Storm damage beyond wind speed - Impacts of wind characteristics and other meteorological factors on tree fall along railway lines

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1 Abstract

Strong winter wind storms can lead to billions in forestry losses, disrupt train services, and necessitate millions of Euros spent on vegetation management along the German railway system. Therefore, understanding the link between tree fall and wind is crucial.

Existing tree fall studies often emphasize tree and soil factors more than meteorology. Using a tree fall dataset from Deutsche Bahn (2017-2021) and meteorological data from ERA5 reanalysis and RADOLAN radar, we employed stepwise model selection to build a logistic regression model predicting the risk of a tree falling on a railway line within a 31 km grid cell.

While daily maximum gust speed (the maximum wind speed in a model time step at 10 m height) is the strongest risk factor, we also found that the duration of strong wind speeds (wind speeds above the local 90th percentile), the gust factor (the ratio of maximum daily gust wind speed to the mean daily gust speed), precipitation, soil water volume, air density, and the precipitation sum of the previous year are impactful. Therefore, our findings suggest that high wind speeds, a low gust factor, and prolonged duration of strong winds, especially in combination with wet conditions (high precipitation and high soil moisture) and high air density, increase tree fall risk. Incorporating meteorological parameters linked to local climatological conditions (through anomalies or in relation to local percentiles) improved the model accuracy. This indicates the importance of considering tree adaptation to the environment.

Key words: tree fall, storm damage, railway traffic, logistic regression, gust speed, wind

2 Introduction

Strong wind speeds are a major factor leading to tree fall and are therefore a risk both to the railway service and forestry. Strong winter wind storms can cost billions of euros in loss for forestry (Gliksman et al., 2023). These losses have been increasing for the last decades (Gregow, Laaksonen and Alper, 2017). Additionally, there is an interconnection between storm damage and other ecological risks like droughts and bark beetle infestation in summer or unfreezing of soils in winter which put further stress on forest ecosystems and are likely to change in a warming climate

(Gregow, 2013; Temperli, Bugmann and Elkin, 2013; Seidl, Rammer and Blennow, 2014; Stadelmann et al., 2014).
In 2018, Deutsche Bahn increased its budget for vegetation management to enhance storm safety, now spending approximately 125 million Euros annually DB (2023). And yet the cost of tree fall remains of the order of millions of Euro per year (Meßenzehl, 2019). With 68% of railway tracks lined by trees and forests, ongoing management is necessary. Since 2018, over 1,000 workers have been employed to monitor and maintain railway vegetation (DB, 2023). Despite these efforts there was an annual average of approximately 3,000 tree fall incidents from 2017 to 2021, causing service disruptions and infrastructure damage. In recent years the interest in the topic has increased. A number of studies on tree fall hazards show that this problem is also present outside the German railway network (Bíl et al., 2017; Koks et al., 2019; Kučera and Dobesova, 2021; Szymczak et al., 2022). Therefore, it is vital to study the relationship of tree fall and wind. Such research aids the management of vegetation alongside transportation routes as well as the development of climate resilient forests. There are many studies which investigate the impact of wind speed on tree fall, including tree motion measurements and tree pulling experiments (Peltola et al., 2000; Kamimura et al., 2012; Schindler and Kolbe, 2020; Jackson et al., 2021), mechanistic modelling (Gardiner et al., 2008; Hale et al., 2015; Kamimura et al., 2016; Costa et al., 2023) as well as statistical and machine learning approaches (Schindler et al., 2009; Schmidt et al., 2010; Hanewinkel et al., 2014; Hale et al., 2015; Jung et al., 2016; Kamimura et al., 2016; Kamo, Konoshima and Yoshimoto, 2016; Hart et al., 2019; Zeppenfeld et al., 2023). Among the statistical approaches, logistic regression models are very common and are also used in our study. Numerous existing studies on storm damage focus on a single storm event or a small spatial region. Consequently, there is a need for long-term and large-scale investigations in this field.

Additionally, previous studies mainly analyse the impact of tree, stand and soil related factors on wind-induced damages but often exclude metrology. Those which consider meteorological predictors often focus on the relationship between tree damage and mean or maximum wind speeds (Schindler et al., 2009; Jung et al., 2016; Morimoto et al., 2019). Yet, there are some other meteorological predictors which are considered in previous works and which we will consider as well:

To account for the turbulent aspect of wind some studies employ the gust factor. There are different understandings of the term gust factor in the fields of meteorology and forestry. In forestry the gust factor is often referred to as the ratio of maximum to mean bending moment experienced by a tree (Gardiner et al., 1997) . In other works the gust factor is defined as the ratio of the maximum short-term averaged wind speed over a shorter duration *t_s* to a long-term averaged wind speed over a longer duration *t_l* (Ancelin, Courbaud and Fourcaud, 2004; Mohr et al., 2017; Gromke and Ruck, 2018). The durations *t_s* and *t_l* then need to be adapted to the specific research questions. Wind load is the wind force per area applied to a tree and the product of a trees specific drag coefficient, air density, a trees exposed frontal area and wind speed (see Eq. 12). Wind load and air density are considered in a few studies on tree fall and storm damage (Schelhaas et al., 2007; Ciftci et al., 2014; Gromke and Ruck, 2018; Sterken, 2021) as well as the wind direction (Akay and Taş, 2019). The role of wind event duration is also discussed in some literature (Gardiner et al., 2013; Mitchell, 2013; Kamimura et al., 2022) but seems to be understudied. Next to wind, snow, frozen soils and precipitation have been identified as impactful meteorological factors (Peltola et al., 2000; Gardiner et al., 2010; Pasztor et al., 2015; Kamo et al., 2016). For example, heavy rain or snow during a storm event may add considerable weight to the crowns and increase tree fall risk (Gardiner et al., 2010). A decrease of frozen soils in the past as well as in future climate scenarios has been found for example for Finland, where it was connected to higher risks of uprooting (Gregow, 2013). Soil moisture is also sometimes considered (Kamo et al., 2016; Csilléry et al., 2017), as excessive water in the soil is expected to weaken root anchorage (Kamimura et al., 2012). On the other hand, the legacy effects of drought may cause lasting changes in tree physiology and weaken the tree (Kannenberg, Schwalm and Anderegg, 2020; Zweifel et al., 2020; Haberstroh and Werner, 2022). Therefore, droughts are expected to increase damage caused by wind (Gardiner et al., 2013). Yet, Csilléry et al. (2017) found both positive and negative effects on tree damage. They suggest that in some stands drought weakens the trees and makes them more vulnerable to wind loading while in others dry soils make them less vulnerable towards overturning.

We aim to develop a meteorology-based tree fall impact model, which is a first step toward a more complex predictive tree fall model. On the one hand, such a predictive model could be used to identify areas at risk and support management decisions, for example, which trees to cut down, especially when environmental and forest data become available and can be taken into account in the future. On the other hand, the model can be applied to climate model data to identify future changes in tree fall risk. To accomplish this, we need to identify meteorological parameters and parameter combinations that impact tree fall risk alongside railway lines in Germany over the long term and across a large-scale area. We aim to deepen the understanding of tree fall risk and wind and to explore how far wind-related parameters like daily maximum gust speed, the gust factor, air density, wind load, the duration of strong wind speeds, or wind direction have an impact on tree fall. We also examine the impacts of other predictors related to meteorology that have been included in previous studies, such as soil moisture, precipitation, snow, or soil frost. Additionally, we study legacy effects of dry and wet spells by including soil water volume and precipitation in antecedent time periods.

We will introduce both the tree fall data as well as the meteorological data used in this study (Chapter 3). We will describe the background theory and the selection process for the logistic regression model (Chapter 4) and we will finally present (Chapter 5) and discuss (Chapter 6) our results and conclude with our most important findings (Chapter 7).

3 Data

3.1 Tree fall data

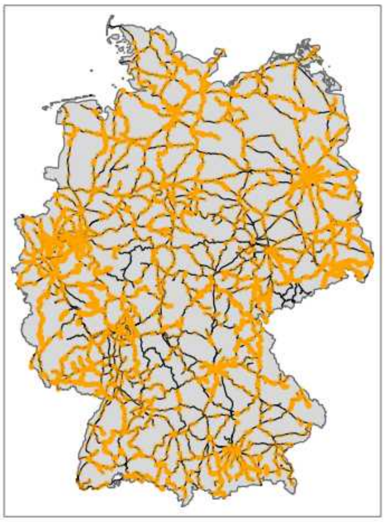

Figure 1: All tree fall events (orange dots) alongside railway lines (black lines) in Germany in the extended winter season (October - March) 2017-2021.

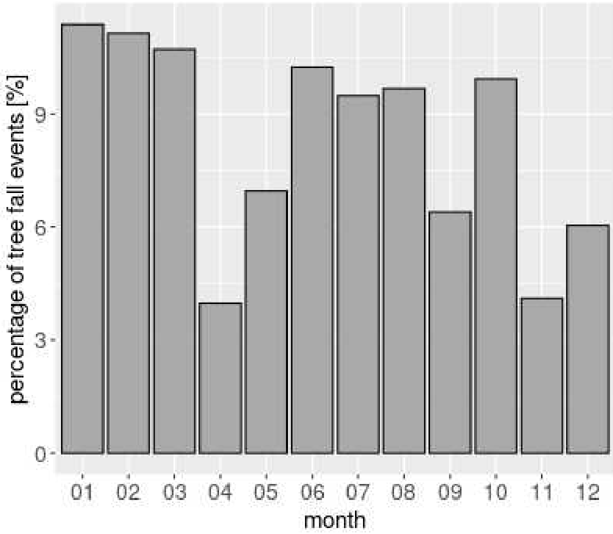

Figure 2: Percentage of tree fall events per month alongside German railway lines for the period 2017-2021.

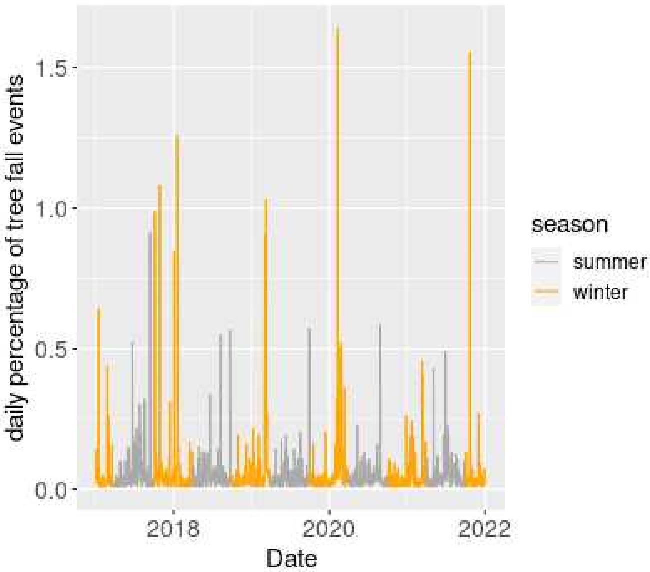

Figure 3: Percentage of tree falls per day relative to the total number of tree falls over the entire period alongside German railway lines. Summer and winter are colour coded. Most extreme peaks of event numbers are caused by winter wind storms, for example Friederike (18.01.2018), Sabine (20.02.2020) and Hendrik (21.10.2021).

Tree fall events along the German railway network were derived from a data set created by the *Deutsch Bahn* (Figure 1). The data consists of disturbance events reported by rail drivers and local inspectors. These reports were later merged into one data set by ailway infrastructure company InfraGo AG (formerly callde Netz AG) of the Deutsche Bahn. For each tree fall event, the date and time of the report, the coordinate of the event and further railway related information like the route section number is included.

The highest monthly numbers tree fall events occur from January to March and from June to August. There is also a peak in October (Figure 2). The most extreme daily numbers of tree fall occur during the winter season and are connected to winter wind storm events due to extra-tropical cyclones (Figure 3).

3.2 Meteorological data

We used hourly ERA5 data (Hersbach et al., 2020; C3S, 2022) for all meteorological parameters, except precipitation. ERA5 (provided by the ECMWF, European Centre for Medium-Range Weather Forecasts) is a reanalysis data set from 1940 to the present with a spatial resolution of ~31km. It was accessed using the ClimXtreme Central Evaluation System framework (Kadow et al., 2021). We performed our analysis only for the extended winter season (October to March) to focus on winter wind storms, which cause the most extreme peaks in tree fall events. We used hourly data to calculate daily means, sums or maxima for each predictor (see Table 1) as well as local percentiles (2^{nd}, 10^{th}, 90^{th} and 98^{th}) in each grid cell over the years 2000 to 2019 for some predictors. The CDO module (Climate Data Operators,Schulzweida (2023)) was used for each of these operations. The advantage of using wind speeds from ERA5 is the coverage of the complete area under investigation. Previous versions of the ECMWF reanalysis have successfully been used to reproduce windstorm-related damage as recorded by the German Insurance Association (Donat et al., 2010; Donat et al., 2011; Prahl et al., 2015), suggesting the usability of these data in spite of deviations with local station measurements (Minola et al., 2020).

For precipitation data we used RADOLAN data provided by the German weather service (Bartels et al., 2004) with a spatial resolution of 1km. RADOLAN combines radar reflectivity, measured by the 16 C-band Doppler radars of the German weather radar network, and ground-based precipitation gauge measurements.

4 Methods

In this section, we describe data pre-processing as well as the theoretical background and the model selection process for the logistic regression model. The aim of this model is to calculate the probability of at least one tree falling on a given day in a 31km grid cell, depending on meteorological parameters. It is used to analyse the impact of a set of predictor variables.

4.1 Data Pre-Processing

A shape file of the German railway lines (DB, 2019) was used to mask the ERA5-grid and select all grid cells in Germany that are crossed by at least one railway line. We calculated the rail density (total length of all railway lines in km) for each grid cell in order to quantify the length of exposed railway lines.

Daily mean air density ρ was calculated as:

$$\rho = p / R \cdot T$$

Equation 1

where p is the daily mean surface air pressure (hPa), *T* is the daily mean near-surface air temperature (K) (both derived from ERA5 hourly data) and *R* is the universal gas constant, 8.314 ($J \cdot K^{-1} \cdot mol^{-1}$).

Daily precipitation sums were calculated from the hourly data. We then remapped the precipitation radar data to the ERA5-grid using bilinear interpolation by applying the remapbil-function of CDO and thus ascribing daily precipitation sums to each grid cell. We calculated percentile exceedance of the 2nd, 10th, 90th and 98th percentile for gust speed maxima, soil water volume and precipitation via the relation of the daily value and the local percentile.

Finally, we collected all these data for the month of October to March 2017 to 2021 in a data set containing grid cell IDs, a variety of daily meteorological predictors (see Table 1), rail density and the daily occurrence of at least one tree fall event in the grid cell given as True or False. This data set contains only grid cells crossed by at least one railway line.

4.2 Logistic Regression

Logistic regression was used to relate the probability of an event to a linear combination of predictor variables which is converted with the logit link function into the scale of a probability:

$$logit(\Theta)=\ln\left(\frac{\Theta}{1-\Theta}\right)=a+b_1\cdot x_1+b_2\cdot x_2+...+b_k\cdot x_k$$

Equation 2

Here, θ is the probability of an event, $x_{1\text{-}k}$ are the predictor variables, $b_{1\text{-}k}$ are the estimated coefficients and a is the intercept term. Equation 2 can be rearranged in the following way to calculate the event probability (MacKenzie et al., 2018):

$$\Theta=\frac{\exp(a+b_1\cdot x_1+b_2\cdot x_2+...+b_k\cdot x_k)}{1+\exp(a+b_1\cdot x_1+b_2\cdot x_2+...+b_k\cdot x_k)}$$

Equation 3

Interactions allow for expressing the dependence of two or more variables on each other in a model. The effect (aka the estimated coefficient) for one predictor might change depending on the value of another predictor. Compared to a model without interaction (see Eq. 2) two predictors that are assumed to have an influence on each other are multiplied and a coefficient is estimated for this new term resulting in:

$$\Theta=\frac{\exp(\mathrm{a}+\mathrm{b}_1\cdot\mathrm{x}_1+\mathrm{b}_2\cdot\mathrm{x}_2+\mathrm{b}_3\cdot\mathrm{x}_1\cdot\mathrm{x}_2...+\mathrm{b}_k\cdot\mathrm{x}_k)}{1+\exp(\mathrm{a}+\mathrm{b}_1\cdot\mathrm{x}_1+\mathrm{b}_2\cdot\mathrm{x}_2+\mathrm{b}_3\cdot\mathrm{x}_1\cdot\mathrm{x}_2+...+\mathrm{b}_k\cdot\mathrm{x}_k)}$$

Equation 4

where b_3 is the estimated coefficient for the interaction of the predictors x_1 and x_2. It represents how the effect of x_1 on the event probability changes with x_2 (and vice versa). A significant b_3 would indicate that the effect of x_1 on the probability is different at different levels of x_2.

For quantifying the model's forecast quality we use the Brier Skill Score (BSS) which is based on the Brier Score (BS) (Wilks, 2011):

$$BS = \frac{1}{N} \sum_{i=1}^{N} (f_i - o_i)^2$$

Equation 5

where N is the number of observations, f is the forecast probability and o is the outcome (either 1 or 0). The BSS is then calculated as:

$$\mathrm{BSS} = 1 - \mathrm{BS}/\mathrm{BS}_{\mathrm{ref}}$$

Equation 6

where BS is the modelled Bier Score and BS_{ref} is the score of a reference model, in this case a model that simply assumes the mean tree fall probability in each grid cell. This mean probability is used as the forecast probability f in BS_{ref} and compared to the outcome o. The BSS ranges from -∞ to 1 where a positive value indicates that the model is better than the reference model. For calculating the BSS we use 10-fold cross validation. Here, the data set is randomly divided in ten equal sequences. The model is trained on nine sequences while the BS score is calculated for the tenth sequence and used for validation. This is repeated ten times, each time using a different sequence for the validation.

We selected a set of meteorological parameters based on the literature cited in the introduction and grouped them into eleven predictor classes, e.g. “wind”, “snow” and “precipitation” (see Table A1 for full list of predictors and classes). To test for legacy effects we also include precipitation sum and soil water volume from antecedent time periods of 3 months, 9 months and one year. The goal is not to build the “perfect” model but to examine which predictor classes influence tree fall, which are not influential and which predictors are most clearly improving the skill of the model against the basic reference model.

Since the length of railway lines in a grid cell is highly influential on the tree fall probability, this variable is included as well.

We were interested in the impact of each predictor class and also the predictor modifications (for example anomalies or relations to local percentiles) which improve the model skill the most. At the same time we wanted to avoid multi-collinearity. Therefore, model selection followed three criteria:

1. There must be exactly one predictor from each predictor class in the model (see Table A1 for full list of predictors and classes)

2. Only the predictor of each class improving the model’s BSS the most is added to the model.

3. The predictor has to be significant with $p < 0.05$ based on the Student’s t-test.

We then moved gradually from class to class. We added and removed each of the predictors in the class in a stepwise approach, keeping only the class predictor with the best BSS performance.

We assume gust speeds to be the key predictor but interactions with other predictors that influence a trees vulnerability are likely. Therefore, we added interaction terms between daily maximum gust speed and each other model predictor in the model in the same stepwise approach. Again, we only kept the the interaction term if it improved the model’s BSS.

After adding all predictors to the model we tested for multicollinearity. Multicollinearity exists when two or more predictors in a regression model are moderately or highly correlated with one another. We used the Variance Inflation Factor (VIF) to test for multicollinearity:

$$VIF_j = \frac{1}{1 - R_j^2}$$

Equation 7

where R^2_j is the R^2-value obtained by regressing the j_{th} predictor on the remaining predictors. All predictors with a VIF<5 were considered to have no critical multicollinearity (Sheather, 2009).

We calculated the standardized effect size for each predictor to estimate their effects on tree fall probability compared to each other. For this**,** we standardized the absolute value of the predictors estimated coefficient by calculating the standardized coefficient or beta coefficient:

$$\beta = b_j \frac{s_{xj}}{s_y}$$

Equation 8

where b_j is the estimated coefficient for the j^{th} predictor, s_{xj} is the standard deviation of the independent predictor x_j and s_y is the standard deviation of the dependent variable y.

Finally, we tested the significance of each independent variable in the model. We kept only those independent variables that are significant (with $p < 0.05$ based on the Student's t-test) and then continued analysis with this reduced model.

5 Results

In this section, we describe the selected model and the impact of the model predictors on tree fall risk.

According to the selection criteria described in section 4 the resulting model (using the McCullagh and Nelder (1989) model notation) is

$$\textit{tree fall} \sim rd + v_{max\_anom} + dur_{90} + gf + sin(2*pi/360 * winddir) + cos(2*pi/360 * winddir) + sd + T_{slfrost} + pr_{90} + swvl_{anom} + pr\_365 + swvl\_365 + \rho + v_{max\_anom}{:}\ dur_{90} + v_{max\_anom}{:}gf$$

Equation 9

Explanations for the different predictor abbreviations are given in Table A1. This model predicts the tree fall risk for each grid cell using the meteorological variables of each cell as input. The terms $v_{max\_anom}{:}dur_{90}$ and $v_{max\_anom}{:}gf$ represent the interactions of gust speed with duration and gust factor. They serve to account for the fact that the individual parameters do not change tree fall risk independently. Their impact in the model becomes apparent mainly on days with relatively high wind speeds. See section 6.3 for further discussion of this effect. Sine and cosine terms are used for *winddir* to ensure that the tree fall probability as a function of *winddir* has the same values at 0° and 360°. The models BSS is 0.069, compared to a BSS of 0.0637 for

$$\textit{tree fall} \sim rd + v_{max}$$

Equation 10

showing an improvement of model skill when using additional meteorological predictors compared to just rail density *rd* and daily maximum gust speed v_{max}.

In Table 1 the predictors, their definitions and corresponding model coefficients and metrics are listed. All coefficients except those for snow depth (*sd*), soil frost ($T_{slfrost}$) and the mean soil water volume during the previous year (*swvl_365*) are significantly different from zero. We find highest effect sizes (with absolute standardized coefficients greater than one) for gust speed anomaly (v_{max_anom}), the interaction of gust speed anomaly and duration of strong wind speeds (dur_{90}), the interaction of gust speed anomaly and the gust factor (*gf*), rail density (*rd*) and the duration of strong wind speeds. Interactions between gust speed anomaly and other predictors (except duration of strong wind speeds and gust factor) do not improve the model's BSS.

For daily precipitation, daily soil water volume and daily maximum gust speed we compare unmodified predictors and predictors related to local conditions (by using anomalies or percentiles) and find that the latter improve the BSS more with pr_{90}, $swvl_{anom}$ and v_{max_anom} being the best predictors.

To test for multicollinearity, we use the VIF and find all values to be below five and therefore not critically correlated with each other. Interaction terms are excluded from this as they are naturally highly correlated with the interaction partners.

In a second step we adapt the model and identify all non-significant predictors: *sd*, $T_{slfrost}$ and the *swvl_365*. To reduce model complexity we remove these predictors. After removing the three non-significant predictors the BSS remains 0.069. This results in the following model:

$$tree\ fall \sim rd + v_{max\_anom} + dur_{90} + gf + sin(2*pi/360 * winddir) + cos(2*pi/360 * winddir) + pr_{90} + swvl_{anom} + pr\_365 + \rho + v_{max\_anom}: dur_{90} + v_{max\_anom}:gf$$

Equation 11

We find that the rail density, anomaly of daily maximum gust speeds v_{max_anom}, duration of strong wind speeds based on the local 90th gust speed percentile dur_{90}, gust factor *gf*, wind direction *winddir*, precipitation related to the local 90th percentile pr_{90}, soil water volume anomaly $swvl_{anom}$, and precipitation sum in the previous year *per_365,* air density ρ as well as the two interactions of the gust speed anomaly with either gust factor or duration of strong wind speeds were significant, improved the model's BSS and therefore meet the model selection criteria. This model is used to plot the functional relationships between tree fall probability and the meteorological predictors (Figure 4). For these plots one model parameter is varied while the others are fixed to a certain value (detailed in the caption of Figure 4) that was determined during a previous data exploration. For the fixed values of $v_{max\ anom}$ and dur_{90} we picked 18 m/s and 5 hours, which represent values of a short but strong winter storm. 18 m/s are exceeded on about 0.5% of days and thus occur approximately two days a year. For $swvl_{anom}$ and pr_{90} we selected values that represent a dry situation, thus very low soil moisture and very low precipitation. For wind direction we picked a north-easterly wind. For the other variables (*pr_365, ρ)* we chose the average over the time period 2017-2021. Based on these plots and the standardized coefficients (Table 1) we find a relatively strong increasing impact on tree fall risk for v_{max_anom}, dur_{90} and *rd*. We find a relatively weak but still significant increasing impact for $swvl_{anom}$, pr_{90}, ρ and *pr_365*. We find a relatively strong decreasing effect for *gf* and a relatively weak impact for *winddir* with easterly to south-easterly winds having a decreasing and westerly to north-westerly winds having an increasing impact respectively.

Based on these findings, we propose that high and prolonged wind speeds, especially in combination with wet conditions (high precipitation and high soil moisture) and a high air density, increase tree fall risk.

Short	**Definition**	**Coefficient**	**Standardized Coefficient**	**Std. Error**	**p**	**VIF**
v_{max_anom}	Daily anomaly of v_{max} (difference to local monthly mean gust speeds at 10 m height) [m/s]	0.1906	5.3527	0.0083	< **0.05**	**3.907**
$v_{max\_anom}:dur_{90}$	Interaction	0.0058	3.6927	0.0003	< **0.05**	**-**
$v_{max\_anom}:gf$	Interaction	-0.0246	-2.2063	0.0027	< **0.05**	**-**
rd	Rail density - total length of all railway lines in a 31km grid cell [km]	0.0102	2.1946	0.0003	< **0.05**	**1.037**
dur_{90}	Daily number of hours where gust speed exceeds the local 90th gust speed percentile [h]	-0.0491	-1.7746	0.0039	< **0.05**	**3.202**
$swvl_{anom}$	Daily anomaly of the daily mean of soil water volume (*swvl*) at a depth of 28 – 100cm (difference to local monthly mean soil water volume) [m^3 m^{-3}]	4.9985	0.7136	0.4001	< **0.05**	**1.144**
pr_{90}	Relation of *pr* to local 90th precipitation percentile (*pr/ p90*) [mm]	0.0019	0.6493	0.0002	< **0.05**	**1.247**
gf	Gust factor: v_{max} /v_{mean} (the ratio of the maximum daily gust speed and the daily mean of the hourly maximum gust speeds at 10m heigth) [-]	0.1559	0.5193	0.0300	< **0.05**	**2.037**
*cos(2 * pi/360 * winddir)*	Mean daily wind direction [°]	0.1843	0.3779	0.0273	< **0.05**	**1.099**

Short	Definition	Coefficient	Standardized Coefficient	Std. Error	p	VIF
ρ	Air density, see Eq. 1 [kg/m^3]	1.8108	0.2704	0.5274	**< 0.05**	**2.109**
*sin(2 * pi/360 * winddir)*	Mean daily wind direction [°]	-0.0916	-0.2178	0.0261	**< 0.05**	**1.293**
pr_365	Sum of daily precipitation sum for previous 365 days [mm]	0.0002	0.1974	0.0001	**< 0.05**	**1.476**
sd	Snow from the snow-covered area of an ERA5 grid box (depth the water would have if the snow melted and was spread evenly over the whole grid box) [m]	0.4455	0.0422	0.6199	> 0.05	**1.199**
swvl_365	Sum of the daily mean of soil water volume at a depth of 28 – 100cm of the previous 365 days	-0.0966	-0.0235	0.2432	> 0.05	**1.223**
$T_{slfrost}$	Frozen soil: True or False (based on T_{sl}< 0K)	-9.0727	-0.0069	70.6317	> 0.05	**1.000**

Table 1 Model predictors (ordered by their effect size) and their corresponding model coefficients and metrics. Bold numbers indicate values below the required threshold for significance and multi correlation (with p < 0.05 based on he Student's t-test and VIF < 5). See Table A1 for further details.

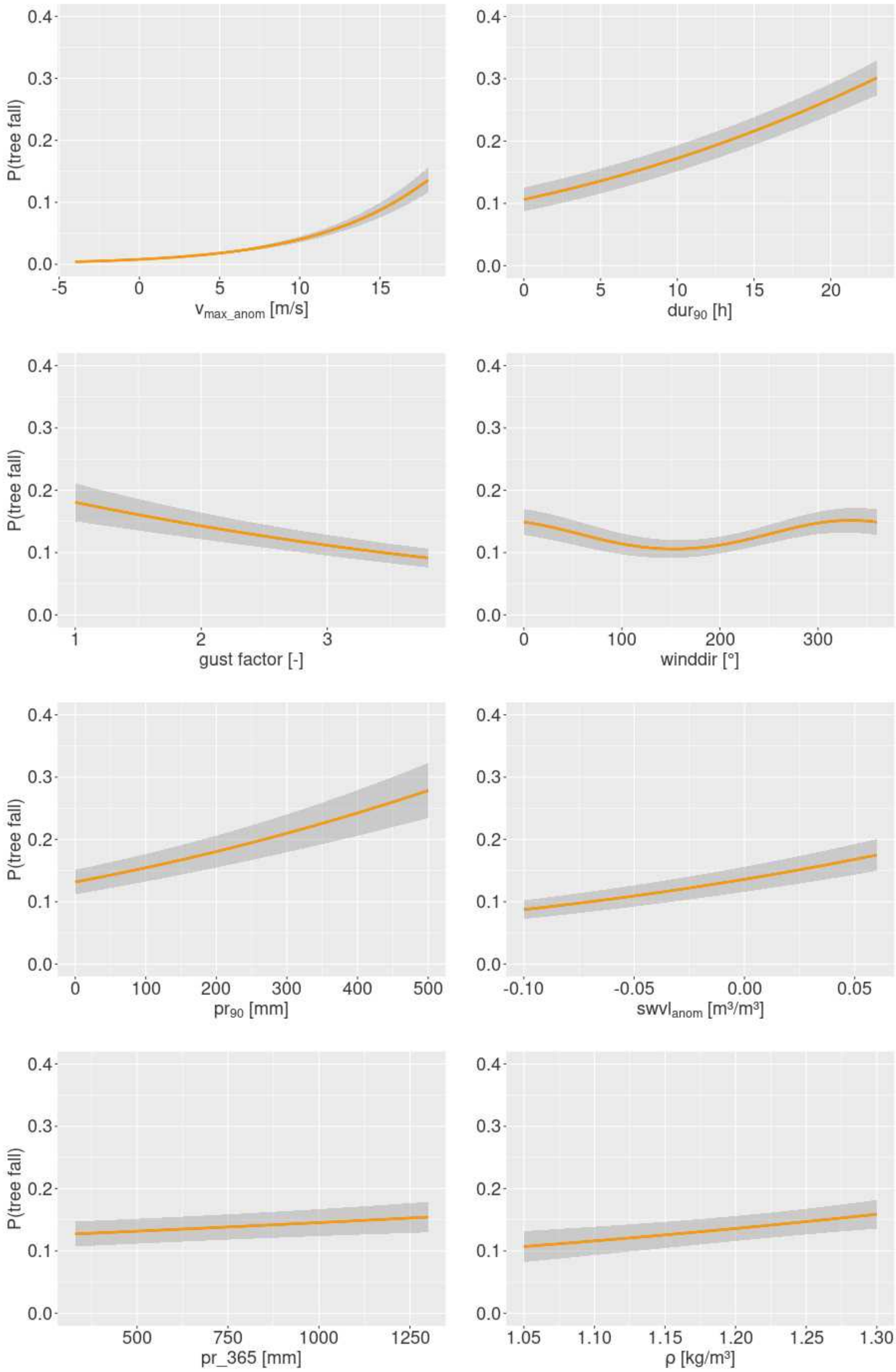

Figure 4: Changes in tree fall probability in an ERA5 grid cell with 100 km railway length (urban conditions) depending on different parameters. In each figure one model parameter is varied while the others are fixed to a certain value: v_{max_anom} *= 18 m/s;* dur_{90} *= 5h; gf = 2.2, ;* pr_{90} *= 20mm; winddir = 41°;* $swvl_{anom}$ *= 0* $m^3\ m^{-3}$*; pr_365 = 663 mm; ρ = 1.2* kg/m^3*. Grey areas signify the confidence interval with a level of 95%.*

6 Discussion

6.1 Predictor Selection

In previous studies on tree fall hazards that consider a statistical modelling approach, a large variety of potential influencing factors can be found. Most of them focus on tree, stand and soil properties like tree age, height, tree species, forest type, soil type or slope (Mayer et al., 2005; Schindler et al., 2009; Kamo et al., 2016; Kabir, Guikema and Kane, 2018; Díaz-Yáñez, Mola-Yudego and González-Olabarria, 2019; Hart et al., 2019; Gardiner, 2021; Wohlgemuth, Hanewinkel and Seidl, 2022). Meteorological predictors like precipitation or soil moisture are considered less often (Schmidt et al., 2010; Hall et al., 2020). Wind is mostly considered as mean hourly or maximum wind speed (Hale et al., 2015; Morimoto et al., 2019; Hall et al., 2020). These limiations regarding meteorological predictors are often also true for studies that consider tree fall on railway lines (Bíl et al., 2017; Kučera and Dobesova, 2021; Gardiner et al., 2024). Additionally many of these studies are both limited in their temporal and spatial range, often restricted to one region or one forest and only one or a few storm events (Hale et al., 2015; Kamimura et al., 2016; Kabir et al., 2018; Hart et al., 2019; Zeppenfeld et al., 2023). In our study we focused on different types of meteorological predictors, including those that describe wind characteristics, but also predictors describing precipitation and soil conditions at different time scales. We showed that meteorological predictors other than mean or maximum wind speed have a significant effect on tree fall risk and improve model skill (with a BSS of 0.0637 for a model including only gust speed maximum and 0.069 for the full meteorological model). Furthermore, with a dataset ranging from 2017 to 2021 and covering the whole of Germany, our study investigates long-term and large-scale storm damage modelling, which is still rare.

The model selection process resulted in a model with ten independent variables and two interactions, raising the possibility of over complexity. To account for this we calculated the Akaike Information Criterion (AIC), which is a relative measure showing how well different models fit the data. It penalizes too high numbers of independent variables. The model with the lowest AIC value is considered the best. We calculated the AIC for the resulting model as well as reduced versions of the model in which we left out 1) the interactions, 2) all predictors with an absolute standardized coefficient < 1 and 3) all predictors with an absolute standardized coefficient < 0.5. We find that our selected model has the lowest AIC (56985.43) compared to options 1) to 3), (57339.14, 57512.49 and 57062.27 respectively).

In accordance with our results, many studies find wind speed to be associated with tree and forest damage (Hale et al., 2015; Morimoto et al., 2019; Hall et al., 2020). We showed that other wind properties like duration of strong wind speeds, gust factor, wind direction and air density are influential, too. In our model the influence of the wind direction on tree fall risk is relatively small compared to the effect of the wind speed itself. Nonetheless, it appears that north-westerly winds slightly increase tree fall risk. This seems counter-intuitive as this is the predominant wind direction in Germany. One would assume the trees adapt to this and thus wind direction would have either no effect or that easterly winds would increase tree fall risk (Bonnesoeur et al., 2016). An explanation might be that westerly winds are on average stronger. ERA5 is not a perfect representation of local winds and sometimes underestimates gust speeds (Molina, Gutiérrez and Sánchez, 2021). Thus, in cases where ERA5 underestimates the real gust speeds but shows westerly winds the wind direction might become a proxy for stronger winds. While Akay and Taş (2019) found wind direction at three stations to be one of the predictors with the highest impact on storm damage risk, it has a relatively small effect in our model. Their result may be related to the role of wind direction on wind speeds at stations located in an area with high orography, which is much weaker in the rather coarse ERA5 data. Certainly there can also be a relationship of wind direction and trees exposure, for example depending on the topography, the tree's acclimation to the average local wind direction (Mitchell, 2013) or the location of the tree to an expose edge (Quine, Gardiner and Moore, 2021). We did not account for these factors. Future modelling might benefit by adding local tree wind exposure.

Duration of strong winds is important because trees do not fail instantly but fail with repeated swaying that fractures the root/soil system and this process can take many hours (Kamimura et al., 2022). Gust factor and air density are also known to be critical components in calculations of tree wind damage risk (see Equations 4.4, 4.12 and 4.15 in Quine et al. (2021)).

This paper for the first time shows clearly that storm duration, gust factor and air density are important factors in calculating the risk of tree fall and they should be included in future studies and modelling efforts.

We found both soil water volume anomaly as well as daily precipitation sum to have an increasing impact on tree fall probability, which is in agreement with previous studies (Kamimura et al., 2016;

Hall et al., 2020). This could be due to the fact that heavy precipitation can contribute to the accumulation of weight on tree crowns, consequently increasing wind-induced stress (Neild and Wood, 1999; Gardiner et al., 2010; Hale et al., 2015). Additionally, water logged soils can have a negative affect on root anchorage (Kamimura et al., 2012; Morimoto et al., 2021).

We also included predictors describing antecedent soil moisture and precipitation conditions, namely mean soil water volume accumulation and precipitation sum of the previous twelve months. Antecedent soil water volume is not significant in our model but the precipitation sum of the previous year is, showing a weak increasing impact on tree fall risk. Previous research on the impact of drought on tree damage are inconclusive. Csilléry et al. (2017) found both positive but mainly negative effect on tree damage. They suggest that in some stands drought weakens the trees and makes them more vulnerable to wind loading while in others dry soils make them less vulnerable towards overturning. We suggest that further research considers antecedent weather situations in more detail. For example, by including indices like the Standardized Precipitation-Evapotranspiration Index (SPEI), which has been used in recent research on forest disturbance (Klein et al., 2019; Gazol and Camarero, 2022). It is also likely that trees react very differently to dry and wet conditions depending on their species, height or the soil type. Whenever such information is available it should be included in the analysis.

Several studies have found snow and frozen soil to be influential (Peltola et al., 2000; Hanewinkel et al., 2008; Kamimura et al., 2012; Kamo et al., 2016). Snow loading can apply stress on canopy and branches and this stress can be increased by additional wind (Kamo et al., 2016; Zubkov et al., 2023). Frozen soil has been shown to prevent uprooting (Gardiner et al., 2010; Pasztor et al., 2015). Yet, in our study snow and soil frost did not prove to be significant. This is likely connected to the rare occurrence of such conditions in Germany between 2017 and 2021. On average, over all model grid cells snow depth exceeded 0.05 m water equivalent only on 1.3% of all winter days and soil frost occurred only 0.03 %. Our snow data is derived from ERA5 and is therefore modelled data. In their evaluation of snow cover properties in ERA5 Kouki, Luojus and Riihelä (2023) found that ERA5 generally over estimates snow water equivalent in the Northern Hemisphere. Thus, snow coverage might even be lower than shown in our data. Using measured instead of modelled snow data could potentially improve the modelling results.

For wind speed, precipitation and soil water volume we compared unaltered predictors with anomalies and percentile exceedances. For all three parameter types, we found that predictors based on percentile exceedances (*pr_{90}*) or anomalies ($swvl_{anom}$, v_{max_anom}) improve the model's BSS the most and thus, reflect the trees' ability to acclimate. Trees adapt to the local climate (Mitchell, 2013; Gardiner, Berry and Moulia, 2016) and what might be windy or dry conditions for a tree in one region might be average in another. When modelling tree damage over larger spatial regions, we therefore suggest relating meteorological predictors to local climatological conditions, for example by using anomalies or percentiles.

We found that air density has a positive impact on tree fall risk. As our model includes both maximum gust speed and air density we considered wind load as a model predictor. Wind load is proportional to air density and the square of wind speed:

$$wl = 1/2\, C \rho A\, v^2$$

Equation 12

where C is a non-dimensional drag coefficient, ρ is the air density (kg/m^3), A is the frontal area and v is the wind speed (m/s) (Ciftci et al., 2014; Gardiner et al., 2016; Quine et al., 2021). Therefore, wind load is highly correlated with wind speed. In our data, v_{max_anom} and wind load have a high Pearson correlation coefficient of 0.95. Due to this, they should not be used together in a single model since high correlation between parameters makes model interpretation difficult. As both the drag coefficient as well as the trees frontal area are unknown, we reduced the equation to:

$$wl = 1/2 \rho v\ 2$$

Equation 13

We tested a model that used wind load instead of air density and v_{max_anom}. We removed air density from the predictors of Equation 11 and exchanged v_{max_anom} with wind load. We found a lower BSS for this model of 0.0678 compared to 0.069. Yet, wind load is highly significant and has a strong effect size with a standardized coefficient of 4.07. Additionally, the wind load model has a marginally lower AIC (56980.45) than the original model (56985.43). Due to the lower BSS *wl* did not meet the selection criteria in our modelling process. Yet, it is certainly influential on tree fall and might add value to other impact models. We suggest considering it in future studies.

6.2 The effect of interaction terms

Interactions can show the combined effect predictors may have on model outcome and how the effect of one predictor is changing depending on the value of the other. We tested if interaction terms with gust speed anomaly add to the model skill and found positive results for the interaction with duration of strong wind speeds as well as gust factor. Both predictor interactions improve the BSS and are highly significant (see Table 1).

A low gust factor could be the result of a day with a high maximum gust speed and a high mean gust speed as well as the result of a low maximum gust speed and a low mean gust speed. Thus, this predictor lacks information without the interaction with maximum gust speed. The duration of strong wind speeds depends on the local 90th gust speed percentile. As the average 90th percentile in our data is 12 m/s, this allows for a wide range of gust speeds exceeding the percentile since v_{max} greater than 30 m/s is possible during strong storms. Here too, does the interaction add missing information to the model. Duration and gust factor are not strongly correlated (with a Spearman's correlation coefficient at 0.15.) and therefore provide complementary information as long durations are a accompanied by a vast range of gust factor values.

In Figure 5 the effect of duration of strong wind speeds and gust factor for the model with and without interaction terms is compared. When the interactions are removed, the decreasing impact of gust factor on tree fall probability is much smaller while duration of strong wind speeds seems to be not at all connected to tree fall probability. The effect size of these predictors also decreases strongly: In a model without interactions, the standardized coefficient of the gust factor is -0.3181 and of duration of strong wind speeds 0.0275 (compare Table 1). Only when we add the interaction the impact of these predictors gets visible, thus showing their combined effect. Furthermore, the model without interactions has a BSS of only 0.0678 compared to 0.069 for the model that includes interactions (Eq. 11).

The combined effect of the predictors is illustrated in Figure 6. We compare the model outcome depending on the duration of strong wind speeds for two values of v_{max_anom} , 10 m/s and 18 m/s. Both represent values that exceed the 98th percentile of daily gust speeds in most grid cells, but one represents a low exceedance while the other is very high. The duration of strong wind speeds has a much stronger increasing impact on tree fall probability in the second scenario. This also fits with the observations of Kamimura et al. (2022) who showed that even in a typhoon with very high wind speeds the duration of the storm was important for damage to occur.

A high maximum daily gust speed could be the result of just one strong gust but also the result of a stormy day with lasting high wind speeds. Adding additional wind properties like the gust factor or duration of strong wind speeds can help differentiate between these scenarios. Figure 7 illustrates this. Here, we compare modelled tree fall probabilities for a day with a high gust factor and low duration of strong wind speeds (a gusty day) and a day with a low gust factor and long duration of strong wind speeds (a day of sustained high wind speeds). The relationship between v_{max_anom} and tree fall probability is much weaker on the gusty day, showing how strongly the interaction with additional wind properties can change tree fall risk.

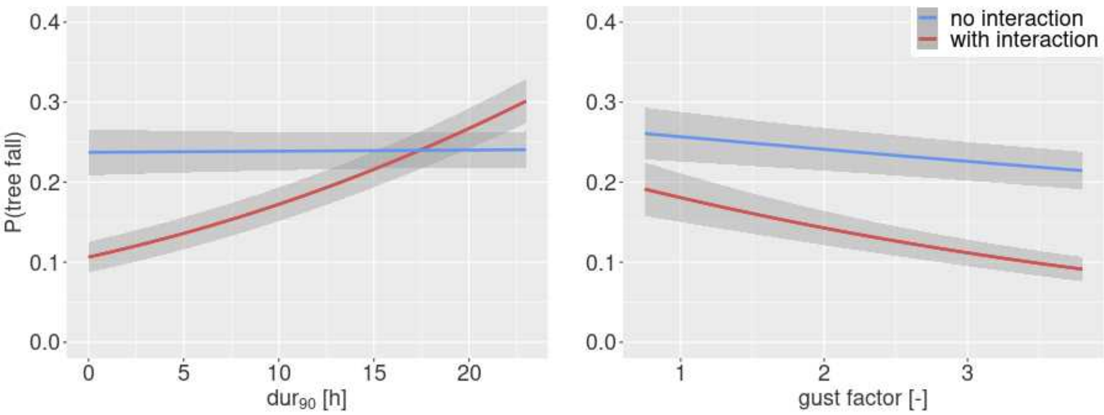

Figure 5: Comparison of the effects of duration of strong wind speeds (dur_{90}, left) and the gust factor (gf, right) on tree fall risk for the model with and without interaction terms. Parameters are fixed to the same values as in Figure 4 with v_{max_anom} = 18 m/s. Grey areas signify the confidence interval with a level of 95%.

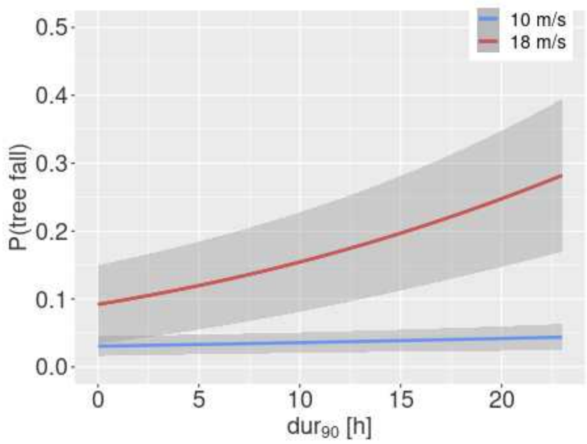

Figure 6: Interaction effect of v_{max_anom} and storm duration for two different values of v_{max_anom} (10 m/s and 18 m/s). All other parameters are fixed to the same values as in Figure 4. Grey areas signify the confidence interval with a level of 95%.

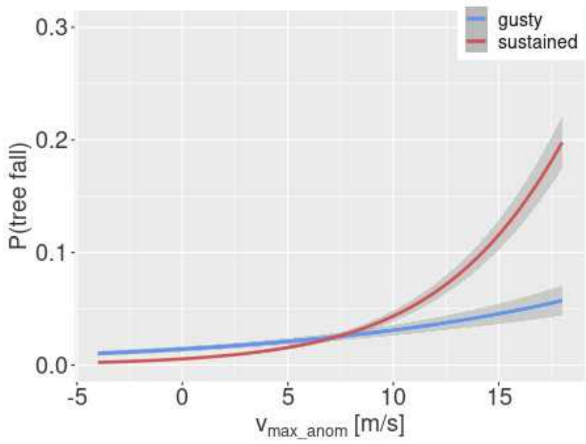

Figure 7: Comparison of interaction effect. Gusty day: dur_{90} = 2h and gf = 5; sustained day: dur_{90}=12h and gf=2. All other parameters are fixed to the same values as in Figure 4.Grey areas signify the confidence interval with a level of 95%.

6.3 Limitations

This study aimed, among other things, to create a meteorological basis for a predictive tree fall model that can support decisions regarding the management of vegetation alongside transportation routes, as well as climate-resilient forests. However, local ecological information (soil, tree species, stand structure, etc.) is not taken into account. Thus, the results are not representative of every individual setting but rather for an average setting across Germany.

Many studies have pointed out the influence of tree, stand and soil factors (Mayer et al., 2005; Kamo et al., 2016; Kabir et al., 2018; Díaz-Yáñez et al., 2019; Hart et al., 2019; Gardiner, 2021; Wohlgemuth et al., 2022) on wind damage vulnerability. Such data is unfortunately not available for the scope of our study. Thus, model results could vary if such information were to be incorporated. The tree fall risk according to this model might vary at the same gust speed level for different trees and different stands. For example, Gardiner et al. (2024) demonstrated how critical wind speeds for tree fall along railway lines vary significantly depending on factors such as tree height, canopy shape, and whether the tree is coniferous or deciduous. However, our results show clear evidence for the importance of specific meteorological predictors in tree fall and storm damage modelling. Finding the specific relationships for meteorological predictors and different tree species, forest types and soil types should be the next step in understanding the impact of different meteorological conditions on wind damage.

In the data set about 25% of tree fall events occur at maximum daily gust speed below 11 m/s. On the one hand, these tree fall events might be caused by processes unrelated to meteorology. On the other hand, these events might be related to meteorological events not resolved by the ERA5 reanalysis. For example, convection is not explicitly resolved by the underlying atmospheric model of ERA5. Therefore, the wind speeds caused by convective events are likely to be underestimated. Additionally, the coarse resolution of ERA5 is generally suboptimal when trying to connect small scale events such as a single tree fall with meteorological data. Yet, at the time of our research ERA5 was the only reanalysis data set covering the years 2017 to 2021. While evaluations of ERA5 gust speeds with observational data point out some limitations they also find the data in general to be a good representation of local measurements. Molina et al. (2021) compare hourly 10 m wind speed from ERA5 with wind observations from 245 stations across Europe. They find that „Most of the stations exhibit hourly [Pearson correlation coefficients] ranging from 0.8 to 0.9, indicating that ERA5 is able to reproduce the wind speed spectrum range [...] for any location over Europe“.

Minola et al. (2020) compare ERA5 with hourly near-surface wind speed and gust observations across Sweden for 2013–2017. They, too, find Pearson correlations of 0.8 and higher for daily maximum gust speeds. However, they do point out that „evident discrepancies are still found across the inland and mountain regions“ and that higher wind speeds and gust speeds display stronger negative biases. Data with higher spatial resolutions that include convective effects might help in understanding the effects of thunderstorms and other small-scale phenomena in future research. There is already some concern that such phenomena are becoming more problematic in Europe (Suvanto et al., 2016; Sulik and Kejna, 2020).

The adding and removal of model predictors during the stepwise model selection process caused only very small changes in the model's BSS, which was very low to begin with. This is quite likely connected to all of the limitations listed above. Models which are able to add tree, soil or stand data or have access to meteorological data of a higher spatial resolution will likely produce better model skill and be able to examine the relationships of tree fall and meteorology in more detail. Nonetheless, our approach provides clear evidence of which meteorological predictors have a significant impact and indicates the magnitude of their effect.

7 Conclusion

Our aim was to investigate the relationship between tree fall and wind as well as other meteorological conditions. For this, we used a stepwise approach to build a logistic regression model predicting the tree fall risk.

We showed that high and prolonged wind speeds, especially in combination with wet conditions (high precipitation and high soil moisture) and a high air density, increase tree fall risk. We find a relatively strong increasing impact on tree fall risk for daily maximum gust speeds anomaly and duration of strong wind speeds. We find a relatively weak but still significant increasing impact for the daily soil water volume anomaly, the daily precipitation exceedance of the 90^{th} percentile, daily air density and the precipitation sum of the previous year. We find a relatively strong decreasing effect for the gust factor and a relatively weak impact for wind direction with easterly to south-easterly winds having a decreasing and westerly to north-westerly winds having an increasing impact. Snow and soil frost predictors which have been found important in past research have no significant impact in our model.

To account for potential acclimation of trees to local climate we compared unmodified predictors and predictors related to local conditions (by using anomalies or percentiles) for daily precipitation, daily soil water volume and daily maximum gust speed. We find that the latter predictors, which reflect acclimation, improve the model’s skill the most.
Finally we showed that the inclusion of interaction terms improved the model’s skill score, changed modelled risk probabilities and helped to illustrate the combined effect meteorological predictors may have on tree fall probability.

Many previous studies on tree fall and forest storm damage are restricted to a single event or small research region. Additionally, past research has primarily focused on tree, soil and stand parameters. When studies have taken meteorology into account they often implemented only mean or maximum gust speeds. We were able to conduct a long-term and large-scale study on tree fall risk and were able to show that other wind related parameters such as gust factor, duration of strong wind speeds or air density as well as other predictors related to meteorology, including precipitation and soil moisture, have a significant impact on tree fall risk. Our results also highlight the importance of using anomalies or relations to local percentiles for meteorological predictors in large scale studies to account for the acclimation of trees to their local climatic conditions.

This work is a step towards future research on the topic of wind damage and tree fall. It shows how meteorological factors can be incorporated into a probabilistic tree fall model. Such a model can be applied to climate model data to estimate changes in tree fall risk in future climate scenarios. We aim to elaborate on these goals in future research.

8 Appendix

Predictor class	Short name	Definition	Unit
Wind	v_{max}	Maximum daily gust speed of the maximum 3 second wind at 10 m height	m/s
	v_{mean}	Daily mean of the hourly maximum gust speeds	m/s
	$v_{max}2d$	Maximum daily gust speed of current and previous day	m/s
	v_{max_90}	Relation of v_{max} to local 90th gust speed percentile (v_{max}/ *p90*)	[-]
	v_{max_98}	Relation of max. daily gust speed to local 98th gust speed percentile (v_{max}/ *p98*)	[-]
	v_{max_anom}	Daily anomaly of v_{max} (difference to local monthly mean gust speeds)	m/s
	wl	Wind load: Wind force per area applied to a tree, see Eq. 13	N/m²
Air density	ρ	Air density, see Eq. 1	kg/m^3
Duration of strong wind speeds	dur_{90}	Daily number of hours where gust speed exceeds the local 90th gust speed percentile	h
	dur_{98}	Daily number of hours where gust speed exceeds the local 98th gust speed percentile	h
	dur_{90}_2d	Number of hours where gust speed exceeds the local 90th gust speed percentile during current and previous day	h
	dur_{98}_2d	Number of hours where gust speed exceeds the local 98th gust speed percentile during current and previous day	h
Wind direction	*winddir*	Mean daily wind direction	°
Gust factor	*gf*	Gust factor - v_{max} /v_{mean} (the ratio of the maximum daily gust speed and the daily mean of the hourly maximum gust speeds at 10m heigth)	[-]
precipitation	*pr*	Daily precipitation sum derived from hourly RADOLAN radar data	mm
	pr_log	log(1+*pr*)	mm
	pr_{90}	Relation of pr to local 90th precipitation percentile (*pr*/ *p90*)	[-]
	pr_{98}	Relation of pr to local 98th precipitation percentile (*pr*/ *p98*)	[-]
	pr_{90}_T	Exceedance local 90th precipitation percentile: True or False	[T,F]
	pr_{98}_T	Exceedance local 98th precipitation percentile: True or False	[T,F]
Snow	*sf*	Daily sum of snow that falls to the Earth's surface	m of water equivalent
	sd	Snow from the snow-covered area of an ERA5 grid box -	m of water

		depth the water would have if the snow melted and was spread evenly over the whole grid box	equivalent
	sf_T	Snow is present: True or False (based on *sf*)	[T,F]
	sd_T	Snow is present: True or False (based on *snd*)	[T,F]
Soil temperature	T_{sl}	Daily mean of soil temperature at a depth of 28 – 100cm	K
	T_{sl98}	Relation of T_{sl} to local 98th T_{sl} percentile (T_{sl}/ $T_{sl}98$)	[-]
	T_{sl90}	Relation of T_{sl} to local 90th T_{sl} percentile (T_{sl}/ $T_{sl}90$)	[-]
	T_{sl10}	Relation of T_{sl} to local 10th T_{sl} percentile (T_{sl}/ $T_{sl}10$)	[-]
	T_{sl02}	Relation of T_{sl} to local 2nd T_{sl} percentile (T_{sl}/ $T_{sl}02$)	[-]
	T_{sl98}_T	Exceedance local 90th T_{sl} percentile: True or False	[T,F]
	T_{sl90}_T	Exceedance local 98th T_{sl} percentile: True or False	[T,F]
	T_{sl10}_T	Exceedance local 10th T_{sl} percentile: True or False	[T,F]
	T_{sl02}_T	Exceedance local 2nd T_{sl} percentile: True or False	[T,F]
	T_{sl}_anom	Daily anomaly of T_{sl} (difference to local monthly mean soil temperature)	K
	$T_{slfrost}$	Frozen soil: True or False (based on T_{sl}< 0K)	[T,F]
Soil moisture	*swvl*	Daily mean of soil water volume at a depth of 28 – 100cm	$m^3\ m^{-3}$
	$swvl_{98}$	Relation of swvl to local 98th swvl percentile (*swvl/ swvl98*)	[-]
	$swvl_{90}$	Relation of *swvl* to local 90th *swvl* percentile (*swvl/ swvl90*)	[-]
	$swvl_{10}$	Relation of *swvl* to local 10th *swvl* percentile (*swvl/ swvl10*)	[-]
	$swvl_{02}$	Relation of *swvl* to local 2nd *swvl* percentile (*swvl/ swvl02*)	[-]
	$swvl_{98}\_T$	Exceedance local 90th *swvl* percentile: True or False	[T,F]
	$swvl_{90}\_T$	Exceedance local 98th *swvl* percentile: True or False	[T,F]
	$swvl_{10}\_T$	Exceedance local 10th *swvl* percentile: True or False	[T,F]
	$swvl_{02}\_T$	Exceedance local 2nd *swvl* percentile: True or False	[T,F]
	$swvl_{anom}$	Daily anomaly of *swvl* (difference to local monthly mean soil water volume)	$m^3\ m^{-3}$
Antecedent soil moisture	*swvl_30*	Sum of *swvl* for previous 30 days	$m^3\ m^{-3}$
	swvl_90	Sum of *swvl* for previous 90 days	$m^3\ m^{-3}$
	swvl_365	Sum of *swvl* for previous 365 days	$m^3\ m^{-3}$
Antecedent precipitation	*pr_30*	Sum of *pr* for previous 30 days	mm
	pr_90	Sum of *pr* for previous 90 days	mm
	pr_365	Sum of *pr* for previous 365 days	mm

Table A1: List of meteorological predictors tested in the logistic regression model (ECMWF, 2023).

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10 Data availability

Due to the data protection policies of the data provider Deutsche Bahn, the data cannot be made available.

11 Author contribution

Rike Lorenz: Data curation, Formal analysis, Methodology, Software, Visualization, Writing – original draft preparation, Writing – review & editing

Nico Becker: Conceptualization, Supervision, Project administration

Barry Gardiner: Advise & Counsel, Writing – review & editing

Marc Hanewinkel: Advise & Counsel, Supervision, Project administration, Writing – review & editing

Uwe Ulbrich: Conceptualization, Supervision, Funding acquisition, Project administration, Writing – review & editing

Benjamin Schmitz: Resources (provision of data), Data curation

12 Competing interests

Some authors are members of the editorial board of journal NHESS.

13 Declaration of AI tools used in the writing process

The generative AI ChatGPT has been used to aid the writing process for parts of this text. It was used solely to improve grammar and readability. The authors reviewed and edited all artificially generated output carefully.

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