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A spatially-explicit database of wind disturbances in European forests over the period 2000-2018

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Abstract. Strong winds may uproot and break trees and represent one of the major natural disturbances for European forests. Wind disturbances have intensified over the last decades globally and are expected to further rise in view of the climate change effects. Despite the importance of such natural disturbances, there are currently no spatially-explicit databases of wind-related impact at Pan-European scale. Here, we present a new database of wind disturbances in European forests (FORWIND). FORWIND comprises more than 80,000 spatially delineated areas in Europe that were disturbed by wind in the period 2000-2018, and describes them in a harmonized and consistent geographical vector format. Correlation analyses performed between the areas in FORWIND and land cover changes retrieved from the Landsat-based Global Forest Change dataset and the MODIS Global Disturbance Index corroborate the robustness of FORWIND. Spearman rank coefficients range between 0.27 and 0.48 (p-value<0.05). When recorded forest areas are rescaled based on their damage degree, correlation increases to 0.54. Wind-damaged growing stock volumes reported in national inventories (FORESTORM dataset) are generally higher than analogous metrics provided by FORWIND in combination with satellite-based biomass and country-scale statistics of growing stock volume. Overall, FORWIND represents a valuable and open-access spatial source to improve our understanding of the vulnerability of forests to winds and develop large-scale monitoring/modelling of natural disturbances. Data sharing is encouraged in order to continuously update and improve FORWIND. The dataset is available at https://doi.org/10.6084/m9.figshare.9555008 (Forzieri et al., 2019).

1 Introduction

Natural forest disturbances represent a serious peril for maintaining productive forests. Studies indicate that their excess can reduce primary production and partially offset carbon sinks or even turn forest ecosystems into carbon sources (Kurz et al., 2008; Yamanoi et al., 2015; Ziemblińska et al., 2018). This is particularly critical for windthrow and tree breakage due to strong winds, which represent one of the major natural disturbance for European forests (Schelhaas et al., 2003; Seidl et al., 2017). Such disturbances are intensifying globally, a trend which is expected to continue with further climate change (Bender et al., 2010; Knutson et al., 2010; Seidl et al., 2014).

European windstorms are associated with areas of low atmospheric pressure that typically occur in the autumn and winter months(Martínez-Alvarado et al., 2012). Deep low-pressure areas frequently track across the North Atlantic Ocean towards Western Europe, pass the north coast of Great Britain and Ireland and into the Norwegian Sea. However, when they track further south, they can potentially hit any country in Europe. In 1999, storm Lothar damaged approximately 165 million m^3 of timber, which is equivalent to 43% of the average annual harvest rate, mainly in France, Germany, Switzerland and Scandinavia(Gardiner et al., 2010). In 2005, 75 million m^3, equivalent to one year's cuttings, were damaged by storm Gudrun in Sweden. In 2007, the storm Kyrill caused the loss of 49 million m^3 of timber in Germany and the Czech Republic. In 2009 and 2010, storms Klaus and Xynthia hit forests in France and Spain and caused timber losses totalling approximately 45 million

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m^3. In 2018, the Vaia storm hits the North-Eastern regions of Italy causing a damaged growing stock volume of about 8.5 million m^3.

The socio-economic consequences of wind disturbances can be critical especially for local economies highly dependent on the forest sector. Countries in Northern Europe and Central-Eastern Europe, where the forest sector may cover up to 6% of the national GDP(FOREST EUROPE, 2015), are, therefore, potentially more vulnerable to wind-related impacts.

Despite the risks they pose, spatially explicit databases of wind disturbances across European currently do not exist. Recent assessments of current and future forest damages due to windstorms at European scale are based on catalogues of disturbances collected at country level(Gregow et al., 2017; Schelhaas et al., 2003; Seidl et al., 2014; Senf et al., 2018). Such databases are subject to multiple sources of bias and uncertainty associated to the diversity of the underlying inventories. Furthermore, estimates of forest damage aggregated at national scale may only partially represent the spatial variability of the phenomenon. In fact, the coarse spatial resolution of such data hampers inferential analysis of potential drivers of forest vulnerability and their use in spatially explicit models to monitor or forecast wind-related impacts(Masek et al., 2015; Phiri and Morgenroth, 2017). Despite the lack of systematic mapping of wind disturbances in European forests, a multitude of local, national, and transnational initiatives have accurately mapped forest areas affected by wind over the last decades These data represent highly informative observational records to characterize spatial patterns of forest damages. However, they are collected by different institutes, and are often difficult to retrieve or poorly documented. Since 2012, the Copernicus Emergency Management Service (https://emergency.copernicus.eu/) produces maps of natural disasters throughout the world based on the analysis of satellite images and other geospatial data. While this important initiative can help map wind-affected areas, it only covers recent years and, being an on-demand service, it is not comprehensive as it depends on the interests of individual authorized users of the service to map a given forest disturbance.

In this study, we try to fill the above-mentioned gap. To this aim, we collected and harmonized 89,434 forest areas damaged by wind into a consistent geospatial dataset. The work was carried out through a unique joint effort of 26 research institutes and forestry services across Europe. This collaboration led to the first spatially-explicit database of wind disturbances in European forests over the period 2000-2018, hereafter referred to as the FORWIND database. We believe that it provides essential spatial information to improve our understanding of forest damage from wind and can assist in large-scale systematic monitoring and modelling of forest disturbances. In the following sections, we describe the data collection, the harmonization process, and the cross-comparison performed against satellite-retrievals of changes in vegetation cover and data from national inventories of forest disturbances. We conclude the data description with some examples of the possible usage of the FORWIND database.

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2 Methods

We collected wind disturbances events caused by windstorms or tornadoes that occurred in Europe between 2000 and 2018. A wind disturbance event is represented by a georeferenced polygon that delineates the damaged forest stand, regardless of the degree of damage. The data were managed mostly on the Google Earth Engine platform (Gorelick et al., 2017) to efficiently quantify the extent of disturbances over large scales and extract additional informative attributes (e.g., Hansen et al., 2013; McDowell et al., 2015). We structured the data collection process in four main phases, described below.

- **Literature review and data gathering.** We searched PubMed and Scopus for articles published up to January 2019, with no language restrictions, using the search terms "wind disturbance" OR "windthrow" OR "forest damage" OR "wind damage" OR "forest disturbance" AND "Europe" OR single country name in the publication title OR abstract. The identified studies had mainly mapped the effects of wind on forests for single events and/or for a limited areal extent. We then retrieved the spatial delineation of the observed wind damages from the corresponding authors or contact persons responsible for the data acquisition. The collected data were originally recorded by different research institutes and international initiatives across Europe using diverse methodologies. Table 1 lists the data providers and the acquisition methods.
- **Coordinate system transformation.** The wind disturbances were transformed to the same geographical unprojected coordinate system (World Geodetic System 1984, WGS84, EPSG:4326).
- **Spatial segregation.** The spatial segregation of each record was verified. In case multiple features for the same event overlapped, they were merged.
- **Harmonization of the degree of damage.** A damage classification for forest disturbances was originally recorded for windstorms that occurred in France in 2009, in Lithuania in 2010, in Germany in 2017, in Italy in 2015 and –for part of the records - in 2018. In order to make these records comparable in terms of the severity of damage, the original classes were harmonized into a single damage metric following the rationale reported in Table 2.

3. Data records

The FORWIND database is the final output of the data collection procedure and it is publicly available at https://doi.org/10.6084/m9.figshare.9555008 (Forzieri et al., 2019). The FORWIND dataset contains records as polygon features in shapefile format (.shp). The geometry of a feature is stored as a shape comprising a set of vector coordinates corresponding to the boundaries of the area of a given wind disturbance. Records are georeferenced in geographical coordinates, i.e. latitude and longitude, following the WGS84 standard (EPSG:4326). Basic attributes of each disturbance (Table 3) are provided in an associated table, stored in a .dbf file.

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Overall, FORWIND includes 89,434 records, corresponding to ~1 million ha of forest area affected by wind disturbances during the 2000-2018 period. Each record should not be viewed as independent as a single storm may cause multiple, geographically disjunct, disturbances. At European level, the median wind-caused forest disturbance measures 1.08 ha (Table 4). However, there is substantial variability across disturbances and countries likely driven by the high heterogeneity of forest and landscape characteristics. Figure 1 shows the spatial and temporal variations of records in the FORWIND database. In order to better visualize the data, we summed the areas affected by wind disturbances in 0.5-degree cells (Fig. 1a). A similar aggregation was used to show the timing of the disturbances, here expressed as the year in which most area was disturbed within a given cell (Fig. 1b). The current release of FORWIND includes wind disturbances that occurred in Austria, Switzerland, the Czech Republic, France, Germany, Ireland, Italy, Lithuania, Poland, Romania, Russia, Slovakia and Sweden. The major windstorms that occurred in the last two decades are included in FORWIND, particularly Gudrun in 2005 (Sweden), Kyrill (Germany) in 2007, Klaus in 2009 (France), Xhynthia in 2010 (Germany) and Vaia in 2018 (Italy). The high spatial detail of FORWIND is illustrated in Figure 2 for some key windstorms.

4. Technical validation

The lack of alternative datasets with the same spatially explicit mapping of wind disturbances as in FORWIND does not allow for a standard validation exercise. Therefore, we evaluated the validity of FORWIND based on the plausibility of the collected spatial delineations of wind disturbances with respect to two satellite-based proxies of forest disturbances and estimates of forest damages reported in national inventories.

4.1 FORWIND versus LANDSAT-based forest cover loss

FORWIND was initially compared with satellite-based estimates of forest cover loss derived from the Global Forest Change maps(Hansen et al., 2013) (GFC, https://earthenginepartners.appspot.com/science-2013-global-forest). GFC maps characterize the annual forest coverage at global scale during the period 2000–2018 at 30-meter spatial resolution based on time-series analysis of Landsat images. Forest cover loss is defined as an area that has changed from a state of forest to non-forest, following a given disturbance event (natural or anthropogenic). The change detection is based on the variation in the spectral properties of the land surface. Windstorm events in Europe often occur in autumn and the beginning of winter, when the availability of cloud-free images is typically much more limited than in summer. Hence, satellite retrievals of forest cover loss may miss the exact timing of the disturbance. Therefore, the GFC-based forest cover loss may only record wind disturbances the year after the event occurred. In addition, fallen trees following a windstorm or tornado often maintain their leaves for months. This may lead to limited or no change in land reflectance properties, even when cloud-free images are available. Therefore, satellite-based products may underestimate forest cover loss in the short-term (interannual scale). In order to account for these effects, we considered the forest cover loss by summing up the forest loss over the year of a given event

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together with that of the following year (lag-01). The loss estimate was quantified with respect to the pre-event conditions (the forest cover in the year before the event). To reduce potential contamination effects from other disturbances on the resulting total forest cover loss, we removed areas affected by fires the year following a wind event. Information on forest areas affected by fires were retrieved from the European Forest Fire Information System (EFFIS, http://effis.jrc.ec.europa.eu/). Insect outbreaks, which may be triggered by large numbers of dead trees following wind disturbances(Stadelmann et al., 2013), generally lead to a slow change in tree cover, which may only marginally affect the 1-year temporal lag used for our estimates of forest cover loss. Furthermore, forest logging following a wind event can be considered a secondary effect of the strong winds, as it is often employed to reduce the risk of other forest disturbances (specifically insect outbreaks and fires). Therefore, the resulting estimates of forest cover loss for the selected areas should reflect wind disturbances first and foremost. We emphasize that Landsat-derived estimates of forest cover loss are affected by the uncertainty in satellite retrievals and do not represent the true impacts. However, their suitability for detecting forest disturbances over large scale has been widely recognized(Curtis et al., 2018; Hansen et al., 2013) and, therefore, they are here considered a good proxy of forest loss.

For each selected FORWIND record we computed the area of affected forest based on the spatial delineation of the polygon and the corresponding Landsat-derived forest cover loss and calculated the correlation between the two sets of estimates. In order to account for the spatial dependence structure of FORWIND data, correlation values were derived for 100 subsets of 1000 records randomly selected from the entire dataset. The final estimate of correlation was then quantified as the average of the correlation values derived from the 100 subsets.

Results for the whole dataset are shown in Figure 3a. Overall, we found a modest but significant Spearman rank correlation coefficient (ρ_k=0.48, p-value<10^{-3}), which supports the validity of FORWIND in mapping areas subject to changes of forest coverage due to wind disturbances. We point out that for this calculation we did not mask the data based on the degree of damage, because such information is available only in some countries. However, a similar correlation analysis performed by rescaling the recorded areas based in their damage degree (for those records that report the information) led to higher correlation values up to 0.54. We further tested the sensitivity of our results to the temporal lag used to quantify the forest cover loss. To this aim, we complemented the previous analysis (lag-01) using Landsat-based forest cover loss estimated for the year of the event only (lag-0) and the following year only (lag-1). In order to investigate possible scaling relations, the correlation analysis was performed accounting for the FORWIND records with a spatial extent above a given threshold derived from the percentiles 0, 0.25, 0.50 and 0.75 of the full dataset (corresponding to about 0, 0.5, 1, and 3.5 ha, respectively). Results show that correlation values between FORWIND affected areas and lag-0 forest cover loss tends to slightly decrease with an increasing size of the wind disturbance (Fig. 3b). The opposite pattern is observed for correlation values with lag-1 forest cover loss. The forest cover loss accumulated over the two years considered (lag-01) appears dominated by the contribution of lag-1 forest cover loss. We argue that such contrasting tendencies may be linked to the scale and climatology of extreme winds. Wind-related forest impacts of limited areal extent originate from local windstorms or tornadoes that may occur throughout the year. For these events, most of the damage is probably well captured by lag-0 effects, as it is more likely that cloud-free images are available after the event. In contrast, the larger and more damaging windstorms, which affect larger forest areas,

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typically occur in autumn and early winter (decreasing the likelihood of cloud-free images after the storm and before the end of the year). For these events, the inclusion of the lag-1 effect is key to characterize the impact on forest cover.

4.2 FORWIND versus MODIS Global Disturbance Index

FORWIND was also compared with an independent dataset of satellite-based estimates of forest disturbance as expressed by the MODIS-based Global Disturbance Index(Mildrexler et al., 2007, 2009) (MGDI, http://files.ntsg.umt.edu/data/NTSG_Products/MGDI/). MGDI maps quantify the overall annual forest disturbance globally for the period 2004-2012 at 500-meter spatial resolution. The disturbance retrieval is based on the variations in the Enhanced Vegetation Index and land surface temperature following a given sudden change in forest cover. Consistent with the previous Landsat-based analysis - the total change in MGDI potentially related to a given wind disturbance was computed as the accumulated net change in MGDI over the event year and the following year (lag-01). The change was quantified with respect to the pre-event conditions (MGDI in the year before the event). The technique used to disentangle the fire signal, as well as the correlation and sensitivity analyses with respect to the temporal lags and wind disturbance size, were performed analogously to the previous validation exercise.
Overall, we found a low but significant correlation coefficient (ρ_k=0.27, p-value<10^{-3}) (Fig. 3c). The lower correlation compared to the Landsat-based dataset is presumably due to the coarser spatial resolution of MGDI that probably does not fully capture the changes in land surface properties due to wind disturbances(Mildrexler et al., 2009). This seems to be supported by the generally increasing correlation values up to 0.31 for wind disturbances of 1 ha consistently across the different temporal lags (Fig. 3d).

4.3 FORWIND versus FORESTORM

FORWIND data were finally compared with estimates of damaged growing stock volume (GSV) that are recorded at country level in the FORESTORM database (http://www.iefc.net/storm/) for five windstorm events: Slovakia in 2004; Sweden in 2005 (Gudrun storm), Germany in 2007 (Kyrill storm), the Czech Republic in 2007 (Kyrill storm) and France in 2009 (Klaus storm). We derived the damaged GSV by multiplying the estimated GSV by the percentage damaged, both of which are reported in FORESTORM. An analogous metric was derived from FORWIND data by first calculating for each FORWIND record the amount of GSV lost by multiplying the areal average GSV by the damage level reported for the record. As the damage level was only reported for Klaus, for the other events we assumed a damage level equal to the average level reported for Klaus weighted on the spatial extent of each record. The GSV was retrieved from the GlobBiomass dataset(Santoro et al., 2018) (https://doi.pangaea.de/10.1594/PANGAEA.894711) which is based on multiple remote sensing products and is considered the state-of-the-art global biomass product. This satellite-based GSV estimate refers to the year 2010 and has a spatial resolution of 100 meter. The damages to GSV were then summed by event and country. Event-scale FORWIND damaged GSVs were then compared with estimates derived from FORESTORM.

Overall, results show that the magnitude of damages estimated from FORWIND and FORESTORM are largely different, except for the 2009 Klaus storm in France for which we found a very good agreement (Fig. 3e). For most of the events, however, FORESTORM tends to systematically give higher forest damage estimates than FORWIND with differences exceeding 90%. We note that such differences persist when we derive FORWIND estimates of damaged GSV assuming a 100% damage degree for all records (not shown). Therefore, the uncertainty in the damage degree in FORWIND does not affect substantially the difference between FORWIND and FORESTORM. We recognize that estimates of forest damages based on FORWIND are fully dependent on the GSV derived from GlobBiomass. Indeed, any deviations of the mapped GSV from the true forest state are inherently translated into our damaged GSV estimates. In particular, the GSV map refers to the year 2010, therefore it is very likely that it largely reflects the biomass conditions following, rather than preceding, the windstorm events (all the five events considered in this validation exercise occurred before 2010).

In order to disentangle such source of bias we derived country-scale estimates of average GSVs for the year 2000 (pre-event conditions) from the State of Europe's Forest(FOREST EUROPE, 2015) (https://www.foresteurope.org/docs/SoeF2015/OUTPUTTABLES.pdf). We then derived the damages GSVs by multiplying Forest Europe-derived GSVs by the total forest area affected for each of the considered wind events by assuming a 100% degree of damage. Similar to the previous results, expect for the Klaus storm, we found higher values of damaged GSVs in FORESTORMS than in our estimates based on the integration of FOREWIND and country values of GSVs (Fig. 3f). We recognize that FORWIND could miss some wind damage occurrences. However, according to the institutions responsible for the data acquisition, the forest areas affected by the windstorm events considered in this validation exercise were exhaustively mapped. Therefore, possible residual omissions are expected to only marginally affect our results. We therefore argue that a possible source of error may be associated to the FORESTORM database. Estimates of forest damages from FORESTORM originate from different sources and are collected by multiple actors. Hence, the loss figures should be viewed in light of their potential biases, including a possible overestimation of the true impacts.

5 Data usage and conclusions

The FORWIND database is the first Pan-European collection of spatially delineated forest areas affected by wind disturbances and includes all major events that occurred over the 2000-2018 period. FORWIND provides fundamental spatial and temporal information to improve our understanding of the vulnerability of forests to winds and develop large-scale monitoring and modelling of natural disturbances.

For demonstration purposes, we show how FORWIND data can be used to quantify forest vulnerability as a function of the fraction of evergreen needleleaf forest (ENF) and annual maximum wind speed. The fraction of ENF was derived from the annual land cover maps of the European Space Agency's Climate Change Initiative(ESA, 2017) (ESA-CCI, https://www.esa-landcover-cci.org/) aggregated at 0.5 degree spatial resolution. Annual maximum wind speeds were computed from

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NCEP/NCAR Reanalysis 2 data(Saha et al., 2010) (NCEP2, https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis2.html). Daily average wind data at 0.5 degree spatial resolution were acquired and the two horizontal components combined to derive the magnitude of the wind vector. For each cell, the fraction of ENF and the annual maximum wind concomitant with a wind disturbance were then selected from the time series and used in our experiment as potential drivers of vulnerability (Fig. 4a,c). The values of fraction of ENF and annual maximum wind speed (predictors) were linked with the corresponding FORWIND affected area (response variable) within each 0.5 degree cell. In order to increase the spatial consistency of the emerging relationships, spatial averages in the response variable were derived using bins that spanned the sampled ranges of the predictors (bin sizes of 10% and 2 m/s for fraction of ENF and annual maximum wind speed, respectively). The resulting datasets were ultimately fitted by linear regression models (Fig. 4b,d).

Wind disturbance areas manifest a substantial variability, as evident form the generally high values of the coefficient of variation. However, when data are spatially averaged at bin level, simple linear regression models show a reasonably good fit, with R^2 values of 0.52 and 0.81 for the fraction of ENF and annual maximum wind speed, respectively. Emerging patterns are largely consistent with expectations and previous studies. An increasing fraction of ENF leads to an increase in wind disturbance area (growing rate of 12 ha of affected forest per 0.1 increase in ENF fraction). Indeed, this plant functional type is typically characterized by shallower rooting systems compared to other forest types. Combined with the limited flexibility of its branches and trunk this makes ENF more prone to uprooting and breakage by strong winds(Klaus et al., 2011; Ruel, 1995). A similar pattern emerges with respect to annual maximum wind speed(Seidl et al., 2011). Wind disturbance area tends to increase with rising wind speed (growing rate of 32 ha of affected forest per 1 ms^{-1} increase in wind speed). Maximum wind speeds are the primary determinant of wind disturbances. However, we point out that the coarse spatial and temporal resolution on NCEP2 data largely underestimate the speed of wind gusts and may completely miss peak winds originating from tornados. This is clearly evident from the range of values of annual maximum wind speed (6-22 m/s) which are far lower than the wind speeds reported in country-scale inventories of forest disturbance (e.g., 42 m/s for Gudrun, FORESTORM).

We recognize that the above example is an oversimplification of the biomechanical processes that may cause wind disturbances. Multiple variables, susceptibility factors, and drivers (e.g., tree species, tree dimension, management regimes, planting patterns, soil depth, snow cover), contribute concurrently to the vulnerability of trees(Hart et al., 2019; Klaus et al., 2011; Mitchell, 2013) and therefore their contribution should be analysed in a multidimensional space. Therefore, the approach described here should not be considered as a reference methodology to analyse the vulnerability of forests but only as an informative application to explore the usefulness of the FORWIND database.

FORWIND could also be suitable in diverse contexts for large-scale monitoring and modelling of forest ecosystems. For instance, some pioneering studies have begun producing classification maps of various forest disturbance agents based on remote sensing data(Cohen et al., 2016; Hermosilla et al., 2015; Potapov et al., 2015; White et al., 2017). However, the attribution of forest change to windstorms remains challenging. Previous systematic monitoring has been performed only over limited areal extents and showed considerable uncertainty(Baumann et al., 2014; Schroeder et al., 2017) mostly due to the limited number of sampled wind-affected areas available for training/testing classification algorithms(Schroeder et al., 2017). Similar critical issues affect land surface models (LSM) now widely applied to support policy-relevant assessments on the impact of climate change on terrestrial ecosystems. Recently, windstorm effects have been incorporated in LSMs(Bonan and Doney, 2018; Chen et al., 2018). However, these models are hampered by the lack of harmonized spatially-explicit information on windstorms required as input for robust model parameterization and large-scale representation of wind disturbance. In such contexts, the FORWIND database represents a valuable source of harmonized wind-affected forest areas for improving model calibration and validation.

6 Data availability

Data are freely available at https://doi.org/10.6084/m9.figshare.9555008 (Forzieri et al., 2019) and will be periodically updated with new and historical events. To this effect, the authors welcome further data contributions and commit to properly acknowledging them.

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Data provider	Number of records	Event type	Acquisition method
Alto Adige province forest service, Italy	1457	Windstorm	Aerial photointerpretation and field survey
Copernicus Emergency Service	4425	Windstorm	Aerial photointerpretation
Department of Cartography and Geoinformatics, Perm State University, Perm, Russia	3056	Tornado	Satellite data classification [a]
Department of Forest Management, Geomatics and Forest Economics, Institute of Forest ResourcesManagement, Faculty of Forestry, University of Agriculture in Krakow, Poland	321	Windstorm	Aerial photointerpretation
Department of Forest Resource Planning and Informatics, Faculty of Forestry, Technical University in Zvolen, Slovakia	14	Windstorm	Aerial photointerpretation and field survey
Department of Geoinformatics, Faculty of Science, Palacky University, Czech Republic	1175	Windstorm	Aerial photointerpretation
Department of Land Change Science, Swiss Federal Institute for Forest, Snow and Landscape Research WSL, Birmensdorf, Switzerland	64	Windstorm	Aerial photointerpretation
Department of forestry Mecklenburg-Vorpommern state, Germany	2073	Windstorm	Aerial photointerpretation
Forest national service of Sweden, Sweden	19358	Windstorm	Semiautomatic classification [b]
Friuli Venezia Giulia forest service, Italy	191	Windstorm	Aerial photointerpretation and field survey
Ign-Institut National de information geographique et forestiere	21691	Windstorm	Aerial photointerpretation
Laboratory of Geomatics, Institute of Land Management and Geomatics, Aleksandras Stulginskis University, Lithuania	14571	Windstorm	Aerial photointerpretation
National Forest Centre, Forest Research Institute, Slovakia	555	Windstorm	Aerial photointerpretation
North Rhine-Westphalia forest service, Germany	13642	Windstorm	Aerial photointerpretation
Tesaf Department- Padua University	1532	Windstorm	field survey and aerial photointerpretation
Trento province forest service, Italy	3596	Windstorm	Aerial photointerpretation and field survey
University of Bucharest, Faculty of Geography, Romania	186	Windstorm	Aerial photointerpretation and field survey
University of Lorraine	256	Windstorm	Aerial photointerpretation
geoLAB - Laboratory of Forest Geomatics, Department of Science and Technology in Agriculture, Food, Environment and Forestry, University of Florence, Italy	1271	Windstorm	Field survey

Table 1: List of institutions responsible of wind disturbance mapping and corresponding number of records collected and acquisition methods employed. [a] Spatial delineation of tornado-related impacts on forests have been based on a semi-automatic algorithm and every record has been singularly validated based on visual inspection of high-resolution of satellite images(Shikhov and Chernokulsky, 2018). [b] Area subject to wind disturbances have been retrieved for FORWIND by intersection of the 2005 registered forest clear-cuts between 2005-01-07 and 2005-12-31 larger than 500 m^2 (http://skogsdataportalen.skogsstyrelsen.se/Skogsdataportalen/) with the spatial delineation of the Gudrun storm(Gardiner et al., 2010). The use of forest clear-cuts as proxy for wind-affected areas is reasonable because the morning after the storm all normal felling activity stopped and moved to storm damaged areas (Swedish Forest Agency, personal communication).

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	Class of damage	Definition of damage (D)	Degree of damage
France 2009	0	no forest area (not included in FORWIND)	
	1	D ≤ 20%	0.1
	2	20% < D ≤ 40%	0.3
	3	40% < D ≤ 60%	0.5
	4	60% < D ≤ 80%	0.7
	5	80% < D ≤100%	0.9
	6	marginally affected	missing data
	7	missing data	missing data
Lithuania 2010	0	no damage (not included in the FORWIND)	
	1	D ≤ 25%	0.125
	2	25% < D ≤ 50%	0.375
	3	50% < D ≤ 75%	0.625
	4	D > 75%	0.875
Germany 2017	1	D ≤ 50%	0.25
	2	50% < D ≤ 90%	0.7
	3	90% > D	0.95
Italy 2018	1	D ≤ 30%	0.15
	2	30% < D ≤ 50%	0.4
	3	50% < D ≤ 90%	0.7
	4	D > 90%	0.95

Table 2: Conversion table to pass from class of damage to degree of damage. Records of windstorms occurred in Italy in 2015 are already expressed as damage degree in a consistent range between 0 (no damage) and 1 (full destruction of forest pattern).

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Attribute name	Description
Id_poly	Identifier code
EventDate	Date of event (MM/DD/YYYY)
StormName	Storm name
EventType	Type of event: windstorm/tornado
Country	Country where the wind disturbance occurred
Area	Area affected by wind disturbance (in hectares)
Perimeter	Perimeter of the forest area affected by wind disturbance (in meters)
Damage_deg	Damage degree (in %)
Methods	Acquisition method
Dataprovid	Data provider responsible of the wind disturbance mapping
Source	Original source of the data

Table 3: Attribute table of the FORWIND database. Name and description of the attributes associated to each wind disturbance in FORWIND and listed in the .dbf file. Missing data are reported as -999.

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Country	Number of records	Accumulated affected area (ha)	Median affected area (ha)	Standard deviation of affected area (ha)
AU	646	1222.15	0.78	5.69
CH	64	41.28	0.26	0.79
CZ	1175	540.98	0.14	1.67
DE	18909	34075.95	0.64	5.33
FR	21947	875407.23	8.79	993.80
IR	561	541.03	0.36	1.60
IT	8047	33991.61	1.06	14.18
LT	14571	13378.80	0.53	1.28
PL	345	46065.34	24.03	573.29
RO	186	417.59	0.80	4.92
RU	3056	17188.38	0.85	25.41
SE	19358	24450.73	0.82	1.73
SK	569	9150.24	0.65	118.65
Europe	89434	1056471.32	1.08	494.05

Table 4: Statistics of wind disturbance records collected in the FORWIND database aggregated at country level and for whole Europe.

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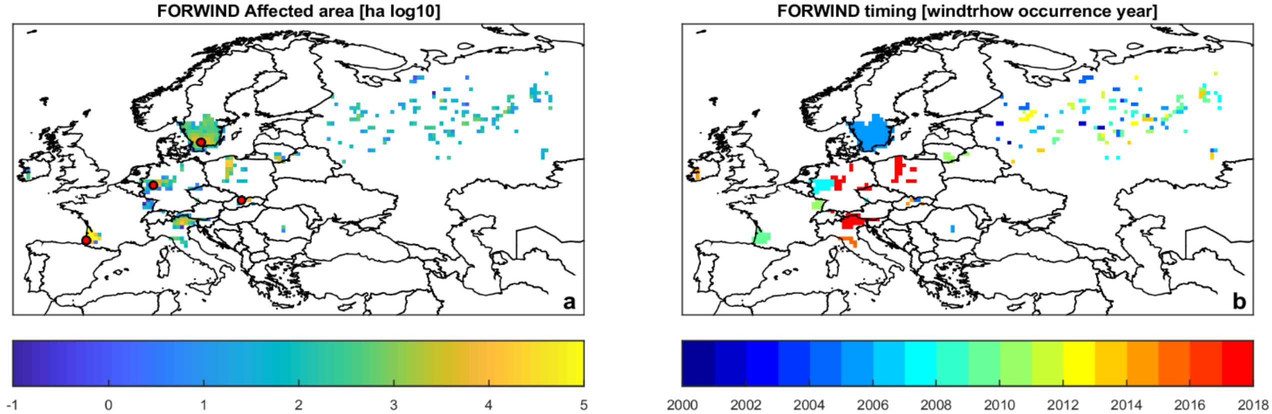

Figure 1: Spatial and temporal distribution of wind disturbances in the FORWIND database. (**a**) The total area affected by wind disturbances over the multi-year observational period (2000-2018) in 0.5-degree cells. (**b**) Wind disturbance occurrence year in the same cells. Red circles in (**a**) refer to site locations shown in Fig. 2.

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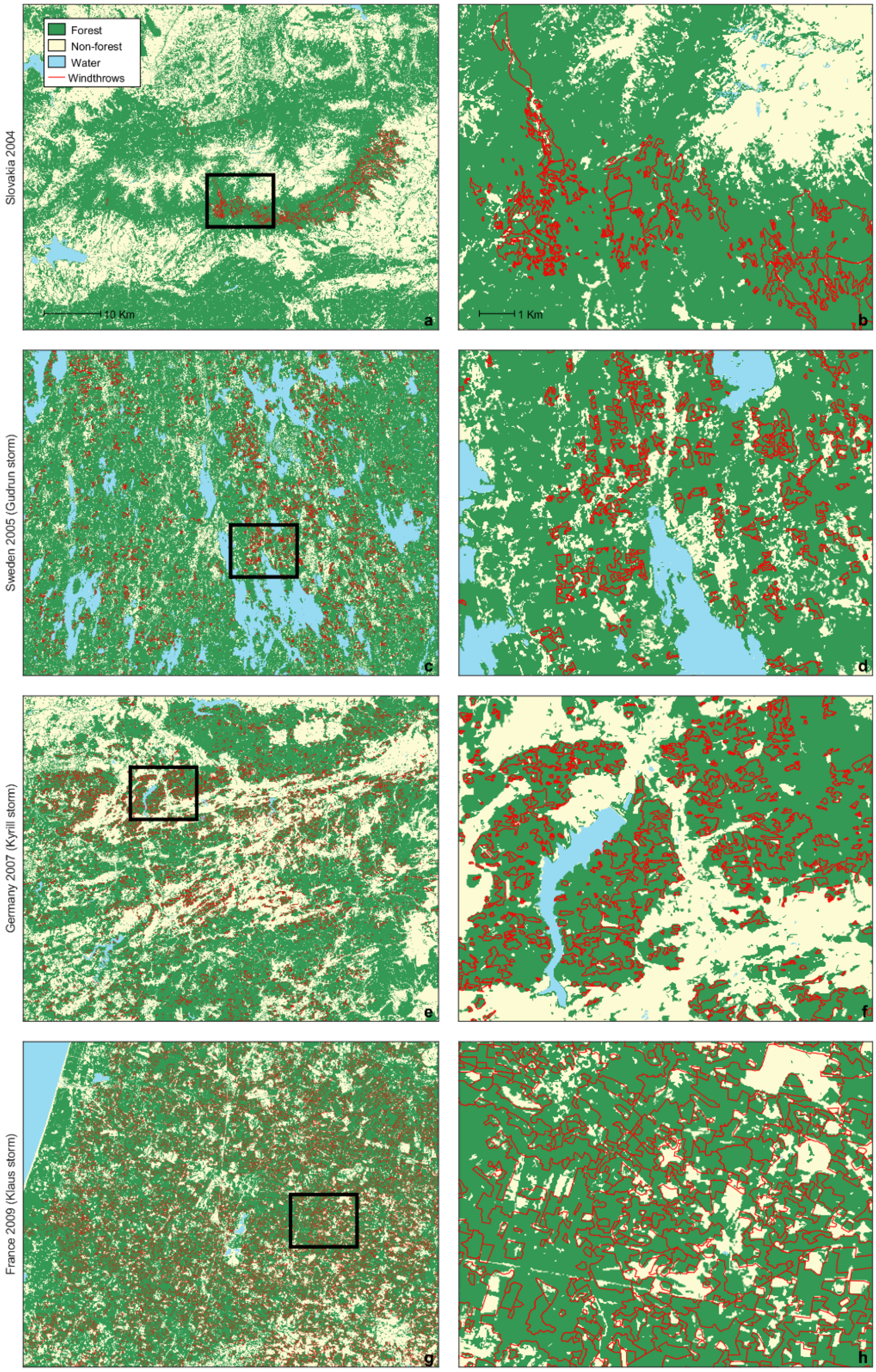

460 **Figure 2: Examples of wind disturbances recorded in the FORWIND database.** (**a**,**b**) Tatra Mountains, Slovakia, affected by a windstorm in 2004. (**c**,**d**) Southern Sweden affected by the Gudrun storm in 2005. (**e**,**f**) Western Germany affected by the Kyrill storm in 2007. (**g**,**h**) Western France affected by the Klaus storm in 2009. Wind disturbances recorded in the FORWIND database are shown as red polygons. Background colors show forest and non-forest areas derived from the 25-meter forest cover map of 2000(Pekkarinen et al., 2009)

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while water bodies are derived from the 25-meter land cover type map of 2006(Kempeneers et al., 2011) (https://forest.jrc.ec.europa.eu/en/past-activities/forest-mapping/#Downloadforestmaps). Site locations in (**a**,**c**,**e**,**g**) are shown in Fig. 1a whereas zoomed plots in (**b**,**d**,**f**,**h**) refer to black boxes in (**a**,**c**,**e**,**g**).

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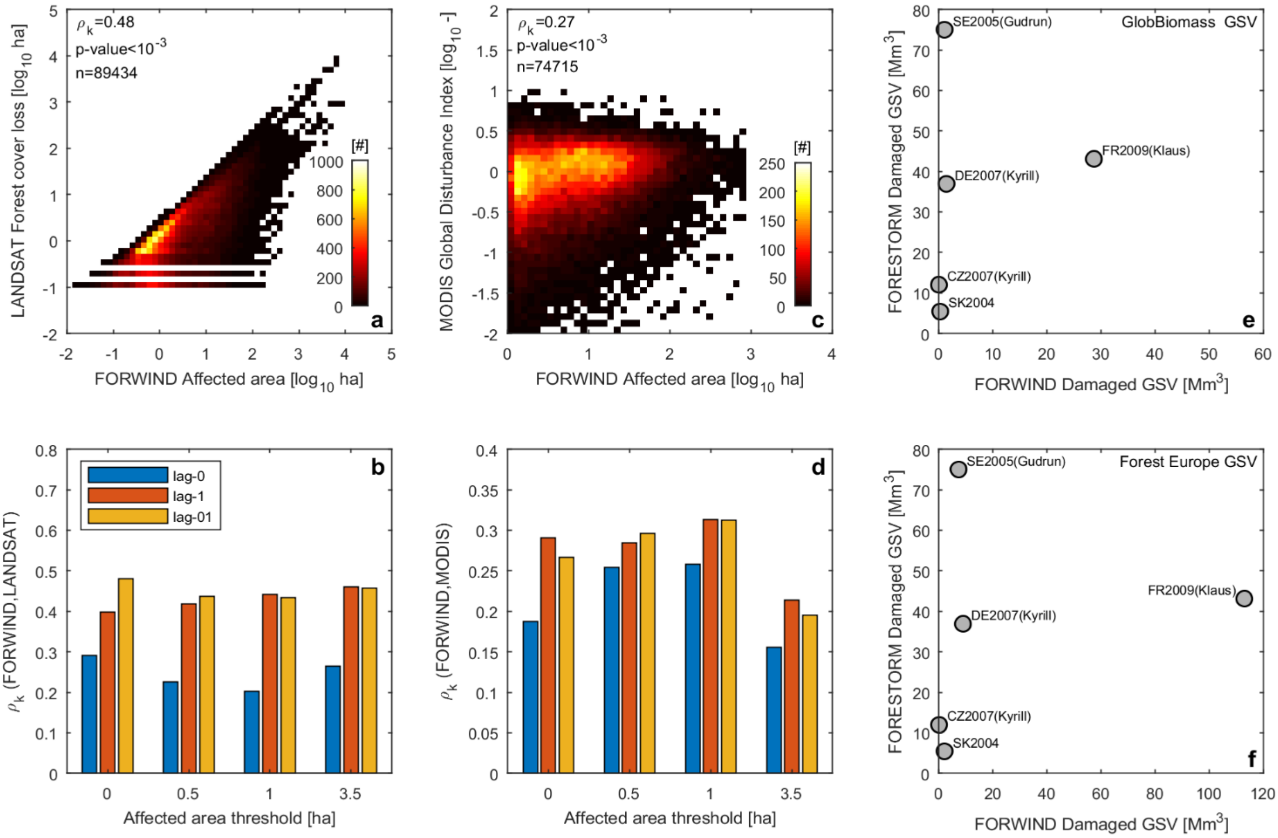

Figure 3: Validation of the FORWIND database. (**a**) Density plot of FORWIND affected area versus LANDSAT-derived forest cover loss, both expressed in logarithmic scale and for lag-01 effects. The color reflects the number of records, top left labels report the Spearman rank correlation coefficient (ρ_k), the significance (p-value) and the sample size (n). (**b**) Spearman rank correlation coefficients for different affected area thresholds (on the x-axis) and different lagged effects displayed in color bars. Lagged effects considered include the forest cover loss cumulated over the event of a given year together with that of the following year (lag-01), forest cover loss estimated for the year event only (lag-0) and forest cover loss estimated for the following year only (lag-1). (**c**) and (**d**) as (**a**) and (**b**) but for the MODIS-derived Global Disturbance Index in place of Landsat-derived forest cover loss. (**e**) Scatter plot of damaged growing stock volume estimated from FORWIND (on the x-axis) and FORESTORM (on the y-axis) for five windstorms: Slovakia in 2004 (SK2004); Sweden in 2005 (SE2005 (Gudrun)), Germany in 2007 (GE2007 (Kyrill), the Czech Republic in 2007 (CZ2007 (Kyrill)) and France in 2009 (FR2009 (Klaus)). FORWIND estimates are derived using GlobBiomass-derived estimates of GSVs and reported damage degree information. (**f**) as (**e**) but with estimates of GSVs derived from Forest Europe national inventories and assuming a 100% damage degree for all FORWIND records.

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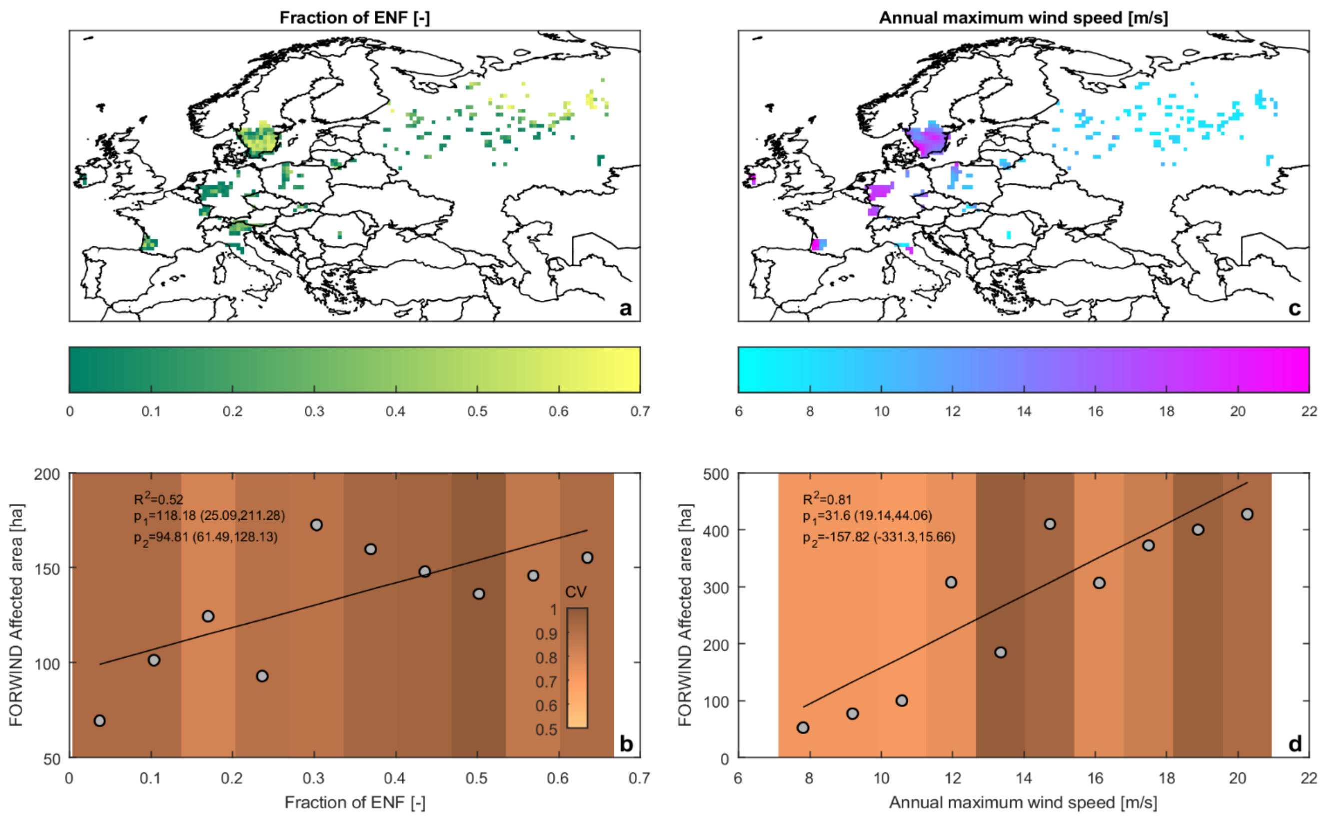

Figure 4: Use of FORWIND to explore susceptibility factors and drivers of forest vulnerability to wind disturbances. (**a**) Spatial map of the fraction of evergreen needleleaf forest (ENF). (**b**) Relation between the fraction of ENF (on the x-axis) and area affected by wind disturbances (on the y-axis) as derived from the FORWIND database. Averaged values, shown in grey circles, were derived using bins that spanned the sampled range. Colour patterns reflect the coefficient of variation within each bin. The fitted linear regression model is shown in black line with the coefficient of determination (R^2), slope (p_1) and intercept (p_2) reported in the labels. The confidence interval for each of the coefficient is shown in brackets. (**c**) Spatial map of annual maximum wind speed; (**d**) as (**b**) but for annual maximum wind speed in place of the fraction of ENF. The grid cells in (**a**) and (**c**) with no wind disturbances occurred over the 2000-2018 period are masked out.