Supplementary Information

Supplementary Note 1
Limitations of the observational data

The limited timeseries covered by the Landsat observations relative to \( \tau \) in most ecosystems induces uncertainty as to whether the observed disturbance rates are characteristic of the long-term disturbance regimes. There are two cases that might invalidate our implicit assumption that the occurrence of disturbances over our time windows is characteristic of current disturbance regimes in those forests. The first is a strong bias in forest age in a grid cell towards particularly young or old forests, relative to the long-term average age, which could result in our calculated \( \tau_0 \) not being representative of the long-term average, as forest age (or more properly size) affects disturbance probability. Given that the 1° scale is much larger than that at which forest disturbances occur (Methods), we expect this to be unlikely in most locations, with any deviations from the long-term mean \( \tau \) at that location resulting from a recent change in the disturbance regime. The exception to this is areas which have gone large-scale reforestation, such as the eastern U.S.A., central Europe and south-eastern China, as discussed in Suppl. Note 2. The second case is disturbance resulting from extreme climatic events, such as hurricanes or extreme and coherent hot droughts across large regions. Such events may be under-sampled by the 14-year sampling period here, but reliable methods to assess the possible importance of such events are lacking. Rapid regreening times in highly productive tropical ecosystems, combined with high levels of cloud cover, might limit the ability of Landsat to capture disturbances in this region, but the consistency of our results with previous studies (Suppl. Note 3) suggests that such long \( \tau \) values are realistic here.

Supplementary Note 2
Comparison of \( \tau \) with a dataset of global forest age

We compared our results against an inventory-based compilation of forest stand age (GFADv1.1, Suppl. Fig. 1). The relatively low \( \tau_0 \) in the south-eastern U.S.A. (ca. 50 years) and Scandinavia (ca. 100 years) match with large fractions of forest stands below 50 years of age in GFAD, and likely reflect the effect of intensive forest management in
these regions. Higher $\tau_0$ over the Russian and Canadian boreal regions is reflected by a smaller fraction of young stands in GFAD. However, in the eastern U.S.A., central Europe and China, there exist relatively high fractions of young forest despite high $\tau_0$. This is likely at least partially a reflection of past afforestation in these regions leading to a younger stand age distribution than our $\tau_0$ would suggest; China, in particular, has aggressively reforested over recent decades. Since many stand-replacing disturbance events become more likely with older, larger, stands, this may also mean that our calculations overestimate the long-term mean $\tau_0$ in these regions. Additionally, high $\tau_0$ may also reflect a dominant type of disturbance that is non-stand-replacing, e.g. selective harvest, small windthrows. For instance, in Europe selective harvest practices (i.e. non-stand-replacing) are very common and evidence of these practices is seen in Catalonia, the Alps, Bavaria and Slovenia, corresponding with the high $\tau_0$ in our dataset. The land-use change correction is also high in central Europe (Suppl. Fig. 7) suggesting a large amount of cycling between forest and non-forest land uses and leading to a high uncertainty in $\tau_0$ (Fig. 1b).

In tropical regions there are several factors likely behind the discrepancies observed between $\tau_0$ and GFAD outside of the core rainforest zones:

- There is a relatively large uncertainty in our $\tau_0$ results in several parts of these regions (Fig. 1b) due to the size of the land-use change correction (Suppl. Fig. 7).
- Many of these regions are converting forest into plantations, e.g. oil palm or rubber. Plantations of trees, however, remain forest by the definition of Hansen et al.\textsuperscript{5}, used here. Because these plantations undergo relatively rapid rotations, a lower $\tau_0$ is found. For instance, the low $\tau_0$ assigned to tropical evergreen forests in South-East Asia likely reflects the palm oil plantations in these regions, which are also classified as forest, rather suggesting than a substantially higher prevalence of disturbances in rainforests in this region.
- Several studies have shown that land-use change in the tropics tends to lead to reductions in carbon stocks of nearby forests\textsuperscript{6,7}, which likely results at least in part from an enhanced prevalence or vulnerability to certain types of disturbance such as fire or windthrow\textsuperscript{8,9}.
- Finally, the high $\tau_0$ reported here for tropical deciduous forests does not imply a lack of fire disturbance in African savannahs, because in focusing on closed-canopy forest, we have explicitly excluded savannahs from our analysis. In contrast, GFAD includes savannahs in its age assessment.
Supplementary Note 3
Comparison of $\tau_0$ with other studies

Cross-comparison of our results with existing regional syntheses demonstrates that the Landsat-based approach is consistent with knowledge of fire regimes in Canada, with $\tau_0$ of the order of 100 years in the West Boreal Shield where fire return times are known to be short, but increasing to 500-1000 years in the area south of Hudson Bay and in the temperate rainforests of the west coast, where disturbances are known to be much rarer. The relative length across different Canadian ecoregions of $\tau_0$ calculated herein, is consistent with $\tau$ estimated based on a dedicated study for Canada using Landsat imagery (Suppl. Fig. 2). That the absolute values of $\tau_0$ are much greater in this study than in White et al. is to be expected, as the latter study included open canopy forested areas whereas ours restricted the analysis to closed canopy. Given that the existence of an open canopy is in many cases likely to be a result of a more frequent disturbance regime, and that canopy gaps increase the exposure of trees to wind and allow litter to dry more rapidly, it stands to reason that calculations conducted over both open- and closed-canopy forest would lead to much lower values of $\tau_0$.

Our results of $\tau_0 > 1000$ years for much of the tropical evergreen forest are consistent between both approaches here and also with a previous synthesis for the Amazon based on Landsat and LIDAR observations, and with field observations, although we cannot exclude the possibility that some disturbances in these fast-recovering forests may be missed. Some regions such as Sweden and the south-east USA show through clearly with $\tau_0$ equal to ca. 80 years or less respectively in both datasets, perhaps due to the effects of management, for with rotation times in managed forest being of this order or less.

Recognising biotic outbreaks also represents a challenge for satellite observations. However, cross-comparing our results with $\tau$ derived for biotic outbreaks alone ($\tau_{\text{bio}}$) for the case of the U.S.A. (Suppl. Fig. 3) gives little support for stand-replacing biotic disturbances being systematically missed. If $\tau_{\text{bio}}$ is much smaller than $\tau_0$ this might be an indicator that $\tau_0$ is under-sampling stand-replacing biotic disturbances. This would not be conclusive, however, as $\tau_{\text{bio}}$ also includes non-stand-replacing disturbances. However, if $\tau_{\text{bio}}$ is larger than $\tau_0$, this indicates that it is unlikely that an under-sampling of stand-replacing biotic disturbances is substantially influencing our estimate of $\tau_0$. For the vast
majority of the eastern U.S.A. \( \tau_{\text{bio}} \) is greater than \( \tau_0 \), indicating that a potential under-sampling of biotic disturbances is either not present or at least does not appear to substantially influence our estimates of \( \tau_0 \). \( \tau_{\text{bio}} \) is derived by replacing \( \overline{\Delta} \) in Eq. 1 with the annual mean area of trees lost due to biotic outbreak disturbances. Biotic disturbance data was taken from the US Insect and Disease Survey database for the years 1997-2015 (http://foresthealth.fs.usda.gov, accessed: 23rd March 2017). As these surveys delineate the area affected by the biotic disturbance, rather than the area of trees killed, a multiplicative correction factor of 0.1 was applied to convert area affected into area of mortality\(^{17}\).

Espírito-Santo et al.\(^{12}\), based on a combination of Landsat and LIDAR for subsets of the Amazon region, find that stand-replacing disturbances (named intermediate and large disturbances in their paper) affect 0.016 % of forest area in the Amazon per year, equivalent to a \( \tau \) much greater than 1000 years. From another study located in the north-western Amazon\(^{18}\), which used combined Landsat and inventory data, we infer \( \tau \) of approximately 500 years for wind-driven tree fall events with a size of 0.1 ha. It is notable that the frequency of events at less than 0.1 ha scale was much higher. A reported stem mortality rate of 0.18 % a\(^{-1}\) due to disturbances of 7-10 trees or more at a central Amazon site, based on a combination of Landsat data, inventory data and modelling, is also consistent with long return periods for disturbances\(^{19}\), although stem and areal mortality rates cannot be directly compared and the minimum scale of a disturbance in their study is smaller than that of ca. 0.1 ha which we use here. Similarly, Cole et al.\(^{20}\) report a \( \tau \) of ca. 1000 years (reported as number of events per thousand years) based on several sites scattered across the tropics. The \( \tau \) of Cole et al. is based on fossil pollen records and thus it is not clear whether disturbances were stand-replacing or not, but the character of their reported \( \tau \) is consistent with ours herein.

**Supplementary Note 4**

**Estimation of potential bias in \( \tau_0 \) calculation**

The sampling-based approach to uncertainty does not assess whether there is an overall bias introduced by classification errors. We make an approximation of the bias in our calculation of \( \tau_0 \) due to classification errors using the regional and global error matrices provided for Hansen et al.\(^5\) and ESA CCI respectively. We thus recalculate \( \tau_0 \) estimating the bias on each of the terms in Eq. 1 as follows:
1) For $A_L$ we calculate $A_{L,bias} = \left( \frac{A_{L,prod}}{A_{L,ref}} \right) - 1$, where $A_{L,prod}$ is the total loss fraction in the forest loss product and $A_{L,ref}$ the total loss fraction in the reference data. A detailed spatial-breakdown of classification error is not available, thus this is carried out for each of the four climate regions for which these statistics are reported in Hansen et al.\textsuperscript{5}. Multiplying $A_{L,bias}$ by $A_L$ gives an estimate of the absolute bias per grid cell. Propagating this bias alone through Eq. 1 gives a fractional difference in $\tau_0$ (Suppl. Fig. 8a).

2) No explicit validation of the year 2000 base map in Hansen et al.\textsuperscript{5} is provided. However, an evaluation of a 2010 map for part of South America using the same source data and classification models is available\textsuperscript{21}. For $A_T$, thus we apply the bias values from Table 4 of Pengra et al.\textsuperscript{21} globally, calculated as for $A_L$. Propagating both this bias and that on $A_L$ through Eq. 1 gives a fractional difference in $\tau_0$ as shown in Suppl. Fig. 8b.

3) ESA\textsuperscript{22} provide a detailed error matrix for individual landcover types, but do not provide error information for forest to non-forest transitions. We cannot assume that all transitions of “forest” go to “non-forest”, because our “non-forest” class is defined to cover agricultural and urban land for which a land-use change is clear, but not land which simply has limited tree cover, as this could still be recovering from a disturbance rather than undergoing land-use change. In the absence of appropriate error statistics, we make a speculative approximation of $A_C$ assuming that classification accuracy of forest and non-forest categories can be applied as biases on the transition. $A_{C,bias,for} = \left( \frac{A_{C,prod,for}}{A_{C,ref,for}} \right) - 1$, where $A_{C,prod,for}$ is the total number of forest samples in the in the landcover product and $A_{C,ref,for}$ is the total number of forest samples in the reference data. $A_{C,bias,non}$ is calculated analogously and the overall bias estimated as $A_{C,bias} = A_{C,bias,for} + A_{C,bias,non}$. Multiplying $A_{C,bias}$ by $A_C$ gives an estimate of the absolute bias per grid cell. Propagating all these biases through Eq. 1 gives a fractional difference in $\tau_0$ as shown in Suppl. Fig. 8c.

Overall, the results of this calculation suggest that there may be a modest underestimation of $\tau_0$ globally, with the underestimation stronger in parts of the tropics. These biases are small, with a mean fractional change in the temperate/boreal zone of 0.04, -0.02 and -0.03 for panels a, b and c, respectively, and in the tropical zone of -0.04, -0.09 and -0.11. Their influence on our results is therefore likely to be small and they lie within uncertainty ranges estimated through the bootstrapping approach. An improved
estimate of bias would require detailed spatial breakdowns of classification error on both states and transitions.

**Supplementary References**

1. Poulter, B. *et al.* The global forest age dataset and its uncertainties (GFADv1.1). (2019). doi.pangaea.de/10.1594/PANGAEA.897392
2. Song, X. *et al.* Global land change from 1982 to 2016. *Nature* 560, 639–643 (2018).
3. Seidl, R., Schelhaas, M.-J. & Lexer, M. J. Unraveling the drivers of intensifying forest disturbance regimes in Europe. *Glob. Chang. Biol.* 17, 2842–2852 (2011).
4. Schelhaas, M. J. *et al.* Actual European forest management by region, tree species and owner based on 714,000 re-measured trees in national forest inventories. *PLoS One* 13, e0207151 (2018).
5. Hansen, M. C. *et al.* High-resolution global maps of 21st-century forest cover change. *Science* 342, 850–853 (2013).
6. Chaplin-Kramer, R. *et al.* Degradation in carbon stocks near tropical forest edges. *Nat. Commun.* 6, 10158 (2015).
7. Laurance, W. F., Laurance, S. G. & Delamônica, P. Tropical forest fragmentation and greenhouse gas emissions. *For. Ecol. Manage.* 110, 173–180 (1998).
8. Brando, P. M. *et al.* Abrupt increases in Amazonian tree mortality due to drought-fire interactions. *Proc. Natl. Acad. Sci. U. S. A.* 111, 6347–52 (2014).
9. Gardiner, B., Peltola, H. & Kelloma, S. Comparison of two models for predicting the critical wind speeds required to damage coniferous trees. *Ecol. Modell.* 129, 1–23 (2000).
10. Stocks, B. J. *et al.* Large forest fires in Canada, 1959–1997. *J. Geophys. Res.* 108, 8149 (2003).
11. White, J. C., Wulder, M. A., Hermosilla, T., Coops, N. C. & Hobart, G. W. A nationwide annual characterization of 25 years of forest disturbance and recovery for Canada using Landsat time series. *Remote Sens. Environ.* 194, 303–321 (2017).
12. Espírito-Santo, F. D. B. *et al.* Size and frequency of natural forest disturbances and the Amazon forest carbon balance. *Nat. Commun.* 5, 3434 (2014).
13. Pickett, S. T. A. & White, P. S. *The ecology of natural disturbances and patch dynamics.* (Academic Press Inc, Orlando, 1985).
14. Milodowski, D. T., Mitchard, E. T. A. & Williams, W. Forest loss maps from regional
satellite monitoring systematically underestimate deforestation in two rapidly changing parts of the Amazon. *Environ. Res. Lett.* **12**, 194003 (2017).

15. Roberge, J.-M. *et al.* Socio-ecological implications of modifying rotation lengths in forestry. *Ambio* **45**, S109–S123 (2016).

16. Neigh, C. S. R., Bolton, D. K., Diabate, M., Williams, J. J. & Carvalhais, N. An Automated Approach to Map the History of Forest Disturbance from Insect Mortality and Harvest with Landsat Time-Series Data. *Remote Sens.* **6**, 2782–2808 (2014).

17. Kautz, M., Arneth, A., Anthoni, P., Meddens, A. J. H. & Pugh, T. A. M. Simulating the recent impacts of multiple biotic disturbances on forest carbon cycling across the United States. *Glob. Chang. Biol.* **24**, 2079–2092 (2018).

18. Negrón-Juárez, R. I. *et al.* Vulnerability of Amazon forests to storm-driven tree mortality. *Environ. Res. Lett.* **13**, (2018).

19. Chambers, J. Q. *et al.* The steady-state mosaic of disturbance and succession across an old-growth Central Amazon forest landscape. *Proc. Natl. Acad. Sci. U. S. A.* **110**, 3949–3964 (2013).

20. Cole, L. E. S., Bhagwat, S. A. & Willis, K. J. Recovery and resilience of tropical forests after disturbance. *Nat. Commun.* **5**, 3906 (2014).

21. Pengra, B., Long, J., Dahal, D., Stehman, S. V & Loveland, T. R. Remote Sensing of Environment A global reference database from very high resolution commercial satellite data and methodology for application to Landsat derived 30 m continuous field tree cover data. *Remote Sens. Environ.* **165**, 234–248 (2015).

22. ESA. *Land Cover CCI Product User Guide Version 2.0* (ESA, 2017). http://maps.elie.ucl.ac.be/CCI/viewer/download/ESACCILC-Ph2-PUGv2_2.0.pdf

23. Avitabile, V. *et al.* An integrated pan-tropical biomass map using multiple reference datasets. *Glob. Chang. Biol.* **22**, 1406–1420 (2016).

24. Avitabile, V. *et al.* Comparative analysis and fusion for improved global biomass mapping. in *Global Vegetation Monitoring and Modeling* 3 – 7 February 2014, Avignon (France) (2014).

25. Santoro, M. *et al.* Remote Sensing of Environment Forest growing stock volume of the northern hemisphere: Spatially explicit estimates for 2010 derived from Envisat ASAR. *Remote Sens. Environ.* **168**, 316–334 (2015).

26. Thurner, M. *et al.* Carbon stock and density of northern boreal and temperate forests. *Glob. Ecol. Biogeogr.* **23**, 297–310 (2014).

27. Smith, B. *et al.* Implications of incorporating N cycling and N limitations on
primary production in an individual-based dynamic vegetation model. 

*Biogeosciences* **11**, 2027–2054 (2014).
Supplementary tables

Supplementary Table 1. Values of $\tau_{\text{crit}}$ with 95% confidence intervals due to uncertainty in line fitting.

| Forest type | $\tau_{\text{crit},90}$ (years) | $\tau_{\text{crit},80}$ (years) |
|-------------|-------------------------------|-------------------------------|
| TrBE        | 594 (554-644)                 | 289 (278-303)                 |
| TrBD        | 523 (445-621)                 | 218 (171-252)                 |
| TeBE        | 289 (261-319)                 | 125 (114-138)                 |
| TeBD        | 426 (393-460)                 | 96 (50-130)                   |
| NE          | 417 (394-461)                 | 203 (195-213)                 |
| ND          | 323 (311-338)                 | 178 (171-184)                 |
| MX          | 406 (382-443)                 | 187 (175-196)                 |
| Global      | 444 (429-457)                 | 206 (201-211)                 |

Supplementary Table 2. Mapping of ESA CCI landcover classes to forest types used in this analysis.

| Code | Forest type                      | ESA CCI landcover classes | Additional conditions |
|------|----------------------------------|---------------------------|-----------------------|
| TrBE | Tropical broadleaved evergreen   | 50                        | latitude $\leq$ 23°   |
| TrBD | Tropical broadleaved deciduous   | 60, 61, 62                | latitude $\leq$ 23°   |
| TeBE | Temperate broadleaved evergreen  | 50                        | latitude $>$ 23°      |
| TeBD | Temperate broadleaved deciduous  | 60, 61, 62                | latitude $>$ 23°      |
| NE   | Needleleaved evergreen           | 70, 71, 72                | n/a                   |
| ND   | Needleleaved deciduous           | 80, 81, 82                | n/a                   |
| MX   | Broadleaved-needleleaved mixed   | 90                        | n/a                   |
|      | forest                           |                           |                       |
Supplementary figures

Supplementary Figure 1. $\tau_0$ (years, panels a, c, e) and fraction of forest stands under 50 years of age (panels b, d, f) aggregated to administrative units as used in the GFAD dataset\(^1\) for consistency of comparison. Panels a and e show the lower and upper 95% confidence intervals for $\tau_0$ respectively, whilst panel c shows the central estimate. Panels b and f show the upper and lower confidence intervals for the fraction of young stands (ordered for comparability with $\tau_0$), with d showing the central estimate.
Supplementary Figure 2. Comparison of $\tau_0$ calculated in this study with estimates of $\tau$ based on forest area and total area disturbed for 12 Canadian forest ecozones presented in White et al.\(^{11}\). Values of $\tau_0$ from this study are the means over the same ecozones used in White et al. and error bars show the 95% confidence intervals. The line is the best fit linear regression line, forced through the origin.
Supplementary Figure 3. Comparison of $\tau_O$ (years) with rotation period of biotic disturbances, $\tau_{bio}$ (see Suppl. Note 3). Panel a shows $\tau_O$ and panel b shows $\tau_{bio}$ (USA only).
Supplementary Figure 4. Difference between $\tau_0$ (years) calculated using the standard, forest-area based, approach and an alternative canopy-area based approach (see Methods). Positive values indicate higher $\tau_0$ in the standard approach.
Supplementary Figure 5. Total forest cover loss (million km$^2$ per grid cell) per 1° x 1° grid cell over the period 2000-2014 as calculated based on Hansen et al.$^5$ (Methods) minus forest cover loss due to land-use change, as calculated based on ESA CCI landcover v2.0.7 (Methods). The total loss based on Hansen et al. nearly always exceeds the loss due to land-use change based on ESA CCI.
Supplementary Figure 6. Average $\tau_0$ over the grid cells of each forest type as a function of the number of years of satellite data used to calculate $A_L$ and $A_C$. Six data years indicates forest loss data from 2000-2006, eight years indicates 2000-2008, etc. Only grid cells with at least 25% closed-canopy forest cover are included. Numbers above each inset indicate the number of grid cells of that forest type considered.
Supplementary Figure 7. a, $\tau_0$ calculated with no land-use change correction, displayed as in Fig. 1a. b, Difference between $\tau_0$ (years) calculated using the standard approach with the land-use change correction, and a calculation where the land-use change correction is excluded. Positive values indicate higher $\tau_0$ in the standard approach.
Supplementary Figure 8. Estimation of possible fractional bias in $\tau_o$. Positive values indicate that $\tau_o$ is overestimated. 

a, Only bias in $A_L$; 
b, biases in $A_L$ and $A_H$; 
c, biases in $A_L$, $A_T$ and $A_C$. 


Supplementary Figure 9. As for Fig. 3d,e except only for simulations with biomass transferred to litter, and with the shaded areas indicating $\pm 1\sigma$ of the mean value across each vulnerability class.
Supplementary Figure 10. Change in total (vegetation, litter and soil) carbon pools summed across all global closed-canopy forest area as a function of multiplicative perturbation in $\tau_D$, split according to weakly (green) and strongly (purple) sensitive forest areas. The simulations are the same ones as underlying Fig. 3d,e but here presented as global totals. Shaded areas indicate the range across three simulation set-ups testing assumptions on the type of disturbance assumed (disturbed material transferred directly to litter, harvested, or burnt). Solid lines are for the simulation where disturbed material is transferred directly to the litter.
Supplementary Figure 11. Forest type regions based on the ESA CCI landcover map and used in this analysis. The “Other” category accounts for only a small fraction of forest and is included in global totals, but not presented as a separate forest type.
Supplementary Figure 12. Comparison of modelled total biomass carbon, as simulated by LPJ-GUESS for the period 2001-2010, and observation-based estimates (as used in the empirical cross-checks in Fig. 23-26). Panel a shows the results of a simulation with the standard LPJ-GUESS disturbance settings (τ = 100 years globally, fire model turned on27) and panel b shows the results of the simulation forced by τ. Each point is one model grid cell, with brighter colours indicating a higher density of points. The 1:1 line is shown in black and the best-fit linear regression in red. RMSE is the root mean square error of the model.
Supplementary Figure 13. As for Fig. 3b, but with fits for each forest type explicitly separated. Dashed lines show the 95% confidence limits of the fit, as calculated using 1000 bootstrap samples.