Received: 9 April 2021 | Revised: 27 August 2021 | Accepted: 3 September 2021

DOI: 10.1111/geb.13406

Global Ecology and Biogeography A Journal of Macroecology WILEY

RESEARCH ARTICLE

Post-disturbance canopy recovery and the resilience of Europe's forests

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Funding information
H2020 European Research Council, Grant/Award Number: 101001905

Handling Editor: Benjamin Poulter

Abstract

Aim: Forest ecosystems around the globe are facing increasing natural and human disturbances. Increasing disturbances can challenge forest resilience, that is, the capacity of forests to sustain their functions and services in the face of disturbance. Quantifying resilience across large spatial extents remains challenging, as it requires the assessment of the ability of forests to recover from disturbance. Here we analysed the resilience of Europe's forests by means of satellite-based recovery and disturbance indicators.

Location: Continental Europe (35 countries).

Time period: 1986–2018.

Major taxa studied: Gymnosperm and angiosperm woody plant species.

Methods: We used a comprehensive set of manually interpreted reference plots and random forest regression to model annual canopy cover from remote sensing data across more than 30 million disturbance patches in Europe over the time period 1986–2018. From annual time series of canopy cover, we estimated the time it takes disturbed areas to recover to pre-disturbance canopy cover levels using space-for-time substitution. We quantified forest resilience as the ratio between canopy disturbance and recovery intervals, with critical resilience defined as forest areas where canopy disturbances occurred faster than canopy recovery.

Results: On average across Europe, forests recover to pre-disturbance canopy cover within 30 years. The resilience of Europe's forests to disturbance is high, with recovery being > 10 times faster than disturbance on 69% of the forest area. However, 14% of Europe's forests had low or critical resilience, with disturbances occurring as fast or faster than forest canopy can recover.

Main conclusions: We conclude that Europe's forests are widely resilient to past disturbance regimes, yet changing climate and disturbance regimes could erode resilience.

KEYWORDS

disturbance, Landsat, recovery, remote sensing, resilience, tree mortality

1 | INTRODUCTION

Natural disturbances, such as windthrow, bark beetle outbreaks or wildfire, are important drivers of forest ecosystem dynamics (Turner, 2010). Disturbances structure forest ecosystems across multiple spatial scales (Perry, 2002), from the death of individual trees creating gaps in the canopy to a large-scale reset of successional trajectories following stand-replacing disturbances. Disturbances occur abruptly (i.e., on time-scales of hours to years), but have long-lasting impacts on forest demography (McDowell et al., 2020; Schurman et al., 2018; Senf et al., 2021). They create biologically valuable early seral stages (Swanson et al., 2011), and generate a wide range of biological legacies (Franklin et al., 2002). Forest disturbances are thus essential drivers of forest ecosystem functioning and biodiversity (Bengtsson et al., 2000; Mori et al., 2018).

There is accumulating evidence that forest disturbances are increasing around the globe, in response to both climate change and human land use (Cohen et al., 2016; Seidl et al., 2014; Senf et al., 2018, 2021). Warmer and drier conditions as well as an increasing frequency of climatic extremes are fuelling natural disturbance regimes (Bowman et al., 2020; McDowell & Allen, 2015; Seidl et al., 2014, 2017; Senf, Buras, et al., 2020; Senf & Seidl, 2021b). Furthermore, humans disturb forests by extracting timber for the support of human wellbeing (Curtis et al., 2018; McDowell et al., 2020). Both the changes in natural disturbance regimes as well as increasing human land use have raised concerns that forests are losing their capacity to maintain their structure, functions and services (Millar & Stephenson, 2015; Trumbore et al., 2015). In other words: there is increasing concern that forests globally are losing their resilience (Albrich et al., 2020; Johnstone et al., 2016; Reyer et al., 2015; Stevens-Rumann et al., 2018; Whitman et al., 2019).

Quantifying resilience is a key objective of contemporary ecology (Carpenter et al., 2001; Nikinmaa et al., 2020), and a quantitative understanding of a system's resilience is a prerequisite for determining the risk of losing it (Lindenmayer et al., 2016). There is a multitude of definitions and indicators of resilience in the literature (Nikinmaa et al., 2020; Scheffer et al., 2015), which can create confusion on how to measure resilience (Hodgson et al., 2015). We here adopt a resilience definition that is rooted in past research on ecological stability (Turner et al., 1993) and adopts recently proposed ideas for quantifying resilience in ecology (Ingrisch & Bahn, 2018): post-disturbance recovery. Post-disturbance recovery is a widely accepted and commonly used measure of resilience to disturbance (Hodgson et al., 2015; Ingrisch & Bahn, 2018; Nimmo et al., 2015; Willis et al., 2018). Post-disturbance recovery can be expressed as recovery rate (i.e., the rate at which an ecosystem state recovers), or as recovery interval (i.e., time it takes for a system to recovery to a pre-disturbance state). However, recovery alone is not sufficient to quantify resilience. In the context of forest disturbance, for example, a recovery interval of 50 years could indicate high resilience if the average disturbance interval is long (e.g., 500 years), meaning that forests recover important properties long before they will be disturbed again. However, the same recovery interval could indicate a high risk of ecosystem collapse if the average disturbance interval in a system is 25 years, indicating that the system is not able to successfully recover from disturbances and that a state change (e.g., to open, non-forest systems) is likely. Hence, the resilience of a system does not only depend on its ability to recover from disturbance, but also on the degree to which it is exposed to disturbance. In analogy to recovery rate or recovery interval, the degree to which a system is exposed to disturbance can be expressed as disturbance rate or disturbance interval, that is the average proportion of a forest experiencing disturbance or the average time between two disturbance events. Quantifying the resilience of forest ecosystems to (increasing) disturbances thus requires the joint analysis of both forest disturbance and recovery (Hodgson et al., 2015; Ingrisch & Bahn, 2018; Nimmo et al., 2015).

Quantifying disturbance and recovery at regional to continental scales requires spatially explicit and exhaustive long-term data. With recent advances in data processing and the availability of multi-decadal time series, remote sensing fulfils all of these requirements and is a potent means to quantify resilience across large spatial domains. While long-term spatial analysis of disturbance using remote sensing data is de facto operational (M. C. Hansen et al., 2013; Hermosilla et al., 2016; Senf & Seidl, 2021a), mapping forest recovery over broad spatial and long temporal scales remains challenging. Recent studies have addressed this challenge by using spectral recovery (i.e., the time it takes until a pixel has similar spectral reflectance properties as prior to disturbance) as a proxy of recovery (Frazier et al., 2015; Kennedy et al., 2012; Pickell et al., 2015). Spectral recovery allows for the quantification of disturbance recovery rates at national scales (White et al., 2017), and has been shown to correlate well with structural measures of recovery (Chirici et al., 2020; Senf et al., 2019; White et al., 2018, 2019). Despite these advances in mapping forest recovery at the case study level, there is still a lack of information on patterns and drivers of recovery across large spatial scales, for example, for all of Europe. This knowledge gap hampers the development of recovery-based resilience indicators for Europe's forests, and constitutes a crucial knowledge gap given the sharp increase in forest disturbances in Europe in recent years (Senf et al., 2018, 2021; Senf & Seidl, 2021b).

Here, our aim was to analyse the resilience of Europe's forests to disturbance using satellite-based disturbance and recovery indicators. Disturbance and recovery here focus on canopy cover and resilience is defined as the ratio between average canopy disturbance and average canopy recovery intervals (hereafter referred to simply as disturbance and recovery intervals). Disturbance interval was defined as the average time between two disturbance events. Recovery interval was defined as the average time until a disturbed area will recover to pre-disturbance canopy cover. Hence, a resilience greater than 1 indicates a resilient landscape with faster recovery than disturbance, while a resilience around 1 indicates similar disturbance and recovery intervals, resulting in increasing landscape variability (Fraterrigo & Rusak, 2008; Turner et al., 1993). A resilience of less than 1 indicates a critical state where disturbances outpace recovery, suggesting that forest cover will decline over time (e.g., forests shifting to open woodlands, savanna, shrublands, or grasslands). We address our overall aim by focusing on three specific objectives: (a) estimate pre- and post-disturbance canopy cover across all disturbance patches mapped for Europe in the period 1986–2018 from satellite data (Senf & Seidl, 2021a); (b) quantify recovery intervals across Europe; (c) analyse how recovery intervals vary by disturbance patch size and severity, that is, two important descriptors of the disturbance regime; and (d) estimate forest resilience across Europe by calculating the ratio between disturbance and recovery intervals.

2 | MATERIALS AND METHODS

2.1 | Satellite-based canopy cover estimates

We used time series of Landsat satellite images to predict annual pre- and post-disturbance canopy cover for more than 36 million disturbance patches mapped throughout Europe in a previous study (Senf & Seidl, 2021a). A disturbance patch was defined as contiguous pixels (30-m grain) that were disturbed in the same year, with a minimum mapping unit of two pixels (0.18 ha). As a first step, we built annual medoid composites using all available Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) and Operational Land imager (OLI) Tier-1 surface reflectance observations between 1 June and 30 September following methods described in Flood (2013). Before doing so, we masked out all cloud, cloud shadow and snow pixels using the Landsat quality band. We further matched images from OLI to TM/ETM+ to avoid bias from the different spectral response functions (Roy et al., 2016). We then used the LandTrendr algorithm—a time series segmentation approach that partitions time series into linear segments (Kennedy et al., 2010)—to smooth the annual spectral time series, that is to remove remaining inter-annual variability caused by phenological variations, clouds not detected during the cloud screening process or other artefacts not addressed in the Landsat quality band (Moisen et al., 2016; Oeser et al., 2020; Senf, Laštovička et al., 2020; Vogeler et al., 2018). Specifically, this processing step interpolates annual Landsat spectral time series from the linear segments and thus removes unwanted inter-annual variability for stable segments, but keeps larger changes caused by disturbances. The temporal segmentation was done based on the normalized burn ratio (NBR), which is a normalized difference index of the shortwave infrared reflectance bands and which is highly sensitive to disturbance (Hermosilla et al., 2015). From the interpolated spectral Landsat time series, we derived a set of seven spectral indices: (a) the normalized difference vegetation index (NDVI), (b) the enhanced vegetation index (EVI), (c) the soil-adjusted vegetation index (SAVI), (d) the modified soil-adjusted vegetation index (mSAVI), (e) the normalized difference moisture index (NDMI), (f) the NBR, and (g) the NBR-2. All calculations were done in a cloud environment (Gorelick et al., 2017) using existing code and implementations and described in detail in Kennedy et al. (2018).

To predict canopy cover from the segmented annual Landsat time series, we created a reference database of canopy cover estimates using image interpretation of high-resolution imagery available in Google Earth. We first created a random sample of 1,000 Landsat pixels stratified across countries based on relative land area. The stratification, whilst not affecting the probabilistic nature of the sample, ensured that references from all countries were included in the final reference database (see Supporting Information Figure S1 for details on the location of reference pixels). We then selected a 5 × 5 pixel neighbourhood centred on the reference pixel (i.e., total of 25 pixels or 2.25 ha) as a reference site, accounting for a potential spatial mismatch between Landsat pixels and high-resolution imagery used for the interpretation of canopy cover (Senf, Laštovička, et al., 2020; Vogeler et al., 2018). For estimating canopy cover from high-resolution imagery, we placed a regular grid of 10 × 10 points into the reference site and counted the number of points intersecting with a tree crown in all high-resolution imagery available in Google Earth (see Supporting Information Figure S2 for examples of the interpretation setup). That is, at each of the 1,000 reference sites, we estimated canopy cover for all time points where high-resolution imagery was available, even if no change in canopy cover occurred. This was done in order to collect reference canopy cover estimates for different points in time and different successional stages (i.e., before and after disturbance). If there was shadow and we were unable to determine whether the point intersected with a crown or not, the point was labelled as *not available*. If no high-resolution imagery was available in Google Earth, the reference site was dropped. In total, we estimated canopy cover for 963 sites and 11,221 site–year combinations.

We extracted all Landsat spectral bands and indices for each of the site–year combinations (i.e., matching both the location and year of the estimate) and built a random forest regression model (Breiman, 2001) to predict canopy cover from the smoothed Landsat spectral data and vegetation indices (Moisen et al., 2016; Vogeler et al., 2018). We evaluated the model using 10-fold cross-validation, and calculated the variance explained, the root mean squared error and the normalized root mean squared error as measures of model accuracy. We predicted canopy cover for each disturbed pixel over the time period 1986 to 2018, resulting in more than 12 billion individual canopy cover predictions across Europe. Subsequently, we averaged the canopy cover predictions per disturbance patch and year, resulting in approximately 1.1 billion canopy cover estimates across Europe. Based on this data we calculated the average canopy cover 5 years before disturbance (i.e., pre-disturbance canopy cover) and the annual canopy cover for each year after disturbance (i.e., post-disturbance canopy cover) per patch. We excluded patches for which less than 5 years of data prior to disturbance were available to avoid unreliable estimates of pre-disturbance canopy cover. This restricted our analysis to the time period 1991–2018 or a maximum of 28 years of disturbance recovery estimates.

2.2 | Estimating recovery intervals

For assessing post-disturbance recovery intervals, we used a space-for-time substitution approach to develop a chrono-sequence of relative canopy cover after disturbance. Relative canopy cover here means canopy cover in relation to the pre-disturbance canopy cover, and was used because forest definitions based on absolute canopy cover vary widely across Europe. To create the chrono-sequences, we sorted all relative canopy cover observations along years (t) after disturbance, with t = {1 ,..., 28}, and calculated the average relative canopy cover per year, following named r_t. The resulting chrono-sequence of r_t shows the average relative canopy cover (i.e., in relation to pre-disturbance canopy cover) for 1 to 28 years after disturbance (see Figure 1 for examples). From the chrono-sequence, we derived the recovery interval as the first year of complete recovery (i.e., relative canopy cover ≥ 1), following the definition given in the Introduction (see also Figure 1 for examples). Because not all chrono-sequences fully recover within 28 years, we used a statistical model to extrapolate our chrono-sequences beyond 28 years. We fitted logistic functions to the chrono-sequences, predicting the relative canopy cover dependent on t:

$$r_t = n + \frac{m}{\left(1 + \exp^{-k(t-t_0)}\right)} \quad (1)$$

with n, m, k and t_0 being model parameters estimated from the data using a Levenberg–Marquardt algorithm implemented in the *minpack.lm* package (Elzhov et al., 2016) available in the statistical programming language R (R Core Team, 2020). We used the fitted model to predict relative canopy cover for up to 1,000 years post-disturbance, and derived the recovery interval (i.e., the first year of complete recovery) from the model predictions.

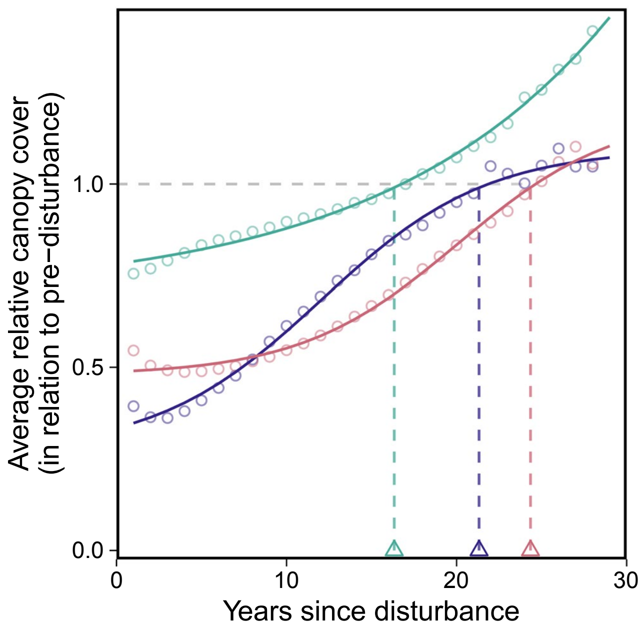

FIGURE 1 Three example trajectories (different colours) of average relative canopy cover (dots) over time since disturbance. A logistic function fit to the observed data (solid lines) was used to estimate the recovery interval, that is the time it takes until—on average—a patch has fully recovered (i.e., average relative canopy cover ≥1; see vertical dashed lines and triangles in figure). [Correction added on 23 October 2021, after first online publication: Figure 1 has been replaced.]

As our aim was to assess the spatial variation in recovery intervals, and subsequently resilience, a spatial aggregation unit was needed to create chrono-sequences. We used three different spatial aggregation levels: (a) A grid of hexagons distributed equally across Europe along a 50 km grid with each hexagon sized 2,165 km^2 and used in previous studies to assess spatial patterns of disturbance regimes (Senf & Seidl, 2021a). This hexagon grid allows for assessing spatial variation in recovery across Europe. (b) Individual countries to assess differences in recovery intervals and subsequently resilience between countries. (c) Different patch sizes and disturbances severities, testing their influence on recovery. Disturbance severities were calculated from the canopy cover estimates described above by (1−min(canopy cover$_{post}$)/canopy cover$_{pre}$) × 100, resulting in values from 0 (no change in canopy) to 100 (complete loss of canopy); and were classified into < 50 (low severity), 50–90 (high severity) and > 90 (very high severity). Patch size was classified into < 1, 1–10 and > 10 ha.

2.3 | Assessment of disturbance resilience

Resilience was here defined as the ratio between disturbance and recovery intervals. Recovery intervals were estimated as described in the previous section. Disturbance intervals were based on a Landsat-based disturbance map published previously (Senf & Seidl, 2021a) and available from Senf (2021; version 1.0.0). The disturbance map depicts any abrupt declines in the dominant forest canopy—regardless of their cause—that are detectable at a spatial grain of 30 m, including disturbances that only remove a part of the canopy within a pixel. It does, however, not detect any changes in sub-canopy tree layers. Using relatively short data series, such as the remote sensing-based disturbance maps used in this study (covering the period 1986 to 2016), it is challenging to estimate true disturbance intervals (i.e., the time between two disturbance events). We hence used rotation period as a proxy for disturbance interval. Rotation period is the average time needed to disturb an area of the size of the focal area (e.g., forest area of a hexagon or country), and is calculated by dividing the total forest area by the average annual forest area disturbed (Pugh et al., 2019; Turner & Gardner, 2015). Both forest area and average annual forest area disturbed were derived from the previously published disturbance maps (Senf & Seidl, 2021a). We neglected land use conversions in the calculation of disturbance rotation periods, because they play a minor role in European forest disturbance dynamics (Senf et al., 2021). While rotation period and return intervals are, strictly speaking, not equivalent, there is no possibility of calculating disturbance intervals directly from the relatively short time series available from satellite data. While differences between disturbance rotation period and return interval can be potentially large at small spatial scales, the two concepts—however—converge at large spatial scales.

The resultant indicator of resilience (i.e., ratio between disturbance and recovery intervals) ranges from 0 to ∞, with larger values indicating more resilient systems (i.e., infrequent disturbance, fast recovery). A resilience value smaller than 1 (i.e., higher disturbance interval than recovery interval) was defined as critical, because it indicates that a system is no longer able to recover from disturbance, which can indicate system change (i.e., long-term loss of forest area). A resilience value between 1 and 5 was defined as low resilience. In a low resilience state, the forest ecosystem is highly variable in time (Fraterrigo & Rusak, 2008; Turner et al., 1993), and a gradual increase in average disturbance rates or a sudden large pulse of disturbance might push the system into a critical state. We further defined moderate resilience as a resilience value between 5 and 10; and high resilience as a system exceeding a resilience value of 10 (i.e., with 10 times higher recovery intervals than disturbance intervals). We derived resilience indicators for each hexagon grid cell (see Section 2.2), as well as at the country level.

3 | RESULTS

3.1 | Mapping forest cover across Europe

The Landsat-based model accurately predicted canopy cover with a R^2 of .96 and an average error of 7.9 percentage points (Figure 2). The average canopy cover for Europe's forests (with forests defined as areas with > 10% canopy cover; Chazdon et al., 2016) was 57%, with a standard deviation of 33 percentage points. Based on these

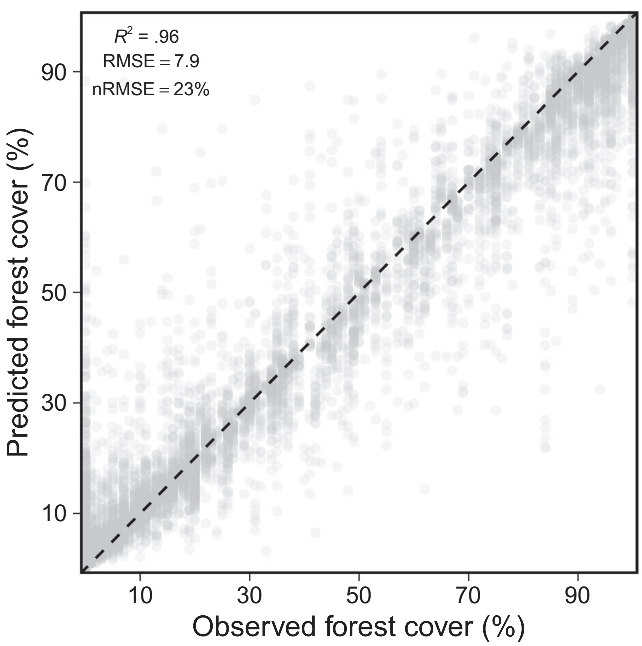

FIGURE 2 Assessment of the Landsat-based canopy cover model via 10-fold cross-validation. RMSE, root mean squared error; nRSME, normalized root mean squared error. [Correction added on 23 October 2021, after first online publication: Figure 2 has been replaced.]

canopy cover estimates we calculated disturbance severity, that is, the percent loss of forest canopy during disturbance relative to pre-disturbance canopy cover. Across all disturbed patches recorded in Europe between 1986 and 2016, the average disturbance severity was 66%. Approximately 75% of all disturbances in Europe were high severity events with > 50% canopy loss. Approximately 10% of all disturbances in Europe had very high severity (> 90% canopy loss; see also Supporting Information Figure S3).

3.2 | Recovery intervals

Using annual canopy cover estimates we quantified how quickly disturbed patches recover, on average, to pre-disturbance canopy cover. The trajectories of recovery were well described by the logistic model's' fit to the data, with only a few instances of failed model convergence (1.2%). All estimates given in the following are based on the model fit and not on raw data. The distribution of recovery intervals across Europe was left-skewed with a forest-area weighted median recovery interval of 18 years and a forest-area weighted mean recovery interval of 35 years. Overall, in 87% of Europe's forests canopy cover recovered to pre-disturbance values in less than 30 years. Longer recovery intervals for canopy cover (30–100 years) were found in mountain regions of the Alps and Carpathians as well as in large parts of Fenno-Scandinavia (in total 9% of Europe's forest area; Figure 3 and Table 1). Only in a few regions did it take forest canopy > 100 years to recover from disturbance, including parts of the Iberian Peninsula, France and Greece (totalling to approximately 2% of Europe's forest area; Figure 3 and Table 1). For less than 1% of Europe's forests recovery intervals exceeded 1,000 years and were capped at this value. For those regions we estimate that, given our data, the majority of disturbances will not reach pre-disturbance canopy cover again within ecological time frames.

Disturbance patch size and severity influenced recovery intervals (Figure 4). For disturbance patches up to 10 ha, we observed little variability in recovery intervals, with forests recovering within the first 30 years of disturbance. For patches above 10 ha, however, the proportion of patches with very long recovery intervals (> 100 years) increased, and a considerable proportion of patches did not recover at all (i.e., recovery intervals of >1,000 years). Furthermore, recovery slowed with increasing disturbance severity. Low severity disturbances (≤50% of canopy lost) recovered almost exclusively within the first 30 years after disturbance. High severity disturbances (50% < canopy loss ≤ 90%) led to a substantially higher proportion of long recovery intervals (30–100 years). Very high severity disturbances (>90% canopy loss) were most likely to experience very long recovery intervals (>100 years) and had the highest proportion of forests not recovering at all (i.e., with disturbance intervals >1,000 years). From this analysis we conclude that disturbance severity is a more important driver of recovery than disturbance size (Figure 4).

We did find substantial variation in average recovery intervals between countries (Table 1), with fastest post-disturbance recovery in Bulgaria, Hungary, Moldova and the Netherlands (11 years)

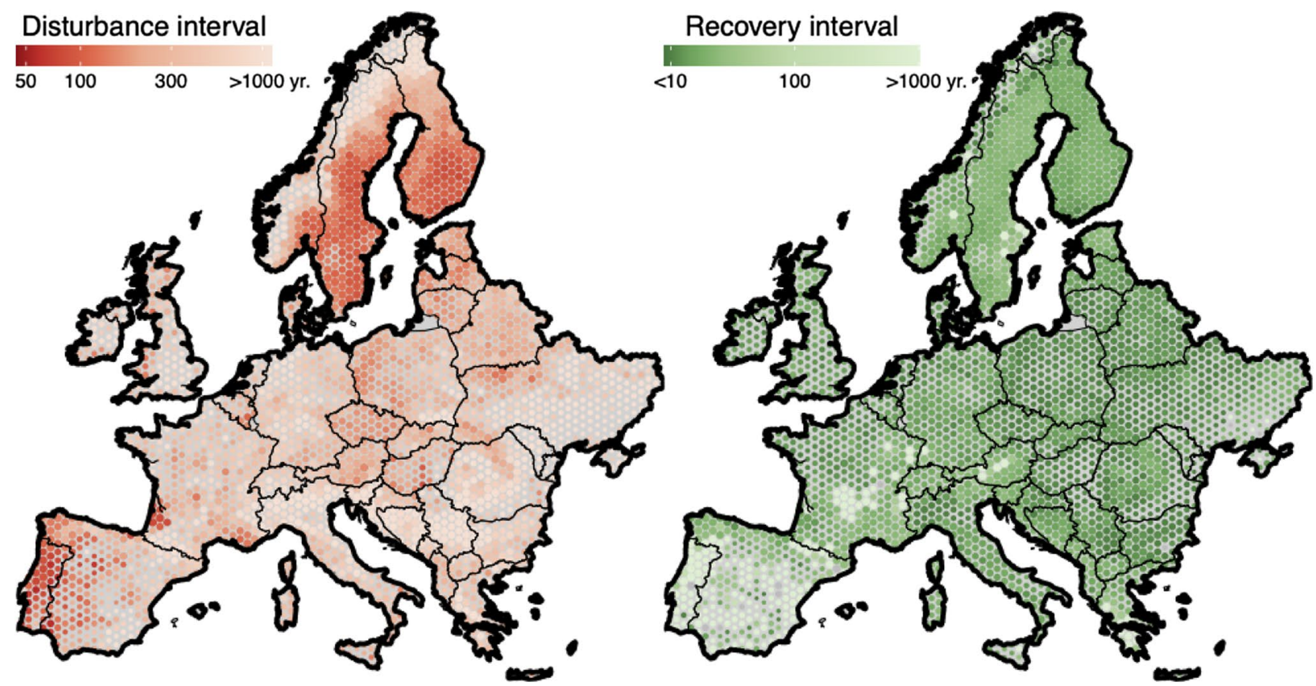

FIGURE 3 Disturbance and recovery intervals across Europe's forests. Shown are the centroids of the 50-km hexagon grid, with point size scaled to the forest area within each hexagon. Grey dots indicate missing data. [Correction added on 24 October 2021, after first online publication: Figure 3 has been replaced.

and longest average recovery times in Portugal (228 years), Spain (87 years) and Greece (33 years). Except for these three countries, canopy recovered within 30 years post-disturbance in all other European countries.

3.3 | Resilience of Europe's forests to disturbance

We quantified and mapped forest resilience to disturbance by calculating the ratio between disturbance and recovery intervals (Figure 5). We found that the majority of Europe's forest area (approximately 69%) can be considered highly resilient to the currently prevailing disturbance regime, with ratios of disturbance interval to recovery interval of greater than 10 (i.e., 10 times faster recovery than disturbance). Regions of high resilience were found on the Balkan Peninsula, the southern side of the Alps, northern Fenno-Scandinavia, and parts of Central and Eastern Europe. Approximately 17% of Europe's forests have moderate resilience, with ratios of disturbance to recovery intervals between 5 and 10. Regions of moderate resilience were found in parts of the Alps and the Carpathians (especially Austria and Czechia), the United Kingdom and Ireland, large parts of Fenno-Scandinavia, northern Spain, southern France, and Greece (see also Table 1). Another 12% of Europe's forests have low resilience, with disturbance intervals approaching recovery intervals (i.e., resilience values smaller than 5 but larger than 1). Those forests can still be considered resilient, but they exhibit high variability over time and a gradual decrease in average recovery rates or a sudden large pulse of disturbances might push them into a critical state. Those regions were found in southern Sweden and Finland as well as central France and Spain. Critical states, that is areas where disturbances occur faster than forests can recover (i.e., resilience values < 1), were identified for 2% of Europe's forest area. Those regions were largely concentrated on the Iberian Peninsula and occurred particularly in Portugal (Table 1).

4 | DISCUSSION

We here provide the first quantitative assessment of disturbance resilience in Europe's forests, calculating remote sensing-based recovery and disturbance intervals. We found that the majority of Europe's forest area is resilient to the recent rate of disturbance by human and natural causes. This result reflects the observation that forest area in Europe has increased over recent decades (Forest Europe, 2020), and that rates of timber extraction (from planned harvesting and salvage harvesting of naturally disturbed areas) remain below annual increment in most of Europe's countries (Levers et al., 2014). We further document that even regions affected by large-scale natural disturbance events since the mid-1980s have generally high resilience (e.g., regions affected by large cyclonal storms; Forzieri et al., 2020; Senf & Seidl, 2021c). This underlines that Europe's forests are well adapted to disturbance, and that infrequent, large pulses of tree mortality do not generally threaten Europe's forest ecosystems. We did, however, also identify several regions of low resilience to prevailing disturbance regimes (approximately 12% of Europe's forests). In these areas a sudden pulse of tree mortality caused by natural disturbance could push forests into a critical state. Regions of low

TABLE 1 Average disturbance and recovery intervals, as well as resilience (i.e., disturbance interval/recovery interval), for the 35 countries included in this study . [Correction added on 23 October 2021, after first online publication: Table 1 has been modified.]

Country	Average recovery interval (years)	Average disturbance interval (year)	Resilience
Albania	20	205	9.78
Austria	19	212	10.61
Belarus	12	238	19.83
Belgium	15	175	10.93
Bosnia and Herzegovina	15	533	31.36
Bulgaria	11	387	35.19
Croatia	17	363	20.18
Czechia	11	175	14.47
Denmark	13	180	12.03
Estonia	20	146	6.63
Finland	18	141	7.44
France	19	212	9.62
Germany	15	242	15.12
Greece	27	207	6.26
Hungary	10	206	18.71
Ireland	14	166	11.10
Italy	15	322	20.15
Latvia	14	138	9.20
Lithuania	11	180	15.03
Moldova	12	678	61.64
Montenegro	20	321	14.59
Netherlands	10	384	34.87
North Macedonia	16	272	16.01
Norway	20	279	12.15
Poland	11	231	19.27
Portugal	>100	56	0.25
Romania	13	359	25.65
Serbia	11	497	41.40
Slovakia	13	231	16.50
Slovenia	20	417	18.98
Spain	>100	111	1.28
Sweden	23	136	5.21
Switzerland	16	418	24.59
Ukraine	12	280	23.33
United Kingdom	16	183	10.19

resilience mostly occurred in areas with high or very high management intensity (Levers et al., 2014; Nabuurs et al., 2019). According to our analysis, these regions have very low safety margins against additional disturbances and might already be in "resilience debt" (Johnstone et al., 2016; Lindenmayer et al., 2016).

We found approximately 2% of Europe's forest area to be in a critical state with regard to disturbance resilience, that is, they are disturbed faster that they can recover. For these regions a loss of forest area (e.g., due to immaturity risk) and a shift to an alternative, non-forest ecosystem state have to be expected. Regions with critical resilience were exclusively found in Portugal and Spain. Portugal currently has the shortest disturbance intervals in Europe, due to a combination of intensively managed short-rotation plantation forests (mostly *Eucalyptus globulus*, covering approximately one quarter of Portugal's forest area and approximately 10% of its land area; Fernandes et al., 2019; Forest Europe, 2020) and a high prevalence of fires (Nunes et al., 2019; Senf & Seidl, 2021c). Furthermore, high disturbance rates coincide with long recovery intervals here, which might be related to the Mediterranean climate in general and to increasing fire severity in the region. Climate change, plantation management, and increasing fuel availability and continuity have led to larger and more intense fires in recent decades across

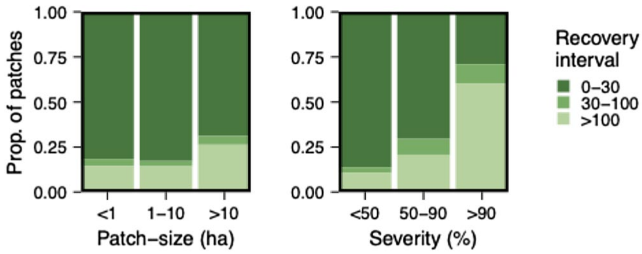

FIGURE 4 Distribution of recovery intervals over disturbance patch size and severity. [Correction added on 23 October 2021, after first online publication: Figure 4 has been replaced.]

the Iberian Peninsula (Fernandes et al., 2014; Moreira et al., 2020). Those larger and more intense fires can transition the widespread plantation forests to mixed forests or open systems dominated by shrubs (Fernandes et al., 2019; Silva et al., 2011). In fact, official data suggest that Portugal's forest area has already declined in the past 20 years (Forest Europe, 2020), most likely as a consequence of fire (Fernandes et al., 2019; Oliveira et al., 2017), supporting our remote sensing-based assessment of forest resilience.

While we show that the majority of Europe's forests is resilient to prevailing disturbance regimes, an important question remains unanswered: Can future disturbances push Europe's forests across resilience thresholds and into a critical state? Forest disturbances have increased across Europe in recent decades as a result of both land use and climate change (Senf et al., 2018, 2021). Furthermore, there has been an increase in large-scale forest diebacks in response to drought (Senf, Buras, et al., 2020; Senf & Seidl 2021b), as well as an increase in wind disturbances (Senf & Seidl, 2021c). A continued change in disturbance regimes along the trajectories of the recent past could thus bring Europe's forests closer to critical resilience thresholds. Yet, even for a doubling of disturbance intervals only an additional 1% of Europe's forest area will be in a critical state based on our analysis, assuming stable recovery intervals. However, the recovery rate will likely also be affected by climate change: first, larger disturbance patches under climate change can hamper natural regeneration after disturbances (Figure 4; Hansen et al., 2018; Harvey et al., 2016); second, a higher prevalence of high-severity disturbances can hamper the establishment of new forests (Figure 4; Buma & Wessman, 2011; Rydgren et al., 2004); third, drought has been found to impede natural regeneration by increased seedling mortality (Hansen et al., 2018; Harvey et al., 2016; McDowell et al., 2008). Climate change could, however, also foster recovery in some parts of Europe, for example, in mountain forests where tree establishment has been limited by temperature (Mina et al., 2017). Furthermore, it remains unclear to what extent elevated CO_2 could compensate drought effects and foster post-disturbance recovery (Pretzsch et al., 2020). Hence, further research on the future resilience of Europe's forests to disturbance is urgently needed.

Our analysis is the first continental-scale assessment of forest disturbance resilience in Europe. While this type of analysis would

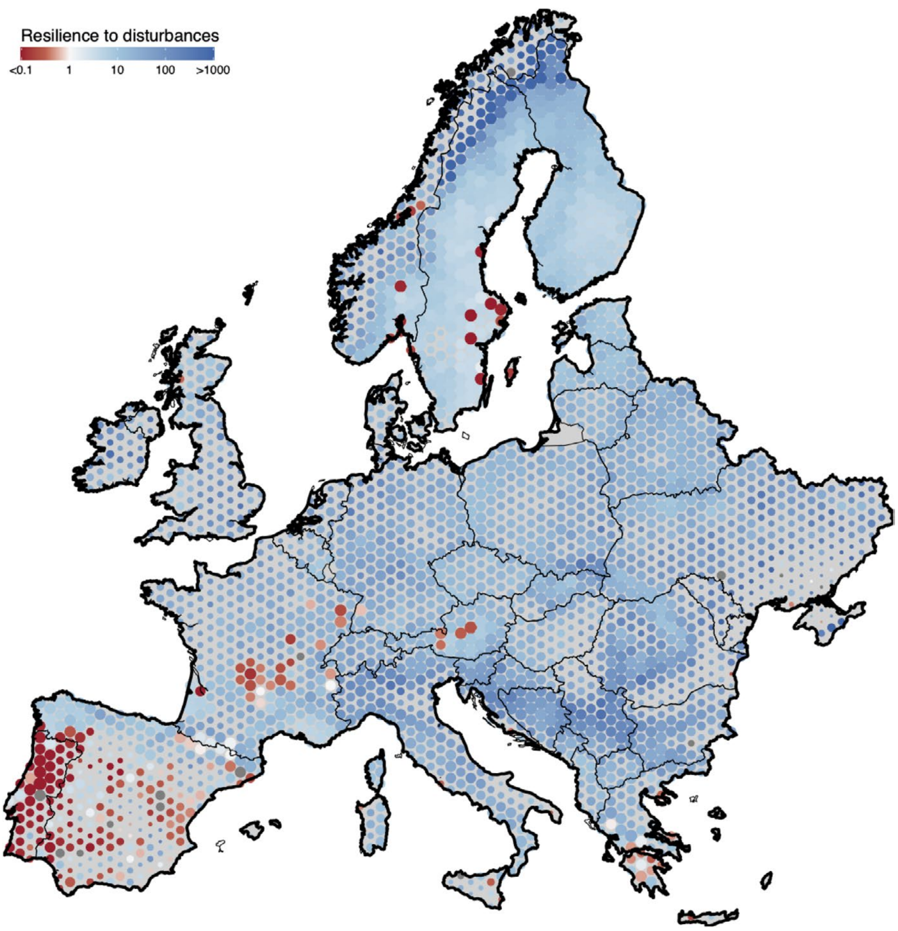

FIGURE 5 The resilience of Europe's forest ecosystems to disturbance. Resilience was defined as the ratio between disturbance and recovery intervals (see Sections 1 and 2.3 for detailed definitions). Shown are the centroids of a 50-km hexagon grid, with point size scaled to the forest area within each hexagon. Grey dots indicate missing data. [Correction added on 23 October 2021, after first online publication: Figure 5 has been replaced.]

have been impossible without the spatially exhaustive and historic archives of Landsat, it also comes with limitations and uncertainties. First, the remote sensing data employed here have a relatively coarse resolution of 30 m. Many disturbances in Europe are small compared to this grain of analysis (Senf & Seidl, 2021a), and post-disturbance forest recovery might operate at much finer scale (e.g., surviving residual trees; Bolton et al., 2015). Our analysis thus provides a coarse view on recovery dynamics at the continental scale, and should be amended with local, field-based studies in the future to reach robust conclusions at the regional scale (e.g., Zeppenfeld et al., 2015). In addition, emerging studies showing the potential of remote sensing to also monitor forest recovery locally (e.g., Chirici et al., 2020) suggest a combination of field-based approaches with remote sensing analyses as a potent way forward for forest resilience studies. Second, our time series cover a relatively short time period given the longevity of trees. This is a limitation inherent to the underlying data that must be taken into account when interpreting our results. We suggest that future research should verify our results with more localized but long-term data such as dendroecological data. Third, we note that resilience can be defined in manifold ways, and the utility of our quantification might vary with context. Here, we used local canopy cover before a disturbance as the reference state for recovery. This means that if canopy cover pre-disturbance was very high (as is the case for plantations in Portugal, for instance), a lower canopy cover post-disturbance indicates a loss of resilience. However, the lower level of canopy cover might still sustain important ecological functions and services, and might thus not constitute a loss of resilience in terms of ecosystem service supply (Seidl et al., 2016). Likewise, increasing canopy cover does not per se indicate higher resilience in terms of ecosystem functions and services. The socio-ecological resilience of Europe's forests (cf. Nikinmaa et al., 2020) is thus likely considerably different from the quantification presented here. Third, we here only focused on one important parameter to define recovery: canopy cover. Hence, our view on recovery is limited and does not provide information on whether forests have recovered to their pre-disturbance structure, nor to their pre-disturbance composition. It remains difficult, however, to map forest structure from optical remote sensing data, because optical signals saturate at tree cover > 25 m (Potapov et al., 2021). The use of spaceborne Lidar data for estimating structural recovery might help in overcoming this challenge in the future (Dubayah et al., 2020).

5 | CONCLUSION

We here provide the first continental-scale analysis of post-disturbance forest recovery in Europe. Based on our experience we conclude that large-scale remote sensing of forest recovery is an innovative way to assess forest resilience. We encourage further research on assessing forest resilience from remote sensing data, and suggest that an integration of remote sensing information with empirical and experimental approaches is a promising way forward for quantifying forest resilience. We here showed that the majority of Europe's forests is resilient to the disturbance regimes of the recent past. We, however, also highlight that a considerable share of Europe's forests (14%) has only low resilience or is already in a critical state regarding forest disturbance and recovery. Given that climate change could further amplify disturbance and impede recovery, fostering forest resilience should be a central focus of forest management in Europe. Management could improve resilience by aiding post-disturbance recovery, for example, via retaining a considerable portion of live trees in management interventions (i.e., reducing the severity of anthropogenic disturbances, cf. Figure 4; Gustafsson et al., 2012) or aiding recovery with tree planting (i.e., reducing the recovery interval). A second level for management is to increase the resistance of forests to natural disturbance, and to compensate increasing natural disturbance rates by reducing planned canopy openings (and thereby increasing the disturbance interval). We conclude that resilience is a central property of forest ecosystems in a changing world, and should be a focus of forest research and management.

ACKNOWLEDGMENTS

We gratefully acknowledge help from Laura Steinbach with collecting reference data. R. Seidl further acknowledges support from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement no. 101001905).

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest that could be perceived as prejudicing the impartiality of the research reported.

AUTHOR CONTRIBUTIONS

Cornelius Senf and Rupert Seidl developed the research idea. Cornelius Senf curated the data collection and performed all analysis. Cornelius Senf wrote the manuscript with input from Rupert Seidl.

DATA AVAILABILITY STATEMENT

All data and code produced/used in this study are available at: https://github.com/corneliussenf/DisturbanceRecoveryEurope, with a permanent version being available at https://doi.org/10.5281/zenodo.5484270. The disturbance maps used in this study are available from https://doi.org/10.5281/zenodo.3924380 (version 1.0.0).

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BIOSKETCH

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of the article at the publisher's website.

How to cite this article: Senf, C., & Seidl R. (2022). Post-disturbance canopy recovery and the resilience of Europe's forests. *Global Ecology and Biogeography*, 31, 25–36. https://doi.org/10.1111/geb.13406