Forestry *An International Journal of Forest Research*

Forestry 2022; **95**, 301–311, https://doi.org/10.1093/forestry/cpab056
Advance Access publication 1 February 2022

Nonresponse bias in change estimation: a national forest inventory example

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Received 3 August 2021

Nonresponse in national forest inventories primarily occurs in forested areas due to accessibility issues or where hazardous conditions exist. As with all surveys, nonresponse has the potential to impart empirical bias into sample-based estimates and care should be taken to minimize any effects. A less-studied aspect is the effects of nonresponse when estimating change between two points in time. In this study, potential bias in change estimates was evaluated using imputed values for nonresponse inventory plots to compare differences between response and nonresponse means. Analysis of forest area and tree biomass density attributes revealed that systematic differences in probabilities of nonresponse that occur due to ownership type and forest/nonforest status produce overall estimates of change that are too small. The empirical bias appears to worsen as nonresponse rates increase. Underestimation of change inhibits detection of statistically significant shifts in forest resource attributes and concurrently thwarts effective management and policy responses. Thus, further study to ameliorate this issue is warranted, including improved strategies for defining populations and strata to better conform to nonresponse assumptions and/or alternative estimation methods that account for differential nonresponse probabilities due to ownership or forest/nonforest status.

Introduction

Nonresponse is an issue faced in nearly all types of surveys. As such, its treatment has been widely studied with various methods being suggested to minimize adverse effects on reported results. In national forest inventories (NFIs), nonresponse occurs for various reasons across the landscape and is generally not random in occurrence. For example, some NFI use a prescreening component to the inventory where plot locations are examined using high-resolution remotely sensed imagery to determine whether the plot needs a field measurement based on the presence of forest land (Patterson *et al.*, 2012; Fattorini, 2015). Thus, only plots selected for field measurement are subject to being nonresponse sample units due to reasons such as denial of access by private landowners or hazardous conditions on or near the plot. Nonresponse occurs when either the entire plot or a portion thereof cannot be measured and rates of nonresponse are often highly variable depending on a number of factors. In the US NFI, nonresponse rates vary from nearly zero in some areas while rates in other locations exceed 20 per cent. Nonresponse often does not occur randomly within the sample (Patterson *et al.*, 2012; Figure 2) and has the potential to impart bias in the realized sample and associated sample-based estimates of population parameters such as means or totals.

Primarily, NFIs address nonresponse through either imputation (Eskelson *et al.*, 2009; Magnussen *et al.*, 2017) or post-stratification (Goeking and Patterson, 2013; Gormanson *et al.*, 2018), although other methods such as ignoring or replacing nonresponse plots have been presented (Gillis *et al.*, 2005; Domke *et al.*, 2014). Although nonresponse rates can be large when making estimates of current conditions, the issue becomes exacerbated for change estimation where nonresponse over two measurement cycles requires proper accounting. In particular, there will likely exist sample units that are (1) observed at the initial measurement but are unobserved at the subsequent measurement, (2) unobserved at the initial measurement but are observed at the subsequent measurement and (3) are unobserved at both times. The conventional change estimation approach requires observed data at both measurements for a sample unit to be included in change evaluations (Scott *et al.*, 2005; Poso, 2006). Thus, change estimates suffer from greater nonresponse rates than current status assessments. This situation is particularly troubling as change estimates tend to be more highly variable than those for current status, with the reduction of sample size only worsening the problem. Thus, nonresponse impedes the ability to detect statistically significant changes in forest resources. Generally, failure to detect change during environmental monitoring is problematic due to the perception that no modifications to current policy or management directives are necessary to maintain current conditions (Fairweather, 1991; Mapstone, 1995).

Additional concern arises due to the common practice of ignoring the presence of entirely nonresponse plots and proceeding with estimation based on the sample units where a response was obtained (McRoberts, 2003) with an adjustment factor to account for plots only partially measured (Scott *et al.*, 2005). This approach relies on an implicit assumption that on average the unobserved units are equal to the mean from the observed units in the post-stratum. If this assumption does not hold, a bias of unknown magnitude will be present in the results. As such, a better understanding of the factors that influence the veracity of this assumption and the potential bias in change estimates is needed. In this study, missing value imputation was used to create forest area and tree biomass density observations for entirely nonresponse plots to: (1) compare the mean change of nonresponse with the observed mean change within strata, (2) identify the factors that cause large discrepancies between observed and nonresponse change means and (3) assess effects of nonresponse on bias and precision of change estimates for the population.

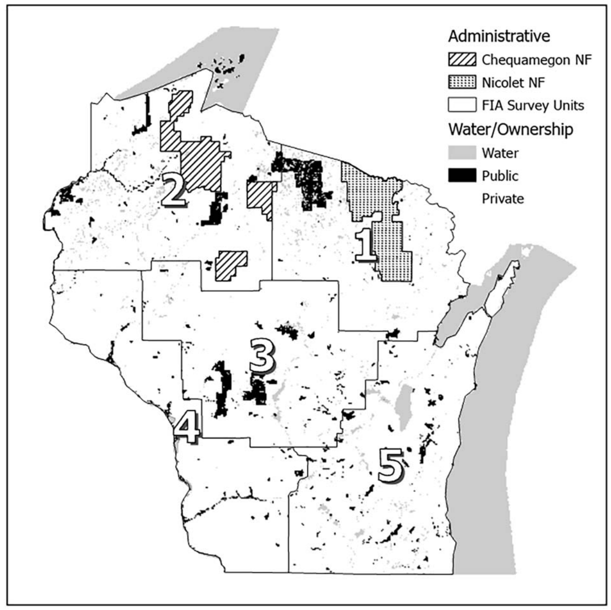

Figure 1 Map of the state of Wisconsin with estimation units defined by survey unit number and water/ownership status or National Forest (NF) designation.

Methods

Data

The analyses were based on NFI data available from the Forest Inventory and Analysis (FIA) program of the US Forest Service (https://apps.fs.usda.gov/fia/datamart/datamart.html). The state of Wisconsin was chosen as the study area due to the wide range of landscape characteristics across the state (highly urbanized areas to remote forest) and the statewide availability of imputed plot data over an extended time period. The inventory was implemented under a quasi-systematic, rotating-panel design with a sampling intensity of ∼1 plot per 1214 ha (Reams *et al.*, 2005; Kurtz *et al.*, 2017). The FIA plot configuration contains four subplots per plot (0.067-ha total area), with each subplot having having a radius of 7.3 m. Each subplot has a 2.1-m radius microplot with centre offset 3.7 m at 90° azimuth (Bechtold and Scott, 2005). Trees with diameter breast-height (dbh) ≥ 12.7 cm are measured within the subplot area, and trees with 2.5 cm ≤ dbh < 12.7 cm are recorded within the microplot. Field measurements included a mapped-plot protocol, which allows for determination of plot area proportions corresponding to certain characteristics. For this study, proportion of forestland area on the plot is of interest, as well as the proportion of the plot that was able to be sampled (sampled area proportion). On forested areas of plots, tree species and size characteristics are recorded and subsequently used to predict individual-tree biomass from statistical models (U.S. Forest Service, 2012). Nonforest areas of plots have zero forest tree biomass by definition. Plot-level tree biomass is obtained by summing model predictions over all trees and expanding to a per-hectare basis. The data used in this study correspond to the 2001–2005 and 2010–2015 inventory cycles and for change estimates these cycles are referred to as T1 and T2, respectively.

Analytical populations are defined based on administrative boundaries (a county or group of counties) in combination with a map that differentiates public land ownership, private land ownership and water (Figure 1). The division by ownership in developing these distinct areal aggregations (termed estimation units) is intended to reduce nonresponse bias as nonresponse primarily occurs on private land. Within each estimation unit, post-stratified estimation is employed to both reduce variance and further mitigate potential nonresponse bias (Scott *et al.*, 2005; Patterson *et al.*, 2012). Each plot i is assigned to a post-stratum h in estimation unit g based on the location coordinates and the corresponding pixel value from the National Land Cover Dataset (NLCD) tree canopy cover map (Jin *et al.*, 2019), which consists of 30-m pixel-based estimates of canopy cover proportion between 0 and 1 across the US. Construction of the post-strata followed FIA methods in the region, which uses tree canopy cover proportion classes 0.00–0.05, 0.06–0.20, 0.21–0.50, 0.51–0.75 and 0.76–1.00 to construct five post-strata. In some cases, fewer post-strata were defined by collapsing the original classes to attain post-stratum sample sizes of at least 10 plots. Post-stratum weights (W_{hg}) within each estimation unit g are determined as the proportion of map pixels in the canopy cover class pertaining to post-stratum h divided by the total number of pixels in estimation unit g. For change estimation, post-stratum sample sizes (n_{hg}) are the number of plots observed at both T1 and T2 such that forest area and biomass density change observations for the plot could be calculated. In these data, there were 61 post-strata across 17 estimation units—relevant summary statistics are shown in Table 1.

FIA estimation protocols specify dropping plots that were entirely nonresponse (Scott *et al.*, 2005). In the context of change estimation, the sample sizes in Table 1 reflect only those plots where an observation was obtained at both time points. To utilize the full sample, replacement of missing observations is needed for plots having nonresponse at either T1, T2, or both T1 and T2. In

Table 1 Summary statistics for observed change in forest area proportion and tree biomass (tonnes) and nonresponse rates on both all plots and field visited plots bases by estimation unit and post-strata therein as indicated by canopy proportion range.

Estimation unit	Post-stratum canopy proportion	n_{hg}	W_{hg}	Change in forest area proportion			Change in tree biomass (tonnes)			Nonresponse %	
				Mean	Min.	Max.	Mean	Min.	Max.	All	Field
Chequamegon NF	0.00–0.05	11	0.060	0.0002	0.0000	0.0022	1.28	0.00	4.29	0.0%	0.0%
Chequamegon NF	0.06–0.20	24	0.100	0.0098	−1.0000	1.0000	−0.33	−31.25	32.26	0.0%	0.0%
Chequamegon NF	0.21–0.50	22	0.069	0.0275	−0.2500	0.2500	0.18	−19.87	15.46	0.0%	0.0%
Chequamegon NF	0.51–0.80	52	0.186	0.0088	−0.2500	1.0000	4.06	−28.35	35.05	0.0%	0.0%
Chequamegon NF	0.81–1.00	203	0.585	0.0021	−0.2500	1.0000	5.24	−36.06	39.22	0.0%	0.0%
Water Unit 1	0.00–1.00	79	1.000	0.0164	0.0000	0.6850	0.93	−3.74	43.01	0.0%	0.0%
Water Unit 2	0.00–1.00	90	1.000	0.0067	0.0000	0.2500	0.64	0.00	18.66	0.0%	0.0%
Water Unit 3	0.00–1.00	54	1.000	−0.0033	−1.0000	0.7110	0.75	−12.78	28.15	3.6%	14.3%
Water Unit 4	0.00–1.00	49	1.000	0.0304	0.0000	1.0000	1.72	−1.37	53.18	2.0%	10.0%
Water Unit 5	0.00–1.00	100	1.000	0.0027	0.0000	0.2685	0.20	0.00	16.59	0.0%	0.0%
Nicolet NF	0.00–0.50	22	0.126	0.0041	−0.0344	0.0999	−2.59	−34.61	14.70	0.0%	0.0%
Nicolet NF	0.51–0.80	80	0.304	0.0230	0.0000	0.8295	6.93	−10.38	101.90	0.0%	0.0%
Nicolet NF	0.81–1.00	141	0.570	−0.0023	−0.1332	0.0000	6.52	−16.44	20.87	0.0%	0.0%
Private Unit 1	0.00–0.05	292	0.217	0.0464	−0.5000	1.0000	0.42	−37.88	18.70	2.0%	7.8%
Private Unit 1	0.06–0.20	188	0.152	0.0952	−0.7717	1.0000	−0.15	−109.05	36.76	5.1%	5.6%
Private Unit 1	0.21–0.50	87	0.076	0.0511	−0.6346	1.0000	4.99	−35.40	48.14	9.4%	9.5%
Private Unit 1	0.51–0.80	272	0.228	0.0158	−0.6217	1.0000	1.31	−64.92	65.54	6.8%	6.9%
Private Unit 1	0.81–1.00	403	0.328	0.0032	−0.5000	1.0000	4.02	−58.29	55.55	6.7%	6.7%
Private Unit 2	0.00–0.05	503	0.298	0.0240	−1.0000	1.0000	−0.23	−65.06	18.17	4.6%	13.5%
Private Unit 2	0.06–0.20	245	0.157	0.0674	−1.0000	1.0000	0.50	−54.18	60.05	13.1%	14.2%
Private Unit 2	0.21–0.50	144	0.102	0.0214	−1.0000	1.0000	0.71	−69.95	38.08	19.1%	19.2%
Private Unit 2	0.51–0.80	269	0.182	0.0270	−0.2500	1.0000	1.64	−54.74	70.06	15.7%	15.8%
Private Unit 2	0.81–1.00	398	0.260	0.0045	−0.2996	1.0000	4.34	−63.26	52.32	15.5%	15.5%
Private Unit 3	0.00–0.05	1030	0.488	0.0144	−1.0000	1.0000	0.22	−37.57	47.08	1.1%	5.3%
Private Unit 3	0.06–0.20	293	0.163	0.0442	−1.0000	1.0000	2.09	−56.32	52.92	9.6%	10.8%
Private Unit 3	0.21–0.50	102	0.054	0.0929	−0.9170	1.0000	3.19	−68.73	45.00	12.8%	12.8%
Private Unit 3	0.51–0.80	250	0.138	0.0244	−0.4612	1.0000	4.64	−54.59	53.97	12.3%	12.3%
Private Unit 3	0.81–1.00	289	0.158	0.0113	−0.3353	1.0000	4.99	−75.75	59.57	16.7%	16.7%
Private Unit 4	0.00–0.05	1106	0.563	0.0125	−1.0000	1.0000	0.34	−21.09	31.11	2.5%	15.0%
Private Unit 4	0.06–0.20	238	0.136	0.0742	−1.0000	1.0000	3.37	−84.50	154.08	14.4%	15.6%
Private Unit 4	0.21–0.50	73	0.043	−0.0230	−1.0000	0.7561	0.71	−81.10	63.01	16.1%	16.3%
Private Unit 4	0.51–0.80	169	0.103	0.0394	−0.2500	1.0000	3.95	−59.89	71.65	12.4%	12.5%
Private Unit 4	0.81–1.00	265	0.155	0.0132	−0.1181	1.0000	3.91	−80.05	74.17	16.1%	16.1%
Private Unit 5	0.00–0.05	1776	0.706	0.0164	−0.7484	1.0000	0.28	−10.72	29.65	0.9%	9.4%
Private Unit 5	0.06–0.20	385	0.161	0.0497	−0.7500	1.0000	2.26	−36.14	44.38	5.6%	10.5%
Private Unit 5	0.21–0.50	69	0.024	0.1525	−0.4978	1.0000	7.81	−11.29	45.91	2.8%	3.0%
Private Unit 5	0.51–0.80	125	0.060	0.0424	−0.6195	1.0000	4.78	−87.83	56.57	14.4%	14.9%
Private Unit 5	0.81–1.00	122	0.049	0.0104	−0.1329	1.0000	4.74	−54.30	38.66	10.3%	10.3%
Public Unit 1	0.00–0.05	27	0.065	−0.0033	−0.1629	0.0342	−2.36	−29.86	8.98	0.0%	0.0%
Public Unit 1	0.06–0.20	49	0.130	0.0644	−0.2500	1.0000	−4.52	−40.65	15.72	0.0%	0.0%
Public Unit 1	0.21–0.50	28	0.081	−0.0066	−0.1281	0.0225	−1.00	−36.85	13.66	0.0%	0.0%
Public Unit 1	0.51–0.80	112	0.277	0.0141	−0.2500	1.0000	3.58	−32.07	28.25	0.0%	0.0%
Public Unit 1	0.81–1.00	166	0.447	0.0104	−0.0448	1.0000	4.58	−39.26	44.96	0.0%	0.0%
Public Unit 2	0.00–0.05	76	0.132	0.0440	−0.5000	1.0000	−3.72	−57.82	33.40	0.0%	0.0%
Public Unit 2	0.06–0.20	76	0.122	0.0487	−0.5000	1.0000	−3.89	−41.37	19.17	1.3%	1.4%
Public Unit 2	0.21–0.50	73	0.124	0.0455	−0.4421	1.0000	−0.97	−48.53	26.56	1.4%	1.4%
Public Unit 2	0.51–0.80	122	0.227	0.0754	−0.2803	1.0000	1.73	−31.88	54.74	2.4%	2.4%
Public Unit 2	0.81–1.00	245	0.395	0.0087	−0.0656	1.0000	3.34	−51.35	33.42	2.0%	2.0%
Public Unit 3	0.00–0.05	46	0.186	0.0249	0.0000	0.4562	−3.21	−51.81	8.92	0.0%	0.0%

(Continued)

Table 1 Continued

Estimation unit	Post-stratum canopy proportion	n_{hg}	W_{hg}	Change in forest area proportion			Change in tree biomass (tonnes)			Nonresponse %	
				Mean	Min.	Max.	Mean	Min.	Max.	All	Field
Public Unit 3	0.06–0.20	66	0.197	0.0580	−0.5000	1.0000	0.01	−43.85	20.24	0.0%	0.0%
Public Unit 3	0.21–0.50	30	0.095	0.0603	−0.2863	1.0000	2.05	−18.47	14.52	0.0%	0.0%
Public Unit 3	0.51–0.80	60	0.253	0.0510	−0.0649	1.0000	4.64	−34.35	39.77	1.6%	1.6%
Public Unit 3	0.81–1.00	71	0.270	0.0087	0.0000	0.3811	5.31	−28.56	25.85	0.0%	0.0%
Public Unit 4	0.00–0.05	25	0.327	0.0351	−0.7500	1.0000	−0.87	−26.10	11.09	0.0%	0.0%
Public Unit 4	0.06–0.20	16	0.151	0.1772	−0.1721	1.0000	1.73	−23.43	35.37	0.0%	0.0%
Public Unit 4	0.21–0.80	18	0.292	−0.0090	−0.1318	0.0000	8.85	−8.77	35.58	0.0%	0.0%
Public Unit 4	0.81–1.00	17	0.231	−0.0039	−0.0428	0.0000	8.99	−3.76	35.53	5.6%	5.6%
Public Unit 5	0.00–0.05	68	0.573	0.0147	−0.5000	1.0000	0.02	−7.33	5.52	0.0%	0.0%
Public Unit 5	0.06–0.50	16	0.181	0.0156	−0.6784	0.5354	2.83	−6.55	14.20	0.0%	0.0%
Public Unit 5	0.51–0.80	14	0.111	0.1156	−0.2500	1.0000	6.73	1.07	22.54	0.0%	0.0%
Public Unit 5	0.81–1.00	10	0.135	−0.0750	−0.7500	0.0000	−0.73	−13.20	7.80	0.0%	0.0%
		11 451		0.0249	−1.0000	1.0000	1.73	−109.05	154.08	5.7%	9.3%

this study, values for missing observations were generated from two 5-year epochs (2001–2005 and 2011–2015) corresponding with the T1 and T2 inventory data described previously.

Raster maps of imputed plots were created for each epoch by assigning plots measured during the epoch to pixels based on proximity in feature space. Features were derived both from a digital elevation model as well as satellite imagery. The compound topographic index (CTI, Beven and Kirkby, 1979), used as a proxy relative landscape position (e.g. ridge top *vs* valley bottom) and correlated with mean soil moisture, was calculated based on the National Elevation Dataset (Gesch *et al.*, 2002). The six reflective bands for all Landsat 7 ETM+ (Collection 1) scenes collected during an epoch (i.e. between January 1 of the first year and December 31 of the fifth year) were transformed to the tasselled cap (TC) components of brightness, greenness and wetness (Huang *et al.*, 2002). A total of 2165 scenes were used for T1 (2001–2005), and 2158 scenes were used for T2 (2011–2015).

Harmonic regression, based on a third-order Fourier series (Wilson *et al.*, 2018), was employed to characterize the shape of the spectro-temporal profile for each pixel and TC component for each of the epochs. Using the same notation as Wilson *et al.* (2018), the time series of values for each pixel was approximated with a trigonometric polynomial, $\hat{Y}_t = a_0 + \sum_{j=1}^{m} a_j \cos(\frac{j2\pi t}{n}) + b_j \sin(\frac{j2\pi t}{n})$ where t is the scene timestamp (ephemeris days), n is the length of the cycle (365.2421891 ephemeris days) and m (= 3) is the order of the polynomial. Using the Collection 1 Level-1 pre-processing quality assessment band provided with each scene, all cloud, cloud shadow, snow/ice and dropped pixel values were removed from each series. The a_j and b_j coefficients of the Fourier series were estimated for each pixel using ordinary least squares regression.

An ecological ordination of tree species was conducted using a canonical correspondence analysis (CCA) model (ter Braak, 1986). The predictor variables used were CTI and the 21 (i.e. 3 TC components × 7 coefficients per series arising from the third-order ($m = 3$) polynomial) fitted Fourier series coefficients for each pixel at the location of the plots measured during the epoch. The response variables used were live tree aboveground biomass by species for trees located on the central subplot of the plots measured during the epoch. There were 13 353 plots measured in T1 (2001–2005) and 12 141 plots measured in T2 (2011–2015). All non-forest plots were removed from the CCA model, but were used in the subsequent and respective imputation for each epoch and assigned a value of 0 forest area and biomass density.

The fitted CCA model coefficients formed the feature space for the epoch for measuring proximity between each pixel and the set of measured plots (Ohmann and Gregory, 2002; Wilson *et al.*, 2012). Leave one out cross-validation was used to determine the value of k for the k-nearest neighbors algorithm that minimized mean squared error in the predictions. The optimal value was 55 for T1 and 30 for T2. After leaving out the nearest plot and for consistency across epochs, the set of the remaining nearest 30 plots, using the Manhattan distance metric, was assigned to each pixel respectively for each epoch. Although there are 30 nearest neighbors for each pixel, in this study only pixels corresponding with nonresponse plot locations were used.

Analysis

Plots are completely dropped from the estimation when entirely nonsampled and post-stratum variances often increase due to the decrease in sample size that arises from only using the plots where data were obtained (Scott *et al.*, 2005). Partially nonsampled plots are those where only a portion of the plot could be measured, which are accounted for in estimation by a stratum-level adjustment factor calculated as

$$\bar{p}_{hg} = \frac{n_{hg}}{\sum_{i=1}^{n_{hg}} a_{ihg}} \quad (1)$$

where $\bar{p}_{hg}$ = mean proportion of measured plot area for plots entirely or partially sampled in post-stratum h of estimation unit

g, and a_{ihg} = the sampled area proportion for plot i in post-stratum h of estimation unit g. The plot observations used in estimation are now formulated by

$$y_{ihg,t} = \bar{p}_{hg} y'_{ihg,t} \quad (2)$$

here $y_{ihg,t}$ = the observation for plot i in post-stratum h of estimation unit g at time t (= T1 or T2) adjusted for partial nonresponse and $y'_{ihg,t}$ = the original (unadjusted) observation for plot i in post-stratum h of estimation unit g at time t. For clarity, envision a post-stratum with 10 plots where half of one plot was unable to be accessed (partial nonresponse) and therefore the sampled area proportion (a_{ihg}) for that plot is 0.5 and a_{ihg} = 1.0 for the remaining 9 plots. In this case, $\bar{p}_{hg}$ = 10/9.5 = 1.053 (Equation (1)) and when used in Equation (2) provides an increase to all plot values to account for the unmeasured plot area.

Change can be estimated by either taking the difference between estimates from two points in time or directly using the observed change on each sample plot. The latter method is used in this study and thus a key component in change estimation is to pair the T1 and T2 observation for each plot such that the difference in the attribute can be calculated. This difference value is obtained from:

$$d_{ihg} = y_{ihg,T2} - y_{ihg,T1} \quad (3)$$

where $y_{ihg,T2}$ = the T2 observation of plot i in post-stratum h of estimation unit g, $y_{ihg,T1}$ = the T1 observation for plot i in post-stratum h of estimation unit g and d_{ihg} is the difference for plot i in post-stratum h of estimation unit g. The sample mean of plot difference observations d_{ihg} in post-stratum h of estimation unit g is then given by:

$$\bar{d}_{hg} = \sum_{i=1}^{n_{hg}} d_{ihg}/n_{hg} \quad (4)$$

This estimate is used to calculate total change estimates $\hat{T}$ and the associated variance $v(\hat{T})$ in estimation unit g for forest area and tree biomass attributes. The post-stratified estimate of $\hat{T}$ is given by

$$\hat{T}_g = A_g \sum_{hg=1}^{Hg} W_{hg} \bar{d}_{hg} \quad (5)$$

where A_g = total area of estimation unit g (ha), W_{hg} = weight for post-stratum h in estimation unit g and $hg = 1, \ldots, Hg$ denote the strata for estimation unit g.

The variance of the total, $v(\hat{T}_g)$, has been derived in various sampling texts, and is used in the FIA program without correction for a finite population (Scott *et al.*, 2005):

$$v\left(\hat{T}_g\right) = \frac{A_g^2}{n_g}\left[\sum_{i=hg}^{Hg} w_{hg} n_{hg} v\left(\bar{d}_{hg}\right) + \sum_{i=hg}^{Hg} \left(1 - w_{hg}\right) \frac{n_{hg}}{n_g} v\left(\bar{d}_{hg}\right)\right] \quad (6)$$

where n_g = the sample size for estimation unit g and $v(\bar{d}_{hg})$ = variance of the mean ($\bar{d}_{hg}$) for post-stratum h of estimation unit g:

$$v\left(\bar{d}_{hg}\right) = \frac{\sum_{i=1}^{n_{hg}}\left(d_{ihg} - \bar{d}_{hg}\right)^2}{n_{hg}\left(n_{hg} - 1\right)} \quad (7)$$

The standard error of $\hat{T}_g$ results from $se(\hat{T}_g) = \sqrt{v(\hat{T}_g)}$. The statewide estimates and variances are constructed via sums across the G (=17) estimation units:

$$\hat{T} = \sum_{g=1}^{G} \hat{T}_g \quad (8)$$

$$v\left(\hat{T}\right) = \sum_{g=1}^{G} v\left(\hat{T}_g\right) \quad (9)$$

The standard error of the estimated statewide total is calculated as:

$$se\left(\hat{T}\right) = \sqrt{v\left(\hat{T}\right)}. \quad (10)$$

In this study, imputed values were used in place of nonresponse plots for various nonresponse scenarios to examine potential bias in estimates and assess the assumption of nonresponse plot attributes being on average equal to the post-stratum mean. Initially, the realized sampling outcome was assessed where the overall nonresponse rate was ~5.7 per cent but varied widely by estimation unit and post-stratum (Table 1). The analysis was conducted via Monte Carlo (MC) simulation where the nonresponse plots were replaced with an observation randomly selected from the 30 nearest neighbors associated with each nonresponse plot. Estimation of forestland area and biomass/ha change then proceeded using these replaced values as plot observations. This process was repeated for 1000 iterations to capture a wide range of potential outcomes.

When imputed values are used as substitutes for missing observations, different sample-based estimates and associated variances will result. To differentiate the estimates, $\bar{d}_{hg}^{I}$ is calculated analogously to [4] but is based on both observed and imputed values such that the corresponding sample size is n_{hg}^{I} (where the I superscript indicates the inclusion of imputed values). As the primary variance calculations occur at the post-stratum level, the post-stratum variance composed of both random variation due to sampling and uncertainty in the imputation process is specified as:

$$v\left(\bar{d}_{hg}^{*}\right) = \bar{v}\left(\bar{d}_{hg}^{I}\right) + \left(1 + \frac{1}{m}\right) v\left(\bar{d}_{hg}^{MC}\right) \quad (11)$$

where $v(\bar{d}_{hg}^{I})$ is calculated analogously to [7] using both observed and imputed observations (n_{hg}^{I}) such that $\bar{v}(\bar{d}_{hg}^{I}) = \sum_{r=1}^{m} v(\bar{d}_{hg}^{I})/m$

is the average variance in post-stratum h for estimation unit g across the entire set of m (= 1000) simulation iterations, $v(\overline{d}_{hg}^{MC}) = \sum_{r=1}^{m}(\overline{d}_{hgr}^{I} - \overline{d}_{hg}^{m})^2/(m-1)$ where $\overline{d}_{hgr}^{I}$ is the mean difference based on both observed and imputed observations in post-stratum h for estimation unit g at simulation iteration r, and $\overline{d}_{hg}^{m} = \sum_{r=1}^{m}(\overline{d}_{hgr}^{I})/m$ is average difference in post-stratum h for estimation unit g across the entire set of $r = 1$ to m simulation iterations. The second term of [11] is the additional variance due to the random selection of nearest neighbor imputation values used in place of nonresponse plots (Rubin, 1987). Calculation of statistics for each estimation unit proceeded as follows:

$$\hat{T}_g^I = A_g \sum_{hg=1}^{Hg} W_{hg}\overline{d}_{hg}^{I} \tag{12}$$

$$v\left(\hat{T}_g^I\right) = \frac{A_g^2}{n_g^I}\left[\sum_{i=hg}^{Hg} W_{hg}n_{hg}^I v\left(\overline{d}_{hg}^{*}\right) + \sum_{i=hg}^{Hg}(1-W_{hg})\frac{n_{hg}^I}{n_g^I}v\left(\overline{d}_{hg}^{*}\right)\right] \tag{13}$$

with $n_g^I = \sum_{hg=1}^{Hg} n_{hg}^I$

$$se\left(\hat{T}_g^I\right) = \sqrt{v\left(\hat{T}_g^I\right)} \tag{14}$$

Although empirical bias due to nonresponse cannot be strictly assessed due to the true population values being unknown, it can be approximated under the assumption that the imputed values represent on average the actual values of the nonresponse plots. To simplify comparison of results, a root mean squared error (RMSE) statistic is calculated for the realized sample in each estimation unit g that accounts for both the variance and bias of the estimate:

$$RMSE_g = \sqrt{v\left(\hat{T}_g\right) + \left(\hat{T}_g^I - \hat{T}_g\right)^2} \tag{15}$$

To examine the assumption of nonresponse plot observations being on average equal to the post-stratum mean, at each iteration r the mean values of the response and nonresponse (imputed) observations were calculated by post-stratum at each time period:

$$\overline{y}_{hg.t(R)} = \sum_{i=1}^{n_{hg.t(R)}} y_{ihg.t(R)}/n_{hg.t(R)} \tag{16}$$

$$\overline{y}_{hg.t(NR)} = \sum_{i=1}^{n_{hg.t(NR)}} y_{ihg.t(NR)}/n_{hg.t(NR)} \tag{17}$$

where $\overline{y}_{hg.t(R)}$ is the mean value of the response plots in post-stratum h of estimation unit g at time t, $y_{ihg.t(R)}$ is the observed value for response plot i in post-stratum h of estimation unit g at time t and $n_{hg.t(R)}$ is the number of response plots in post-stratum h of estimation unit g at time t. The calculation of the mean for nonresponse plots follows analogously using imputed values for nonresponse observations as depicted by the (NR) subscript in [17]. To facilitate visual comparison and understanding of relationships between $\overline{y}_{hg.t(R)}$ and $\overline{y}_{hg.t(NR)}$, the differences were expressed relative to the response mean on an absolute value basis:

$$\Delta_{hg.t} = \left|\left(\overline{y}_{hg.t(NR)} - \overline{y}_{hg.t(R)}\right)/\overline{y}_{hg.t(R)}\right| \tag{18}$$

A more complex formulation is necessary to examine the differences on a change basis, where the mean change for both response and nonresponse plots are of interest.

$$\overline{y}_{hg.T2-T1(R)} = \overline{y}_{hg.T2(R)} - \overline{y}_{hg.T1(R)} \tag{19}$$

$$\overline{y}_{hg.T2-T1(NR)} = \overline{y}_{hg.T2(NR)} - \overline{y}_{hg.T1(NR)} \tag{20}$$

$$\Delta_{hg.T2-T1} = \left|\left(\overline{y}_{hg.T2-T1(NR)} - \overline{y}_{hg.T2-T1(R)}\right)/\overline{y}_{hg.T2-T1(R)}\right| \tag{21}$$

It was also of interest to examine outcomes where a higher rate of nonresponse was present.

An ~10 per cent overall nonresponse rate based on all sample plots (~20 per cent nonresponse rate for the subset of field visited plots) was simulated by selecting additional field measured plots beyond those already existing as nonresponse in the sample and treating them as though no observation was obtained. At each iteration of the simulation, plots chosen for field measurements were considered potential candidates for nonresponse and a proportional number were randomly chosen within each post-stratum to obtain approximately the desired 10 per cent overall nonresponse rate. The same analytical procedures as described above were used to analyse the data.

Results

Of interest are comparisons between the estimates arising from the realized sample and those obtained when imputed values were substituted as observations for the nonresponse plots. In comparison with methods that used imputed values ($\hat{T}_g^I$) to account for nonresponse, it is generally shown that smaller estimated changes in both forest area and biomass are realized when using only the observed values and assuming that nonresponse plots on average represent the post-stratum mean ($\hat{T}_g$) (Table 2). These larger $\hat{T}_g^I$ estimates also tend to have larger standard errors, $se(\hat{T}_g^I) > se(\hat{T}_g)$, because (1) it is commonly the case that larger means are accompanied by greater uncertainty, and (2) additional uncertainty arises from the imputation process. Under the assumption that $\hat{T}_g^I$ provides an empirically unbiased estimate, the error as expressed by $RMSE_g$ is greater than $se(\hat{T}_g^I)$ for some estimation units, but is smaller in others. Statewide, the results suggest that dropping the nonresponse plots and assuming their equivalence to the post-stratum mean produces estimates that are too small for forest area change (7.8 per cent) and total biomass change (5.0 per cent).

Simulation of an increased overall nonresponse rate of ~10 per cent showed several expected results. Increased amounts

Table 2 Estimates and uncertainty statistics for change in forest area and biomass density based on the realized 5.7% sample nonresponse ($\hat{T}_g$, $se(\hat{T}_g)$, $RMSE_g$) and on imputed value substitution for nonresponse plots ($\hat{T}_g^I$, $se(\hat{T}_g^I)$) by estimation unit.

	Forest area (ha)					Biomass (Gg = 1000 tonnes)				
Estimation unit	$\hat{T}_g$	$se(\hat{T}_g)$	$RMSE_g$	$\hat{T}_g^I$	$se(\hat{T}_g^I)$	$\hat{T}_g$	$se(\hat{T}_g)$	$RMSE_g$	$\hat{T}_g^I$	$se(\hat{T}_g^I)$
Chequamegon NF	1983.4	2745.7	2745.7	1983.4	2745.7	3301.1	442.1	442.1	3301.1	442.1
Water Unit 1	1732.3	1201.0	1201.0	1732.3	1201.0	243.9	157.5	157.5	243.9	157.5
Water Unit 2	776.9	468.7	468.7	776.9	468.7	182.3	82.1	82.1	182.3	82.1
Water Unit 3	−206.5	1535.4	1794.2	721.8	2182.3	115.1	108.0	117.4	161.0	152.1
Water Unit 4	1743.1	1225.4	1225.4	1743.1	1225.4	244.2	162.9	162.9	244.2	162.9
Water Unit 5	359.2	359.2	359.2	359.2	359.2	67.7	56.2	56.2	67.7	56.2
Nicolet NF	1642.1	1114.1	1114.1	1642.1	1114.1	3615.4	401.8	401.8	3615.4	401.8
Private Unit 1	52 698.6	8351.3	8983.9	56 010.2	9691.1	8148.1	1290.9	1389.8	8663.2	1341.5
Private Unit 2	56 454.7	10 059.0	10 784.1	52 567.2	11 865.4	8098.3	1356.4	2249.5	9892.8	1648.7
Private Unit 3	62 586.7	10 284.0	16 835.9	75 916.6	12 362.8	12 980.3	1309.4	1311.8	12 900.5	1555.5
Private Unit 4	53 337.3	9294.6	9532.1	55 451.8	11 275.1	10 033.6	1415.9	1455.8	9694.8	1542.9
Private Unit 5	80 687.1	9396.8	17 732.3	95 724.9	10 766.9	9628.6	935.1	1582.5	10 905.3	1092.1
Public Unit 1	7134.3	2679.9	2679.9	7134.3	2679.9	2415.5	630.9	630.9	2415.5	631.0
Public Unit 2	26 595.0	5215.9	5223.8	26 307.3	5263.1	1075.1	889.4	898.7	1204.0	908.8
Public Unit 3	11 767.6	3341.9	3346.8	11 948.8	3384.9	1731.8	549.4	550.0	1706.2	548.8
Public Unit 4	2888.1	2167.8	2168.2	2842.1	2160.9	954.0	234.0	234.0	952.9	251.7
Public Unit 5	1647.2	2560.0	2560.0	1647.2	2560.0	341.0	124.4	124.4	341.0	124.4
Statewide	363 827.1	22 860.8	38 262.4	394 509.3	26 551.7	63 176.0	3176.6	4592.0	66 492.0	3543.4

of variability were exhibited for all estimation units and uncertainty statistics: (1) $se(\hat{T}_g)$ were larger due to smaller realized sample sizes, (2) $RMSE_g$ were increased due to both increases in $se(\hat{T}_g)$ as well as larger empirical bias [15], and greater $se(\hat{T}_g^I)$ values resulted from the increased number of imputed values for nonresponse plots. Generally, in the private estimation units where nonresponse primarily occurs, the use of imputed values suggests mean change in both forest area and biomass density were larger on nonresponse plots compared with response plots. At the state level, the results show an underestimation for forest area change of 19.4 per cent and biomass density change of 12.5 per cent. Comparison with the results based on the actual 5.7 per cent nonresponse rate suggests increasing bias in estimates as the nonresponse rate increases.

Generally, the validity of the assumption that nonresponse plots are on average equal to the post-stratum mean depends on the mean proportion of forest area in a post-stratum (and correspondingly the biomass density present). Often, the unobserved plots are on forest land and thus the nonresponse mean proportion of forest is relatively large, e.g. >0.75. However, strata with low mean forest area proportions tend to have many nonforest plots (forest area proportion = 0) observed from remotely sensed imagery and not subject to nonresponse. Nonresponse plots are usually partially or completely forested such that the mean forest area proportion of the nonresponse plots tends to be much larger than the mean forest area proportion of the response plots in these strata (Figure 2a,b). With the exception of a few extreme values (not shown), the post-stratum means for both forest area and biomass density from nonresponse plots can be up to ∼15 times larger than means from response plots. The assumption of equivalence between response and nonresponse means seems to hold well for strata having forest area proportion of ∼0.7 or larger and biomass density greater than 25 tonnes. The trend is similar for mean change in forest area proportion and biomass density (Figure 2c,d), although even larger differences are attained (up to ∼25 times larger). The larger change on the nonresponse plots may in part be attributed to nonforest plots becoming both forested and nonresponse at T2 as evidenced by increasing forest area along with a higher nonresponse rate at T2 (401 plots at T1 *vs* 435 plots at T2). It should also be noted that some strata have very low nonresponse, such that the outcome may be driven by only one or two nonresponse plots in some cases.

Discussion

Based on the phenomenon uncovered by using imputed values for nonresponse plots and comparative results based on actual nonresponse (5.7 per cent) and simulated increased nonresponse (∼ 10 per cent), it seems clear that increases in empirical bias[1] will accrue as nonresponse rates increase. This is of concern for two reasons: (1) recent analyses have shown increasing nonresponse rates in the state of Wisconsin (Figure 3) as well as other states in the region, and (2) there is an implication that empirical bias

1 The term empirical bias is used to indicate bias in estimates that occurs due to nonrandom nonresponse in the sampling outcome. This is used to differentiate between the typical use of the term bias to indicate a theoretical property of an estimator.

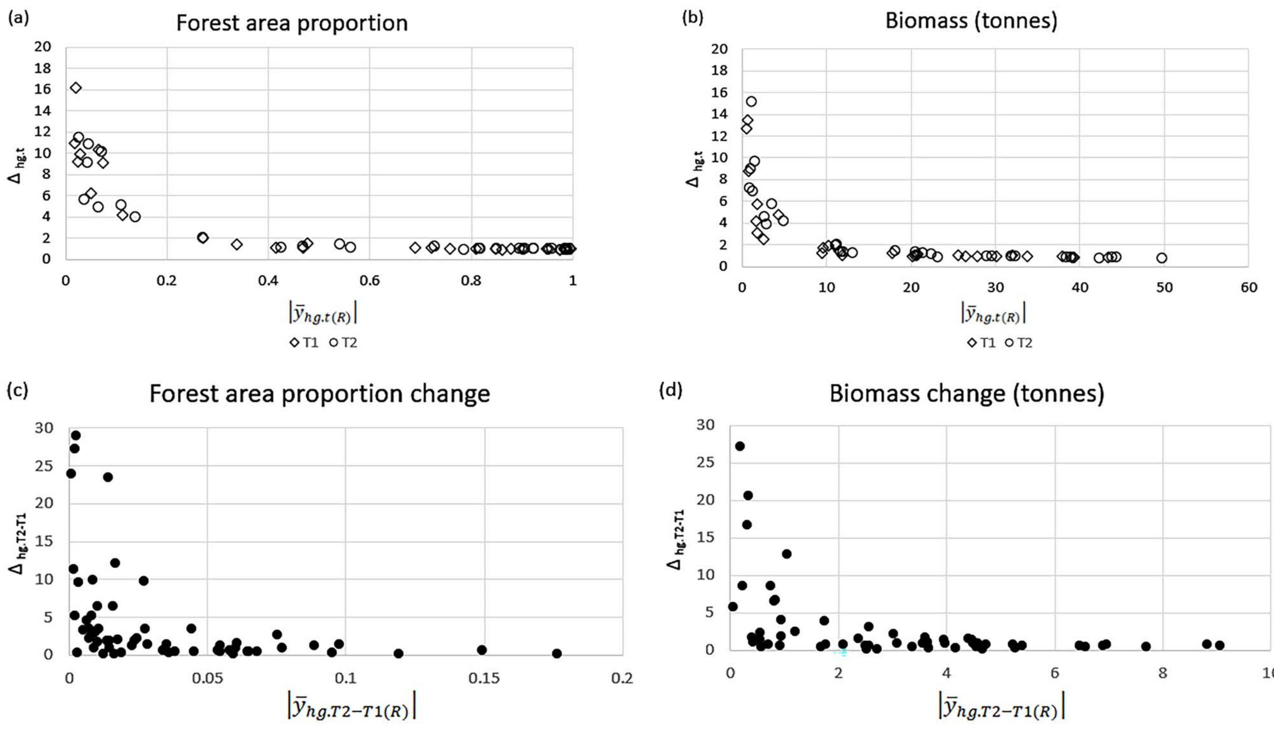

Figure 2 Scatterplots of absolute differences between response *vs* nonresponse means (Equation (18)) relative to the response means (Equation (16)) for T1 and T2 (a,b) and absolute difference in T2–T1 change means (Equation (21)) relative to the response change mean (Equation (19)) (c,d) by estimation unit and post-stratum using the 10 per cent nonresponse rate simulations. Not shown are several extreme values resulting from near-zero denominators in Equations (18) and (21) that were primarily in Water Unit 5.

magnitude may be even larger in areas exhibiting higher nonresponse rates than those realized in Wisconsin. A common axiom is that bias at two points in time will cancel when calculating the difference, however this implies the bias is constant. In this study case, nonresponse rates differ at each time point as well as increasing forest area in the population changes the sample units that may be subject to nonresponse, i.e. some nonforest plots at T1 become forest and nonresponse at T2. In areas where forest area was decreasing, there would be plots at T1 being both forest and nonresponse that become observed nonforest T2 and thus the nonresponse at T1 would cause underestimation of forest loss.

It seems clear the assumption that nonresponse plots, on average, are equal to the post-stratum mean based on response plots is sound only for strata primarily composed of forested plots (and corresponding nonzero biomass density). When the assumption is largely unsatisfied, strata are often composed of a mix of forest and nonforest plots. Strict control of the plot assignments to strata is limited because post-stratification is performed after the plot locations are selected. For example, when no forest area is present on a plot a field visit is not required and these 'office' plots having zero forest area and zero biomass density are not subject to nonresponse. This situation contributes to post-stratum heterogeneity where plots that have large forest area proportion and biomass density are mixed with the 'office' plots such that the response mean is relatively small (driven by the many zero-valued plots) and the nonresponse mean arises from plots having large forest/biomass values. As was shown in Figure 2, this can result in the nonresponse mean being up to ~25 times different than the response mean; with even more extreme values possible in certain cases where the response mean is very small. Consequently, the estimated means in these strata are empirically biased, which contributes to inaccurate population change totals in each estimation unit (Tables 2 and 3). Thus, the stratification model may deserve further study and restructuring, such as use of alternative or additional sources of auxiliary data and maximizing the temporal correlation between plot measurements and stratification source data to promote post-stratum homogeneity in terms of response values (minimize variance) and similar nonresponse probabilities (minimize bias).

The best remedy to the situation is to eliminate nonresponse entirely such that no assumptions are necessary. Given this outcome is unlikely in practice, practitioners should strive to develop strategies to minimize bias. Obviously, replacement of missing values due to nonresponse through the use of imputation can be a viable approach. An appealing aspect is that observations of actual conditions are used instead of e.g. model predictions, which provides protection from introduction of incongruous values into the data. As described for this study, some effort is necessary to identify appropriate imputation candidates that have similar characteristics to the nonresponse plot. Studies have shown that imputation can be successfully applied to forest inventory applications (Van Deusen, 1997; McRoberts, 2003), however it would be important to further explore potential issues related to effects of varying rates of nonresponse and corresponding reliance on imputed values. For

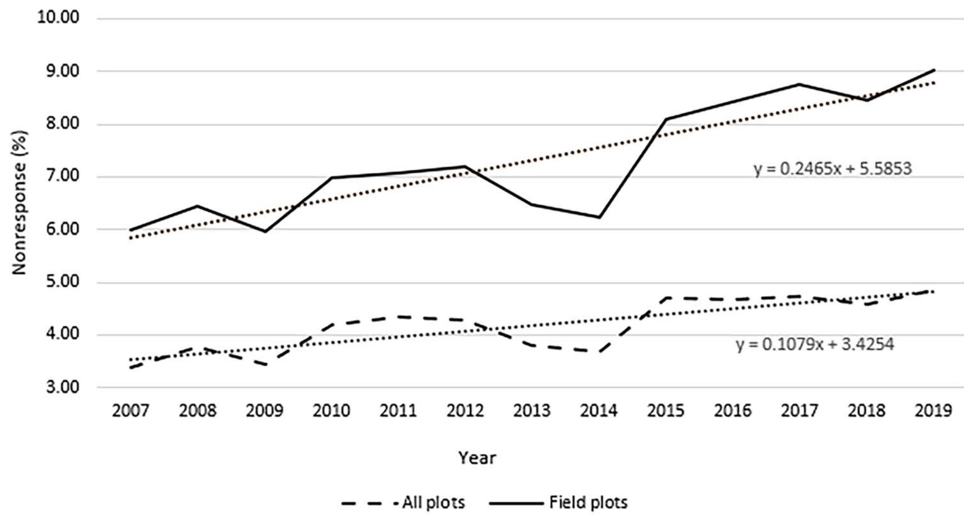

Figure 3 Nonresponse rates by year based on all sample plots and only the field-visit subset of plots for the state of Wisconsin 2007–2019.

Table 3 Estimates and uncertainty statistics for change in forest area and biomass density based on a simulated 10 per cent sample nonresponse ($\hat{T}_g$, $se(\hat{T}_g)$, $RMSE_g$) and on imputed value substitution for nonresponse plots ($\hat{T}^I_g$, $se(\hat{T}^I_g)$) by estimation unit.

	Forest area (ha)					Biomass (Gg = 1000 tonnes)				
Estimation unit	$\hat{T}_g$	$se(\hat{T}_g)$	$RMSE_g$	$\hat{T}^I_g$	$se(\hat{T}^I_g)$	$\hat{T}_g$	$se(\hat{T}_g)$	$RMSE_g$	$\hat{T}^I_g$	$se(\hat{T}^I_g)$
Chequamegon NF	2026.2	2783.5	2799.0	2320.3	3273.8	3247.4	440.0	441.1	3278.5	579.4
Water Unit 1	1532.6	1128.7	1171.8	1847.6	1653.6	208.3	144.5	150.2	249.1	205.5
Water Unit 2	665.2	435.3	437.7	710.8	1204.6	150.9	74.8	75.3	159.4	150.2
Water Unit 3	−108.0	1441.8	1804.7	977.4	2391.6	104.3	102.4	121.2	169.2	270.4
Water Unit 4	1212.2	1099.2	1249.1	1805.4	1602.3	91.1	55.4	112.4	188.9	316.9
Water Unit 5	46.2	74.7	271.6	307.3	1594.2	17.1	21.5	65.2	78.6	168.3
Nicolet NF	1660.1	1121.7	1130.0	1523.1	1639.9	3574.1	400.4	401.8	3540.4	530.8
Private Unit 1	44 855.0	8700.3	14 220.2	56 103.1	10 391.3	7485.0	1257.7	1710.0	8643.6	1510.2
Private Unit 2	51 109.2	9833.7	10 259.4	54 033.9	13 027.5	7635.6	1288.2	2696.5	10 004.4	1835.3
Private Unit 3	55 090.9	10 384.2	25 088.1	77 929.1	13 538.5	12 278.8	1267.8	1427.9	12 935.8	1717.4
Private Unit 4	40 269.4	9233.8	19 799.8	57 784.2	12 020.0	7768.7	1239.9	2378.0	9797.9	1697.9
Private Unit 5	76 384.1	9083.8	23 376.2	97 923.2	11 660.5	9302.5	856.1	1908.3	11 008.0	1274.6
Public Unit 1	7383.4	2728.6	2749.7	7043.4	3487.8	2398.0	626.3	626.4	2403.5	756.6
Public Unit 2	26 497.4	5245.3	5254.6	26 185.2	5996.8	1132.2	875.1	888.1	1283.1	1045.9
Public Unit 3	11 995.3	3376.9	3377.3	11 945.4	4138.5	1756.1	542.4	542.4	1752.7	641.3
Public Unit 4	2968.5	2161.8	2163.0	2896.9	2475.7	946.7	231.7	233.2	920.1	356.6
Public Unit 5	1586.8	2549.4	2597.6	2085.1	3061.8	338.2	123.4	126.8	367.3	245.1
Statewide	325 174.3	22 788.2	81 497.8	403 421.3	29 165.2	58 435.1	3005.7	8870.5	66 780.8	4031.7

example, understanding the effects of imputed observations on estimates and standard errors compared with known parameters from a synthetic population. To be formally adopted into a forest inventory production environment, an implementation framework would be needed to define the imputation method, prescribe estimation processes and specify a data storage structure.

Other measures may also be taken in an attempt to mitigate nonresponse bias. For example, the recognition that nonresponse tends to occur on privately owned lands prompted the estimation unit delineation shown in Table 1, i.e. there was an explicit effort to separate public and private ownerships to account for differing probabilities of nonresponse. Examination of the nonresponse rates in Table 1 suggest this was successfully accomplished, however the co-mingling of 'office' plots and field plots within strata still remains an issue. Patterson *et al.* (2012) suggest adoption of a specific estimation strategy when office and field plots are mixed within a post-stratum and a constant nonresponse rate is assumed for field plots (Särndal *et al.*, 1992, result 15.6.6). Roesch *et al.* (2012) propose two potential estimation strategies that decrease nonresponse bias in comparison with the standard post-stratified estimator described earlier. Goeking and Patterson (2013) describe stratification concepts similar to those used in this study, as well as separation of field and office plots into substrata to account for the differing nonresponse probabilities. With this approach, the post-stratum weights must be estimated and although the need to account for this uncertainty in variance estimation was acknowledged there was no variance estimator provided for this double sampling for post-stratification sample design. A potential solution to variance estimation when post-stratum weights are estimated in a post-stratified design was presented by Westfall *et al.* (2019); this specific scenario being a special case where the plot locations alone serve as the sample to estimate the weights. These solutions are posited for estimates of current status, such that some further consideration may be required for application to change estimation where response probabilities may differ at two points in time depending on office or field status, public *vs* private ownership, or possibly other factors.

Conclusion

In the context of this study, the primary consequence of nonresponse is underestimation of change in forest resources. Regardless of increasing or decreasing direction, estimates that do not reflect the full magnitude of population change make it difficult for data consumers to evaluate the effectiveness of current management and/or policy structures. Thus, it may appear that current conditions are being maintained when there is actually a decline or improvement occurring. The trade-off is the substantial cost-reduction attained through the use of office plots when observing nonforest conditions and only making field visits when forest area is present, which makes many NFIs financially viable. Yet the differential nonresponse between office and field plots is problematic for application of standard estimation approaches. The situation is more complex for change estimation that involves plot observation at two points in time where nonconstant response probabilities may exist and nonresponse at either time point results in no observation of change. Further complications arise due to forested plots in private-ownership (high-nonresponse rate) occurring within categories intended to isolate low nonresponse rates, i.e. non-private estimation units and low canopy cover strata primarily comprised of office plots. Although these issues have been studied in the context of current status estimates, further work is warranted to develop robust strategies and/or estimators that specifically address the issues in a change estimation context.

Acknowledgements

The authors are indebted to the Editor and three anonymous reviewers for their insightful suggestions that led to valuable improvements in the manuscript.

Conflict of interest statement

None declared.

Data Availability

The national forest inventory data from Wisconsin are publicly available (https://apps.fs.usda.gov/fia/datamart/datamart.html). The imputation data are available from the authors upon request.

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