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A spatial and temporal assessment of nonresponse in the national forest inventory of the U.S

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Abstract In nearly all national forest inventories (NFI), some sample plots are unable to be measured such that nonresponse may be an issue of concern. Thus, it is of particular interest to understand the phenomenon in terms of current status and temporal change in nonresponse rates and the associated spatial distribution on the landscape. In the NFI of the USA, denial of access permission on privately owned forest land and hazardous conditions has led to an overall nonresponse rate of 9.8% with some areas exceeding 20% of plots being inaccessible. Further, it was found that nearly 50% of the areas studied were exhibiting increasing rates of nonresponse over time. Comparisons between response and nonresponse plots via remote sensing characteristics suggested there may be systematic differences in some parts of the country, which may cause bias in the sample and resulting estimates. The findings indicate that improved communication strategies with private landowners are needed to reduce nonresponse rates. Due to the unlikelihood of eliminating nonresponse entirely, methods to mitigate potential nonresponse bias should be considered for incorporation into the estimation of population parameters.

Keywords Denied access · Ownership · Tasseled cap · Sample bias · Population estimates

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Introduction

Nonresponse is a problem faced by many survey practitioners and its treatment has been widely studied (Särndal & Lundström, 2005). In the context of a national forest inventory (NFI), nonresponse occurs in the form of inability to access field plot areas either partially or completely. The primary reasons for nonresponse include denial of access by the landowner, hazardous conditions that present a safety concern for field crews, and other miscellaneous reasons such as skipped visits or plot data file corruption. (Magnussen et al., 2018; Patterson et al., 2012). All of these causes contribute to nonresponse in the NFI of the USA, which has been conducted by the Forest Inventory and Analysis (FIA) program for nearly a century to provide long-term information on status and trends in forest resources (Hoover et al., 2022). As is done in many countries, FIA gains considerable efficiency via a priori determination of whether a sample plot may contain forest land or is entirely nonforest (Reams et al., 2005; Fattorini, 2015; Tomppo et al., 2010). Information for nonforest plots

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is obtained from remotely sensed imagery, whereas plots possibly having forest land are designated for field measurement. Thus, the nonresponse occurs only for those plots requiring field observation.

The treatment of nonresponse by FIA in a post-stratified estimation framework is described by Scott et al. (2005), i.e., completely nonresponse plots are dropped from the estimation and partially nonresponse plots are used to calculate an adjustment factor that is applied to all plots except complete nonresponse. The assumption is that partial nonresponse is a random process and the expected value of the attribute of interest for the area where partial nonresponse occurred is equal to the expected value of the attribute of interest for the area where measurements were obtained. It is acknowledged this assumption may not always be tenable (Bechtold & Scott, 2005). This key nonresponse assumption is implemented at the post-stratum level; thus, some effort is made to construct post-strata such that plots within have similar attributes and therefore response areas suitably characterize the locations where nonresponse occurred (Goeking & Patterson, 2013). An approach widely used is incorporating ownership information in the creation of the post-strata to separate public and private ownerships, for the primary purpose of accounting for denied access plots mostly occurring on privately owned land (Patterson et al., 2012). Also, there exists contiguous areas in which many of the plots are not accessed due to hazardous conditions (e.g., Okefenokee National Wildlife Refuge). These situations may be addressed by creating strata specific to the area. Other spatial data may also be used, such as canopy cover, forest type, topography, or other information that is highly correlated with characteristics of nonresponse areas (Gormanson et al., 2018).

Despite having methods to account for nonresponse in the estimation process, it remains an important issue for many NFI around the world (Birigazzi et al., 2019; Corona et al., 2014; Henry et al., 2021; Zeng et al., 2015). In the context of the U.S. NFI, there is no assurance the within-stratum assumption holds in all situations (Goeking & Patterson, 2013) and decreased sample sizes produce estimates with less precision. Thus, it is sensible to make efforts to minimize nonresponse to the extent possible. As such, the objective of this study is to better understand current nonresponse circumstances and potential impacts on estimation of forest resources from U.S. NFI data. This requires activities such as (1) spatiotemporal empirical assessments of nonresponse rates, and (2) examination of spectral information to evaluate potential differences between nonresponse and forested response plot characteristics.

Methods

Data

The data used in this study were collected by the FIA program while conducting the NFI of the USA in 48 states where the annual inventory system (McRoberts, 2005) is implemented statewide. FIA maintains a network of permanent sample plots, of which a portion are measured each year until all plots are completed in the inventory cycle that ranges from 5 to 10 years. This same plot network is remeasured in subsequent inventory cycles. The most recent data (~2019) for each state were used to assess current nonresponse rates, with the time series of yearly nonresponse rates providing the basis for temporal trend assessments. The time series length for each state varied depending on the beginning year of implementation of the annual inventory system. The primary response design is a 0.067 ha (0.166 acre) cluster plot, where each plot is composed of four circular subplots having 7.32 m (24 ft) radius with one subplot located at plot center and the remaining three subplots centered at azimuths 120, 240, and 360 degrees and distance of 36.58 m (120 ft) from plot center (Bechtold & Scott, 2005). In terms of quantifying nonresponse, FIA employs a mapped plot protocol which allows for specifying the proportion of the plot where no observations could be taken and the reason why. Complete nonresponse plots are those where all four subplots were inaccessible, whereas partial nonresponse occurs when only a portion of the plot was inaccessible. A secondary factor pertinent to the analyses is that an a priori determination of plots requiring a field visit is accomplished via examination of remotely sensed imagery. When there is high confidence that a plot has no forestland, zero values are assigned for forest attributes and the plot is not subject to nonresponse because no field visit is required.

Analysis

One of the most important statistics is the percent of plot areas that are affected by nonresponse. There are two basic ways to calculate and interpret these values: (1) assessing the percent of plots for which no information was obtained (only complete nonresponse plots), and (2) assessing the total percent of plot area that was unable to be observed (includes both complete and partial nonresponse plots). Generally, the percent nonresponse can be calculated, respectively, as:

$$\mathrm{CNR\%} = \frac{\sum_{i=1}^{n} p_{i(\mathrm{NR})}\delta_i}{n} \times 100 \tag{1}$$

$$\mathrm{TNR\%} = \frac{\sum_{i=1}^{n} p_{i(\mathrm{NR})}}{n} \times 100 \tag{2}$$

where CNR% is the percentage of plots having complete nonresponse, TNR% is the percentage of sample plot areas having either complete or partial nonresponse, $p_{i(\mathrm{NR})}$ is the proportion of plot i area that was nonresponse, δ_i is an indicator variable (=1 if plot i is complete nonresponse, 0 otherwise), and n is the total number of plots selected for field measurement. CNR% and TNR% were calculated by survey unit, which is usually a county or multi-county area (Fig. 1). To assess the current nonresponse rates on a nationally consistent basis in time, the plots included in the most recent evaluation (primarily 2019; Pugh et al., 2018, Ch. 2) were used for each survey unit.

Because FIA collects new data every year (McRoberts, 2005), it is also possible to calculate nonresponse rates over time and assess trends. The number of years for which these statistics are available depends on the length of time the annualized system has been used in the survey unit. Assessment of temporal trends within survey units was accomplished via simple linear regression where a rejection of the hypothesis that the estimated slope parameter was equal to zero at the 95% confidence level indicated statistically significant change in the nonresponse rate:

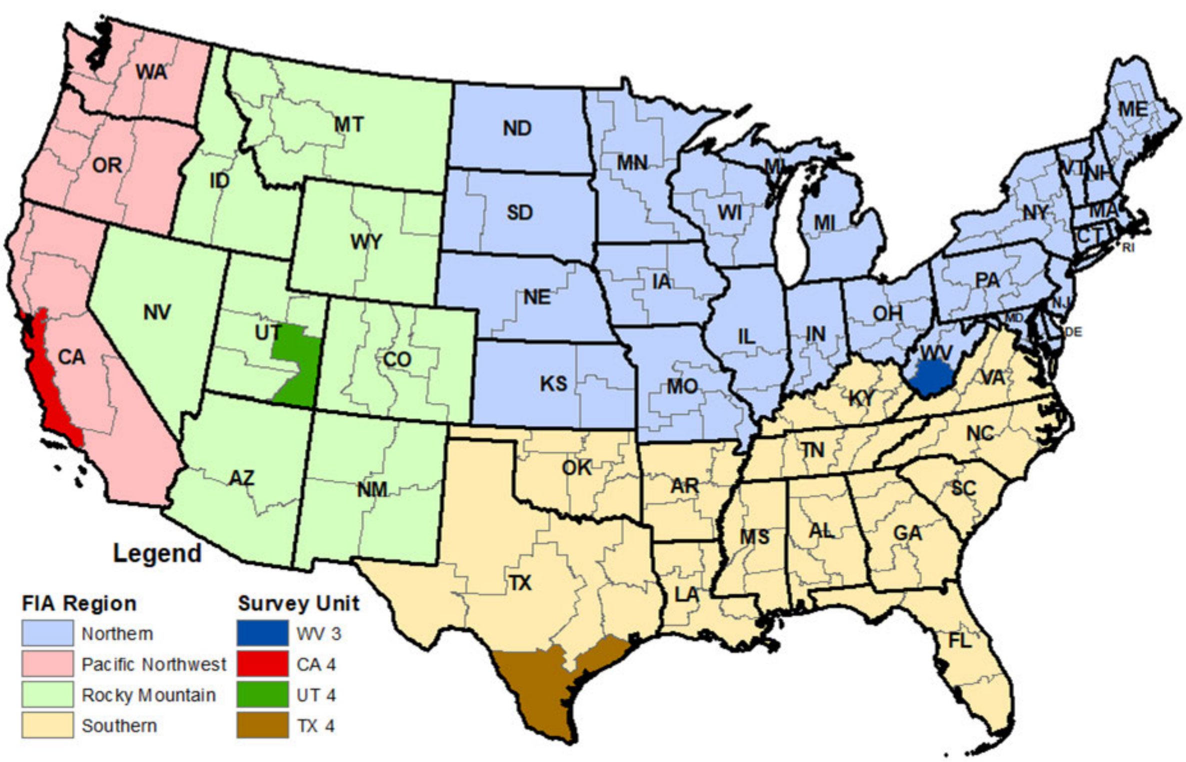

Fig. 1 US states and survey units therein by regional FIA unit (Northern, Southern, Pacific Northwest, Rocky Mountain). Survey units WV3, CA4, TX4, and UT4 are highlighted as areas in this study that received additional analysis via remote sensing

$$\mathrm{TNR}\%_{\mathrm{Year(SU)}} = \hat{\beta}_{0(\mathrm{SU})} + \hat{\beta}_{1(\mathrm{SU})}\mathrm{Year} + \varepsilon_{(\mathrm{SU})} \quad (3)$$

where $\mathrm{TNR}\%_{\mathrm{Year(SU)}}$ is the total nonresponse rate in survey unit SU for the survey year (Year), $\hat{\beta}_{0(\mathrm{SU})}$ and $\hat{\beta}_{1(\mathrm{SU})}$ are estimated intercept and slope parameters for survey unit SU, and $\varepsilon_{(\mathrm{SU})}$ is random residual error.

In addition to the slope value, it was also of interest to assess the strength of the relationship between time and nonresponse rate via the model R^2 statistic. For survey units with at least 10 years of data, an index of concern was created via multiplication of the slope coefficient against the model R^2 value where large outcomes indicate a strong likelihood of consistent increases in nonresponse over time:

$$C_{\mathrm{SU}} = \hat{\beta}_{1(\mathrm{SU})} R^2_{\mathrm{SU}} \quad (4)$$

where C_{SU} is the concern index value for survey unit SU and R^2_{SU} is the R^2 statistic for survey unit SU determined from model Eq. (3).

Another key analytical assessment is whether the nonresponse plots have similar characteristics to the plots where observations were obtained. The estimation procedures used by FIA proceed under the assumption that the stratum nonresponse plots are on average equal to the stratum mean calculated from observed plots (Scott et al., 2005). A deviation from this assumption would result in biased estimates. As actual values from nonresponse plots are unknown, an approximate comparison was conducted using remotely sensed data. Harmonic regression coefficients (similar to Wilson et al., 2018) derived from 3rd order Fourier series models fit to dense time series (2014–2018) of Landsat tasseled cap components (brightness, greenness, and wetness; Crist & Cicone, 1984; Kauth & Thomas, 1976) were used to test for statistical differences between forest and nonresponse plots. In this context, the time series harmonics allow capture of changing conditions near the time most of the FIA plots were measured, while use of tasseled cap data provides a well-calibrated, ecologically interpretable framework (Cohen & Goward, 2004) from which to evaluate potential differences in forest structure via wetness (Cohen & Spies, 1992; Collins & Woodcock, 1996), leaf area via greenness (Cohen et al., 2001; Hall et al., 1991), and vegetation cover via brightness (Li & Strahler, 1985; Cohen et al., 1995). Since structural differences could lead to bias in estimates, the analysis focuses on tasseled cap wetness as it has a predictable and well understood response to forest successional recovery after disturbance (e.g., see Fig. 3 in Cohen et al., 2010), is a strong indicator of maturity and structure in closed canopy forests (Cohen et al., 1995), and is relatively insensitive to variations in solar incidence caused by topography (Cohen & Spies, 1992; Cohen et al., 1995; Jin & Sader, 2005). In general, recent clear cuts and low-density forests (e.g., pinyon/juniper, oak woodlands) with large areas of bare soil have the lowest wetness values (−0.15 or less), while young-closed canopy stands ~ 5–20 years of age (depending on forest type) have the highest (−0.05 to 0.10). As a stand matures past 30 + years of age, there is a slight darkening of the spectral response due to more frequent gaps from advanced competition, canopy die back, and disturbance. In this older, more advanced structural state wetness becomes much less variable with mean values approaching 0.0 (e.g., see Landsat wetness trajectories for western conifers shown in Fig. 4, Schroeder et al., 2008). Based on this interpretation, wetness is used as a surrogate measure of stand structure (i.e., open canopy vs. closed canopy forests) and maturity that varies in well understood ways based on forest type and stand composition, allowing us to compare the forest sample and unmeasured nonresponse plots to determine if they are similar. We realize wetness only captures information about the upper canopy and can change based on factors other than age; however, given the similarity of forests in each survey unit, we feel it provides a well-calibrated, physically interpretable reference from which to identify and explain differences in forest characteristics between the two populations. To test this approach, four survey units with high nonresponse rates (CNR%) were chosen for evaluation (one from each FIA region: CA Unit 4, WV Unit 3, UT Unit 4, TX Unit 4). For each survey unit, Kolmogorov-Smirnoff (KS) tests (Hollander & Wolfe, 1999; Massey, 1951) are used to determine if the mean wetness values observed for the forest and nonresponse plots are from the same population. The non-parametric KS test uses the maximum distance between two cumulative distributions (referred to as *D*) to look for differences in shape, spread or median between the two groups. To minimize noise from other land uses, only FIA single condition forest plots are used for the KS tests.

Table 1 Complete (CNR%) and total (TNR%) nonresponse rates by type and FIA region

FIA region	Denied access		Hazardous		Other		All	
	CNR%	TNR%	CNR%	TNR%	CNR%	TNR%	CNR%	TNR%
Pacific NW	4.52%	4.74%	2.44%	3.71%	1.14%	1.18%	8.10%	9.63%
Rocky Mtn	7.36%	7.49%	1.21%	1.78%	1.23%	1.30%	9.79%	10.58%
Southern	7.15%	7.21%	0.50%	0.65%	0.00%	0.00%	7.66%	7.86%
Northern	10.73%	11.70%	0.34%	0.65%	0.06%	0.08%	11.13%	12.43%
All	7.79%	8.13%	0.85%	1.27%	0.40%	0.43%	9.04%	9.83%

Results

Current nonresponse rates

A national-scale analysis indicated the total rate of nonresponse (TNR%) due to denied access (8.1%), hazardous conditions (1.3%), and miscellaneous other reasons (0.4%) is about 9.8% (Table 1). The primary cause is complete nonresponse due to denied access (CNR% = 7.8%), with hazardous conditions and other reasons being relatively minor contributors. Complete nonresponse comprises 92.0% of all nonresponse and therefore partial nonresponse is of relatively minor significance. The Northern region stands out as having a larger denied access rate than the other regions, with Western regions (Rocky Mountain and Pacific NW) exhibiting the most hazardous conditions. However, there was considerable spatial variability as shown in unit-level analyses (Figs. 2 and 3). Survey units in the Northeastern and North Central, South Central, and Southwest regions tended to have the highest rates of denied access (> 20%), whereas the Southeastern and Northwestern regions had the lowest rates. Similarly, hazardous conditions were more

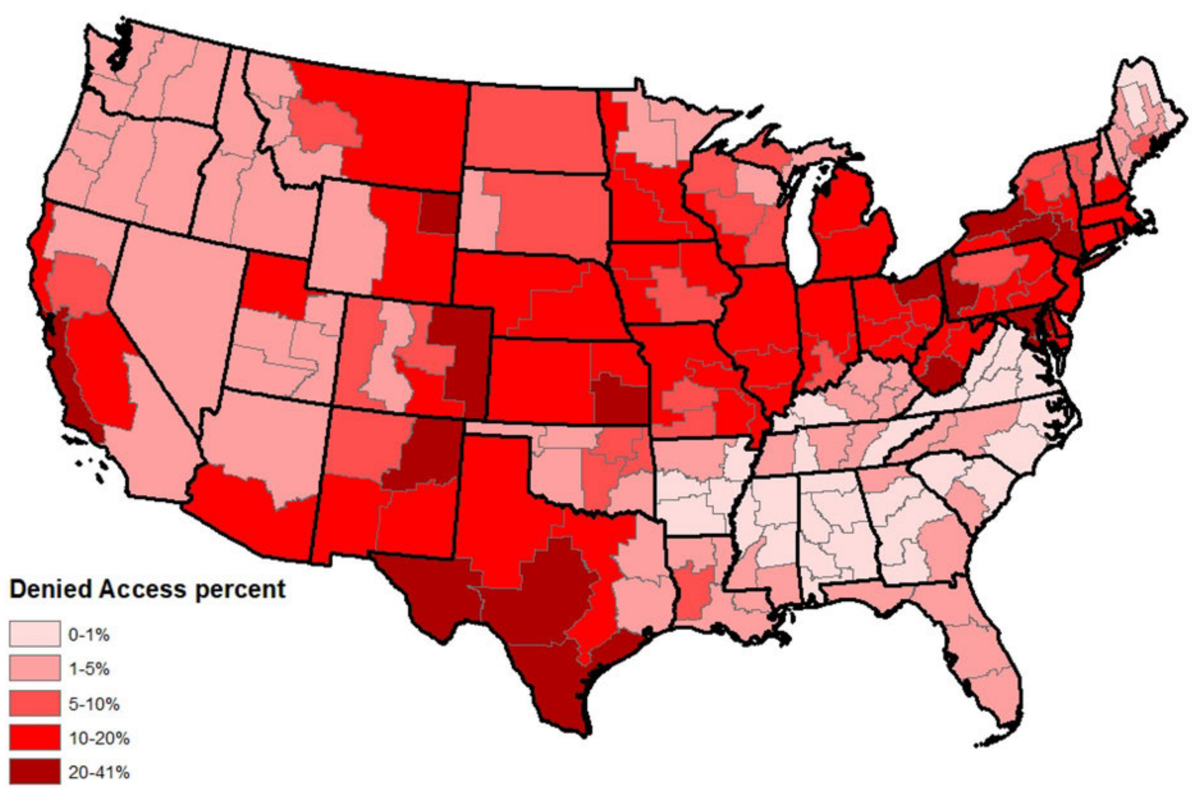

Fig. 2 Percentage of field plots that were complete nonresponse due to denied access permission by FIA survey unit

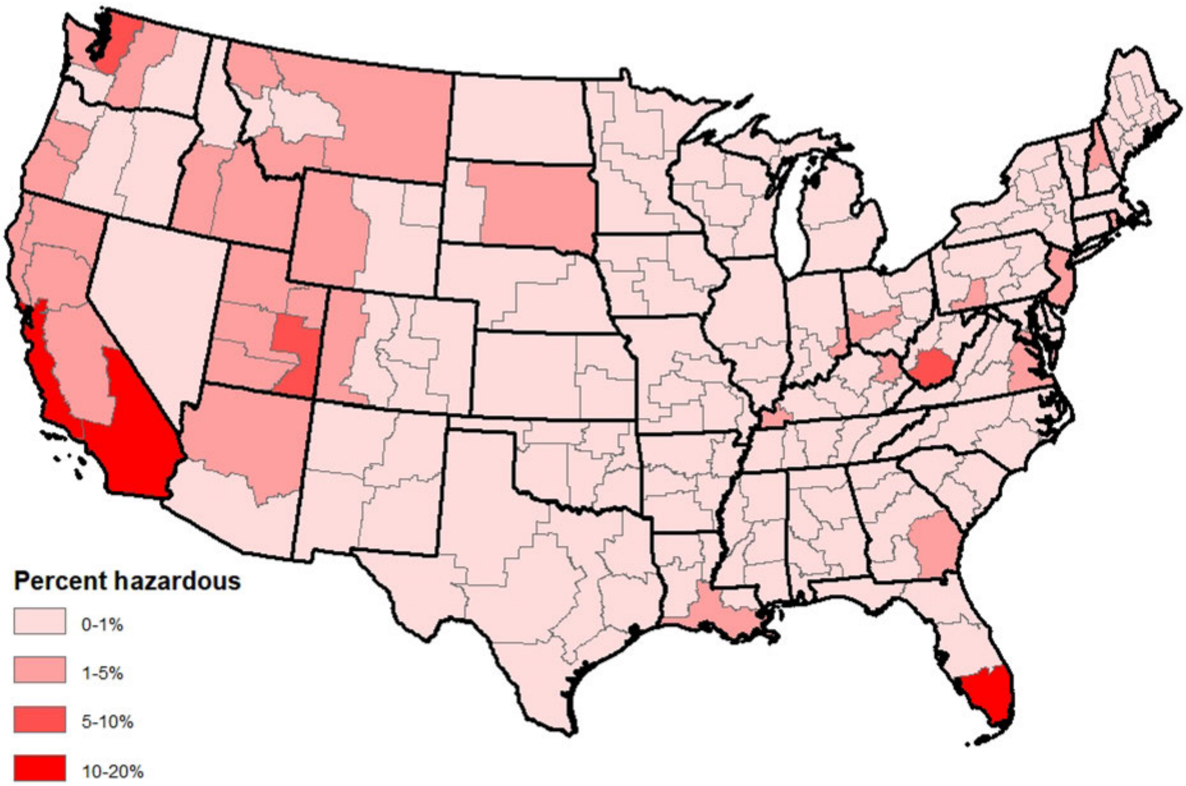

Fig. 3 Percentage of field plots that were complete nonresponse due to hazardous conditions by FIA survey unit

prevalent in the Western U.S. where phenomena such as wildfire, dangerous wildlife, and extreme terrain are more commonly encountered.

Partial nonresponse is relatively rare compared to complete nonresponse and is easily quantified in the context of Table 1 as TNR% minus CNR%. The presence and magnitude of partial nonresponse implies differing levels of landscape fragmentation in terms of land ownership and/or rapidly changing topography that makes only a portion of the plot accessible. Indeed, many of the survey units having high partial nonresponse rates occur in the Northeastern U.S. where the population density is high and many small privately owned forest holdings exist (Butler et al., 2021). Similarly, other areas exhibiting high partial nonresponse are survey units in the Western U.S. where steep mountainous terrain is often encountered that creates hazardous conditions on portions of plots. Nearly 33% of nonresponse due to hazardous conditions occurs as partial nonresponse (Table 1).

Ultimately, the total amount of nonresponse is of particular interest regardless of cause and complete or partial configuration (Fig. 4). The Southern FIA region stands out as having low nonresponse rates for much of the region, the exception being in western/southern portions of Texas (TX). Much of the field data collection in the region is done by employees of individual states, which may reduce denied access nonresponse relative to use of federal U.S. Forest Service personnel. A number of survey units in the northeastern portion of the Northern region exhibit nonresponse rates exceeding 10%. The relatively high population density in this part of the USA may be a contributing factor, although further investigation would be needed to better understand the phenomenon. The largest nonresponse rates in the RMRS region occur in the eastern portions where at least some of the high rates occur in areas having only small amounts of forestland and few plots requiring a field visit. High rates coupled with few forested plots result in very little information being obtained on forest characteristics in these areas. In the Pacific NW region, the state of California (CA) generally has large nonresponse rates throughout with particular

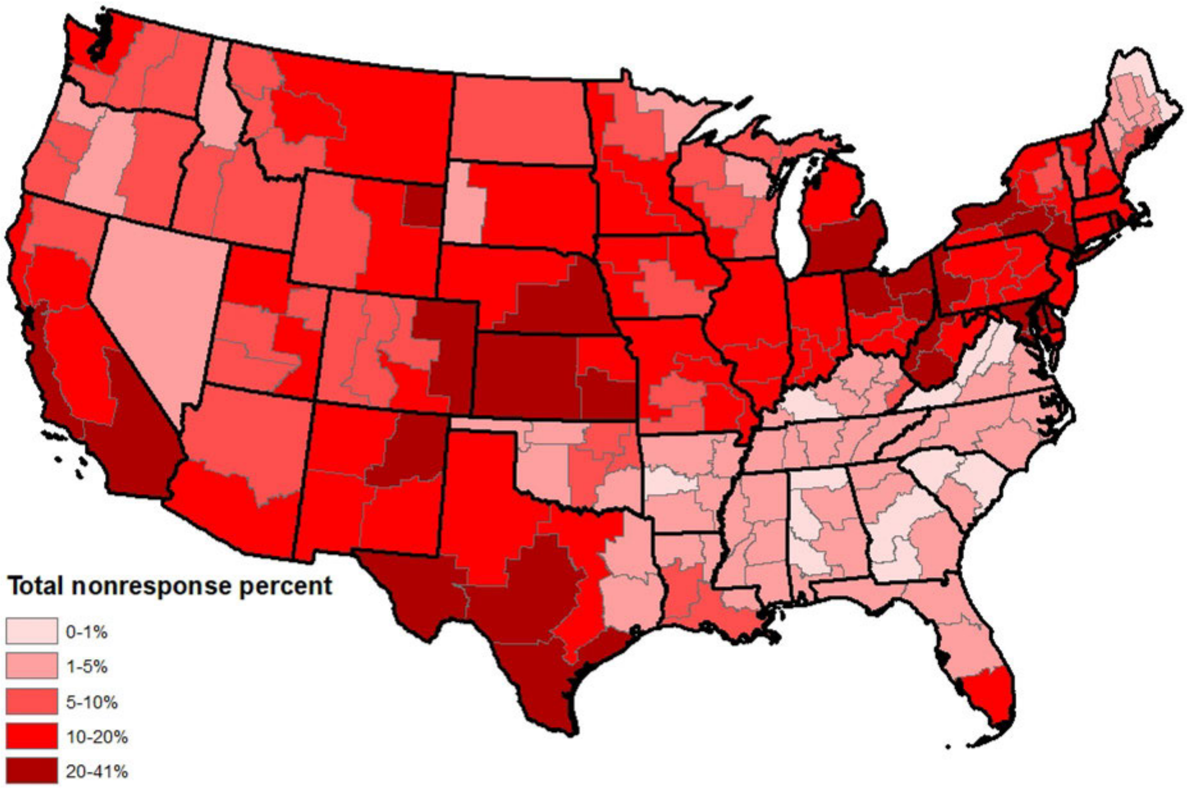

Fig. 4 Total nonresponse (TNR%) as a percentage of field plots by FIA survey unit

emphasis on many of the coastal survey units (also of high population density).

Temporal nonresponse trends

Although quantification of current nonresponse rates is valuable, it is also important to understand changes in nonresponse rates over time that may result from numerous and possibly interrelated factors. Of particular concern are increasing rates that have the potential to further degrade inventory results due to nonresponse bias and/or decreasing precision of estimates. In the temporal analyses, the assessment of statistically significant change via simple linear regression produced a wide range of results. At the 95% confidence level, statistically significant slope coefficients were all positively valued (increasing nonresponse over time). Across the country, 92 of 194 (47.4%) survey units exhibited a significant slope coefficient (Table 2). The NRS and RMRS regions had about 60% of the survey units showing increased levels of nonresponse, whereas approximately 30% of survey units in the SRS and PNW regions had significantly more nonresponse over time. In addition to statistical significance, the value of the slope coefficient is important as an indicator of rate of increase. Although increasing nonresponse is always a concern, areas having relatively large slope coefficients are the most troubling and may warrant further attention (Fig. 5). Identification of survey units having both large slope values in combination with strong correlation between nonresponse and

Table 2 Number and percent of regression results by FIA region using model Eq. (3) where the $\widehat{\beta}_{1(SU)}$ parameter was statistically significant at the 95% confidence level

FIA region	Significant models	% significant
Northern	49	59.8%
Southern	20	29.4%
Rocky Mtn	18	64.3%
Pacific NW	5	31.3%
Total	92	47.4%

time via the concern index C_{SU} from (Eq. (4)) reinforced earlier results suggesting the Northeastern U.S. is an area of concern (Table 3). These results also highlight two survey units in Wyoming (WY) where there is strong evidence that nonresponse rates are increasing at over 1% per year.

Tasseled cap wetness comparisons

Apart from reduced sample sizes, concern regarding nonresponse is warranted when the characteristics of nonresponse plots differ from those where a response was obtained. The Kolmogorov-Smirnoff (KS) tests based on the Landsat tasseled cap harmonics showed statistically significant differences in tasseled cap wetness values for three of the four survey units examined (Table 4). Survey unit WV3 stood out as the exception where no differences in wetness were found, although we note the p-value for TX4 is only weakly significant ($p = 0.048$). To help visualize the spectral differences, the cumulative distributions and kernel density estimates for the forest and nonresponse plots are presented in Fig. 6.

Table 3 Top 10 survey units with largest C_{SU} values from Eq. (4) where $\hat{\beta}_{1(SU)}$ and R^2_{SU} are the respective regression slope coefficient and R^2 statistic for survey unit SU determined from model Eq. (3)

State	Survey unit	Unit location	$\hat{\beta}_{1(SU)}$	R^2_{SU}	C_{SU}
MD	2	N. Central	2.291	0.690	1.581
PA	5	Western	1.707	0.823	1.405
MD	3	Southern	2.490	0.517	1.287
NY	2	N. Western	1.677	0.761	1.276
OH	4	N. Eastern	1.685	0.752	1.267
PA	0	S. Central	1.511	0.775	1.172
WV	3	Southern	1.881	0.581	1.092
WY	3	S. Eastern	1.501	0.693	1.040
WY	2	N. Eastern	1.201	0.860	1.033
OH	6	N, Western	1.632	0.595	0.971

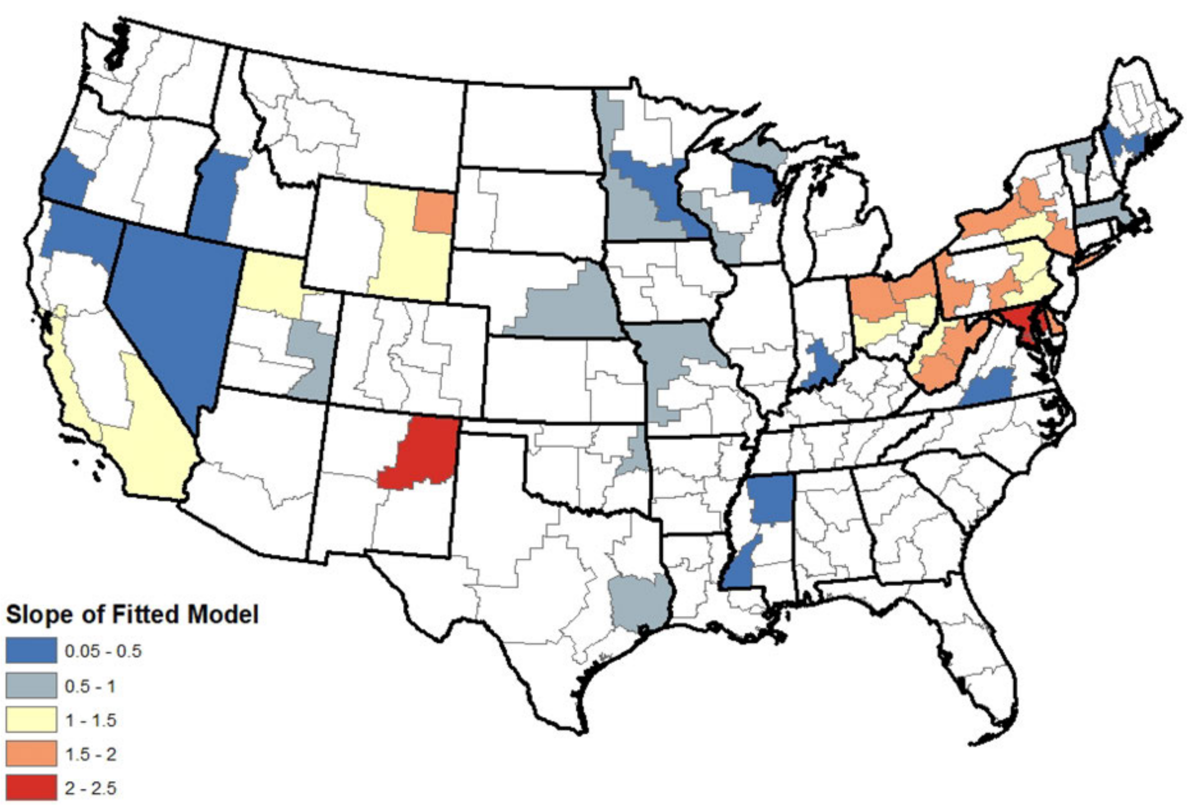

Fig. 5 Map of statistically significant (95% confidence level) regression slope coefficients ($\hat{\beta}_{1(SU)}$) for survey units where $R^2 \geq 0.40$

Table 4 Results of Kolmogorov-Smirnoff (KS) tests for differences between forested and nonresponse distributions of tasseled cap wetness values. Statistically significant differences at the 95% confidence level are indicated by *p*-values less than 0.05 (bold). The number of plots in each distribution are shown by survey unit. Note, FIA plots with multiple land use conditions are not included in this analysis; thus, nonresponse rates cannot be derived from the numbers in this table. *D* represents the maximum distance between the two groups' cumulative distributions (shown in Fig. 6, top row)

Survey unit	Forest plots	Nonresponse plots	*D*	*p*-value
CA4	151	201	0.064	**0.000**
TX4	701	1351	0.271	**0.048**
UT4	454	86	0.061	**0.001**
WV3	331	244	0.227	0.678

Statistically significant differences at the 95% confidence level are indicated by p-values less than 0.05 (bold)

Discussion

Nonresponse rates and trends

The results have shown that substantial variation in rates of nonresponse exists both spatially and temporally within the NFI of the USA. In some areas, high nonresponse rates are likely causing a nontrivial loss in precision for estimates of forest resource attributes. For example, there is an approximate 12% increase in the standard error of the estimate when CNR% = 20%. Further, when nonresponse does not occur randomly, there may be bias in the sample as certain population attributes are potentially underrepresented and resulting estimates from the realized sample may be misleading. The concern is escalated in areas experiencing marked increases in nonresponse (Table 3, Fig. 5), as there is a possibility that shifting estimates of current status might suggest changes in forest resources that are not actually occurring. Although not specifically addressed in this study, estimates of change are even more susceptible to potential sample bias and loss of precision due to nonresponse. Change estimates rely on observations at two points in time and thus plots lacking one or both observations are not included. Given that the set of nonresponse plots can differ at each time point, nonresponse rates for change estimates are higher than those applicable to estimates of current status.

Spectral analysis of nonresponse

High nonresponse rates elevate concern as to whether assumptions related to ensuring sample unbiasedness for estimation of stratum means are being upheld. Comparisons of tasseled cap wetness values suggest that in some areas of the country, forest structure may be different on sampled plots than on nonresponse plots (Table 4, Fig. 6). For example, the kernel density estimates in Fig. 6 show that in CA4 and UT4, wetness distributions for forest and nonresponse plots are noticeably shifted in different directions indicating potential differences in forest structure, whereas in TX4 and WV3, there was very little to no difference in forest structure between the two groups. Given the high (and increasing) prevalence of denied access in the FIA inventory, it is likely some of the forest structural differences inferred from Landsat wetness in CA4 and UT4 are the result of broadscale differences in forest density and composition resulting from different landowners. Because landowners influence forest composition and structure via management and conservation (e.g., Cohen et al., 1995 found a higher proportion of older forest on public lands), as well as impact the probability of denied access (e.g., Goeking & Patterson, 2013 used ownership to improve stratification of FIA estimates in New Mexico), it is important that FIA sample the full landscape to ensure its estimates remain unbiased. Although limited to resolving upper canopy dynamics wetness did provide an interpretable, wall-to-wall source of information from which to better understand the types of forests that may be under sampled due to nonresponse. Here, a detailed analysis of the wetness distributions revealed that in CA4, denied access on private lands resulted in under sampling of blue oak woodlands (which are sparser, more open grown deciduous forests with wetness values falling near the left peak in the forest distribution shown in Fig. 6), while hazardous plots on public land (i.e., Los Padres National Forest) contributed to under sampling of denser, closed canopy oak and pine forests (which have higher wetness values falling near the right peak in the forest distribution in Fig. 6). On the other hand, in UT4, the forest distribution is skewed toward drier, less structurally complex forest conditions (with peak wetness around − 0.15) due to the large number of plots falling in pinyon/juniper

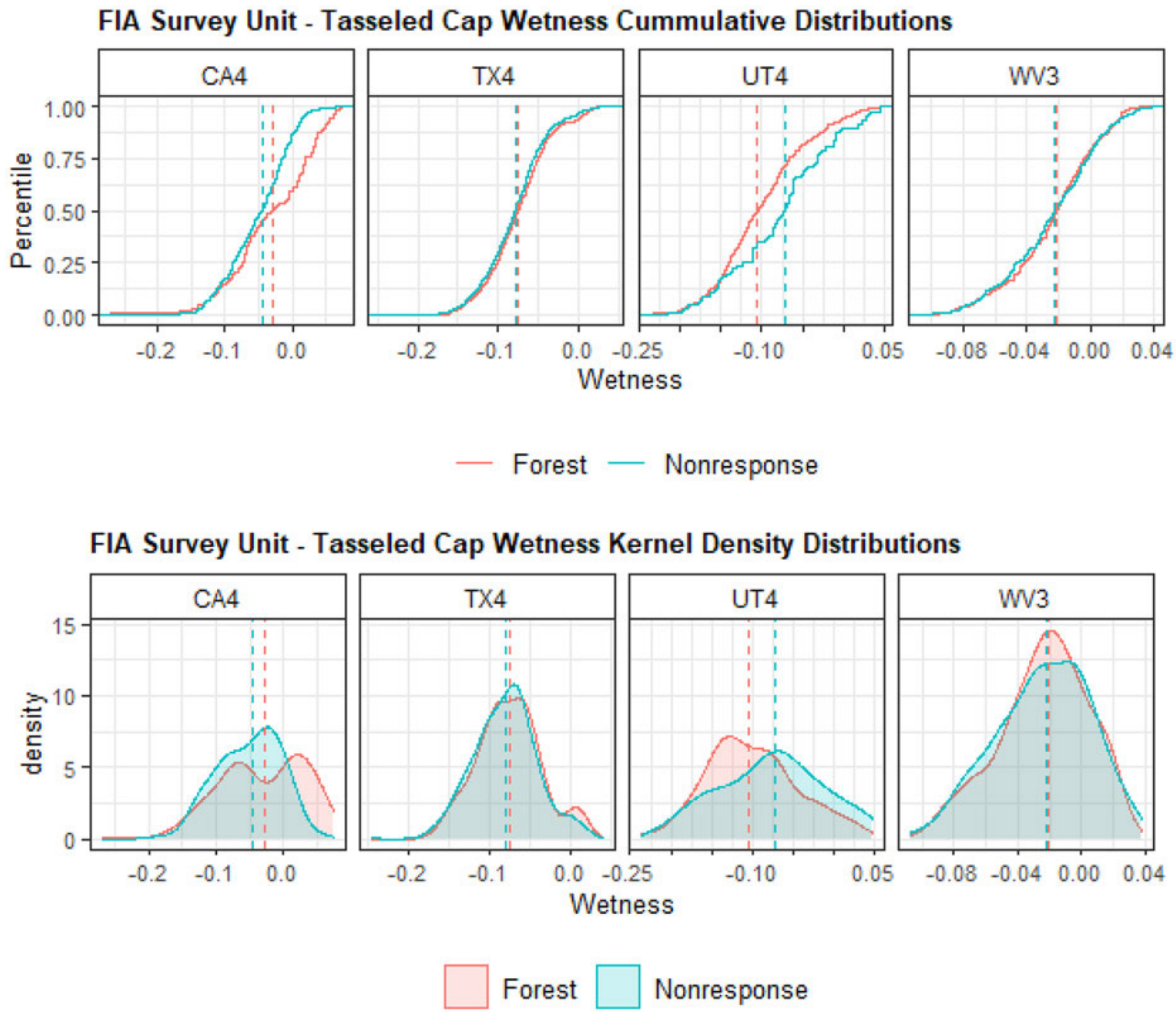

Fig. 6 Cumulative frequency distributions (top row) and kernel density estimates (bottom row) of tasseled cap wetness for the forest and nonresponse plots. Dashed vertical lines represent the median wetness values for each group

forest compared to the nonresponse plots, which were mostly in remote, high elevation areas where denser stands of oak, aspen, and pine resulted in higher wetness values (near the forest median $> = -0.10$).

From a statistical perspective, we recognize spectral differences should be viewed with caution, especially considering the effect sample size has on the significance of the KS tests (e.g., larger sample sizes have increased statistical power, Razali & Wah, 2011). For example, in TX4, the wetness distributions for the forest and nonresponse plots are very similar (Fig. 6); however, the KS test still returned a weakly significant *p*-value (Table 4) due to the fact TX4 has 3–4 times as many plots as the other survey units, and therefore has a much lower minimal bound for finding a significant relationship. Despite this limitation, our results suggest that spectrally based nonparametric distribution tests may be a useful way of automating identification of other survey units where potential bias between forest and nonresponse plots warrants closer inspection. Because not all field visited plots end up having forest, there is a strong likelihood that several nonresponse plots are actually nonforest; thus, a stricter minimum effect size (<0.05) would help minimize detection of minor structural differences in areas like TX4, which are dominated by low density forest. Based on the KS tests in CA4 and UT4 (Table 2), a higher cutoff around 0.001 would likely be a good lower bound for identifying other survey units with significant potential for nonresponse bias.

Differences in wetness found here are at the survey unit-level as opposed to the stratum-level, which further breakdown the survey units into finer resolution classes often based on various combinations of NLCD land cover and tree canopy cover data (Coulston et al., 2012). The analysis here suggests formally testing statistical differences in wetness at the stratum-level will be challenging due to a lack of sufficient sample sizes. Based on initial exploration of the NLCD land cover data, it was found that most of the forest classes (i.e., deciduous, mixed, and evergreen) had sufficient sample sizes but many of the other classes did not (results not shown). The NLCD forest classes showed similar patterns of significant wetness differences, as well as offered a refined look at the distributional differences between groups, which aided the interpretation of the broader scale patterns found at the survey unit-level. Despite various sources of uncertainty, the evidence presented highlights potential under sampling of denser, closed canopy forest, as well as habitats which are experiencing effects from climate change (e.g., oak woodlands in CA4, see Dwomoh et al., 2021); thus, there is a need for more in-depth analysis of sample bias and its potential effects on FIA estimates. Although our use of multispectral remote sensing data focused solely on tasseled cap wetness, there are many other vegetation indices and time series metrics that could be used to further investigate differences in forest characteristics of the FIA sample. Future efforts will focus on analyzing wetness differences at finer scales (e.g., using land cover, tree canopy and disturbance maps) and researching new stratification techniques to correct for missing observations (Goeking & Patterson, 2013).

Nonresponse mitigation

Various initiatives aimed at reducing nonresponse have met with little progress, such that the issue remains a concern to the FIA program. Initial research into the problem and potential solutions were reported by Patterson et al. (2012), which led to increased emphasis on improving post-stratification efforts to better contend with potential sample bias issues in estimation and maintaining the policy to preserve existing plot locations regardless of nonresponse frequency. At the national level, current data suggests about 7.7% of field plots change status from inaccessible to accessible (or vice versa) at time of remeasurement. Further, less than 1% of plots were consistently denied access for three successive measurements. However, mostly due to differences in inventory cycle lengths, not all plots in the FIA inventory have been subjected to three measurements and this statistic deserves continued attention in future years. These outcomes suggest a plot replacement effort would be largely ineffective and FIA should not alter the original sample plot selection.

Given the results of this study, additional effort to lessen nonresponse rates would benefit NFIs. Hazardous situations are often beyond the control of inventory practitioners, but generally comprise a small amount of the total nonresponse. Therefore, improving access permission to privately owned lands is logically the most impactful pursuit. Private landownership is the primary driver of nonresponse in the FIA inventory and the spatial patterns in Figs. 2 and 4 suggest high population density may be a contributing factor. However, the lowest nonresponse rates are in the southeastern U.S. despite having some of the most densely populated areas in the country. This circumstance suggests other factors are also influencing nonresponse patterns. One theory is that southeastern U.S. private forest landowners tend to have larger holdings that are more actively managed for economic gain than in other areas of the country (Wear, 1996) so individual landowners may be more inclined to grant access to their lands because they also rely on FIA data to help them improve their investment. In other areas of the country where forests are less productive and holdings tend to be smaller, many private landowners have less to gain from participating because they have fewer management objectives and economic interests at stake. There is some evidence that suggests a lack of awareness of the national forest inventory in conjunction with a general distrust of federal government agencies results in landowners denying access to their property (Gao et al., 2020; De'Arman, 2020; Shindler et al., 2009). Landowners may also have concerns about incurring liability by allowing crews to occupy their property. These hypotheses illustrate that effective nonresponse mitigation will likely require better understanding of landowner attitudes and concerns such that more effective communication strategies can be developed to increase access to plot locations.

Despite potential reductions in nonresponse due more effective communications, almost surely some nonresponse will always be present. In addition to various potential stratum-level assumptions (Domke et al., 2014), other estimation-based approaches have been presented, such as nonresponse calibration weighting (Fattorini et al., 2013) and formation of response homogeneity groups (Goeking & Patterson, 2013; Westfall, 2022). Replacement of missing values using imputation methods has also been suggested as a method to overcome nonresponse problems (Magnussen et al., 2017; McRoberts, 2001, 2003). The most appropriate methods for reducing nonresponse rates and accounting for nonresponse to avoid bias in estimation should be assessed in the context of circumstances specific to a given NFI.

Conclusion

In most NFIs, nonresponse occurs in several forms and can be spatially and temporally dynamic. In the NFI of the USA, almost 10% of field plot areas were inaccessible due primarily to denial of access permission on privately owned forest lands. However, substantial spatial variability was encountered which suggests an array of factors may contribute to the underlying causes of nonresponse and the inherent difficulties faced by inventory practitioners to ameliorate the issue.

Although only four survey units were analyzed to assess potential nonresponse bias, the significant differences found in the tasseled cap wetness values of forest and nonresponse plots indicated there may be considerable dissimilarities in forest structure between these two populations in certain areas of the country that could lead to bias in forest resource estimates. Further, substantial temporal increases in nonresponse were also identified in many of the same areas such that nonresponse is a continual and likely growing concern that warrants further attention.

Ultimately, NFI specialists are faced with the task of trying to reduce nonresponse while also recognizing that eliminating all nonresponse is not a practical expectation. Because denied access is the primary issue for the U.S. FIA program, meaningful reductions in nonresponse will likely require investments in social science research to understand private landowners underlying concerns regarding admission to their land. Broader use of multispectral satellite data and existing spatial data sets can also help identify areas where significant structural differences exist between sampled and unsampled forest, facilitating further study into the causes and potential drivers of nonresponse and informing mitigation efforts so resources are targeted in areas of highest concern. Subsequently, more sophisticated communication strategies may lead to improvements in positive landowner responses. A review of current estimation methods is also warranted to evaluate the effectiveness of underlying assumptions and procedures to minimize sample bias that nonresponse may impart.

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Data availability The NFI data analyzed during the current study are available in the FIA database, [https://apps.fs.usda.gov/fia/datamart/datamart.html].

Declarations

Competing interests The authors declare no competing interests.

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