has been a substantial increase in the amount of environmental data, estimates for national and international assessments are often compiled from surveys conducted at finer geopolitical scales; therefore, definitional and methodological consistency are important (Mather, 2005). Inconsistency can result in poor baselines and unreliable trend information (Grainger, 2008). For example, anecdotal evidence suggests that the global forestland base has been shrinking. However, according to United Nations Food and Agriculture Organization (FAO) estimates, the forestland base increased from 3442 billion ha in 1990 to 3869 billion ha in 2000 (FAO, 1995, 2001). This point is further illustrated by forest area estimates for Australia which were 40 million ha and 155 million ha in 1990 and 2000, respectively (Mather, 2005). The large increase of forest area in Australia was attributed to a definitional change used in the 2000 assessment. After accounting for changed definitions, improved data and revised national classifications, the 1990 worldwide forest area estimate was revised from 3442 billion ha to 3963 billion ha. Consistency

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among estimates or calibration of estimates is critical for creating a time series of comparable forestland area estimates at the national and international geopolitical scales.

As required by the Forest and Rangeland Renewable Resources Planning Act of 1974, the US produces an assessment of its renewable resources on a 10-year cycle. One aspect of the Resource Planning Act assessment is estimating the amount of forestland within the US. These data serve as the basis for upward reporting for international assessments. Definitional and methodological changes or inconsistencies influence the compatibility of estimates over time and are a major concern to the US Forest Service Forest Inventory and Analysis (FIA) programme. While the US has been conducting forest surveys in some states since 1930 and all states have been inventoried, certain marginal or difficult to access areas were excluded. For example, the western part of Texas and the interior of Alaska have not been completely inventoried with *in situ* observations. However, the extent of west Texas and interior Alaska forests has been estimated based on remotely sensed data; a deviation in observation scale compared with field measurements.

West Texas is a 60.5 million ha area that has undergone significant vegetative changes since the 1870s (Van Auken, 2000) but, as noted above, has not been completely inventoried using *in situ* measurements. The major ecoregion provinces in this area are the Chihuahuan Semi-Desert Province and the Southwest Plateau and Plains Dry Steppe and Shrub province (Bailey, 1995) (Figure 1). Based on the 1953 forest statistics of the US (USDA, 1958), there were 10.5 million ha of forestland in west Texas. Based on the 1997 forest statistics, there were ~2.8 million ha of forestland in west Texas. The 1953 estimate was based on interpretation of aerial photographs (Smith *et al.*, 2003) and

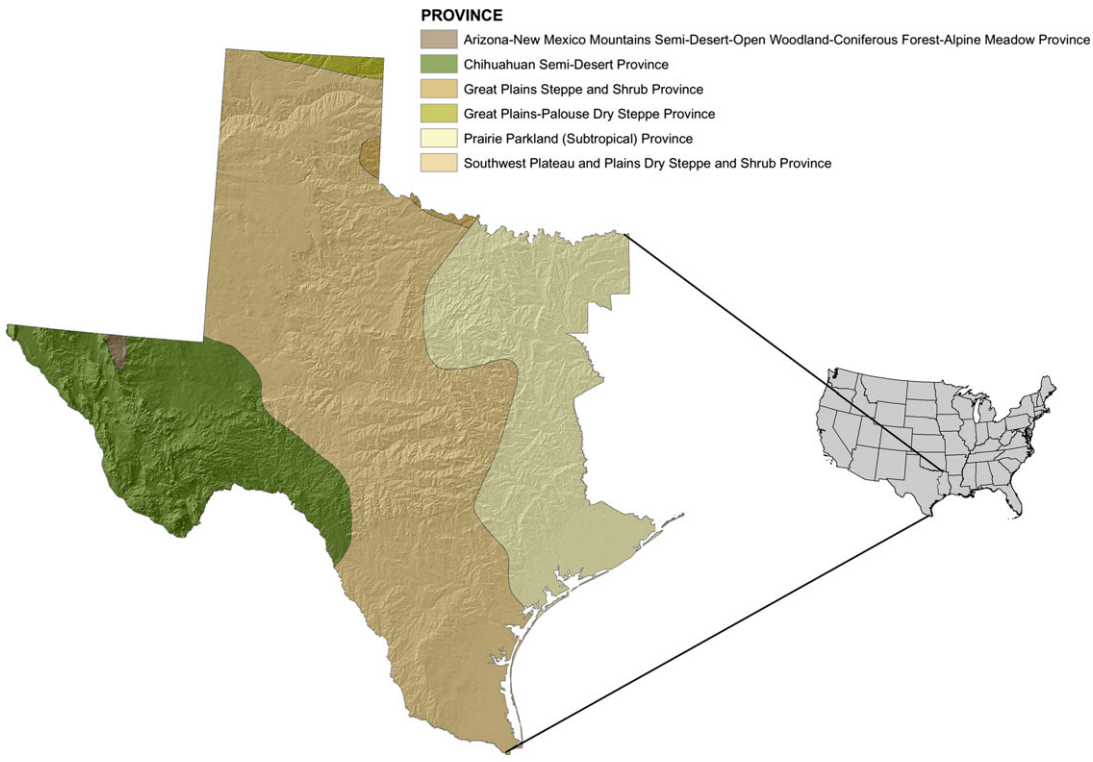

Figure 1. Delineation of west Texas and ecoregion provinces.

the 1997 estimate was partially based on classified Advanced Very High Resolution Radiometer (AVHRR) satellite imagery (Zhu and Evans, 1994). Each of these estimates was made from a different scale of observation. Therefore, they are not directly comparable and do not provide an adequate baseline of the amount of forestland in west Texas. The goal of this research is to provide an estimate of forestland area in west Texas based on FIA permanent field plot network that is in compliance with the Federal Geographic Data Committee (FGDC) Subcommittee on Vegetation Classification standards and the FAO forestland definition.

The FAO definition of forestland is 'Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 per cent, or trees able to reach these thresholds *in situ*. It does not include land that is predominantly under agricultural or urban land use'. The FAO definition of forest coincides with the FGDC definition. The definition of forestland used by FIA in woodland areas is similar; however, forests have been sampled based on a 5 per cent canopy cover threshold rather than 10 per cent canopy cover threshold in some regions (USDA, 2006). There is also a departure in forestland definitions when considering areas comprised of seedlings. Seedlings are defined as tree species less than 1 inch in diameter. The FIA definition for woodland areas requires 99 seedlings ha^{-1} to meet stocking thresholds, and FIA considers these areas to have the ability to become forest. In the eastern US, most forested areas have the potential to become stocked forest based on all mentioned forest definitions. However, in areas of sparse woody vegetation, such as the semi-arid areas of west Texas, using a 5 per cent canopy cover threshold and 99 seedlings ha^{-1} to define forestland may produce substantially different forestland area estimates than required for compliance with the FGDC forest definition established for all federal agencies in the US.

Forestland area estimates based on different scales of observation can vary substantially. The scale of observation is the scale at which the world is translated into data (Li and Reynolds, 1995). Defining the scale of observation is an important, yet often overlooked, step in providing estimates of forest extent. The spatial pattern that can be resolved from an *in situ* inventory is substantially different from the pattern that can be resolved from most remote sensing approaches to inventory. Simply, in sparsely vegetated heterogeneous landscapes, the amount of forestland in a given area depends on the ability to resolve pattern. Therefore, even when using the same definition of forestland, without calibration we would not expect the estimate of the amount of forestland based on AVHRR (1 km^2 resolution) to equal the estimate based on 1 : 15 840 scale aerial photography or *in situ* field-based measurements (Baccini *et al.*, 2007). In fact, unaccounted for changes in the scale of observation can lead to discrepancies among estimates (Achard *et al.*, 2002; DeFries *et al.*, 2002; Inger *et al.*, 2008).

Based on data from 40 per cent of the rotating panel survey and the FIA forestland definition (5 per cent canopy cover), there were ~23.09 million ha of forestland in west Texas. This estimate was substantially different than the previous estimates described above. The main objective of this research was to provide an estimate of forest area in west Texas based on 10 per cent canopy cover threshold rather than FIA's forestland definition. To accomplish this, we developed and compared three classification models to discriminate between FIA plots with 5–10 per cent canopy cover and those with greater or equal to 10 per cent cover. For convenience, we refer to the 5–10 per cent canopy cover class as less than 10 per cent cover.

Materials and methods

Data from the FIA programme as well as data from the National Land Cover Database (NLCD; Huang *et al.*, 2001; Homer *et al.*, 2004) were used to develop canopy cover models. The FIA programme uses a fixed plot rotating panel survey design (Bechtold and Patterson, 2005). In 2004, a 10-panel annual inventory was implemented in west Texas. In 2008, field-based observations from 4 of 10 panels (40 per cent) have been completed. Each panel is a systematic sample which enables the FIA programme to provide population estimates before all panels are measured. In the first four panels, there were 10 062 (forest and non-forest) inventory plots with a denied access rate of 14.4 per cent. Each plot consisted of four 168 m^2 subplots and four 13.5 m^2 microplots (Figure 2). Each tree larger than 12.7 cm (diameter at breast

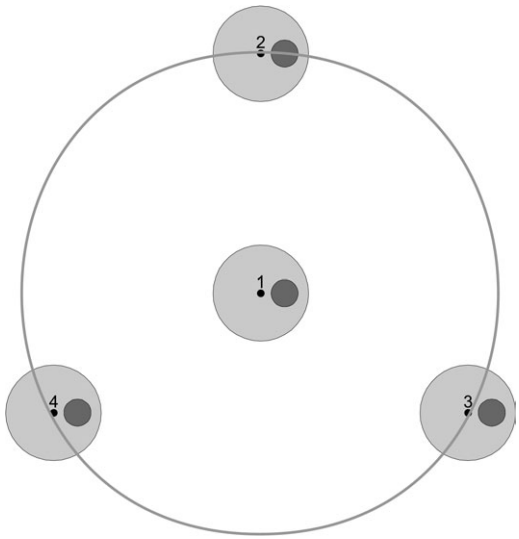

Figure 2. FIA plot design for west Texas. Subplots are denoted by the light grey shading and microplots are denoted by the dark grey shading. Subplot centres are 36.6 m apart. The circle connecting the centres of subplot 2, 3 and 4 denotes the area used to estimate canopy cover in the field.

height (d.b.h.) or root collar diameter (d.r.c.)) was mapped and numbered on the subplot. Trees less than 12.7 cm but at least 2.54 cm (d.b.h. or d.r.c.) were mapped on the microplot. The number of seedlings was also counted on each microplot. Attributes such as species, d.b.h. and crown ratio, for example, were recorded for each tree (USDA, 2006). Condition variables, such as forest type and physiographic class (PC), were recorded for each condition on the inventory plot (USDA, 2006.). Field-observed canopy cover estimates were recorded for 308 plots based on estimated crown area in a 0.47 ha plot (Figure 2). The canopy cover estimates from these plots served as the response data for model development. Explanatory variables were derived from modelled canopy cover of the plot, other plot-level variables and the NLCD satellite-derived canopy cover estimates.

Explanatory variables

Six potential explanatory variables were considered. Total plot-level seedling count (n_s), the dominant plot-level forest-type group (FTG) (USDA, 2006) and the dominant plot-level PC, were taken directly from the inventory data. Remotely sensed canopy cover (cc_{rs}) was attached to each inventory plot using spatial overlay. The proportion canopy cover based on the subplots (cc_s) and the proportion canopy cover based on the microplots (cc_m) were modelled using spatial reconstruction.

Spatial reconstruction of the inventory plots refers to applying crown diameter models to each tree on a plot in a spatially explicit manner using the stem-mapped tree locations and crown diameter models. The primary source of crown diameter models was Bechtold (2003, 2004). The crown diameter model for *Prosopis* spp. was obtained from Shaw (2005). When a species-specific model was not available, either a model from the same genus was used or the general models presented by Wiedinmyer *et al.* (2000) were used. These general models estimated crown diameter based on d.b.h. However, woodland species are generally measured at the root collar. In a few situations, d.b.h. was estimated from d.r.c. using the models presented by Chojnacky and Rogers (1999) and then the generalized crown models were used. The Cartesian coordinate of each tree and the modelled crown diameters were then transferred to a geographic information system (GIS). Once in a GIS, the centre of each tree was buffered based on the radius of the crown and clipped by the subplot boundary and microplot boundary. This technique accounted for overlap in tree crown area such that the result was a depiction of the subplot and microplot when looking straight down on the plot. While this technique does not directly account for crown competition, crown competition is accounted for as part of the crown diameter models because the models were developed from field inventory data (Bechtold, 2003, 2004). The estimate of proportion canopy cover based on the spatial reconstruction of the subplots was then the total crown area across subplots divided by the total area of the subplots. In cases where the plot was less than 100 per cent forested, the total area of the plots was adjusted by proportion of the plot in a forest condition. This same technique was used at the microplot level. The result of this reconstruction was two potential explanatory variables: (1) proportion canopy cover based on the subplots (cc_s) and (2) the proportion canopy cover based on the microplots (cc_m).

Model development and comparison

Three modelling techniques were examined. Non-linear regression was used to develop a model that estimates the proportion canopy cover for each plot using cc_s, cc_m, cc_{rs} and n_s as potential explanatory variables. Classification and regression trees (CART) was used to develop a model classifying each plot as less than 10 per cent canopy cover or at least 10 per cent canopy cover using all variables as potential explanatory variables. Logistic regression was used to develop a model that estimated the probability that each plot had less than 10 per cent canopy cover using all variables as potential explanatory variables. For the non-linear regression approach and the logistic regression approach, quadratic terms and interactions were also examined. We optimized each model to minimize classification bias in the canopy cover greater than or equal to 10 per cent category. Bias was defined as

$$\text{Bias} = \frac{C_{\text{cc}\geq 10\%} + e_{\text{cc}\geq 10\%}}{C_{\text{cc}\geq 10\%} + e_{\text{cc}<10\%}}, \tag{1}$$

where, $C_{\text{cc}\geq 10\%}$ = the number of plots where both the observed category and predicted category were canopy cover greater than or equal to 10 per cent (cc ≥ 10%); $e_{\text{cc}\geq 10\%}$ = the number of plots where the predicted category was canopy cover greater than or equal to 10 per cent and the observed was canopy cover less than 10 per cent (cc < 10%); $e_{\text{cc}<10\%}$ = the number of plots where the predicted category was canopy cover less than 10 per cent and the observed category was canopy cover greater than or equal to 10 per cent.

The range of equation (1) was zero to infinity where a score of one denotes no bias. Our goal was to minimize bias (i.e. bias from equation (1) = 1). For the CART model, the complexity parameter (used to prune the model and reduce over fitting) was optimized and we selected the complexity parameter that minimized the classification bias. For the logistic model, we selected the probability of a plot having less than 10 per cent cover that minimized classification bias. For the non-linear regression model, we selected the plot-level estimate of proportion canopy cover that minimized the bias.

We used 'leave one out' cross-validation to assess the accuracy of each technique. One observation was withheld from the dataset, each model was then fit, thresholds were determined as described above and the withheld observation was then classified based on each model. Both the field-observed classification and the predicted classification for the plot were recorded. This was done sequentially for each of the 308 observations in the dataset and a 2 × 2 agreement matrix was constructed. We compared the models based on the Khat statistic (Congalton and Mead, 1983), equitable threat source (ETS) (see Cartwright and Krishnamurti, 2007, for example), producer's accuracy, user's accuracy and overall agreement. The Khat statistic (equation 2) was used to determine the overall agreement after adjusting for agreement due to random chance. ETS (equation 3) was used to determine how well the predicted canopy cover greater than or equal to 10 per cent events corresponded with the observed canopy cover greater than or equal to 10 per cent events after accounting for agreement by random chance. The range of ETS was −1/3 to 1 with 0 representing the expected agreement based on random chance within the canopy cover greater than or equal to 10 per cent category and 1 representing a perfect score. The producer's accuracy (equation 4) was the probability that an observation was classified correctly. The user's accuracy (equation 5) was the probability the classified observation represented the correct category on the ground. The overall agreement (equation 6) was the proportion of plots correctly classified. For example, consider the agreement matrix

$$A = \begin{pmatrix} C_{\text{cc}\geq 10\%} & e_{\text{cc}\geq 10\%} \\ e_{\text{cc}<10\%} & C_{\text{cc}<10\%} \end{pmatrix},$$

where, $C_{\text{cc}<10\%}$ = the number of plots where both the observed category and predicted category were canopy cover less than 10 per cent and $C_{\text{cc}\geq 10\%}$, $e_{\text{cc}\geq 10\%}$ and $e_{\text{cc}<10\%}$ are previously defined. Based on A, the following statistics were calculated to compare the classification models:

$$\text{Khat} = \frac{N\sum_{i=1}^{2} A_{ii} - \sum_{i=1}^{2}(A_{i+}A_{+i})}{N^2 - \sum_{i=1}^{2}(A_{i+}A_{+i})}, \tag{2}$$

where, N = 308; A_{i+} = row sum of the ith row; A_{+i} = column sum of the ith column.

$$\text{ETS} = \frac{A_{11} - E(A_{11})}{A_{+1} + A_{12} - E(A_{11})}, \tag{3}$$

where, $E(A_{11}) = (A_{1+}A_{+1})/N$; the expected value of $C_{cc} \geq 10\%$ by random chance.

$$\text{User's accuracy} = A_{ii} / A_{i+}, \quad (4)$$

$$\text{Producers's accuracy} = A_{ii} / A_{+i}, \quad (5)$$

$$\text{Overall agreement} = \frac{\sum_{i=1}^{2} A_{ii}}{N}. \quad (6)$$

Estimating total forestland area based on per cent canopy cover

In 2000, the FIA programme implemented a nationally consistent annualized survey design. The design is assumed to produce random equal probability samples (McRoberts and Hansen, 1999). We used the procedures described by Bechtold and Patterson (2005) to estimate total forest area with canopy cover of at least 10 per cent. As described by Bechtold and Patterson (2005), post-stratification (Cochran, 1977) was used to increase precision. The estimate of the total was

$$\hat{A}_f = A_t \sum_{h=1}^{H} W_h \overline{P}_h, \quad (7)$$

where, $\hat{A}_f$ = estimate of total forest area with canopy cover greater than or equal to 10 per cent; A_t = the total area of interest (hectares); W_h = the weight of stratum h (the proportion of A_t occupied by stratum h). These weights were determined using the NLCD (Homer *et al.*, 2004) based on four strata (forest, forest-edge, non-forest and non-forest-edge). $\overline{P}_h$ = the mean plot-level proportion forest with canopy cover greater than or equal to 10 per cent across i plots in stratum h.

The population variance was adapted from Cochran (1977) and described by Bechtold and Patterson (2005). Ignoring the finite population correction factor, the population variance was

$$v(\hat{A}_f) = \frac{A_t^2}{n}\left[\sum_{h=1}^{H} W_h n_h v(\overline{P}_h) + \sum_{h=1}^{H}(1 - W_h)\frac{n_h}{n} v(\overline{P}_h)\right], \quad (8)$$

where, n = the total number of FIA plots; n_h = the total number of FIA plots in stratum h.

$$v(\overline{P}_h) = \frac{\sum_{i=1}^{n_h} P_{hi}^2 - n_h \overline{P}_h^2}{n_h(n_h - 1)}; \text{ the within stratum variance.}$$

The SE of the estimate was $\sqrt{v(\hat{A}_f)}$. Equations (7) and (8) were also used to estimate total area and SE of the estimate of each FTG. In this case, however, $\overline{P}_h$ was the mean plot-level proportion forest with canopy cover greater than or equal to 10 per cent and the FTG of interest, across i plots in stratum h.

Results

Model development and comparison

Three models were developed and fit using the R statistical package (R Development Core Team, 2006). The CART model was developed using the rpart package (Therneau *et al.*, 2008). The verification package (NCAR, 2008) was used to produce the statistics used to compare each classification (e.g. Khat, ETS). Our implementation of CART was strictly categorical. Based on the recursive partitioning of the explanatory variables, each forested (FIA definition) field plot was placed in a category: (1) less than 10 per cent canopy cover or (2) at least 10 per cent canopy cover. The final classification model was based on cc_s, n_s and cc_m (Figure 3). Based on the cross-validation, the overall agreement (accuracy) of the CART model was 90.3 per cent and Khat was 0.517 (Table 1). The value of ETS, which quantifies how well the at least 10 per cent canopy cover class was classified, was 0.47. As noted earlier, the complexity parameter was optimized to minimize bias; however, based on the cross-validation results, the model was slightly bias towards the canopy cover greater than or equal to 10 per cent category.

We also developed a logistic regression model to estimate the probability that each plot had less than 10 per cent canopy cover. The significant explanatory variables used were cc_s and n_s. The final model was

$$P(cc < 0.1) = \frac{1}{1 + e^{-0.319 + 36.594 cc_s + 0.14 n_s}}, \quad (9)$$

where, $P(cc < 0.1)$ = the probability that the canopy cover proportion was less than 0.1 or 10 per cent. The value of $P(cc < 0.1)$ that minimized equation (1) was 0.411 and when the modelled probability of a field plot with less than 10 per

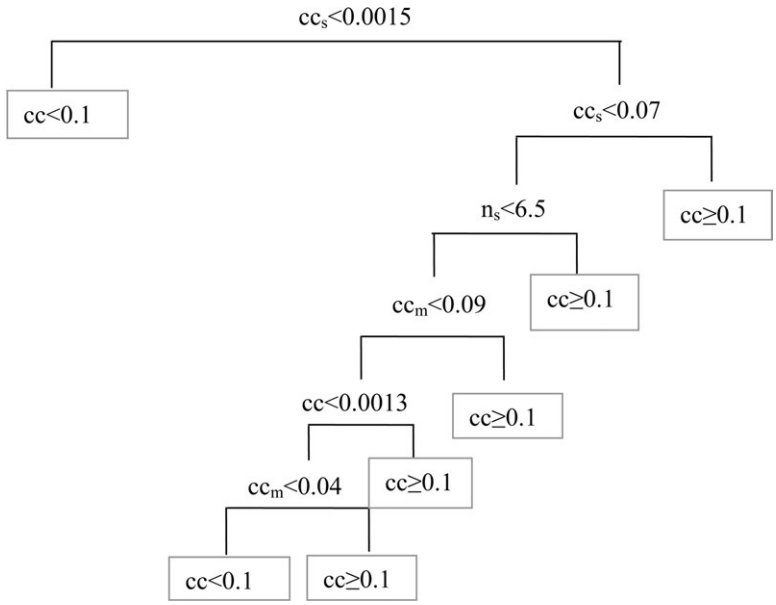

Figure 3. Decision model, based on CART analysis, used to classify each inventory plot as less than 10% cover (cc < 0.1) or at least 10% cover (cc ≥ 0.1). The tree structure is read from top to bottom, and at each level the inequality is evaluation. When the inequality is true, readers are directed to the left of the inequality. When the inequality is false, readers are directed to the right of the inequality. The final classification is denoted at the terminal node (boxes with grey border).

Table 1: Cross-validation summary statistics for each modelling approach

	Modelling approach		
	CART	Logistic regression	Non-linear regression
Producer's accuracy			
cc ≥ 10%	95.2%	94.1%	94.1%
cc < 10%	54.1%	59.5%	56.8%
User's accuracy			
cc ≥ 10%	93.8%	94.4%	94.1%
cc < 10%	60.6%	57.9%	56.8%
Agreement	90.3%	89.9%	89.6%
Bias	1.015	0.996	1.000
ETS	0.470	0.458	0.450
Khat	0.517	0.529	0.509

cent canopy cover was greater than or equal to 0.411; we considered this sufficient information to place the corresponding plot in the less than 10 per cent category. Based on cross-validation results, the logistic regression model had an overall accuracy of 89.9 per cent and the Khat statistic was 0.529 (Table 1). This technique was slightly bias based towards canopy cover less than 10 per cent.

An exponential model was developed, using non-linear least squares regression, to estimate the proportion canopy cover of each field plot based on the significant explanatory variables cc_s, cc_{rs} and n_s. The final model was

$$cc = 1 - e^{-2.93cc_s - 0.42cc_{rs} - 0.007n_s}, \qquad (10)$$

where, cc = proportion canopy cover.

When using equation (10) as a classification model, bias was minimized when the threshold cc ≥ 0.071 was used to discriminate between field plots with less than 10 per cent cover and those with at least 10 per cent cover. Based on cross-validation results, the model had an overall accuracy of 89.6 per cent and the Khat statistic was 0.509 (Table 1).

The three classification models all had similar accuracies with the CART model having the highest Khat statistic. The non-linear regression

approach was the only method that produced an unbiased classification based on the cross-validation. However with respect to ETS, which in this case quantifies how well the at least 10 per cent canopy cover class was classified, the CART model and logistic regression model were marginally better than the non-linear regression model. Because of the similar results observed with each modelling technique, we applied all three models to the west Texas data to estimate forestland area.

Estimating forestland area based on per cent canopy cover

Each of the field inventory plots that met FIA's forest definition was classified using each of the three models. The estimate of forest area based on FIA's current definition was 23.09 million ha (SE 0.25 million ha) (Table 2). The estimate of forestland with canopy cover greater than or equal to 10 per cent was 19.97 million ha (SE 0.25 million ha) based on the logistic region model (Table 2). This was the highest estimate. The estimate based on the non-linear regression classification was 19.17 million ha (SE 0.24 million ha) which was the lowest estimate for forest area with at least 10 per cent canopy cover. The estimate based on the CART model was 19.52 million ha (SE 0.25 million ha). Based on the modelling results, between 3.1 and 3.9 million ha of forestland was in the less than 10 per cent canopy cover category. However, as expected, this area was not evenly spread across FTGs.

Most (over 64 per cent) of the forest classified as having less than 10 per cent canopy cover was in the non-stocked category. Based on FIA definitions, an area was considered non-stocked forestland if the area was less than 10 per cent stocked by trees of any size. An additional 18–27 per cent (depending on classification method) of the forest classified as having less than 10 per cent canopy cover was classified as Mesquite woodland, which is part of the other western hardwoods groups listed in Table 2. Notably, all the loblolly shortleaf group and the oak pine group were classified in the less than 10 per cent canopy cover category.

Discussion

There are several techniques available to estimate per cent canopy cover based on stand and tree attributes. Crookston and Stage (1999), for example, use tree characteristics such as height, diameter and measured or modelled crown width and assume a random spatial arrangement of stems to estimate per cent canopy cover. As Shaw

Table 2: Forest area estimates for each FTG and modelling technique

	cc ≥ 10%			cc < 10%			
FTG	CART	Logistic regression	Non-linear regression	CART	Logistic regression	Non-linear regression	FIA total
Elm/ash/cottonwood	1 036 956	1 042 995	1 034 387	43 989	37 949	46 558	1 080 945
Loblolly/shortleaf pine	32 412	32 412	32 412	0	0	0	32 412
Non-stocked	2 565 184	2 602 210	2 367 438	2 309 519	2 272 493	2 507 265	4 874 703
Oak/gum/cypress	291 913	297 243	299 304	17 741	12 411	10 350	309 654
Oak/hickory	4 757 385	4 890 977	4 841 871	295 131	161 538	210 644	5 052 515
Oak/pine	82 146	83 230	83 230	1084	0	0	83 230
Other western hardwoods	7 021 370	7 289 903	6 811 453	838 032	569 498	1 047 948	7 859 401
Pinyon/juniper	3 665 059	3 661 687	3 625 404	53 856	57 228	93 511	3 718 915
Western oak	65 290	74 088	74 088	10 716	1917	1917	76 006
Total	19 517 715	19 974 746	19 169 586	3 570 066	3 113 034	3 918 194	23 087 781
SE	248 109	247 083	243 673	–	–	–	253 237

Non-stocked is defined as forested area that was less than 10% stocked by trees of any size. FIA total refers to the estimate based on current forestland definitions (USDA, 2006).

(2005) points out, trees may be arranged in several ways including random, clumped or uniform and assuming a random arrangement may not be adequate in all situations. Law *et al.* (1994) developed a per cent crown cover chart for oak savannahs expressed as a function of mean stem diameter, basal area per acre and number of trees per acre. However, the sample size used in Law *et al.* (1994) study was small and the results were not applicable to most west Texas systems. Toney *et al.* (2009) developed a technique to spatially reconstruct the stem-mapped trees on FIA field plots. Their technique was similar to the technique presented here except their goal was to estimate canopy cover as a continuous variable and as such they allowed for tree crown that fell outside of the subplot boundary to contribute to the estimate of cover. Given the heterogeneous landscape of west Texas and the potential importance of moisture, past land use and fire frequency as limiting factors in the pattern of vegetation, we chose to use a relatively simple approach to discriminate between plots with less than 10 per cent canopy cover and those with at least 10 per cent canopy cover. Our method of reconstructing each plot relied on clipping crowns by the subplot boundary; therefore, portions of crowns that extended past the subplot boundary were not considered as contributing to the per cent canopy cover. This method of spatial reconstruction of the plot is consistent with the definition of canopy cover and given that our goal was to discriminate between plots with less than 10 per cent canopy cover and those with at least 10 per cent canopy cover, it makes sense not to include the crown area that extends past the subplot boundary. However, if our goal was strictly to model proportion canopy cover, including the crown area that extends past the subplot boundary, as suggested by Toney *et al.* (2009), to compensate for unmeasured trees would likely be more appropriate.

We used field-observed per cent canopy cover estimates to form the categorical response variable which led to two potential issues. First, the field-based estimates were derived by examining a larger support area than four subplots on which tree and condition-level attributes were recorded (Figure 2). This caused situations where, for example, the field-observed canopy cover was greater than 10 per cent but no trees or saplings were tallied on the four subplots. Using different support areas for our modelling effort likely contributed to the fair to moderate accuracies of the classification models. Second, the field-observed estimates suffer from similar boundary issues as described in the previous paragraph. For example, only trees whose stems originate from within the 0.47 ha plot were considered when estimating canopy cover in the field. As Williams *et al.* (2002) points out, an unbiased estimate of per cent canopy cover cannot be made without including trees whose stems originate from outside the fixed area plot. Clearly, this is an issue when estimating canopy cover as a continuous variable. However, in areas with sparse vegetation such as west Texas, it is unclear how much bias this led to in the response variable.

We used three different classification techniques to classify each measured forest inventory plot as having at least 10 per cent canopy cover or less than 10 per cent crown cover. While measures of accuracies among classification techniques were very similar, substantially different forest area estimates were produced. For example, the forest area estimate based on the non-linear regression model was ~3.3 SEs away from the estimate based on the logistic regression model. The estimate based on the CART model was ~1.8 and 1.4 SEs away from the estimate based on the logistic regression model and the non-linear regression model, respectively. As a practical matter though, only one model can be used to produce the estimate of forest area with at least 10 per cent crown cover for reporting purposes. In this case, we adopted the estimate based on the non-linear regression model which was ~3.9 million ha (17 per cent) less than the estimate based on the FIA definition of forest. The primary reason was that all models were optimized to minimize bias and the non-linear regression model was the only model that was unbiased based on cross-validation results. However, we acknowledge that for all practical purposes, the models are equivalent and that further research is needed to correctly account for both modelling error and sampling error in population estimates. Additionally, the model selection process could be improved and Bayesian model averaging (Hoeting *et al.*, 1999) may offer another avenue for future research.

Both the FAO forestland definition and the FIA forestland definition combined the concepts of cover, use and potential. For example, under

both definitions, areas predominantly in agricultural use were classified as non-forest regardless of whether the 10 per cent canopy cover threshold was met. Predominantly urban areas were treated similarly. While the distinction between cover and use was relatively clear in this case study, the concept of potential was more difficult to apply in marginal forestlands. Traditionally, the concept of potential in forestland definitions was used to ensure that areas comprised of seedlings that would soon become forest were included in the forestland area estimate. Based on the current (2008) methods used by FIA, an area may be considered forestland based on the seedling count. In western woodland forest types, 99 seedlings ha^{-1} are required to consider the condition as forest. However, Van Auken *et al.* (2004) examined the growth and survival of *Juniperus ashei* seedling in *Juniperus* woodlands in west Texas and found high rates of mortality (~8 per cent per year) over a 9-year period. The seedlings had very low height and diameter growth rates, and these rates differed depending on whether the seedlings were under a canopy or at the forest edge. Van Auken *et al.* (2004) also noted that the observed mortality rates generally lead to complete mortality of a cohort within 15 years. It is debatable whether sparsely vegetated areas in perpetual seedling states should qualify as forest regardless of the number of seedlings observed. To address issues like those noted by Van Auken *et al.* (2004), additional research is needed to determine the appropriate threshold for classifying areas comprised of seedlings as having the potential to meet the definition of forest based on a per cent cover definition. Also, the temporal characteristics of the vegetation should be included when determining whether an area has the potential to become forest.

One primary goal of environmental assessments is to quantify baseline conditions, and forestland area estimates are a principle measure for environmental assessments across geopolitical scales. As the geopolitical scale broadens, the complexity of using consistent definitions and a consistent scale of observation increases. The west Texas case presented here illustrates the difficulties associated with establishing a baseline when the scale of observation has changed and when modelling approaches are used to implement definitions. Clearly, significant changes in forest area occurred in west Texas since 1953 when the forest area estimate was 10.5 million ha. The results presented here indicate an approximate doubling of forest area since the 1953 estimate. It was unlikely the change in scale of observation completely explains these changes and the scenarios that Van Auken (2000) described were not captured because an annual forest inventory was not in place. Furthermore, the broad-scale land cover and used dynamics that were the potential drivers of the likely changes are difficult to elucidate because of the lack of an annual monitoring system in west Texas. We recommend that the FIA programme be proactive and collect the variables necessary for international reporting in order to minimize the reliance on modelling. We also note that the scale of observation can influence estimates and suggest that, to the extent possible, the scale of observation remain static. Finally, we suggest that the definition of forestland include a temporal dimension in order to succinctly define forestland and reduce variability in status and trend information.

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