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Forest disturbance regimes and trends in continental Spain (1985–2023) using dense landsat time series

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ABSTRACT

Forest disturbance regimes across biomes are being altered by interactive effects of global change. Establishing baselines for assessing change requires detailed quantitative data on past disturbance events, but such data are scarce and difficult to obtain over large spatial and temporal scales. The integration of remote sensing with dense time series analysis and cloud computing platforms is enhancing the ability to monitor historical disturbances, and especially non-stand replacing events along climatic gradients. Since the integration of such tools is still scarce in Mediterranean regions, here, we combine dense Landsat time series and the Continuous Change Detection and Classification - Spectral Mixture Analysis (CCDC-SMA) method to monitor forest disturbance in continental Spain from 1985 to 2023. We adapted the CCDC-SMA method for improved disturbance detection creating new spectral libraries representative of the study region, and quantified the year, month, severity, return interval, and type of disturbance (stand replacing, non-stand replacing) at a 30 m resolution. In addition, we characterised forest disturbance regimes and trends (patch size and severity, and frequency of events) of events larger than 0.5 ha at the national scale by biome (Mediterranean and temperate) and forest type (broadleaf, needleleaf and mixed). We quantified more than 2.9 million patches of disturbed forest, covering 4.6 Mha over the region and period studied. Forest disturbances were on average larger but less severe in the Mediterranean than in the temperate biome, and significantly larger and more severe in needleleaf than in mixed and broadleaf forests. Since the late 1980s, forest disturbances have decreased in size and severity while increasing in frequency across all biomes and forest types. These results have important implications as they confirm that disturbance regimes in continental Spain are changing and should therefore be considered in forest strategic planning for policy development and implementation.

1. Introduction

Forest disturbance is any discrete event that influences the structure, species composition and resources available (Pickett and White, 1985), and is considered a primary driver of forest heterogeneity (Franklin et al., 2002). Disturbances can occur abruptly and rapidly within hours to few months, leading to stand replacing events, or subtly and gradually over time, leading to non-stand replacing events (Oliver and Larson, 1996; Turner, 2010). The origin of disturbances may be abiotic (e.g., windstorms, wildfires, tornadoes, droughts), biotic (e.g., pests, invasive species), anthropogenic (e.g., timber harvesting) or result from a combination of these (e.g., non-native species may be more prone to wildfires) (Stahl et al., 2023). The spatial and temporal characteristics of discrete disturbance events that occur over long periods define *disturbance regimes* (Turner, 2010) which are characterised by multiple components, such as the disturbance size (i.e., area disturbed), severity (i.e., magnitude of the disturbance event on the ecosystem) and frequency (i.e., mean or median number of events occurring per unit of time).

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Since forest dynamics are deeply connected to climate, concerns about the impact of global change on disturbance are rising (Seidl et al., 2017). Evidence suggests temporal changes in forest disturbance regimes across all continents, which might be critically altering forest ecosystems, biodiversity, functions and services (Patacca et al., 2022; Senf and Seidl, 2021; Sommerfeld et al., 2018). Detailed information on forest disturbances is essential to understand ecosystem dynamics, understand baselines and predict novel trajectories, as well as to develop effective adaptation strategies in response to global change (Turner and Seidl, 2023). The relevance of such information explains why international reports on forest change and degradation are increasing their requirements on the provided data (Mackey et al., 2015). However, accurate data on forest disturbances at large spatial and temporal scales are still scarce and difficult to obtain (Patacca et al., 2022).

Field surveys and inventories usually employ a consistent set of criteria and indicators to assess the condition of forests (e.g., forest area, wood volume, biomass, growth, forest health) at the national and regional levels (Cubbage et al., 2007), and this information is crucial for forest assessment, management, and decision-making processes (Wulder, 2004). However, the exclusive use of in-situ data to monitor forest health is often subject to limitations, including inconsistency between data sets (Senf et al., 2018), cost and time, and non-continuous spatial and temporal information (Pause et al., 2016). Remote sensing is an increasingly used tool for monitoring forests as it overcomes some of these limitations (Masek et al., 2015; McDowell et al., 2015) by providing valuable information at large spatial and temporal scales (Ruiz-Benito et al., 2020).

In the past, remote sensing techniques for forest change detection employed bi-temporal approaches based on images acquired before and after disturbance events (Cohen et al., 2010). However, since the opening of the Landsat archive in 2008, new techniques based on long-term analysis emerged (Hansen et al., 2013; Kennedy et al., 2010). Since then, pixel-based image compositing has become a commonly used technique, as it helps to reduce a large amount of data and produces cloud-free representations of an area at different temporal scales (typically annual), allowing continuous forest monitoring over long periods (Zhu, 2017). Several open databases use annual composites to analyse stand-replacing disturbance events at regional and global scales (Hansen et al., 2013; Senf and Seidl, 2021). These datasets are valuable and widely used for reporting in institutional programmes and forest assessments (Vogelmann et al., 2016). However, the use of annual composites (hereafter composite-based methods) has limitations related to difficulties in detecting forest disturbances with rapid recovery as well as non-stand replacing disturbances (Matricardi et al., 2020; Vogelmann et al., 2016).

The integration of remote sensing data into recently developed cloud computing platforms such as Google Earth Engine has enabled the integration of dense time series analysis over large spatial and temporal scales (Gorelick et al., 2017). Forest disturbance monitoring methods that incorporate such advances, e.g., CCDC (Zhu and Woodcock, 2014); VCT (Huang et al., 2010), take advantage of all available observations within a given period to extract interannual and phenological trends, making it easier to detect both, stand and non-stand replacing disturbances when compared to bi-temporal and composite-based approaches (Vogelmann et al., 2016). The Continuous Change Detection and Classification - Spectral Mixing Analysis (CCDC-SMA), proposed by Chen et al. (2021), is a novel method that combines the widely used CCDC (Zhu and Woodcock, 2014) with SMA (Souza et al., 2005) to perform dense Landsat time series analysis in Google Earth Engine. The CCDC-SMA transforms the original Landsat spectral bands into spectrally unmixed data by quantifying the fraction of different cover classes contributing to each pixel spectrum (Souza et al., 2005, 2013) and, subsequently, analyses the trajectory of the forest canopy using harmonic models. The CCDC-SMA has been particularly effective in detecting both stand and non-stand replacing disturbances in tropical and temperate forests (Chen et al., 2021, 2023; Cortner et al., 2024), but has not been yet tested in Mediterranean regions where multidecadal information on stand and non-stand replacing disturbance is crucial for characterising forest regimes and trends, and for developing well-adapted forest management practices and policies (Forzieri et al., 2021). This is particularly important in countries such as Spain, where forests are highly vulnerable to global change factors such as anomalous temperatures, drought, and invasive species (Doblas-Miranda et al., 2017).

To fill this gap, we monitored forest disturbance in continental Spain using the novel CCDC-SMA method and the full Landsat collection from January 1985 to June 2023. Our main objectives were to (i) develop a consistent database of forest disturbances with detailed information on each event, and (ii) assess long-term disturbance regimes and trends over a large temperate Mediterranean gradient. To this end, we detected and mapped the year, month, severity, type of disturbance (stand replacing, non-stand replacing) and recovery time of the events. We also characterised the overall forest disturbance regimes and trends (considering patch size and severity, and frequency of events as descriptive components) for the whole of continental Spain. As climatic biomes and forest types can be associated with different management practices and different vulnerability to disturbance, we analysed disturbance regimes and trends by biome (temperate and Mediterranean), and by forest type (broadleaf, needleleaf and mixed forests). Finally, we quantified the accuracy of the CCDC-SMA method detecting disturbances associated with different drivers (i.e. defoliation, drought and heat-induced mortality, wildfire, clearcutting) and compared with the results of other forest change products derived from composite-based methods (i.e., Hansen et al. (2013) and Senf and Seidl (2021)).

2. Material and methods

2.1. Study area

Continental Spain (49 Mha) covers a wide range of climatic and altitudinal gradients distributed across two main biomes: the temperate in the north and the Mediterranean (Fig. 1) in the remainder of the country (Blanco, 1997; Olson et al., 2001). Forested areas cover for 27 Mha, with broadleaf forests dominating (10.1 Mha) and being common in the south and centre-west of the country, coniferous forests (6.8 Mha) in the centre and centre-east, and mixed forests (1.4 Mha) in the northeast, northwest and centre-east. The most dominant species are *Quercus ilex* (15.3% of woodlands), *Pinus halepensis* (11.4%) and *Pinus sylvestris* (5.7%) (Bravo et al., 2017).

Since the mid-1970s, forests in Spain have expanded as a result of the afforestation plans initiated in the 1940s when forests reached their lowest extent of 24 Mha. In addition, natural succession was boosted by the abandonment of rural areas and the intensification of agriculture (i.e., less land was needed to produce the same amount as with extensive farming) (Vadell et al., 2016, 2022). The implementation of the European Common Agricultural Policy in the 1990s further accelerated this trend, increasing forest cover by an average of 1.33% per year between 1991 and 2017, making Spain the third largest country within the EU28 in terms of forest cover (Bravo et al., 2017).

As in other Mediterranean regions, forest disturbances in Spain are strongly influenced by fires, which have affected more than 1.2 Mha since 1991, especially in the northern regions (Dupuy et al., 2020; MAPAMA, 2018a). Nevertheless, the area of forests disturbed by fires has gradually decreased from 6.5% of the total area in 1981–1990 to 1.4% in 2011–2017 (MAPAMA, 2018a). Other drivers of forest disturbance are climate change (especially drought) and invasive species, which often interact and facilitate the outbreak of insect pests and pathogens (MAPAMA, 2018b). These factors are the main causes behind the observed changes in tree defoliation at the national level, which increased from 12.3% in 1986 to 25.2% in 2015, affecting slightly more broadleaf forests than needleleaf forests (i.e. around 5%) (Adame et al., 2022).

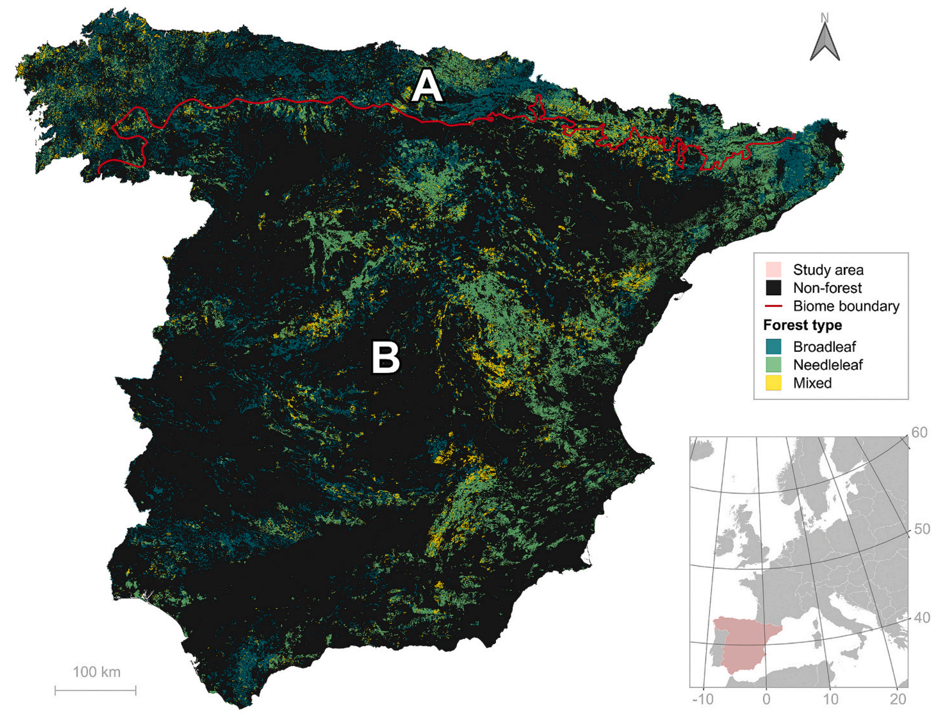

Fig. 1. Map of continental Spain, showing the types of forest as derived from CORINE Land Cover 2018 (ESA, 2023). The red line divides the temperate (A) and Mediterranean (B) biomes (Olson et al., 2001).

2.2. CCDC-SMA application to detect forest disturbances

Forests disturbances detection was performed in Google Earth Engine in four steps, as detailed in the sections below.

2.2.1. Satellite data pre-processing and forest masking

First, we pre-processed the satellite images used as input in the CCDC-SMA. We used the entire Landsat Collection 2 Level 2 archive from January 1985 to June 2023, covering continental Spain (38 Landsat tiles) after filtering out images with more than 90% cloud cover. The pre-processing included: (i) matching the bands of the different Landsat sensors (i.e., Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), Operational Land Imager (OLI) and OLI-2); (ii) filtering of noisy pixels (i.e. cloud contamination, cloud shadow, snow and radiometric saturation) using the quality assessment bands (USGS, 2023); and (iii) topographic correction based on the Sun-Canopy-Sensor + C correction method (Soenen et al., 2005). Topographic correction is an important step to account for variations in reflectance values due to illumination effects from terrain (Young et al., 2017), which particularly affect mountainous and rugged terrain. Forest cover was masked using a land cover map (see section S1, Supplementary Material).

2.2.2. Spectral mixture analysis (SMA)

The original Landsat surface reflectance data was used to quantify the fraction of five different pure cover classes (known as endmembers) contributing to the value of each pixel in an image. These endmembers are green vegetation (GV, i.e., photosynthetically active vegetation), non-photosynthetic vegetation (NPV, i.e., vegetation with low concentrations of chlorophyll), soil, shade, and cloud. The cloud fraction was used to perform a second cloud masking (Chen et al., 2021). The fractions of the other endmembers were used to calculate the Normalised Difference Fraction Index (NDFI, Eq. (1) and Eq. (2)) at the pixel level for the entire Landsat collection. The NDFI is a sensitive indicator of gradual, subtle changes in the forest canopy and is particularly useful for monitoring both stand and non-stand replacing disturbances (Souza et al., 2013).The NDFI ranges from −1 to 1, with higher values indicating denser canopy cover.

$$NDFI = \frac{GV_{shade} - (NPV + soil)}{GV_{shade} + (NPV + soil)} \tag{1}$$

$$GV_{shade} = \frac{GV}{1 - shade} \tag{2}$$

To calculate the fractions of the endmembers, spectral libraries representative of the study area were needed. Previous studies have created libraries for tropical and temperate forests (Chen et al., 2021; Souza et al., 2005, 2013), but none were representative of the temperate Mediterranean forests of Spain. Therefore, we created individual spectral libraries for GV and NPV in both the temperate and Mediterranean biomes, and for soil at the national level. An existing library was used for shade (Souza et al., 2005; Zhu and Woodcock, 2014). To create the spectral libraries, we followed the steps described in Chen et al. (2021). First, we acquired a set of pure land cover samples per endmember (i.e., 235 polygons of at least 120 × 120 m) using very high spatial resolution (<0.35 m) orthophotos (2019–2021) from the Spanish National Orthophotography Plan (PNOA) (see Table S2 in the Supplementary Material). For each sample, we then calculated the mean (within the percentile range of 5–95) and standard deviation of the Landsat surface reflectance images. We used images acquired from May to September 2019–2021 to calculate the statistics of GV and soil samples, and from November 2019–2021 for NPV samples. Finally, we grouped the results by endmembers and obtained the spectral profiles (Fig. 2 and Table S2 in the Supplementary Material).

2.2.3. Application of the Continuous Change Detection and Classification (CCDC)

The CCDC algorithm uses the SMA-derived Landsat data as input to adjust harmonic models (i.e. harmonics). These harmonics are used to predict the values of the endmembers and the NDFI values at the pixel level on any given date. Disturbance detection is based on the comparison of the harmonic model predictions with new observations. When

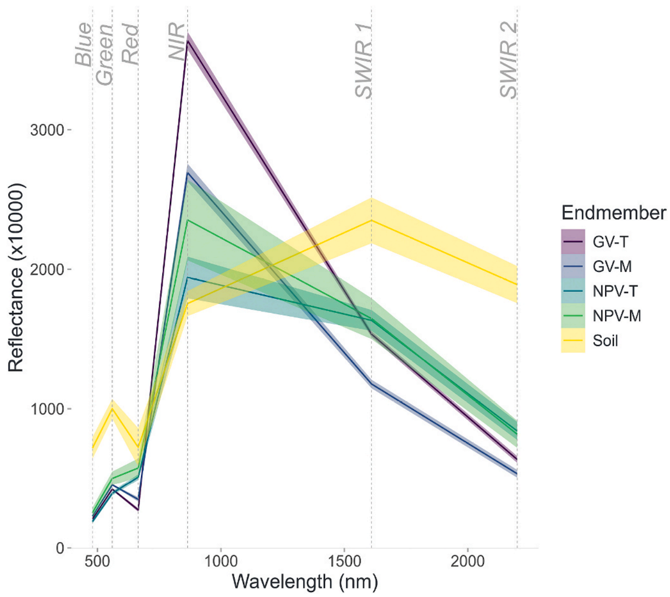

Fig. 2. Spectral profile of the green vegetation (GV) and non-photosynthetic vegetation (NPV) endmembers collected in temperate (T), and the Mediterranean (M) and the soil endmember collected in continental Spain. We used PNOA orthophotos (spat. res. < 0.35 m) to pinpoint pure endmembers that were later used to extract the spectral profiles.

the new values deviate from the prediction in more than five consecutive observations, the algorithm flags a disturbance event and adjusts a new harmonic model. Harmonics can be adjusted a maximum of six times per pixel during the analysis period, allowing mapping multiple disturbances over the same area. Note that as the first 12 observations of each pixel are used to adjust the model, the method tends to miss disturbances that occur in the first years of the period (i.e., 1985–1987) (Zhu and Woodcock, 2014).

For each pixel disturbed, the CCDC extracts relevant information that we used to create multiple maps. Namely, information on the start (i.e., date of disturbance detection) and end date (i.e., time when the NDFI reaches the pre-disturbance value or experiences a new disturbance) of every event was used to create maps of the year, the month, and the recovery time (years) of disturbance. Information on the magnitude of change (i.e., observed minus predicted NDFI values) was used to obtain the severity map after rescaling to the 0 to 1 range, with zero representing no change and one representing a complete change in canopy cover. In addition, the magnitude of change together with other coefficients (detailed, along with the thresholds, in Table S3, Supplementary Material) were used to classify the type of disturbance. We distinguished between stand replacing (i.e., disturbance with rapid and abrupt change in the value of the NDFI and endmembers), non-stand replacing (i.e., disturbance with a subtle and gradual positive trend of the soil fraction) and stand plus non-stand replacing (e.g., disturbance caused by an insect outbreak followed by salvage logging).

2.2.4. Postprocessing

To limit potential classification errors and reduce the salt and pepper aspect of the disturbance maps, we removed isolated pixels classified as disturbed using a 3 × 3-pixel moving window. We also reclassified disturbed pixels using the surrounding majority class and a kernel-based estimate of local quantiles to provide consistent data on disturbance patches from the same event (Chen et al., 2021). We applied this step to all maps described in section 2.2.3. except for the severity map.

2.3. Reference data

We validated our forest disturbance maps with four different datasets, two of which mainly contain information on stand replacing events and two on non-stand replacing events. The two stand replacing related datasets are (i) the 2018 Eurostat Land Use and Coverage Area Frame Survey (LUCAS), and (ii) a dataset generated through visual interpretation of very high resolution orthophotos. LUCAS is an in-situ survey, started in 2006 and updated every ~3 years, that provides detailed information on land use and land cover at several sites across the EU (d'Andrimont et al., 2021). Since 2018, the survey has recorded information on disturbance events at the study sites, with additional information on the potential drivers (e.g. wildfire, clear-cutting). We filtered the LUCAS dataset by selecting the records in forest areas with recorded disturbances (84 samples in total) and randomly selecting an equal number of samples without disturbances. The second dataset was obtained by visual interpretation of PNOA (Centro Nacional de Información Geográfica, 2020) orthophotos with a spatial resolution below 0.35 m. The orthophotos were acquired between 2016 and 2020, depending on the region. Following the sampling design recommendations of Olofsson et al. (2014), the interpreter randomly selected an even number of disturbed and undisturbed samples (386 in total). For each disturbed sample, the interpreter annotated the date of the event, the percentage of canopy affected within a 30-m buffer, the potential driver (i.e. clearcut, wildfire, or unknown), and the confidence level (low, medium, high). In occasional cases (10% of the total sample) where orthophotos did not provide sufficient information for the interpretation, we relied on PLANET images (<5 m spatial resolution) from similar dates.

The two non-stand replacing related datasets are in situ records covering a longer period of study than LUCAS and PNOA (2016–2020): (i) the International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests (ICP Forests) Level I, which provides data on defoliation, and ii) the European dataset of Caudullo and Barredo (2019), which provides data on drought and heat-induced tree mortality. The ICP Forests is an annual forest inventory that collects data at a continental scale in a systematic grid of 16 × 16 km. We considered tree crown defoliation records from 1987 to 2019 and grouped the original defoliation into three levels: (25–50], (50–75], and (75–100] %. The Caudullo and Barredo (2019) dataset contains a collection of forest sites recording climate-induced disturbances and their coordinate, and was obtained from a systematic literature review. We considered records in this dataset from 1987 to the most recent year recorded in Spain (i.e., 2014).

2.4. Accuracy assessment

We calculated the accuracy of the disturbance map (i.e., year of disturbance) using the stand replacing datasets as reference data and considering 2016–2020 as the reference period. For each reference sample, we created a 30 m radius buffer that we compared with prediction data. Each sample was classified as either *stable forest* (i.e. forest with no disturbance events during the reference period) or *disturbed forest* (i.e. forest with at least one disturbance event during the reference period). We calculated the accuracy of LUCAS and PNOA separately, by biome (i.e., Mediterranean and temperate), and by underlying driver (i.e., clear-cutting, wildfires, and unknown drivers) to assess whether CCDC-SMA performed better in certain circumstances. In addition, we performed a second accuracy assessment with the stable forest stratum and another one we called *possible disturbed forest* (i.e. forest classified as disturbed in the pre-processed map and maintained as disturbed or reclassified as stable forest in the postprocessed map, see Chen et al. (2021)). The purpose of calculating the accuracy with the possible disturbed stratum was to account for those disturbed pixels that were erroneously reclassified as stable in the postprocessing step.

We used the two non-stand replacing reference datasets to calculate the sensitivity (percentage of true positives) of the disturbed stratum (i.e., forest with at least one non-stand replacing disturbance), and considered 1987–2014 (i.e., Caudullo and Barredo) and 1987–2019 (i.

e., ICP Forest) as the reference periods. We created the 30 m radius buffers around the reference samples and compared them with the predicted data. Disturbed samples were considered correctly detected (true positives) if a predicted disturbed pixel overlapped the reference sample within a time window of ±2 years. We did not include this reference data in the main accuracy assessment because the information it provides has certain limitations (i.e. uncertainty about whether the disturbance affects a few scattered trees or a specific group, and the precision of the coordinates), but we believed that the sensitivity test provided relevant insights into how the CCDC-SMA performs detecting subtle, gradual, non-stand replacing disturbances.

Finally, we calculated the accuracy of the other two forest change products that exist in Spain (the Global Forest Change of Hansen et al. (2013) and the European Disturbance Map of Senf and Seidl (2021)), using the stand-replacing disturbance datasets as reference data. We also calculated the sensitivity test with the other non-stand replacing disturbance datasets and compared the results with those obtained with our disturbance map.

2.5. Forest disturbance regimes and trends analyses

Using the disturbance maps we characterised forest disturbance regimes and trends at the national scale, by biome (temperate and Mediterranean), and by forest type (broadleaf, needleleaf, and mixed). Namely, we characterised three common disturbance components (patch size, patch severity, and disturbance frequency) used in the literature (Johnstone et al., 2016; Senf and Seidl, 2021; Turner et al., 1998) as they relate to the spatial, temporal, and intensity dimensions of disturbance (Pickett and White, 1985; Van Der Maarel, 1993). Quantifying these components not only provides information on disturbance regimes but is also important for understanding regeneration dynamics. For example, disturbance patch size determines microclimate gaps and distances to seed sources that affect colonisation; severity affects soil properties and the presence of material legacies of the organisms that affect recovery rate and composition (Swanson and Franklin, 1992); and frequency relates to the lifetime and recovery time of organisms and the probability of a disturbance event in a given area and period (Pickett and White, 1985).

Using the 'landscapemetrics' package (Hesselbarth et al., 2019) in R 4.3.1 (R Core Team, 2023), we extracted patch-level information (i.e. individual disturbance events) of disturbances. Namely, we calculated the patch size (in hectares, obtained by multiplying the number of disturbed pixels in a patch by the minimum mapping unit of 0.09 ha, 30 × 30 m), the mean severity (mean magnitude of change in NDFI within a patch, rescaled to a range of 0–1) and the frequency for the entire period (number of events per forest ha^{-1}) and annually (number of events per forest ha^{-1} $year^{-1}$).We removed all disturbance patches smaller than 0.5 ha from the analyses to account for patterns of larger disturbances.

We characterised the disturbance regime at the national scale, by biome, and by forest type considering the mean of the three components. We tested if significant differences existed in regimes between paired groups (i.e., temperate *vs* Mediterranean, broadleaf *vs* needleleaf forests, broadleaf *vs* mixed forests, and needleleaf *vs* broadleaf forests) with the non-parametric Wilcoxon signed-rank test ($p < 0.05$) (Wilcox, 2010). We obtained the trends per component and group (national scale, biome, forest type) using the non-parametric Theil-Sen estimator, an outlier-insensitive technique for estimating linear trends in time series (Wilcox, 2010). The 1985–1987 data were excluded from the trend calculations to avoid the limitations of the CCDC-SMA algorithm, which tends to largely omit disturbances at the beginning of the analysis period (Zhu and Woodcock, 2014).

Lastly, we calculated the regimes and trends of the three components in a systematic hexagonal grid (of 25 km side to side and 1022 grids in total) covering the whole country, and assessed the spatial variability.

3. Results

3.1. Forest disturbance regimes

We generated a database at 30-m resolution with all disturbances detected from 1985 to 2023, providing here an example of the first detected disturbance (Fig. 3A), month (Fig. 3B), severity (Fig. 3C), recovery time (Fig. 3D), and type of change (Fig. 3E) of the last detected disturbance.

We detected more than 2.9 million disturbed forest patches larger than 0.5 ha, covering an area of 4.6 Mha, between 1985 and 2023, with 2022 being the year with the highest disturbed area (i.e., 417,775 ha). The majority of the disturbances were classified as stand replacing (90%), while non-stand replacing and non-stand plus stand replacing accounted for a small proportion (3% and 7% respectively). On average, it took 15 ± 0.95 years for forests to recover after a disturbance (i.e. the number of years it takes for a pixel to reach the pre-disturbance NDFI level) or to experience a new one. Summer and autumn were largely the seasons with the highest number of disturbances detected (74% occurring between July and November).

We found that the disturbance regime in continental Spain is characterised by a high occurrence of small disturbances, being 86.1% of patches below 2 ha, while large patches (>50 ha) represent only 1.3% of the disturbances (Fig. 4A), showing a strong right-skewed distribution (Fig. 4D) and a mean patch size of 1.8 ha. Disturbances are predominantly of medium severity (Fig. 4B), with 93.8% of patches reaching values between 0.4 and 0.8 on the zero to one scale (Fig. 4E) and with an overall mean severity of 0.6. Remarkably, the spatial pattern of disturbance size and severity follows a marked north-south gradient along continental Spain (Fig. 5A and B), with hotspots of large and severe disturbances observed at the transition between the Mediterranean and the temperate biomes. In terms of frequency, 73.50% of the grids had less than 0.005 disturbed patches ha^{-1} $year^{-1}$ (Fig. 4C and F), and few grids (11%) exceeding 0.01 patches ha^{-1} $year^{-1}$, mostly in the north and southwest (Fig. 5C). The disturbance frequency had a right-skewed distribution pattern with a mean annual frequency of 0.004 disturbed patches ha^{-1} $year^{-1}$.

The Mediterranean biome had larger disturbance patches than the temperate biome (Fig. 4A), with annual means of 1.6 ha *vs* 1.8 ha (Wilcoxon test, $p > 0.05$), while the temperate biome had higher severities (Wilcoxon test, $p < 0.05$), with annual means of 0.65 *vs* 0.62. Both biomes had similar annual frequencies of 0.004 events ha^{-1} $year^{-1}$ (Wilcoxon test, $p > 0.05$) (Fig. 4B and C). By forest type, needleleaf forests showed significantly larger and more severe disturbances than mixed and broadleaf forests (Wilcoxon test, $p < 0.05$), with mean annual patch sizes of 1.8, 1.7 and 1.4 ha (Fig. 4A), and mean annual severities of 0.7, 0.7 and 0.6 (Fig. 4B). The frequency was similar across all forest types (Wilcoxon test, $p > 0.05$), with a mean of 0.004 events ha^{-1} $year^{-1}$ (Fig. 4C).

3.2. Forest disturbance trends

Since the late 1980s, forest disturbances in continental Spain decreased in both size and severity (Fig. 4A and B), with average annual rates of change of −1.2% and −0.4% respectively, as estimated by the Theil-Sen estimator. In contrast, the frequency of disturbances showed a positive trend, increasing by 5.4% per year (Fig. 4C). We found an important spatial variability, with higher negative trends in patch size in the southwest (Fig. 5D), while few areas, mostly in the north and mid-east showed an increase in size. Negative trends in severity were particularly high in the temperate-Mediterranean transition zone and eastern regions, whereas positive and no trends were common in the mid-west and southwest. (Fig. 5E). Positive trends in disturbance frequency were widespread across the country, except in the southwest (Fig. 5F).

The Mediterranean biome experienced a greater negative trend in

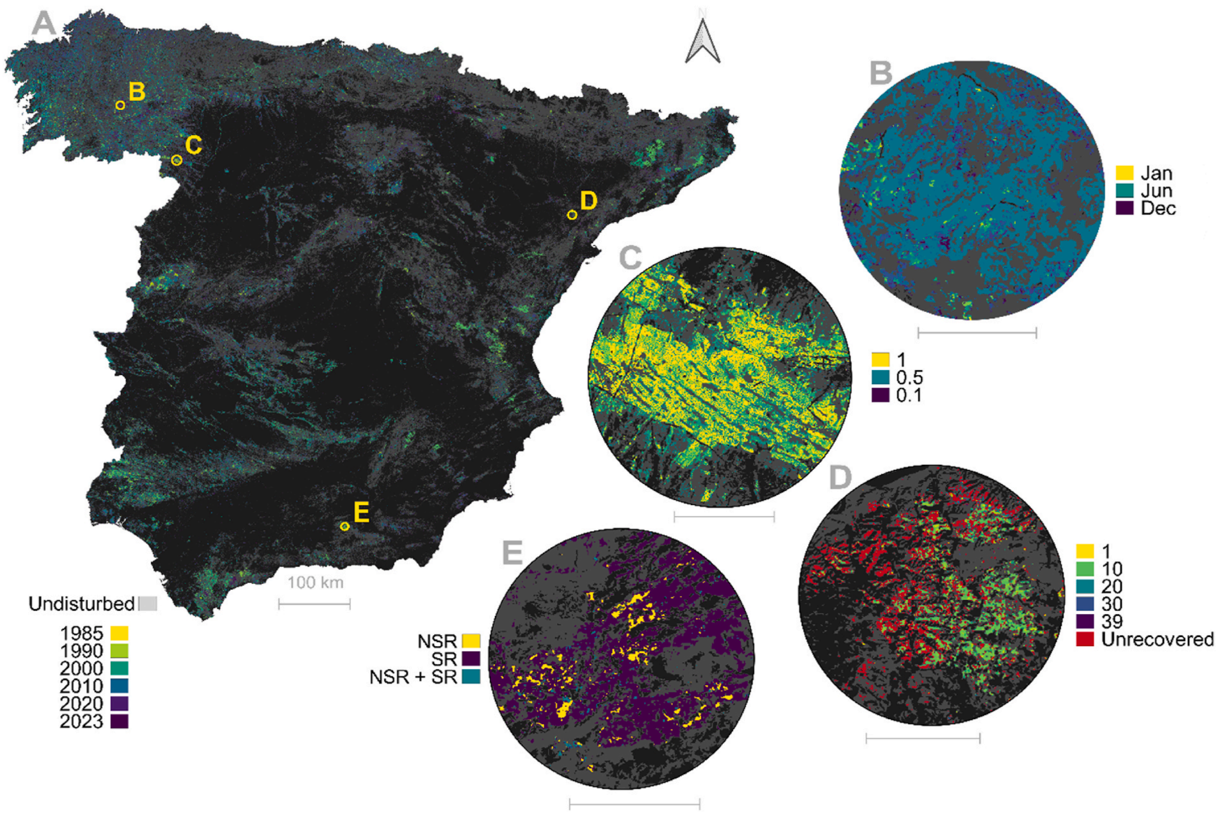

Fig. 3. Forest disturbance in Spain, 1985–2023. A, first year of disturbance; B, month of detection; C, severity; D, recovering time; E, type of disturbance (NSR, Non-Stand Replacing; SR, Stand Replacing; NSR + SR, Non-Stand Replacing plus Stand Replacing). The map scale of the snapshots is 5 km.

size compared to the temperate biome, with an average annual rate of change of −1.3% *vs* −0.5%. However, the trends in severity and frequency were similar between the two biomes, with rates of change of −0.4% *vs* −0.3% for severity and 5.3% *vs* 5.2% for frequency in the Mediterranean and temperate biomes, respectively. When analysed by forest type, mixed forests had the greatest decrease in size, with a rate of change of −1%, compared to −0.6% for broadleaf forests and −0.5% for needleleaf forests. Both needleleaf and mixed forests showed negative trends in severity of −0.4%, compared to −0.2% for broadleaf forests, and similar positive trends in frequency were observed across forest types, with annual rates of 5.4% in needleleaf forests, 5.2% in mixed forests, and 5% in broadleaf forests.

3.3. Accuracy assessment and sensitivity comparison

The overall accuracy considering the stable and disturbed strata was 85% (95% CI [81.8, 87.9] %, $p < 0.05$), with omission and commission errors below 16% (Table 1). When also considering the stable and possible disturbed strata, the accuracy increased to 89.7% (95% CI [86.9, 92.1] %), with significant decreases in both, omission and commission errors (see Tables S4 and S5 in Supplementary Material).

A higher overall accuracy was obtained with the PNOA dataset than with the LUCAS dataset, albeit the difference was marginal (2.8%, Table 2A). The algorithm performed better detecting disturbances that occurred in temperate than in the Mediterranean forests (difference of 3.1%, Table 2A) and events driven by clear-cutting (differences of 2.5% with wildfires and 5.8% with unknown agents). The sensitivity tests (i.e., true positives) performed with the ICP-Forests and Caudullo and Barredo (2019) datasets were low but improved significantly in the possible disturbed strata (from <36.1% to 14.9% to 45.2 and 54.1%; see Table 2B).

When comparing our results with other forest change products, our dataset showed the lowest omission error for the disturbed layer, 14.4% *vs* 23.5% of Hansen et al. (2013) and 47.3% of Senf and Seidl (2021). Conversely, the commission errors were higher in our dataset, reaching 15.4% *vs*. 4.1% in Hansen et al. (2013) and 2% in Senf and Seidl (2021). The overall accuracy was slightly higher in Hansen et al. (2013), 86.6%, than in ours, 85%, and lower in Senf and Seidl (2021), 75.6%. However, our accuracy was highest when considering stable and possible disturbed strata (89.7%). Our product was also more sensitive to defoliation events (ICP-Forests dataset) and drought and heat mortality (Caudullo and Barredo, 2019) than the other products (see Table 2B).

4. Discussion

4.1. Mapping forest disturbances in continental Spain and characterisation of the disturbance regime

We generated data on intra-annual forest disturbances in continental Spain using dense Landsat time series and calibrated the CCDC-SMA method with spectral libraries for the temperate and, for the first time, the Mediterranean biomes. We found that disturbance events larger than 0.5 ha were more extensive than previously reported, with approximately 4.6 Mha of forest affected between 1985 and June 2023 (see Hansen et al. (2013); Senf and Seidl (2021)). The discrepancy in the extent of disturbed forest when comparing products derived from dense time series and composite-based methods has been previously reported in studies conducted in temperate and tropical regions (Matricardi et al., 2020; Milodowski et al., 2017; Pearson et al., 2017), and there are two main reasons for this. First, composite-based methods tend to focus on easily detectable stand replacing events, thus omitting large areas affected by disturbances with rapid recovery or gradual, subtle non-stand replacing changes (Bullock et al., 2020; Chen et al., 2021). Second, definitions of forest and forest disturbance often vary between studies, contributing to inconsistencies in reported disturbance extent (Ghazoul et al., 2015).

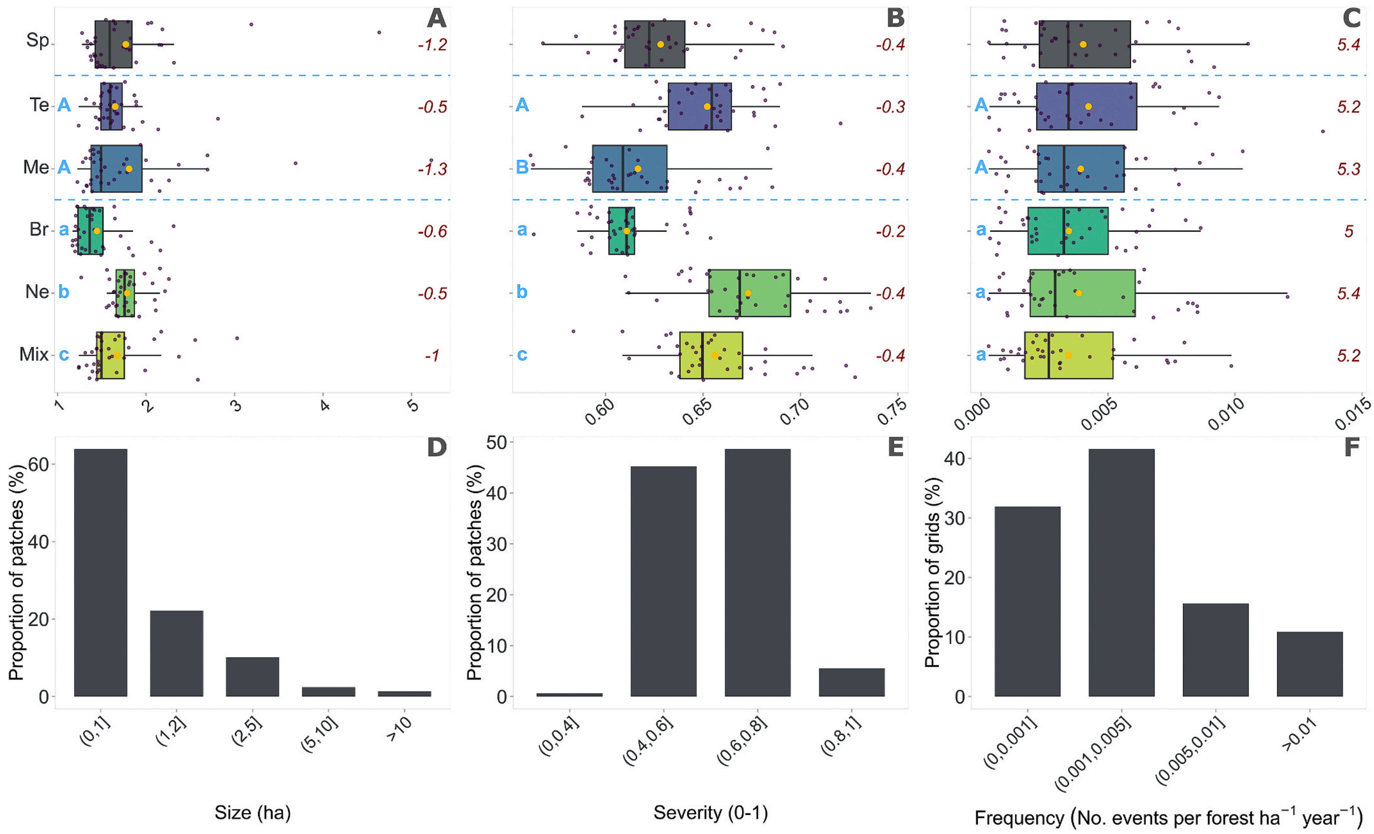

Fig. 4. On the upper side, box and jitter plots characterizing the mean annual forest disturbances by (A) size, (B) severity and (C) frequency in the entire continental Spain (Sp), by biome (temperate (Te) and Mediterranean (Me)) and by forest type (broadleaf (Br), needleleaf (Ne) and mixed (Mix)). The orange dots show the overall mean of all years (1988–2023) and the values in red on the right side of the plots show the trend (according to the Theil-Sen estimator). Blue letters show if there are differences (Wilcox test <0.05) in the annual means per biome between temperate and Mediterranean forests (uppercase letters) and per forest type between broadleaf, needleleaf and mixed forests (lowercase letters). On the bottom side, the distribution of patches (%) in continental Spain by their (D) size and (E) severity, and the distribution of grids by their (F) annual frequency.

Our results suggest that most disturbance patches in continental Spain are smaller than 2 ha (86.1%)and of medium severity (93.8% with a severity between 0.4 and 0.8), and the frequency of disturbance is below 0.005 patches per forest ha^{-1} per year^{-1} (73.5% of grids). These results are consistent with a previous study in Spain reporting disturbance regimes characterised by small patches of medium-high severity and high frequency (Senf and Seidl, 2021). Significant differences in spatial patterns of disturbance were found across geographic regions, biomes and forest types.

On average, the Mediterranean had larger forest disturbances but of lower severity than the temperate biome, and important hotspots of large and severe events were reported in the biome transition zone. Significant changes in species distribution and tree demography rates have previously been reported in this transition zone (Benito-Garzón et al., 2013; Bonannella et al., 2024; Hernández et al., 2017), suggesting that this hotspot pattern may be related to climate change. The observed differences in disturbance size between biomes indicate that Mediterranean forests have more variability and are more affected by large events, as hot and dry summers in this biome have led to extensive fires and biotic disturbances (Peñuelas and Sardans, 2021). Conversely, the wet and mild temperate climate of the northern Iberian Peninsula has led to a productivity rather than protection-oriented approach to forest management (Vadell et al., 2022), which could lead to a high contribution of rather small and high-severity disturbances caused by clear-cutting.

The frequency of disturbance was particularly high in the northwest, southwest and easternmost regions of the country, in agreement with field-based information reporting a high frequency of fires and harvesting in these hotspots (see Suvanto et al., 2023, preprint, and Urbieta et al. (2019). We suggest that the observed spatial variability from high to low frequency may be driven by contrasting practices and policies, as there is a strong climatic and management gradient from the temperate to the Mediterranean zone (Bravo et al., 2017). The high frequency of events in northern temperate regions may be associated with intensively managed forests with production of fast-growing species with short rotations (Unrau et al., 2018; Vadell et al., 2022). Hotspots in the northwest are also explained by the high frequency of wildfires, which are associated with the type of vegetation and spatial distribution of urban and vegetated areas in this region (De Rigo et al., 2017). Conversely, the high frequency of disturbances in the southwest and east of Spain is associated with low average annual precipitation and high vulnerability to wildfires (De Rigo et al., 2017; Martínez-Fernández et al., 2013)

Needleleaf forests experienced larger and more severe disturbances compared to mixed and broadleaf forests, and the three groups had similar frequency of events. These results differ from recent field-based studies that reported higher tree damage and mortality in mixed forests than in deciduous and broadleaf forests (Adame et al., 2022; Rebollo et al., 2024). This discrepancy may be explained by the fact that mixed forests show greater spectral variation in the satellite sensor data compared to other forest types, which may result in less accurate classification of these areas in the disturbance map (Chen et al., 2023). However, other studies have reported higher vulnerability in needleleaf forests compared to broadleaf and mixed forests in temperate and boreal biomes (Pukkala, 2018; Thom et al., 2017). Lower effect of disturbances in broadleaf forests compared to other forest types has been linked to

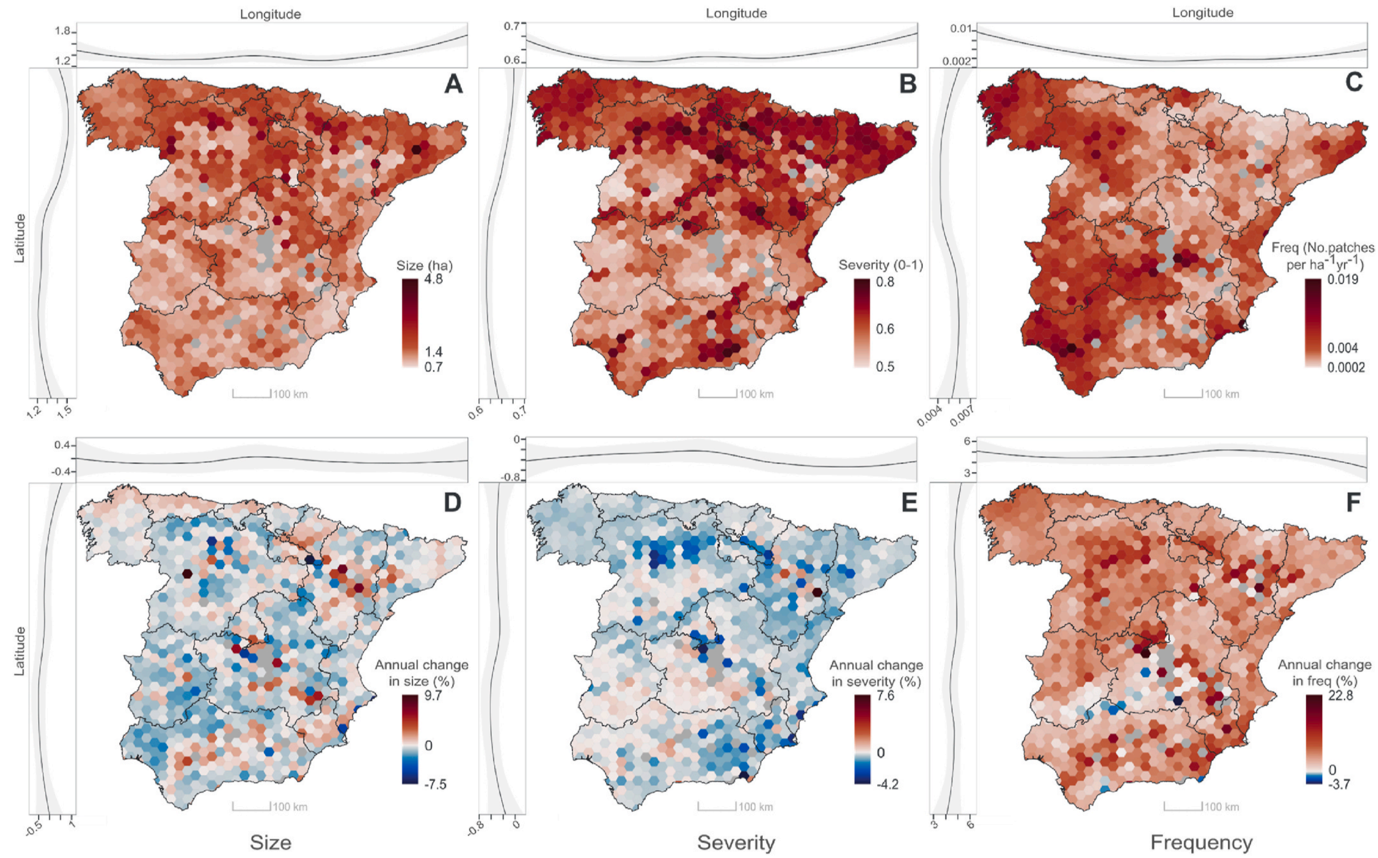

Fig. 5. Forest disturbance regimes (A, B, C) and trends (D, E, F) in Spain by size (A, D), severity (B, E) and frequency (C, F) by hexagons on a 25 km grid, and the latitudinal and longitudinal gradient calculated with a loess curve. Grids in grey show areas with insufficient data to define the regime or trend (i.e., areas with less than 400 ha of forest and disturbance data from less than 10 years).

Table 1
Confusion matrix of stable and disturbed forests. Period: 2016–2020.

Reference class					
Map strata	**Stable forest**	**Disturbed**	**Total**	**Omission error**	**Commission error**
Stable forest	234	40	274	15.5%	14.6%
Disturbed	43	237	280	14.4%	15.4%
Total	277	277	554	**Overall accuracy:**	85.0%

better site fertility, better albedo and higher timber density, which improve climate change mitigation (Kuusinen et al., 2013; Lukeš et al., 2014; Reyer et al., 2017). Additionally, the higher severity of disturbances in needleleaf forests may be related to different management strategies, as they have traditionally been used more for timber production (associated with high severity disturbances) than other forest types (Pukkala, 2018; Vadell et al., 2022).

4.2. Forests disturbance trends

Our results suggest that forest disturbances have decreased in size and severity over the last decades, which is consistent with previous reports at national and continental scales. Higher negative trends in disturbance size and severity were observed in the Mediterranean than in the temperate biome, which may be influenced by improved fire suppression policies (Tedim et al., 2015) and reduced timber production in the Mediterranean region (Vadell et al., 2016). In addition, positive trends in the frequency agree with previous reports using forest inventories in Spain that found increasing rates of tree damage and mortality over time (see Astigarraga et al. (2020); Rebollo et al. (2024)). We believe that the positive trend in frequency might be related to higher temperatures and increased occurrence of droughts and insect outbreaks (Anderegg et al., 2015; Astigarraga et al., 2020; Díaz-Martínez et al., 2023), as well as increased timber production in the northern temperate forests where water availability is high, favouring high turnover rates (Lecina-Diaz et al., 2018; Ruiz-Benito et al., 2013).

The observed trends in disturbance severity and frequency in Spain affected needleleaf and mixed forests more than broadleaf forests, which is consistent with previous national reports on tree damage and mortality trends (Adame et al., 2022; Astigarraga et al., 2020; Rebollo et al., 2024), but the reasons explaining such findings (other than the differences between forest types in their functional and structural characteristics, and management (Foster, 2017; Toïgo et al., 2020; Wiley and Helliker, 2012)) are unclear.

4.3. Accuracy assessment and sensitivity comparison

We obtained an overall accuracy of the disturbance map (i.e., year of disturbance) of 85% (95% CI [81.8, 87.9] %). When we considered the possible disturbed stratum, the accuracy increased to 89.7% (95% CI [86.9, 92.1] %), mainly because the omission errors improved. This means that while the post-processing step (see Section 2.2.4) removes the salt and pepper appearance of the disturbance map, it often reclassifies truly isolated disturbed pixels as stable forest, and depending on the purpose of the user of the disturbance map, the pre-processed map may be preferable to the post-processed one. It should also be noted that while we used very high resolution reference data (i.e., <0.35 m resolution for the PNOA dataset and field surveys for the LUCAS dataset) to

Table 2
(A) Summary of accuracy assessments obtained from different reference datasets, percentage of canopy loss, biome, potential driver of the disturbed sample, and other forest change products. Information on canopy loss and potential drivers was collected from the interpreter who created the PNOA dataset and from information provided by LUCAS. Period: 2016–2020. (B) Detection rates according to different validation datasets and disturbance maps. Period: ICP Forest, 1987–2019, and Caudullo and Barredo (2019), 1987–2014.

(A)				Omission error		Commission error		
Validation dataset		Overall accuracy	95% Confidence intervals	Stable Forest	Disturbed	Stable Forest	Disturbed	N
Reference data	PNOA	84.2	[80.2, 87.7]	19.2	12.4	13.3	18.0	386
	LUCAS	81.6	[74.8, 87.1]	17.9	19.1	18.8	18.1	168
Canopy Loss (PNOA & LUCAS)	<20%	81.4	[72.5, 88.4]	17.7	19.6	19.2	18.0	102
	20–80%	84.5	[79.1, 89.0]	16.8	14.2	14.6	16.4	226
	>80%	85.4	[80.1, 89.7]	16.8	12.4	13.0	16.1	226
Biome (PNOA & LUCAS)	Mediterranean	82.3	[77.0, 86.8]	18.9	16.5	16.9	18.5	254
	Temperate	85.4	[79.6, 90.0]	14.6	14.6	14.6	14.6	192
Driver (PNOA & LUCAS)	Clear-cut	85.6	[81.3, 89.3]	18.1	10.6	11.5	16.9	320
	Wildfires	83.1	[75.5, 89.0]	16.9	16.9	16.9	16.9	130
	Unknown	79.8	[70.8, 87.0]	17.3	23.1	21.8	18.4	104
Existing products	Hansen et al. (2013)	86.6	[83.5, 89.4]	3.3	23.5	19.5	4.1	554
	Senf and Seidl (2021)	75.8	[72.0, 79.3]	1.1	47.3	32.4	2.0	554

(B) Validation dataset		**Detection rates Class**	**SAFoD[a] (including possible disturbed strata)**	Hansen et al. (2013) [b]	Senf and Seidl (2021)	**N**
ICP Forest	Defoliation Interval	25–50 %	14.0 (45.2)	3.7	6.5	1811
		50–75 %	24.4 (63.0)	9.8	14.2	127
		75–100 %	36.1 (72.1)	7.1	31.2	61
Caudullo and Barredo (2019)		Drought and heat mortality	14.9 (54.1)	6,9%	10.8	74

[a] We refer to our map as the Spanish Atlas of Forest Disturbance (SAFoD).
[b] Reference data subset to period 2001–2021, total number (N) of samples: ICP Forest 25–50 %, 1297; 50–75 %, 82; 75–100 %, 28; drough and heat mortality, 29.

calculate the overall accuracy, these values are representative of the 2016–2020 period. However, due to differences in the availability of Landsat data, especially before 1999 (Hemati et al., 2021), accuracy levels vary from year to year (see variations in section S2, Supplementary Material).

There are no previous studies estimating forest disturbances through dense time series analysis in continental Spain at a similar spatial and temporal scale. However, previous works using CCDC-SMA or similar algorithms in temperate and tropical regions reported accuracies close to ours, with user and producer accuracies of the disturbed stratum ranging from 68 to 88% (Chen et al., 2021; Hirschmugl et al., 2017; Schultz et al., 2018). Comparing our accuracy with that obtained by other forest change products in Spain based on different methodologies (i.e., Hansen et al. (2013) and Senf and Seidl (2021)), our map achieved the lowest omission error but the highest commission error in the disturbed stratum. This means that our product correctly detected more disturbed forests than the others but also misclassified more stable forest. The better balance between low omission errors and low commission errors in the two strata in Hansen et al.'s (2013) product compared to ours explains their slightly higher overall accuracy (1.6% difference).

The detection rates for non-stand replacing disturbances (i.e., caused by defoliation, drought, and heat-induced mortality) were significantly lower than for stand-replacing disturbances (i.e., primarily caused by clear-cutting and wildfires). This disparity is also evident in the disturbance type map we generated, as there is a significantly higher proportion of disturbances classified as stand replacing than non-stand replacing (90% *vs* 10%), suggesting that while the CCDC-SMA captures subtle, gradual ecological processes, it still has limitations. This finding highlights the importance of attempting to estimate how well non-stand replacing disturbances are represented in forest disturbance products for two main reasons: (i) these disturbances are not necessarily less frequent than stand replacing disturbances, but they are more difficult to detect and require more observations for accurate classification (Vogelmann et al., 2016), and (ii) because most current forest change products only focus on validating stand replacing disturbances using reference data derived from the same or similar remote sensing sensors, leading to large uncertainties about the actual extent of subtle, gradual non-stand replacing disturbances (Ghazoul et al., 2015; Pearson et al., 2017).

4.4. Limitations

The data we generated has certain limitations and uncertainities. First, forest disturbances occurring in the early years of the study period (i.e. 1985 to 1987) are underrepresented due to fewer images being available and the available data being prioritised to fit the harmonic models in the CCDC-SMA. Second, the accuracies of the disturbance map we report were obtained using the period 2016–2020 as a reference, but values may vary from year to year depending on the availability of Landsat data (see section S2, Supplementary Material). In particular, the accuracy decreases in years before 1999, when only Landsat 5 data are available, and to a lesser extent between the SLC failure of Landsat 7 in 2003 and the launch of Landsat 8 in 2014 (Hemati et al., 2021; Potapov et al., 2020). Third, there may be a lag between the occurrence and detection of some disturbances in the absence of sufficient data (e.g., cloudy months), which may affect the month and year of detection of disturbances.

5. Conclusions

The results presented here highlight the advantages of using the CCDC-SMA method to generate detailed quantitative data on forest disturbance events at fine spatial and long temporal scales. We adapted the CCDC-SMA to the temperate Mediterranean biomes of continental Spain by generating new spectral libraries of three endmembers (i.e. GV, NPV and soil) and believe that these libraries can be used in further studies applying spectral mixture analysis in similar temperate Mediterranean regions.

We created an extensive database of forest disturbances from 1985 to June 2023 at 30 m resolution, providing information on multiple aspects of the events (e.g. year, severity, type of change) and found that the extent of forest disturbed in continental Spain during this period is greater than previously reported. Gradual, non-stand replacing disturbances were a small proportion of the events, suggesting that the CCDC-SMA is effective but still faces challenges detecting this type of disturbances. This finding feeds the debate on the importance of validating forest change products with fine-scale reference data and for different types of drivers (e.g. wildfire, clear-cutting, drought, heat mortality) to understand which ecological processes may be missing.

Furthermore, our results show that changes in disturbance regimes are occurring in continental Spain and vary across regions, biomes and forest types, supporting growing evidence that this is a general trend in forests around the world (Aguiar et al., 2016; Grünig et al., 2023; Patacca et al., 2022). Such results highlight the importance of characterising disturbance regimes to establish baselines against which to assess change, and to inform strategic planning for policy development and implementation in forest ecosystems (Turner and Seidl, 2023). Further research into the classification of the underlying drivers of the disturbance events we mapped could provide relevant information for policy making.

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CRediT authorship contribution statement

S. Miguel: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **P. Ruiz-Benito:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **P. Rebollo:** Writing – review & editing. **A. Viana-Soto:** Writing – review & editing, Methodology. **M.C. Mihai:** Writing – review & editing. **A. García-Martín:** Writing – review & editing, Data curation. **M. Tanase:** Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2024.119802.

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