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Post-classification approaches to estimating change in forest area using remotely sensed auxiliary data

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ABSTRACT

Multiple remote sensing-based approaches to estimating gross afforestation, gross deforestation, and net deforestation are possible. However, many of these approaches have severe data requirements in the form of long time series of remotely sensed data and/or large numbers of observations of land cover change to train classifiers and assess the accuracy of classifications. In particular, when rates of change are small and equal probability sampling is used, observations of change may be scarce. For these situations, post-classification approaches may be the only viable alternative. The study focused on model-assisted and model-based approaches to inference for post-classification estimation of gross afforestation, gross deforestation, and net deforestation using Landsat imagery as auxiliary data. Emphasis was placed on estimation of variances to support construction of statistical confidence intervals for estimates. Both analytical and bootstrap approaches to variance estimation were used. For a study area in Minnesota, USA, estimates of net deforestation were not statistically significantly different from zero.

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1. Introduction

The Land Use, Land Use Change Forestry (LULUCF) sector plays a vital role in the global greenhouse gas (GHG) balance. Although the approximately 13 million hectares (ha) of forest that are converted to other land uses annually worldwide account for as much as 25% of anthropogenic GHG emissions (Achard et al., 2002; FAO, 2005, p. 13; Gullison et al., 2007), the LULUCF sector also has the greatest potential to remove GHGs from the atmosphere.

Carbon accounting includes assessment of the scale of GHG emissions from the forestry sector relative to other sectors. The gain–loss approach to carbon accounting is the most commonly used approach for estimating GHG emissions for national measurement, reporting, and verification (MRV) systems under the auspices of the Intergovernmental Panel on Climate Change (IPCC) (Giardin, 2010). With this approach, the net balance of additions to and removals from a carbon pool is estimated as the product of the rates of land use area changes and the responses of carbon stocks for those land use changes. Remote sensing-based approaches to estimating rates of forest area change have been emphasized as an important tool for monitoring changes in forest area (GOFC-GOLD, 2010, chap. 2). Further, good practice requires that the uncertainty in estimates of forest area change should be reported, regardless of the method used to obtain the estimates (Köhl, Baldauf, Plugge, & Krug, 2009; Watson, 2009).

Remote sensing-based change detection methods include two primary categories, trajectory analyses and bi-temporal methods. Trajectory analyses use time series of three or more images to assess not only the type and extent of change but also the trends and temporal patterns of change over time. Bi-temporal methods entail the analyses of images for two different dates and can be further separated into two subcategories. With post-classification, two forest/non-forest classifications constructed separately using two sets of forest/non-forest training data and two images are compared to estimate change, whereas with direct classification, a single classification of change is constructed using a single set of forest change training data with data for two images. Although trajectory analyses produce more detailed information such as type and timing of change and direct classification focuses explicitly on the change categories of interest, both methods have rather severe data requirements. With trajectory analyses, an extensive time series of imagery is typically required (Kennedy, Cohen, & Schroeder, 2007; Zhu, Woodcock, & Olofsson, 2012). With direct classification, large numbers of change observations may be necessary for training the classifier and/or assessing accuracy, a difficult task when rates of change are small and change observations are acquired using equal probability sampling designs. The advantage of post-classification is that the data requirements are much less severe. The disadvantage is that two sets of classification errors must be accommodated, although forest/non-forest classification errors are often less frequent than forest change classification errors.

The overall objective was to estimate parameters related to forest area change using multiple approaches to inference. Response variables of interest included gross deforestation, defined as loss of forest area; gross afforestation, defined as gain in forest area including reforestation; and net deforestation defined as the net result of gross deforestation and gross afforestation. For a study area in northeastern Minnesota in the United States of America (USA), two datasets were used, observations of forest/non-forest for national forest inventory (NFI) plots and corresponding summer Landsat imagery for the years 2002 and 2007. Because

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the combined dataset included few observations of forest area change, only post-classification approaches were used. An intermediate technical objective was to estimate areal population means, $\hat{\mu}$, and variances, $V\hat{a}r(\hat{\mu})$, for proportion forest for each year. The final technical objective was to use the two sets of estimated means and variances, one set for each of 2002 and 2007, to construct approximate 95% confidence intervals for estimates of parameters related to forest area change between the two years.

A nonlinear logistic regression model was used to estimate the relationship between forest/non-forest observations and Landsat spectral information, and the analyses included investigations of the effects on estimates of means and variances using different combinations of spectral variables in the model. Both a probability-based, model-assisted regression estimator and a model-based estimator were used.

2. Data

The study area was defined by the portion of the row 27, path 27, Landsat scene in northeastern Minnesota, USA, which was cloud-free for the two image dates, 16 July 2002 and 30 July 2007 (Fig. 1). The Landsat Thematic Mapper (TM) spectral data were transformed using the normalized difference vegetation index (NDVI) transformation (Rouse, Haas, Schell, & Deering, 1973) and the three tasseled cap transformations (TC_{green}, TC_{bright}, TC_{wet}) (Crist & Cicone, 1984; Kauth & Thomas, 1976) for each image. These four transformations were used as independent variables when constructing models of the relationship between ground and remotely sensed data.

Ground data were obtained for plots established by the Forest Inventory and Analysis (FIA) program of the U.S. Forest Service which conducts the NFI of the USA. The program has established field plot centers in permanent locations using a sampling design that is regarded as producing an equal probability sample (McRoberts, Bechtold, Patterson, Scott, & Reams, 2005). Each FIA plot consists of four 7.32-m (24-ft) radius circular subplots that are configured as a central subplot and three peripheral subplots with centers located at distances of 36.58 m (120 ft) and azimuths of 0°, 120°, and 240° from the center of the central subplot. Centers of forested, partially forested, or previously forested plots are estimated using global positioning system (GPS) receivers, whereas centers of non-forested plots are verified using aerial imagery and digitization methods.

Data were available for 249 FIA plots measured in both 2002 and 2007. Field crews visually estimate the proportion of each subplot that satisfies the FIA definition of forest land: minimum area of 0.4 ha (1.0 ac), minimum crown cover of 10%, minimum crown cover width of 36.6 m (120 ft), and forest land use. Field crews also observe species and measure diameter at-breast-height (dbh) (1.37 m, 4.5 ft) and height for all trees with dbh of at least 12.7 cm (5 in.). Growing stock volumes are estimated for individual measured trees using statistical models, aggregated at subplot-level, expressed as volume per unit area, and considered to be observations without error. For this study, data for only the central subplot of each plot were used to avoid dealing with spatial correlation among observations for subplots of the same plot. Doing so resulted in little loss of information, because the correlation among observations for subplots of the same plot was greater than 0.85. Subplot-level proportion forest and volume data were combined with the values of the spectral transformations for pixels containing subplot centers. For future reference, the term *plot* refers to the central subplot of each FIA plot cluster.

Two concerns must be addressed when constructing datasets using the FIA plot data and Landsat imagery. First, because the smaller 168.3-m^2 plots may not adequately characterize the larger 900-m^2 TM pixels, observations for the four plots that were not completely forested or completely non-forested were deleted from the analyses. Second, because FIA field crews classify plots with respect to land use, not land cover, plots whose tree cover has been removed are still classified as forest if trees are expected to regenerate and forest land use is expected to continue. Thus, observations of land cover for plots with forest land use but no measurable volume were considered to be missing at random and were also deleted from the analyses. These two data issues are discussed in detail in Section 4.1. Following deletions, land cover observations for 199 plots remained.

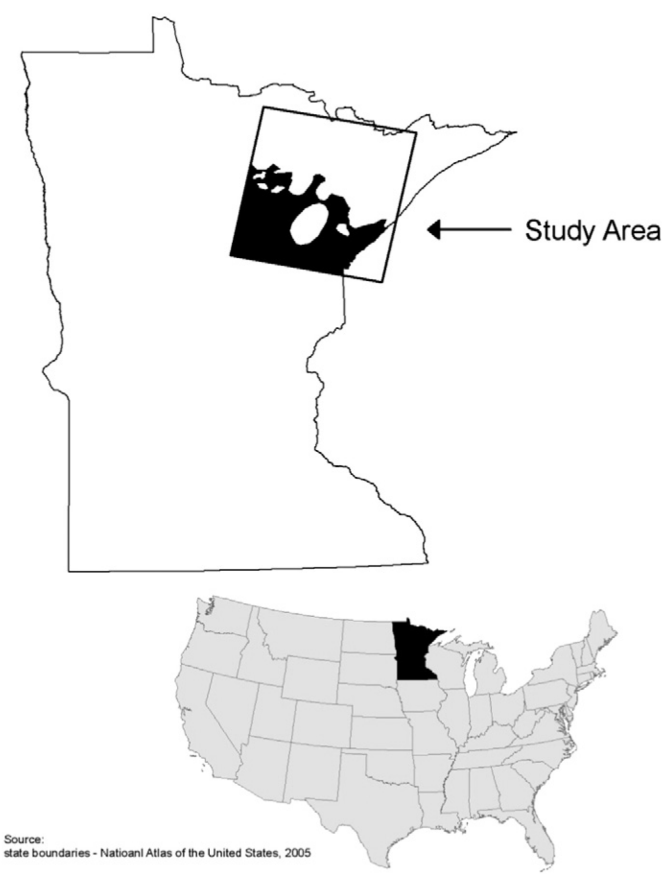

Fig. 1. Study area in northeastern Minnesota, USA.

3. Methods

3.1. Inferential assumptions

All analyses were based on three underlying assumptions: (1) a finite population consisting of N units in the form of square, 900-m^2 Landsat pixels, (2) a sample of n population units in the form of pixels that contain FIA plot centers, and (3) availability of auxiliary data in the form of the Landsat spectral transformations for all pixels. In the following sections, the terms *population unit* and *pixel* are used interchangeably.

For areal assessments, the objective is typically to estimate the area for a class of the response variable. Because the estimate of class area is simply the product of total area which is usually known and the estimate of the class area proportion, the focus of this study was estimation of the proportion, in this case proportion forest which was denoted μ. Thus, the analytical objective was construction of an approximate 95% confidence interval for $\hat{\mu}$ expressed as,

$$\hat{\mu} \pm 2 \cdot \sqrt{V\hat{a}r(\hat{\mu})}, \quad (1)$$

where $V\hat{a}r(\hat{\mu})$ is the estimate of the variance of $\hat{\mu}$.

3.2. Inference for post-classification estimates of change in forest area

For the post-classification approach to change assessment, the estimator of net deforestation is,

$$\Delta\hat{\mu} = \hat{\mu}^{2007} - \hat{\mu}^{2002}, \tag{2}$$

where Δ denotes change, μ denotes proportion forest, and the superscripts denote years. The estimator of $Var(\Delta\hat{\mu})$ is,

$$\begin{aligned} V\hat{a}r(\Delta\hat{\mu}) &= V\hat{a}r\left(\hat{\mu}^{2007} - \hat{\mu}^{2002}\right) \\ &= V\hat{a}r\left(\hat{\mu}^{2007}\right) - 2\cdot C\hat{o}v\left(\hat{\mu}^{2007}, \hat{\mu}^{2002}\right) + V\hat{a}r\left(\hat{\mu}^{2002}\right). \end{aligned} \tag{3}$$

Methods for estimating the individual components of Eq. (2) vary depending on the sampling design and the approach to inference. However, post-classification approaches all require two forest/non-forest classifications. Thus, the first step in estimating change is to construct a model of the relationship between forest/non-forest and the spectral transformations, and the second step is to use the model to construct forest/non-forest classifications.

3.3. Binomial logistic regression model

The relationship between a dichotomous response variable such as forest/non-forest, here denoted Y ($y = 0$ denotes non-forest, $y = 1$ denotes forest), and continuous independent variables, $\mathbf{X}$, is often expressed in the form,

$$p_i = f(\mathbf{X}_i; \boldsymbol{\beta}), \tag{4}$$

where i indexes population units, p_i is the probability that $y_i = 1$, and $\boldsymbol{\beta}$ is a vector of parameters to be estimated (Agresti, 2007). The function, $f(\mathbf{X}_i;\boldsymbol{\beta})$, expresses the statistical expectation of Y in terms of $\mathbf{X}$ and $\boldsymbol{\beta}$ and is often formulated using the logistic function as,

$$p_i = f(\mathbf{X}_i; \boldsymbol{\beta}) = \frac{\exp\left(\sum_{j=1}^{J} \beta_j x_{ij}\right)}{1 + \exp\left(\sum_{j=1}^{J} \beta_j x_{ij}\right)}, \tag{5}$$

where $j = 1, 2, \ldots, J$ indexes the independent variables, and exp(.) is the exponential function. The model parameters are estimated by maximizing ℓ, the natural logarithm of the likelihood, L,

$$\ell = \ln(L) = \sum_{i=1}^{n} p_i^{\,y_i}(1-p_i)^{(1-y_i)} = \sum_{i=1}^{n} f(\mathbf{X}_i;\boldsymbol{\beta})^{y_i}[1-f(\mathbf{X}_i;\boldsymbol{\beta})]^{(1-y_i)}, \tag{6}$$

and the covariance matrix for the parameter estimates is estimated as,

$$\hat{\mathbf{V}}_{\hat{\beta}} = -\mathbf{D}^{-1} \tag{7}$$

where the elements of $\mathbf{D}$ are $d_{jk} = \sum_{i=1}^{n} \frac{\partial^2 \ell\left(\mathbf{X}_i;\hat{\boldsymbol{\beta}}\right)}{\partial\beta_j \partial\beta_k} = \sum_{i=1}^{n} \hat{p}_i(1-\hat{p}_i)x_{ij}x_{ik}$ (Agresti, 2007).

3.4. Probability-based inference

Probability-based inference, also characterized as design-based inference, is based on three assumptions: (1) population units are selected for the sample using a randomization scheme; (2) the probability of selection for each population unit into the sample is positive and known; and (3) the value of the response variable for each population unit is a fixed value as opposed to a random variable. Properties of probability-based estimators are based on random variation resulting from the probabilities of selection of population units into the sample, thus the characterization of these estimators as probability-based (Hansen, Madow, & Tepping, 1983).

Observations of the categorical forest/non-forest response variable, Y, for the kth year are of the form,

$$\hat{y}_i^k = \begin{cases} 0 & \text{if the forest class is observed for the ith population unit} \\ 1 & \text{if the non-forest class is observed for the ith population unit} \end{cases} \tag{8a}$$

and for probability-based inference, predictions are of the form,

$$\hat{y}_i^k = \begin{cases} 0 & \text{if the non-forest class is predicted } \left(\hat{p}_i^k < 0.5\right) \\ & \text{for the ith population unit} \\ 1 & \text{if the forest class is predicted } \left(\hat{p}_i^k \geq 0.5\right) \\ & \text{for the ith population unit} \end{cases} \tag{8b}$$

where $\hat{p}_i^k$ is the predicted probability of forest from Eq. (5). Multiple probability-based estimators are commonly used including simple random sampling, stratified, ratio, and model-assisted difference and regression estimators.

Model-assisted estimators use a model to predict the attribute of interest but rely on probability samples for validity. Multiple forms of these estimators with satellite, LiDAR, and InSAR data have been reported recently for forest inventory applications (Gregoire et al., 2011; McRoberts, 2010, 2011; McRoberts & Walters, 2012; McRoberts, Gobakken, & Næsset, 2013; McRoberts, Næsset, & Gobakken, 2013; Næsset et al., 2011; Næsset, Bollandsås, Gobakken, Gregoire, & Ståhl, 2013; Næsset, Gobakken, et al., 2013; Vibrans, McRoberts, Moser, & Nicoletti, 2013; Sannier, McRoberts, Fichet & Makaga, 2014–this issue). With model-assisted approaches, an initial estimator of proportion forest, μ^k, for the kth year is,

$$\hat{\mu}^k_{\text{initial}} = \frac{1}{N}\sum_{i=1}^{N} \hat{y}_i^k \tag{9}$$

where N is the population size. However, systematic classification errors induce bias into this estimator which, for equal probability samples, can be estimated as,

$$B\hat{i}as\left(\hat{\mu}^k_{\text{initial}}\right) = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i^k - y_i^k\right), \tag{10}$$

where n is the sample size. One form of the model-assisted regression estimator (Särndal, Swensson, & Wretman, 1992, Section 6.5) for μ^k is defined as the difference between the initial estimator and the expectation of its bias estimate which, under the assumptions that N is both large and much larger than n, can be expressed as,

$$\hat{\mu}^k = \frac{1}{N}\sum_{i=1}^{N}\hat{y}_i^k - \frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i^k - y_i^k\right). \tag{11}$$

Under the assumptions that N is both large and much larger than n, that the classification errors are independent, and that simple random sampling was used, the variance of $\hat{\mu}^k$ can be expressed as,

$$V\hat{a}r\left(\hat{\mu}^k\right) = \frac{1}{n(n-1)}\sum_{i=1}^{n}\left(\varepsilon_i^k - \bar{\varepsilon}^k\right)^2, \tag{12}$$

where $\varepsilon_i^k = \hat{y}_i^k - y_i^k$ is the classification error, and $\bar{\varepsilon}^k$ is the mean of the errors. When systematic sampling rather than simple random sampling is used, variances may be overestimated (Särndal et al., 1992, p. 83).

Estimates $\hat{\mu}^{2002}$ and $\hat{\mu}^{2007}$ obtained using Eq. (11) are used with Eq. (2) to estimate proportion forest area change, and estimates $V\hat{a}r\left(\hat{\mu}^{2002}\right)$ and $V\hat{a}r\left(\hat{\mu}^{2007}\right)$ obtained using Eq. (12) are used with Eq. (3) to estimate the variance of the forest change estimate.

However, Eq. (3) also requires an estimate of $Cov\left(\hat{\mu}^{2007},\hat{\mu}^{2002}\right)$. Under the assumption that classification errors for 2002 and 2007 are independent for different population units, $\hat{Cov}\left(\hat{\mu}^{2007},\hat{\mu}^{2002}\right)$ is calculated using the sample data as,

$$\hat{Cov}\left(\hat{\mu}^{2007},\hat{\mu}^{2002}\right)=\frac{1}{n(n-1)}\sum_{i=1}^{n}\left(\varepsilon_i^{2007}-\overline{\varepsilon}^{2007}\right)\left(\varepsilon_i^{2002}-\overline{\varepsilon}^{2002}\right) \quad (13)$$

where $\varepsilon_i^{2007}=\hat{y}_i^{2007}-y_i^{2007}$ and $\varepsilon_i^{2002}=\hat{y}_i^{2002}-y_i^{2002}$ are classification errors, and $\overline{\varepsilon}^{2002}$ and $\overline{\varepsilon}^{2007}$ are the respective means of the errors.

3.5. Model-based inference

The assumptions underlying model-based inference differ considerably from the assumptions underlying the more familiar probability- or design-based inference. With model-based inference, the observation for a population unit is a random variable whose value is considered to be a realization from a distribution of possible values, rather than a fixed value as is the case for probability-based inference. Further, the basis for model-based inference is the validity of the model, not the probabilistic nature of the sample as is the case for probability-based inference. Finally, randomization for model-based inference enters through the random realizations from the distributions for individual population units, regardless of how they are selected for the sample, whereas randomization for probability-based inference enters through the random selection of population units into the sample.

The assumptions underlying model-based inference produce important contrasts with probability-based, model-assisted inference. First, model-based approaches have the potential to alleviate problems related to small sample sizes; second, they can produce estimates of uncertainty for individual population units; and third, lack of a probability sample does not necessarily inhibit model-based inference. Current approaches to model-based inference originated in the context of survey sampling (Brewer, 1963; Mátern, 1986; Royall, 1970) and are used increasingly for forest inventory applications (Gregoire, 1998; Mandallaz, 2008; Rennolls, 1982), particularly with remotely sensed data (McRoberts, 2006, 2010, 2011; McRoberts, Gobakken, et al., 2013; McRoberts, Næsset, et al., 2013; Ståhl et al., 2011).

For model-based inference, the mean and standard deviation of the distribution of the categorical forest/non-forest response variable, Y, for the ith population unit for the kth year are denoted μ_i^k and σ_i^k, respectively. The mean for the ith population unit is estimated as,

$$\hat{\mu}_i^k=\hat{p}_i^k=f\left(\mathbf{X}^k;\hat{\boldsymbol{\beta}}^k\right), \quad (14)$$

from Eq. (5), and σ_i^k, is estimated as the standard deviation of differences between observations, y_i^k, and estimates of corresponding means, μ_i^k. Thus, for the kth year, the model-based estimator of the population mean is based on the set of estimates, $\left\{\hat{\mu}_i^k, i=1,2,\ldots,N\right\}$, of the probabilities of forest for individual population units and is expressed as,

$$\hat{\mu}^k=\frac{1}{N}\sum_{i=1}^{N}\hat{\mu}_i^k. \quad (15)$$

An additional distinction between probability-based and model-based approaches merits comment. With probability-based approaches, apart from adjustment for estimated bias, the population mean is estimated as the proportion of population units predicted to be in the forest class, whereas with the model-based approach, the estimate is calculated as the mean estimated probability of forest. Although the two approaches are related and may produce similar estimates, they are not equivalent.

The variance of the estimate of the model-based mean for a particular year can be estimated as,

$$\hat{Var}\left(\hat{\mu}^k\right)=\frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}\hat{Cov}\left(\hat{\mu}_i^k,\hat{\mu}_j^k\right), \quad (16)$$

where,

$$\hat{Cov}\left(\hat{\mu}_i^k,\hat{\mu}_j^k\right)=\mathbf{Z}'^k_i\hat{\mathbf{V}}_{\hat{\beta}^k}\mathbf{Z}_j^k, \quad (17a)$$

$\hat{\mathbf{V}}_{\hat{\beta}^k}$ is the covariance matrix for the model parameter estimates, and $z_{ij}^k=\frac{\partial f\left(\mathbf{X}_i^k;\hat{\beta}^k\right)}{\partial\beta_j^k}$. The variance of the prediction for the ith population unit is estimated as,

$$\hat{Var}\left(\hat{\mu}_i^k\right)=\hat{Cov}\left(\hat{\mu}_i^k,\hat{\mu}_i^k\right). \quad (17b)$$

However, Eq. (3) also requires an estimate of $Cov\left(\hat{\mu}^{2007},\hat{\mu}^{2002}\right)$ which, because the 2002 and 2007 samples were not independent, cannot be assumed to be negligible. Analytical methods for estimation of this covariance are not readily available.

As an alternative to the analytical approach, a bootstrap approach was used to estimate variance and covariances. For resampling purposes, the FIA sampling design was considered to be a simple random sample. Variances and covariances for estimates of μ_i^k and μ^k were estimated using the following standard bootstrap approach (Efron & Tibshirani, 1994):

(1) the original plots with observations for both years were randomly sampled with replacement to construct a bootstrap sample with the same number of observations as the original sample;
(2) the binomial logistic regression model was fit separately to the 2002 and 2007 portions of each bootstrap sample;
(3) the model was used to calculate $\tilde{\mu}_{i,j}^{2002}$ and $\tilde{\mu}_{i,j}^{2007}$ where i indexes population units and j indexes bootstrap samples;
(4) steps (1)–(3) were replicated n_{boot} times.

Following replications, bootstrap means, variances and covariances for individual population units were estimated as:

$$\overline{\tilde{\mu}}_i^{2002}=\frac{1}{n_{boot}}\sum_{j=1}^{n_{boot}}\tilde{\mu}_{i,j}^{2002} \text{ and } \overline{\tilde{\mu}}_i^{2007}=\frac{1}{n_{boot}}\sum_{j=1}^{n_{boot}}\tilde{\mu}_{i,j}^{2007}, \quad (18)$$

where the tilde (~) denotes a mean calculated from a bootstrap sample, i indexes population units, and j indexes bootstrap samples;

$$\hat{Var}\left(\hat{\mu}_i^{2002}\right)=\frac{1}{n_{boot}}\sum_{j=1}^{n_{boot}}\left(\tilde{\mu}_{i,j}^{2002}-\overline{\tilde{\mu}}_i^{2002}\right)^2 \text{ and} \quad (19a)$$

$$\hat{Var}\left(\hat{\mu}_i^{2007}\right)=\frac{1}{n_{boot}}\sum_{j=1}^{n_{boot}}\left(\tilde{\mu}_{i,j}^{2007}-\overline{\tilde{\mu}}_i^{2007}\right)^2.$$

and

$$\hat{Cov}\left(\hat{\mu}_i^{2002},\hat{\mu}_i^{2007}\right)=\frac{1}{n_{boot}}\sum_{j=1}^{n_{boot}}\left(\tilde{\mu}_{i,j}^{2002}-\overline{\tilde{\mu}}_i^{2002}\right)\left(\tilde{\mu}_{i,j}^{2007}-\overline{\tilde{\mu}}_i^{2007}\right). \quad (19b)$$

Population means and variances were estimated as,

$$\tilde{\mu}_j^{2002}=\frac{1}{N}\sum_{i=1}^{N}\tilde{\mu}_{i,j}^{2002} \text{ and } \tilde{\mu}_j^{2007}=\frac{1}{N}\sum_{i=1}^{N}\tilde{\mu}_{i,j}^{2007}; \quad (20a)$$

$$\overline{\tilde{\mu}}^{2002}=\frac{1}{n_{boot}}\sum_{j=1}^{n_{boot}}\tilde{\mu}_j^{2002} \text{ and } \overline{\tilde{\mu}}^{2007}=\frac{1}{n_{boot}}\sum_{j=1}^{n_{boot}}\tilde{\mu}_j^{2007}; \quad (20b)$$

$$\hat{Var}\left(\hat{\mu}^{2002}\right) = \frac{1}{n_{boot}} \sum_{j=1}^{n_{boot}} \left(\tilde{\mu}_j^{2002} - \tilde{\tilde{\mu}}^{2002}\right)^2, \tag{21a}$$

$$\hat{Var}\left(\hat{\mu}^{2007}\right) = \frac{1}{n_{boot}} \sum_{j=1}^{n_{boot}} \left(\tilde{\mu}_j^{2007} - \tilde{\tilde{\mu}}^{2007}\right)^2,$$

and

$$\hat{Cov}\left(\hat{\mu}^{2002}, \hat{\mu}^{2007}\right) = \frac{1}{n_{boot}} \sum_{j=1}^{n_{boot}} \left(\tilde{\mu}_j^{2002} - \tilde{\tilde{\mu}}^{2002}\right)\left(\tilde{\mu}_j^{2007} - \tilde{\tilde{\mu}}^{2007}\right). \tag{21b}$$

Replications in step (4) continued until all bootstrap estimates of means, variances, and covariances stabilized. The analytical and bootstrap estimates of variances for $\hat{\mu}^{2002}$ and $\hat{\mu}^{2007}$ can be compared as a means of checking the validity of the bootstrap approach.

3.6. Analyses

3.6.1. Model assessment

The model was fit to the 2002 and 2007 data separately. All combinations of the four independent variables were evaluated with respect to *accuracy* defined as the proportion of plots correctly classified for probability-based inference and with respect to $\ell = \ln(L)$ from Eq. (6) for model-based inference. The quality of fit of the binomial logistic regression model to each dataset was assessed using a four-step approach: (1) all pairs of observations and predictions, $(y_i, \hat{p}_i)$, were ordered with respect to $\hat{p}_i$; (2) the ordered pairs were grouped into categories of approximately equal numbers of pairs; (3) the group means of the observations and the group means of the predictions were calculated; and (4) a graph of the group means of observations versus the group means of predictions was constructed (Hosmer & Lemeshow, 1989). If the model is correctly specified, the graph of group means of observations versus group means of model predictions should coincide approximately with the 1:1 line with intercept 0 and slope 1. McRoberts and Walters (2012) demonstrate the relationship between accuracy and estimates of both classification bias and precision. For model-based estimators, assessment of the quality of fit of the model to the data is crucial because no adjustment for estimated bias is used as for the model-assisted regression estimator and because lack of fit is indicative of a biased estimator.

3.6.2. Probability-based, model-assisted inference

For each combination of independent variables, the model-assisted regression estimator was used as described in Section 3.4 to estimate mean proportion forest for each of 2002 and 2007 and to estimate net deforestation. With model-assisted methods, each plot receives two forest/ non-forest categorical predictions, one for 2002 and one for 2007. If the categorical predictions are different, the plot is assigned to a change category. However, this categorical approach is not very discriminating. For example, if $\hat{p}_i^{2002} = 0.99$ and $\hat{p}_i^{2007} = 0.01$, then the ith population unit would be estimated to have changed from forest ($y_i = 1$) to non-forest ($y_i = 0$); similarly, if $\hat{p}_i^{2002} = 0.51$ and $\hat{p}_i^{2007} = 0.49$, the ith population unit would also be estimated to have changed from forest to non-forest. However, confidence in the change estimate for the first case would be large, whereas confidence in real change for the second case would be quite small. Model-based inference as described in Section 3.5 provides a mechanism for dealing with this issue.

Initial estimates of gross afforestation and gross deforestation may be calculated as proportions of population units estimated to have changed from non-forest to forest or forest to non-forest, respectively. However, reliable probability-based estimates of bias and variance could not be calculated using probability-based methods because of insufficient numbers of observations of change.

3.6.3. Model-based inference

For each combination of independent variables, estimates of the 2002 and 2007 means for the entire population were calculated using Eq. (15), and estimates of variances were calculated using both the analytical estimators of Eq. (16) and the bootstrap estimators of Eq. (21a). The analytical and bootstrap estimates of variances for $\hat{\mu}^{2002}$ and $\hat{\mu}^{2007}$ were compared as a consistency check. Covariances between $\hat{\mu}^{2002}$ and $\hat{\mu}^{2007}$ were estimated using only the bootstrap estimator of Eq. (21b). Finally, the analytical estimates of the means and the bootstrap estimators of the variances and covariances were used to construct an approximate 95% confidence interval for the estimate of change in mean probability of forest and to test if the estimate was statistically significantly different from zero.

An advantage of the model-based estimators is that the variance estimates calculated for individual population units support construction of confidence intervals for estimates of gross afforestation and gross deforestation. These variance estimates further facilitate discrimination between the cases that cannot be distinguished using model-assisted methods as described in Section 3.6.2. A test of the statistical significance of the change in estimated probabilities of forest between years for the ith population unit was conducted using,

$$t_i = \frac{\hat{\mu}_i^{2007} - \hat{\mu}_i^{2002}}{\sqrt{\hat{Var}(\hat{\mu}_i^{2007}) - 2 \cdot \hat{Cov}(\hat{\mu}_i^{2002}, \hat{\mu}_i^{2007}) + \hat{Var}(\hat{\mu}_i^{2002})}}, \tag{22}$$

where estimates of the means were calculated using the analytical estimator of Eq. (15), and estimates of the variances and covariances were calculated using the bootstrap estimators of Eqs. (19a, 19b). For values of t_{crit} ranging from 0.1 to 3.0, the ith population unit was assigned to one of three categories of forest change, C:

$$C_i = \begin{cases} \text{deforestation} & \text{if } \hat{\mu}_i^{2002} \geq 0.5,\ \hat{\mu}_i^{2007} < 0.5,\ \text{and } |t_i| > t_{crit} \\ \text{afforestation} & \text{if } \hat{\mu}_i^{2002} < 0.5,\ \hat{\mu}_i^{2007} \geq 0.5,\ \text{and } |t_i| > t_{crit} \\ \text{no change} & \text{otherwise} \end{cases}. \tag{23}$$

For each category of C, the proportions of population units assigned to the category and the mean changes in the estimates of the probabilities of forest were calculated. In addition, net deforestation was estimated based only on population units for which $|t_i| \geq t_{crit}$.

4. Results and discussion

4.1. Data issues

When observations for response and auxiliary variables are obtained from different sources, multiple factors add complexity and uncertainty to the analyses. For this study, observations of response variables were acquired via measurement of 7.32-m (24-ft) radius ground plots over 12-month time intervals in years 2002 and 2007, whereas observations of the auxiliary variables were acquired from satellite sensors for 30-m × 30-m pixels at single dates in each of 2002 and 2007. Thus, spatial differences between the 168.3-m^2 subplots and the 900-m^2 pixels mean that in some instances the plot measurements may not adequately characterize entire pixels. For this study, the concern was at least partially alleviated by deleting the four plots that were not completely forested or completely non-forested. Doing so also facilitated use of the binomial logistic regression model which requires categorical classes for observations of the response variable.

Temporal differences are also a factor contributing complexity and uncertainty to the analyses. Because plot measurement dates could differ by six months or more from the satellite image dates, some plots could have been cleared or otherwise greatly disturbed between the image and measurement dates. If so, spectral signatures corresponding to forest cover would be associated with plots whose forest cover had been removed. For this study, data were also available for plots measured from years 2000 to 2009. To minimize the effects of temporal differences, plots not measured in the same years as the image dates were deleted from the analyses.

Care must also be exercised to accommodate missing data. The primary cause of missing data in the satellite imagery was cloud cover. Because the areas of cloud cover for this study were contiguous and large, they were simply deleted from the analyses (Fig. 1).

Missing plot observations constitute a more difficult problem. As noted in the Data section, FIA field crews assess plots with respect to land use, not land cover. Thus, land use for a plot whose forest cover has been removed is still classified as forest if trees are expected to regenerate and forest land use is expected to continue. However, these plots could vary widely with respect to forest cover, ranging from recently clear cut to large numbers of trees whose diameters barely fail to satisfy the minimum requirement of 12.7 cm (5 in.). Thus, the primary concern is that a plot with no forest cover may be associated with spectral values characteristic of forest land cover and vice versa. For these plots, three options may be considered: (1) accept the forest use observation as a proxy for forest land cover and classify the plots as having forest cover; (2) accept the lack of measurable volume as a proxy for non-forest land cover and classify the plots as having non-forest cover; and (3) delete the plots from the analyses with the argument that the land cover observations are missing. Although none of the options is particularly appealing, a decision is necessary.

For this study, models using all four independent variables were constructed for all three options and corresponding classification accuracies were estimated. When forest cover was assigned to these plots and the models based on the augmented datasets were used, classification accuracies for 2002 and 2007 for these plots ranged from 0.780 to 0.840, whereas classification accuracies for plots known to have forest cover ranged from 0.978 to 1.000. When non-forest cover was assigned and the corresponding models were used, classification accuracies for these plots were 0.580–0.660, whereas classification accuracies for plots known to have non-forest cover were 0.817 for both 2002 and 2007. The large differences in the classification accuracies suggest that some of these plots with missing land cover observations have non-forest cover and some have forest cover. However, given the proxy information available, there is no way to separate them into the correct classes subsequent to field measurement. Attempts to force them all into the forest cover class or all into the non-forest cover class produced substantially reduced accuracies. Therefore, the observations for these plots were characterized as missing observations and the plots were deleted from the analyses.

Considerable caution must be exercised when deleting plots; otherwise, the validity of probability-based inferences may be compromised as a result of the introduction of non-randomness into the sample. For this study, additional analyses were conducted to discern meaningful patterns for other attributes of the deleted plots such as their spatial distribution. Because no such patterns were found, the deleted plot observations were characterized as missing at random, thus preserving the randomness of the sample (Allison, 2001; Rubin & Little, 2002).

4.2. Model assessment

Graphs of group means of observations versus group means of model predictions were similar for 2002 and 2007 and indicated no systematic lack of fit of the model to the data (Fig. 2). Values of $\ell = \ln(L)$ from Eq. (6) were uniformly smaller when the NDVI and TC_{green} spectral transformations were included in the set of independent variables. Accuracies for forest/non-forest classifications were slightly less than 0.9 and uniformly greater when the NDVI and TC_{green} spectral transformations were included in the set of independent variables. Accuracies in this range are comparable to those obtained for the study area using similar datasets and other classification methods (Finley, Banerjee, & McRoberts, 2008; Haapanen, Ek, Bauer, & Finley, 2004; McRoberts, 2006). However, because the same data were used for estimating the model parameters as for assessing accuracy, these results may be somewhat optimistic. Nevertheless, for another study (McRoberts & Walters, 2012) these same data were augmented with data for other years, accuracy was assessed using independent datasets, and similar accuracies were obtained. Overall, for both years and for both $\ell = \ln(L)$ and accuracy, the combination of independent variables that included all four spectral transformations produced as good or better results than other combinations and is the only combination that is further considered.

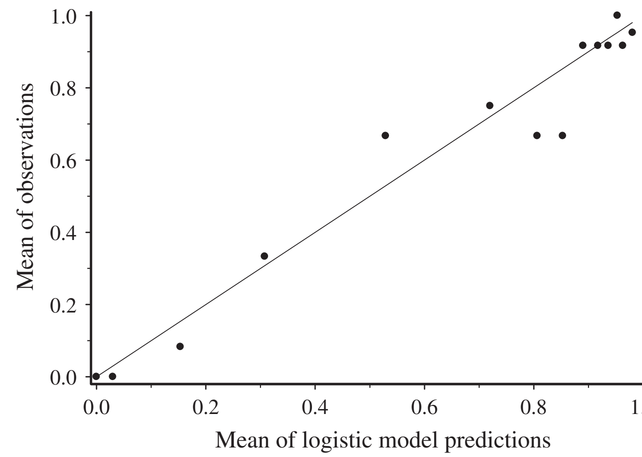

Fig. 2. Group means of 2002 forest/non-forest observations versus group means of logistic model predictions.

4.3. Model-assisted inference

For the model-assisted regression estimator, estimates of proportion forest were $\hat{\mu}^{2002} = 0.6347$ with $SE\left(\hat{\mu}^{2002}\right) = 0.0248$ and $\hat{\mu}^{2007} = 0.6294$ with $SE\left(\hat{\mu}^{2007}\right) = 0.0239$, and the respective bias estimates were 0.0615 and 0.0410. The estimate of net deforestation was $\Delta\hat{\mu} = -0.0053$ with $SE(\Delta\hat{\mu}) = 0.0229$. An approximate 95% confidence interval for the estimate of proportion change in forest area was (−0.0511, 0.0405) which, because it included zero, indicated that the estimate was not statistically significantly different from zero.

4.4. Model-based inference

4.4.1. Population analyses

For the model-based estimator, the analytical estimates of mean probability of forest were $\hat{\mu}^{2002} = 0.6369$ and $\hat{\mu}^{2007} = 0.6294$ with bootstrap standard errors of $SE\left(\hat{\mu}^{2002}\right) = 0.0226$ and $SE\left(\hat{\mu}^{2007}\right) = 0.0222$. The bootstrap and analytical standard errors for $\hat{\mu}^{2002}$ and $\hat{\mu}^{2007}$ deviated by less than 0.0022 in absolute value. The analytical estimate of change in mean probability of forest between 2002 and 2007 was $\Delta\hat{\mu} = -0.0075$ with bootstrap standard error of $SE(\Delta\hat{\mu}) = 0.0157$. An approximate 95% confidence interval was (−0.0389, 0.0239) which, because it included zero, indicated that the estimate was not statistically significantly different from zero.

4.4.2. Population unit analyses

Population units for which the change in the 2002 and 2007 estimates of the probabilities of forest was statistically significant different from zero were assigned to one of two classes: (1) if the 2002 estimate was less than 0.5 and the 2007 estimate was greater than or equal to 0.5, the unit was assigned to the gross afforestation class, and (2) if the 2002 estimate was greater than or equal to 0.5 and the 2007 estimate was less than 0.5, the unit was assigned to the gross deforestation class. The

Table 1
Model-based change estimates based on population unit-level analyses.

t_{crit}	Afforestation		Deforestation		Net deforestation	
	Proportion[a]	Mean change in estimates of probabilities of forest[b]	Proportion[a]	Mean change in estimates of probabilities of forest[b]	Proportion[a,c]	Mean absolute value of change in estimates of probabilities of forest[b]
0.10	0.0447	0.4642	0.0705	−0.5503	0.0258	0.5169
0.50	0.0441	0.4691	0.0700	−0.5541	0.0258	0.5212
1.00	0.0425	0.4825	0.0683	−0.5644	0.0258	0.5330
1.50	0.0398	0.5012	0.0658	−0.5790	0.0259	0.5497
2.00	0.0361	0.5234	0.0623	−0.5968	0.0262	0.5699
2.50	0.0316	0.5477	0.0580	−0.6173	0.0264	0.5928
3.00	0.0266	0.5732	0.0528	−0.6402	0.0262	0.6177

[a] Proportion of population units for which change was statistically significant different from zero.
[b] Mean change in estimated probabilities of forest for units whose changes in estimates are statistically significant different from zero.
[c] These proportions represent net loss of forest area.

analyses focused on estimating the proportion of population units in each class. In addition, the mean change in the estimated probabilities of forest was also calculated for each class.

Depending on the value of t_{crit}, the proportion of population units assigned to gross afforestation ranged from 0.0266 to 0.0447, and the proportion of population units assigned to gross deforestation ranged from 0.0528 to 0.0705 (Table 1). Proportions of population units assigned to both classes decreased as t_{crit} increased which is as expected because as t_{crit} increased, estimates of change for fewer population units were declared statistically significantly different from zero. However, mean change in estimated probabilities of forest increased in absolute value for the afforestation and deforestation classes as t_{crit} increased. This result is also as expected because as t_{crit} increased, more population units with smaller absolute values of change in estimated probabilities of forest were declared statistically non-significantly different from zero, leaving fewer population units but with greater absolute values of change in estimated probabilities of forest. Finally, the ranges of proportions for gross afforestation and gross deforestation were all small, regardless of the values of t_{crit}. This result can be attributed to the finding that few population units had changes in estimates of probability of forest that were only marginally statistically significantly from zero, i.e., if a change in the estimated probabilities of forest for a population unit was statistically significantly different from zero, the statistical significance was generally large.

Estimates of net deforestation, calculated as differences between proportions for the gross afforestation and proportions for gross deforestation and representing loss of forest cover ranged from 0.0258 to 0.0264. These estimates were remarkably similar despite larger changes in estimates of gross afforestation and gross deforestation. Further, the estimates were within the confidence intervals for both the model-assisted and model-based estimates of net deforestation.

4.5. Effects of measuring the same plots in both years

For the model-assisted regression estimator, the estimate of the covariance between the 2002 and 2007 population estimates was $\hat{Cov}\left(\hat{\mu}^{2002},\hat{\mu}^{2007}\right)=0.0009$, and for the model-based estimators, the bootstrap estimate of the covariance was $\hat{Cov}\left(\hat{\mu}^{2002},\hat{\mu}^{2007}\right)=0.0004$. Of importance, for both approaches to inference, covariance estimates were positive with the beneficial effect of reducing $\hat{Var}(\Delta\hat{\mu})$ as calculated using Eq. (3). These results can be attributed to measurement of the same set of plots in both 2002 and 2007. If the covariances in Eq. (3) were set to zero, as would be expected and justified for measurements of different sets of plots in 2002 and 2007, the model-assisted standard error estimates would have been increased by a factor of approximately 1.5 and the model-based standard error estimates would have been increased by a factor of approximately 2.0.

5. Conclusions

Four conclusions may be drawn from the study. First, the binomial logistic regression model produced sufficiently accurate predictions to serve as the basis for both model-assisted and model-based approaches to inference for estimating forest area and change in forest area. Although other model forms can be used with both the model-assisted regression and model-based estimators, the binomial logistic regression model is particularly useful for categorical response variables with two classes. Second, post-classification approaches to estimating change in forest area are appropriate, if not the only alternative, when observations of change are rare. The analyses illustrated methods for constructing confidence intervals for post-classification estimates of change in forest area. Third, model-based inference is a useful alternative to probability-based inference when probability accuracy assessment samples are not available and/or when estimates of uncertainty for all population units are required. Fourth, with the model-based approach, and using the bootstrap approach for estimating variances, estimates of gross afforestation, gross deforestation, and net deforestation were obtained based only on population units for which change in estimates of probabilities of forest was significantly different from zero. The appeal of this approach is that it discriminates between population units whose categorical predictions indicate forest/non-forest change but whose change in estimates of the probabilities of forest is small, and units whose categorical predictions indicate change and whose change in estimates of the probabilities of forest is statistically significantly different from zero.

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