Remote Sensing of Environment 262 (2021) 112502

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Human or natural? Landscape context improves the attribution of forest disturbances mapped from Landsat in Central Europe

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ARTICLE INFO

Editor name: Marie Weiss

ABSTRACT

Disturbances have increased in Central Europe's forests, but whether changes in disturbance regimes are driven by natural or human causes remains unclear. Satellite-based remote sensing provides an important data source for quantifying forest disturbance change. Separating causes of forest disturbance is challenging, however, particularly in areas such as Central Europe where disturbance patches are small and disturbance agents interact strongly. Here we present a novel approach for the causal attribution of forest disturbance agents and illustrate its utility for 1.01 million disturbance patches mapped from Landsat data in Austria for the period 1986–2016. We gathered reference data on 2620 disturbance patches by conducting targeted field observations and structured interviews with 21 forest managers. We developed a novel indicator class characterizing the landscape context of a disturbance patch (i.e., the spatio-temporal autocorrelation of disturbance patches on the landscape), and combined it with other predictor variables describing the spectral signal, topography, and patch form of each disturbance patch. We used these predictors to identify the causal agents for disturbances mapped in Austria using Random Forest classification. Landscape context was the most important predictor of disturbance agent, improving model performance by up to 26 percentage points. Wind, bark beetles and timber harvesting were separated with an overall accuracy of 63%. Bark beetle patches were most difficult to identify correctly (producer's accuracy = 15%, user's accuracy = 30%), while regular timber harvesting was classified with highest certainty (producer's accuracy = 68%, user's accuracy = 82%). Harvesting dominates the disturbance regime of Austria's forests, with 70.5% of the disturbed area (76.7% of the disturbed patches) attributed to human causes and 29.5% (23.3%) to natural causes (wind: 23.0% [14.8%], bark beetles: 6.5% [8.5%]). Increases in disturbance since 1986 were driven by natural causes, with wind increasing by 408% and bark beetles increasing by 99% between the first and the second half of the observation period. Wind-disturbed patches were also considerably larger than those caused by bark beetles and harvesting (+102% and + 67%, respectively). Our novel approach to mapping causal agents of forest disturbance, applicable also to highly complex and interactive disturbance regimes, provides an important step towards a comprehensive monitoring and management of forest disturbances in a changing world.

1. Introduction

Disturbance is an important process in forest ecosystem dynamics. Disturbances are relatively discrete events in time that disrupt the structure of an ecosystem, community or population and change resource availability (Pickett and White, 1985). As such, disturbances shape the structure, species composition and demography of forests for decades to centuries (Schuler et al., 2019; Schurman et al., 2018; Senf et al., 2021; Thom et al., 2018). Besides their ecological importance, disturbances directly affect human well-being through their impact on the supply of ecosystem services (Thom and Seidl, 2016), such as timber production (Seidl et al., 2008), protection against natural hazards

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https://doi.org/10.1016/j.rse.2021.112502
Received 26 November 2020; Received in revised form 4 May 2021; Accepted 11 May 2021
Available online 20 May 2021

(Sebald et al., 2019), or carbon storage (Dobor et al., 2018; Pugh et al., 2019; Seidl et al., 2014). Forest disturbances also affect wildlife habitat (Kortmann et al., 2018; Thom et al., 2017; Thorn et al., 2017), and are a strong driver of the prevalence of many forest-dwelling species (Hilmers et al., 2018). Given their relevance for both humans and the environment, there is increasing interest in monitoring forest disturbances from local to global scales (Griffiths et al., 2014; Hansen et al., 2013; Masek et al., 2013; White et al., 2017), especially because forest disturbances are highly sensitive to climate change (Seidl et al., 2020, 2017; Sommerfeld et al., 2018).

Disturbances have increased over the past thirty years in Central Europe, but the causes of this increase remain unresolved. Since 1986, disturbance rates have doubled in Central Europe (Senf et al., 2018) with the highest disturbance rate of the period 1986–2018 observed in 2018 (Senf et al., 2021). Increases in disturbance rates resulted primarily from increasing disturbance frequency rather than increasing patch size, while disturbance severity generally decreased in Central Europe (Senf and Seidl, 2021). Yet, the root causes of disturbance and the contribution of individual disturbance agents to the observed increase remain disputed. While some studies identify forestry to be the driving force behind increasing disturbances in Central Europe (Ceccherini et al., 2020; Curtis et al., 2018), others suggest that climate change and increased natural disturbances are a major driver (Klein and Hartmann, 2018). It remains unclear whether the increases in forest disturbance reported for Central Europe are due to elevated human resource use (i.e., timber harvest) or increased natural disturbances (e.g., wind-throw and bark beetle outbreaks, the two most important agents of natural disturbance in Central Europe, Thom et al., 2013). It is of central relevance for policy and resource management to understand the drivers underlying recent changes in Europe's forests (McDowell et al., 2015). While human disturbances are the result of active decision making – their occurrence, frequency, extent and severity are directly controlled by managers on the ground – the dynamics of natural disturbances remain difficult to control, especially under climate change (Seidl et al., 2017). Natural disturbances frequently upend management plans and challenge the stable and continuous supply of ecosystem services to society (Albrich et al., 2018). Further, natural disturbances are expected to intensify due to climate change (McDowell et al., 2020), potentially exceeding the ecological resilience of forests and resulting in regime shifts (Hughes et al., 2013). Therefore, it is necessary to accurately identify the causes of forest disturbance in order to develop appropriate response strategies to the ongoing changes in Europe's forests.

Remote sensing using moderate-resolution sensors has evolved as a key tool for forest disturbance ecology. Since the opening of the Landsat archive in 2008, numerous studies have utilized the long and dense time series of Landsat for mapping forest disturbances in a variety of different ecosystems (e.g., Neigh et al., 2014a; Schroeder et al., 2017; White et al., 2017; Zhu, 2017). While mapping forest disturbances from Landsat data is thus quasi-operational (e.g., Hansen et al., 2013; Senf and Seidl, 2021), the attribution of causal agents of disturbance remains a major challenge (Anderegg et al., 2020). Previous attempts have jointly used spectral information, topography and patch metrics (e.g., the size and shape of a disturbance patch) to identify causal agents of forest disturbance (Hermosilla et al., 2015; Kennedy et al., 2015; Schroeder et al., 2017). Reference data has often been collected via the interpretation of high-resolution imagery (e.g., Shimizu et al., 2017). While such approaches led to satisfactory results in some regions of the world (e.g., Canada: Hermosilla et al., 2015, USA: Kennedy et al., 2015; Schroeder et al., 2017), its application in Central Europe revealed a number of challenges (Oeser et al., 2017; Senf et al., 2017; Senf and Seidl, 2021): First, patch sizes are generally much smaller in Central Europe, compared to the US or Canada, inherently reducing the diversity of patch forms at a given pixel size and limiting the inferential potential of patch metrics for distinguishing causal agents of disturbance. Hermosilla et al. (2015), for example, report an average size of 98 ha for disturbance patches caused by timber logging in Canada, while patches created by wildfire were on average more than three times larger (324 ha). In contrast, approximately 99% of all disturbances patches from both natural and human causes are smaller than 10 ha in Central Europe (Senf and Seidl, 2021), limiting the use of patch metrics to distinguish between disturbance agents. Second, the forests of Central Europe are intensively managed and salvage logging after natural disturbance is a common practice (Leverkus et al., 2018; Thorn et al., 2020, 2017). Consequently, the spectral signal of natural disturbances is frequently inseparable to that of human disturbances, especially when working with annual resolution Landsat time series (Senf et al., 2017). Third, freely available high-resolution imaginary is often limited to recent years, underlies access restrictions, and/or has low temporal resolution. This, in combination with immediate salvage logging, limits the instances where the causal agent of a forest disturbance can be determined with confidence from high resolution imagery in Central Europe.

The fact that the forests of Central Europe are coupled human and natural systems might also provide an advantage for disturbance attribution. In particular, planned logging traditionally aims at sustainable timber supply, which leads to largely constant disturbance rates in space and time (Sebald et al., 2019; White et al., 2017). In contrast, natural disturbances often occur in localized pulses (Kennedy et al., 2015; Schroeder et al., 2017, 2011; Senf and Seidl, 2018). For example, cyclonic storm events leave distinct tracks of spatially autocorrelated disturbance patches visible at the landscape-scale (Forzieri et al., 2020; Turner and Gardner, 2015). Similarly, bark beetles only disperse for a few tens to hundreds of meters, and infestations are thus spatially autocorrelated (Seidl et al., 2016b; Turner et al., 1989). Consequently, natural disturbances create a distinctly different landscape pattern surrounding a given disturbance patch compared to planned harvest. Here, we hypothesized that the landscape context (e.g., how a disturbance patch relates to disturbances in the landscape surrounding it) holds important information for identifying the causal agent of a disturbance. Additionally, we aimed at taking advantage of the intensive management of Central Europe's forests for creating a reliable reference database for disturbance attribution. Forest managers are an excellent source of information on causal agents of disturbance, because they are the ones planning and implementing management interventions, and because they usually have good knowledge of the natural disturbances affecting their management district. In Central Europe, management districts are typically small (1000–5000 ha), and managers often spend their entire professional life in the same district. They thus have detailed local knowledge on disturbances. Yet this information can be difficult to integrate with remote sensing data because it is distributed across many individuals and hard to quantify. Here we combine established methods of qualitative GIS (Cope and Elwood, 2009), participatory mapping (Cadag and Gaillard, 2012; Chambers, 2006) and citizen science (Bonney et al., 2009; Dickinson et al., 2010) to tap into the available knowledge of forest managers.

We present a novel approach harnessing managers' knowledge and information on landscape context for improving the attribution of forest disturbances mapped from satellite data to causal agents. Our main motivation was to improve our understanding of the drivers of recent increases in disturbance rates in Central Europe, i.e., to determine whether elevated timber harvesting or increased natural disturbances are behind recent changes in the forest disturbance regime. We focused on Austria, a country representing several important European forest types because of its high environmental variation. Our specific objectives were to:

(1) establish a local reference database on the causal agents of forest disturbance through conducting structured interviews with forest managers;
(2) investigate the discriminating power of landscape context indicators (i.e., the spatial-temporal autocorrelation of disturbances) for the attribution of causal agents, focusing on (planned) harvest, wind and bark beetle disturbances;

(3) attribute a total of 1.01 million disturbance patches in Austria for the period 1986–2016 to either harvest, wind or bark beetles, and quantify their patterns, prevalence and trends; and
(4) compare the prevalence and trends of disturbance agents to official statistics, testing the applicability of our approach in the context of the forest disturbance regimes of Central Europe.

2. Methods

2.1. Study area

Austria is a topographically diverse country located in Central Europe. It is characterized by high mountains in the west and south, while plains dominate the east and uplands characterize the north of the country. A total of 48% (~4,000,000 ha) of the land area is forested, with forests extending over an elevation gradient from the natural tree line at between 1800 and 2300 m a.s.l. to forests near the lower tree line at 100 m a.s.l. Forests are dominated by conifers (80.2% of growing stock, BFW, 2020), with Norway spruce (*Picea abies* (L.) Karst), European larch (*Larix decidua* L.), Scots pine (*Pinus sylvestris* L.) and Silver fir (*Abies alba* Mill.) being the most important tree species (BFW, 2020). The most common broadleaved tree species are European beech (*Fagus sylvatica* L.) and pedunculate oak (*Quercus robur* L.) (BFW, 2020). The natural disturbance regime of Austria is dominated by wind and bark beetle infestations (Thom et al., 2013). Forest fires do not play an important role in Austria at the moment, but might become more important in the future (Müller et al., 2013).

Austria's forests are intensively managed, with a high ratio of professional forestry staff per forest area (7.8 professional forest managers per 10,000 ha forest area, BMFLUW, 2008). Forest owners with a property larger than 1000 ha are required by law to hire professional staff for managing their forest. Further, the law strictly regulates forestry operations such as clearcutting, replanting and salvage logging. For example, the clear-cut size is restricted to <2 ha, standing or uprooted trees that are infested by bark beetles have to be salvage logged within two weeks after detection, and both natural disturbances and clear-cuts must be restocked within five years. Consequently, mean patch sizes are small and regeneration periods are short, making causal agent attribution from satellite data challenging (Senf et al., 2017).

2.2. Forest disturbance map

We used an existing Landsat-based European forest disturbance map to identify disturbance patches (Senf and Seidl, 2021, available from doi:://doi.org/10.5281/zenodo.4570157; version 1.0.0). The disturbance map was created at a spatial grain of 30 m and identifies disturbances at annual resolution for the period from 1986 to 2016. It is based on all available Collection 1 Level 1 surface reflectance images from the USGS Landsat archive and a well-established disturbance detection algorithm (Kennedy et al., 2010) implemented in the Google Earth Engine cloud computing platform (Gorelick et al., 2017a; Kennedy et al., 2018). Disturbances in Europe were mapped with an overall accuracy of 92.5%, a commission error of 14.6% and an omission error of 32.8%. Disturbance patches were defined annually using rook-contiguity. The mean absolute error of the mapped disturbance year is 3 years and 77% of disturbance years were classified within this range (Senf and Seidl, 2021).

2.3. Reference data

For attributing causal agents of disturbance, we collected reference data across Austria from March to December of 2019. The data was collected in nine forest enterprises and two national parks (Fig. 1, Table 1). Forest enterprises in Central Europe are the administrative entities responsible for management, and are comprised by multiple forest management units. We contacted ten forest enterprises distributed across Austria, of which nine agreed to contribute to our analysis. Contact information for all forest enterprises managing a forest area larger than 500 ha in Austria is publicly available in a forestry yearbook. In each forest enterprise we conducted structured interviews with professional foresters, obtaining local expert information on the occurrence of harvest, bark beetle and wind disturbances (comparable to participatory mapping approaches see Cadag and Gaillard, 2012; Chambers, 2006). In addition to these three major disturbance agents we also recorded patches caused by fire, gravitational events and land use change. Their frequency was too low, however, to be included in our analysis (fire $n = 1$, gravitational events $n = 114$, land use change $n = 74$, of the 2809 patches recorded). Enterprises were typically structured into management units with a size between 1000 and 5000 ha. Each of these management units had a responsible forest manager, in charge of the executive management decisions in the district (e.g. timber harvesting, replanting, salvage logging). Managers thus have detailed, first-hand knowledge on all harvesting operations and natural disturbances that happen in their area of responsibility. During the interviews, the interviewer and the forest manager went through patches of the Landsat-based disturbance map (Senf and Seidl, 2021) and determined the causal agent of disturbance patches. Patches for which forest managers were not able to identify the causal agent with certainty were skipped. If more than one agent was responsible for a disturbance patch, the agent that had caused the largest proportion of the patch was recorded. We preferably interviewed experienced foresters who had been in charge of their district for more than 20 years, thus covering the majority of the time span covered by the European forest disturbance map (1986 to 2016). In total, we interviewed 21 foresters, managing a forest area of ~37,000 ha, accessing the combined knowledge of 501 cumulative years of professional experience (Table 1). The distribution of reference data over time is displayed in the Appendix (SI 1).

In addition to structured interviews with forest managers we collected reference data in two Austrian national parks to extend our reference dataset also to unmanaged forests. In contrast to forest companies, national parks do not conduct planned timber harvesting operations, and their core zones are excluded from the legal obligation to salvage log natural disturbances. Wind-thrown and bark beetle infested trees thus remain on site, allowing an experienced field crew to distinguish wind disturbance (root plates, uprooted trees, broken trees) from bark beetle patches (standing deadwood, red crowns) for several years after the disturbance event (Copass et al., 2018). Field crews were equipped with disturbance maps and GPS devices to identify specific disturbance patches in the field. After a close inspection of the

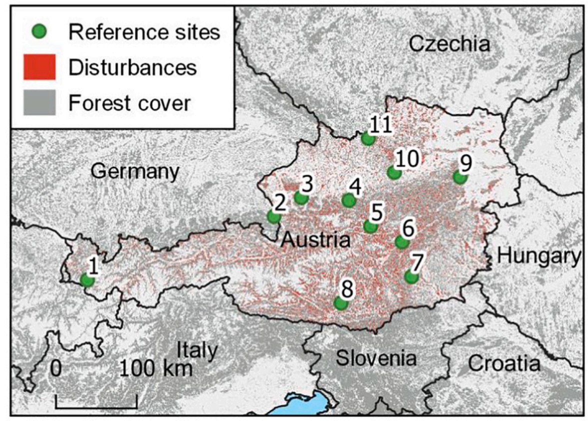

Fig. 1. Disturbance map showing the study area (Austria) and the sites for which reference data on disturbance agents were collected. Disturbances (canopy removal) were mapped from Landsat data at a spatial grain of 30 × 30 m (Senf and Seidl, 2021). Reference site 4 and 5 five are National parks, reference site 1–3 and 6–11 are forest enterprises.

Table 1
Summary of the reference data on disturbance agents collected. We recorded reference data on the causal agents of forest disturbance in nine forest enterprises and two national parks throughout Austria. We conducted structured interviews with 21 forest managers, harnessing 501 years of cumulative professional experience. Further, we collected reference data in the field for the two national parks. From both data sources we gathered information on the causal agents of disturbance for 2620 disturbed patches. For the location of each reference site see ids in Fig. 1.

Id	Type		Elevation [m a.s.l.]				Number of foresters / cumulative years of experience	Forest area [ha]	Attributed patches	
	Forest enterprise	National park	Min	Max	Mean	SD			Number	Hectares
1	x		677	2051	1415	227	4/120	7500	390	309
2	x		434	1499	793	251	2/52	4400	204	311
3	x		489	810	629	80	3/75	2628	242	361
4		x	541	1546	1138	204	–	15,629	309	319
5		x	603	1303	885	151	–	9676	91	72
6	x		609	1497	1001	236	3/70	6650	194	347
7	x		385	1709	1099	414	2/55	3290	82	142
8	x		1154	1731	1471	138	1/33	1850	135	150
9	x		231	1422	465	161	3/64	4860	285	299
10	x		246	688	379	82	1/34	1600	211	311
11	x		773	1022	897	53	2/32	4400	477	483
Overall	9	2	161	2051	924	385	21/501	62,298	2620	3240

disturbance patch and the available on-site disturbance legacies, field crews determined the causal agent of disturbance. Patches that were inconclusive were not included in the reference database. The core zones of the two National parks are 15,629 ha (Kalkalpen National Park) and 9676 ha (Gesaeuse National Park) in size. Over both parks, disturbance agents were determined in the field for 400 patches. From both sources (i.e., national parks and forest enterprises), we determined agent information for 2620 disturbance patches in our reference database, of which 455 were caused by bark beetles, 760 by wind, and 1405 by timber harvest.

2.4. Attribution model

We utilized the reference data to train a Random Forest classifier (Breiman, 2001), predicting the causal agent of all disturbance patches mapped for Austria between 1986 and 2016, based on predictors describing the spectral signal, topography, patch form, and landscape context of each patch (Table 2). To identify the importance of individual predictors and to test our hypothesis on the importance of landscape context for attributing agents we built three models and compared their predictive performance. The first model only included predictors describing shape, topography and spectral properties of a patch; the second model additionally included four predictors describing the landscape context of a disturbance patch. For the third model, we removed all predictors of the second model that became redundant by adding the landscape context predictors. In the following, we describe the predictor variables in detail, followed by details on the Random Forest model, variable selection, the application of the model, and the evaluation of our results.

Table 2
List of all predictors that were considered for attributing causal agents of disturbance in Austria. Those with the highest predictive power were included in the final model (underlined). For additional information on all predictors see Table SI 2.

Domain	Predictors (included in final model)
Topography	
	Easterness, Northerness, Slope, Topographic ruggedness index
Patch	
	Area, Core area Index, Related circumscribing circle, Contiguity index, Core area, Euclidean nearest neighbor distance, Fractal dimension index, Radius of gyration, Number of core areas, Perimeter-area ratio, Patch perimeter, Shape index
Spectral	
Pre-disturbance mean	B1, B2, B3, B4, B5, B7, NBR, NBR2, NDMI, NDVI, SAVI
Change magnitude	B1, B2, B3, B4, B5, B7, NBR, NBR2, NDMI, NDVI, SAVI
Post disturbance minimum	B1, B2, B3, B4, B5, B7, NBR, NBR2, NDMI, NDVI, SAVI
Landscape context	
	Same year, one year before, two years before, three years before

2.4.1. Predictor variables

We calculated three metrics describing the spectral characteristics of a disturbance: the pre-disturbance spectral mean, the spectral change magnitude during disturbance, and the post-disturbance spectral minimum (Fig. 2). The pre-disturbance mean describes the "normal" spectral reflectance of the surface before a disturbance has happened. The change magnitude describes the "disturbance impact", that is how strongly the spectral signal changes in response to the disturbance. The

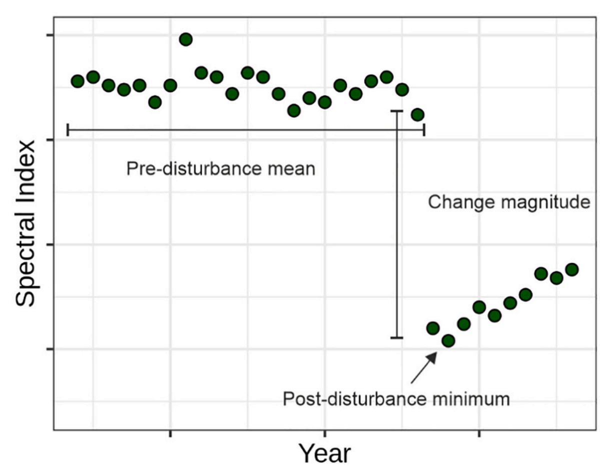

Fig. 2. Conceptual figure explaining how we quantified the spectral signal of a disturbance using three metrics: the pre-disturbance spectral mean, the spectral change magnitude, and the post-disturbance spectral minimum. We calculate all three metrics for the six spectral bands of Landsat (excluding the Cirrus band for Landsat 8) and five spectral indices: The Normalized Burn Ratio (NBR), the Normalized Burn Ratio 2 (NBR2), the Normalized Difference Moisture Index (NDMI), the Normalized Difference Vegetation Index (NDVI), and the Soil-Adjusted Vegetation Index (SAVI). All metrics were calculated per Landsat pixel and then averaged over all pixels of a disturbed patch. For the distributions of predictor values and correlations among final predictors see SI 2, SI 3 and SI 4.

post disturbance minimum describes the spectral reflectance after the disturbance event. Spectral variation after disturbance is often high and recovery trajectories can quickly resemble pre-disturbance spectral characteristics, especially if understory vegetation is present (Hais et al., 2009). We therefore used the minimum value over the mean to depict the spectral characteristics directly after disturbance, instead of the mean spectral characteristics of the post-disturbance recovery trajectory. Metrics were derived from annual medoid composites (see Flood, 2013), which were created from all Tier-1 surface reflectance images available between 1st of June and 30th of September. Data from TM/ETM+ and OLI were spectrally aligned using coefficients provided by Roy et al. (2016) prior to compositing, and clouds, cloud shadows and snow observations were filtered using the quality flags accompanying the Tier-1 products. The image acquisition, processing and compositing was done with help of the Google Earth Engine cloud computing environment (Gorelick et al., 2017b). We calculated the three spectral metrics (pre-disturbance mean, change magnitude, and the post-disturbance minimum) for all six spectral bands (excluding the Cirrus band for Landsat 8) as well as for five spectral indices: The Normalized Burn Ratio (NBR), the Normalized Burn Ratio 2 (NBR2), the Normalized Difference Moisture Index (NDMI), the Normalized Difference Vegetation Index (NDVI), and the Soil-Adjusted Vegetation Index (SAVI). These indices have been employed for causal agent attribution in the US and Canada in previous studies (Hermosilla et al., 2015; Kennedy et al., 2015) and we here test their inferential power in Central Europe. The three metrics were calculated at the pixel-level for each index (i.e., 30 m Landsat resolution) and were subsequently averaged at the patch-level. This resulted in a total of 21 predictor variables.

In addition to spectral characteristics we included a set of topographic metrics found to be important in previous studies (Kennedy et al., 2015; Oeser et al., 2017; Shimizu et al., 2017), including two indicators describing the exposition of a patch (i.e., easterness and northerness), one indicator quantifying the average slope of a disturbance patch, and one indicator expressing terrain ruggedness (Terrain Ruggedness Index, TRI, Riley, 1999) within a disturbance patch. Previous research also suggested patch form (e.g., rectangle, round, strip, highly complex) to hold relevant information for distinguishing disturbance agents (e.g., Kennedy et al., 2015; Shimizu et al., 2017). We consequently also included a comprehensive set of 12 patch metrics (Hesselbarth et al., 2019), describing both the size and form of a disturbance patch (Table 2). Patch metrics were calculated using the *landscapemetrics* package (Hesselbarth et al., 2019) in the R software environment for statistical computing (R Core Team, 2020).

In addition to these established predictors used in past studies we here propose a new metric describing the landscape context of a disturbance patch. Specifically, we calculated the cumulative forest area that was disturbed in the same year as the focal patch within a given radius around the focal patch (see Fig. 3). The new metric is based on the press-pulse dichotomy of disturbance (Bender et al., 1984) and follows the assumption that wind and bark beetle disturbances occur in pulses (Senf and Seidl, 2018), while human resource use leads to relatively stable harvesting rates over time (White et al., 2017), thus creating a press disturbance regime (Sebald et al., 2019). Our metric also accounts for the fact that natural disturbances are often spatially clustered (Kautz et al., 2011; Pasztor et al., 2014; Seidl et al., 2016b; Turner et al., 1989). In simple terms, we expected a disturbance patch that is surrounded by many disturbance patches occurring in the same year to be more likely caused by a natural disturbance agent (i.e., wind or bark beetle) compared to a patch that is surrounded by disturbance patches occurring in many different years (see Fig. 3). Wind disturbances increase the amount of suitable breeding material for bark beetles on the landscape, frequently triggering mass outbreaks (Marini et al., 2013; Seidl et al., 2016b). Consequently, the years after a wind disturbance are often characterized by severe bark beetle outbreaks in adjacent forests of wind thrown patches (Stadelmann et al., 2014; Wermelinger, 2004). We accounted for these spatio-temporal interactions between wind and bark

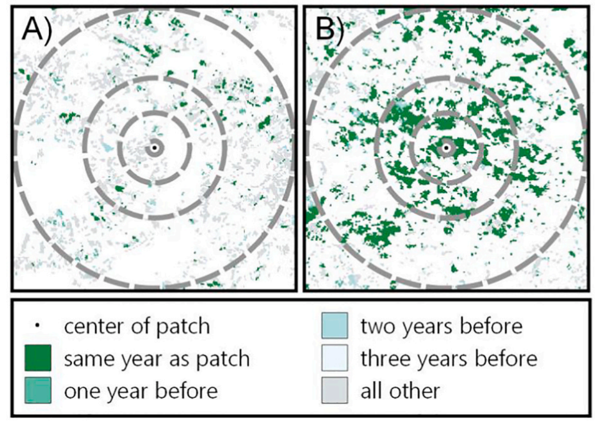

Fig. 3. Example of how landscape context - quantified in a certain radius around a focal patch – was used to distinguish between natural and human disturbances. A) focal patch is caused by regular harvesting, B) focal patch is caused by windthrow. The underlying assumption is that natural disturbances occur in pulses and are spatially clustered, while human resource use aims for stable harvesting rates over time, thus creating a press disturbance regime with lower spatio-temporal clustering. To characterize landscape context, we calculated the cumulative forest area disturbed in the same year as the focal patch within a fixed radius. The dashed circles correspond to different radii tested (i.e., 500 m, 2500 m, 5000 m, 10,000 m). We also calculated the cumulative disturbed area in the three years preceding the disturbance of the focal patch in order to account for temporal autocorrelation.

beetle disturbances by not only including the cumulative disturbed area of the same year as the focal patch in our new metric, but also accounting for the disturbed area of the three previous years. The landscape context metric was calculated on the level of patches. We measured the radius around a patch from its centroid, thus if the centroid of the patch fell within the radius the entire patch was included. The landscape context predictors were only weakly correlated among each other (see SI 5). As no a priori information on landscape size (i.e., here the radius around a focal patch within which context information is considered) was available, we tested different radii from 500 to 10,000 m (but see also Section 2.4.2).

2.4.2. *Variable selection*

Important variables were selected using the VSURF package based on the variable importance measure of the Random Forest package (Genuer et al., 2015, 2010). Variable importance is calculated from the difference in out-of-bag accuracy for different models with varying variables expressed as mean decrease in Gini index. The VSURF packages selects influential variables in three steps. In a first step (“thresholding step”) it computes 50 Random Forests and sorts variables according to their mean variable importance, in decreasing order. Next, a threshold is computed, which is the minimum predicted value of a pruned CART tree fitted to the curve of the standard deviations of variable importance. Finally, the actual “thresholding step” is performed: only variables with a mean variable importance larger than the threshold are kept. The second step (“interpretation step”) considers only variables selected by the first step and computes again 25 Random Forest models, starting with the Random Forest build with only the most important variable and ending with all variables selected in the first step. Then, the minimum mean out-of-bag (OOB) error of these models and its associated standard deviations are computed. Finally, the model with the lowest error (and hence its corresponding variables) is selected. In a third step (“prediction step”) the starting point is the same than in the second step. However, now the variables are added to the model in a stepwise manner. A mean jump value is calculated using variables that have been left out by the second step. A variable is included in the model if the mean OOB error decrease is larger than the mean jump value. The idea is that the

OOB error decrease must be significantly greater than the average variation obtained by adding noisy variables.

2.4.3. Random forest model

The parametrization of the Random Forest models was based on the recommended default values of the *randomForest* package in R (ntrees = 500, cutoff = 1/k = 1/3 see Breiman, 2001; R Core Team, 2020). Random Forest classifiers are a powerful method for causal agent attribution (Hermosilla et al., 2015; Kennedy et al., 2015; Oeser et al., 2017; Shimizu et al., 2017). Here, we applied them in a three-step approach: In the first step, we trained a base model including all predictors describing the spectral signal, topography and patch form (a total of 52 predictors), and selected 18 predictors with the highest predictive power via the *VSURF* procedure for variable selection described above (Genuer et al., 2015, 2010). In a second step, we added the newly developed landscape context predictor to the model. We tested different radii (i.e., 500 m, 2500 m, 5000 m, 10,000 m) to quantify the additional information that is provided by the spatial context of a patch, and to determine the landscape radius with the highest inferential power for determining causal agents of disturbance. In a third step, we selected the predictors of the final model by removing all variables that became redundant by adding the landscape context predictor, again using the *VSURF* procedure. We deliberately did not include disturbance year as predictor, as including this variable would have led to a potential bias in predictions stemming from an unequal temporal distribution of reference data. We trained the Random Forest classifier with all attributed disturbance patches of the reference sample ($n = 2620$).

2.4.4. Disturbance pattern analysis

We employed the final model to predict causal agents of disturbance (i.e., wind, bark beetles, harvest) for all disturbance patches identified in Austria between 1986 and 2016 ($n = 1{,}006{,}449$). Subsequently, we calculated annual disturbance rates (i.e., annual forest area disturbed / total forest area) for the three causal agents and investigated temporal rates and the prevalence of individual agents over time (with prevalence here describing the annual forest area disturbed per agent divided by the total forest area disturbed). Further, we analyzed spatial and temporal patterns as well as patch size distributions of the attributed maps and compared them among the three agents. All data analysis and visualization were conducted using R version 4.0.2. (R Core Team, 2020).

2.4.5. Causal agent model evaluation

We evaluated model performance on the basis of the Random Forest out of bag accuracy and on the basis of a spatial block cross-validation. While the former serves as estimation of model performance and is used for model selection, the latter presents an estimate of generalization power. Out of bag accuracy was calculated following the standard procedure implemented in the Random Forest package (Breiman, 2001). Spatial block cross-validation, which splits the data into spatial blocks before splitting into training and validation data, is helpful in avoiding overoptimistic map accuracies with large spatial datasets that might have high spatial correlation among training and validation data when randomly split (Meyer et al., 2019; Valavi et al., 2019). Here we used our 11 reference sites (i.e., nine forest enterprises and two national parks) as spatial blocks, as spatial correlation within reference sites is likely higher than between reference sites. By training the model on 10 reference sites and predicting causal agents for the remaining 11th site not used during model training, we obtained an estimate of the generalization power of the model when confronted with new data that is likely less correlated with the training data than using pure random splits (Meyer et al., 2019). We calculated average accuracy measures (overall accuracy, user's accuracy and producer's accuracy) and quantified uncertainty using bootstrapping.

In addition to formal model evaluation we further tested the potential of our model to reproduce national-scale trends in forest disturbance. We compared the prevalence of all three causal agents with official logging records compiled by the Austrian Forest Service. We determined mean errors between the two data sources by calculating annual deviations and averaging over the study period (1986–2016). Data on salvage logging following wind and bark beetle disturbance were digitized from the website of the Federal Forest Research Institute (BFW, 2017). Data on total harvested timber volume were obtained from the Austrian Ministry of Forests (BMNT, 2008; Ebner, 2018). We compared prevalence of agents rather than absolute numbers due to differences in measurement units: official records report the timber volume disturbed, while we here quantified disturbed area.

3. Results

Landscape context was the most important predictor for determining causal disturbance agents in Austria. Using only predictors describing the spectral signal, topography and patch shape enabled us to determine the causal agent of disturbance with an overall accuracy of 43% (spatial block cross-validation) and 69% (out-of-bag) (SI 6 and SI 7). Including the landscape context significantly improved model performance (Fig. 4), resulting in an overall accuracy of 63% (spatial block cross-validation) and 75% (out-of-bag) (Table 4, SI 6, SI 7). Model performance improved with increasing radii up to 5000 m, but remained relative constant for larger radii. The landscape context was particularly important for identifying wind disturbance patches, but improved the classification of all three causal agents. The final model included eight predictors, with one predictor describing the topography of the patch (slope), three predictors from the spectral domain (pre-disturbance value in blue reflectance and NBR; change magnitude in NDVI), and all four landscape context predictors (same year, one year before, two years before, three years before) (Table 2, SI 8).

The spatial block cross-validation revealed user's accuracies between 30% and 68% and producer's accuracies between 15% and 84% per agent (Table 3). Bark beetle patches were most often confused with harvest patches, yet there was also a considerable number of patches that were falsely attributed to wind. In total, we observed 455 bark beetle patches but predicted only 223. The map thus underestimates the number of bark beetle patches in Austria and overestimates the number of harvest patches (with bark beetle patches being falsely labeled as harvest). Wind disturbances were mainly confused with harvest patches. We observed 760 wind patches but our model predicted only 660 patches. Harvest was the most accurately classified category, and confusions occurred with bark beetle and wind patches in equal parts. We predicted 1737 harvest patches but observed only 1405 in the reference data. Our attribution thus overestimates the number of regular harvests and underestimates the number of disturbance patches due to natural causes.

The comparison of the mapped prevalence per agent class across Austria (based on disturbed area) with official harvesting records (based on timber volume) yielded very good agreement, with mean errors of +0.40 percentage points for harvest, −2.34 percentage points for wind and + 1.94 percentage points for bark beetle (Fig. 5). The temporal trajectories of wind and harvest disturbances were highly similar between both data sources. The well-known years with large wind disturbances (1990, 2003, 2007, 2008) are reflected in both trajectories with comparable magnitude, however differences of ± one year occurred in some disturbance years (e.g., 2003). The trajectories of bark beetle disturbance generally describe the same temporal pattern, however peak years (1993, 2005, 2009) are more distinct in the data of the Austrian Forest Service compared to Landsat-based estimates.

Regional and elevational hotspots of disturbance activity differed distinctly for wind, bark beetle and harvest disturbance (Fig. 6, SI 9, SI 10). Regional hotpots of wind disturbance were found on the Northern Front Range of the Alps (district Gmunden), in the south east of Austria (district Voitsberg) and in some valleys of the Central Alps (districts Tamsweg, Stainach and Zell am See) (SI 9). The highest prevalence of bark beetle disturbance was mapped in northern and south-eastern

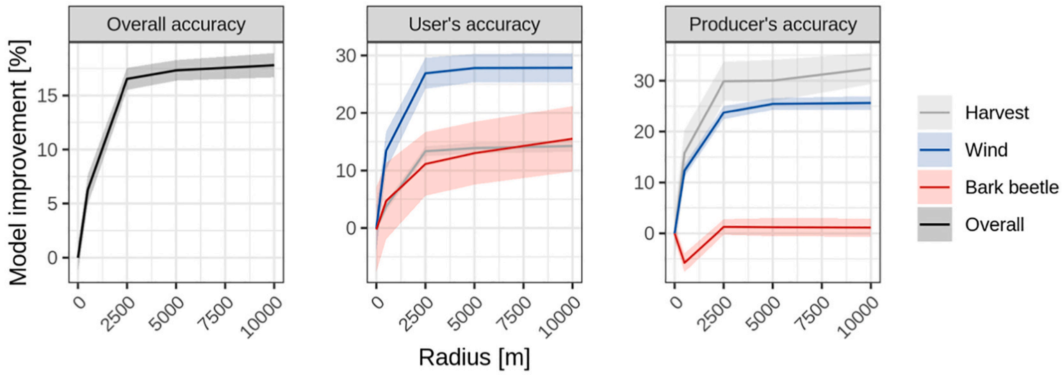

Fig. 4. Model improvement through adding predictors describing the landscape context (i.e., spatio-temporal autocorrelation of disturbances). Model improvement was evaluated based on overall accuracy (out-of-bag), user's accuracy and producer's accuracy. Panels show the relative model improvement over different radii used for calculating the landscape context (i.e. 500 m, 2500 m, 5000 m, 10,000 m). Note the individual scaling of the y-axes. A radius of zero corresponds to the base model without any metric quantifying the spatial context of a patch.

Table 3
Performance of the final model based on spatial block cross-validation. The confusion matrix shows number of patches per agent class (i.e., harvest, wind, bark beetle) in the reference database (columns) and the results of the model predictions (rows). Further, the table reports user's and producer's accuracy ± standard error, calculated per agent class as well as the overall accuracy.

	Harvest observed [n]	Wind observed [n]	Bark beetle observed [n]	User's accuracy [%]	
Harvest predicted [n]	1175	298	264	67.7 (±1.16)	
Wind predicted [n]	121	416	123	63.0 (±1.88)	
Bark beetle predicted [n]	109	46	68	30.6 (±3.21)	
Producer's accuracy [%]	84.6 (±1.01)	54.8 (±1.78)	15.0 (±1.73)		
Overall accuracy [%]					**63.4 (±0.97)**

Austria. Elevational hotspots of wind disturbance were found between 756 and 1302 m a.s.l. (i.e., the interquartile range [IQR] of all mapped wind disturbance patches) with a median elevation of 1025 m. Median elevation of bark beetle patches was considerably lower (512 m, IQR 364–769 m), while harvest patches had the widest elevational distribution, with the IQR ranging from 622 to 1255 m (median = 922 m) (SI 10).

We identified considerable differences in the patch size distributions of the three causal agents analyzed (Table 4). Median patch sizes were similar among wind (0.45 ha), harvest (0.36 ha) and bark beetle (0.36 ha) disturbances, but maximum values varied considerably between agents (Table 4). Wind disturbances generally caused larger patches, compared to regular harvest. The largest disturbance patch in Austria between 1986 and 2016 was caused by wind, affecting a forest area of 354 ha. The largest bark beetle patch was 22 ha, and the largest patch identified as regular harvest was 38 ha. The average disturbance rotation period (i.e., the time needed to disturb an area that is equal to the total forest area) over all three agents was 206 years and was up to ten times higher for natural, compared to human causes. Average disturbance frequency ranged from 0.0005 patches ha year^{-1} for bark beetles to 0.0054 patches ha year^{-1} for harvest.

Wind and bark beetles strongly contributed to the observed increase in disturbance over the last thirty years in Austria (Fig. 7). We here note that we report map-based estimates of disturbance rate and agent prevalence, which cannot be validated rigorously (Palahí et al., 2021). The numbers reported in the following can thus only provide an

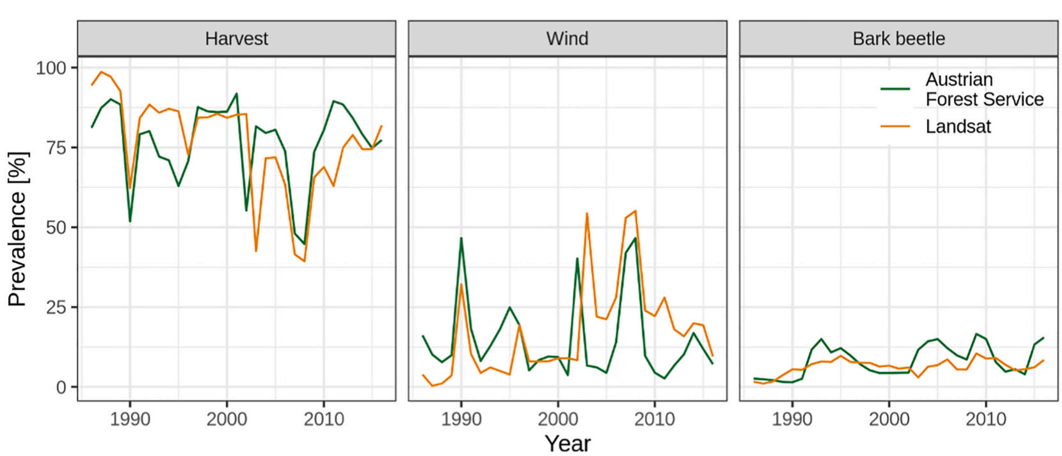

Fig. 5. Comparison of prevalence mapped from Landsat data (orange line) and official records from the Austrian Forest Service (green line) per agent. Note that the Austrian Forest Service reports extracted timber volume per agent class (i.e., harvest, wind, bark beetle), while we calculated the disturbed area per agent class based on Landsat data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

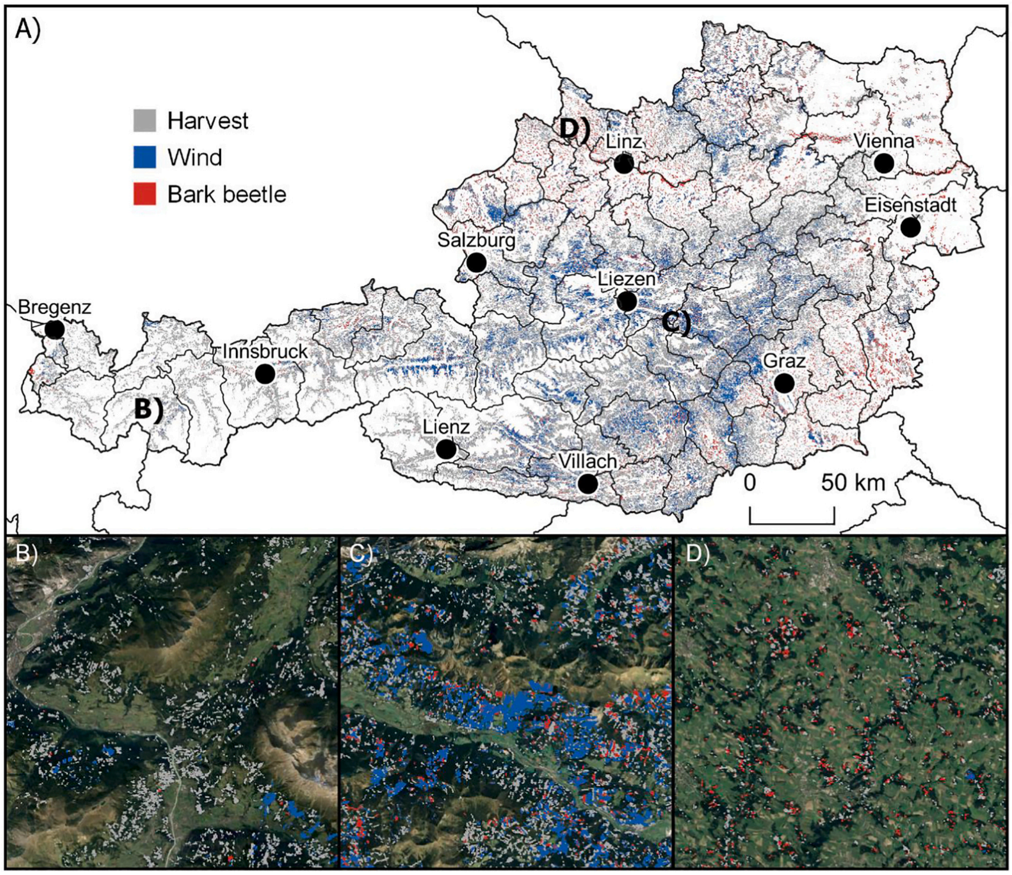

Fig. 6. Map of the causal agents of disturbance in Austria from 1986 to 2016, aggregated to a resolution of 200 × 200 m (A). Colors indicate the dominant agent per 200 × 200 m grid cell. Zoom-ins show landscapes, that are dominated by harvest (B), wind (C) and bark beetle (D) disturbances at the original resolution of the disturbance map (i.e., 30 × 30 m). The background of panels B—D is a high-resolution image provided by Google Maps.

Table 4
The Austrian forest disturbance regime 1986–2016. Disturbance rotation period is the average time it takes an agent to disturb an area equally to the total forest area. Q = quantile.

Agent	Patch size [ha]								Number of patches		Area		Rotation period	Frequency
	Min	Q5	Q25	Q50	Mean	Q75	Q95	Max	n	%	ha	%	years	n ha year^{-1}
Harvest	0.09	0.18	0.27	0.36	0.64	0.72	1.8	38.9	772,111	77	491,605	71	293	0.0054
Wind	0.09	0.18	0.27	0.45	1.07	0.99	3.33	354.0	149,169	15	160,060	23	898	0.0010
Bark beetles	0.09	0.18	0.27	0.36	0.53	0.54	1.44	22.0	85,142	9	45,427	7	3165	0.0006
Overall	**0.09**	**0.18**	**0.27**	**0.36**	**0.69**	**0.72**	**1.98**	**354.0**	**1,006,449**		**697,093**		**206**	**0.70**

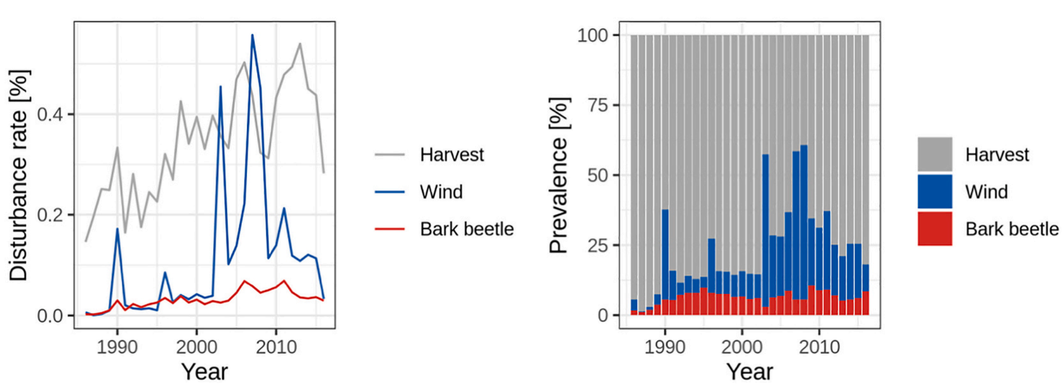

Fig. 7. Disturbance rate (i.e., disturbed area per year relative to the total forest area) and prevalence (i.e., % of disturbed forest area by agent) for harvest, wind and bark beetle disturbances in Austria from 1986 to 2016.

indication for interested ecologists and forest managers. Disturbance rates of wind and bark beetles increased by 408% and 99% between the first (1986–2000) and the second (2001–2016) half of the observation period. In contrast, regular harvests increased by only 43% over the same time period. Furthermore, not only absolute disturbance rates changed, but also the prevalence between the three causal agents of disturbance. In the first half of the observation period, on average 86% of the disturbed area were regular harvests. The prevalence of harvests decreased to 68% in the second half of the observation period, and that of wind and bark beetle disturbances increased from 14% to 32%. Increasing disturbance rates were primary driven by changes in disturbance frequency and only to a lesser extent by increases in patch size. Average disturbance frequency increased by 355% for wind, 77% for bark beetles, and 26% for harvest. Average patch size increased by 8% for wind, 14% for bark beetles, and 13% for harvest.

4. Discussion

4.1. Attributing causal agents of disturbance in Central Europe

The attribution of forest disturbances mapped from satellite data to causal agents is a central objective of current remote sensing research (McDowell et al., 2015). Here we determined the causal agents of ~1 million disturbance patches mapped in Austria between 1986 and 2016. We built upon previous works that have established a patch-based approach using Random Forest classifiers as the state-of-the-art for causal agent attribution of forest disturbances (Hermosilla et al., 2015; Kennedy et al., 2015; Oeser et al., 2017; Schroeder et al., 2017; Shimizu et al., 2017). We advanced the state-of-the-art by showing that the additional consideration of landscape context can considerably reduce error in the attribution of causal agents of forest disturbance.

A key innovation of our work lies in the establishment of a local reference database on agents of forest disturbances, utilizing the abundant local knowledge that is available in intensively managed regions such as in Central Europe. Involving stakeholders to address questions of environmental management has been established more than twenty years ago (Pretty, 1995). Specifically, research can benefit strongly from the interaction of scientist and resource managers (Reed, 2008). Recent studies emphasize that close science-management interactions are a powerful way forward for tackling complex problems (Asah and Blahna, 2020; Gaydos et al., 2019). Increasing forest disturbance is a problem that is highly relevant for forest managers in Austria (Seidl et al., 2016a), which is generally beneficial for the outcome of science-practice interactions (Bennett, 2017). This was also confirmed by a high willingness of forest enterprises to take part in our research. Out of the ten forest enterprises initially contacted, nine agreed to contribute. The amount of reference data that we collected could not have been obtained with classical field work alone. On average, we collected data on 194 patches in one day of interviews with managers, while a field crew of two persons collected, on average, data on 24 patches per day in the national parks surveyed. While being a very efficient approach for reference data collection, the interviews with managers also revealed a central conceptual challenge of causal agent attribution in the forests of Central Europe: for some patches, a single agent of disturbance cannot be determined, as multiple factors interacted in the creation of the patch. As mentioned above, forest managers often respond quickly to natural disturbances (with salvage and sanitation logging), and often fell trees when they are still in the green attack stage of bark beetle infestation (i.e., before the trees are actually killed by bark beetles). Furthermore, managers also fell adjacent trees that are suspected to be infested by bark beetles without conclusively diagnosing each trees infection status. Also, bark beetle infestations and wind-throw often co-occur within a single patch. The true agent of disturbance is thus often a mix of individual agents that cannot be conclusively disentangled because of their causal interrelations. Here, we circumvented this conceptual problem by focusing on the agent that is responsible for the largest proportion of a disturbed patch. However, for similar analyses at larger scales a “mixed” class might be more appropriate, explicitly highlighting the strong interactions between individual agents. Future work on causal agent attribution in Central Europe might also investigate the potential of pixel-based instead of patch-based approaches. Further, data sources with higher temporal and spatial resolution compared to the Landsat archive might help improving causal agent attribution, especially for instances were human and natural agents of disturbance interact strongly.

Including the landscape context of a disturbance patch as predictor substantially improved model performance compared to models based only on spectral signal, topography, and patch form. In particular, the discrimination between disturbances caused by wind and timber harvest improved through adding landscape context. While the spatial and temporal autocorrelation of wind and bark beetle disturbances are well documented in disturbance ecology (Everham and Brokaw, 1996; Turner et al., 1989; Turner and Gardner, 2015; Wermelinger, 2004), and landscape context predictors have been suggested for causal agent attribution previously (Kennedy et al., 2015), we here present the – to our knowledge –first formal test of their discriminating power. Our results indicate that in the intensively managed forests of Central Europe, landscape context is considerably more important for correctly predicting disturbance agents than any spectral or patch indicator. The high importance of landscape context in our study might, however, be specific to forests in Central Europe. First, disturbances in Austria are small (84% of the patches are below 1 ha), due to the applied silvicultural regimes and the prevailing management regulations. A high number of small patches limits the diversity of patch forms (i.e., given the fixed spatial grain of 30 m, there is a limited number of patch forms that can emerge for an average disturbance patch of 10 pixels). This might be the reason why none of the patch metrics were retained in the final model, despite the fact that patch metrics have been shown to be important predictors in other parts of the world (Kennedy et al., 2015; Schroeder et al., 2017; Shimizu et al., 2017). Another factor potentially contributing to a reduced importance of predictors describing the spectral signal and patch form is salvage logging. Post-disturbance salvage logging frequently simplifies patch forms and equalizes differences between natural disturbances and regular harvests, e.g. by removing standing and downed deadwood. We thus emphasize that in Central Europe, landscape context predictors are more important for causal agent attribution than the patch-based indicators used in previous studies (Kennedy et al., 2015; Schroeder et al., 2017; Shimizu et al., 2017). Whether these metrics are also useful in fire-driven disturbance regimes remains to be tested.

An evaluation of our results with spatial block cross-validation yielded an overall accuracy of 63% and (Table 3), whereas the out-of-bag accuracy was 75% (SI 6). These results underline the importance of spatial cross validation for machine learning applications in order to avoid overly optimistic estimates of model performance (Meyer et al., 2019). Comparing user’s accuracies (OOB) of individual agent classes to those obtained in previous studies suggests that our results are comparable to those obtained in other regions of the world. We obtained user’s accuracies of 75.0% for disturbances caused by harvest, while studies in other parts of the world report, e.g., 87.3% for Russia (Baumann et al., 2014), 98.8% for Minnesota (USA) (Baumann et al., 2014), 92% for Washington (USA) (Kennedy et al., 2015), between 63 and 87% (Schroeder et al., 2017) and 82.3% (Schleeweis et al., 2020) across the USA, 80.9% (Senf et al., 2015) and 91.8% (Hermosilla et al., 2015) for different regions in Canada, and 86.4% for Myanmar (Shimizu et al., 2017). Disturbances caused by wind were attributed with a user’s accuracy of 78.7% here, while Baumann et al. (2014) report 71.9% for Russia and 63.0% for Minnesota (USA), and Schroeder et al. (2017) report 62% and 76% for two Landsat scenes in the USA. Bark beetle disturbances were attributed with a user’s accuracy of 69.2% using our approach, compared to 66.7% (Schleeweis et al., 2020), 56%(Neigh et al., 2014a) and 38% (Neigh et al., 2014b) for insect disturbances in the USA; and 70.8% in Canada (Senf et al., 2015). For Central Europe, only one study attributing harvest, wind and bark beetle disturbances existed to date: Oeser et al. (2017) report user's accuracies of 82.6% for harvest, 86.1% for bark beetle, 80.4% for windthrow and an overall accuracy of 83.0% for three National parks in Central Europe. They used intra-annual Landsat time series for attributing causal agents of disturbance from 1986 to 2016. However, their study focused on national parks (i.e., areas with little human influence), and they found elevation and disturbance year to be among the most important predictors. We deliberately excluded these two variables in our analyses, in order to prevent the model from learning the idiosyncrasies of the data (e.g., the occurrence of a large wind disturbance in a given year), and retain its ability for generalization beyond the reference data set. For example, there is a general pattern of increasing bark beetle occurrence with decreasing elevation, since bark beetles are more competitive in warmer climates (Jakoby et al., 2019). However, this relationship is not linear because in low elevations the share of suitable host trees (e.g., Norway spruce) decreases. Consequently, the true probability of bark beetle infestations first increases with decreasing elevation and subsequently decreases again after a threshold in host availability is crossed. A model that includes elevation likely misclassifies small clear-cuts in low elevation areas as bark beetle patches. The same is true for disturbance year as predictor, which can severely bias predictions if reference data is not equally distributed across years (i.e., the model learns that certain years are characterized by bark beetle disturbance and has trouble predicting bark beetle disturbance for years not included during model training). While the accuracy of our models was higher when elevation and disturbance year were included as predictors (data not shown), we excluded these variables at the cost of accuracy in order to ensure model generality.

Temporal trends in disturbance activity derived from Landsat data were remarkably consistent with official harvest records (Fig. 5). We thus conclude that our satellite-based analyses reflect the temporal patterns of wind, bark beetle and harvest disturbances in Austria well. Temporal dissimilarities between harvest records and Landsat-based trajectories can be attributed to uncertainties in the year attribution in the original map product, as well as to differences in the recording of dates (i.e., harvesting records = end of calendar year, Landsat = mid of vegetation period). Furthermore, harvesting records and Landsat-derived values differ because of different underlying indicators. While harvesting records report timber volume extracted, Landsat based maps report area disturbed.

4.2. Limitations

Although our results are based on a large and detailed reference data set, rigorous evaluations of our approach revealed limitations which should be considered when interpreting our results. First, correct model predictions depend on the reference data set representing the environmental conditions occurring in the domain of application. Disturbance regimes or environmental conditions that are not covered by our reference data set are thus prone to misclassification. A prominent example are ecosystems in flood plain forests along rivers (cf. Fig. 6, east of Vienna along the Danube river). These systems are often characterized by a high frequency of small clear-cuts in Central Europe, creating similar patterns as bark beetle disturbances. Yet bark beetle infestations do not occur in these areas, because they lack suitable conifer hosts. Second, our analysis focuses on the three most important agents causing stand-replacing disturbances in Central Europe – wind, bark beetles, and harvest (Thom et al., 2013) – and neglects all other disturbance agents. However, a number of additional processes cause forest disturbances in Austria, such as avalanches (Höller, 2009), debris flows (Scheidl et al., 2020), forest fires (Müller et al., 2013), and land use change (Nestroy, 2006). We recorded these events in our reference database, but their frequency was too low for them to be included in classification (fire $n = 1$, gravitational events $n = 114$, land use change $n = 74$, of the 2809 patches initially recorded in the reference data set). Third, we here utilized an existing disturbance map that does not contain information on sub-canopy processes and very low severity disturbances (e.g., single tree wind-throw, thinning from below). A considerable amount of disturbance might thus not be included in our analysis. Although the minimum mapping unit of the final disturbance map is 1 pixel (see Table 4), single pixel patches account for only 0.1% of all attributed patches ($n = 2017$) thus their influence on the accuracy of the final map is very limited. Fourth, although we believe that reference data collection with the help of forest managers is a promising approach to efficiently collect data on causal agents of forest disturbance in Central Europe, it is limited to areas where foresters spend long time periods of their professional career in the same district. It further depends on interviewers who sufficiently explain the process of reference data collection and subsequent analyses to participating forest managers. Forest managers should, for instance, be aware that a falsely attributed disturbance patch affects the prediction results more negative than a skipped patch (i.e., they should not guess the causal agent if they are not entirely sure, but rather skip such an uncertain patch).

5. Conclusions

We here present an important methodological advance of the causal attribution of forest disturbance agents. Our approach extends the previously applied method, developed for areas characterized by large disturbance patches, so that it is also applicable in areas characterized by small disturbances and intricate disturbance interactions. Here we demonstrate the utility of our approach for Austria, yet we are confident that it is transferable also to other countries of Central Europe, since the disturbance regimes prevailing in large parts of the continent are similar (Senf and Seidl, 2021). Our results are of central importance for forest policy and management. They show that changes in disturbance rates in Austria are mainly the result of increasing wind disturbances. Our results thus refute the notion that forest disturbance dynamics in Central Europe is primarily driven by management (Ceccherini et al., 2020; Curtis et al., 2018). We did, however, find increases in all three disturbance agents investigated here, indicating substantial changes in forest disturbance regimes. As global change continues to alter natural disturbance regimes, compensatory actions by management might be needed in future. We here demonstrate that disturbance change is more strongly driven by increases in disturbance frequency rather than size, which provides an important leverage point for adapting forest management. In conclusion our research provides an important step towards a comprehensive monitoring and management of forest disturbances in a changing world.

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.

Acknowledgements

J. Sebald and R. Seidl acknowledge funding from the Austrian Science Fund FWF START grant Y895-B25. The fieldwork and structured interviews for this research were funded by the Fund 120 Years University of Natural Resources and Life Sciences (BOKU), Vienna.

We thank the forest managers and forest enterprises for their help with collecting the reference data. We further thank Katharina Albrich, Laura Steinbach and Winslow D. Hansen for their help with field work in the two national parks.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.

org/10.1016/j.rse.2021.112502.

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