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RESEARCH ARTICLE

Quantifying patch size distributions of forest disturbances in protected areas across the European Alps

Michael Maroschek[1,2] | Rupert Seidl[1,2] | Benjamin Poschlod[3] | Cornelius Senf[2]

[1]Berchtesgaden National Park, Research and Monitoring, Berchtesgaden, Germany

[2]Ecosystem Dynamics and Forest Management Group, School of Life Sciences, Technical University of Munich, Freising, Germany

[3]Research Unit Sustainability and Climate Risks, Center for Earth System Research and Sustainability, Universität Hamburg, Hamburg, Germany

Correspondence
Michael Maroschek, Berchtesgaden National Park, Research and Monitoring, Doktorberg 6, 83471 Berchtesgaden, Germany.
Email: michael.maroschek@npv-bgd.bayern.de

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Abstract

Aim: Natural disturbances are key drivers of forest ecosystem dynamics and are highly sensitive to global change. Despite their importance, central disturbance characteristics remain unknown for many forests worldwide. Here, we quantified an important component of the forest disturbance regime—the distribution of patch sizes—in strictly protected areas by asking: (i) How are patch sizes of naturally occurring disturbances distributed across the Alps and how can they best be quantified? (ii) Are patch size distributions stochastic or can they be explained by environmental drivers? (iii) What are the return periods of extreme disturbance events?

Location: European Alps.

Methods: We analysed satellite-based disturbance maps for the period 1986–2020 across a network of 12 strictly protected areas, modelling patch sizes of all observed disturbance patches as well as of annual extreme events. We tested the influence of temperature, precipitation, topographic complexity and forest type on patch size distributions.

Results: Disturbance patch sizes across the Alps (median 0.36 ha, 5th percentile 0.18 ha and 95th percentile 1.71 ha) as well as their annual extremes (0.72 ha, 0.18–7.11 ha) are best described by a Fréchet distribution. The size of annual extreme events significantly increased with intra-annual temperature amplitude (+0.98 ha with a one standard deviation increase) and the share of evergreen trees (+0.63 ha). On average, disturbance patches of 5.5 ha (95% credible interval 2.6–17.5 ha) occur once every 30 years, whereas patches of 2.6 ha (1.2–7.0 ha) occur once every 10 years.

Main Conclusions: Disturbances caused by natural agents are generally small and stochastic across the Alps. Extreme events are driven by climate, suggesting sensitivity of disturbance patch sizes to climate change. Our results provide a baseline for monitoring climate-induced changes in forest disturbance regimes, and provide important information for the management and conservation of forest ecosystems.

KEYWORDS
disturbance patch size, disturbance regime, extreme disturbance events, high-severity disturbances, mountain forests, natural disturbances

1 | INTRODUCTION

Natural disturbances are pulses of tree mortality caused by naturally occurring agents such as windthrow, wildfire, avalanches, landslides or bark beetle outbreaks and drive the dynamics of forest structure across temporal and spatial scales (Perry, 2002; Romme et al., 1998; Senf et al., 2021). From a temporal perspective, they are discrete events, occurring abruptly over minutes to a few years, yet they have long-lasting impacts on the demography of forest ecosystems (McDowell et al., 2020; Senf et al., 2021). The spatial extent of disturbances ranges from the death of individual trees, leaving a small gap in the canopy, to large-scale resets of successional trajectories following stand-replacing disturbances (Seidl & Turner, 2022; Sommerfeld et al., 2018). This considerable variation in the temporal and spatial patterns of forest disturbances creates diverse habitats for many forest-dwelling species (Swanson et al., 2011).

Natural disturbances are of particular importance in mountain forests. The steep topographic gradients characteristic for mountain forests generate gravitational forces that create disturbances that are unique for mountain areas, such as snow avalanches, rock fall, debris flows or landslides (Kulakowski et al., 2017; Scheidl et al., 2020; Stritih, Bebi, et al., 2021; Vacchiano et al., 2017). Moreover, weather phenomena related to mountain topography, such as foehn winds as well as convective thunderstorms, can result in windthrow and stem breakage (Bebi et al., 2017; Nagel et al., 2017). Furthermore, mountain slopes are often characterised by shallow, well drained soils that have low water-holding capacity (Zhang et al., 2018). This can increase the susceptibility to drought and further predispose forests to biotic disturbance agents, such as bark beetles (Hlásny et al., 2021).

Disturbances in mountain forests are of high ecological and socioeconomic importance, because they have widespread impact on biodiversity and ecosystem services (e.g. Thom & Seidl, 2016; Viljur et al., 2022). Disturbances, for instance, determine the patchiness and thus heterogeneity of mountain forest landscapes, rendering disturbances crucial drivers of biodiversity (Beudert et al., 2015; Mori et al., 2018; Swanson et al., 2011). More specifically, disturbed forests provide important habitat for ground nesting birds, ungulates and apex predators (Filla et al., 2017; Kortmann et al., 2018; Oeser et al., 2020). Disturbances also generate ecologically valuable early-successional stages and biological legacies, such as standing and downed deadwood, which have positive effects on biodiversity (Franklin et al., 2002; Hilmers et al., 2018; Swanson et al., 2011). However, disturbances can also have detrimental effects on wildlife populations, for example, via the fragmentation or loss of key habitat (Fischer & Lindenmayer, 2007; Venier et al., 2022). From a socioeconomic perspective, mountain forests provide numerous ecosystem services, among which the protection of human infrastructure against gravitational processes such as avalanches, rock fall, debris flows and landslides is of prime importance (Maroschek et al., 2015; Stritih, Bebi, et al., 2021; Vacchiano et al., 2016). This protective function of forests essentially depends on a continuous forest cover and disturbances can thus impair the provisioning of these vital ecosystem services (Sebald et al., 2019).

A key characteristic of forest disturbances is their patch size (Turner, 2010). A patch here describes a contiguous area affected by one distinct disturbance event. The size of disturbance patches is an important determinant of many ecological processes. Tree regeneration after stand-replacing disturbance, for instance, is strongly driven by patch size, because distance to undisturbed forest edges of mature trees dictates seed availability (Dobrowolska et al., 2022; Mantero et al., 2023). Particularly, the establishment of late-seral species, which often have heavier seeds and low frequency of mast years, will be delayed in large disturbance patches (Muscolo et al., 2014; Terborgh et al., 2020). Likewise, local microclimatic conditions are strongly affected by disturbance patch size. Larger openings in the canopy disproportionally affect radiation, temperature and humidity close to the forest floor (Thom et al., 2020) leading to a temporary loss of the microclimatic buffering capacity of closed canopy forests (De Frenne et al., 2019). The resultant climatic differences, in turn, influence processes like nutrient and water cycling (Mikkelson et al., 2013), which are key to seed germination and seedling establishment. Changes in disturbance patch sizes, for example, as a result of increased disturbance activity under climate change, might thus alter post-disturbance recovery trajectories and ultimately the structure and composition of future forests (Seidl & Turner, 2022). Also a number of important ecosystem services are influenced by disturbance patch size. The protective function of forests, for instance, frequently decreases with increasing area of canopy openings (Maroschek et al., 2015; Sebald et al., 2019). As such, patch size is a crucial metric for characterizing and understanding forest disturbance regimes (Goulamoussène et al., 2017; Hobi et al., 2015; Jucker, 2021), especially in mountain forests. Likewise, information on patch sizes of naturally occurring disturbances is key for the sustainable management of forest ecosystems (Zimová et al., 2020), and can inform management that aims to mimic natural processes (Aszalós et al., 2022).

In general, the frequency distribution of patch sizes tends to be positively skewed with a heavy tail, that is, there are much more small patches than large patches (De Lima et al., 2008; Romme et al., 1998). Although rare, large patches are of disproportional ecological and economic importance (Katz et al., 2005; Mahecha et al., 2022; Millington et al., 2006). Yet, they remain difficult to quantify, because of limited data availability at local scales. Substantial efforts have been made to quantify patch size distributions in a variety of ecosystems (De Römer et al., 2007; Malamud et al., 2005; Moritz, 1997); especially given the recent increase in the availability of remote sensing data (Goulamoussène et al., 2017; Jucker, 2021). However, many forest ecosystems are intensively managed (e.g. most of Europe, large parts of the United States), restricting the analysis of disturbance patch sizes by means of remote sensing data to both human and natural disturbances (Senf & Seidl, 2021). In such areas, the characteristics of disturbances that are caused by natural agents often remain unknown. An important means for understanding disturbance regimes in the absence of human intervention is to learn from protected areas, that is, landscapes where naturally occurring disturbances can unfold unimpeded (Potterf et al., 2022; Sommerfeld et al., 2018). While protected areas allow insights into forest dynamics in the absence of human intervention, generalization from one area to a larger region remains challenging, because protected areas are often located in distinct environmental settings with often unique land use legacies (Muise et al., 2022; Sabatini et al., 2020). To gain a comprehensive picture of the characteristics of disturbances caused by naturally occurring agents, synthesizing over a range of protected areas might strongly increase inferential capacities. Specifically, comparing disturbance regimes between landscapes allows for insights into how strongly disturbance patch size distributions are determined by local idiosyncrasies, or whether generalizable disturbance patch size distributions can be derived across landscapes. The generalizability of disturbance patch size distributions has been discussed intensively in the context of wildfire (Malamud et al., 2005; Schoenberg et al., 2003), yet remains largely unanswered for forest disturbance regimes dominated by other agents. Developing robust statistical models of patch size distributions is, however, essential for deriving meaningful statistics (e.g. return intervals) from short observations.

Here our aim was to quantify patch size distributions of forest disturbances across unmanaged forest landscapes of the European Alps. Focusing on a large network of protected areas and harnessing an existing remote sensing-based dataset on forest disturbances (Senf & Seidl, 2021), we addressed the following questions:

1. How are patch sizes of naturally occurring, high-severity disturbances distributed across the European Alps and how can they best be quantified? To answer this question, we tested different theoretical distribution models against observed data for (i) all observed disturbance patches and (ii) annual extreme events. Distribution models were chosen based on theoretical grounds and prior studies quantifying patch size distributions.
2. Are patch size distributions and their extremes purely stochastic or do they vary with environmental drivers? To answer this question, we estimated the effects of a set of environmental predictors on the distribution of disturbance sizes and their annual extremes.
3. What are the return periods of extreme disturbance events in the European Alps? To answer this question, we calculated return levels (i.e. patch sizes) of events with return periods of 3, 10 and 30 years.

Our study provides a baseline for the assessment of disturbance change in a rapidly changing environment (Thom et al., 2022) and fills an important information gap for the management and conservation of forest ecosystems in the European Alps.

2 | MATERIALS AND METHODS

2.1 | A network of protected forest landscapes

We compiled information on 12 strictly protected forest landscapes in seven countries (Austria, France, Germany, Italy, Lichtenstein, Slovenia and Switzerland) across the European Alps, covering a total area of 5383 km^2 in 2020 (Figure 1). The spatial extent of the European Alps was defined by the perimeter of the Alpine Convention (Permanent Secretariat of the Alpine Convention, 2020). Criteria for the selection of forest landscapes were strict protection status according to the International Union for Conservation of Nature (IUCN categories I or II; Dudley, 2013) and a forest area exceeding 4 km^2. Using the World Database on Protected Areas (UNEP-WCMC & IUCN, 2021), we preselected protected areas that met these criteria (21 preselected, 12 finally included in the study, the remaining nine were not able to contribute or had no spatial information on zonation). We invited protected areas to participate by providing spatial information on extent and zonation (i.e. non-intervention zone, management zone) for the period of 1986–2020. Furthermore, protected area representatives were asked to provide qualitative information on forest cover, land use legacies and dominant disturbance agents via a questionnaire (cf. Data S1). For the protected areas included in the analysis, we homogenized all spatial datasets, resulting in maps delineating non-intervention and management zones at annual resolution to account for changes in extent and zonation. The 12 protected areas had a total forest area of 1724 km^2 (median: 106 km^2) within the non-intervention zones in 2020.

2.2 | Disturbance data

We used an existing forest disturbance map derived from Landsat time series for quantifying disturbances patch sizes (Senf & Seidl, 2021). The map has a spatial grain of 30 × 30 m and provides information on where and when a disturbance has occurred between 1986 and 2020 at annual resolution. It is based on the analysis of all available Landsat images. Disturbances are defined as a loss of the majority of the trees forming the canopy (minimum mapping unit: 0.18 ha). An analysis across Europe by Senf and Seidl (2022) showed that the average disturbance severity in the dataset was 66%, with approximately 75% of all disturbances being high-severity events with >50% canopy loss and approximately 10% being very high-severity events (>90% canopy loss). Consequently, we focus on high-severity disturbance events, low-severity disturbances such as ephemeral defoliation or the breakage of individual stems are not considered. The current version of the forest disturbance map does not differentiate between disturbance agents and we thus analyse all agents jointly. We vectorized the disturbance map using an eight-neighbour rule, converting disturbed pixels of each year to polygons of contiguous disturbance patches. We focused on disturbance patches that had their centroid within a non-intervention zone of

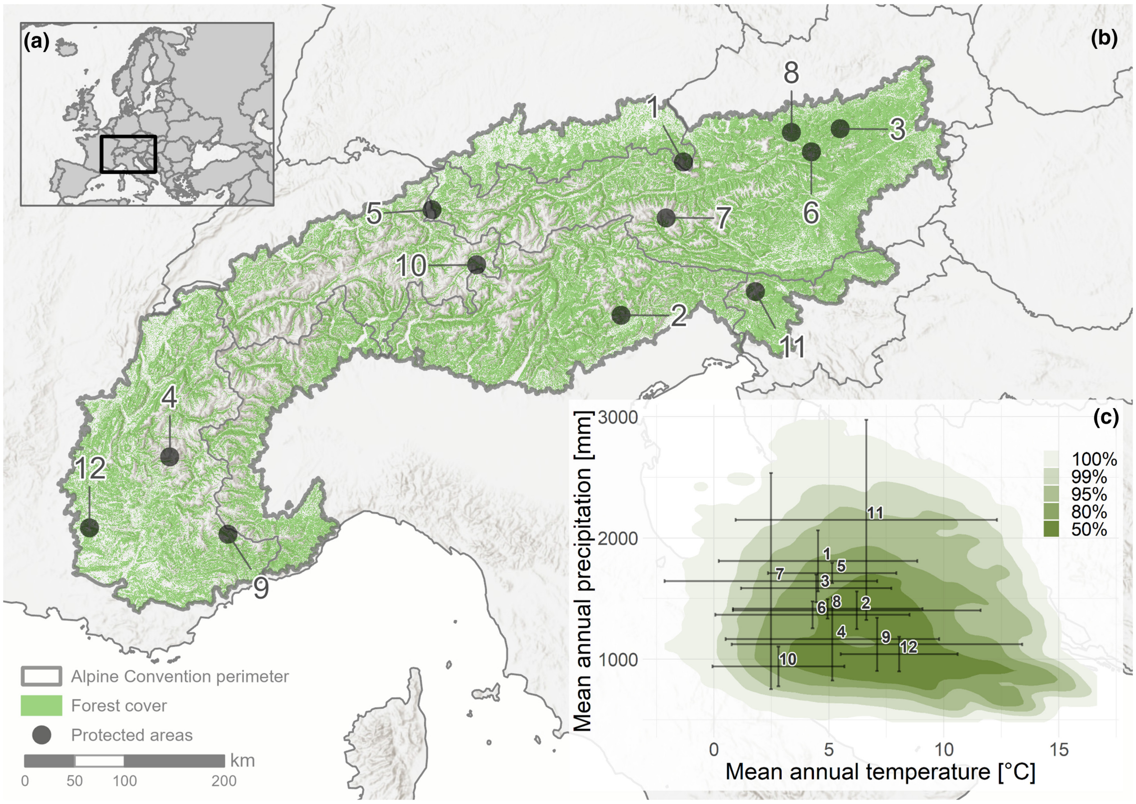

FIGURE 1 A network of 12 strictly protected landscapes in the European Alps for the analysis of forest disturbance regimes. (a) The location of the Alps in Europe. (b) The location of the landscapes within the perimeter of the European Alps (Permanent Secretariat of the Alpine Convention, 2020), and (c) Their location in climate space. The area covered by forest is indicated in green (b, c). See Table S1 for more detailed information on the individual landscapes. The climatic envelope of the forests of the European Alps in (c) is based on 100 m × 100 m grid cells for temperature and 1000 m × 1000 m grid cells for precipitation. The shades of green indicate densities of forest area distribution. The climatic conditions of the forests in protected areas are shown by points and whiskers, indicating the mean and range of conditions for each protected area. The protected areas are: Berchtesgaden National Park (1), Dolomiti Bellunesi National Park (2), Dürrenstein Wilderness Area (3), Ecrins National Park (4), Garsälli/Zegerberg Forest Reserve (5), Gesäuse National Park (6), Hohe Tauern National Park (7), Kalkalpen National Park (8), Mercantour National Park (9), Swiss National Park (10), Triglav National Park (11) and Mont Ventoux Integral Reserve (12). Map projection: EPSG:3035, ETRS89-extended/LAEA Europe.

one of the 12 protected landscapes. This effectively excluded disturbances by management and focused the analysis on disturbances caused by natural agents. Additionally, it allowed us to exclude other human interventions before, during, and after a disturbance event, such as disturbance risk management measures, salvage logging, or replanting. In total, 1.76×10^6 disturbance patches were identified in the European Alps, of which 3103 patches were located within non-intervention zones of protected areas. Disturbance time series in the protected areas under study were on average 27.1 years long (7 years minimum and 35 years maximum), with the start of the observation period determined either by data availability (i.e. consistent records available from 1986 onwards) or by protection status (establishment after 1986). Based on the information collected from local experts via a questionnaire wind, bark beetles and avalanches were the most important disturbance agents, being among the three most important disturbance agents in at least half of the protected areas. Other agents reported by local experts, but with more local relevance were breakage from snow and ice, wildfires, landslides and drought (cf. Table S1).

To derive maximum annual patch sizes for our extreme value analyses, we determined extremes according to the block maxima approach, a standard method to determine extreme events from time series data, frequently applied in other fields (e.g. rainfall intensities, Poschlod, 2021). Maxima are derived for a certain block length, for example, a season or year (Coles, 2001; Katz et al., 2005). Here, we derived the maximum disturbance patch size per protected area and year, resulting in a dataset of 214 annual extremes across all protected areas.

2.3 | Analyses

2.3.1 | Patch size distributions

To determine which distribution function best describes disturbance patches and their extremes across the Alps, we considered a set of eight candidate distribution functions based on theory and previous work: the exponential, two-parameter Fréchet, gamma, generalized extreme value (GEV), log-normal, negative binomial, Poison and two-parameter Weibull distributions (Table S2). We used a Bayesian framework to fit distributions to observed patch sizes. We sampled joint posteriors for all distribution parameters based on the likelihood derived from the observations and prior assumptions about the approximate location of the distribution parameters. Instead of using uniform "flat" priors, we regularized the priors using normal or Student's *t* distributions, as regularization of priors helps to avoid overfitting in small sample sizes (McElreath, 2020). Joint posteriors were sampled using Stan (Stan Development Team, 2021) via the R packages 'brms' version 2.15.0 (Bürkner, 2017) in R 4.0.2 (R Core Team, 2020). We used four chains with 4500 iterations each, of which the first 2500 iterations were discarded as warm-up. The joint posteriors were subsequently explored and visualized using the 'bayesplot' package 1.8.1 (Gabry et al., 2019).

As a first step, we compared fully pooled patch size models, without any information on protected area and year of disturbance, across all eight candidate distributions. Second, for the two best performing distribution functions, we compared a fully pooled model without any information on protected area and year of disturbance to a partially pooled model with crossed random effects on the intercept for protected area and year of disturbance. This allowed us to test whether there is variation in the average disturbance size (i.e. the location parameter of the distribution) between protected areas and years, or whether a pooled disturbance size distribution is sufficient for explaining disturbance patch sizes across all landscapes. We further tested if a partially pooled dispersion parameter improved model fit. A partially pooled dispersion parameter allows the dispersion of patch sizes to vary by protected area and/or year, assuming that some landscapes will have higher variation in disturbance sizes than others. Model fits were compared among all model specifications by graphical posterior predictive checks (Gabry et al., 2019); and by calculating the theoretical log pointwise predictive density (ELPD; a measure of relative model performance) via leave-one-out cross-validation (Vehtari et al., 2017). While ELPD is well suited for quantifying the overall predictive performance of a model, we additionally checked whether the models were able to capture the quartiles, mean, minimum and maximum values of the observed patch size distribution using posterior predictive checks (Gabry et al., 2019).

To test whether patch sizes and their extremes are stochastic or can be explained by environmental drivers, we selected a set of variables based on mechanistic understanding of disturbance dynamics. Variables were considered for which a mechanistic effect on disturbance size could be hypothesized (Table 1) and for which consistent, spatially explicit data were available throughout the European Alps. After initial screening, we selected variables for the categories topography, climate and land cover as predictors. Within each category we omitted variables that were highly correlated by calculating pairwise Pearson's correlation coefficients. In case of high collinearity ($p > 0.8$), we decided to use the simpler parameter. We calculated averages of each variable for the forest extent within the non-intervention zone of each protected area, allowing for analyses between the protected areas and across the Alps (Table S1). The climatic variables temperature amplitude (i.e. the temperature difference between the warmest and coldest months) and mean annual precipitation were derived from the ClimateEU historical climate dataset for Europe (Marchi et al., 2020), using a reference period from 1986 to 2017. We used a 25 m resolution Digital Elevation Model (DEM) (European Environment Agency, 2016) to downscale climate variables (initial resolution 2.5 arcminutes) to 100 m (temperature) and 1000 m (precipitation) spatial resolution. Downscaling was conducted with the ClimateEU software tool 4.63 (Marchi et al., 2020). We chose a coarser resolution for precipitation following recommendations by Marchi et al. (2020), suggesting that orographic precipitation and rain shadows of mountain ranges are driving local climatology at the scale of a few kilometres, while temperature is strongly driven by elevational gradients and thus more accurately represented at finer spatial resolution. We used the same DEM to derive two topographic attributes: average elevation (treated as confounding variable, see explanation below) and the coefficient of variation in elevation. A dominant leaf type map (European Environment Agency, 2020) provided information on forest cover and share of evergreen and deciduous tree species. All attributes were calculated in R 4.0.2 (R Core Team, 2020) using packages 'sf' 1.0-2 (Pebesma, 2018), 'raster' 3.4-13 (Hijmans, 2021), 'terra' 1.5-21 (Hijmans, 2022) and 'exactextractr' 0.6.1 (Baston, 2021). Variables were standardized and centred using a z-transformation to make model estimates comparable and improve sampling efficiency. Models were compared to intercept only models using leave-one-out cross-validated log pointwise predictive

TABLE 1 Environmental variables and their expected effect on patch sizes of natural disturbances in the Alps.

Variable	Variable group	Expected effect on patch size	Mechanism
Coefficient of variation of elevation	Topography	Negative correlation	More rugged topography, more break points for the spread of wildfires or bark beetles (Senf & Seidl, 2018)
Mean annual precipitation	Climate	Negative correlation	Higher water availability reduces disturbances due to drought, wildfire or bark beetles (Grünig et al., 2022; Netherer & Nopp-Mayr, 2005)
Temperature amplitude	Climate	Positive correlation	Larger temperature amplitudes indicate more climatic extremes (Neumann et al., 2017)
Share of evergreen tree species	Land cover	Positive correlation	Conifers are more susceptible to windthrow, wildfires and bark beetles (Oliveira et al., 2012)

densities (Vehtari et al., 2017), testing whether the predictors better explain disturbance patch size distributions than a model without predictors. To identify potential casual biases in our analysis, we used a directed acyclic graph to identify potential confounding variables (McElreath, 2020). As our landscapes are distributed along an elevational gradient, we assumed average elevation to be an important confounder (pipe type; McElreath, 2020) on all variables, as precipitation, temperature, the share of evergreens and the variation in elevation change along elevation. Likewise, we included forest area as a confounding variable, because landscapes with more forest area could potentially include larger disturbances. To be able to estimate the true effect of our variables, we included both elevation and forest area as confounders in the model. However, as we use them as confounders we do not report and interpret them in the results and discussion. To test whether the inclusion of the confounders and all other predictors would bias our estimates, we calculated a set of models omitting one parameter at a time and checked the robustness of the size and direction of effects. We compared the effect of predictors to our expectations by calculating the joint posterior probability for the predictor having a positive or negative effect on patch size (cf. Table 1). We did this based on the 8000 joint posterior draws from the posterior predictive distribution of the models using the R package 'brms' 2.15.0 (Bürkner, 2017).

2.3.2 | Return periods of extreme events

Extreme disturbance events are of particular relevance for forest ecosystem functioning (i.e. regeneration, microclimate) and society (i.e. protection function). To improve our quantitative understanding of disturbance extremes, we here focused on two relevant dimensions: return levels and return periods of extreme disturbance patch sizes. Estimating return levels of events with a given return period is a common method in fields such as civil engineering, applied meteorology, hydrology or natural hazard science (Coles, 2001; Katz et al., 2005; Poschlod, 2021). In our case, the return level is the patch size for a given return period R (timespan in years), which is expected to be exceeded only once in R years (Coles, 2001). We calculated the return period R for extreme events by relating their return levels (patch size) to the cumulative probability p of not exceeding the extreme event in 1 year according to Equation (1) (Coles, 2001; Makkonen, 2006).

$$R = \frac{1}{1 - p} \tag{1}$$

By drawing patch sizes 8000 times from the posterior predictive distribution of the best model on annual extremes we derived a cumulative density function for annual extreme patch sizes. We obtained return levels across all study areas and report patch sizes that are expected to occur at return periods of three, 10 and 30 years. Ten years represents a typical planning cycle in forestry in Central Europe, and thus gives an indication of the extremes that need to be expected within one planning period, while 30 years approximates the work-life of a forest manager (and thus corresponds to the personal experience of extremes by practitioners).

3 | RESULTS

3.1 | Patch size distributions

Within our network of protected forest landscapes 3103 disturbance patches were detected between 1986 and 2020. Patch sizes varied widely, ranging from 0.18 to 15.30 ha with a median patch size of 0.36 ha (mean: 0.58 ha). Consistently across all protected areas, patch size distributions are positively skewed with a heavy tail. The patch sizes of the annual extremes varied more strongly on a year-by-year basis and had a median patch size of 0.72 ha (mean: 1.64 ha). While the empirical probability density functions of all observations across protected areas had similar shapes, the empirical distributions of the annual extremes showed more variation (Figure 2; Table S3).

Our first objective was to test different distribution functions with regard to their ability to capture the size distributions of observed disturbance patches. We found that the GEV, Fréchet and log-normal distributions performed best in approximating patch size distributions of all observations as well as of annual extreme values. All other distribution functions showed substantially lower capacity to describe the observed data (Table 2).

Performing graphical posterior predictive checks both the Fréchet and GEV distributions showed a good fit to the data. The density plots drawn from both the Fréchet and GEV models matched the empirical density functions, capturing their positive skew and heavy tails well. All other distribution functions deviated to various degrees from the empirical density distributions (Figures S1 and S2). Predicting patch sizes from model draws, the Fréchet model captured the observed maximum of 15.3 ha well (within the 95% credible interval of the model), while the GEV model overestimated the maximum patch size by several orders of magnitude (Figure S3). Overall, we found that the Fréchet distribution (which is a special case of the GEV distribution) was able to describe the data best, and we used this distribution function for all further analyses.

We further tested if including a partially pooled mean parameter (scale) and dispersion parameter (shape) improved model fit. The Fréchet model with partial pooling on both the scale and shape parameters among protected areas and years performed best for all observations (Table S4). For the annual extremes, however, partial pooling of the dispersion parameter did not improve the model fit. Here, the Fréchet model with variable scale parameters among protected areas and years performed best (Table S4). Hence, we selected those two models for further analysis.

3.2 | What drives patch size distributions?

Our second objective was to investigate if patch size distributions and their extremes are significantly influenced by environmental

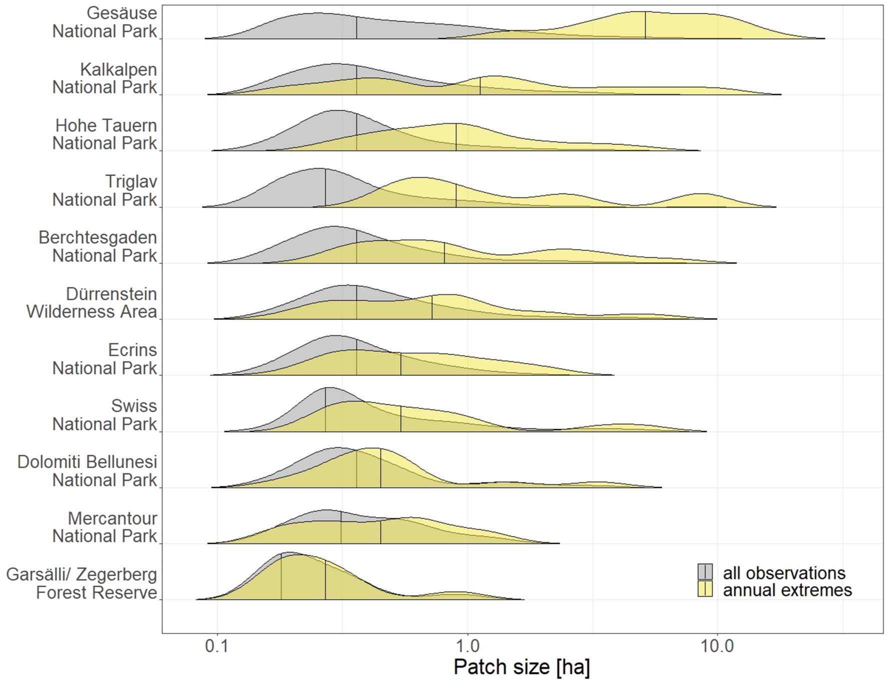

FIGURE 2 Density plots of all observed disturbance patch sizes (grey) and of annual extreme disturbance patch sizes (yellow) in protected areas across the Alps. The protected areas are arranged in the order of decreasing median patch size (indicated by the vertical lines) from top to bottom. Mont Ventoux Integral Reserve was omitted due to too few disturbance patches being recorded. Note the logarithmic scale of the *x*-axis.

TABLE 2 Model comparison across all investigated distribution functions (intercept only models) for (a) all observations and (b) annual extreme patch sizes.

	(a) All observed patches		(b) Annual extremes	
Distribution function	**ELPD**	**ELPD difference**	**ELPD**	**ELPD difference**
Generalised extreme value	**−7431.2**	**0.0**	−752.1	−16.3
Fréchet	−7530.2	−98.9	**−735.8**	**0.0**
Log-normal	−7974.1	−542.9	−744.1	−8.4
Gamma	−8595.4	−1164.1	−759.9	−24.1
Exponential	−8802.7	−1371.4	−778.1	−42.4
Negative binomial	−8830.2	−1398.9	−769.3	−33.6
Poisson	−14526.3	−7095.1	−1558.5	−822.7
Weibull	−14529.6	−7098.3	−1557.2	−821.4

Note: Theoretical log pointwise predictive density (ELPD) was calculated via leave-one-out cross-validation. ELPD difference is calculated as the difference to the highest ELPD. Less negative ELPD difference values (in bold) indicate better model performance.

drivers. Including environmental predictors in our models did not increase predictive performance for all observations, but improved models for annual extreme events (Table S5). This suggests that the occurrence of large disturbance patches is more strongly influenced by environmental drivers, while all disturbance patches—including many very small canopy openings—are better described by a purely stochastic distribution.

The environmental effects on disturbance patch size were similar for all observations and annual extremes, yet effect sizes were more pronounced for annual extremes (Figure 3). This pattern mirrors the better predictive performance of the environmental drivers for annual extreme patch sizes than for all patch sizes (see paragraph above). The majority of drivers did influence patch size as hypothesized (Table 1). An exception was the coefficient of variation of elevation, where we found increasing disturbance patch sizes with increasing topographic complexity (low confidence, Figure 3).

Temperature amplitude had the largest effect on patch sizes. There was a 98% probability that temperature amplitude affects average patch sizes positively, as hypothesized (95% for annual extremes). With a one standard deviation increase in temperature amplitude, average patch size increased by 0.15 ha (−0.06 to 0.45; 95% credible interval), and annual extreme patch sizes increased by 0.98 ha (−0.47 to 5.72). The second most important variable was the share of evergreen tree species, which had a 93% probability of affecting extreme patches positively (93% for all patches). A one standard deviation increase in evergreen share increased the average patch size by 0.07 ha (−0.09 to 0.28) and the annual extreme patch size by 0.63 ha (−0.49 to 3.81). Higher annual precipitation influenced patch sizes negatively (97% and 83% probability for all patches and extremes, respectively), with average patch size decreasing by −0.09 ha (−0.20 to 0.07) and extreme patch sizes by −0.25 ha (−0.75 to 1.28) with an increase of one standard deviation.

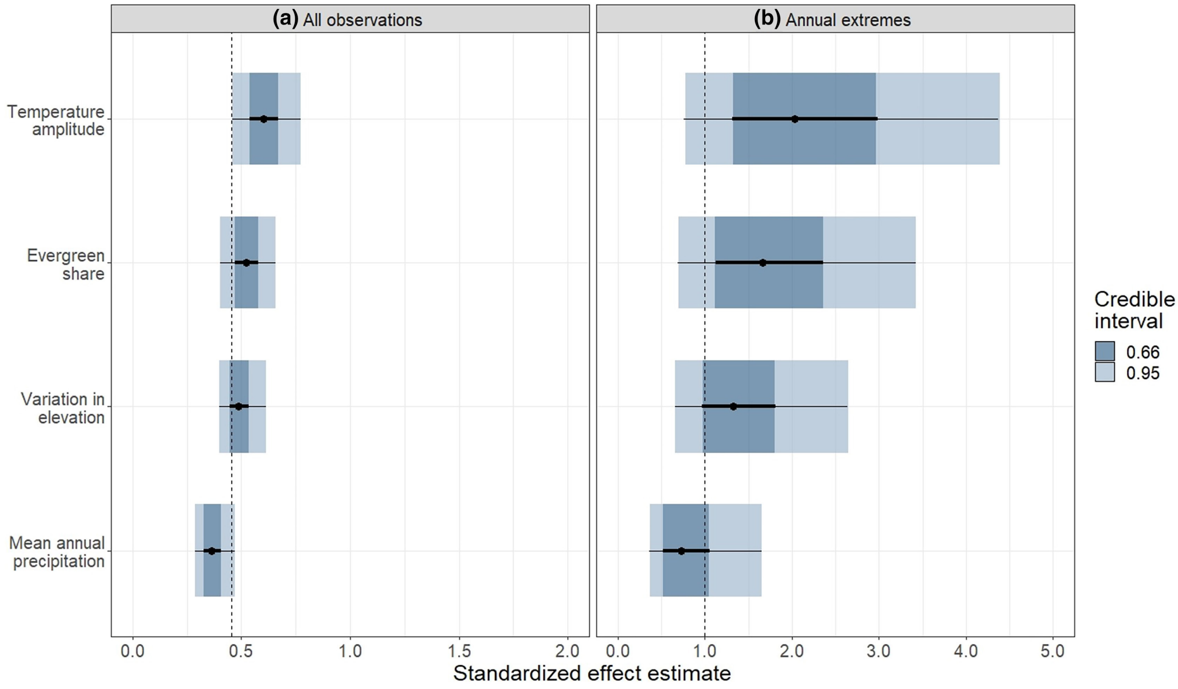

FIGURE 3 Estimated effect sizes (hectare change in patch size per change in one standard deviation in the predictor) for environmental drivers of patch size for (a) all observations and (b) annual extreme events. The results are based on 8000 draws from the joint posterior predictive distribution of the final models. The intercepts of the models are indicated by dashed lines. Note the different scales for the two *x*-axes.

3.3 | Return periods of extreme events

Our third objective was to calculate return levels of extreme events, that is, the patch size that is exceeded only with a certain periodicity (here: 3, 10, and 30 years). For a return period of 3 years, the expected extreme patch size was 1.1 ha (0.8–2.6, 95% credible interval, Figure 4). This means that, on average, a patch of 1.1 ha (i.e. roughly three times the median patch size) will occur in one out of 3 years. We note, however, that this value is derived by a large number of draws from the underlying distribution, and that in any given 3-year period (i.e. a single realization), a 3-year event may occur once, twice, three times, or not at all. For a 10-year return period, the patch size was 2.6 ha (1.2–7.0, 95% credible interval), and 5.5 ha (2.6–17.5) for a 30-year return period (Figure 4). Consequently, a disturbance patch that is roughly 15 times larger than the median patch size will, on average, only occur once in 30 years. Also, the largest disturbance patch observed across all 12 protected areas since 1986 (an avalanche disturbing 15.3 ha of forest in Gesäuse National Park, Austria in 2005) was statistically a 1 in 106 years event.

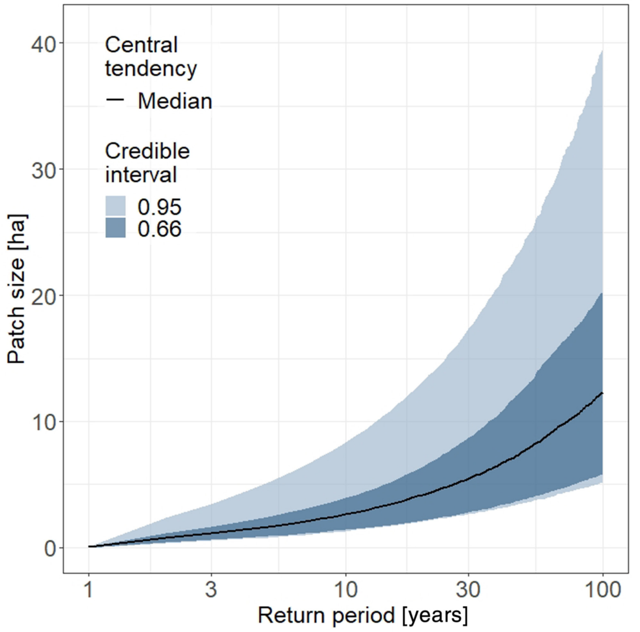

FIGURE 4 Return periods of patch sizes caused by natural disturbances in the European Alps. The results are based on 8000 draws from the posterior predictive distribution of the model for annual extreme patch sizes without conditioning on group-level parameters. Note the logarithmic scale of the *x*-axis.

4 | DISCUSSION

Here, we present the first empirical characterization of disturbance patch size distributions in unmanaged systems across the European Alps. Our data and analyses fill an important knowledge gap on the disturbance regimes of mountain forests. We show that patches caused by disturbances from naturally occurring agents are comparatively small in the European Alps, even when considering extreme values. This is in line with findings for other European mountain ranges like the Carpathians and Scandes (Kulakowski et al., 2017). In general, many temperate forests are dominated by small-scale disturbance events, caused by wind and bark beetles as primary disturbance agents, while landscapes prone to wildfires are often associated with larger disturbance sizes (Sommerfeld et al., 2018). In the Alps, disturbances are largely driven by wind and subsequent bark beetles (Kulakowski et al., 2017; Sebald et al., 2021) and the dominance of those two agents likely explains the relatively small patch sizes found in our study. In temperate mountain forest ecosystems strongly driven by fire, for example, the Rocky Mountains in western North America, average patch size can be in the hundreds or even thousands of hectares (Seidl et al., 2020; Sommerfeld et al., 2018). Furthermore, patch size has been found to decrease with topographic complexity (Senf & Seidl, 2018). This could account for the fact that protected areas in other European mountain ranges had higher average patch sizes compared to what we report here (mean 0.58 ha), for example, in the Bavarian Forest/Šumava National Parks in Germany/Czechia (10.43 ha), the Tatra National Park in Slovakia (2.91 ha) or the Harz National Park in Germany (1.70 ha) (Senf & Seidl, 2018). Future changes in the prevalence of disturbance agents, such as an increase in fire activity in temperate Europe (Grünig et al., 2022), could thus have profound consequences for forest disturbance regimes, particularly since regeneration processes in the Alps are naturally adapted to small-scale canopy openings (Kulakowski et al., 2017).

We showed that patch sizes of high-severity disturbances in the protected areas of the Alps are best approximated by a Fréchet distribution. Several distribution functions have been used to successfully describe disturbance patch sizes previously (De Lima et al., 2013; Hobi et al., 2015; Katz et al., 2005). The Fréchet distribution is an extreme value distribution; it thus works well in describing the annual maxima of the disturbance patch sizes. We here showed that, although it is rarely used to model disturbance patch sizes in general, the Fréchet distribution also worked well in characterizing the frequency distribution of all disturbance patches. The positive skewness and heavy tails of the data are captured well by the Fréchet distribution. Allowing both distribution parameters—mean (scale) and dispersion (shape)—to vary in space and time improved our model for all observations. This suggests that not only the central tendency but also the spread of the distribution varies across the 12 study areas. That is, disturbance patches have been more variable over the past 35 years in some areas of the Alps (e.g. Gesäuse National Park or Kalkalpen National Park) than in others (e.g. Hohe Tauern National Park or Ecrins National Park). Our quantification of disturbance patch size distributions provides a foundation for the consideration of disturbances in simulation models, which is one of the current challenges for earth system modelling (McDowell et al., 2020). Specifically, our analyses show that modelling disturbance patches with a constant variance across space and time is not supported by data, suggesting that distribution parameters need to be chosen carefully in model applications.

We found that environmental drivers had only moderate predictive power over patch size distributions, and that the effect of the environment on patch size was more pronounced for annual extremes compared to all disturbances. This finding allows two insights: First, stochasticity is high in disturbance patch sizes across the Alps, particularly for the many but very small disturbance patches (50% of patches <0.36 ha). Alternatively, other predictor variables—not considered here because of lack of understanding or data availability—would be needed to explain the observed variation in disturbance patch sizes. Future work should further investigate potential drivers of patch sizes at the landscape scale, where better information (e.g. on forest composition and structure, soil conditions, etc.) are available. Second, the finding that extreme patches are more strongly determined by environmental drivers suggests that there is no decoupling between disturbance processes and the environment as a result of cross-scale amplification (e.g. as in large wildfires, that create their own weather systems, Peters et al., 2004). In contrast, the dominant processes causing the largest disturbance patches in the Alps (i.e. avalanches and wind) are triggered by climatic extremes and their impact is modulated by topography (Doane et al., 2023; Schweizer et al., 2003; Teich et al., 2012). While effect sizes for individual variables had wide confidence bands, temperature amplitude was found to be the most important factor influencing disturbance size distributions. In general, temperature amplitude increases from west to east and from high to low elevation in the Alps. Climate variability has been linked to tree mortality previously (Neumann et al., 2017), and a higher intra-annual amplitude indicates that forests are more exposed to extreme conditions in both summer and winter. More specifically, areas that have high-temperature amplitude might be more prone to being affected by multiple disturbances simultaneously, such as bark beetle outbreaks in summer and snow avalanches in winter (as is, e.g. the case in Dürrenstein Wilderness Area and Gesäuse National Park). The share of evergreen tree species had the second largest effect, a result that is in line with several other studies finding conifers to be more susceptible to disturbances by wind (Dobor et al., 2020), wildfires (Oliveira et al., 2012) and bark beetles (Raffa et al., 2008; Sommerfeld et al., 2021). In contrast to our expectation (cf. Table 1), patch size increased with the coefficient of variation of elevation. One reason for this finding could be the important role of avalanches in the disturbance regimes of the Alps. Avalanches caused the largest patches observed within our data set, and 7 out of 12 protected areas listed avalanches or disturbance by snow and ice among the top three disturbance agents (cf. Table S1). Slope angle is an important driver of avalanche occurrence (Schweizer et al., 2003) and the higher share of avalanche-prone (i.e. steep) landforms in more rugged landscapes could be responsible for increasing disturbance patch size with increasing topographic complexity.

We note that we here focus on high-severity canopy disturbances (Senf & Seidl, 2021). Low- to mid-severity disturbances also play an important role in forest dynamics (Meigs et al., 2017; Nagel et al., 2017), yet they are not considered in our analysis. Furthermore, the dominance of small and very small disturbance patches in the Alps suggests that our minimum mapping unit of 0.18 ha might be too large to capture the full patch size distribution of forest disturbances in the Alps. Future work could use active remote sensing approaches such as Light Detection and Ranging (LiDAR) to obtain a finer grained picture of small-scale gap dynamics in mountain forests (Goodbody et al., 2020; Jucker, 2021). Further, we here modelled annual patch sizes, yet disturbance patches can grow over multiple years, resulting in realized patch sizes that are considerably larger than what we report here. In the context of ecosystem dynamics, realized patch sizes are often more important, because they determine, for example, the distance to the next seed source and thus forest recovery potential (Falk et al., 2019; Mantero et al., 2023). However, annual disturbance distributions are of particular relevance for the implementation of disturbances in simulation models or the evaluation of their outcomes (Seidl, Fernandes, et al., 2011). They furthermore allow for a more direct link to the underlying environmental drivers.

Disturbances by agents such as wind, bark beetles, avalanches and wildfires are important risk factors in forestry, and quantitative information on risks is a prerequisite for successfully managing them (Seidl, 2014). One approach to address risks is to collectivize them, for example, via insurance. Estimating return intervals of extreme events is an important foundation for considerations of insurance (Embrechts et al., 1997). While forest insurance is more common in Fennoscandia there is currently a low prevalence of forest insurance in Central Europe (Brunette et al., 2015; Korená Hillayová et al., 2021). The return intervals of extreme events provided here could help in making insurance considerations more tangible also for the Alps. However, we note that our dataset only covers a period of 35 years, which is comparatively short in the context of forest disturbance dynamics. While it would be desirable to have longer time series for analyses of disturbance regime characteristics, extreme value statistics offer powerful tools for analysing datasets that might miss information on very rare events. Our model showed a high goodness of fit to the annual extremes and thus meets an important prerequisite for extrapolating return intervals (Coles, 2001).

Strictly protected areas offer a window into the effects of naturally occurring disturbance agents, a factor that is of great value particularly in regions heavily influenced by human land-use (i.e. the European Alps). Here, we showed how protected areas can be used to quantify important properties of the disturbance regime, providing an important baseline for forest ecology and management. Management has ceased decades ago in the protected areas analysed here. However, most landscapes were subject to human land-use in the past, as primeval forest in the European Alps are scarce (Sabatini et al., 2018). Consequently, legacies from former land use might still persist (Albrich et al., 2021). These legacies can influence current disturbance patterns (Mantero et al., 2020; Pausas & Fernández-Muñoz, 2012; Stritih, Senf, et al., 2021). Yet, our focus on protected areas can successfully control for the effects of recent risk management measures as well as for salvage and sanitation logging, that is, human interventions that modulate disturbance patch size in managed forests. With regard to spatial representation, we found that the 12 protected areas analysed cover the bio-climatic envelope of the forests of the Alps remarkably well. Gaps mainly exist for warm and dry forests, especially in the south-western Alps (Figure 1c). As fire is a major disturbance agent in these Mediterranean-influenced forests (Bebi et al., 2017; Valese et al., 2014), the role of fire might be underrepresented in our analysis.

Disturbances are strongly climate sensitive processes and are expected to increase under climate change (Lucash et al., 2018; Seidl et al., 2017). To detect and monitor change, we require a good quantitative understanding of the prevailing disturbance regime and its variation. Our results provide such a baseline, with high relevance for management and conservation. Mimicking disturbance processes in silviculture has been proposed as an approach to provide multiple ecosystem services and maintain valuable habitats (Aszalós et al., 2022; Thom & Keeton, 2020). Patch size distributions can inform management on the size and variation of interventions needed in order to achieve a near natural landscape configuration and structure (Čada et al., 2020; Collins & Stephens, 2010). Our findings, for the first time, describe disturbance patch sizes in the absence of human intervention over a large spatial extent in Europe. They can subsequently be contrasted against the coupled human and natural disturbance regime that affects the Alps outside of protected areas, which can help to better characterize where managed forests are actually "close-to-nature" (Brang et al., 2014) and where disturbance regimes are outside of their natural range of variability.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

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ORCID

Michael Maroschek https://orcid.org/0000-0003-1032-9806

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BIOSKETCH

Michael Maroschek is co-head of research at Berchtesgaden National Park, broadly interested in forest dynamics. This paper is a chapter of his PhD work at Berchtesgaden National Park and the Technical University of Munich, focusing on natural forest disturbance patterns in the mountain forests of the European Alps.

Author contributions: Michael Maroschek, Cornelius Senf and Rupert Seidl conceived the ideas; Michael Maroschek collected the data on protected areas and compiled disturbance data with the help of Cornelius Senf; Michael Maroschek analysed the data with the help of Cornelius Senf and Benjamin Poschlod; Michael Maroschek led the writing with contributions of all co-authors.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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