Harvested area did not increase abruptly – How an inconsistency in satellite-based mapping led to erroneous conclusions

Johannes Breidenbach[1], David Ellison[2-4], Hans Petersson[2], Kari T. Korhonen[5], Helena M. Henttonen[5], Jörgen Wallerman[2], Jonas Fridman[2], Terje Gobakken[6], Rasmus Astrup[1], Erik Næsset [6]

[1] Department of Forestry and Forest Resources, Norwegian Institute of Bioeconomy Research (NIBIO), Ås, Norway. Contact: [first_name].[last_name]@nibio.no

[2] Department of Forest Resource Management, Swedish University of Agricultural Sciences, Umeå, Sweden

[3] Land Systems and Sustainable Land Management Unit, Institute of Geography, University of Bern, Bern, Switzerland

[4] Ellison Consulting, Baar, Switzerland

[5] Natural Resources Institute Finland (Luke), Helsinki, Finland

[6] Faculty of Environmental Sciences and Natural Resource Management, Norwegian University of Life Sciences, Ås, Norway

Using satellite-based maps, Ceccherini et al.[1] report abruptly increasing harvested area estimates in several EU26-countries beginning in 2015. They identify Finland and Sweden as countries with the largest harvest increases and the biggest potential effect on the EU's climate policy strategy. Using more than 120,000 field reference observations to analyze the satellite-based map employed by Ceccherini et al.[1] we found that the map's ability to detect harvested areas abruptly increases after 2015. While the abrupt detected increase in harvest is merely an artifact, Ceccherini et al.[1] interpret this difference as an indicator of increasing intensity in forest management and harvesting practice.

Ceccherini et al. [1] use satellite-based Global Forest Change (GFC) [2] data to estimate the yearly harvest area in each of the EU26-states over the period 2004 to 2018. They report abruptly increasing harvested area estimates in several countries beginning in 2015 and claim this will impede the EU's forest-related climate-change mitigation strategy, triggering additional required efforts in other sectors to reach the EU climate neutrality target by 2050.

We employ more than 120,000 field observations from repeated measurements in 44,000 sample plots from the Finnish and Swedish national forest inventories (NFIs) as reference data in statistically rigorous estimators in order to analyze the accuracy of Ceccherini et al. [1] findings (see Supplement). We find that GFC's ability to detect harvested areas and thinnings[*] abruptly increases after 2015 (**Figure 1**). When the ability to detect harvest improves, the overall harvested area in GFC will increase, even without a real change in management activity. As a result, more harvested areas and thinnings were detected by GFC after 2015, and this explains why the "harvested area" reported by Ceccherini et al. [1] abruptly increases. In other words, the reported abrupt increase in harvest is to a large degree simply a technical artifact (bias) inherent in the GFC timeseries and not a real-world

[*]"Thinnings" are forest management activities where typically 20 – 40 % of growing stock is harvested to give more space to the remaining trees to grow before final felling.

phenomenon. Their conclusions, however, are the product and direct consequence of an inconsistent time series and are thus both incorrect and misleading.

Assuming the average proportion of correctly identified harvested areas before 2015 also applies after 2015, the GFC area after 2015 can be modeled without this increasing sensitivity. This indicates that the GFC recorded increase in "harvested area" of 54% and 36% in Finland and Sweden, reported by Ceccherini et al.,[1] represents an overestimate of 188% and 851% compared to our reference data, respectively (**Figure 2**). Because this modelled area still includes commission error, thinnings and other harvests, additional calculations would be required to provide improved estimates of the actual harvested area change [3].

In addition to generating harvested area estimates subject to systematic error, Ceccherini et al. [1] do not provide any estimates of uncertainty and further assume all the biomass in their mapped harvested areas was in fact removed. Given that a considerable share of the harvested areas in the period 2016-2018 are thinnings and not final harvests (**Figure 2**), the latter results in even larger errors with respect to C-losses. Ceccherini et al.[1] likewise assume the biomass map they utilize is accurate and without uncertainty, which is unrealistic [4]. We focus on the problems related to the harvested area estimate in Ceccherini et al.[1] as this is the most fundamental issue and is adequate for illustrating the erroneous conclusions drawn by the authors.

Though inconsistencies in GFC's time series have previously been reported [3,5], we acknowledge the strong desire for sound and independently verifiable monitoring strategies driven by their potential for supporting the promotion of forest-related climate benefit [6-8]. Without this, much hesitation has accompanied interest in mobilizing forest resources behind the climate challenge. Earth observation remote sensing (RS) and related mapping efforts embody the promise of providing very important tools for monitoring land use change, tropical deforestation and forest restoration [2,9,10]. As such, they likewise hold the promise of supporting efforts to better integrate forest resources into the framework of climate change mitigation strategies.

RS products, however, can be used in ways that potentially result in severely biased estimates as we have seen in this study. Because RS data measure reflections of electromagnetic waves (e.g., visual light in the case of optical satellites) rather than the direct object of interest such as forest cover loss and carbon stock, algorithmic models are required for interpreting these reflections. Models, however, are frequently imprecise tools and generally require reference data to correct their data output and thereby provide unbiased estimates [4,11]. The compilation of RS data results in nice, colorful maps and scientific-looking figures further distract attention. The collection of the required reference data, however, is tedious, expensive and their enormous importance not well understood[12]. Combining the GFC map with adequate reference data into reliable estimators can prove very useful for estimating harvested area and related C-stock losses, as illustrated in various studies[3,5,11,13].

We certainly agree with the authors that one of the more important elements of the Paris Agreement is to; "achieve a balance between anthropogenic emissions by sources and removals by sinks of greenhouse gases in the second half of this century"[14]. Based on the data at hand, however, it would be erroneous to lay blame for the failure to achieve these goals at the feet of the forestry sector. We remain hopeful future debate over the role of the European forest sector will remain based on a more scientific foundation.

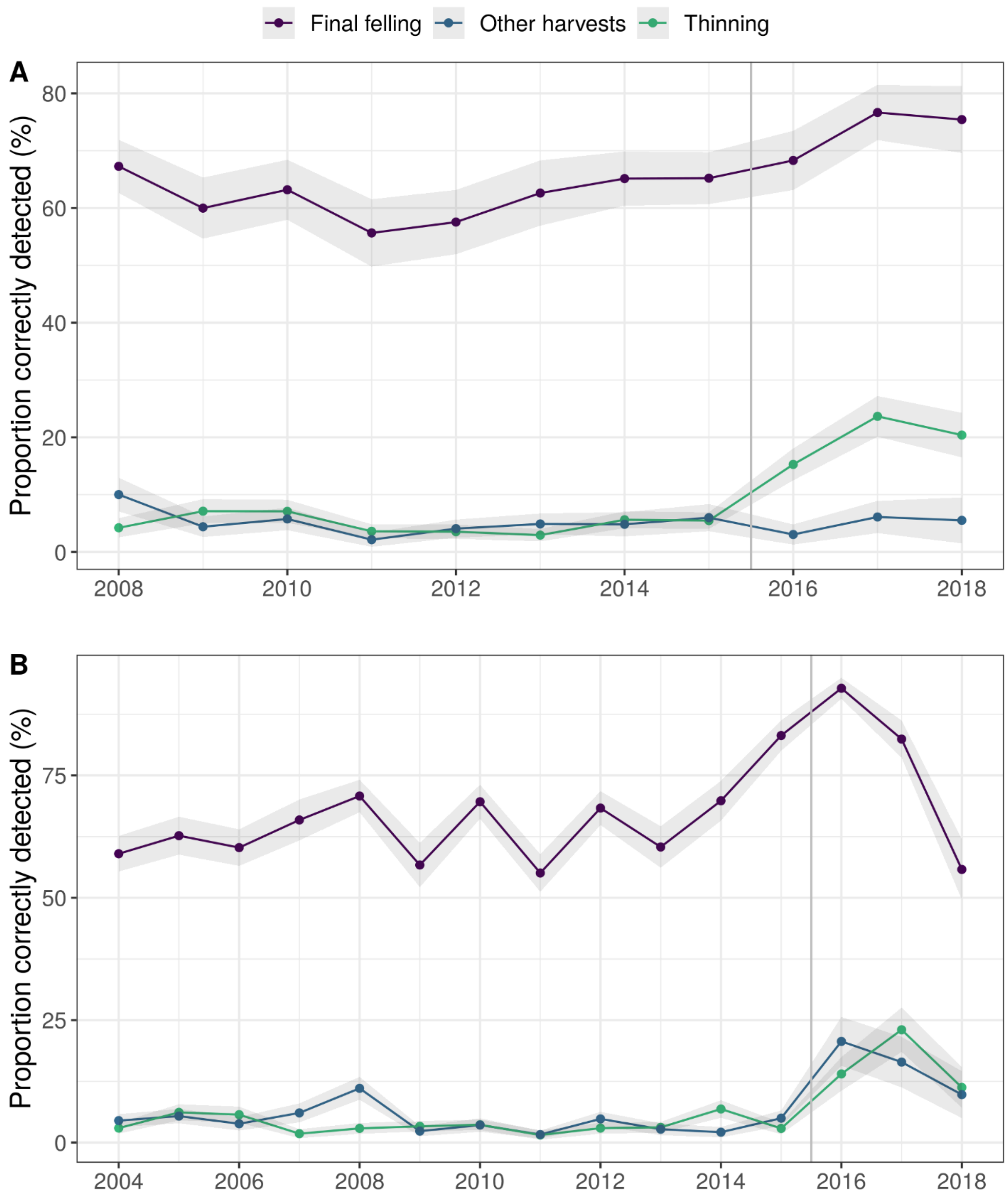

Figure 1: Proportion and 95% confidence interval of correctly detected areas by GFC given change cause as represented by NFI data. A) Finland; B) Sweden.

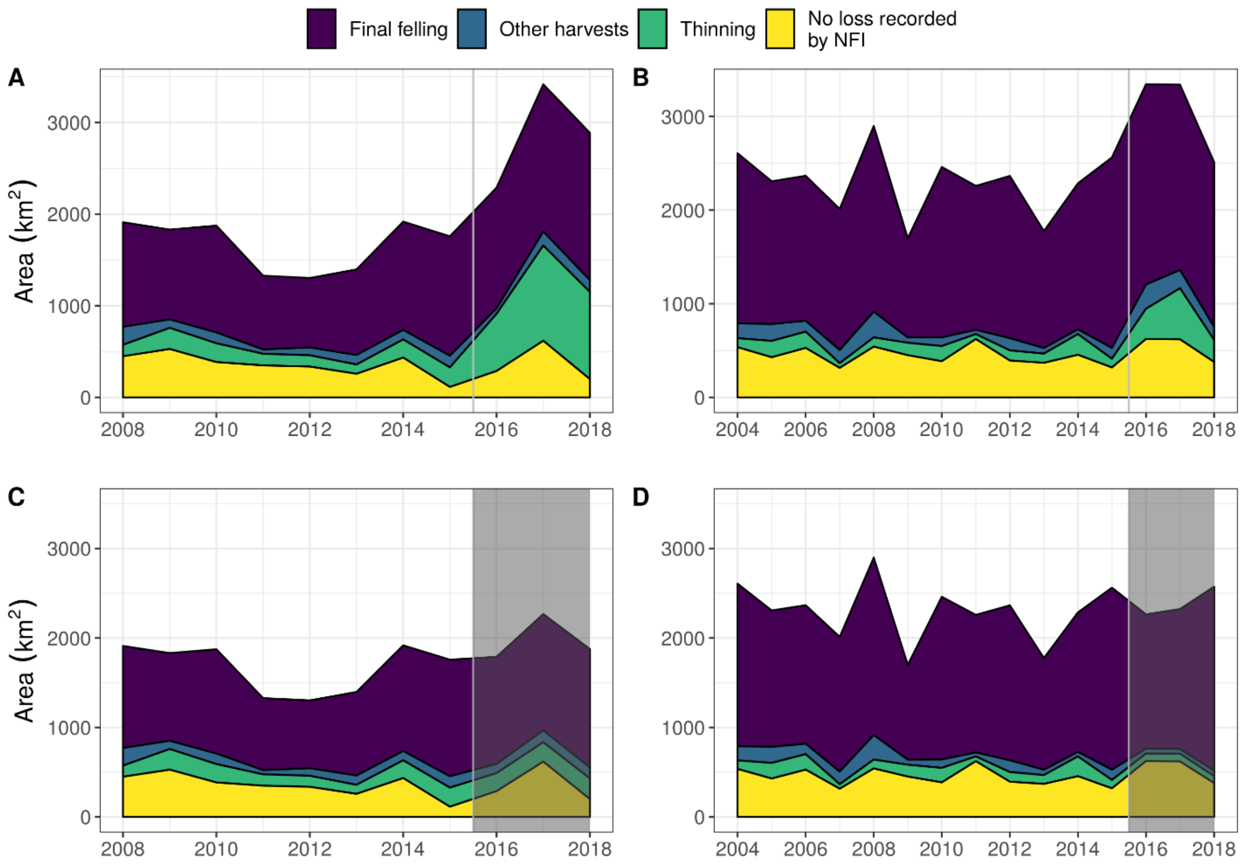

Figure 2: GFC harvested area estimate based on NFI plots with and without correction for an increase in GFC's detection ability after 2015. The two top figures provide the uncorrected timeseries of GFC harvested area for A) Finland and B) Sweden along with their field-observed management outcomes (final fellings, other harvest, thinnings, no management). The area with final fellings is relatively stable while the area with detected thinnings increases considerably after 2015. The two bottom figures provide the timeseries of GFC harvested area corrected for GFC's increased detection ability after 2015 for C) Finland and D) Sweden. For the period 2016-2018, the area is estimated assuming the correct detection proportion would have stayed the same as before. Based on these corrected area estimates, there is no abrupt increase in the harvested area after 2015. See spreadsheet in Supplement for standard errors of estimates.

Supplementary material

<u>The Finnish NFI</u>

The Finnish NFI [15] is a systematic nation-wide cluster sampling survey composed of permanent and temporary clusters. In this study, only data from the permanent clusters were used. Since the 10th NFI (2004-2008), the inventory is continuous with a 5-year cycle such that 20% of the clusters are measured in each year. Finland is divided into six regions denoted as *strata*, with decreasing sampling intensity towards the north. In two of these strata, the partly autonomous Åland islands and the low-productivity, northmost Lapland region, the continuous design is not applied and all plots are measured in a single field season. Because of this inconsistency compared to the vast majority of the

NFI data, these two strata were not included in this analysis. The distance between the permanent clusters ranges from 12 to 20 km.

Each permanent cluster consists of 10 – 14 sample plots. Depending on the sampling stratum, a distance of 250 or 300 meters separates adjacent plots. Each sample plot position is recorded with a high-precision Global Navigation Satellite Systems (GNSS) device. Until 2013, the plot design was restricted angle count sampling (ACS) with a basal area factor (BAF) of 2 and maximum radius of 12.52 m in southern Finland and a BAF of 1.5 and maximum radius 12.45 m in northern Finland. Since 2014, tree-level measurements have been carried out on concentric circular plots with radii of 9.00 and 5.56 m for trees with a diameter at breast height (dbh) ≥ 95 mm and ≥ 45 mm, respectively. Trees with a dbh < 45 mm are still sampled using ACS with a BAF of 1.5. As of 2019, the radius of the smaller circle was changed to 4.00 m.

A large number of forest stand, site and tree variables are assessed on each plot. The tree level measurements are used to estimate stem volume and biomass. At re-inventory, trees are re-measured and, if logged, harvested trees and time of logging are estimated and recorded. In this study, “logging-type” is defined as; 1) final felling consisting of clear cutting, cutting for natural regeneration and cutting before deforestation, 2) thinning (first thinning and later thinnings), and 3) other harvests (removal of seed trees, salvage cutting tree removal along ditches and other locations). Time of logging is defined by harvest season, not calendar years, and the harvest season starts on the 1st of June.

For this study, the last calendar year of a harvest season determined the loss year and forest cover losses have been assessed since 2008 using 33,846 observations from 15,565 permanent sample plots visited from 2009 to 2019. The NFI data used represent a total land area including wetlands of 27 Mha.

<u>The</u> <u>Swedish</u> <u>NFI</u>

The Swedish NFI [16] is a systematic nation-wide cluster sampling survey composed of permanent and temporary clusters. In this study, only data from the permanent clusters were used. The inventory is continuous with a 5-year cycle such that 20% of the clusters are measured in each year. Sweden is divided into five strata, with decreasing sampling intensity towards the north. The distance between clusters ranges from 11 to 26 km.

Each permanent cluster consists of 4 – 8 sample plots. Depending on the sampling stratum, a distance of 300 to 1,200 meters separates adjacent plots. Each sample plot position is recorded with a hand-held GNSS device. A consistent plot design has been applied in the time period considered and tree-level measurements are carried out on concentric circular plots with radii of 10.0, 3.5 and 1.0 m for measurements of trees with a dbh ≥ 100 mm, ≥ 40 mm and ≥ 0 mm dbh respectively.

A large number of forest stand, site and tree variables are assessed on each plot. The tree level measurements are used to estimate stem volume and biomass. At re-inventory, trees are re-measured and, if logged, volume loss, logging type and time of logging are estimated and recorded. In this study, “logging-type” is defined as 1) final felling consisting of clear cutting, cutting for natural regeneration and cutting before deforestation, 2) thinning (first thinning and later thinnings), or 3) other harvests (removal of seed trees, salvage cutting, other tree removal). Time of logging is defined by harvest seasons, not calendar years, where harvest season is defined as the time between the start of the vegetation period (between end of April and end of May, depending on region) in one calendar year to the start of the vegetation period in the next calendar year. The first three harvest seasons before the measurement of the plot are determined using this method and prior harvests are grouped into one harvest class.

For this study, the first calendar year of a harvest season determines the loss year and forest cover losses have been assessed since 2004 using 91,304 observations from 28,544 permanent sample plots visited from 2004 to 2019. The NFI data used represent all of Sweden; a total land area including wetlands of 45 Mha.

GFC data and determination of the loss year

We intersected the GFC map version 1.6 map used by Ceccherini et al. [1] with the center coordinates of the NFI plots. The GFC loss year, if available, was then attributed to the respective NFI period. Because the NFI-based loss year is estimated, we replaced the NFI loss year by the GFC loss year where both were observed for individual plots. We use the NFI plots to analyze which changes in the forest can be detected by GFC. In other words, we use the field observations as ground-truth to evaluate how well GFC captures harvests over time.

Estimators

The estimators and notation used here closely follow [11] but deviate in important ways when it comes to the application. The estimators are repeated here for completeness and with minor adjustments for this context.

The estimates utilizing only NFI data are based on the basic expansion (BE) estimator i.e., the sum of total estimates within each NFI stratum (region)

$$\hat{t}_{\tau} = \sum_{h} \hat{t}_{h} \quad (1)$$

where *t* represents the total of a variable of interest, the "^" identifies this as an estimate of a population parameter and *h* indexes the strata. Uncertainty can be estimated by the variance estimator

$$\hat{V}(\hat{t}_{\tau}) = \sum_{h} \hat{V}(\hat{t}_{h}) \quad (2)$$

and the standard error $\mathrm{SE}(\cdot) = \sqrt{\hat{V}(\cdot)}$. Estimates in the figures are accompanied by a 95% confidence interval (CI) calculated as $CI = \hat{t} \pm 2\mathrm{SE}(\cdot)$.

The total within a stratum is estimated using n_h clusters indexed by *i* within the sample of clusters s_h located within the stratum. The design of the NFI clusters is fixed resulting in single-stage cluster sampling. To simplify the notation and improve readability, we drop the subscript *h* indexing the strata using the estimators in this section

$$\hat{t}_{h} = \hat{t} = \lambda \frac{\sum_{i \in s} m_i y_i}{\sum_{i \in s} m_i} \quad (3)$$

where λ is the area of the stratum and y_i is the mean over the variable of interest observed on m_i plots of the i-th NFI cluster. To estimate the population parameter of interest for a certain domain such as the area of final felling in a certain year, a domain indicator variable I_d is used. This domain indicator is 1 if the plot belongs to the domain of interest and 0 otherwise such that

$$y_i = \frac{\sum_j^{m_i} I_d y_{ij}}{m_i} \tag{4}$$

where y_{ij} is the observed value of the variable of interest on the j-th plot of the i-th cluster [17, p. 65]. In the case of area estimation, y_{ij} is an n-vector of ones. (In the case where other variables would be of interest such as carbon stocks, y_{ij} is the observed carbon stock on the plot scaled to per-hectare values.) The number of plots m_i is typically fixed within a stratum but can vary due to the irregular shape of the stratum. In other words, m_i is the number of plots on land which usually is constant but can vary for clusters located close to the coast or along stratum borders.

To develop the variance estimator of the total, it is convenient to write the total estimator as

$$\hat{t} = \lambda\hat{\mathrm{Y}} = \lambda \frac{\sum_{i \in s} m_i y_i}{\sum_{i \in s} m_i} \tag{5}$$

where $\hat{Y}$ is the mean over all plots irrespective of the cluster structure [17, p. 66]. This is the ratio of two random variables because m_i is not fixed. Therefore, variance is estimated as

$$\hat{\mathrm{V}}(\hat{\mathrm{Y}}) = \frac{1}{n(n-1)} \sum_{i \in s} \left(\frac{\mathrm{m_i}}{\bar{\mathrm{m}}}\right)^2 \left(y_i - \hat{Y}\right)^2 \tag{6}$$

where n is the number of observations (clusters), $\bar{m} = \frac{1}{n}\sum_{i \in s} \mathrm{m_i}$ is the average number of plots per cluster [17, p. 68]. The variance of the total is then estimated by multiplying the squared area of the stratum with the variance estimate of the mean

$$\hat{\mathrm{V}}(\hat{\mathrm{t}}) = \lambda^2 \hat{V}(\hat{\mathrm{Y}}). \tag{7}$$

We assume simple random sampling and accept that the variance estimates are likely conservative due to the systematic distribution of the clusters in the NFIs. Other options are possible [18] but will not generally change our case or conclusions.

<u>Application</u> <u>of</u> <u>the</u> <u>estimators</u>

The loss year determined by GFC if available or otherwise determined by the field crews, was the primary domain of interest (*d*). All sample plots that covered a loss year were used for estimating the variables of interest. For example, for estimates of the domain of interest “final felling area for the loss year 2018”, all sample plots measured in 2018 and 2019 were used and the indicator variable was set to 1 for sample plots with loss year 2018 and final felling was recorded based on the particular logging type. The indicator variable was set to 0 for all other plots. Because GFC information was not used in this estimate apart from adjustments to the felling year, we refer to this estimator as $\hat{\mathrm{t}}_\tau^{\mathrm{NFI}}$.

Correspondingly, for estimating the area of final felling detected by GFC, the indicator variable was set to 1 for sample plots with the GFC-based loss year 2018 and final felling recorded as the logging type. The indicator variable was set to 0 for all other plots. We refer to this estimator as $\hat{\mathrm{t}}_\tau^{\mathrm{GFC}}$.

The proportion of correctly detected final fellings (thinnings, or other harvests) by GFC is a ratio of the two estimates [17, p. 68]

$$\hat{\mathrm{r}}_\tau = \hat{\mathrm{t}}_\tau^{\mathrm{GFC}}/\hat{\mathrm{t}}_\tau^{\mathrm{NFI}} \tag{8}$$

with variance

$$\hat{\mathrm{V}}(\hat{r}_\tau) = \frac{1}{(\hat{\mathrm{t}}_\tau^{\mathrm{NFI}}/\lambda)^2}\sum_{\mathrm{h}} \hat{V}(\hat{r}_{\mathrm{h}})(\lambda_h/\lambda)^2 \tag{9}$$

where λ_h is the area of the *h*-th stratum and

$$\hat{V}(\hat{r}_{\mathrm{h}}) = \frac{1}{n_h(n_h-1)}\sum_{i\in s_h}\left(\frac{\mathrm{m_i}}{\overline{\mathrm{m}}_h}\right)^2\left(y_i^{GFC} - \hat{\mathrm{r}}_\tau y_i^{NFI}\right)^2 \tag{10}$$

where y_i^{GFC} is y_i [eq. (4)] resulting in $\hat{\mathrm{t}}_\tau^{\mathrm{GFC}}$ and y_i^{NFI} is y_i [eq. (4)] resulting in $\hat{\mathrm{t}}_\tau^{\mathrm{NFI}}$.

While our approach is suitable for assessing the accuracy of GFC, it is not optimal for estimating actual harvested area for two reasons. First, the use of the GFC loss year can introduce bias in estimates if the GFC loss year has a systematic error. Second, official NFI statistics include measurements from both permanent and temporary sample plots and utilize stand level observations around the sample plots for area estimation rather than only plot level measurements. We have employed this approach because plot level measurements conceptually match the pixel-level GFC data better than stand level observations.

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Author contributions

Conceptualization: D.E., E.N. and J.B.

Methodology and Data Analysis: J.B.

Data Processing: K.T.K., H.M.H., J.F., J.W., and H.P.

Interpretation: All authors.

Writing – Original Draft: J.B. and D.E.

Writing – Review and Editing: All authors.

Competing interests

We declare no competing interests.

Data and materials availability

Data and code are available from https://doi.org/10.5281/zenodo.4625358.

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