



HOKKAIDO UNIVERSITY

Title	Comparison of vulnerability to catastrophic wind between Abies plantation forests and natural mixed forests in northern Japan
Author(s)	Morimoto, Junko; Nakagawa, Kosuke; Takano, Kohei T. et al.
Citation	Forestry, 92(4), 436-443 https://doi.org/10.1093/forestry/cpy045
Issue Date	2019-10
Doc URL	https://hdl.handle.net/2115/79388
Rights	This is a pre-copyedited, author-produced version of an article accepted for publication in Forestry: An International Journal of Forest Research following peer review. The version of record "Comparison of vulnerability to catastrophic wind between Abies plantation forests and natural mixed forests in northern Japan" Volume 92, Issue 4, October 2019, Pages 436-443 is available online at: https://doi.org/10.1093/forestry/cpy045
Type	journal article
File Information	Forestry-2017-190-R3_HUSCAP.pdf



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

**Junko Morimoto^{1*}, Kosuke Nakagawa¹, Kohei T. Takano^{2,3,4}, Masahiro Aiba², Michio
Oguro³, Yasuto Furukawa⁶, Yoshio Mishima⁵, Kenta Ogawa⁶, Rui Ito⁷, Tetsuya
Takemi⁸, Futoshi Nakamura¹, and Chris J. Peterson⁹**

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

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

40

41 **Introduction**

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

47 Wind disturbance is a major natural event that is essential to sustaining the integrity of temperate
48 forest ecosystems (Nakashizuka, 1989; Schelhaas *et al.*, 2003; Yamamoto, 1989). For example, various
49 sizes of windthrow patches serve as available locations for the recruitment of new seedlings (Ulanova,
50 2000) and diversification of the age structure and species composition of forests (Mitchell, 2013).
51 However, catastrophic disturbances that occur at a scale and severity beyond the ability of the forest
52 to recover will degrade forest ecosystems and in turn reduce resilience against subsequent disturbance
53 events (Munang *et al.*, 2013). Furthermore, simplified artificial ecosystems are often more vulnerable
54 than natural ecosystems and thus may suffer from substantial deterioration due to small changes in
55 environmental conditions or mild disturbances (Elmqvist *et al.*, 2003; Timpane-Padgham *et al.*, 2017).
56 A plantation forest is an example of an artificial ecosystem that is commonly converted from a primary
57 or natural forest (Brockerhoff *et al.*, 2008). Globally, the area of plantations created by seeding and
58 planting has increased by approximately 5 million ha annually from 2005 to 2010 (FAO, 2010). Thus,
59 globally, forest ecosystems are likely to become more vulnerable to storm damage.

60 Several studies suggest that the conversion to plantations (Schelhaas *et al.*, 2003) and silvicultural
61 interventions (Albrecht *et al.*, 2012) have contributed to the spread of windthrow on a regional scale.
62 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 ($^{\circ}$), tree density ($n \text{ ha}^{-1}$), broad-leaved tree density ($n \text{ ha}^{-1}$), 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 ($> 1,200/\text{ha}$), 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.

Funding

This work was supported by JSPS KAKENHI Grant Numbers 24580034 and 17H01516 awarded to J.M. and the Programme for Risk Information on Climate Change (SOUSEI Programme), the Social Implementation Programme on Climate Change Adaptation Technology (SI-CAT), and the GRENE-ei Programme by the Ministry of Education, Culture, Sports, Science, and Technology, Japan (MEXT).

Acknowledgements

We thank the Hokkaido Regional Forest Office of the Forestry Agency and the Hokkaido government's Bureau of Forestry for providing forest registry data. We also thank Prof. Hideaki Shibata, Prof. Tohru Nakashizuka, Prof. Toshiya Yoshida, Dr. Nobuko Saigusa, and Dr. Masato Hayashi for their discussion about typhoon disturbances on forest ecosystems. We appreciate the editors and reviewers for providing valuable suggestions for improving the manuscript.

Conflict of interest statement

No conflicts of interest are declared.

References

Abe, N. 1989 Studies on the system for thinning of *Abies sachalinensis* Mast. planted forest. *Bulletin of the Hokkaido Forest Experiment Station* (No. 26), 1-95.

- 329 Albrecht, A., Kohnle, U., Hanewinkel, M. and Bauhus, J. 2012 Storm damage of Douglas-fir
330 unexpectedly high compared to Norway spruce. *Annals of Forest Science*, **70** (2), 195-
331 207.
- 332 Bonnesoeur, V., Fournier, M., Bock, J., Badeau, V., Fortin, M. and Colin, F. 2013 Improving
333 statistical windthrow modeling of 2 *Fagus sylvatica* stand structures through
334 mechanical analysis. *Forest Ecology and Management*, **289** (Supplement C), 535-543.
- 335 Breiman, L. 2001 Random Forests. *Machine Learning*, **45** (1), 5-32.
- 336 Brockerhoff, E.G., Jactel, H., Parrotta, J.A., Quine, C.P. and Sayer, J. 2008 Plantation forests and
337 biodiversity: oxymoron or opportunity? *Biodiversity and Conservation*, **17** (5), 925-951.
- 338 Cutler, D.R., Edwards, T.C., Beard, K.H., Cutler, A., Hess, K.T., Gibson, J. *et al.* 2007 Random
339 forests for classification in ecology. *Ecology*, **88** (11), 2783-2792.
- 340 Dupont, S., Ikonen, V.-P., Väisänen, H. and Peltola, H. 2015 Predicting tree damage in
341 fragmented landscapes using a wind risk model coupled with an airflow model.
342 *Canadian Journal of Forest Research*, **45** (8), 1065-1076.
- 343 Elmqvist, T., Folke, C., Nyström, M., Peterson, G., Bengtsson, J., Walker, B. and Norberg, J. 2003
344 Response diversity, ecosystem change, and resilience. *Frontiers in Ecology and the*
345 *Environment*, **1**, 488–494.
- 346 Everham, E.M. and Brokaw, N.V.L. 1996 Forest damage and recovery from catastrophic wind.
347 *The Botanical Review*, **62** (2), 113-185.
- 348 FAO. 2010 Global Forest Resources Assessment 2010 Main report. Food and agriculture
349 organization of the United Nations Rome, Italy, p. 340.
- 350 Forest Research Institute in Hokkaido. 2004 Preliminary report on damage caused by Typhoon
351 No.18 (Summary),
352 <https://www.hro.or.jp/list/forest/research/fri/kanko/fukyu/pdf/cd-t18sokuhou.pdf>.
- 353 Foster, D.R. and Boose, E.R. 1992 Patterns of Forest Damage Resulting from Catastrophic Wind
354 in Central New England, USA. *Journal of Ecology*, **80** (1), 79-98.

355 Friedman, J.H. 2001 Greedy Function Approximation: A Gradient Boosting Machine. *The*
356 *Annals of Statistics*, **29** (5), 1189-1232.

357 Gardiner, B., Blennow, K., Carnus, J.-M., Fleischer, P., Ingemarsson, F., Landmann, G. *et al.*
358 2010 Destructive storms in European forests: past and forthcoming impacts, p. 138.

359 Gardiner, B., Byrne, K., Hale, S., Kamimura, K., Mitchell, S.J., Peltola, H. *et al.* 2008 A review of
360 mechanistic modelling of wind damage risk to forests. *Forestry*, **81** (3), 447-463.

361 Gardiner, B.A., Stacey, G.R., Belcher, R.E. and Wood, C.J. 1997 Field and wind tunnel
362 assessments of the implications of respacing and thinning for tree stability. *Forestry:*
363 *An International Journal of Forest Research*, **70** (3), 233-252.

364 Garzón, M.B., Blazek, R., Neteler, M., Dios, R.S.d., Ollero, H.S. and Furlanello, C. 2006
365 Predicting habitat suitability with machine learning models: The potential area of *Pinus*
366 *syvestris* L. in the Iberian Peninsula. *Ecological Modelling*, **197** (3), 383-393.

367 GRASS Development Team. 2012 Geographic Resources Analysis Support System (GRASS 6.4)
368 Programmer's Manual. O.S.G.F. Project. (ed.).

369 Wickham., H. 2009 *Elegant Graphics for Data Analysis*. Springer: New York, NY.

370 Hanewinkel, M., Kuhn, T., Bugmann, H., Lanz, A. and Brang, P. 2014 Vulnerability of uneven-
371 aged forests to storm damage. *Forestry*, **87** (4), 525-534.

372 Hothorn, T., Bühlmann, P., Dudoit, S., Molinaro, A. and Van Der Laan, M.J. 2006 Survival
373 ensembles. *Biostatistics*, **7** (3), 355-373.

374 IPCC. 2013 *Climate Change 2013 The Physical Science Basis Working Group I Contribution to*
375 *the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*.
376 Cambridge University Press: Cambridge, United Kingdom and New York, NY, USA, 1535
377 p.

378 Ito, R.T., Tetsuya; Arakawa, Osamu. 2016 A Possible Reduction in the Severity of Typhoon
379 Wind in the Northern Part of Japan under Global Warming: A Case Study. *SOLA*, **12**,
380 100-105.

- 381 Jalkanen, A. and Mattila, U. 2000 Logistic regression models for wind and snow damage in
382 northern Finland based on the National Forest Inventory data. *Forest Ecology and*
383 *Management*, **135** (1), 315-330.
- 384 Kamimura, K., Gardiner, B., Dupont, S., Guyon, D. and Meredieu, C. 2015 Mechanistic and
385 statistical approaches to predicting wind damage to individual maritime pine (*Pinus*
386 *pinaster*) trees in forests. *Canadian Journal of Forest Research*, **46** (1), 88-100.
- 387 Kawasaki, A. 2016 In lieu of summary of a special feature: silviculture workers now. *Shinrin*
388 *Kagaku*, **78**, 2-4. (in Japanese)
- 389 Kramer, M.G., Hansen, A.J., Taper, M.L. and Kissinger, E.J. 2001 Abiotic Controls on Long-Term
390 Windthrow Disturbance and Temperate Rain Forest Dynamics in Southeast Alaska.
391 *Ecology*, **82** (10), 2749-2768.
- 392 Languaye-Opoku, N. and Mitchell, S.J. 2005 Portability of stand-level empirical windthrow risk
393 models. *Forest Ecology and Management*, **216** (1-3), 134-148.
- 394 Matthews, B.W. 1975 Comparison of the predicted and observed secondary structure of T4
395 phage lysozyme. *Biochimica et Biophysica Acta (BBA) - Protein Structure*, **405** (2), 442-
396 451.
- 397 Miller, K.F., Quine, C.P. and Hunt, J. 1987 The Assessment of Wind Exposure for Forestry in
398 Upland Britain. *Forestry: An International Journal of Forest Research*, **60** (2), 179-192.
- 399 Mitchell, S.J. 2013 Wind as a natural disturbance agent in forests: a synthesis. *Forestry*, **86** (2),
400 147-157.
- 401 Mitchell, S.J., Hailemariam, T. and Kulis, Y. 2001 Empirical modeling of cutblock edge
402 windthrow risk on Vancouver Island, Canada, using stand level information. *Forest*
403 *Ecology and Management*, **154** (1), 117-130.
- 404 Mitchell, S.J. and Ruel, J.-C. 2015 Modeling Windthrow at Stand and Landscape Scales. In
405 *Simulation Modeling of Forest Landscape Disturbances*. A.H. Perera, B.R. Sturtevant
406 and L.J. Buse (eds.), Springer International Publishing, Cham, pp. 17-43.

407 Munang, R., Thiaw, I., Alverson, K., Mumba, M., Liu, J. and Rivington, M. 2013 Climate change
408 and Ecosystem-based Adaptation: a new pragmatic approach to buffering climate
409 change impacts. *Current Opinion in Environmental Sustainability*, **5** (1), 67-71.

410 Nakajima, T., Lee, J.-s., Kawaguchi, T., Tatsuhara, S. and Shiraishi, N. 2009 Risk assessment of
411 wind disturbance in Japanese mountain forests. *Écoscience*, **16** (1), 58-65.

412 Nakashizuka, T. 1989 Role of Uprooting in Composition and Dynamics of an Old-growth Forest
413 in Japan. *Ecology*, **70** (5), 1273-1278.

414 Nieuwenhuis, M. and Fitzpatrick, P.J. 2002 An assessment of stem breakage and the reduction
415 in timber volume and value recovery resulting from a catastrophic storm: an Irish case
416 study. *Forestry: An International Journal of Forest Research*, **75** (5), 513-523.

417 Oguro, M. 2016 *cv.models*: Model selection and hyper-parameter tuning by cross validation.
418 <https://github.com/Marchen/cv.models>

419 Powers, D.M.W. 2011 Evaluation: From precision, recall and f-measure to roc, informedness,
420 markedness & correlation. *Journal of Machine Learning Technologies*.

421 Prasad, A.M., Iverson, L.R. and Liaw, A. 2006 Newer Classification and Regression Tree
422 Techniques: Bagging and Random Forests for Ecological Prediction. *Ecosystems*, **9** (2),
423 181-199.

424 Pukkala, T., Laiho, O. and Lähde, E. 2016 Continuous cover management reduces wind damage.
425 *Forest Ecology and Management*, **372**, 120-127.

426 QGIS Development Team. 2015 QGIS Geographic Information System. O.S.G.F. Project. (ed.).

427 R Core Team. 2017 R: A Language and Environment for Statistical Computing. R.F.f.S.
428 Computing (ed.).

429 Robin, X., Turck, N., Hainard, A., Tiberti, N., Lisacek, F., Sanchez, J.-C. *et al.* 2011 pROC: an
430 open-source package for R and S+ to analyze and compare ROC curves. *BMC*
431 *Bioinformatics*, **12** (1), 77.

- 432 Ruel, J.C., Pin, D. and Cooper, K. 1998 Effect of topography on wind behaviour in a complex
433 terrain. *Forestry*, **71**, 261-265.
- 434 Sandri, M. and Zuccolotto, P. 2006 Variable Selection Using Random Forests. In *Data Analysis,*
435 *Classification and the Forward Search: Proceedings of the Meeting of the Classification*
436 *and Data Analysis Group (CLADAG) of the Italian Statistical Society, University of Parma,*
437 *June 6–8, 2005.* S. Zani, A. Cerioli, M. Riani and M. Vichi (eds.), Springer Berlin
438 Heidelberg, Berlin, Heidelberg, pp. 263-270.
- 439 Schelhaas, M.-J.N., Gert-Jan & Schuck, Andreas. 2003 Natural disturbances in the European
440 forests in the 19th and 20th centuries. *Global Change Biology* **9**,1620–1633.
- 441 Schütz, J.-P., Götz, M., Schmid, W. and Mandallaz, D. 2006 Vulnerability of spruce (*Picea abies*)
442 and beech (*Fagus sylvatica*) forest stands to storms and consequences for silviculture.
443 *European Journal of Forest Research*, **125** (3), 291-302.
- 444 Seidl, R., Schelhaas, M.-J. and Lexer, M.J. 2011 Unraveling the drivers of intensifying forest
445 disturbance regimes in Europe. *Global Change Biology*, **17** (9), 2842-2852.
- 446 Skamarock, W.C., J. B. Klemp, J. Dudhia, D. O. Gill, D. M. Barker, M. G. Duda, X.-Y. Huang, and
447 W. Wang, a.J.G.P. 2008 A description of the Advanced Research WRF version 3. *NCAR*
448 *Tech.Note,, NCAR/TN-47 + STR*, .
- 449 Strobl, C., Boulesteix, A.-L., Kneib, T., Augustin, T. and Zeileis, A. 2008 Conditional variable
450 importance for random forests. *BMC Bioinformatics*, **9**, 307-307.
- 451 Strobl, C., Boulesteix, A.-L., Zeileis, A. and Hothorn, T. 2007 Bias in random forest variable
452 importance measures: Illustrations, sources and a solution. *BMC Bioinformatics*, **8** (1),
453 25.
- 454 Strobl C, H.T., Zeileis A. 2009 A New, Conditional Variable-Importance Measure for Random
455 Forests Available in the party Package. *Party on! R Journal*, **1**, 14-17.
- 456 Swets, J.A. 1973 The Relative Operating Characteristic in Psychology. *Science*, **182** (4116), 990.

457 Takemi, T., Okada, Y., Ito, R., Ishikawa, H. and Nakakita, E. 2016 Assessing the impacts of global
 458 warming on meteorological hazards and risks in Japan: Philosophy and achievements
 459 of the SOUSEI program. *Hydrological Research Letters*, - **10** (- 4), - 125.

460 Timpane-Padgham, B.L., Beechie, T. and Klinger, T. 2017 A systematic review of ecological
 461 attributes that confer resilience to climate change in environmental restoration. *PLOS*
 462 *ONE*, **12** (3), e0173812.

463 Ulanova, N.G. 2000 The effects of windthrow on forests at different spatial scales: a review.
 464 *Forest Ecology and Management*, **135** (1), 155-167.

465 Valinger, E. and Fridman, J. 1997 Modelling probability of snow and wind damage in Scots pine
 466 stands using tree characteristics. *Forest Ecology and Management*, **97** (3), 215-222.

467 Valinger, E. and Fridman, J. 2011 Factors affecting the probability of windthrow at stand level
 468 as a result of Gudrun winter storm in southern Sweden. *Forest Ecology and*
 469 *Management*, **262** (3), 398-403.

470 Yamamoto, S.-I. 1989 Gap dynamics in climax *Fagus crenata* forests. *The botanical magazine*
 471 *= Shokubutsu-gaku-zasshi*, **102** (1), 93-114.

472 Yoshida, K., Sugi, M., Mizuta, R., Murakami, H. and Ishii, M. 2017 Future changes in tropical
 473 cyclone activity in high-resolution large-ensemble simulations. *Geophysical Research*
 474 *Letters*, **44**, 9910-9917.

475 Youden, W.J. 1950 Index for rating diagnostic tests. *Cancer*, **3** (1), 32-35.

476

477

478 **Table and figure captions**

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

481 **Figure 2** Preparing the dataset.

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

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

489 **Table 1** Annual mean temperature, precipitation, and soil type in each site (statistics from
490 1988 to 2010).

491 **Table 2** Properties of the study sites.

492 **Supplementary Table**

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

495 **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 ($^{\circ}$); 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.

507 **Table 1** Annual mean temperature, precipitation, and soil type in each site (statistics from
508 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	

509

510

511

512 **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)

513

514

515

516

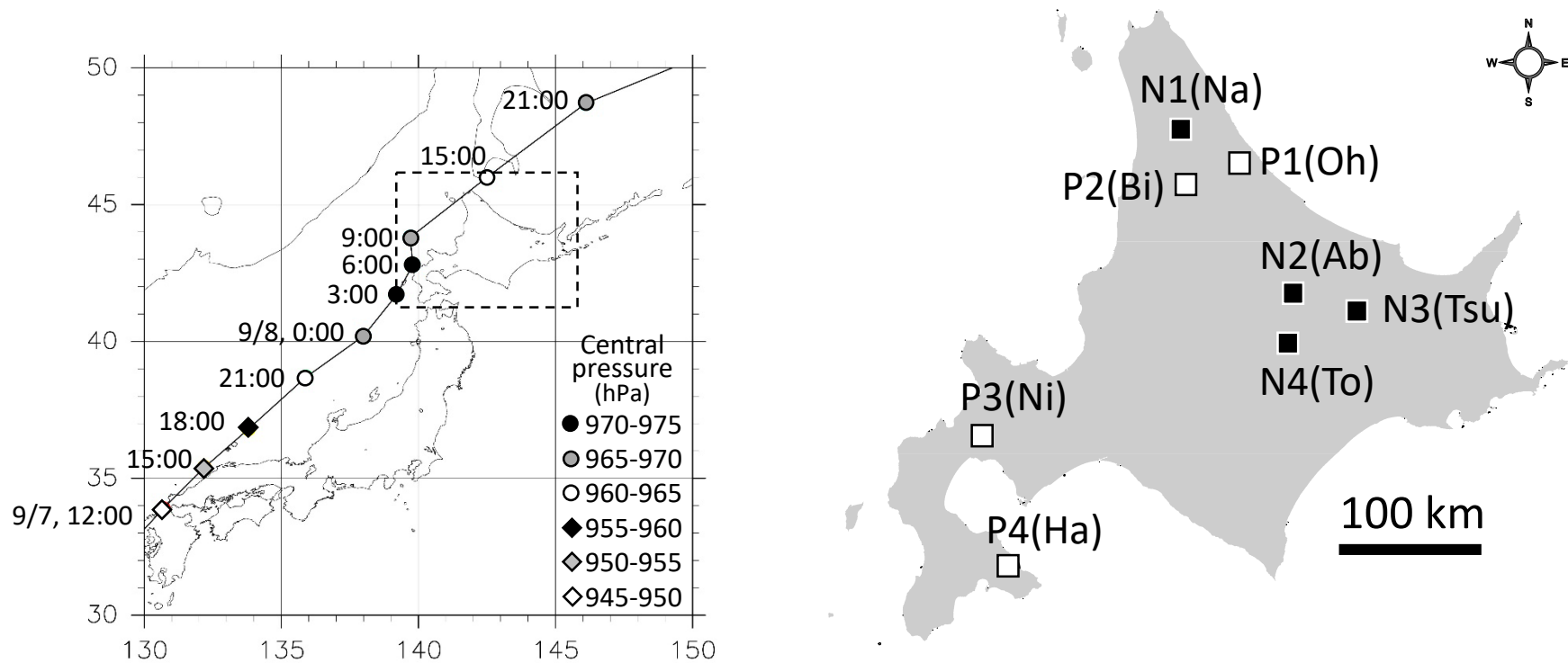


Fig. 1 – Typhoon track (left) and study site locations (right). Hokkaido is the area enclosed by a dotted line, which includes plantation forest sites (□) and natural forest sites (■).

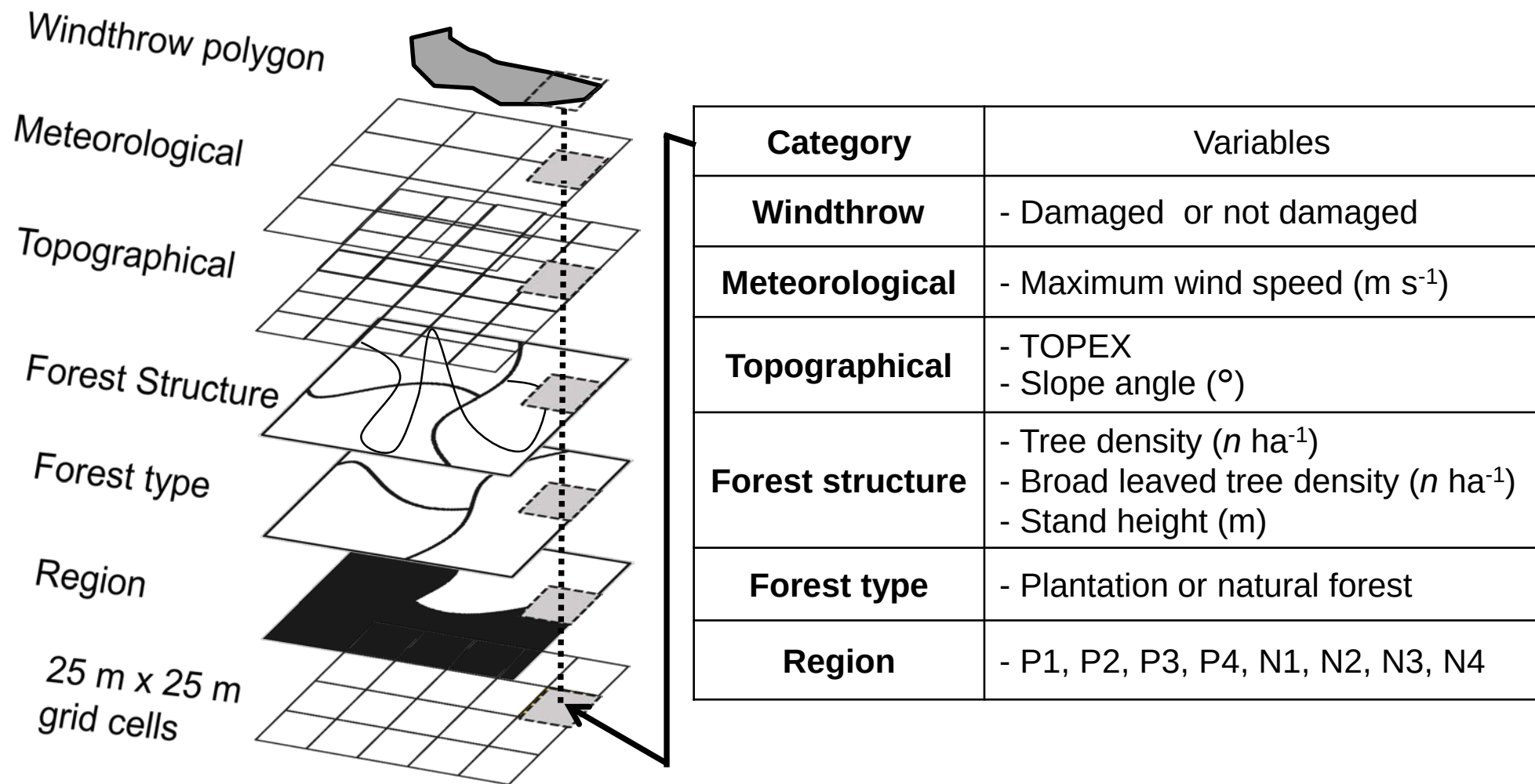


Fig. 2– Preparing the dataset

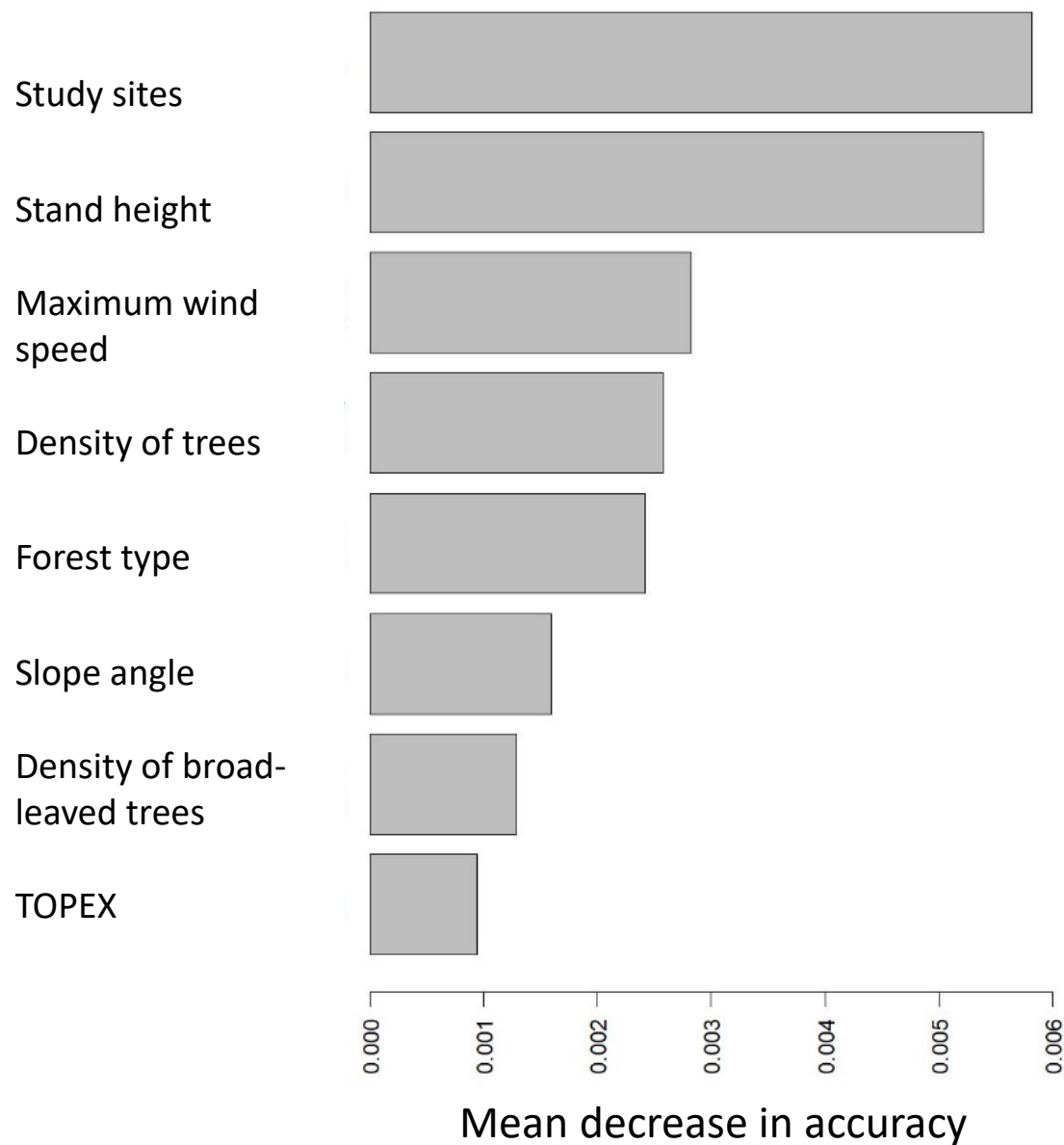


Fig. 3 - Variable importance plots for predictor variables from random forest (RF) classifications for predicting windthrow. Abbreviations: Forest type, artificial plantation or natural forest.

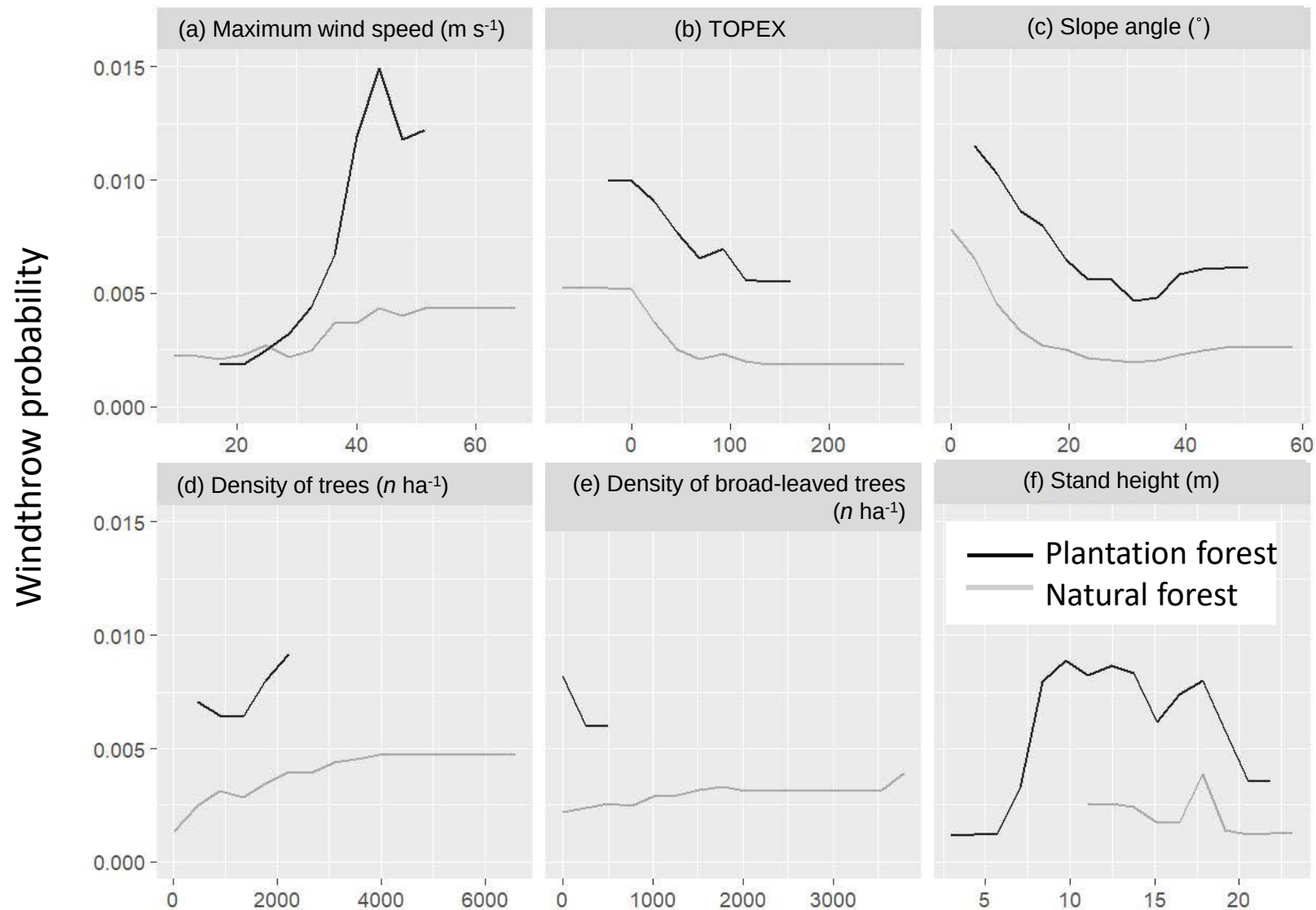


Fig. 4 - Partial dependence plots for selected predictor variables for random forest predictions of the windthrow occurrence. (a) maximum wind speed (m s^{-1}), (b) TOPEX, (c) slope angle ($^{\circ}$), (d) density of trees ($n \text{ ha}^{-1}$), (e) density of broad-leaved trees ($n \text{ ha}^{-1}$), 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)	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	Kramer et al. (2001)	Spatially explicit logistic regression	Zaremba Island (external validation)		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										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	4-fold CV	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)	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 (WoE)	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 (WoE)																		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							



Figure S1: Plot matrix of the eight explanatory variables.

The figure was created with *ggpairs* function of *ggplot2* package (Wickham, 2009) in R. Colors (magenta or cyan) represent 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. A histogram is, or a scatterplot and the 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 ($^{\circ}$); $density$, 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.