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Comparison of vulnerability to catastrophic wind between *Abies* plantation forests and natural mixed forests in northern Japan

Junko Morimoto[1*], Kosuke Nakagawa[1], Kohei T. Takano[2,3,4], Masahiro Aiba[2], Michio Oguro[3], Yasuto Furukawa[6], Yoshio Mishima[5], Kenta Ogawa[6], Rui Ito[7], Tetsuya Takemi[8], Futoshi Nakamura[1], and Chris J. Peterson[9]

1 Graduate School of Agriculture, Hokkaido University, Japan

2 Graduate School of Life Sciences, Tohoku University, Japan

3 Forestry and Forest Products Research Institute, Japan

4 Nagano Environmental Conservation Research Institute, Japan

5 National Institute for Environmental Studies, Japan

6 Rakuno Gakuen University, Japan

7 National Research Institute for Earth Science and Disaster Resilience, Japan

8 Disaster Prevention Research Institute, Kyoto University, Japan

9 Dept. of Plant Biology, University of Georgia

*+81-11-706-2515, jmo1219@for.agr.hokudai.ac.jp

The risk of extreme events due to weather and climate change, such as winds of unprecedented magnitude, is predicted to increase throughout this century. Artificial ecosystems, such as coniferous plantation forests, can suffer irreversible deterioration due to even a slight change in environmental conditions. However, few studies have examined the effects of converting natural forests to plantations on their vulnerability to catastrophic winds. By modelling the 2004 windthrow event of Typhoon Songda in northern Japan using the random forest machine learning method, we answered two questions: do *Abies* plantation forests and natural mixed forests differ in their vulnerability to strong winds and how do winds, topography, and forest structure affect their vulnerability. Our results show that *Abies* plantation forests are more vulnerable to catastrophic wind than natural mixed forests under most conditions. However, the windthrow process was common to both types of forests, and the behaviour of wind inside the forests may determine the windthrow probability. Future management options for adapting to climate change were proposed based on these findings, including modifications of plantation forest structure to reduce windthrow risk and reconversion of plantations to natural forests.

Key words: artificial plantation forests, wind disturbance, risk management, stand structure, susceptibility to winds

Introduction

The risk of disasters caused by extreme weather and climate events is increasing. The Intergovernmental Panel on Climate Change (IPCC) projected that the risk of extreme events, such as intense heat, heavy rain, typhoons, and drought, will increase on an unprecedented scale throughout this century, although variations are observed in the predicted intensity and certainty depending on the region (IPCC, 2013).

Wind disturbance is a major natural event that is essential to sustaining the integrity of temperate forest ecosystems (Nakashizuka, 1989; Schelhaas *et al.*, 2003; Yamamoto, 1989). For example, various sizes of windthrow patches serve as available locations for the recruitment of new seedlings (Ulanova, 2000) and diversification of the age structure and species composition of forests (Mitchell, 2013). However, catastrophic disturbances that occur at a scale and severity beyond the ability of the forest to recover will degrade forest ecosystems and in turn reduce resilience against subsequent disturbance events (Munang *et al.*, 2013). Furthermore, simplified artificial ecosystems are often more vulnerable than natural ecosystems and thus may suffer from substantial deterioration due to small changes in environmental conditions or mild disturbances (Elmqvist *et al.*, 2003; Timpane-Padgham *et al.*, 2017). A plantation forest is an example of an artificial ecosystem that is commonly converted from a primary or natural forest (Brockerhoff *et al.*, 2008). Globally, the area of plantations created by seeding and planting has increased by approximately 5 million ha annually from 2005 to 2010 (FAO, 2010). Thus, globally, forest ecosystems are likely to become more vulnerable to storm damage.

Several studies suggest that the conversion to plantations (Schelhaas *et al.*, 2003) and silvicultural interventions (Albrecht *et al.*, 2012) have contributed to the spread of windthrow on a regional scale. Reported factors that regulate the vulnerability of forests to strong winds are generally wind characteristics (Nakajima *et al.*, 2009), topography (Kramer *et al.*, 2001), and forest structure (Jalkanen and Mattila, 2000; Mitchell *et al.*, 2001). However, few studies have compared the vulnerability of plantation forests relative to that of natural forests. In addition, the mechanisms by which the above factors (i.e., wind, topography, and forest structure) affect vulnerability to catastrophic winds in both types of forests remain unclear.

The windthrow disturbances that occur in plantation forests result in broken and uprooted trees and cause direct economic loss for forest managers (Nieuwenhuis and Fitzpatrick, 2002). They are also known to have many socio-economic impacts through the collapse of timber prices due to the massive influx of windthrown timber to the market (Gardiner *et al.*, 2010). If we understand the impact of conversion to plantations and the process of windthrow under current climate, we will be able to contribute to efficient forest management in the future under altered climate conditions.

In this research, we addressed the following two questions by modelling the 2004 windthrow event of Typhoon Songda in northern Japan in *Abies* plantation forests and natural mixed forests: 1) do *Abies* plantation forests and natural mixed forests have different vulnerabilities to catastrophic wind? and 2) how do winds, topography, and forest structure affect the vulnerability to storms of *Abies* plantation forests and natural mixed forests?

Based on our interpretation of the results, we propose several management options to minimize catastrophic damage to existing and future plantation forests under altered climate conditions.

Materials and methods

Study area

On September 8, 2004, the 18th typhoon of the year (Typhoon Songda) hit Hokkaido in northern Japan (annual mean temperature of 8.9°C and annual mean precipitation of 1,107 mm in Sapporo, the prefectural capital), and it disturbed 36,956 ha of forested area (Forest Research Institute in

Hokkaido, 2004). We chose 8 study sites affected by the typhoon, including 4 plantation sites and 4 natural forest sites (Figure 1, Table 1). These sites were 450 ha or more of plantation or natural forest, and the expectation was that each forest type would show a unique windthrow pattern. The species planted in the plantation sites was *Abies sachalinensis* (F. Schmidt) Mast., which is the major species for silviculture in Hokkaido. In the natural forest sites, the dominant species were *A. sachalinensis*, *Tilia japonica* (Miq.) Simonk., and *Quercus crispula* Blume, which are typical species in natural mixed forests in Hokkaido. We targeted forest compartments with steep slopes of more than 15° on average to analyse the effect of exposure to wind in mountainous regions. Our intention was to analyse the windthrow mechanisms in mountainous regions with hilltops and valleys; therefore, our study sites covered entire slope angles.

Identification of windthrow patches

Windthrow patches were identified by comparing aerial photos before (1998-2004) and after (2004-2009) Typhoon Songda using stereoscopy. We also used urgent survey data collected by Hokkaido Prefecture in the aftermath of the Songda typhoon to accurately identify the damaged area. We defined windthrow patches as grid cells of 25 m × 25 m with > 80 % canopy loss. Easy Stereo View (PHOTEC Co., Ltd.) was used for stereoscopy, and QGIS2.8.4 (QGIS Development Team, 2015) and ArcMap10.0 (Esri) were used to create shapefiles of windthrow patches.

Preparing the dataset

Six meteorological, topographical, and forest structural variables, i.e., maximum wind speed (m s^{-1}), topographic exposure index (TOPEX, Miller et al. 1987), slope angle (˚), tree density (*n* ha^{-1}), broad-leaved tree density (*n* ha^{-1}), and stand height (m), were selected and calculated (Table 2, Figure 2) to be tested for a relationship to wind disturbance. These are crucial factors identified by previous studies

(Nakajima *et al.*, 2009; Kramer *et al.*, 2001; Mitchell *et al*., 2001) focused on windthrow risk assessments.

The meteorological simulations for Typhoon Songda were conducted by Ito *et al.* (2016) with the use of a regional meteorological model, the Weather Research and Forecasting (WRF) model (Skamarock *et al.* 2008), which was dynamically downscaled for the three two-way nested domains that covered the Japanese islands and surrounding areas in 9-km grid intervals, the Japanese main islands in 3-km grid intervals, and Hokkaido in 1-km grid intervals. Typhoon Songda is considered as a worst-case scenario for wind disasters in Hokkaido (Takemi *et al.*, 2016). In the present study, the WRF model was used to simulate local-scale strong winds due to Typhoon Songda by further downscaling from a 1-km grid domain to local-scale domains in 200-m grid intervals to focus on the current study areas. We applied the two-way nesting technique between the parent (1 km) and child (200 m) domains; hence, simulations were conducted for the four domains from the 9-km grid domain down to the 200-m grid domain. Then, the maximum wind speeds from 0300 UTC on 7 September to 0000 UTC on 9 September were obtained from the time series of the surface wind speeds recorded for each grid cell in the simulation domains.

The TOPEX and slope angle were calculated using a digital elevation model with 10-m resolution (Geospatial Information Authority of Japan) by QGIS 2.8.4 (QGIS Development Team, 2015) and GRASS 6.4 (GRASS Development Team, 2012). The distance-limited TOPEX is the sum of the elevation angles (above the horizon) or depression angles (below the horizon) at specified intervals on straight lines of length that radiate out from a certain point in 8 directions. A positive TOPEX value indicates a sheltered topography, a value of 0 indicates a flat plain, and a negative value indicates an exposed topography. In our study, we set the straight line as 2000 m and the interval as 100 m based on Lanquaye-Opoku and Mitchell (2005) and Mitchell et al. (2001).

Data that were first recorded in 2003, the density of all trees, the density of broad-leaved trees only, and stand height given per forest compartment, i.e., management unit, were obtained from a forest inventory, which has been updated annually since by the Hokkaido Forest Management Bureau. For the sites without data, these variables were estimated using the field survey data by the Forest Science Centre for Northern Biosphere in Hokkaido University on representative samples of forest identified by aerial photographs. Forests identified in the aerial photographs were classified into six categories using e-Cognition software (Trimble Inc.): dense, middle, and sparse coniferous forest and dense, middle, and sparse mixed forest. Data from a standard quadrat from any forest category were universally applied to other areas in the same category.

Polygons of windthrow areas and forest structures (density of all/broad-leaved trees and stand heights), grid cells of topographic data (TOPEX and slope angle) and maximum wind speeds were divided into 25 m × 25 m cells (Figure 2).

Our datasets contained a total of 227,316 grid cells (43,409 in plantation sites + 183,907 in natural mixed forest sites) measuring 25 m × 25 m. In the *Abies* plantation sites, 1,948 cells were defined as "windthrow", and these were equivalent to 4.49 % of the total *Abies* plantation cells. In the natural mixed forest sites, 1,640 cells were defined as "windthrow", and they accounted for 0.89 % of the total natural mixed forest cells (Table 2).

Statistical analysis

Modelling approaches for assessing windthrow risk

Various models accounting for windthrow risk have been developed to facilitate forest management. The approaches are roughly divided into two categories: mechanistic modelling and empirical modelling. Recent progress in the development of mechanistic modelling has primarily occurred in Europe and North America (e.g., DuPont *et al.*, 2015; Gardiner *et al.*, 2008). The advantages of mechanistic modelling include being able to perform universal evaluations without information on real wind-damaged forests because such modelling is based on physical processes (Kamimura et al., 2015; Mitchell and Ruel, 2015). Conversely, some disadvantages of mechanistic modelling have also been noted. For example, it requires information on the material strength of each species obtained by destructive testing and wind condition information based on high-resolution simulations. Therefore, difficulties are observed when targeting forests located in complex topographies, where local simulations of wind conditions are difficult and natural mixed forests present diverse structures and various tree species (DuPont et al., 2015).

On the other hand, empirical modelling, which has been widely used for the assessment of windthrow risk, is a suitable approach to examining the relative effects of various factors on windthrow (Bonnesoeur *et al.*, 2013; Kamimura et al., 2015). One of the major empirical models, logistic regression (e.g., Albrecht et al., 2012; Hanewinkel *et al.*, 2014; Valinger and Fridman, 1997, 2011), has been commonly used because it is effective in analysing the factors that influence wind damage, and this modelling process can be performed without choosing a target scale, from a single tree level to a regional level. The weakness of the logistic regression model is, however, that its ability to predict wind damage decreases when there is a complicated nonlinear pattern between the variables. The random forest (RF) (Breiman, 2001) machine learning method is a powerful tool for variable selection, and it is particularly suited to handling prediction problems that include nonlinear relationships between predictor and response variables and complex interactions between variables (Sandri and Zuccolotto, 2006; Strobl *et al.*, 2007). RF combines many classification trees to produce more accurate classifications. The by-products of the RF calculations include measures of variable importance and similarity among data points that may be used for clustering, multidimensional scaling, graphical representation, and missing value imputation (Cutler *et al.*, 2007). This method permits the development of a flexible model with high-dimensional interactions among explanatory variables, nonlinear responses and high prediction performance without overfitting. Ecological applications of RF have shown its effectiveness on habitat analysis (Garzón *et al.*, 2006; Prasad *et al.*, 2006) and windthrow risk assessment (Seidl *et al.*, 2011).

We used empirical modelling to pursue our objectives, i.e., identifying the factors that cause wind damage in natural mixed forests with various tree species and in *Abies* plantations in complex topographies where precise wind conditions are hard to simulate. Then, we selected RF to model the windthrow probability based on our dataset, which includes many variables with possibly complex nonlinear relationships.

Windthrow modelling by RF and model validation

We generated a subsample to avoid overfitting the model to large forest compartments by applying the RF method to model windthrow occurrence. First, we removed forest compartments with less than 30 grid cells. Next, we generated a subsample from the data and maintained a virtually identical windthrow ratio (number of windthrow cells / total number of cells) in each forest compartment.

The subsequent windthrow model used the resultant subsample (n = 46,950 grid cells). The forest type (plantation or natural) and study sites (as a nominal variable, n = 8) were incorporated into the model along with six continuous variables (maximum wind speed, TOPEX, slope angle, density of all trees, density of broad-leaved trees, and tree height). The plot matrix of the explanatory variables area is shown in Figure S1. As hyperparameters (i.e., parameters of model construction) of RF, *ntree* (the number of decision trees to grow) was set to 500 and *mtry* (the number of variables randomly sampled as candidates at each split) was set to 3. The variable importance was evaluated as the mean decrease in accuracy after permutations of each variable. The variables with higher "mean decrease in accuracy" values are more important for the classification by RF. When implementing RF models and calculating the importance of explanatory variables, variable selection is biased in favour of explanatory variables, with more potential cutpoints (Strobl *et al.*, 2009). To avoid this variable selection bias, the *cforest* function in the *party* package (Hothorn et al., 2006; Strobl *et al.*, 2008; Strobl et al., 2007) of R was used in the RF model. We also represented partial dependence plots (Friedman 2001) for six continuous variables that showed the dependence of the probability of occurrence on one predictor variable after averaging out the effects of the other predictor variables in the model. We depicted them for plantation and natural mixed forest separately as the calculated result of the 2-way marginal effect of windthrow prediction by RF.

A 10-fold cross-validation was conducted, and several model performance indices were calculated by the R *cv.models* package (Oguro 2016). A threshold value of windthrow occurrence was determined with the *coords* function in the R *pROC* package (Robin *et al.*, 2011). This threshold is based on Youden's J statistics (sensitivity + specificity –1: Youden, 1950) and divides windthrow occurrence by non-occurrence. The performance indices were accuracy, sensitivity, specificity, positive predictive value, negative predictive value, Kappa, mean squared sensitivity error, informedness (as Youden's J statistics; Powers, 2011), the Matthews correlation coefficient (MCC; Matthews, 1975), and AUC (area under the curve) of the receiver operating characteristic (ROC; Swets, 1973). True positive represents a case where both the actual and predicted values are positive. False positive represents a case where the actual value is negative, but the prediction is positive. False negative represents a case where the actual value is positive but the prediction is negative. True negative represents a case where both the actual and predicted values are negative. These performance indices were then compared to indices from previous studies.

The analyses were conducted with R version 3.4.1 (R Core Team, 2017).

Results

Modelling and validation of windthrow probability

Most of the model performance indices (accuracy = 0.88, sensitivity = 0.84, specificity = 0.88, positive predictive value = 0.11, negative predictive value = 0.997, Kappa = 0.17, informedness = 0.72, MCC = 0.28, and AUC = 0.93) were reasonably high compared with that of previous studies (Table S1).

Prediction of windthrow probability

Figure 3 shows the importance of the predictor variables from RF classifications used for predicting windthrow. Conspicuously significant variables related to windthrow were the study site and stand height, followed by the maximum wind speed, tree density, and forest type. The influence of slope angle, broad-leaved tree density, and TOPEX were smaller than that of other factors.

Figure 4 (a)-(f) shows the partial dependence plots for continuous predictor variables for RF predictions of the windthrow occurrence in plantations and natural mixed forests. In most of the domain, the windthrow probability of plantations was higher than that of natural mixed forests at the same value of each explanatory variable. In plantations, the windthrow probability monotonically increased with increasing maximum wind speed and tree density but monotonically decreased with increasing TOPEX, slope angle, and broad-leaved tree density. Stand height showed a high probability of windthrow in the range from 8 m to 18 m. The behaviours of partial plots in the plantations for most variables except wind speed and broad-leaved tree density were nearly consistent with that of the natural mixed forests.

Discussion

Abies plantations showed consistently higher windthrow ratios than natural mixed forests under all conditions (Figure 4), which confirms that *Abies* plantations are more vulnerable to catastrophic winds than natural mixed forests. However, the effects of most factors on windthrow were not different between the *Abies* plantations and natural mixed forests, indicating that these factors influence the risk of wind damage similarly in both types of forest (Figure 4).

The stand height and density of all trees, which are components of the forest structure, were major influential factors for wind damage along with maximum wind speed (Figure 3), suggesting that the windthrow probability is highly dependent on the behaviour of wind inside the forests. In general, the greatest differences in forest structure between plantations and natural forests are the age and size distribution of trees and the presence of previous gaps created in the canopy cover. After reviewing 119 reports on wind damage, Everham and Brokaw (1996) noted that even-aged stands generally had greater damage than uneven-aged stands and uneven-aged stands were often older, composed of species mixes, and often of natural rather than planted origin (Mitchell, 2013). The vulnerability of plantations to catastrophic winds appeared to be due to their even-aged size structure (Everham and Brokaw, 1996) according to the authors' insights. Based on empirical data from silvicultural experiments, Pukkala et al. (2016) analysed the probability of wind damage to the inner portions of stands that had experienced several storm events. They suggested that stand structures with a range of tree sizes can decrease the probability of windthrow because they decrease wind speed in the inner parts of stands. Previous gaps created by thinning also affect damage susceptibility. Gardiner's experiments (1997) on the effects of different thinning patterns on the subsequent stability of trees showed that the risk of destabilization increases significantly with gap size because the loading on the exposed trees is increased with gap size.

Accordingly, plantations with even-sized structures and thinning gaps enable strong winds to enter and pass through the forests, which might easily cause swaying and overturning of trees (Schütz *et al.*, 2006). Our data on the behaviour of windthrow probability in relation to stand height and tree density also support this finding. *Abies* plantations in the range from ca. 8 to 18 m stand height or higher densities (> 1,200/ha), which are at high risk of windthrow (Figure 4 (d) (f)), generally comprise a single canopy and are at stand ages that experience occasional thinning operations (Abe, 1989). The even-sized structure of *Abies* plantations with thinning gaps might allow strong winds to penetrate the forest without losing speed, therefore leading to high windthrow probability.

The slope angle and TOPEX, which are topographic factors, had limited effects on wind damage in our study (Figure 3), although previous studies have shown how wind direction and topography interact to determine fine-scale variability in the location of damage (Foster and Boose, 1992; Mitchell, 2013). When the valley line and wind direction are parallel, the wind converges along the terrain and damage occurs along the valley floor (Ruel *et al.*, 1998). When the wind direction is perpendicular to the valley line, the windthrow occurs on the ridge since valley floors are sheltered (Everham and Brokaw, 1996). A higher probability of windthrow in locations with a gentle slope angle and exposed topography (Figure 4 (b) (c)) mean that the forests on the ridges were highly disturbed in our case. Therefore, if plantations on ridges have the highest risk of windthrow, it may be possible to reduce risk by selecting mountain hillsides for planting.

A possible explanation for the study site being the most influential factor on windthrow is that the wind direction, soil type, and disturbance history are unique to each site. Another possible reason is the biased distribution of the natural mixed forest study sites towards the west (Figure 1), which was inevitable because natural forests that meet the study conditions are primarily distributed in the western part of Hokkaido and are not uniformly distributed. Additional efforts to mitigate the effect of the biased distribution of study sites, such as targeting other typhoon events that took different paths or further developing the analysis method, will be necessary for more universal modelling in all regions.

Implications for management

The importance of stand structure in windthrow vulnerability demonstrates the importance of appropriate forest management even in mountainous areas. We might decrease the risk of windthrow by refraining from generating large gaps, performing thinning and increasing the structural complexity of plantations. Technical developments making those management options possible are needed. Given the situation in Japan, where forestry labour is declining and plantation forests are difficult to manage (Kawasaki, 2016), reconversion of plantations to a more natural forest structure is an option for forest management. The plantations in locations with high windthrow risk should be prioritized in the future for natural forest restoration from the viewpoint of efficient forest management because the risk of extreme typhoons is expected to increase throughout this century (Yoshida et al, 2017). Our model is based on the effects of only one typhoon in a relatively small area, thus limiting its applicability to other situations. The relationships between windthrow occurrences and their explanatory variables are complex and differ in response to numerous factors, including typhoon tracks, wind direction against slopes, and forest types. Therefore, additional case studies should be performed to better understand the trends in climate-change effects on windthrow risk in Japan.

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Conflict of interest statement

No conflicts of interest are declared.

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Table and figure captions

Figure 1 Typhoon track (left) and study site locations (right). Hokkaido is the area enclosed by a dotted line, which includes plantation forest sites (□) and natural forest sites (■).

Figure 2 Preparing the dataset.

Figure 3 Variable importance plots for predictor variables from random forest (RF) classifications for predicting windthrow. Abbreviations: Forest type, artificial plantation or natural forest.

Figure 4 Partial dependence plots for selected predictor variables for random forest (RF) predictions of the windthrow occurrence. (a) Maximum wind speed (m s^{-1}), (b) TOPEX, (c) slope angle (˚), (d) tree density (*n* ha^{-1}), (e) broad-leaved tree density (*n* ha^{-1}), and (f) stand height (m). Each plot is drawn only in a range or ranges of the subsample used for modelling.

Table 1 Annual mean temperature, precipitation, and soil type in each site (statistics from 1988 to 2010).

Table 2 Properties of the study sites.

Supplementary Table

Table S1 Model performance indices of the present study and previous studies. No.0 is the reference case that all samples are correctly estimated by a model.

Supplementary Figure

Figure S1 Plot matrix of the eight explanatory variables. The figure was created with the *ggpairs* function of *ggplot2* package (Wickham, 2009) in R. Colours (magenta or cyan) represent the forest types (a natural forest or an artificial plantation). Numbers in the right triangular matrix represent the Pearson's correlation coefficient. The density plot (for a numerical variable) or ratio (for a categorical variable) of each variable is shown on the diagonal. Either a histogram or a scatterplot and linear regression line are shown below the diagonal for each variable pair. Abbreviations: w_max, maximum wind speed (m s^{-1}); topex, TOPEX; slope, slope angle (°); density, tree density (n ha^{-1}); bl_dens, broad-leaved tree density (n ha^{-1}); height, stand height (m); Forest_type, artificial plantation or natural forest; region, study sites.

Table 1 Annual mean temperature, precipitation, and soil type in each site (statistics from 1988 to 2010).

Forest type	Study site		Annual mean temperature (° C)	Annual mean precipitation (mm)	Soil type
Plantation forests	P1	Ohmu	5.7	865	brown forest soil
	P2	Bifuka	5.5	1,143	
	P3	Niseko	7.6	1,203	brown forest soil/andosol
	P4	Hakodate	8.4	1,448	
Natural forests	N1	Nakagawa	5.5	1,225	brown forest soil
	N2	Abashiri	4.8	702	
	N3	Tsubetsu	5.9	790	andosol
	N4	Tokachi	3.7	1,315	

Table 2 Properties of the study sites.

Study site	Total number of grid cells	Percentage of grid cells of windthrow (%)	WIND			TOPEX			Slope			Density			BL_Density			Height		
			mean	min	max	mean	min	max	mean	min	max	mean	min	max	mean	min	max	mean	min	max
P1	9,058	2.8	28	14	44	64	−18	179	19	2	48	538	0	2240	46	0	700	11	4	22
P2	13,635	1.0	25	16	44	43	−29	140	17	1	46	531	60	2100	108	0	1000	11	4	21
P3	9,742	10.4	34	22	48	75	−5	174	21	3	48	559	100	2450	69	0	850	10	3	21
P4	7,218	5.5	36	22	53	79	−16	214	23	2	56	887	110	2880	10	0	600	10	4	21
N1	42,059	0.1	31	17	51	65	−47	203	21	0	54	244	0	323	0	0	1	20	0	22
N2	11,171	0.4	36	17	66	78	−69	276	22	1	58	1256	0	1732	675	0	1011	21	0	23
N3	67,953	1.0	23	10	43	63	−47	227	20	0	57	629	0	1800	300	0	1000	16	14	18
N4	39,667	2.1	29	11	67	89	−72	208	23	0	60	1681	0	6600	862	0	3800	13	0	17

WIND, maximum wind speed (m s^{-1}); TOPEX, topographic exposure index; Slope, slope angle (°); Density, tree density (n ha^{-1}); BL_density, broad-leaved tree density (n ha^{-1}); Height, stand height (m)

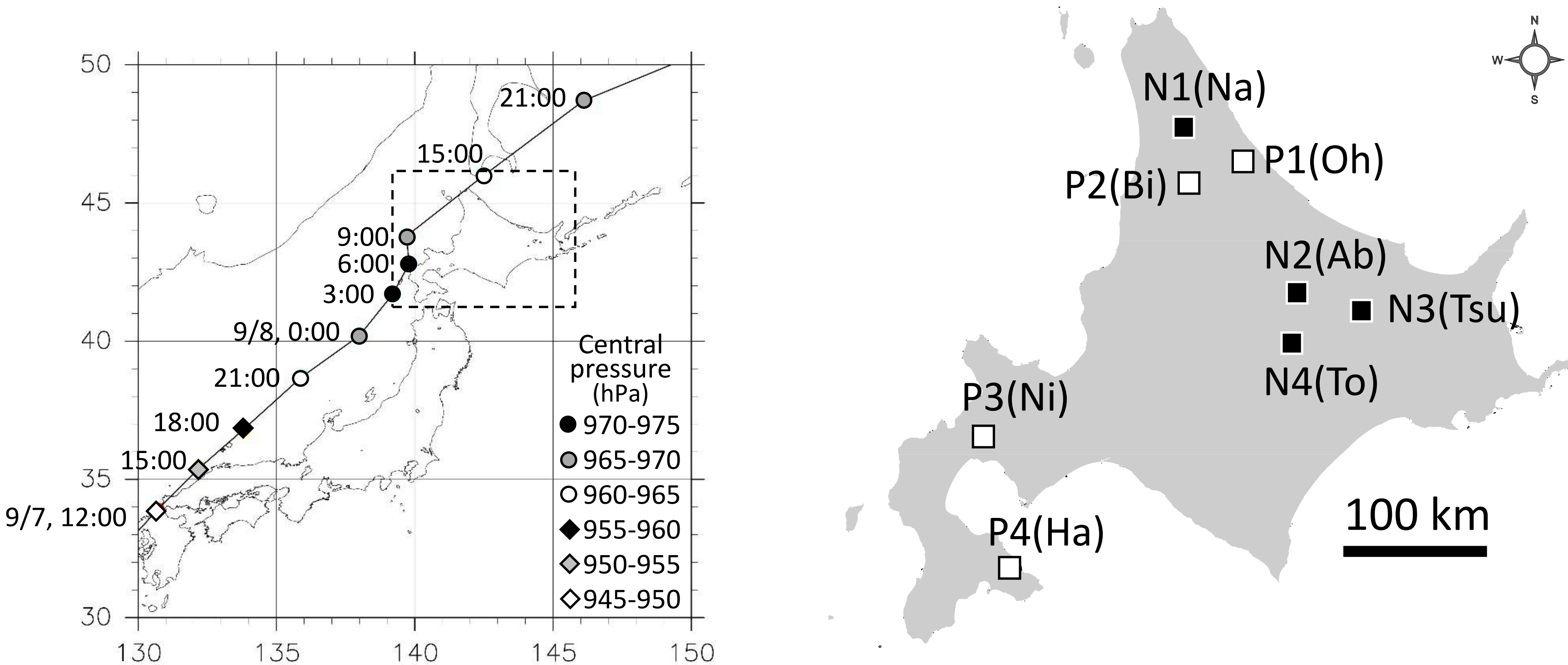
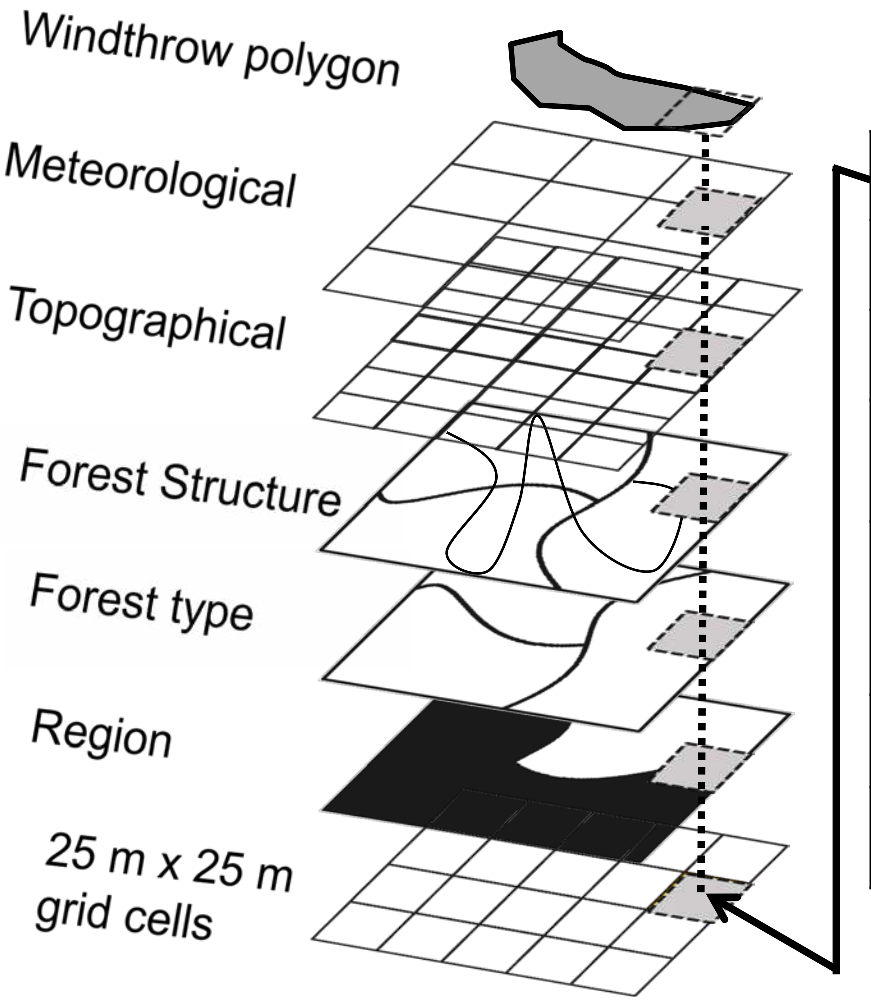
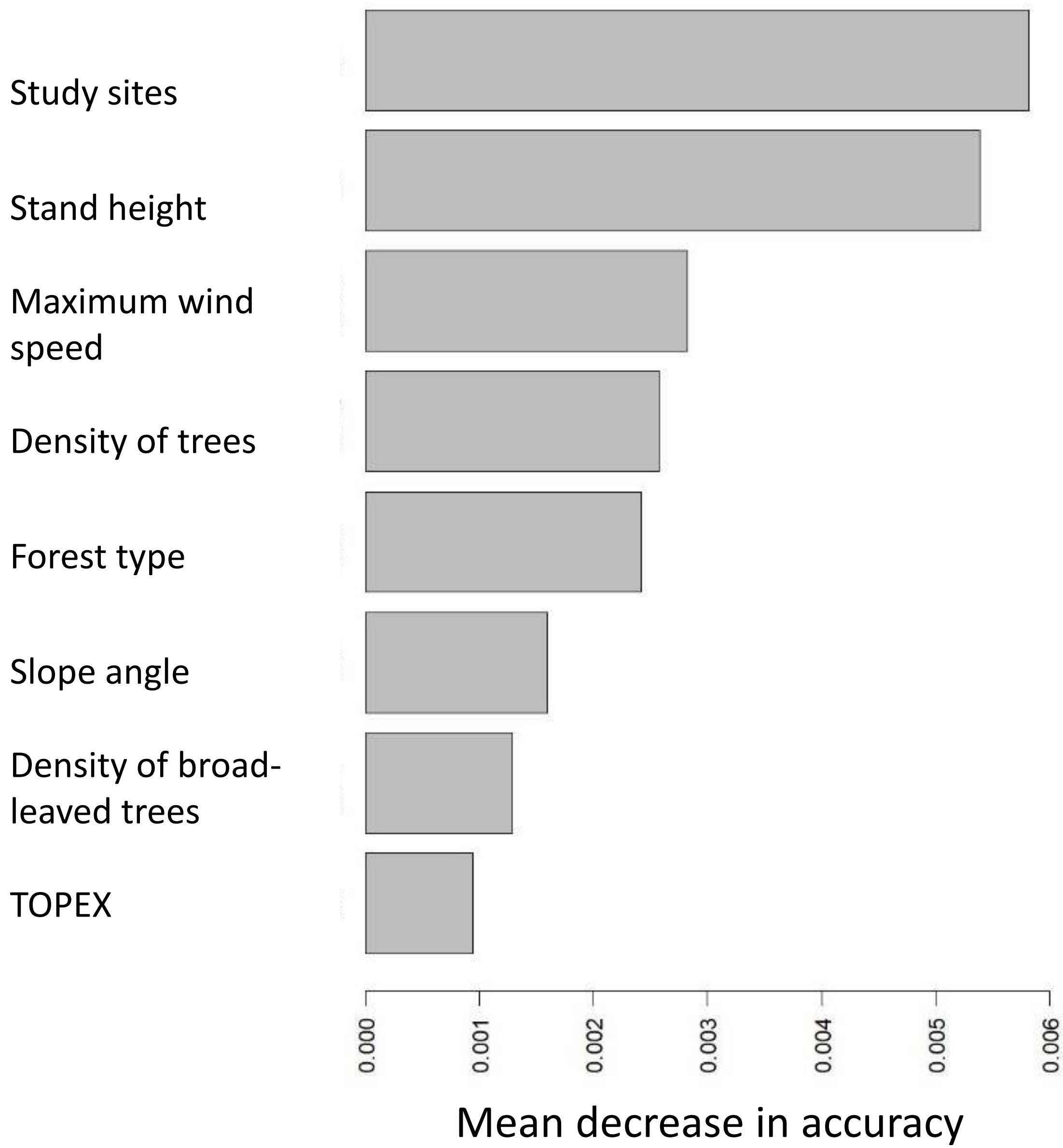


Fig. 1 – Typhoon track (left) and study site locations (right). Hokkaido is the area enclosed by a dotted line, which includes plantation forest sites (□) and natural forest sites (■).



Category	Variables
Windthrow	- Damaged or not damaged
Meteorological	- Maximum wind speed (m s^{-1})
Topographical	- TOPEX - Slope angle (°)
Forest structure	- Tree density (*n* ha^{-1}) - Broad leaved tree density (*n* ha^{-1}) - Stand height (m)
Forest type	- Plantation or natural forest
Region	- P1, P2, P3, P4, N1, N2, N3, N4

Fig. 2– Preparing the dataset



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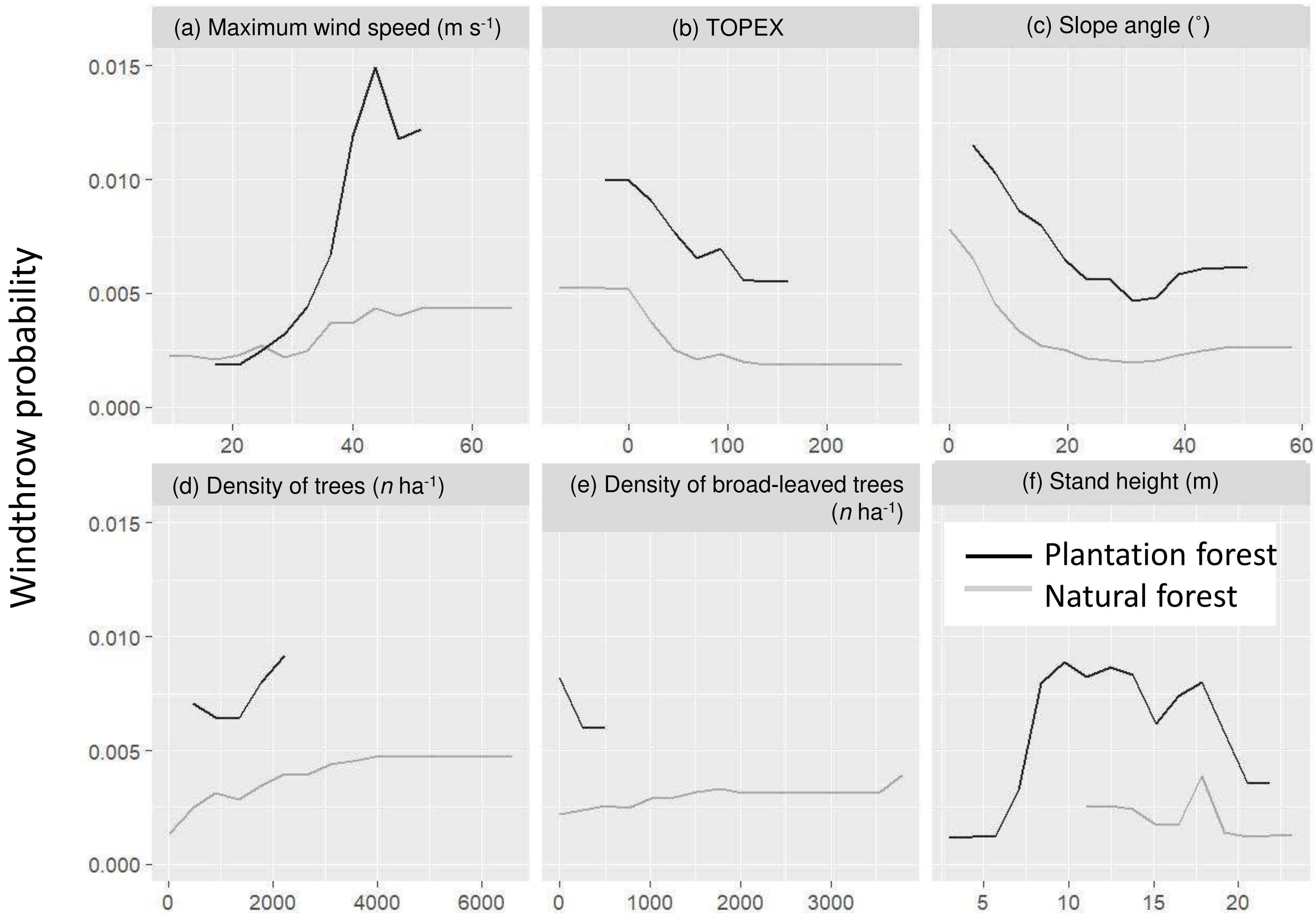
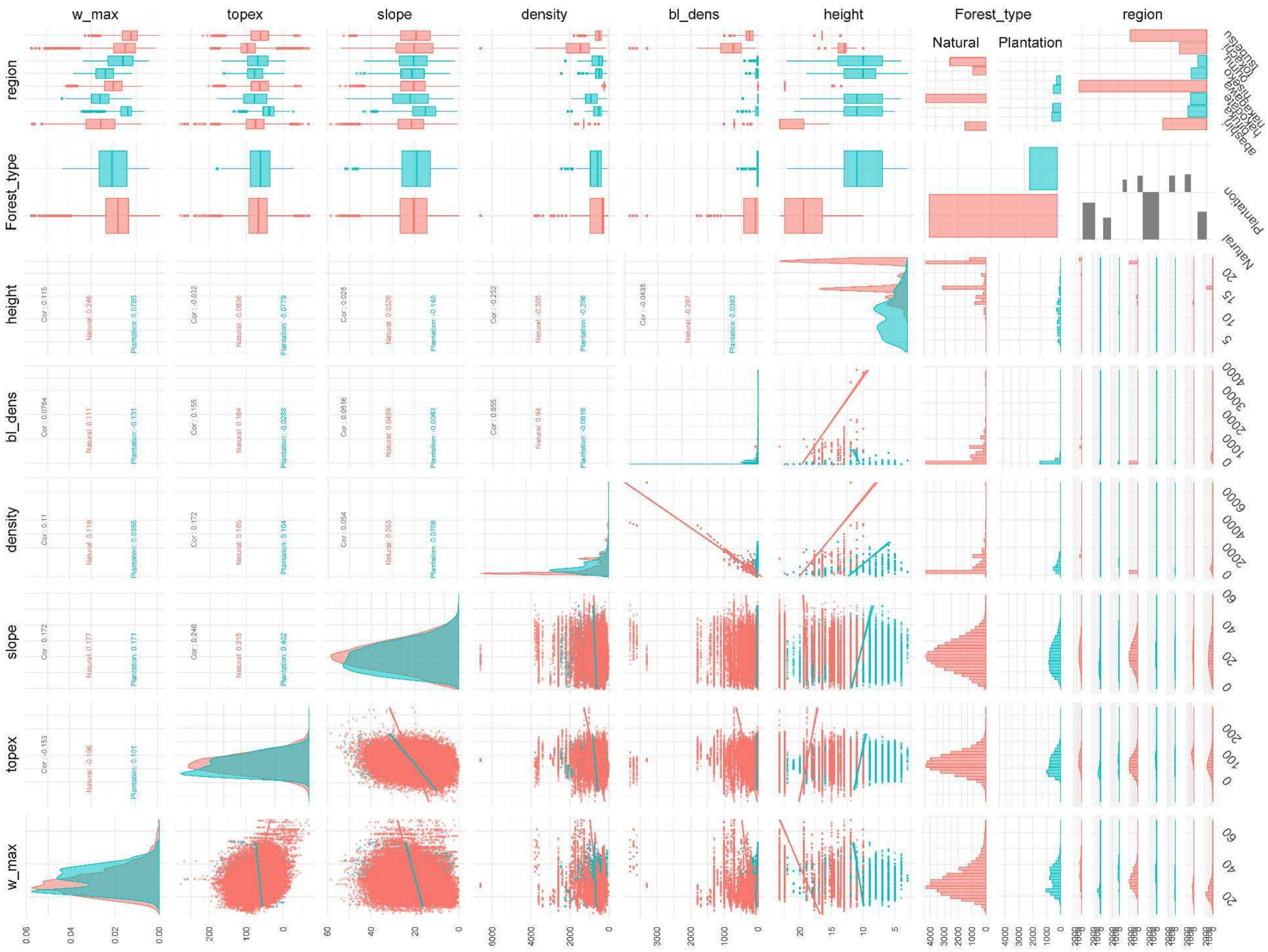


Fig. 4 - Partial dependence plots for selected predictor variables for random forest predictions of the windthrow occurrence. (a) maximum wind speed (m s^{-1}), (b) TOPEX, (c) slope angle (˚), (d) density of trees (*n* ha^{-1}), (e) density of broad-leaved trees (*n* ha^{-1}), and (f) stand height (m). Each plot is drawn only in a range or ranges of the subsample, which was used for modeling.

Table S1 : Model performance indices of the present study and previous studies. No.0 is the reference case that all samples are correctly estimated by a model.

No.	Literature	Modeling method	Cross validation (CV) method	Total N	True positive (a)	False positive (b)	False negative (c)	True negative (d)	Prevalence = (a+c)/N	Cutoff value	Model performance metrics									
											Correct classification (accuracy) = (a+d)/N	Sensitivity = a/(a+c)	Specificity = d/(b+d)	Positive Predictive Value (PPV) = a/(a+b)	Negative Predictive Value (NPV) = d/(c+d)	Kappa	Mean squared sensitivity error (MSSE) = 0.5((1−Sensitivity)^2+(1−Specificity)^2)	Informedness = Sensitivity + Specificity −1	Matthews correlation coefficient (MCC)	Areas under the curve (AUC) of ROC
0	The reference			100	50	0	0	50	0.50		1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00	
1	The present study	Random forest	10-fold CV	46950	672	5489	128	40661	0.02	0.03	0.88	0.84	0.88	0.11	0.997	0.17	0.02	0.72	0.28	0.93
2	Valinger & Fridman (1997)	Stepwise logistic regression with logit function	Temporary plots from the same county	429	12	298	3	116	0.03	0.025	0.30	0.80	0.28	0.04	0.97	0.01	0.28	0.08	0.03	
3			Permanent plots from the county of Kalmar	138	3	42	4	89	0.05		0.67	0.43	0.68	0.07	0.96	0.03	0.21	0.11	0.05	
4			Temporary plots from the same county	429	8	110	7	304	0.03		0.73	0.53	0.73	0.07	0.98	0.06	0.14	0.27	0.11	
5			Permanent plots from the county of Kalmar	138	7	131	0	0	0.05		0.05	1.00	0.00	0.05	NA	0.00	0.50	0.00	NA	
6			Temporary plots from the same county	429	9	139	6	275	0.03		0.66	0.60	0.66	0.06	0.98	0.05	0.14	0.26	0.10	
7			Permanent plots from the county of Kalmar	138	5	52	2	79	0.05		0.61	0.71	0.60	0.09	0.98	0.07	0.12	0.32	0.14	
8	Mitchell et al. (2001) *Forest*	Logistic regression	60% train 40% test	1200	145	194	123	738	0.22		0.74	0.54	0.79	0.43	0.86	0.30	0.13	0.33	0.31	
9					95	207	77	821	0.14		0.76	0.55	0.80	0.31	0.91	0.27	0.12	0.35	0.28	
10	Kramer et al. (2001)	Spatially explicit logistic regression	Zarembo Island (external validation)							0.21	0.72									0.44
11	Dobbertin (2002)	Classification and regression trees (CART)	Storm Lothar	422	27	18	129	248	0.37		0.65	0.17	0.93	0.60	0.66	0.12	0.34	0.11	0.16	
12			Storm Lothar	422	26	15	130	251	0.37		0.66	0.17	0.94	0.63	0.66	0.13	0.35	0.11	0.18	
13			Storm Vivian	409	27	62	41	279	0.17		0.75	0.40	0.82	0.30	0.87	0.19	0.20	0.22	0.19	
14			Storm Vivian	409	34	88	34	253	0.17		0.70	0.50	0.74	0.28	0.88	0.18	0.16	0.24	0.20	
15	Lindemann & Baker (2002)	Classification and regression trees (CART)									0.79									
16											0.83									
17											0.85									
18		Stepwise logistic regression									0.81									
19	Peterson (2004)	Computer simulation based on coefficients from logistic regression	Test subplots or trees in five sites	3180 trees							0.68-0.90									
20	Hanewinkel et al. (2004)	Newral network	4-fold CV	1600 stands					0.29	0.50	~0.75	~0.85	>0.40				0.19	~0.25		
21		Logistic regression									0.75	0.89	0.39				0.19	0.29		
22		Newral network							0.19		<0.80	~0.90	~0.30				0.25	~0.20		
23		Logistic regression									0.81	0.96	0.18				0.34	0.14		
24	Hanewinkel (2005)	Newral network		149 divisions					0.40		0.76	0.81	0.82				0.03	0.63		
25		Logistic regression									0.70	0.50	0.86				0.14	0.36		
26		Newral network							0.23		0.73	0.67	0.75				0.09	0.42		
27		Logistic regression									0.84	0.67	0.93				0.06	0.60		
28	Scott & Mitchell (2005) *Forest*	Stepwise logistic regression	2-fold CV	1215 trees from 234 plots					0.60	0.20	0.72									
29											0.74									
32	Schindler et al. (2009)	Weights of evidence (WofE)	338 training points from the 617 wind-damaged areas																	0.78
33		Multivariate logistic regression																		0.79
34	Schindler et al. (2012)	Weights of evidence (WofE)																		0.73
35	Bonnesoeur et al. (2013)	Generalized linear mixed models (GLMM)	Leave-one-out cross validation	384 trees from 51 plots																0.69-0.73
36		Weibull-based model																		0.62-0.71
37	Pasztor et al. (2015)	Binomial generalized linear mixed model (GLMM)									0.90	0.26	0.95							



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