THE IMPROVEMENT OF PRECISION FOR ESTIMATING THE ABUNDANCE OF STANDING DEAD TREES USING AUXILIARY INFORMATION UNDER THE FIA PLOT DESIGN

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Abstract.—Standing dead trees are an important component of forest ecosystems. However, reliable estimates of standing dead tree population parameters can be difficult to obtain due to their low abundance and spatial and temporal variation. After 1999, the Forest Inventory and Analysis (FIA) Program began collecting data for standing dead trees at the Phase 2 stage of sampling. However, the estimates have relatively large variations compared to the estimates of live trees. The results represent that EZ-Hurdle method shows better precision than the FIA method for both spatial patterns and densities of standing dead trees.

INTRODUCTION

Standing dead trees play an important role in forest ecosystems such as maintaining biodiversity and nutrients, and carbon sequestration. Therefore, reliable estimates of standing dead trees are important to assess and monitor healthy forest ecosystems (Gray 2003). Due to high variation in the abundance of standing dead trees and their spatial pattern, designing sampling schemes for estimating standing dead tree abundance can be challenging. According to previous studies, relatively larger plot sizes or higher sampling intensities than those used for live trees have been applied to estimate the abundance of standing dead trees (e.g., Ganey 1999, Stephens 2004). While intensification of sampling efforts or changing plot designs for estimating standing dead tree attributes is a straightforward solution, ultimately the cost of intensification of sampling must be considered and weighed against the value of increased accuracy (Curtis and Marshall 2005, Gregoire and Valentine 2008).

One major consequence of surveying too-small an area (e.g., using plot sizes that are too small) is that there may be a large number of zero observations of standing dead trees. Excess zero observations, a.k.a. zero-inflated data, will increase variation in estimates of standing dead tree parameters (Eskelson et al. 2009, Potts and Elith 2006). Because of the tendency for standing dead trees to be aggregated in space and a generally lower abundance of standing dead trees relative to live ones, the problem of zero-inflated data is likely large. The National Forest Inventory and Analysis (FIA) Program collects the attributes of standing dead trees such as species, diameter, and total height, from Phase 2 plots that consist of four 7.32 m fixed-radius subplots (Bechtold and Patterson 2005). About 44 percent of FIA plots observed had no standing dead trees on them (Woodall et al., in press). In a study by An and MacFarlane (N.d.), the Expected-Zero (EZ)-Hurdle method showed better precision than the fixed-area sampling method for estimating the abundance of standing dead trees when there are large proportions of zero observations in fixed-area plot data.

The main objective of this study was to apply the EZ-Hurdle method to the FIA plot design to estimate the abundance of standing dead trees using auxiliary

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information describing the distance from each subplot center to the nearest standing dead tree.

METHODS

Data

A simulation study was performed to generate distributions of standing dead trees within a simulated area of 900 ha. In order to collect data for standing dead trees, the FIA plot design was applied, and the number of standing dead trees within 7.32 m (24 ft) radius subplots was recorded. For the EZ-Hurdle method, the distance from each subplot center to the nearest standing dead tree was measured. The maximum search radius for the nearest standing dead tree was 17.95 m (120 ft). Two spatial patterns, random and clustered, and two densities, 30 and 45 standing dead trees per ha, were applied. The number of sample plots in each iteration ranged from 30 to 60 plots in 10-plot increments. For each sampling scenario (spatial pattern, density of standing dead trees, and sampling intensity combination), approximately 3,000 iterations were applied. For each iteration, the number of standing dead trees per ha was calculated. The coefficient variation for the estimated density of standing dead trees was compared.

Estimating Density of Standing Dead Trees

First, the density of standing dead trees per ha was estimated by the published method of the FIA program (see Bechtold and Patterson 2005). Second, the EZ-Hurdle method was applied to estimate the density of standing dead trees. The EZ-Hurdle method (An and MacFarlane, N.d.) is a model-based estimation method which employs a modified version of the Hurdle model (Mullahy 1986) called the EZ-Hurdle model. The main difference between the Hurdle and EZ-Hurdle models is how the zero-proportion (π) is specified in the model. In the case of the Hurdle model, π is estimated directly from the count data it is being fitted to. The zero-proportion in the EZ-Hurdle method is estimated from the detection probability of a standing dead tree, which is modeled from auxiliary data describing the distance from a plot center to the nearest standing dead tree (An and MacFarlane, N.d.).

With counts of standing dead trees from FIA subplots, the EZ-Hurdle method estimates the density of standing dead trees in two steps. The first step is estimating the expected-zero proportion for the given subplot size (radius = r) from the detection probability of a standing dead tree given that plot size. The second step is estimating the contribution of nonzero counts (plots with at least one standing dead tree) to the estimate using zero-truncated count distributions such as the Poisson distribution. The procedure to model the nonzero counts is the same as that in the original Hurdle model (Cameron and Trivedi 1998, Mullahy 1986), and the estimated expected-zero proportion and the contribution of nonzero counts are combined.

When applied to fixed-radius plot sampling y_i, $Y = \{y_i, \ldots, y_n\}$, is the number of standing dead trees in sample plot i and d_i, $D = \{d_i, \ldots, d_n\}$, is the distance from the plot center of i to the nearest standing dead tree; n is the number of samples. In order to estimate the expected-zero proportion, the detection probability of a standing dead tree for the given search radius r is modeled from the auxiliary data D because the expected-zero proportion for the given (fixed) search radius r is:

$$P\_ez(r) = 1 - P\_dt(r)$$

where P_ez is the expected-zero proportion, P_dt is the detection probability of a standing dead tree, and r is a fixed search radius to find the nearest standing dead trees. A modified Gompertz function was used to estimate the detection probability of a standing dead tree from the distance data (An and MacFarlane, N.d.).

The EZ-Hurdle model is specified as follows:

$$P\{Y=y\} = \begin{cases} P\_ez(r) & y=0 \\ (1-P\_ez(r))\cdot\dfrac{f(Y=y\mid\mu(r))}{1-f(Y=0\mid\mu(r))} & y>0 \end{cases}$$

where y is the number of trees, $f(Y = y \mid \mu(r))$ / $(1 - (f(Y = 0 \mid \mu(r)))$ is the zero-truncated count distribution with search radius (plot radius) r, $f(Y = 0 \mid \mu(r))$ is the proportion of zero estimated from a model, and $\mu(r)$ is the estimated expected value from zero-truncated count distributions.

For the EZ-Hurdle with a Poisson distribution (EZP) model, the expected value and variance for the count distribution are:

$$E_{EZP}[Y_c] = (1-P\_ez(c,r))\cdot\frac{\mu(c,r)}{1-e^{-\mu(c,r)}}$$

$$Var_{EZP}[Y_c] = (1-P\_ez(c,r))\cdot\frac{\mu(c,r)+\mu(c,r)^2}{1-e^{-\mu(c,r)}} - \left[(1-P\_ez(c,r))\frac{\mu(c,r)}{1-e^{-\mu(c,r)}}\right]^2$$

where $P\_ez(c,r)$ is the expected-zero proportion estimated by the model for the given search radius r and forest condition c, $\mu(c,r)$ is the expected value of the zero-truncated Poisson distribution for the given plot size (radius = r) and forest condition c.

RESULTS

The detection probability increased with increasing density of standing dead trees and was greater with the random pattern than clustered pattern at the same density of standing dead trees. Table 1 shows the estimated density of standing dead trees from 3,000 iterations. The EZ-Hurdle method had smaller standard deviations than the FIA method for all scenarios indicating that the EZ-Hurdle method had better precision than the FIA method. However, the EZ-Hurdle method showed a small bias when standing dead trees were clustered.

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LITERATURE CITED

An, H.S.; MacFarlane, D.W. [N.d.]. **Using auxiliary data and a model to reduce error in estimating standing dead tree abundance where zero inflated data are expected under the sample design.** Manuscript in preparation. On file with corresponding author.

Bechtold, W.A., Patterson, P.L., eds. 2005. **The enhanced Forest Inventory and Analysis Program-national sampling design and estimation procedures.** Gen. Tech. Rep. SRS-80. Asheville, NC: U.S. Department of Agriculture, Forest Service, Southern Research Station. 85 p.

Table 1.—The estimated density of standing dead trees per ha (± standard deviation) by method, spatial pattern, density, and the number of plots. FIA = estimated method by FIA program and EZP = EZ-Hurdle method.

		Number of Plots							
		30		40		50		60	
Spatial Pattern	True Density	FIA	EZP	FIA	EZP	FIA	EZP	FIA	EZP
Random	30	29.91 (3.96)	30.60 (3.71)	29.94 (3.39)	30.51 (3.17)	30.02 (3.01)	30.53 (2.77)	30.01 (2.72)	30.51 (2.54)
	45	45.12 (4.81)	46.31 (4.49)	44.85 (4.06)	45.98 (3.81)	45.01 (3.64)	46.08 (3.43)	45.03 (3.36)	46.04 (3.17)
Cluster	30	30.56 (5.67)	27.81 (4.90)	29.97 (4.79)	27.57 (4.14)	30.02 (4.48)	27.56 (3.83)	29.97 (4.03)	27.45 (3.42)
	45	45.01 (7.74)	40.83 (6.84)	48.18 (6.68)	40.10 (5.86)	45.07 (6.63)	40.48 (4.89)	45.08 (5.64)	40.48 (4.89)

Curtis, R.O.; Marshall, D.D. 2005. **Permanent-plot procedures for silvicultural and yield research.** Gen. Tech. Rep. PNW-GTR-634. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. 86 p.

Cameron, A.C.; Trivedi, P.K. **1998 regression analysis of count data.** Cambridge, UK: Cambridge University Press. 411 p.

Eskelson, B.N.I.; Temesgen, H.; Barrett, T.M. 2009. **Estimating cavity tree and snag abundance using negative binomial regression models and nearest neighbor imputation methods.** Canadian Journal of Forest Reseach. 39: 1749-1765.

Ganey, J.L. 1999. **Snag density and composition of snag populations on two national forests in northern Arizona.** Forest Ecology and Management. 117(1-3): 169-178.

Gray, A. 2003. **Monitoring stand structure in mature coastal Douglas-fir forests: effect of plot size.** Forest Ecology and Management. 175: 1-16.

Gregoire, T.G.; Valentine, H.T. 2008. **Sampling techniques for natural and environmental resources.** New York, NY: Chapman & Hall/CRC Press. 474 p.

Mullahy, J. 1986. **Specification and testing of some modified count data models.** Journal of Econometrics. 33: 341-365.

Potts, J.M.; Elith, J. 2006. **Comparing species abundance models.** Ecological Modelling. 199(2): 153-163.

Stephens, S.L. 2004. **Fuel loads, snag abundance, and snag recruitment in an unmanaged Jeffrey pine-mixed conifer forest in Northwestern Mexico.** Forest Ecology Management. 199(1): 103-113.

Woodall, C.W.; Domke, G.M.; MacFarlane, D.W.; Oswalt, C.M. [In press]. **Comparing field- and model-based standing dead tree carbon stock estimates across forests of the United States.** Forestry.