

# **A NONPARAMETRIC METHOD FOR DEFINING AND USING BIOLOGICALLY BASED TARGETS IN FOREST MANAGEMENT**

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## **ABSTRACT**

Forest policy increasingly relies on the use of biologically determined criteria to quantitatively define desirable forest conditions as targets for forest management. Nonparametric procedures for defining targets and performing assessments relative to those targets have been developed. The target definition and assessment procedures were applied to the problem of defining targets for riparian zone forest management. Four target definition and assessment scenarios were considered: 1) basal area per acre, 2) conifer basal area per acre, 3) trees per acre and quadratic mean diameter, and 4) trees per acre, quadratic mean diameter, and average tree height. Targets were defined using riparian stands having ages between 100 and 180 years. Assessments were performed using stands having a minimum age of 80 years and using acceptance levels of 95%, 90%, 80%, and 50%. Acceptance percentages computed for each scenario were all at least 75% of their respective acceptance levels, with the majority of values being at least 88% of their acceptance levels.

## **INTRODUCTION**

Forest policy increasingly relies on the use of biologically determined criteria such as trees per acre, stand density indices, average tree sizes, species composition, or basal area per acre to quantitatively define a set of desirable forest conditions as a target or reference condition for forest management. Management objectives defined by a set of target criteria may include desirable habitats, clean water, or aesthetically pleasing forests. Effective target criteria must be representative of the desired forest conditions, must be associated with data that are readily obtained, must be easily computed, and must be easy to use with an objective assessment procedure to determine whether the desired forest conditions have been achieved for a particular forest management scenario.

Representative target criteria must recognize the inherent variability of forest ecosystems, whether managed or unmanaged, and their multidimensional nature. These two objectives may be achieved by using multiple, quantitative

stand parameters and their distribution as the basis for defining a desired forest conditions target. Using the distribution allows a neighborhood of acceptable values to be used when specifying a target. Using multiple quantitative parameters to describe the desired forest condition provides a more detailed description than could be obtained using any single parameter or parameter value, thereby increasing the likelihood of actually achieving the desired conditions.

Recognizing the relationship between target definition and assessment is also essential for the development of effective target criteria and an objective assessment procedure. The target definition and assessment procedure are linked through the distribution of parameters used to describe the desired forest conditions. Consistent target definition and assessment procedures must, therefore, be based upon the underlying distribution of parameter values describing the desired forest conditions.

Interest in the problem of defining targets for forest management was motivated by the new forest practices

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In: Bevers, Michael; Barrett, Tara M., comps. 2005. *Systems Analysis in Forest Resources: Proceedings of the 2003 Symposium*. General Technical Report PNW-GTR-656. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

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rules for riparian areas in Washington State. The new rules, known as the Forests and Fish Rules (FFR), were established in 1999 based on the recommendations of the Forests and Fish Report (FFR 1999; WFPB 2001). The primary objectives of the FFR include providing support for harvestable levels of salmonids and the long-term viability of other species, compliance with the Endangered Species Act, meeting or exceeding water quality standards defined by the Clean Water Act, and maintaining the economic viability of the state's forest industry (FFR 1999).

The biological and water quality objectives of the FFR for western Washington are based in part on a desired future condition (DFC) target for riparian forest stands along potentially fish-bearing streams. Along these streams three buffer zones are defined: a 50 foot no-harvest buffer adjacent to the stream, an inner zone where timber harvest is allowed subject to restrictions ensuring the development of the DFC, and an outer zone where up to 20 trees per acre must be left after harvest. The total buffer width is determined by the site potential tree height and can vary from 90 ft to 200 ft based on the site class. The inner zone extends from the core zone to either 67% or 75% of the total buffer width depending on stream size (FFR 1999; Ehlert and Mader 2000; Fairweather 2001; WFPB 2001).

Unmanaged, mature riparian forests were identified as the DFC for western Washington under the FFR, where a mature riparian forest stand was defined to have a reference age of 140 years, the midpoint between 80 and 200 years (FFR 1999; Fairweather 2001; WFPB 2001). The FFR further specifies the DFC targets as site-class specific minimum conifer basal area per acre (CBA) limits. Commercial harvest in the inner buffer zone is permitted only if the post-harvest stand conditions for the combined inner and core zones meet or exceed the minimum CBA target when projected to an age of 140 years using a stand simulator (FFR 1999; Fairweather 2001). Initial estimates of the minimum CBA values were obtained for each of five Douglas-fir (*Pseudotsuga menziesii*) site classes based on data from a sample of riparian stands in western Washington. The data were supplied by the Forest Inventory and Analysis (FIA) program, the forest industry, and the Olympic and Mount Baker-Snoqualmie National Forests (Moffett and others 1998; FFR 1999; Ehlert and Mader 2000; Fairweather 2001).

The selection of CBA to quantify DFC targets was motivated by the desire for simplicity and the need to recognize the variability of riparian forest structures that provide adequate function for streams (FFR 1999; Ehlert and Mader 2000; Fairweather 2001). The moderate to low stand

densities, relative to managed upland stands, and the generally larger diameter trees found in mature riparian forests were some of the key structural features that the DFC targets were intended to represent (Fairweather 2001). Further, CBA was assumed to adequately describe the structural characteristics of a mature riparian forest, and when the target levels of CBA are present, the desired stream functions, in particular the production of large woody debris and shade, are also assumed to be present (FFR 1999; Ehlert and Mader 2000; Fairweather 2001). Assuming that the structure of a mature riparian forest can provide adequate stream function may be reasonable. The use of minimum mean CBA values by site class as target criteria may, however, oversimplify the problem of representing the structure of a mature riparian forest: the targets may be too restrictive or they may not adequately discriminate between conditions that are desired and those that are undesirable.

Given the potential importance of quantitative targets in forest management, biologically and statistically consistent target definition and assessment procedures are necessary. Such procedures have been developed for use with multiple, coupled forest stand parameters using a minimal number of assumptions. A nonparametric approach was used to specify the procedures since the actual parameter value distribution is unknown. The target definition and assessment procedures do not make direct use of a reference age, as was done in the FFR, other than for selecting data for a target. The forest structure is emphasized, rather than a specific point in time, since achieving a desired forest structure sooner than the reference age may be possible and beneficial.

The target definition and assessment procedures and implementations of them are described next. The procedures are then demonstrated by defining riparian management targets within the paradigm of the FFR for western Washington. Finally, a brief discussion of some of the potential benefits of using multiple parameters to define targets and perform assessments is then provided.

## METHODS

A forest stand may be described using quantitative values for a specified set of forest stand parameters, including but not limited to: site index, slope, aspect, stand density, average tree diameter, average height, basal area, volume, species composition, distance to the nearest stream, or measurements of the individual trees comprising the stand. For a particular application the set of parameters used may be large, possibly consisting of a tree list with spatial coordinates for the location of each tree and individual tree measurements, or small, consisting only of stand density

and average diameter, volume, or basal area per acre. For any specific set of parameters there exists a joint, or simultaneous, distribution of their quantitative values for some collection of forest stands.

Let  $k \geq 1$  be the number of quantitative parameters used to describe a forest stand, and let  $x = [x_1, x_2, \dots, x_k]^T$  be the vector of quantitative parameter values for a stand, where each  $x_j, j = 1, 2, \dots, k$ , represents one parameter value and superscript  $T$  indicates the transpose of the vector. A collection of  $N$  forest stands may then be represented by a set of parameter vectors  $x_i, i = 1, 2, \dots, N$ . The distribution of parameter vectors for this collection of forest stands is then described by some unknown probability density function (p.d.f.)  $f(x)$ .

### Target definition and assessment

Given parameter vectors for a collection of forest stands, a target region may be defined based on probabilities derived from the unknown p.d.f. for their distribution. A target defined in this way will be called a *probability based target*. Such a target definition must take into account two factors. First, the target should use the most likely parameter values, those with the largest p.d.f. values. The most likely values then form the *center* of the target, which is not necessarily near the mean value. Second, the extent of the target should be defined using an acceptance region derived from the p.d.f. for a desired probability of hitting the target (Duda and Hart 1973; Mardia and others 1979; Zar 1996). These objectives are met simultaneously by choosing an acceptable level of error specifying the probability of not hitting the target, analogous to the selection of an  $\alpha$  – level in the classical statistical hypothesis testing context (Mardia and others 1979; Zar 1996).

The natural way to define a probability based target is to use the likelihood contours or level sets of the p.d.f.  $f(x)$ . Let  $p$  be the probability of not hitting the target, or the probability of error. The probability of hitting the target is then given by  $1 - p$ , and a target having a  $(1 - p) \times 100\%$  chance of being hit may then be defined as

$$T_{1-p} = \left\{ x \mid f(x) \geq c \text{ and } \int_{\{y \mid f(y) \geq c\}} f(y) dy = 1 - p \right\},$$

where  $c \in [0, \max f(x)]$  is a value defining a level set or contour of the p.d.f.  $f(x)$ , for  $p \in [0, 1]$ . The first condition in the target set definition,  $f(x) \geq c$ , guarantees that the most likely values from the domain of the p.d.f.  $f(x)$  are used first. The second condition in the target set definition,  $\int_{\{y \mid f(y) \geq c\}} f(y) dy = 1 - p$ , guarantees that the target set obtains the

desired acceptance level  $(1 - p) \times 100\%$ . The values of  $x$  such that  $f(x) = c$  define the *critical contour* for the target  $T_{1-p}$ .

An assessment procedure consistent with this target definition may now be obtained. The procedure simply determines whether a parameter vector  $y$  is contained within the target set for the desired acceptance level. If  $y \in T_{1-p}$ , then  $y$  is statistically indistinguishable from the target at the  $(1 - p) \times 100\%$  acceptance level and is considered acceptable. If  $y \notin T_{1-p}$ , then  $y$  is statistically different from the target at the  $(1 - p) \times 100\%$  acceptance level and is considered unacceptable. An assessment of this type will be called a *probability based assessment*.

Assuming that the unknown p.d.f.  $f(x)$  is continuous, unimodal, and symmetric, the problem of identifying critical contours for the target  $T_{1-p}$  is simplified. With these assumptions the critical contours of  $f(x)$  are defined by standardized distances from a central value  $x^c$ , which could be the mean, median or mode. Thus, to define a target only a standardized critical distance  $d_{crit}$  from the central value  $x^c$  for a specified  $(1 - p) \times 100\%$  acceptance level needs to be determined.

The critical distance  $d_{crit}$ , then, determines whether a parameter vector  $y$  is indistinguishable from the distance based target  $T_{1-p}^d = \{d \mid \Pr(d, d_{crit}) = 1 - p\}$ . The superscript  $d$  indicates that the  $(1 - p) \times 100\%$  target is defined using the p.d.f.  $f^d(d)$  based on a distance function  $d(x, x^c)$  and not on the contours of the p.d.f. of the actual distribution (Mardia and others 1979). A parameter vector  $y$  is, then, acceptable relative to the target if its standardized distance  $d_y$  from the central value  $x_c$  is less than the critical distance,  $d_y < d_{crit}$ , for a distance function  $d(x, x^c)$ . An observation is unacceptable otherwise.

Under these simplifying assumptions the mean, median, and mode are coincident. In a more general setting, say without the symmetry assumption, the three central values would all be different. In this situation the mode, as the most likely value, should be used as the central value in the target definition and assessment procedures.

### Implementation

Let  $X = \{x_1, x_2, \dots, x_M\}$  represent a set of parameter vectors  $x_i = [x_{i1}, x_{i2}, \dots, x_{ik}]^T$  containing the values for the  $k$  forest parameters of interest for a collection of  $M$  forest stands. The  $M$  parameter vectors in the set  $X$  are used to represent the p.d.f.  $f(x)$  and, subsequently, to define a target  $T_{1-p}^d$ . Let  $Y = \{y_1, y_2, \dots, y_N\}$  represent a set of  $N$  observed parameter vectors  $y_j = \{y_{j1}, y_{j2}, \dots, y_{jk}\}$  containing values

for the  $k$  forest parameters of interest that are to be assessed relative to the target data set  $X$ . The objective is to determine which of the observation vectors  $y$  are indistinguishable from the target data set  $X$  for a  $(1 - p) \times 100\%$  acceptance level and a level of error  $p$ , where  $0 < p < 1$ . Let  $x^c$  represent a central value, the mean, median or mode from the target data set  $X$ , and let  $d(x, x^c)$  be the distance function used to obtain standardized distances from the central value  $x^c$  for a vector  $x$ .

The  $k$ -dimensional empirical distribution was assumed for the parameter vectors  $x_i$  in the target data set  $X$ , and the distance function

$$d(x, x^c) = (x - x^c)^T S_{x^c}^{-1} (x - x^c),$$

where  $S_{x^c}^{-1}$  is the inverse of the variation matrix  $S_{x^c} = (S_{ij})$ , and

$$S_{ij} = \frac{1}{M-1} \sum_{r=1}^M (x_{ri} - x_i^c)(x_{ri} - x_i^c)$$

for  $i, j = 1, 2, \dots, k$  was used to compute standardized distances from a central value. The critical distance  $d_{\text{crit}}$  for a  $(1 - p) \times 100\%$  acceptance level was computed in three steps. First, the central value  $x^c$  and the variation matrix  $S_{x^c}$  were computed from the  $M$  parameter vectors  $x_i$  in the target data set  $X$ . Second, the standardized distances  $x_i^d = d(x_i, x^c)$  were computed for the  $M$  parameter vectors  $x_i$  in the target set  $X$ . Third, the index for the critical standardized distance,

$$i_{\text{crit}} = \begin{cases} 1, & \text{if } p = 0 \\ \lfloor (1 - p)M \rfloor, & \text{if } 0 < p < 1, \\ M, & \text{if } p = 1 \end{cases}$$

was computed, and  $d_{\text{crit}} = x_{(i_{\text{crit}})}^d$ , where  $\lfloor x \rfloor$  is the floor function, returning the largest integer less than or equal to  $x$ , and  $x_{(i)}^d$  denotes the  $i$ th order statistic,  $x_{(1)}^d \leq x_{(2)}^d \leq \dots \leq x_{(M)}^d$ , for the set of target distances (Mardia and others 1979; Serfling 1980; Zar 1996).

An assessment of the parameter vectors  $y_j$  in the observation data set  $Y$ , relative to the target data set  $X$ , was performed in two steps. First, standardized distances from the central value  $x^c$  were computed for the observed parameter vectors  $y_j$ ,  $y_j^d = d(y_j, x^c)$ . Second, the observed distances  $y_j^d$  were compared to the critical distance  $d_{\text{crit}}$ . If  $y_j^d < d_{\text{crit}}$ , then the observed parameter vector  $y_j$  is statistically indistinguishable from the target data set for a  $(1 - p) \times 100\%$  acceptance level, and is considered acceptable. A parameter vector is considered unacceptable otherwise.

## Application

Following the paradigm of the FFR, the target definition used here was based on mature riparian forest stands having a midpoint age of 140 years and a minimum stand age of 80 years, giving an approximate upper age boundary of 200 years (FFR 1999; Ehlert and Mader 2000; Fairweather 2001; WFPB 2001). Four compatible target definition and assessment scenarios were considered. The same sets of stands were assigned to the target and observation data sets for all scenarios, making the only differences among the scenarios the parameter vector components used. The stand parameters used were: basal area per acre (BA), conifer basal area per acre (CBA), trees per acre (TPA), quadratic mean diameter (QMD), and average tree height (H). The parameter vectors used in each of the four scenarios are listed in table 1.

Letting  $s = 1, 2, 3$ , or 4 be the assessment scenario number, define  $A^s = \{a_1, a_2, \dots, a_N\}$  to be a set of  $N$  available parameter vectors  $a_i$  from a sample of mature riparian forest stands. Identify a subset  $A_{\text{target}}^s$  of  $A^s$ ,  $A_{\text{target}}^s \subset A^s$ , containing  $M$  of the available parameter vectors as the target data set for each assessment scenario. The sets  $X = A_{\text{target}}^s$  and  $Y = A^s$  then, define the target and observation data sets, respectively, for each scenario. Assessments of the observation data set  $Y$  relative to its respective target data set  $X$  were then made for each scenario. The modes of the target data sets were used as the central values in all assessments. Mode estimates were computed using the mean update algorithm (Thompson 2000).

Assessments for each scenario were performed using acceptance levels of 95%, 90%, 80%, and 50%. Acceptance percentages were computed for each assessment scenario and acceptance level as  $(N_{\text{accept}}^s / N) \times 100\%$ , where  $N_{\text{accept}}^s$  is the number of acceptable observations for each acceptance level and scenario  $s$ . Finally, as a measure of the performance of the assessment procedure, relative acceptance percentages, the ratio of the acceptance percentage to the acceptance level, were computed. In the example, the target data set and the observation data set were selected from the same unknown distribution, that of a mature riparian stand, so the empirical acceptance percentages and the acceptance levels should be similar.

## DATA DESCRIPTION

The mature riparian forest data used to define targets for this analysis were obtained from the Forest Inventory and Analysis (FIA) program of the U.S.D.A. Forest Service. The data were collected by the Pacific Resource Inventory, Monitoring, and Evaluation (PRIME) program of the FIA,

**Table 1—Parameter vector descriptions for the four target definition and assessment scenarios.**

Scenario (s)	Parameter vector dimension (k)	Parameter(s)
1	1	BA
2	1	CBA
3	2	TPA, QMD
4	3	TPA, QMD, H

and contain forest inventory data collected from all ownerships except national forest and reserved areas (Woudenberg and Farrenkopf 1995). The FIA PRIME database was used for this analysis since it was readily available and because it was one of the data sets used in the original DFC analysis for the FFR (Moffett and others 1998; Fairweather 2001). The FIA PRIME database was not restricted to unmanaged stands, but data from this source were considered sufficient for the purpose of demonstrating the target definition and assessment procedures, and highlighting the benefits of using multi-parameter targets within the paradigm established by the FFR.

The FIA PRIME data were collected using a stratified sampling scheme with two levels: the plot and subplot. Each plot has multiple subplots whose measurement data are intended to be aggregated to estimate plot level parameters (Woudenberg and Farrenkopf 1995). The number of subplots per plot varied over time due to changes in the sampling protocols, but five subplots has been the standard number since 1994 (Woudenberg and Farrenkopf 1995). The data for the analysis consisted of subplots that met the following four criteria: 1) Subplots were at least 80 years of age as indicated by the FIA age class codes; 2) Subplots were within 215 ft of a stream; 3) Subplots were classified by the FIA as timberland; 4) Diameter at breast height (d.b.h) and height measurements for each tree were both greater than zero. These data selection criteria were largely motivated by a consideration of the original Forests and Fish DFC analysis (Moffett and others 1998; Fairweather 2001).

These criteria yielded tree data from 127 subplots contained in 47 unique plots. The number of subplots obtained for each plot varied from one to five with almost equal frequencies making an analysis at the plot level infeasible. The selected subplots were all from plots having five subplots distributed over an area of approximately 6.67 acres. Using the subplots directly for an analysis seemed reasonable and this is what was done. In doing so a subplot to plot scale factor of five was used when computing area-based values from the subplot data. Using the subplot data

directly simply increases the observed variability in computed stand parameters. The subplot data still provide an unbiased random sample of riparian forest stands, with the caveat that subplots associated with the same plot are not independent.

Tree data extracted from the PRIME database included the d.b.h., height, species, and TPA represented by each sampled tree. The data were originally in metric units and standard conversion factors were used to obtain English units for this analysis. After the data were extracted and converted to English units, the individual tree data from each subplot were filtered to remove trees having d.b.h. values less than 4 inches to reduce the influence of very small trees on stand density. The stand parameters of interest were computed using standard formulas and relationships. Numerical summaries of the stand parameters for the 127 riparian subplots appear in table 2, and a summary for the 42 subplots having stand ages in the range of 100 to 180 years appears in table 3.

For the assessment scenarios the observation and target data sets,  $A^s$  and  $A^{s_{target}}$ , were defined to be the whole data set and the subset of the riparian data having stand ages in the range of 100 to 180 years, respectively. The statistical summaries indicate that the target data sets and the observation data sets are in general agreement, and a visual inspection of the data sets indicated that the target data were well distributed throughout the range of the larger observation data for each assessment scenario.

## RESULTS

Acceptance percentages and relative acceptance percentages for the four assessment scenarios and the four acceptance levels are presented in table 4. A strong correspondence between the acceptance level and the computed acceptance percentages clearly exists. The acceptance percentages decrease as the acceptance levels decrease in all cases for all of the target definition and assessment scenarios. Further, the computed acceptance percentages were all at least 75% of their respective acceptance levels, with the majority being at least 88%, as indicated by the relative acceptance percentages.

## DISCUSSION

The overall performance of the probability based target definition and assessment procedures was quite good. Trends in the acceptance percentage results are in strong agreement with expectations; acceptance percentages decreased for each of the four target definition and assessment scenarios

**Table 2—Stand summary for the 127 riparian subplots defining the observation data sets in the four assessment scenarios.**

Variable	Mean	Std. Dev.	Minimum	Median	Maximum
BA (ft <sup>2</sup> ac <sup>-1</sup> )	252.1	121.1	30.5	241.5	673.8
CBA (ft <sup>2</sup> ac <sup>-1</sup> )	215.1	136.6	0.0	201.2	673.8
H (ft)	97.6	32.5	33.1	99.5	191.2
QMD (in)	19.9	8.9	6.0	17.8	62.3
TPA	180.5	170.1	10.6	135.0	1095.6

**Table 3—Stand summary for the 42 riparian subplots defining the target data sets in the four assessment scenarios.**

Variable	Mean	Std. Dev.	Minimum	Median	Maximum
BA (ft <sup>2</sup> ac <sup>-1</sup> )	247.7	107.8	30.5	239.9	507.6
CBA (ft <sup>2</sup> ac <sup>-1</sup> )	206.9	126.6	0.0	187.8	507.6
H (ft)	99.1	33.0	33.1	96.7	162.3
QMD (in)	18.7	6.9	7.7	16.8	37.2
TPA	190.0	166.6	10.6	141.1	753.5

**Table 4—Acceptance percentages (relative acceptance percentages) for the four target definition and assessment scenarios.**

Parameter(s)	Acceptance level			
	95%	90%	80%	50%
BA	93.7 (98.6)	86.6 (96.2)	76.4 (95.5)	37.8 (75.6)
CBA	94.5 (99.5)	88.2 (98.0)	66.9 (83.7)	47.2 (94.5)
TPA, QMD	92.9 (97.8)	84.3 (93.6)	75.6 (94.5)	53.5 (107.1)
TPA, QMD, H	90.6 (95.3)	81.1 (90.1)	71.7 (89.6)	43.3 (86.6)

as the acceptance levels decreased. Exceptions to the expected trends occurred for the higher dimensional parameter vectors, which may be explained by the relatively small size of the target data sets, which contained only 42 points. The small target data set limits the achievable resolution for computing critical distances and probabilities: the procedures assume a continuous p.d.f., but the parameter vectors are discrete points, providing only an approximation to the distribution. These artifacts may be reduced by increasing the size of the target data set.

The behavior of the acceptance percentages and the high degree of agreement between the acceptance levels and the acceptance percentages would seem to indicate that any of the four targets could be used to successfully define a target

for riparian forest management. A comparison of how well each of the targets performed in terms of identifying riparian stands that would have met the desired forest condition: a mature riparian forest with moderate to low stand densities and larger average tree sizes is warranted. The comparison is based on assessments at a 90% acceptance level. The 90% acceptance level was used since the 95% acceptance level may not be restrictive enough and the lower acceptance levels may be too restrictive. Only the CBA based basal area assessment results are presented here for consistency with the FFR. Results for BA were similar.

The CBA based assessment results had an acceptance percentage of 88.2%. A histogram of the CBA values from the observation data set appears in figure 1 along with the

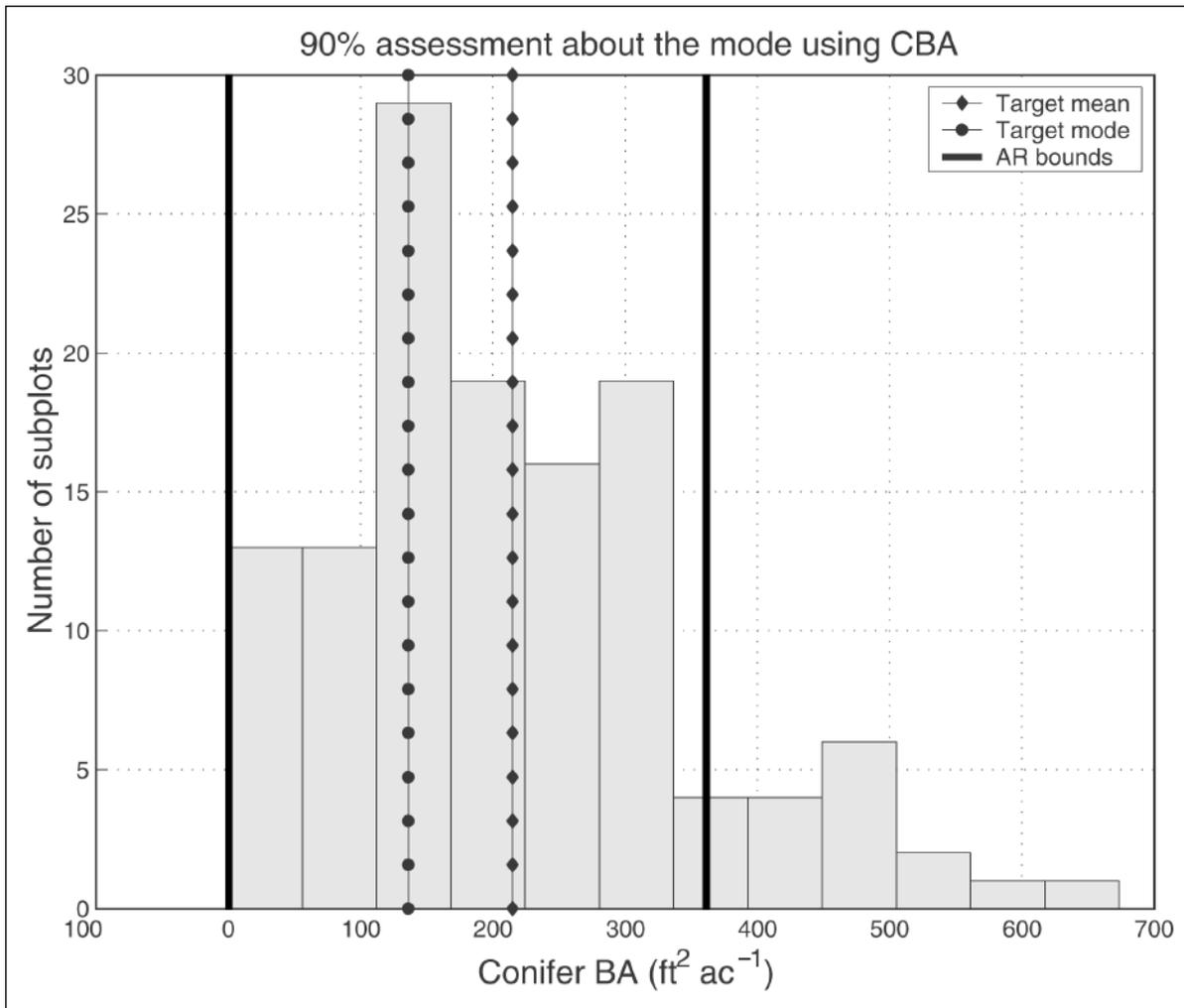


Figure 1—Histogram of CBA showing the 90% acceptance region (AR). The target mean and mode are also shown.

acceptance region boundaries and the mean and mode for the target CBA values,  $215.1 \text{ ft}^2\text{ac}^{-1}$  and  $136.3 \text{ ft}^2\text{ac}^{-1}$  respectively. CBA values between the acceptance region boundaries are considered acceptable. The acceptance region clearly captures the most likely CBA values, rejecting only the largest CBA values on the upper tail of the distribution. Using this figure alone the performance of the target relative to the desired stand density and tree size criteria cannot be determined. The CBA assessment results are plotted in figure 2 using the corresponding TPA and QMD values. The unacceptable stands appear along the TPA-QMD self-thinning curve, where the highest basal area values are generally found. They are also located near the central portion of the TPA and QMD distribution, along its edge. The acceptable stands are distributed throughout the range of TPA and QMD values with no apparent discrimination

between stands of high density and low density. In fact, the highest density stands are considered acceptable under the CBA assessment. This CBA assessment, therefore, failed to identify stands that meet the desired conditions. This result was anticipated, and it clearly demonstrates the difficulty of targeting a desired forest condition using CBA, or BA, as the sole parameter.

The TPA and QMD based assessment had an acceptance percentage of 84.3%. The assessment results appear in figure 3, with the mean and mode vectors for the target TPA and QMD being  $190.0 \text{ TPA}$  and  $18.7 \text{ inches}$  and  $175.2 \text{ TPA}$  and  $16.0 \text{ inches}$  respectively. The acceptable stands for this assessment are clustered about the center of the TPA-QMD distribution, indicated by the mode. High density stands with small tree sizes and low density stands with very large tree sizes are identified as unacceptable relative to the target.

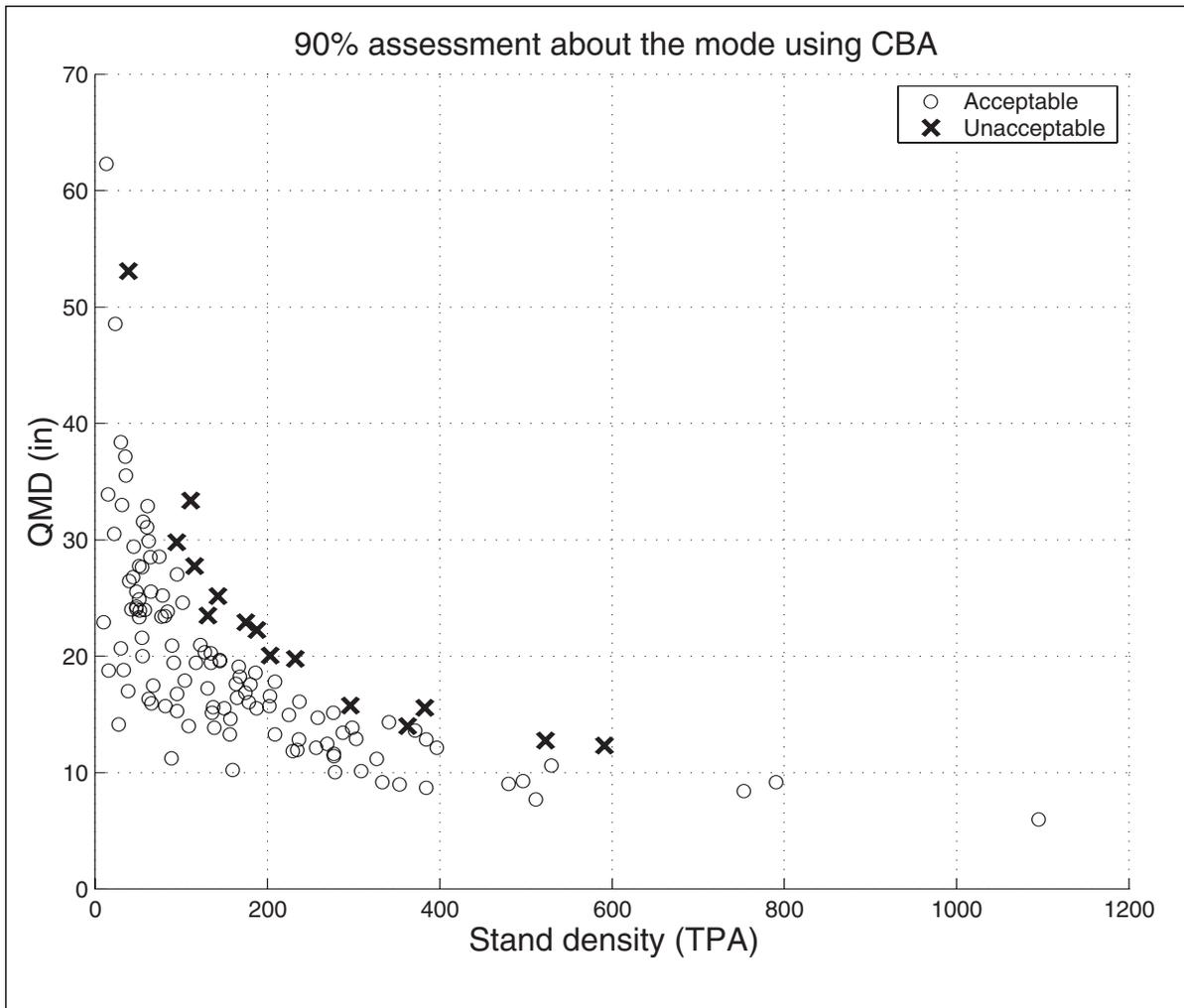


Figure 2—Plot of acceptable and unacceptable TPA and QMD values based on the CBA assessment and a 90% acceptance level.

The TPA and QMD assessment, therefore, succeeded in identifying stands meeting the desired conditions.

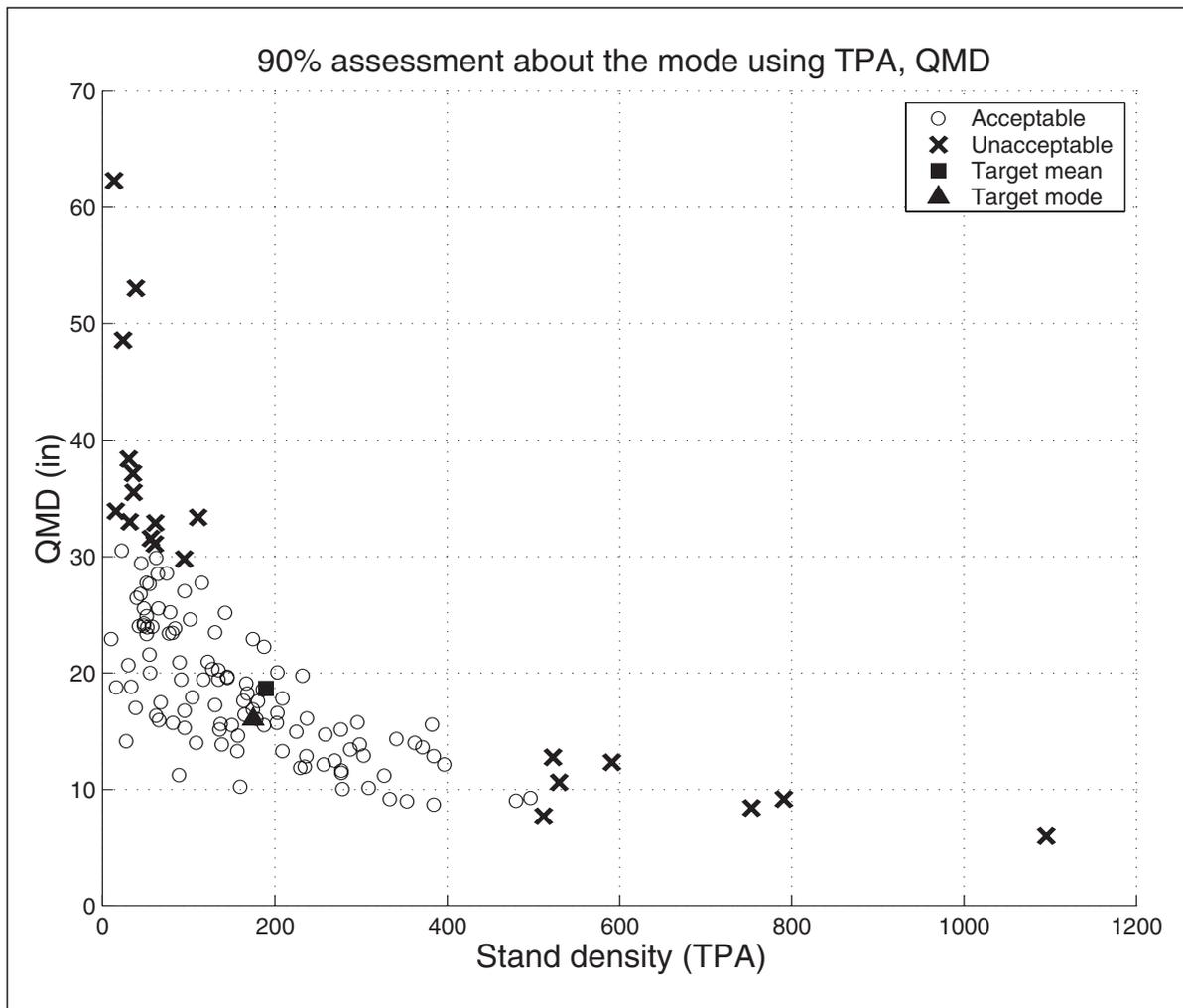
The TPA, QMD and H based assessment had an acceptance percentage of 81.1%. The assessment results appear in figure 4, with the mean and mode vectors for the target TPA, QMD, and H being 190.0 TPA, 18.7 inches, and 99.1 ft and 1750.1 TPA, 15.3 inches, and 78.3 ft respectively. As with the TPA and QMD assessment, the acceptable stands are clustered about the center of the TPA-QMD-H distribution, and both high and low density stands have been identified as unacceptable relative to the target. The TPA, QMD, and H assessment, therefore, also succeeded in identifying stands meeting the desired conditions.

The assessment procedures make no value judgments; they simply identify stands that are far from the target mode.

If, for example, the low density, large tree forest structures are desirable, then a second tier assessment could be performed to accept them. If used in this way the primary assessment identifies stands that are indistinguishable from the target and stands that need further consideration, the unacceptable stands. In a management context, the acceptable stands from a primary assessment could be used to determine appropriate management strategies, whereas the unacceptable stands could be used to identify management strategies that need further investigation or refinement.

## CONCLUSIONS

The uses of quantitatively defined targets and assessment procedures to identify desired conditions and to assess management practices relative to the desired conditions in forest management, or other areas of natural resources



Figure—3 Plot of acceptable and unacceptable TPA and QMD values for a 90% acceptance level. The target mean and mode are also shown.

management, are likely to increase in the future. Target definition and assessment methods must allow for the variability inherent in natural systems and provide for flexibility in the attainment of the desired conditions. Further, effective target definition and assessment methods must be biologically and statistically consistent. Biological consistency is necessary to ensure that the defined targets are relevant, representative of actual conditions, and achievable. Statistical consistency is necessary to ensure the correct interpretation of inferences derived from the target definition and assessment procedures.

The nonparametric target definition and assessment procedures described automatically take into account the inherent variability of a desired forest structure, as identified by a representative data set, and they may be used with parameter vectors of any dimension. The procedures are

both statistically and biologically consistent. Statistical consistency is obtained by using the underlying distribution of parameter values as the basis for the target definition and assessment procedures. Biological consistency is obtained by using actual data for relevant parameters to define the target and perform assessments. Methods like those presented here provide an effective conceptual framework that may enable scientists and policy makers to focus on identifying the relevant biological issues, rather than setting potentially arbitrary targets for management.

## ACKNOWLEDGEMENTS

This work was funded by the Rural Technology Initiative (RTI) at the University of Washington College of Forest Resources and the Family Forest Foundation (FFF), Chehalis, WA. I would like to thank Bruce Lippke and Larry Mason

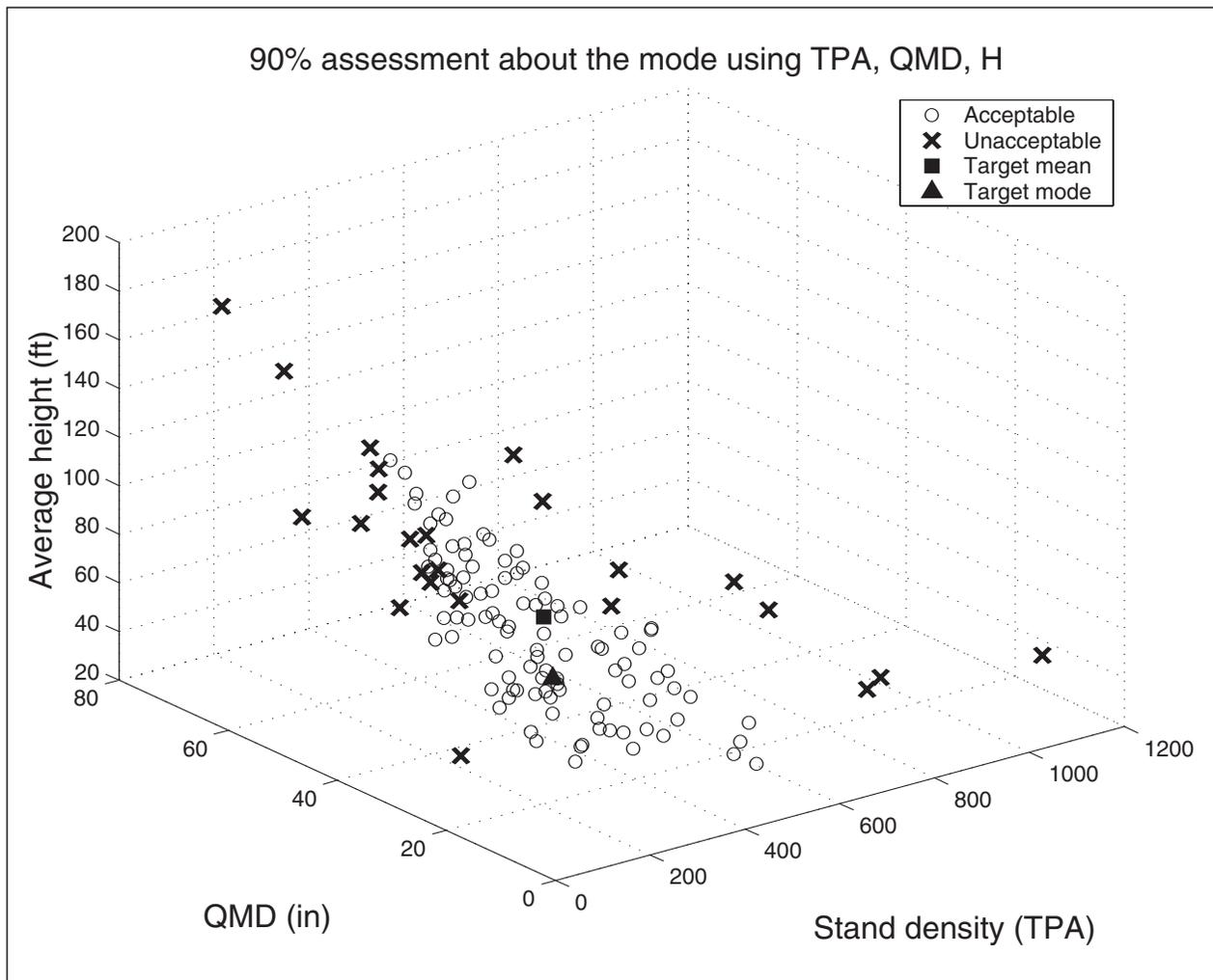


Figure 4—Plot of acceptable and unacceptable TPA, QMD, and H values for a 90% acceptance level. The target mean and mode, obscured by observations appearing in front of it, are also shown.

at RTI and Tom Fox and Steve Stinson at the FFF for providing the funding and the opportunity to work on this problem. I would also like to thank Kevin Zobrist of RTI for proof-reading a draft of this paper.

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