



OPINION PAPER

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Harvested area did not increase abruptly—how advancements in satellite-based mapping led to erroneous conclusions

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Abstract

Key message: Using satellite-based maps, Ceccherini et al. (Nature 583:72–77, 2020) report abruptly increasing harvested area estimates in several EU countries beginning in 2015. Using more than 120,000 National Forest Inventory observations to analyze the satellite-based map, we show that it is not harvested area but the map's ability to detect harvested areas that abruptly increases after 2015 in Finland and Sweden.

Keywords: Global Forest Watch, Landsat, Remote sensing, National Forest Inventory, Greenhouse Gas Inventory

1 Introduction

Using satellite-based maps, Ceccherini et al. (2020) report abruptly increasing harvested area estimates in several EU 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. In a response to comments (Palahí et al. 2021; Wernick et al. 2021) regarding the original study, Ceccherini et al. (2021) reduce their estimates markedly but generally maintain their conclusion that harvested area increased abruptly. Using more than 120,000 field reference observations to analyze the satellite-based map employed by Ceccherini et al. (2020), we confirm the hypothesis by Palahí et al. (2021) that it is not a harvested area but the map's ability to detect harvested areas that abruptly increases after 2015. While

the abrupt detected increase in harvest is an artifact, Ceccherini et al. (2020) interpret this difference as an indicator of increasing intensity in forest management and harvesting practice.

Ceccherini et al. (2020) use satellite-based Global Forest Change (GFC) (Hansen et al. 2013) data to estimate the yearly harvest area in each of 26 EU states over the period 2004 to 2018. They claim that an increase of harvested areas 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.

2 Discussion

In their response to comments, Ceccherini et al. (2021) carry out a stratified estimate of harvested area for the combined area of Finland and Sweden with more than 5000 visually classified reference points based on manual interpretation, using high-resolution aerial images and Landsat data. They compare the time periods 2011–2015 and 2016–2018 to find a 35% increase in harvested area in the second period which is a considerable

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reduction compared to the original article, where a 54% and 36% increase was reported for Finland and Sweden, respectively. Although this approach is more robust than the “pixel counting” (Palahí et al. 2021) of the original article, as can be seen below, this is still a gross overestimation of the change in harvested area. The main issue is the use of Landsat to determine the timing of forest cover losses. Because Landsat became more sensitive in detecting forest cover loss over time, many losses that occurred in or before the first period are thus detected in the second period. This causes errors in the reference data which propagate in the reported estimate. Moreover, Landsat provides the primary data input for GFC, which results in circular reasoning when using Landsat as reference data for GFC. In other words, Landsat cannot be used to validate a Landsat-based product.

Furthermore, Ceccherini et al.’s (2021) argument that abrupt changes in harvested area were not observed in all countries and therefore cannot be caused by data artifacts is inappropriate because the algorithms used to create the GFC map are, due to the modeling procedure applied, inherently non-linear (Hansen et al. 2013). Unexpected changes can therefore happen in some regions but not in others.

Finally, Ceccherini et al. (2021) claim inconsistencies in GFC were unknown. Though inconsistencies in GFC’s time series have previously been reported (Rossi et al. 2019; Galiatsatos et al. 2020), this may indeed not have been well-known. However, it is a well-established fact that Earth observation data and related products can be unreliable and inconsistent (McRoberts 2011; Olofsson et al. 2014). Important interpretations and decisions should therefore not be based on “pixel counting” estimates.

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.’s (2020) findings (see Appendix and our dataset (Breidenbach et al. 2021b)). We find that GFC’s ability to detect harvested areas and thinnings abruptly increases after 2015 (Fig. 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. (2020) abruptly increases. In other words, the reported abrupt increase in harvest is to a large degree simply a technical artifact (bias) caused by the advancement of GFC over time. Ceccherini et al.’s (2020) 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 increases in “harvested area” of 54% and 36% in Finland and Sweden, reported by Ceccherini et al. (2020) represents an overestimate of 188% and 851%, respectively, compared to our reference data (Fig. 2). Because this modeled area still includes commission error, thinnings, and other harvests, additional calculations would be required to provide improved estimates of the actual harvested area change (Rossi et al. 2019). We further highlight that Ceccherini et al.’s (2021) more recent findings do not in any way alter or affect these basic, validated findings.

In addition to generating harvested area estimates subject to systematic error, Ceccherini et al. (2020) do not provide any estimates of uncertainty and further assume all 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 (Fig. 2), the latter results in even larger errors with respect to C-losses. Ceccherini et al. (2020) likewise assume the biomass map they utilize is accurate and without uncertainty, which is unrealistic (Næsset et al. 2020). We focus on the problems related to the harvested area estimate in Ceccherini et al. (2020) as this is the most fundamental issue and is adequate for illustrating the erroneous conclusions drawn by the authors.

We acknowledge the strong desire for sound and independently verifiable monitoring strategies driven by their potential for supporting the promotion of forest-related climate benefits (Griscom et al. 2017; Bastin et al. 2019; Brancalion et al. 2019). Without this, much hesitation has accompanied interest in mobilizing forest resources behind the climate change mitigation 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 (Hansen et al. 2013; Baccini et al. 2017; Harris et al. 2021). 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 estimates subject to severe systematic error, as we have seen in this and other studies (Næsset et al. 2020). Ceccherini et al.’s (2020) claim that a 30% increase of harvested area in France corresponds with national statistics has been invalidated by Picard et al. (2021). These authors find that, despite the already very weak correlation between national statistics and Ceccherini et al.’s (2020) results, this “correlation” itself was caused by one single year that was heavily affected by a storm event. In reliable

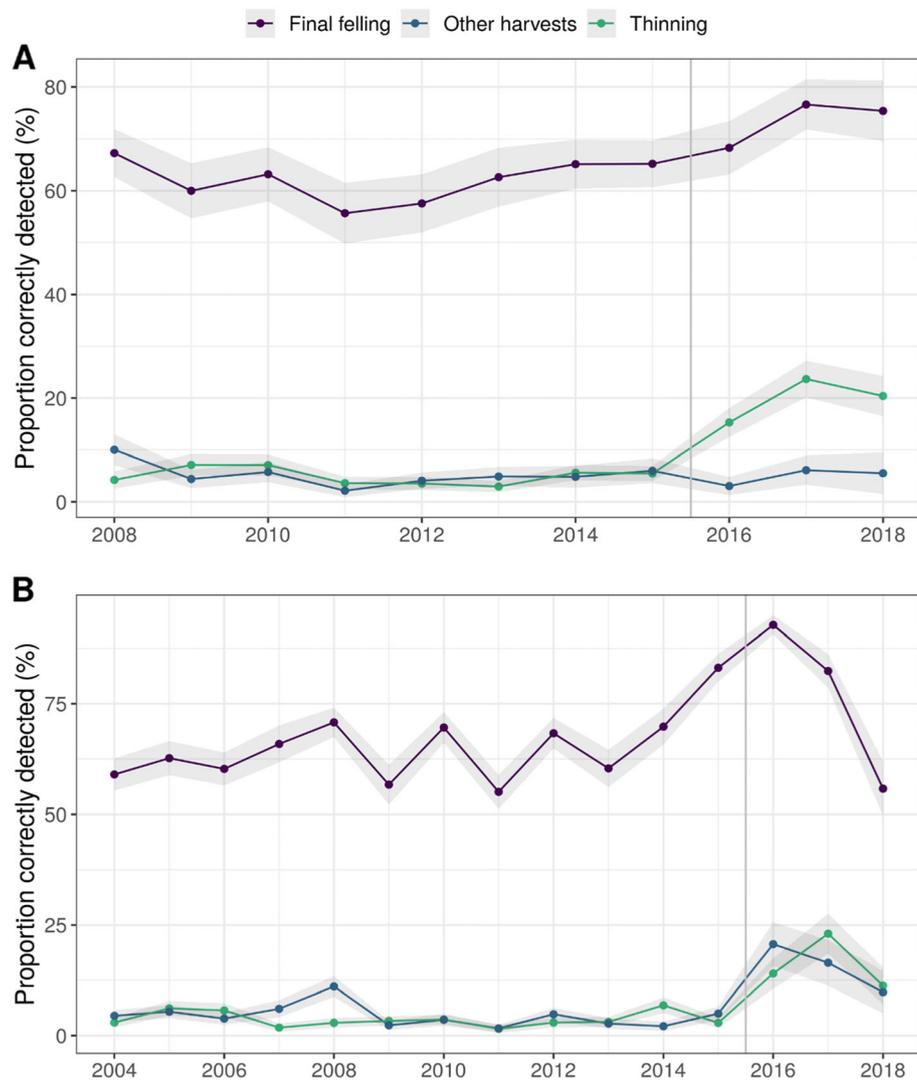


Fig. 1 Proportion and 95% confidence interval of correctly detected areas by GFC given change cause as represented by NFI data. **A** Finland. **B** Sweden. The inverse of the y-axis is the omission error

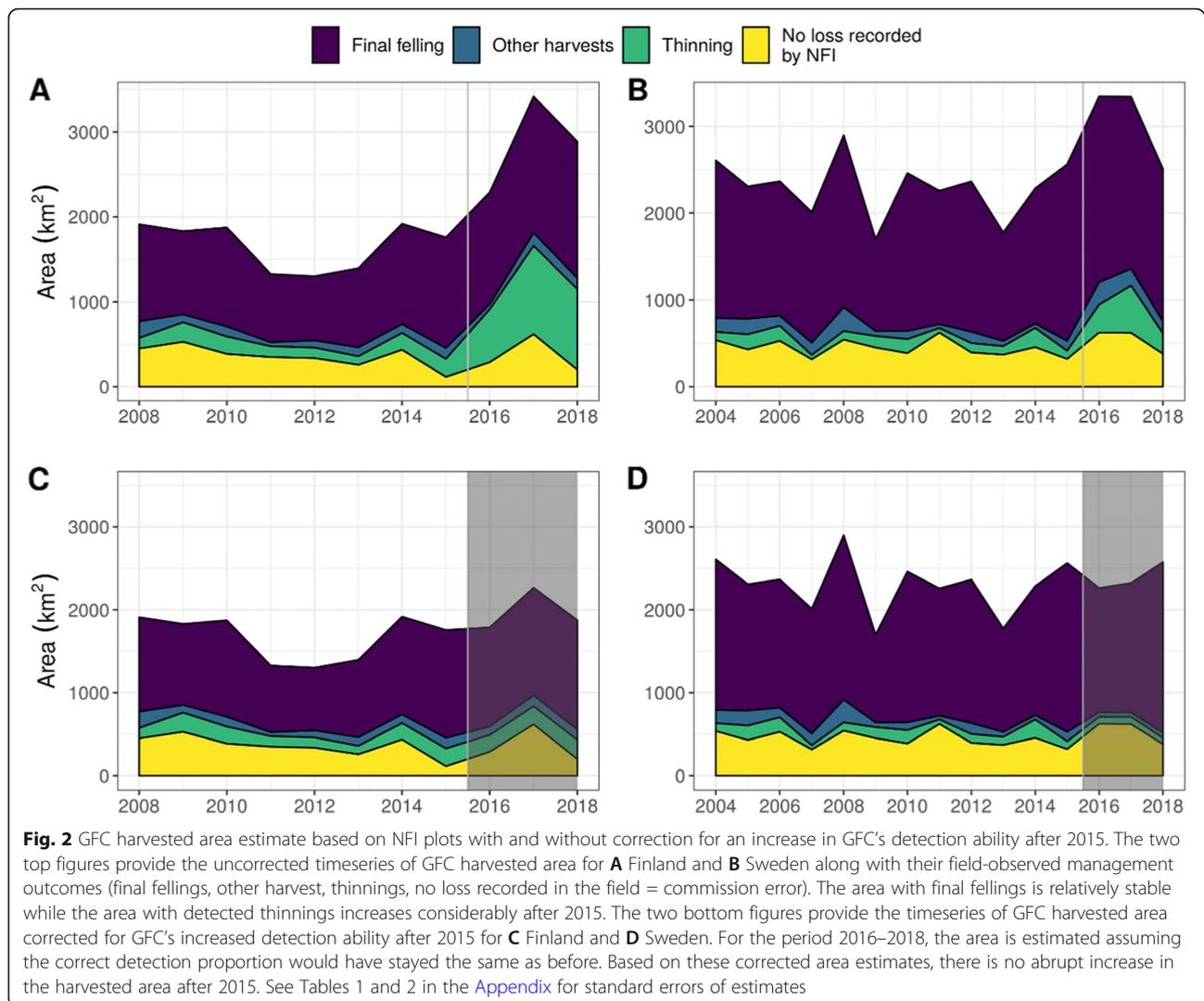
surveys, Picard et al. (2021) were unable to find signs of increased harvested area in France.

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 (Box 1976) and generally require reference data to correct their data output and thereby provide unbiased estimates (Næsset et al. 2020; Breidenbach et al. 2021a). The compilation of RS data results in nice, colorful maps and scientific-looking figures further distract attention. The collection of the required reference data, on the other hand, is tedious, expensive, and their enormous importance not well understood (McRoberts 2011). 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 (Turubanova et al. 2018; Rossi et al. 2019; Galiatsatos et al. 2020; Næsset et al. 2020; Breidenbach et al. 2021a).

3 Conclusion

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” (UN 2015). 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 nonetheless remain hopeful future debate over the role of the European forest sector will remain rooted in more scientific foundations. Certainly, the use of large-scale open data in carbon monitoring and reporting, as Ceccherini et al. (2020) also (as well as many others before them) propose, represents the next great trend and should generally be applauded. However, strong systematic errors in estimated results clearly need to be avoided. This demonstrates why work of this kind should always be accompanied by rigorous collection of field observations and appropriate statistical estimates. Future work should therefore continue in the direction of further combining the use of large-scale, field-based sampling methods with remote sensing data resources.

4 Appendix The Finnish NFI

The Finnish NFI (Korhonen 2016) is a systematic nationwide 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, northernmost 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 m 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.

The Swedish NFI

The Swedish NFI (Fridman et al. 2014) is a systematic nationwide 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 1200 m 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 used by Ceccherini et al. (2020) 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 Bredenbach et al. (2021a) 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 “ \wedge ” 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 $SE(\cdot) = \sqrt{\hat{V}(\cdot)}$. Estimates in the figures are accompanied by a 95% confidence interval (CI) calculated as $CI = \hat{t} \pm 2SE(\cdot)$.

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

$$\hat{t}_h = \hat{t} = \lambda \frac{\sum_{i \in s} m_i y_i}{\sum_{i \in s} m_i} \tag{3}$$

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

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

where y_{ij} is the observed value of the variable of interest on the j th plot of the i th cluster (Mandallaz 2008, 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

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

where \hat{Y} is the mean over all plots irrespective of the cluster structure (Mandallaz 2008, p. 66). This is the ratio of two random variables because m_i is not fixed. Therefore, variance is estimated as

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

where n is the number of observations (clusters), $\bar{m} = \frac{1}{n} \sum_{i \in s} m_i$ is the average number of plots per cluster (Mandallaz 2008, 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

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

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 (Magnussen et al. 2020) but will not generally change our case or conclusions.

Application of the estimators

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{t}_τ^{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{t}_τ^{GFC} .

The proportion of correctly detected final fellings (thinnings, or other harvests) by GFC is a ratio of the two estimates (Mandallaz 2008, p. 68)

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

with variance

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

where λ_h is the area of the h th stratum and

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

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

Standard errors for estimates in Fig. 2

Table 1 Standard errors for estimates in Fig. 2—Finland

Year	Status	Standard error (%)
2018	Thinning	24
2017	Thinning	17
2016	Thinning	20
2015	Thinning	27
2014	Thinning	27
2013	Thinning	38
2012	Thinning	35
2011	Thinning	34
2010	Thinning	30
2009	Thinning	30
2008	Thinning	41
2018	Other harvests	75
2017	Other harvests	47
2016	Other harvests	58
2015	Other harvests	41
2014	Other harvests	46
2013	Other harvests	38
2012	Other harvests	39
2011	Other harvests	58
2010	Other harvests	35
2009	Other harvests	42
2008	Other harvests	31
2018	Final felling	17
2017	Final felling	14
2016	Final felling	14
2015	Final felling	12
2014	Final felling	12
2013	Final felling	15
2012	Final felling	16
2011	Final felling	15
2010	Final felling	13
2009	Final felling	15
2008	Final felling	13
2018	No loss recorded by NFI	45
2017	No loss recorded by NFI	21
2016	No loss recorded by NFI	26
2015	No loss recorded by NFI	38
2014	No loss recorded by NFI	18
2013	No loss recorded by NFI	33
2012	No loss recorded by NFI	22
2011	No loss recorded by NFI	22
2010	No loss recorded by NFI	19
2009	No loss recorded by NFI	17
2008	No loss recorded by NFI	21

Table 2 Standard errors for estimates in Fig. 2—Sweden

Year	Status	Standard error (%)
2018	Thinning	38
2017	Thinning	22
2016	Thinning	27
2015	Thinning	41
2014	Thinning	27
2013	Thinning	36
2012	Thinning	38
2011	Thinning	62
2010	Thinning	29
2009	Thinning	32
2008	Thinning	39
2007	Thinning	50
2006	Thinning	29
2005	Thinning	28
2004	Thinning	39
2018	Other harvests	51
2017	Other harvests	34
2016	Other harvests	27
2015	Other harvests	32
2014	Other harvests	50
2013	Other harvests	45
2012	Other harvests	31
2011	Other harvests	50
2010	Other harvests	39
2009	Other harvests	45
2008	Other harvests	22
2007	Other harvests	34
2006	Other harvests	36
2005	Other harvests	28
2004	Other harvests	30
2018	Final felling	16
2017	Final felling	12
2016	Final felling	10
2015	Final felling	9
2014	Final felling	12
2013	Final felling	11
2012	Final felling	10
2011	Final felling	10
2010	Final felling	10
2009	Final felling	12
2008	Final felling	9
2007	Final felling	11
2006	Final felling	10
2005	Final felling	11

Table 2 Standard errors for estimates in Fig. 2—Sweden
(Continued)

Year	Status	Standard error (%)
2004	Final felling	10
2018	No loss recorded by NFI	31
2017	No loss recorded by NFI	18
2016	No loss recorded by NFI	20
2015	No loss recorded by NFI	19
2014	No loss recorded by NFI	21
2013	No loss recorded by NFI	20
2012	No loss recorded by NFI	19
2011	No loss recorded by NFI	15
2010	No loss recorded by NFI	20
2009	No loss recorded by NFI	18
2008	No loss recorded by NFI	16
2007	No loss recorded by NFI	21
2006	No loss recorded by NFI	17
2005	No loss recorded by NFI	19
2004	No loss recorded by NFI	18

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Authors' contributions

Conceptualization: J.B., D.E., and E.N. 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. The authors read and approved the final manuscript.

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Availability of data and materials

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Declarations**Ethics approval and consent to participate**

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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References

- Baccini A, Walker W, Carvalho L, Farina M, Sulla-Menashe D, Houghton R (2017) Tropical forests are a net carbon source based on aboveground measurements of gain and loss. *Science* 358(6360):230–234. <https://doi.org/10.1126/science.aam5962>
- Bastin J-F, Finegold Y, Garcia C, Mollicone D, Rezende M, Routh D, Zohner CM, Crowther TW (2019) The global tree restoration potential. *Science* 365(6448):76–79. <https://doi.org/10.1126/science.aax0848>
- Box GE (1976) Science and statistics. *J Am Stat Assoc* 71(356):791–799. <https://doi.org/10.1080/01621459.1976.10480949>
- Brançalon PH, Niamir A, Broadbent E, Crouzeilles R, Barros FS, Zambrano AMA, Baccini A, Aronson J, Goetz S, Reid JL (2019) Global restoration opportunities in tropical rainforest landscapes. *Sci Adv* 5:eav3223
- Breidenbach J, Ivanovs J, Kangas A, Nord-Larsen T, Nilsson M, Astrup R (2021a) Improving living biomass C-stock loss estimates by combining optical satellite, airborne laser scanning, and NFI data. *Can J For Res* 51(10):1472–1485. <https://doi.org/10.1139/cjfr-2020-0518>
- Breidenbach J, Korhonen K, Henttonen H, Fridman J, Wallerman J (2021b) Finnish and Swedish NFI data intersected with GFC (1.0) [Data set]. Zenodo. <https://doi.org/10.5281/zenodo.4625358>
- Ceccherini G, Duveiller G, Grassi G, Lemoine G, Avitabile V, Pilli R, Cescatti A (2020) Abrupt increase in harvested forest area over Europe after 2015. *Nature* 583(7814):72–77. <https://doi.org/10.1038/s41586-020-2438-y>
- Ceccherini G, Duveiller G, Grassi G, Lemoine G, Avitabile V, Pilli R, Cescatti A (2021) Reply to Wernick, IK et al.; Palahí, M. et al. *Nature* 592(7856):E18–E23. <https://doi.org/10.1038/s41586-021-03294-9>
- Fridman J, Holm S, Nilsson M, Nilsson P, Ringvall A, Ståhl G (2014) Adapting National Forest Inventories to changing requirements – the case of the Swedish National Forest Inventory at the turn of the 20th century. *Silva Fennica* 48. <https://doi.org/10.14214/sf.1095>
- Galiatsatos N, Donoghue DNM, Watt P, Bholanath P, Pickering J, Hansen MC, Mahmood ARJ (2020) An Assessment of Global Forest Change Datasets for National Forest Monitoring and Reporting. *Remote Sensing* 12(11):1790. <https://doi.org/10.3390/rs12111790>
- Griscom BW, Adams J, Ellis PW, Houghton RA, Lomax G, Miteva DA, Schlesinger WH, Shoch D, Siikamäki JV, Smith P (2017) Natural climate solutions. *Proc Natl Acad Sci* 114(44):11645–11650. <https://doi.org/10.1073/pnas.1710465114>
- Hansen MC, Potapov PV, Moore R, Hancher M, Turubanova SA, Tyukavina A, Thau D, Stehman S, Goetz SJ, Loveland TR (2013) High-resolution global maps of 21st-century forest cover change. *Science* 342:850–853
- Harris NL, Gibbs DA, Baccini A, Birdsey RA, De Bruin S, Farina M, Fatoyinbo L, Hansen MC, Herold M, Houghton RA (2021) Global maps of twenty-first century forest carbon fluxes. *Nat Climate Change* 11(3):1–7. <https://doi.org/10.1038/s41558-020-00976-6>
- Korhonen KT (2016) Finland. In: Vidal C, Alberdi I, Hernández L, Redmond J (eds) *National forest inventories - Assessment of Wood Availability and Use*. Springer, pp 368–384. https://doi.org/10.1007/978-3-319-44015-6_19
- Magnussen S, McRoberts RE, Breidenbach J, Nord-Larsen T, Ståhl G, Fehrmann L, Schnell S (2020) Comparison of estimators of variance for forest inventories with systematic sampling—results from artificial populations. *Forest Ecosyst* 7(1):1–19. <https://doi.org/10.1186/s40663-020-00223-6>
- Mandallaz D (2008) *Sampling techniques for forest inventories*. CRC Press. <https://doi.org/10.1201/9781584889779>
- McRoberts RE (2011) Satellite image-based maps: Scientific inference or pretty pictures? *Remote Sens Environ* 115(2):715–724. <https://doi.org/10.1016/j.rse.2010.10.013>
- Næsset E, McRoberts RE, Pekkarinen A, Saatchi S, Santoro M, Trier ØD, Zahabu E, Gobakken T (2020) Use of local and global maps of forest canopy height and aboveground biomass to enhance local estimates of biomass in miombo woodlands in Tanzania. *Int J Appl Earth Observation Geoinformation* 93:102138
- Olofsson P, Foody GM, Herold M, Stehman SV, Woodcock CE, Wulder MA (2014) Good practices for estimating area and assessing accuracy of land change. *Remote Sens Environ* 148:42–57. <https://doi.org/10.1016/j.rse.2014.02.015>
- Palahí M, Valbuena R, Senf C, Acil N, Pugh TA, Sadler J, Seidl R, Potapov P, Gardiner B, Hetemäki L (2021) Concerns about reported harvests in European forests. *Nature* 592(7856):E15–E17. <https://doi.org/10.1038/s41586-021-03292-x>
- Picard N, Leban J-M, Guehl J-M, Dreyer E, Bouriaud O, Bontemps J-D, Landmann G, Colin A, Peyron J-L, Marty P (2021) Recent increase in European forest harvests as based on area estimates (Ceccherini et al. 2020a) not confirmed in the French case. *Ann Forest Sci* 78:9. <https://doi.org/10.1007/s13595-021-01030-x>
- Rossi F, Breidenbach J, Puliti S, Astrup R, Talbot B (2019) Assessing Harvested Sites in a Forested Boreal Mountain Catchment through Global Forest Watch. *Remote Sens* 11(5):543. <https://doi.org/10.3390/rs11050543>
- Turubanova S, Potapov PV, Tyukavina A, Hansen MC (2018) Ongoing primary forest loss in Brazil, Democratic Republic of the Congo, and Indonesia. *Environ Res Lett* 13(7):074028. <https://doi.org/10.1088/1748-9326/aad1c>
- UN (2015) Paris Agreement. Report of the Conference of the Parties to the United Nations Framework Convention on Climate Change (21st Session, 2015), United Nations, Paris.
- Wernick IK, Ciais P, Fridman J, Höglberg P, Korhonen KT, Nordin A, Kauppi PE (2021) Quantifying forest change in the European Union. *Nature* 592(7856):E13–E14. <https://doi.org/10.1038/s41586-021-03293-w>

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