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Structure-based nonparametric target definition and assessment procedures with an application to riparian forest management

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Abstract

Forest policy makers increasingly desire the use of quantitative descriptions to define desirable forest characteristics as a target for forest management. A framework for quantitative, multivariate target definition and assessment is described. The framework uses the joint distribution of multiple forest structure attributes to describe a set of desired forest structures and to identify a target region. The target region contains the most likely attribute values and its extent is controlled by choosing a probability of acceptance or acceptance level.

Nonparametric procedures implementing the target definition and assessment framework have been developed and are described. The implemented procedures were used with a real data set representing 129 riparian stands in western Washington State, U.S.A. to define a three-dimensional target for riparian forest management in the region using stand density, quadratic mean diameter, and average tree height.

A bootstrap simulation and a 50–50 split representative sample were used to evaluate the consistency of the implemented procedures by testing the null hypothesis that attribute value distributions for a target data set and an observation data set, both randomly drawn from a common distribution, were statistically indistinguishable. Chi-squared goodness of fit tests with $\alpha = 0.05$ were used to compare observed mean acceptance percentages from the bootstrap simulation and observed acceptance percentages from the 50–50 split representative sample to the targeted acceptance levels of 95%, 90%, 80%, and 50%. Evaluation results indicated that the target definition and assessment procedures were consistent by failing to reject the null hypothesis for each evaluation method, with p-values of $p = 0.963$ for the bootstrap simulation and $p = 0.866$ for the 50–50 split representative sample.

Keywords: Nonparametric probability estimation; Nearest-neighbor method; Empirical distribution function; Multivariate distribution; Target definition; Assessment; Forest management; Riparian management

1. Introduction

Forest policy makers increasingly desire the use of quantitative descriptions of forest structure to specify a reference condition identifying a set of desirable forest attributes that are then used to define a target for managed forests. Management objectives identified by such a reference condition may be intended to provide regulatory compliance, desirable habitat, clean water, aesthetically pleasing forests, or other desirable characteristics, and may include attributes measuring stand density, average tree size, species composition, competition indices, canopy closure, snag density, or basal area or volume per hectare. The effective use of a quantitative reference condition to define a target for managed forests requires objective target definition and assessment procedures to determine whether the desired forest structures have been achieved.

Interest in the target definition and assessment problem was motivated by a need to identify a quantitative reference condition and target representing unmanaged, mature, 80–200 year old riparian forest stands using multiple forest structure attributes. The reference condition and target were needed to support the development of riparian management templates for small forest landowners in western Washington State, U.S.A. (Zobrist et al., 2004, 2005). The riparian management templates are being developed to provide small forest landowners in western Washington with management strategies complying with the forest management rules enacted by passage of the Forests and Fish law by Washington State in 1999 (Forests and Fish Report, 1999) and the final forest practices rules, known as the Forests and Fish Rules (FFR), enacted in 2001 (WFPB, 2001).

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1.1. Overview of the forests and fish rules (FFR)

The primary objectives of the FFR included provisions for restoring and maintaining riparian habitat to support harvestable levels of fish 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 (Forests and Fish Report, 1999). The biological and water quality objectives of the FFR for western Washington were based, in part, on defining a quantitative desired future condition (DFC) target for riparian forest stands along potentially fish bearing streams. Unmanaged, mature, riparian forests were identified as the DFC for western Washington under the FFR, where a mature riparian forest stand was defined as having a reference age of 140 years, the midpoint between 80 and 200 years (Forests and Fish Report, 1999; Fairweather, 2001; WFPB, 2001).

The base rules defined by the FFR for western Washington State require three buffer zones along potentially fish bearing streams: a 15.2 m no harvest core zone 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 50 trees per hectare must be left after harvest. The total buffer width is determined by the site potential tree height and can vary from 27.4 to 61 m based on site class. The inner zone extends from the outer edge of the core zone to either 67% or 75% of the total buffer width depending on stream size (Forests and Fish Report, 1999; Ehlert and Mader, 2000; Fairweather, 2001; WFPB, 2001). The base rules further specify the DFC targets as site-class specific minimum live conifer basal area per hectare (CBA) limits. Harvesting 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 (Forests and Fish Report, 1999; Fairweather, 2001; WFPB, 2001). Initial estimates of the minimum CBA values were obtained for each of five Douglas-fir (*Pseudotsuga menziesii*) site classes (King, 1966) based on data from a sample of riparian stands obtained for western Washington (Moffett et al., 1998; Fairweather, 2001).

The base rules of the FFR for western Washington State apply to all private forest landowners in the region and they have been shown to have a significant economic impact on small forest landowners (Zobrist, 2003; Zobrist and Lippke, 2003). A provision in the FFR allows forest landowners to propose alternative plans for riparian forest management so long as the alternative plans provide at least the level of resource protection provided by the base rules (Forests and Fish Report, 1999; WFPB, 2001). The inclusion of alternative plans in the FFR was intended to provide a mechanism for small forest landowners to obtain relief from the base rules. Alternative plans are being used by landowners as a means to develop site specific riparian management strategies and to develop management templates for small forest landowners in western Washington State that comply with the FFR (Zobrist et al., 2004, 2005).

The base rules of the FFR for western Washington State are intended to provide protection or restoration of functions provided by riparian forests that ‘‘include bank stability, the recruitment of woody debris, leaf litter fall, nutrients, sediment filtering, shade, and other riparian features that are important to both riparian forest and aquatic system conditions’’ (Forests and Fish Report, 1999). The base rules, however, do not directly quantify the level of resource protection that they provide. Achievement of the site-class specific minimum CBA targets at age 140, the DFC for the FFR base rules, was assumed to provide a sufficient level of resource protection. The level of resource protection provided by an alternative plan, in contrast, is assessed by a multi-agency interdisciplinary (ID) review team comprised of individuals having the expertise necessary to perform the assessment (WFPB, 2001).

The use of ID review teams to determine the level of resource protection for all alternate plans is time consuming and costly for small forest landowners and the agencies providing the staff for the ID review teams, and is ultimately not sustainable (Zobrist et al., 2004, 2005). Further, the lack of a quantitative target or description of the level of protection provided by the base rules may raise concerns regarding the scientific objectivity of an alternate plan assessment performed by an ID review team. These two factors make the long term implementation of the current alternate plan review process problematic. This situation provided an opportunity to develop a framework for quantitative target definition and assessment, within the paradigm established by the FFR, that could be used to readily identify alternate plans that were consistent with a nominal, quantitatively defined set of desired forest conditions. Within this context, targets are specified by identifying a reference condition that quantitatively describes a set of desirable riparian forest structures. The forest structures identified by the reference condition are then used as an indirect measure of the resource protection provided by the sampled riparian forests. Assessments are then performed by testing whether the structure of a managed forest stand is similar to the targeted forest conditions.

1.2. Forest structure, target definition, and assessment

Direct measures of forest structure, e.g., stand density, average tree size, basal area per hectare, species composition, etc., were emphasized as the basis for defining the quantitative management targets. Direct forest structure measurements were used to represent the desired forest conditions for four primary reasons. First, forest structure characteristics are easily measured and are strongly related to stand development processes (Oliver and Larson, 1996). Second, forest structure characteristics are directly manipulated by silvicultural practices, e.g., density management to obtain forest management objectives. Third, forest structure characteristics provide surrogate measures for the functions provided by forests or habitat availability that may be difficult to measure directly (Franklin et al., 2002). Fourth, forest structure characteristics, including individual tree measurements, provide the primary information used to model and project forest stand development

(Vanclay, 1994; Hann et al., 1997; Donnelly, 1997; McCarter et al., 1998; McCarter, 2001).

Identifying a representative set of desired forest structures for use as a reference condition is an essential component of an effective quantitative target definition and assessment process: you must know what you are aiming for. The nature and scope of the reference condition will vary depending on specific restoration or management objectives, but it should reflect the inherent variability and multidimensional nature of the forest ecosystems represented by the desired forest conditions. The multidimensional nature of forest ecosystems may be directly incorporated into a representative reference condition by using multiple, quantitative attributes to describe desirable forest structures, and the variability may be incorporated by accounting for the distribution of the forest structure attributes specified by the reference condition.

The distribution of desirable forest structures specified by a reference condition plays a fundamental role in the quantitative target definition and assessment framework that has been developed. The distribution of desirable forest structures provides the natural way to obtain statistically consistent target definition and assessment procedures. In this context statistical consistency requires that the target definition and assessment procedures be compatible, or derived from the same distribution, and that the shape of the underlying distribution is compatible with the shape of the distribution of desirable forest structures. Statistical consistency becomes particularly important when using multiple attributes to specify the reference condition, as the shape of the distribution may be unknown or difficult to determine.

Given a reference condition representing the desired forest structure attributes and the distribution of those attributes, a target may be defined by identifying an acceptance region within the domain of the joint distribution. The extent or scope of the acceptance region target is controlled by using a probability of acceptance and the probability contours of the distribution representing the forest structures in a reference condition to select the most likely portion of the domain of the distribution. Larger acceptance probabilities include more of the domain of the distribution in the target, excluding the ‘‘tails’’ and least likely values, while smaller acceptance probabilities produce more focused targets, emphasizing the most likely values. Assessments may then be performed by simply testing whether the structure attribute values for a particular forest are within the acceptance region target or not.

An acceptance region target obtained from the joint distribution of multiple forest structure attributes using a probability of acceptance provides simultaneous ranges of acceptable values for all of the attributes being considered, increasing the likelihood that compatible assessment criteria are defined. Using multiple quantitative attributes to describe the desired forest structures in a reference condition provides a more detailed description of those structures than could be obtained using any single structure attribute or attribute summary, such as the mean and standard deviation, increasing the likelihood that the desired forest structures are actually represented by those being targeted. Emphasizing the joint distribution of multiple, quantitative forest structure attributes and the use of a probability derived acceptance region should enable the development of objective targets for forest management that are achievable and consistent with regulatory or management objectives.

1.3. Representing the distribution of desirable forest structures

Two general statistical approaches are available for representing the joint distribution of desirable forest structures identified by the reference condition: a parametric approach and a nonparametric approach (Duda and Hart, 1973; Silverman, 1986; Thompson and Tapia, 1990; Thompson, 2000). The parametric approach assumes a particular functional form for the distribution a priori, and imposes this distribution on the forest structure attribute values in a reference condition. The nonparametric approach, on the other hand, does not assume a specific functional form for the distribution a priori, but uses available data directly to create an empirical representation of the joint distribution of forest structure attribute values in a reference condition, allowing the data to *speak for itself* in an analysis (Duda and Hart, 1973; Silverman, 1986; Thompson and Tapia, 1990; Thompson, 2000).

A nonparametric approach was chosen to represent the joint distribution of forest structure attributes for several reasons. First, the nonparametric approach automatically provides the required statistical consistency, since a nonparametric approach creates an approximation to the actual joint distribution as represented by the available data. Second, methods for nonparametric probability density estimation in one or more dimensions are readily available, straightforward to use, and the underlying methods are easily adapted to a variety of situations (Silverman, 1986; Thompson and Tapia, 1990; Gehringer, 1990; Gehringer and Redner, 1992; Redner and Gehringer, 1994; Redner, 1999). Third, nonparametric methods may permit the data to be used directly in an analysis without the intermediate step of computing the joint distribution (Thompson, 2000). Finally, an abundance of data is typically available for forest management and policy decision making, a situation that readily lends itself to nonparametric approaches.

1.4. Objectives and application

A framework for developing statistically consistent target definition and assessment procedures is described. The framework may be used to specify structure-based targets of any dimension for use in forest management. A straightforward nonparametric implementation of the target definition and assessment procedures is also described and demonstrated. The procedures were used to define a target for riparian forest management in western Washington State using a three-dimensional reference condition, consisting of stand density and average tree size (diameter and height), represent a set of desirable forest structures.

2. Methods

Let $K \geq 1$ be the number of quantitative attributes used to describe the desirable forest structures represented by a reference condition, and let $x = [x_1, x_2, \ldots, x_K]^{\mathrm{T}}$ be the vector representing those attributes, where each x_k, $k = 1, 2, \ldots, K$, represents the value of an attribute, and T indicates the transpose of the vector. The joint distribution of desirable forest structure attributes is, then, described by some unknown probability density function (PDF) $f(x)$ over the domain of the forest structure attribute vectors x.

The unknown PDF $f(x)$ was assumed to be continuous and bounded to simplify the presentation. That is, $f(x) \leq C$ for some constant $0 < C < +\infty$, allowing probability levels to be matched exactly and guaranteeing the existence of a finite maximum value for the PDF. The domain of the PDF $f(x)$ was also assumed to be bounded, that is, the set of points x such that $f(x) > 0$ was bounded to guarantee that probability contours derived from the PDF were finite.

2.1. Target definition and assessment procedures

Given the PDF $f(x)$ describing the distribution of desirable forest structures representing a reference condition, the natural way to define an acceptance region or target for those forest structures is to use the likelihood contours or level sets of the PDF $f(x)$. The most likely attribute values, those with the largest PDF values, form the *center* of the acceptance region or target. The extent of an acceptance region or target is defined by specifying a percentage acceptance level for the probability represented by the acceptance region, or the probability of acceptance. The probability of acceptance implicitly defines a contour of the PDF by equating the probability contained within a contour and the probability of acceptance using the most likely portion of the domain of the PDF. That portion of the domain contained within the contour for a specified acceptance level, then, defines the acceptance region. This is similar to the use and interpretation of the confidence level and confidence region in statistical hypothesis testing (Duda and Hart, 1973; Mardia et al., 1979; Zar, 1996).

Letting $1 - p$ be the desired probability of acceptance, the probability of rejection is then p, and the $(1 - p)100\%$ acceptance region or target is defined in Eq. (1), where $c \in [0, \max_x f(x)]$ is a value defining the $(1 - p)100\%$ level set or contour of the PDF $f(x)$ for some $p \in [0,1]$.

$$T_{1-p} = \left\{ x \,|\, f(x) \geq c \text{ and } \int_{\{y|f(y)| \geq c\}} f(y)\,\mathrm{d}y = 1 - p \right\} \tag{1}$$

In the target definition, the condition $f(x) \geq c$, guarantees that the most likely values from the domain of the PDF $f(x)$ are used in the acceptance region target. The second condition, $\int_{\{y|f(y) \geq c\}} f(y)\,\mathrm{d}y = 1 - p$, guarantees that the acceptance region target obtains the desired $(1 - p)100\%$ acceptance level. 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 simply determines whether an attribute vector y is contained within the target region T_{1-p} defined by the desired $(1 - p)100\%$ acceptance level. If $y \in T_{1-p}$, then y is statistically indistinguishable from the target at the $(1 - p)100\%$ acceptance level and is considered acceptable. If $y \notin T_{1-p}$, then y is statistically different from the target at the $(1 - p)100\%$ acceptance level and is considered unacceptable.

2.2. Implementation

For the implementation, the unknown PDF $f(x)$ was also assumed to be unimodal and symmetric. The critical contours for the target T_{1-p} derived from the PDF $f(x)$ are then given by circles defined by standardized distances from a central value x^{c}. A distance based target may therefore be defined by determining a standardized critical distance d_{crit} from the central value x^{c} for a specified $(1 - p)100\%$ acceptance level. The central value x^{c} may be the mean or mode of the distribution, which are coincident under the assumption of symmetry. If the symmetry assumption does not hold, the mode, as the most likely value, should be used as the central value in the target definition and assessment procedures.

In an assessment, the critical distance d_{crit} determines whether an attribute vector is indistinguishable from a distance based target T^d_{1-p}. The superscript d indicates that the $(1 - p)100\%$ target is defined using the PDF $f^d(x)$ or the CDF $F^d(x)$ based on the standardized distances obtained using a distance function $d(x, x^{\mathrm{c}})$, rather than on the contours of the actual PDF $f(x)$ (Mardia et al., 1979). An attribute vector y is considered acceptable relative to the distance based target T^d_{1-p} if its standardized distance from the central value d_y is less than the critical distance, $d_y < d_{\mathrm{crit}}$. An attribute vector is considered unacceptable otherwise.

Let $X = \{x_1, x_2, \ldots, x_M\}$ be a set of attribute vectors $x_i = [x_{i1}, x_{i2}, \ldots, x_{ik}]^{\mathrm{T}}$ containing values for the K forest structure attributes of interest for a collection of M forest stands that are representative of the desired forest conditions. The M attribute vectors in the set X are used to represent the continuous, unimodal, symmetric PDF $f(x)$ and, subsequently, to define the CDF $F^d(x)$ and targets T^d_{1-p}. The set X defines the reference condition, and will be called the target data set. Let $Y = \{y_1, y_2, \ldots, y_{\mathrm{N}}\}$ represent a set of attribute vectors $y_j = [y_{j1}, y_{j2}, \ldots, y_{jK}]^{\mathrm{T}}$ containing values for the K forest structure attributes of interest for a collection of N observed forest stands that are to be assessed relative to the target data set X. The set Y will be called the observation data set.

The K-dimensional empirical distribution for the M forest structure attribute vectors x_i in the target data set X was assumed, and the distance function

$$d(x, x^{\mathrm{c}}) = (x - x^{\mathrm{c}})^{\mathrm{T}} S^{-1}_{x^{\mathrm{c}}} (x - x^{\mathrm{c}}) \tag{2}$$

was used, where $S^{-1}_{x^{\mathrm{c}}}$ is the inverse of the variation matrix $S_{x^{\mathrm{c}}}$ centered at x^{c}, given by

$$S_{x^{\mathrm{c}}} = \frac{1}{M - 1} \sum_{r=1}^{M} (x_r - x^{\mathrm{c}})(x_r - x^{\mathrm{c}})^{\mathrm{T}}. \tag{3}$$

When the central value used is the mean, the variation matrix S_{x^c} is the covariance matrix and the distance is the Mahalanobis distance (Duda and Hart, 1973; Mardia et al., 1979).

Critical distances d_{crit} for a $(1-p)100\%$ acceptance level and the target data set X were computed using the empirical CDF $\hat{F}^d(x)$ as an approximation to the CDF of standardized distances $F^d(x)$. The critical distance was computed in four steps. First, the central value x^c and the inverse of the variation matrix $S_{x^c}^{-1}$ were computed from the M attribute 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 attribute vectors in the target data set. Third, the index of the critical standardized distance i_{crit} was computed as

$$i_{\mathrm{crit}} = \begin{cases} 1 & \text{if } p = 0, \\ \lfloor (1-p)M \rfloor & \text{if } 0 < p < 0, \\ M & \text{if } p = 1, \end{cases} \tag{4}$$

where $\lfloor x \rfloor$ is the floor function, returning the largest integer less than or equal to x. Finally, the critical distance was assigned the standardized distance from the target data set identified by the index of the critical distance obtained in Eq. (4)

$$d_{\mathrm{crit}} = x^d_{(i_{\mathrm{crit}})}, \tag{5}$$

where $x^d_{(i)}$ denotes the ith order statistic, $x^d_{(1)} \leq x^d_{(2)} \leq \cdots leq x^d_{(M)}$, for the set of standardized distances in the target data set.

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

If insufficient data were available for use of the nonparametric approach, for example due to the desire to manage for a rare or nonexistent forest structure, or if a nonparametric approach was not acceptable, then the distribution of desirable forest structures could be represented using a parametric distribution. The use of a parametric distribution is consistent with the target definition and assessment framework described but would require customized numerical procedures for identifying the critical probability contours of the target. The multivariate normal distribution could be used with attribute vectors of any dimension, and the SBB distribution (Schreuder and Hafley, 1977) or the bi-variate generalized beta distribution (Li et al., 2002) could be used to represent two-dimensional attribute vector distributions.

3. Application

The performance of the target definition and assessment procedures was evaluated by applying them to the problem of defining a target using multiple forest structure attributes for riparian zone management in western Washington State. Following the paradigm established by the FFR, unmanaged riparian forest stands having an average age of dominant and codominant trees that was at least 80 years were identified as the reference condition of desired riparian forest structures. This target definition was chosen for compatibility with the FFR and to allow the structures from mature and old-growth riparian forest stands to contribute to the reference condition. Structures represented by young riparian stands were intentionally excluded from the target as they were considered to be readily attainable with typical commercial management and were not of concern.

The forest structure attributes used to define the riparian management target were stand density measured as trees per hectare (TPH), quadratic mean diameter (QMD), and average tree height (H). These forest structure attributes were chosen because they were straightforward to measure and simulate with forest growth models, and they are directly affected by management activities, e.g., thinning. Rather than using the combined attribute basal area per hectare (BA), as in the FFR, the individual attributes TPH and QMD were used to allow stand density to directly influence the discrimination between desirable and undesirable riparian forest structures. The inclusion of separate stand density and size components in the target was considered necessary since similar BA values may be produced by stands having a large number of small trees or by stands having a small number of large trees, making BA alone a poor discriminator between these two structural conditions. Average tree height was included in the target since tree height influences stream shading and the potential for production and recruitment of large woody debris from an adjacent stand into a stream (Bilby and Ward, 1989, 1991; Robison and Beschta, 1990; Beechie et al., 2000; Welty et al., 2002). The use of these three attributes was expected to provide at least a first order approximation to the level of resource protection provided by the riparian forest structures identified by the targeted reference condition.

Two methods were used to evaluate the potential effectiveness of the target definition and assessment procedures. First, a bootstrap simulation evaluation was performed using randomly selected subsets of a larger data set to define target and observation data sets. This evaluation was intended to characterize the average behavior of the target definition and assessment procedures for a variety of similar target and observation data sets. Second, a 50–50 split evaluation was performed where a randomly selected representative subset of a larger data set was used to specify a target, that was then used to perform an assessment using the remaining data as observations. This evaluation was used to demonstrate the effectiveness of the target definition and assessment procedures within the context of their expected use.

Target and observation data sets used in the evaluations have the same underlying distribution: the empirical distribution of the larger data set from which they were drawn. Consistency of the target definition and assessment procedures implies that the a priori acceptance levels and empirical acceptance percentages computed for an assessment should agree. The agreement between the a priori acceptance levels and computed acceptance percentages was evaluated by using chi-squared goodness of fit tests. The null hypothesis that the distributions of the target and observation data sets were statistically indistinguishable was tested by comparing the a priori acceptance levels to computed mean acceptance percentages for the bootstrap evaluation and to the computed acceptance percentages for the 50–50 split representative sample evaluation. Assessments were performed for acceptance levels of 95%, 90%, 80%, and 50%. For each assessment an estimate of the mode of the target data set was used as the central value x^c in the target definitions. Mode estimates were computed using the mean update algorithm (Thompson, 2000). Acceptance percentages were computed as

$$\text{acceptance}\,(\%) = \left(\frac{N_{\text{accept}}}{N}\right)100\%, \tag{6}$$

where N_{accept} is the number of acceptable observations for a particular target data set, observation data set, and acceptance level, and N is the number of observations in the observation data set being assessed. The goodness of fit tests were performed using an α-level of 0.05, $\nu = 3$ degrees of freedom for the four acceptance levels, and the critical chi-squared value of $\chi^2_{\text{crit}} = 7.8147$.

3.1. Bootstrap evaluation

The bootstrap procedure is a resampling procedure that is commonly used to estimate values for parameters and to approximate their distributions (Efron, 1982; Efron and Tibshirani, 1998; Thompson, 2000; Davison and Hinkley, 1997). The underlying premise of the bootstrap procedure is that the distribution of parameter estimates may be determined by repeatedly estimating parameter values for randomly selected subsets of a larger data set. The mean and standard deviation for the parameter values may then be computed using the set of estimated values, providing an empirical approximation to the variability of the parameter estimates for a particular problem (Efron, 1982; Efron and Tibshirani, 1998; Thompson, 2000; Davison and Hinkley, 1997).

The algorithm used to compute mean acceptance percentages for the bootstrap evaluation of the target definition and assessment procedures is described by the following four steps. Notation is similar to that of Efron (1982). Let $G(X, Y, a)$ be a function returning an acceptance percentage computed using the target definition and assessment procedures described for a target data set X, an observation data set Y, and an acceptance level a. Given a set of attribute vectors representing the desired forest conditions, a set of acceptance levels a_l, $l = 1, 2, \ldots, L$, a number B of bootstrap trials, and a bootstrap sample size N_B, mean acceptance percentages and standard deviations were computed for the acceptance levels a_l using the following steps:

- *Step 1*. Randomly select, with replacement, a target data set X_b and an observation data set Y_b, each containing N_B attribute vectors from the set of available attribute vectors.
- *Step 2*. Compute the acceptance percentage using the bootstrap target and observation data sets for each acceptance level a_l, $p_{lb} = G(X_b, Y_b, a_l)$.
- *Step 3*. Repeat Steps 1 and 2 for $b = 1, 2, \ldots, B$, obtaining estimated acceptance percentages $p_{11}, p_{12}, \ldots, p_{lB}$ for each acceptance level a_l.
- *Step 4*. Compute mean values and standard deviations for the acceptance percentages as $\bar{p}_l = \frac{1}{B}\sum_{b=1}^{B} p_{lb}$ and $s_l = \sqrt{\frac{1}{B-1}\sum_{b=1}^{B}(p_{lb} - \bar{p}_l)^2}$ for each acceptance level a_l using the bootstrap estimates of the acceptance percentages.

A value of $B = 250$ was used for the number of bootstrap trials with $L = 4$ acceptance levels. The bootstrap sample size N_B used for the target and observation data sets was based on the amount of available data and is defined in Section 3.3.1.

3.2. 50–50 split representative target evaluation

Given a set of attribute vectors representing the desired forest conditions a representative subset containing approximately 50% of the available attribute vectors was randomly selected and assigned to the target data set X. The remaining attribute vectors were assigned to the observation data set Y. Acceptance percentages were computed for assessments at each of the four acceptance levels. The number of attribute vectors used to define the target data set, M, was based on the amount of available data, and its value, as well as the number of attribute vectors in the observation data set, are defined in Section 3.3.2.

3.3. Data description

The riparian forest data used to define targets for the evaluations were obtained from the Forest Inventory and Analysis (FIA) program of the U.S. Forest Service. The data were collected by the Pacific Resource Inventory, Monitoring, and Evaluation (PRIME) program of the FIA and represent forest inventory data collected from all ownerships except national forest and reserved areas (Woudenberg and Farrenkopf, 1995). The FIA PRIME database was used in these analyses for two reasons. First, these data were readily available, and second, the FIA PRIME database provided the majority of the data used in the original desired future conditions analysis for the FFR (Moffett et al., 1998; Fairweather, 2001).

The FIA PRIME data were collected using a stratified sampling design with two levels: the plot and subplot. Each plot contained multiple subplots whose measurement data were to be aggregated to estimate plot level attributes (Woudenberg and Farrenkopf, 1995). The number of subplots per plot has varied over time due to changes in the sampling protocols, with five subplots being the standard since 1994 (Woudenberg and Farrenkopf, 1995). Individual tree data from the PRIME database used in these analyses were: tree age, tree canopy position, tree DBH, tree height, tree species, and the tree expansion factor or the number of trees per hectare represented by each sampled tree. Tree expansion factors were obtained from the FIA PRIME database and were computed using fixed radius or variable radius subplots depending on tree size. Variable radius subplots were based on a metric BAF 7 prism (Hiserote and Waddell, 2004).

The set of attribute vectors representing the desired riparian forest structures for the target definition and assessment evaluations were computed from individual tree data selected from the FIA PRIME database using the following six criteria:

(1) The subplot was classified by the FIA as timberland.
(2) The subplot had not been treated since the last FIA inventory.
(3) The subplot was within 65 m of a stream.
(4) The average age of dominant and codominant trees ($\mathrm{Age}^{\mathrm{D/CD}}$) was at least 80 years for each subplot.
(5) Tree DBH values were at least 10.2 cm.
(6) Tree height values were positive.

These criteria were chosen for their compatibility with the criteria used to select the data for the original FFR data analyses (Moffett et al., 1998). The final criterion provided a filter to remove trees having a DBH value but no height value. For convenience these trees were simply dropped from the inventory used.

A total of 129 subplots from 75 unique plots containing 791 sample trees were obtained using these criteria. The number of subplots obtained for each plot varied from one to five with the majority of plots being represented by only one or two subplots. This made an analysis at the plot level infeasible. The selected subplots, however, were all from plots having five subplots distributed over an area of approximately 2.7 ha, with each subplot representing approximately 0.5 ha. Given the relatively large areas covered by the subplots, tree expansion factors were multiplied by a factor of five, scaling the subplot data to obtain values per hectare. Scaling the subplot data increased the observed variability, since the subplot data were not aggregated. The greater variability was associated with subplots that had low or high stand densities, relative to the stand densities of their respective plots, and the magnification of the characteristics of these subplots produced by the scaling.

While not independent, the subplot data still provided a representative, unbiased sample of riparian forest stands. The use of the subplots in this way is similar to the practice of sampling multiple reaches along the same stream to characterize the stream channel or the properties of the forest adjacent to the stream. The second data selection criterion did not guarantee that selected subplots were unmanaged. With these data it was not possible to identify subplots that were treated, thinned or harvested, prior to the last inventory taken 10 years previously. A comparison of the forest structure attributes represented in the scaled data set with values obtained from other regional data sets (Hiserote and Waddell, 2004) indicated that the attribute values used here were consistent with those computed from other data sets in both their ranges and distributions. These data were considered to be sufficient for demonstrating the target definition and assessment procedures and for the development of a riparian management target.

For each of the 129 subplots values were computed for $\mathrm{Age}^{\mathrm{D/CD}}$, TPH, QMD, and H using the following procedures. Let S be the number of subplots and N_s be the number of trees on subplot s, for $s = 1, 2, \ldots, S$. Define $\mathrm{age}_{\mathrm{st}}$ as the age of tree t on subplot s, $\mathrm{dbh}_{\mathrm{st}}$ as the DBH of tree t on subplot s, h_{st} as the height of tree t on subplot s, and $\mathrm{tph}_{\mathrm{st}}$ as the TPH represented by tree t on subplot s. Further, define D_{st} to be an indicator that tree t on subplot s is a dominant or codominant tree, as in Eq. (7)

$$D_{\mathrm{st}} = \begin{cases} 1 & \text{if tree } t \text{ on subplot } s \text{ is a dominant or} \\ & \quad \text{codominant tree,} \\ 0 & \text{otherwise.} \end{cases} \tag{7}$$

With this notation, the average ages of the dominant and codominant trees for each subplot were computed using Eq. (8)

$$\mathrm{Age}_s^{\mathrm{D/CD}} = \frac{\sum_{t=1}^{N_s} \mathrm{age}_{\mathrm{st}}\,\mathrm{tph}_{\mathrm{st}}\,D_{\mathrm{st}}}{\sum_{t=1}^{N_s} \mathrm{tph}_{\mathrm{st}}\,D_{\mathrm{st}}} \tag{8}$$

and the stand structure attributes TPH, QMD, and H for each subplot were computed using the formulas in Eqs. (9)–(11), respectively. These values were then used to define the set of available attribute vectors. A numerical summary of the stand attributes for the 129 riparian subplots appears in Table 1

$$\mathrm{TPH}_s = 5\sum_{t=1}^{N_s} \mathrm{tph}_{\mathrm{st}}, \tag{9}$$

$$\mathrm{QMD}_s = \left(\frac{\sum_{t=1}^{N_s} \mathrm{dbh}_{\mathrm{st}}^2\,\mathrm{tph}_{\mathrm{st}}}{\sum_{t=1}^{N_s} \mathrm{tph}_{\mathrm{st}}} \right)^{1/2}, \tag{10}$$

$$H_s = \frac{\sum_{t=1}^{N_s} h_{\mathrm{st}}\,\mathrm{tph}_{\mathrm{st}}}{\sum_{t=1}^{N_s} \mathrm{tph}_{\mathrm{st}}}. \tag{11}$$

3.3.1. Data for the bootstrap evaluation

The bootstrap evaluation target and observation data sets, X_b and Y_b, were defined by randomly selecting with replacement N_B attribute vectors from the 129 available attribute vectors for each bootstrap trial, $b = 1, 2, \ldots, B$. To ensure that the target and observation data sets would be comparable and similar to the larger data set, on average, a value of $N_B = 64$ was chosen as the size of the bootstrap samples, selecting approximately half of the available stand structure data for the target and observation data sets in each bootstrap trial.

3.3.2. Data for the 50–50 split representative target evaluation

The 50–50 split representative sample evaluation target and observation data sets were chosen so that they each contained approximately half of the available stand structure data. The size of the target data set was assigned a value of $M = 64$.

Table 1
Numerical summary of the 129 available riparian subplots

Attribute	Mean	S.D.	Minimum	Median	Maximum
$Age^{D/CD}$ (years)	133.8	75.7	80.6	96.9	424.4
TPH	279.7	280.1	11.0	184.9	1460.5
QMD (cm)	62.3	25.9	19.5	60.5	158.3
H (m)	31.7	10.0	10.1	32.1	58.3

Table 2
Numerical summary of the 64 randomly selected riparian subplots used to define the target data set

Attribute	Mean	S.D.	Minimum	Median	Maximum
$Age^{D/CD}$ (years)	127.1	60.6	80.6	99.9	341.2
TPH	275.6	265.6	11.0	222.4	1310.3
QMD (cm)	61.4	26.0	19.5	60.1	143.3
H (m)	25.6	17.0	1.0	20.0	65.0

Random subsets of the 129 available attribute vectors were selected without replacement until a visual inspection indicated that the target data were well distributed throughout the range of the available data, as indicated by a three-dimensional plot of TPH, QMD, and H. These attribute vectors were then assigned to the target data set X. Once the target data set was determined the remaining $N = S - M = 65$ attribute vectors were assigned to the observation data set Y. Numerical summaries of the stand attribute values used for the target and observation data sets are provided in Tables 2 and 3, respectively.

4. Results

Mean acceptance percentages and standard deviations computed for the bootstrap evaluation and acceptance percentages computed for the 50–50 split representative sample evaluation are presented in Table 4 along with the results of the chi-squared goodness of fit tests. A strong correspondence between the a priori acceptance levels and the computed acceptance percentages clearly exists. The computed acceptance percentages decreased as the acceptance levels decreased, with mean values of 92.4%, 87.2%, 78.0%, and 46.6% for the bootstrap evaluation and the 95%, 90%, 80%, and 50%, acceptance levels, respectively. Acceptance percentages for the 50–50 split representative sample evaluation had corresponding values of 96.9%, 89.2%, 83.1%, and 43.1% for the four acceptance levels.

Mean acceptance percentages for the bootstrap evaluation were all less than their respective acceptance levels. Two of the acceptance percentages for the 50–50 split representative sample evaluation were greater than their respective acceptance levels while the other two were less than their respective acceptance levels. The variability of the acceptance percentages increased as the acceptance level decreased, as indicated by the standard deviations from the bootstrap evaluation which increased from a value of 4.6% for the 95% acceptance level to a value of 7.8% for the 50% acceptance level. All of the computed acceptance percentages were within one bootstrap standard deviation of their respective acceptance levels.

Table 3
Numerical summary of the 65 randomly selected riparian subplots used to define the observation data set

Attribute	Mean	S.D.	Minimum	Median	Maximum
$Age^{D/CD}$ (years)	140.3	88.1	80.9	96.7	424.4
TPH	283.7	295.7	11.0	173.0	1460.5
QMD (cm)	63.2	26.1	23.2	60.7	158.3
H (m)	23.8	17.0	1.0	20.0	65.0

Table 4
Acceptance percentages and chi-squared goodness of fit test results

Acceptance level	Acceptance percent		
	Bootstrap		50–50 split
	Mean	S.D.	
95%	92.4	4.6	96.9
90%	87.2	6.0	89.2
80%	78.0	7.2	83.1
50%	46.6	7.8	43.1
χ^2_{obs}	0.283		0.730
p-value	0.963		0.866

The goodness of fit tests were performed using $\alpha = 0.05$, $\nu = 3$ degrees of freedom, and the critical value $\chi^2_{crit} = 7.8147$.

The chi-squared goodness of fit tests indicated that there were no statistically significant differences between the a priori acceptance levels and the computed acceptance percentages for the bootstrap and 50–50 split representative sample evaluations. The mean acceptance percentages for the bootstrap evaluation had an observed chi-squared value of 0.23 ($p = 0.963$), and the 50–50 split representative sample evaluation had an observed chi-squared value of 0.730 ($p = 0.866$).

5. Discussion

Evaluation results were favorable and were in agreement with expectations. Several characteristics of the results and their relationships to the implemented target definition and assessment procedures, however, warrant further discussion. Values and trends observed in the computed acceptance percentages for the bootstrap evaluation and the 50–50 split representative sample evaluation are considered first. The potential impacts of deviations from the assumptions on the performance of the target definition and assessment procedures are then mentioned, followed by a discussion of the statistical consistency and potential robustness of the procedures. Finally a brief description of several possible enhancements to the target definition and assessment procedures are presented.

5.1. Target definition and assessment evaluation

Mean acceptance percentages from the bootstrap evaluation were all less than their respective acceptance levels. This is consistent with the implementation which selects a critical distance for a $(1 - p)100\%$ acceptance level by truncating the value $(1 - p)M$, for $p \in (0,1)$, rather than by rounding. The actual acceptance probability used to select a critical distance and perform an assessment was, therefore, less than or equal to the a priori acceptance level on average. This implies that the target definition and assessment procedures, as implemented, are conservative. Marginal attribute vectors, those located within the actual acceptance region but near the critical distance or contour, will, on average, be identified as unacceptable more frequently than would be the case for a procedure that used an exact match of the acceptance level. This behavior is desirable for many applications since forest structures that are marginal, relative to the target, may require a more detailed assessment.

Standard deviations for the bootstrap evaluation acceptance percentages increased as the acceptance level decreased. This phenomenon may be explained by considering the expected degree of overlap in the probability contours of the approximate distributions for two random samples drawn from the same distribution. For large acceptance levels, the approximate distributions have a large expected degree of overlap, and small differences in their locations and shapes will have little impact on the degree of overlap for the probability contours. For small acceptance levels, the two approximate distributions have a small expected degree of overlap, and small differences in their locations and shapes can have a much greater impact on the degree of overlap for the probability contours. As the acceptance level decreases, the expected degree of overlap for the two approximate distributions decreases, and the uncertainty in the degree of overlap for the probability contours increases. This then increases the variability of the probability contour overlap and produces larger acceptance percentage standard deviations for the smaller acceptance levels.

Variability in the computed acceptance percentages may also have been inflated for all acceptance levels by the use of a small target sample size. The bootstrap sample size of $N_B = 64$ was relatively small for representing a three-dimensional target with high variability. The empirical distribution derived from a set of attribute vectors for any target data set provides only an approximation to the actual distribution, and the obtainable resolution of that approximation is limited by the amount of available data, which then affects the resolution of the critical distance and probability computations. A decrease in the resolution of the critical distance and probability computations for small sample sizes increases the uncertainty in the computed critical distances and probabilities, particularly for regions of low probability. Larger target data sets would permit a higher degree of resolution, and therefore provide a better approximation to the distribution used for the critical distance and probability computations.

The 50–50 split representative sample results were also in line with expectations. The only pattern identified in the over predicted or under predicted acceptance percentage values was that the differences between the computed values and the a priori acceptance levels were larger for the lower acceptance levels. Differences between the computed acceptance percentages for the 80% and 50% acceptance levels were 3.1% and −6.9%, respectively, while the differences were only 1.9% and −0.8% for the 95% and 90% acceptance levels. The variability in these acceptance percentages is attributable to the relatively small sample sizes used for the target and observation data sets and the fact that more restrictive targets with smaller acceptance levels are subject to greater variability. In practice, all of the available data would have been used to define a target data set, not just the smaller subset used here.

5.2. Deviations from the assumptions

The empirical probabilities and critical distances used in the target definition and assessment procedures assumed that the unknown distribution was continuous, symmetric, and unimodal. If any of the assumptions are not valid for a particular application, the target definition and assessment results may be incorrect or misleading. The severity of the consequences for a failure in an assumption varies: a failure of the unimodal assumption will generally be much more severe than a failure of the symmetry assumption, with a failure of the continuity assumption having the least impact.

5.2.1. Target distribution is not unimodal

If the target distribution is multimodal, having multiple peaks or modes in its PDF, then no single value suffices to characterize the center of the distribution for the implemented procedures. Further, critical distances would not be derivable from a single probability contour, but would need to be derived through a consideration of multiple, possibly disjoint probability contours or probability contours having arbitrary shapes that are not compatible with the implemented procedures. These issues may be resolved by using more general methods of determining probabilities and critical contours than those implemented and used here. Use of the target definition and assessment procedures described here with target data that may be from a multimodal distribution is therefore not recommended.

Given that a target data set is intended to represent the distribution of a specific set of desired forest structures, it seems reasonable to expect that a unimodal target could be produced. If a proposed target data set contained multiple modes, this may indicate that the sample size was not sufficient or that there were multiple distinct sub-targets that could be separately identified and targeted. By isolating the distinct modes in this way, multiple modes in a target distribution may be treated as separate unimodal distributions for the purposes of assessments relative to the characteristics of each mode. In this context, an attribute vector would be acceptable if it were located within the critical contour for one of the modes or if it had a distance from the center of one mode that was less than the critical distance for that mode. The specialization of the implemented target definition and assessment procedures to unimodal distributions should not be a significant handicap for its use, particularly given the degree of control that may be exercised when specifying a target data set for a particular application.

5.2.2. Target distribution is not symmetric

If the target distribution is unimodal but not symmetric its mean or median values may not provide an adequate central value for the target definition and assessment procedures. For example, the mean value of a one-dimensional skewed distribution is shifted away from the mode in the direction of the long tail. Using the mean as the central value in the target definition and assessment procedures would introduce a bias relative to the most likely values and would not provide probability contours that were consistent with the distribution.

The implications of a lack of symmetry are more interesting for multidimensional distributions. Consider a unimodal two-dimensional distribution with nonnegative values skewed such that large values in one dimension are associated with small values in the other dimension, giving a banana shape to the distribution, e.g., the distribution of stand density and average diameter. In this case, the mean value would appear near the convex, curved region between its stem and tip. Using the mean value in the target definition and assessment procedures would produce probability contours that were not consistent with the distribution. The mean value may, therefore, not provide an adequate central value for use with the target definition and assessment procedures when they are used with nonsymmetric distributions. A more appropriate central value, such as an estimate of the mode, should be used for these distributions or when the shape of the distribution is not known or difficult to determine.

The central value plays a fundamental role in the empirical probability and critical distance computations, and the target definition and assessment procedures work best if the central value of the target is an estimate of the most likely value or mode of a unimodal distribution. The extent of a target is then expanded or contracted by including the values closest to the mode by increasing or decreasing the acceptance level. A central value that is close to the mode is therefore critical if restrictive targets are desired, e.g., targets having acceptance levels less than 80%. Having a central value close to the mode is not as critical for less restrictive targets, those having acceptance levels greater than 80%, but it is still important. The characteristics of an attribute vector distribution clearly influence the selection of a central value and its probability contours and must be considered when using the target definition and assessment procedures presented here or any other assessment procedure.

5.2.3. Target distribution is not continuous

If the target distribution described by the PDF $f(x)$ or an approximation to it is not continuous, then it may not be possible to guarantee that the a priori acceptance level and the probability contained within a critical contour are equal. The same is true for the distribution of standardized distances from a central value described by the PDF $f^d(x)$ and the CDF $F^d(x)$ that were used to simplify the identification of the critical contours of $f(x)$.

As implemented the empirical CDF $\hat{F}^d(d)$ was used to approximate the CDF $F^d(d)$ for the distribution of standardized distances and to compute critical probabilities and distances. The empirical CDF $\hat{F}^d(d)$, being a step function, has a discontinuity at each of the standardized distances computed for the attribute vectors in the target data set. The impact of using the empirical CDF $\hat{F}^d(d)$ to represent $F^d(d)$ was evident in the bootstrap evaluation results, where the mean acceptance percentages were less than, but not significantly different from, their respective acceptance levels, a direct consequence of using the empirical CDF for the standardized distances and the truncation rule used to obtain the critical distances.

The discrete nature of a sample of attribute vectors can provide only an approximation to the actual attribute vector distribution. The effects of the discrete sample may be minimized by using a large target data set to improve the resolution within the domain of the PDF or by using a more sophisticated representation for the unknown PDF. For example, if discrete jumps in the distance based cumulative probability values are undesirable, a smooth approximation to the CDF $F^d(d)$ may be estimated and used instead to compute the critical contours rather than using the empirical CDF $\hat{F}^d(d)$ as was done here.

A lack of continuity in the PDF $f(x)$ may also occur if there is an attribute that takes on only a discrete set of values. If it makes sense to compute an average value for the discrete values, then they may be used with the target definition and assessment procedures. For example, if the attribute is the number of trees on a particular one hectare plot, which must be an integer, then it may be used with the target definition and assessment procedures since it makes sense to compute an average stand density from a collection of 1 ha plots. If the attribute represents a categorical variable such as vegetation class, e.g., overstory tree, understory tree, etc., then it does not make sense to compute an average value, and the attribute should not be used with the target definition and assessment procedures.

5.2.4. Consistency and robustness

To gain some insight into the behavior of the target definition and assessment procedures the three-dimensional target and observation data sets used in the 50–50 split representative sample evaluation and their associated assessment results are considered in some detail. A plot of the observation and target data sets is presented in Fig. 1 with an estimate of the target mode, $x^c = [275.2, 52.1, 31.1]^T$, the central value used for the assessments, indicated. Assessment results for the 95%, 90%, 80%, and 50% acceptance levels appear in Figs. 2–5, respectively. As the acceptance level decreased, stands having larger stand densities and smaller tree sizes relative to the mode became unacceptable, as did stands having lower stand densities and larger tree sizes. These stand structures were furthest from the mode and were therefore less likely. Clearly demonstrated in the figures is the inside/outside nature of the assessment procedures when used in multiple dimensions.

The figures demonstrate the consistency of the nonparametric target definition and assessment procedures for decreasing acceptance levels when using the mode as the central value. As the acceptance level decreases, the acceptance region contracts about the mode, giving concentric subsets of the points that were accepted for each smaller acceptance level. The small standard deviations and the nearness of the mean acceptance percentages to their respective acceptance levels in the bootstrap evaluation results reinforce these consistency results. The lack of significant differences between the acceptance percentages and their respective acceptance levels

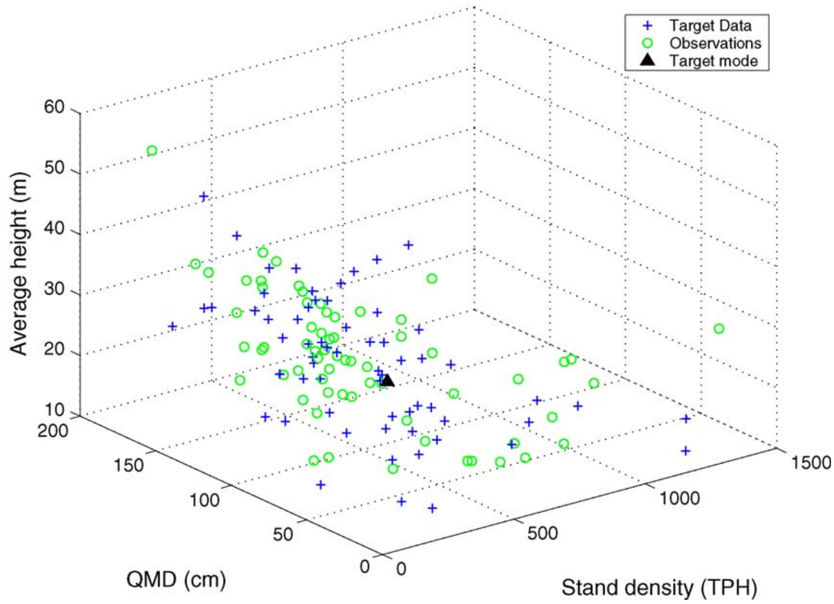

Fig. 1. Observation and target data.

for both the bootstrap and 50–50 split representative sample evaluations provides another indication of the consistency of the target definition and assessment procedures.

The figures also show that the standardized distances computed using the mode as the central value were indeed closer to the mode and hence more acceptable than attribute vectors having large standardized distances. Restrictive targets produced by small acceptance levels identify the most likely attribute vectors when the mode is used as the central value, whether the distribution is symmetric or not. This implies that the target definition and assessment procedures may be robust to deviations from the symmetry assumption when an estimate of the mode is used as the central value. This behavior is desirable, but it may not occur if a value other than the mode is used as the central value.

5.3. Future work, enhancements, and extensions

A number of enhancements to the target definition and assessment procedures are possible. In particular, the procedures used to compute standardized distances and critical probabilities and distances may be improved. The improvements would address performance issues as well as the approximation to the CDF for the standardized distances from the central value. Improving the performance of the procedures will be particularly important when using the procedures with

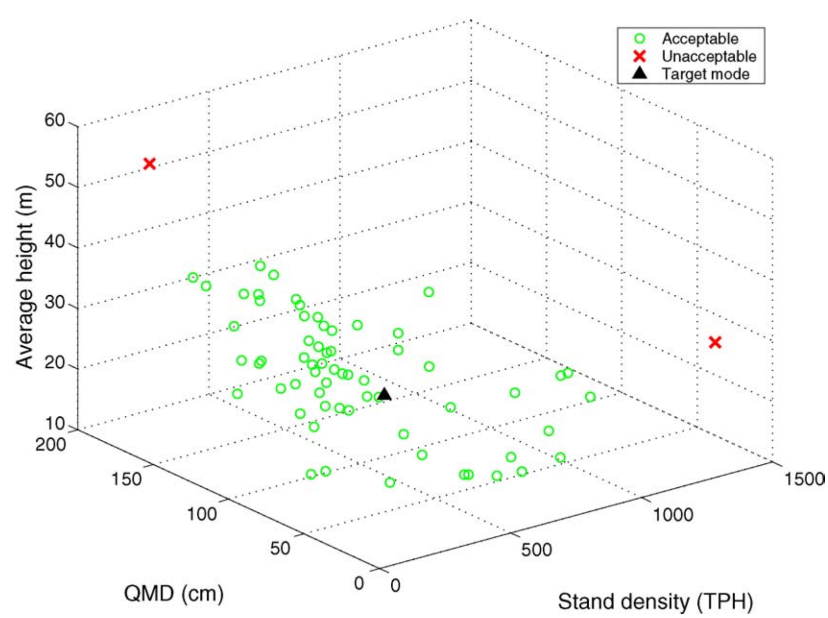

Fig. 2. Assessment results showing the acceptable and unacceptable riparian stands for TPH, QMD, and H using a 95% acceptance level.

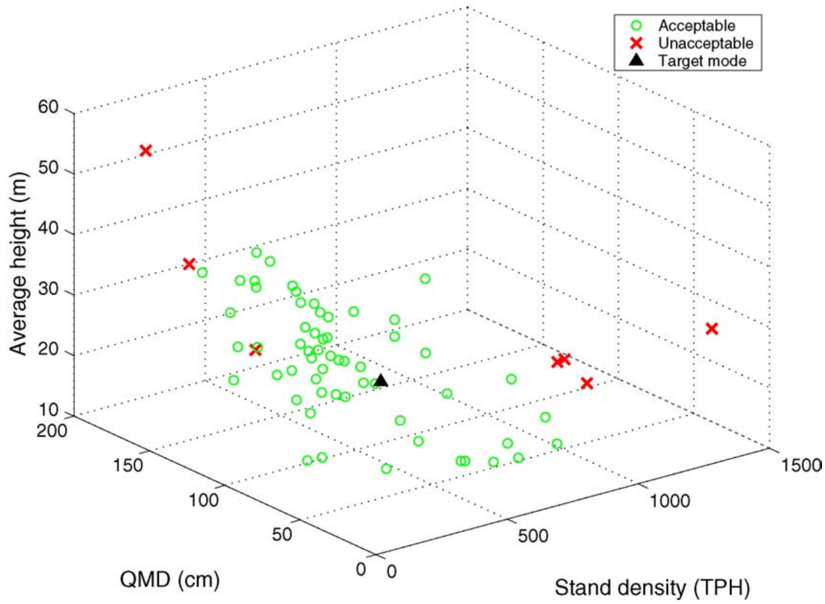

Fig. 3. Assessment results showing the acceptable and unacceptable riparian stands for TPH, QMD, and H using a 90% acceptance level.

large target data sets or when there are a large number of observations to be assessed. Improving the approximation to the CDF, for example by providing a smooth curve rather than the stair step function of the empirical CDF, would increase the resolution available for computing the critical distance and probability values for a particular target data set. Providing a smoothed estimate of the CDF for the standardized distances could also provide a significant reduction in the time necessary to compute critical distances and probabilities.

A direct multidimensional nearest neighbor approximation to the probability or likelihood contours of the distribution represented by the target data set may also be possible. This enhancement would permit the removal of the symmetry assumption that is currently in place to permit distances from a central value to be used instead of the actual attribute vector distribution. Using an alternative to the distance based likelihood approximation may also allow the use of multimodal target distributions. The alternative procedures are more computationally intensive than the current procedures but could provide more accurate probability contours. Preliminary investigation into this approach seems promising.

The target definition and assessment procedures may possibly be extended for use with targets having multiple modes. The fundamental idea is to think of a multimodal target as a mixture distribution, $f(x) = \sum_{i=1}^{N_M} \alpha_i f_i(x)$, where the coefficients α_i are weights giving the influence of each PDF $f_i(x)$ in the mixture and $\sum_{i=1} \alpha_i = 1$, N_M is the number of modes, and each function $f_i(x)$ is itself a PDF (Silverman, 1986;

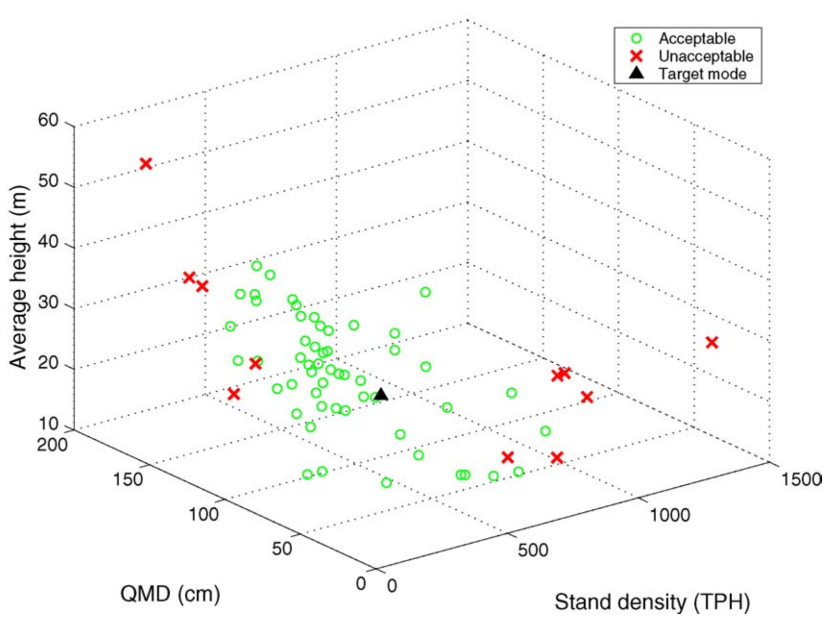

Fig. 4. Assessment results showing the acceptable and unacceptable riparian stands for TPH, QMD, and H using a 80% acceptance level.

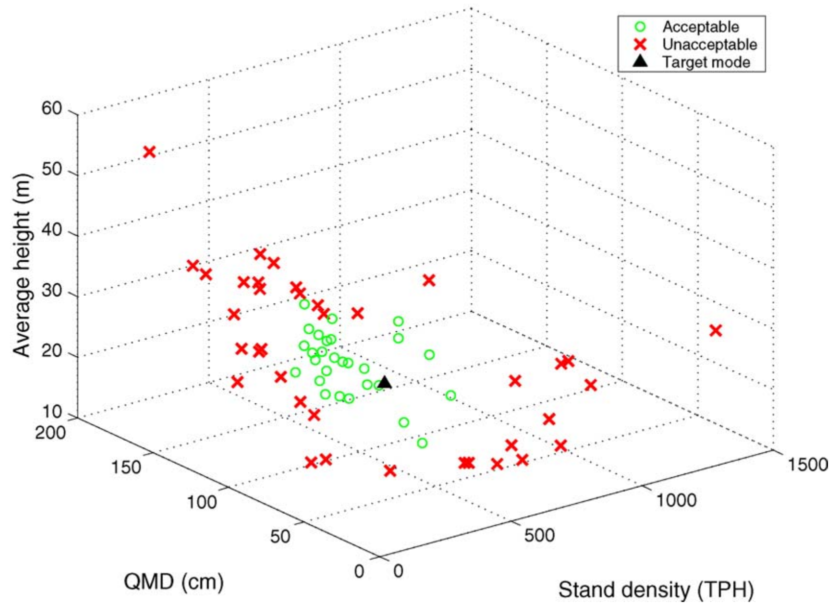

Fig. 5. Assessment results showing the acceptable and unacceptable riparian stands for TPH, QMD, and H using a 50% acceptance level.

Duda and Hart, 1973). Given estimates for the modes, critical contours could be obtained by applying the described target definition and assessment procedures independently for each mode.

Using the target definition and assessment procedures with independent sub-targets for each mode in a multimodal distribution, however, does not address the distribution of multiple desired forest structures across a landscape, or the portion of a landscape that may be desired to be in each structure. This is a more difficult problem and requires knowledge of the proportional representation of the different structures that is desired and the simultaneous consideration of all desired structural targets within the context of a mixture distribution (Silverman, 1986; Duda and Hart, 1973).

6. Conclusions

The target definition and assessment framework and the nonparametric implementation described here may be used within a regulatory context to quantitatively define forest structure targets and to objectively assess the regulatory compliance of forest management practices relative to the targeted set of desirable forest structures. The selection of a target data set and an acceptance level provide simultaneous limits for the components of the attribute vectors based on an approximation to the probability contours of their joint distribution. The simultaneous identification of ranges for the selected attributes should reduce the likelihood that incompatible ranges become specified as a regulatory standard.

The target definition and assessment framework and procedures may be used to automatically discriminate between forested areas that are in agreement with the targeted forest structures and those that are not. By automatically identifying acceptable forested areas, an opportunity for more effective use of scarce regulatory resources, such as the ID teams mandated by the FFR in western Washington State, becomes available, allowing the regulatory agencies to focus their resources on forested areas identified as marginal or unacceptable relative to the targeted forest structures. Further, by quantifying a set of desirable forest structures, the target definition and assessment framework and procedures may be used to screen prospective management strategies to identify those that are most likely to produce the desirable structures, providing the potential for further relief to regulatory agencies that provide review or monitoring of management activities, as well as providing landowners the flexibility to determine how to meet the regulatory objectives.

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 management objectives have been achieved for specific forest management situations. They must also allow for the variability inherent in natural forest ecosystems, provide for management flexibility in the attainment of the desired conditions, and be biologically and statistically consistent to ensure that the defined targets are relevant, representative of the actual desired forest conditions, and achievable.

The target definition and assessment framework and the nonparametric implementation of it described here automatically take into account the inherent variability of the data and are statistically and biologically consistent. The use of quantitatively defined targets and objective assessment procedures to identify desired forest structures and their use in assessing management practices relative to the achievement of those structures provides a robust approach to the problem of identifying management strategies that are likely to produce the desired forest conditions. The use of procedures like those described here should help to enable scientists and policy makers to identify regulatory targets for forest management that are both achievable and beneficial.

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