

Projection of impacts of climate change on windthrows and evaluation of potential adaptation measures in forest management: A case study from empirical modelling of windthrows in Hokkaido, Japan, by Typhoon Songda (2004)

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Abstract:

A windthrow refers to the uprooting and overthrowing of trees by the wind. Typhoons are a major cause of windthrows in Japan and are predicted to intensify under global warming. This study aimed to estimate the impact of climate change on windthrows and evaluate possible adaptation measures for sustainable forest management. We incorporated Typhoon Songda (2004) simulation experiments under current and pseudo-global warming (2075–2099, RCP 8.5 scenario) conditions with windthrow modelling in four natural and four artificial (*Abies sachalinensis*, Pinaceae) forests of Hokkaido. Unexpectedly, pseudo-global warming conditions decreased windthrow probabilities compared with current conditions for both forest types, presumably because wind speeds of the simulated typhoon weakened in Japan's high-latitude regions. Our results indicate that reconversion of artificial forests into natural forests largely decreased windthrow probability, providing a potential adaptation measure for improved forest management. To fully understand the range of climate-change effects on windthrow in Japan, future studies should use different climate scenarios and data from other typhoons, geographical regions, and forest types.

KEYWORDS windthrow risk; typhoon hazards; maximum wind speed; forest vulnerability; random forest modelling; machine learning

INTRODUCTION

'Windthrow' describes trees that are overthrown by wind. In Japan, low-pressure climatic events, including typhoons, are major causes of windthrows (Table 12 of Suzuki *et al.*, 2009), which accounted for 73% of weather-related damage in Japanese forests during 2004–2012 (Forestry Agency of Japanese Government, 2014, 2016).

To date, Typhoon Marie (T5415) in 1954 caused the most

damage, destroying approximately 26,800,000 m³ of trees in an estimated area of 750,000 ha in Hokkaido, the northernmost prefecture in Japan (Tamate *et al.*, 1977). Typhoon Songda (2004) caused the second-severest damage in Hokkaido, destroying a 36,956-ha forest area (Tsushima *et al.*, 2004). Compared to forests of southern Japan, those of northern Japan seem to be more vulnerable against typhoon hazards, presumably because northern Japan is hit by typhoons less frequently: The normal annual frequency of typhoon approach is 7.4 times in Okinawa (southern Japan), 3.1 times in Kanto (central Japan), and 1.8 times in Hokkaido (Japan Meteorological Agency, 2016). However, once the area is struck by a typhoon, forests can be seriously damaged.

In 2016, three typhoons struck Hokkaido for the first time in recorded history, and another typhoon pathed offshore of southern Hokkaido. Moreover, Murakami *et al.* (2012) predicted under the A1B scenario that, although the genesis of tropical cyclones will decrease in the western North Pacific during 2075–2099, intense tropical cyclones will rise in frequency. Therefore, it is becoming more important for sustainable forest management to estimate impacts of anticipated climate change on windthrows in forests of northern Japan, of which vulnerability is potentially high.

Risk of climate-related impacts results from the interaction of climate-related hazards (e.g. frequency and intensity of typhoons) with the vulnerability (e.g. vulnerability against windthrows according to forest types) and exposure (e.g. location of forests) (Intergovernmental Panel on Climate Change, IPCC, 2014). Changes in both the climate system and socioeconomic processes (e.g. forest management) are drivers of hazards, exposure, and vulnerability (IPCC, 2014).

Wind exposure was often represented with topographic exposure indices because direct wind data were unavailable in many previous studies (Mitchell and Ruel, 2015, but see e.g. Usbeck *et al.*, 2011 and Klaus *et al.*, 2011). If topographic exposure is used, however, it is difficult to separate effects of hazards and exposure in climate-change impact

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assessments. Recently, simulated wind data became available by Ito *et al.* (2016) through numerical experiments conducted on Typhoon Songda (2004) under current and future climate conditions to examine how a pseudo-global warming climate affects typhoon intensity and windstorms in high-latitude regions.

As for vulnerability, Nakagawa *et al.* (2015) and Nakagawa (2016) conducted windthrow modelling using a random forest method incorporating the simulated wind data under current climate in Hokkaido, focusing on differences in vulnerabilities of natural and artificial forests. This model inferred the following: 1) windthrow ratios (i.e. probability of windthrow occurrence predicted by random forest modelling) are higher in artificial than in natural forest stands; 2) windthrow ratios monotonically increase with tree density, tree height, and maximum wind speed; 3) windthrow ratios have U-shaped relationships with TOPEX (distance limited topographic exposure; Ruel *et al.*, 1997) and the slope angle (Nakagawa, 2016).

In the present study, we incorporated wind data (i.e. hazardous events and trends) from Ito *et al.* (2016) and hypothetical forest conditions (i.e. vulnerabilities) into the windthrow model of Nakagawa (2016), aiming to project the impact of climate change on windthrows and to evaluate possible adaptation measures in forest management. The novelty of our study is that we conducted climate impact assessments of windthrow using simulated wind data under current and pseudo-climate conditions in Asia for the first time. The projection in this study is also applicable to silvicultural planning (e.g. reconversion of artificial forests into natural forests) aimed at increasing forest management efficiency in Japan, where rapid depopulation and lack of forestry labour are expected (National Institute of Population and Social Security Research, 2013).

MATERIALS AND METHODS

Data preparation

Four artificial and four natural forests were selected as study sites in Hokkaido, the northernmost prefecture of Japan (Figure 1). In the artificial forests, the predominant species is planted Sakhalin fir (*Abies sachalinensis* (F.Schmidt) Mast., Pinaceae), whereas broad-leaved tree species that naturally invaded from surrounding natural forests also sparsely exist there. In the natural forests, predominant tree species are Sakhalin fir, Japanese lime (*Tilia japonica* (Miq.) Simonk, Tiliaceae), and Japanese oak (*Quercus mongolica* var. *grosserrata* (Blume) Rehder & E. H. Wilson, Fagaceae).

The area of study sites ranges between 4.91–43.34 km². Aerial photographs of the study areas before (1998–2004) and after (2004–2009) Typhoon Songda were obtained from Forest Agency, Geospatial Information Authority of Japan, and Hokkaido Prefectural Government. These aerial photographs were orthorectified, and windthrown regions (> 0.05 ha) were detected on GIS using stereoscopic viewing software (Easy Stereo View; PHOTEC, 2015). Tree height and density (all trees and broad-leaved trees only; *n*/ha) for each forest compartment (i.e. a management unit) were obtained from registration data. For the two natural forests without registration data, these variables were estimated using aerial photography (see Nakagawa, 2016 for details).

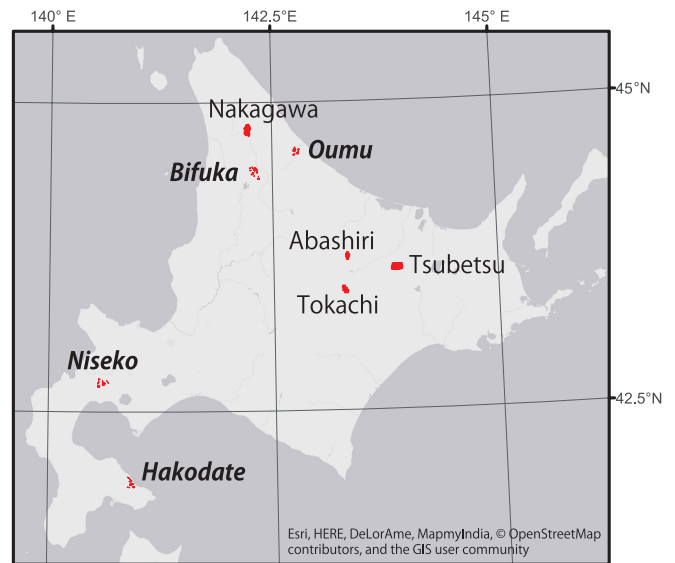


Figure 1. Study site locations (in red). The names of natural forests are indicated in plain font and those of artificial forests in bold italic

Distance limited topographic exposure (TOPEX; for 2,000 m in 100-m intervals) and the slope angle were calculated from a digital elevation model with a 10-m resolution (Geospatial Information Authority of Japan, 2011). TOPEX is calculated by scanning the surrounding landscape for maximum angles from a given pixel. Maximum angles are measured for each of 8 horizontal direction classes and those maximums are summed for the final score. A positive TOPEX value indicates a sheltered topography whereas a value of 0 indicates a flat plain and a negative value indicates an exposed topography.

Grid intervals of the numerical experiments for Typhoon Songda (Ito *et al.*, 2016) was further downscaled from 1 km to 200 m for the current study areas. We applied the two-way nesting technique between the parent (1 km) and the child (200 m) domains. Then the maximum wind speeds from 0300 UTC on 7 September to 0000 UTC on 9 September were recorded for each grid cell.

Polygons of windthrown areas and forest compartments and grid cells of topographic data (TOPEX and slope angle) and maximum wind speed were intersected into 25 × 25 m grid cells (*n* = 227,315). Above data preparations were conducted using a variety of GIS programs (QGIS 2.8.4, QGIS Development Team 2015; GRASS 6.4, GRASS Development Team 2012; ArcMap 10.0, ESRI 2010).

Grid cells with unrealistic values (e.g. density of all trees < density of broad-leaved trees and negative values in the forest registration) were removed, reducing the sample size to 221,538 (*n* = 40,934 for artificial and *n* = 180,604 for natural forests). Tree height and density were identical for each forest compartment because that is the smallest scale available from the registration data.

To avoid model bias that can occur when explanatory variables are dependent on forest size, we generated a subsample for modelling. First we removed forest compartments with less than 30 grid cells. Next, 30 grid cells were randomly sampled from each forest compartment while fixing the windthrow ratio. The subsequent windthrow model used the resultant subsample (*n* = 46,950).

Windthrow modelling

We applied the random forest method (Breiman, 2001) to model windthrow occurrence. This method is a machine-learning technique that assembles numerous relatively independent decision trees. Forest type (artificial or natural) and study sites (as nominal variable, $n = 8$) were incorporated into the model along with the six explanatory variables described under ‘Data preparation’ (maximum wind speed, tree height, density of all trees, density of broad-leaved trees, TOPEX, and slope angle).

As tuning parameters of random forest, *n*tree (number of decision trees to grow) was set to 500. Additionally, *m*try (number of variables randomly sampled as candidates at each split) = 2, 3, 5 and *nodesize* (minimum size of terminal nodes) = 2, 5, 10 were examined. After a 10-fold cross validation, *m*try = 5 and *nodesize* = 5 were selected as the best combination in terms of the Matthews correlation coefficient (MCC: Matthews, 1975).

For detailed ecological interpretations of our model, see Nakagawa *et al.* (2015) and Nakagawa (2016).

Model validation

A 10-fold cross-validation was conducted and several model predictability indices were calculated. 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: Youden, 1950) and divides windthrow occurrence with non-occurrence. These were AUC (area under the curve of receiver operating characteristic (ROC); Swets, 1973), accuracy ($[\text{true positives} + \text{true negatives}]/\text{total } n$), sensitivity ($\text{true positives}/[\text{true positives} + \text{false negatives}]$), specificity ($\text{true negatives}/[\text{false positives} + \text{true negatives}]$), positive predictive value ($\text{true positives}/[\text{true positives} + \text{false positives}]$), negative predictive value ($\text{true negatives}/[\text{false negatives} + \text{true negatives}]$), MCC, and informedness ($\text{sensitivity} + \text{specificity} - 1$; Powers, 2011). True positive represents a case where both actual and prediction are positive, false positive represents where actual is negative but prediction is positive, false negative represents actual is positive but prediction is negative, and true negative represents where both actual and prediction are negative. These predictability indices were then compared to indices from previous studies.

Prediction of global warming effects and evaluation of potential adaptation measures

We predicted windthrow probabilities assuming various hazard intensities (i.e. maximum wind speeds of typhoons under current and pseudo-global warming conditions) and vulnerabilities (forest types and silvicultural scenarios).

To obtain the wind intensity of a future typhoon, grid intervals of the numerical experiments for Typhoon Songda (Ito *et al.*, 2016) were downscaled from 1 km to 200 m under the pseudo-global warming condition, and the maximum wind speed was recorded for each grid cell.

Three silvicultural scenarios for artificial forest management were set: 1) status quo, 2) increase density of broad-leaved trees to $\geq 100/\text{ha}$ in artificial forests (Hokkaido Prefectural Government, 2014), and 3) revert artificial forests into natural forests (Forestry and Forest Products

Research Institute, FFPRI, 2012).

In the first scenario, the status quo was maintained for forest conditions for each grid cell. In the second scenario, broad-leaved tree density in the artificial forests were changed to 100/ha for grid cells where the original values < 100 , whereas ≥ 100 values were maintained. For the third scenario, artificial forest types were replaced with ‘natural forest’ as a factor. Additionally, tree height and density in artificial forests were replaced with the corresponding median values from natural forests in the subsample. Topographic variables were maintained at status quo for all grid cells in all predictions.

To project climate change effects on windthrow risks and to evaluate potential adaptation measures, windthrow probability was predicted for each grid cell. Specifically, the windthrow model was applied to datasets consisting of different typhoon hazards (maximum wind speeds under the current and future conditions) and vulnerable conditions (artificial or natural forest types and hypothetical forests under the three silvicultural scenarios). All analyses were conducted with the *randomForest* package 4.6–12 (Liaw and Wiener, 2002) in R version 3.3.1 (R Core Team, 2016).

RESULTS

Modelling and validation

The mean windthrow ratio for all grid cells in the study area was 0.016, ranging 0.001–0.106 across study sites. The model estimate of windthrow prevalence (i.e. occurrence rate) was 0.017. Model predictability indices (AUC = 0.93, accuracy = 0.93, sensitivity = 0.80, specificity = 0.93, and informedness = 0.74) were reasonably high compared to previous studies (Table I). However, the model’s positive predictive value was low (0.18).

Predictions

In artificial forests ($n = 40,934$), the estimated maximum wind speeds (mean \pm SD) were 29.8 ± 7.0 and 23.8 ± 6.2 m/s under current and pseudo-global warming conditions, respectively; in the natural forests ($n = 180,604$), the wind speeds were 28.0 ± 8.4 and 24.2 ± 6.6 m/s. On average, wind speeds decreased from the current to pseudo-global warming conditions by 6.0 ± 4.6 and 3.8 ± 3.3 m/s in the artificial and natural forests, respectively.

After simulating typhoon intensities, the distributions of windthrow probability predicted for each grid cell were compared among different typhoon hazards and forest management scenarios for each forest type (Figure 2). In comparing different typhoon hazards, pseudo-global warming decreased the percentage of grid cells with high windthrow probabilities (≥ 0.5) from current conditions primarily in artificial forests (0.48% to 0.07%; the change was from 0.08% to 0.03% in natural forests; Figure 2). In comparing forest management scenarios, the percentage of grid cells with high windthrow probabilities (≥ 0.5) were highest under the status quo (0.48% and 0.07% under current and pseudo-global warming, respectively), dropped slightly when increasing broad-leaved trees (0.40% and 0.04%), and dipped further when reverting to natural forest (0.07 and 0.00%) (Figure 2).

Table I. Comparison of model predictability indices between the present and previous studies

Model predictability index* ¹	Present model	Previous studies* ²	References
AUC of ROC	0.93	0.38–0.79	Kramer <i>et al.</i> (2001), Schindler <i>et al.</i> (2009)
Accuracy: $(a + d)/N$	0.93	0.68–0.90	Kramer <i>et al.</i> (2001), Mitchell <i>et al.</i> (2001), Hanewinkel <i>et al.</i> (2004), Peterson (2004), Hanewinkel (2005), Scott and Mitchell (2005), Pasztor <i>et al.</i> (2015)
Sensitivity: $a/(a + c)$	0.80	0.26–0.96	Mitchell <i>et al.</i> (2001), Hanewinkel <i>et al.</i> (2004), Hanewinkel (2005), Pasztor <i>et al.</i> (2015)
Specificity: $d/(b + d)$	0.93	0.18–0.95	Mitchell <i>et al.</i> (2001), Hanewinkel <i>et al.</i> (2004), Hanewinkel (2005), Pasztor <i>et al.</i> (2015)
Positive predictive value: $a/(a + b)$	0.18	0.31–0.43	Mitchell <i>et al.</i> (2001)
Negative predictive value: $d/(c + d)$	0.996	0.86–0.91	Mitchell <i>et al.</i> (2001)
Matthews correlation coefficient (MCC)	0.36	0.28–0.31	Mitchell <i>et al.</i> (2001)
Informedness (Sensitivity + Specificity – 1)	0.74	0.14–0.63	Mitchell <i>et al.</i> (2001), Hanewinkel <i>et al.</i> (2004), Hanewinkel (2005)

*1: a : true positive, b : false positive, c : false negative, d : true negative, N : $a + b + c + d$

*2: Some indices were calculated from original data by the present authors.

DISCUSSION

Impacts of climate change on windthrow

Contrary to general expectations, the model predicted a decrease in windthrow risks under pseudo-global warming for both artificial and natural forests. The decrease in windthrow risks was considered mainly due to decrease in maximum wind speeds in most grid cells for both natural and artificial forests (Figure 3). Ito *et al.* (2016) gives some possible reasons for this outcome:

‘The typhoon intensity at its maturity becomes stronger in a warming climate, and the typhoon while passing over the Sea of Japan weakens more rapidly in the warming climate. Thus the strong wind over the northern part of Japan in the warming climate also becomes weaker... It was found that the environmental meridional gradient of temperature at the 500 hPa level is smaller in the warming climate than in the current climate, which indicates that the baroclinicity becomes weak under global warming. The weak baroclinicity makes the typhoon environment unfavorable for the extratropical transition, and therefore, possibly reduces the severity of typhoon wind in northern Japan.’

Therefore, typhoon-related windthrow risks may be reduced under climate change in Japan’s high-latitude regions depending on typhoon tracks.

Evaluation of potential adaptation measures

The primary objectives of windthrow models are to detect vulnerable forest conditions and improve forest management (Perera *et al.*, 2015). For example, after the storm Kyrill damaged 3% of the forests in northwest Germany, Klaus *et al.* (2011) investigated factors affecting forest sensitivity to storm-induced destruction. Forests in the region are dominated by European beech (*Fagus sylvatica*), pedunculate oak (*Quercus robur*), Norway spruce (*Picea abies*) and Scots pine (*Pinus sylvestris*), and the work found that a high proportion of coniferous trees strongly increased a

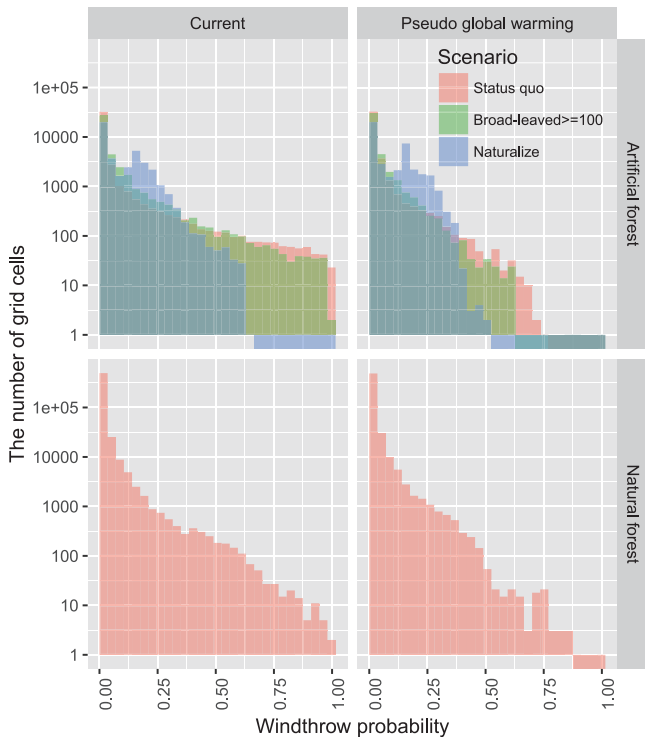


Figure 2. Histogram of windthrow probabilities predicted for each grid cell by the random forest model. The model included different typhoon intensities (maximum wind speeds under current conditions and pseudo-global warming during September of 2075–2099 in the RCP 8.5 scenario), forest types (artificial and natural forests), and silvicultural scenarios (status quo, increasing broad-leaved tree density to ≥ 100 /ha, reconverting artificial forests into natural forests). The vertical axis is on a logarithmic scale. The colored area less than 1 indicates zero

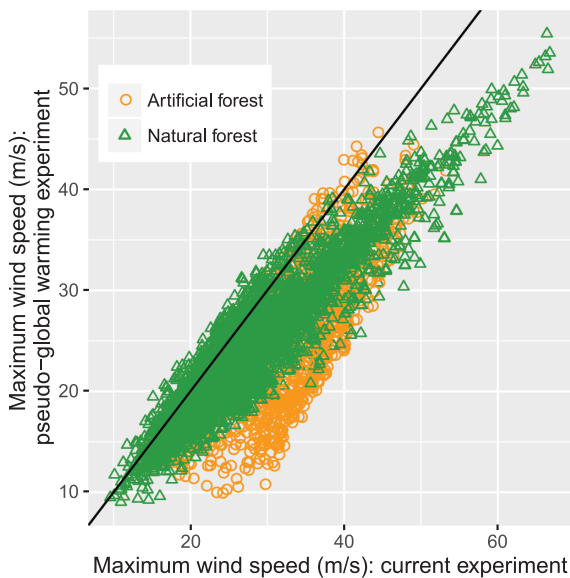


Figure 3. Comparison of maximum wind speeds simulated under current and pseudo-global warming conditions for each grid cell ($n = 221,538$) in the study sites in Hokkaido, northern Japan. Wind speeds were projected to decrease in the pseudo-global warming condition for most grid cells in both natural and artificial forests

stand's vulnerability to windthrow. In the present study, however, increasing broad-leaved trees (a modelling scenario that assumes preserving broad-leaved trees while harvesting planted coniferous trees) failed to greatly reduce the ratios of grid cells with high windthrow probabilities. Thus, a silvicultural operation that preserves broad-leaved trees at the expense of coniferous trees may have only a limited effect on enhancing tolerance of artificial *Abies sachalinensis* forests in Hokkaido against windthrows. For detailed ecological interpretations of our model, see also Nakagawa *et al.* (2015) and Nakagawa (2016).

In contrast, reconversion to natural forest decreased windthrow probabilities of most grid cells to below 0.5. This modelling outcome is in line with our previous work showing that windthrow rate is significantly lower in natural forests (Nakagawa *et al.*, 2015; Nakagawa, 2016). Furthermore, those previous analyses inferred that ridges and valleys are more vulnerable to windthrow than are flat areas. Together, these data suggest that prioritizing the reconversion of artificial forests to natural forests among steep ridges and valleys may be an effective windthrow countermeasure in Japan's high-latitude regions. Such strategies will increase forest management efficiency, which should especially benefit areas where rapid depopulation and lack of forestry workers are expected.

Limitations and opportunities

Our windthrow model outperformed many previous studies, and we considered our model valid for prediction. However, its positive predictive value was low, presumably because windthrow occurrence was extremely sparse (1.58%) in the original data, inevitably raising the false negative ratio in the predictions. Our model is limited to judging windthrow occurrence or non-occurrence (1 or 0) based on a

specific threshold of 0.035. Therefore, we discussed potential risks based on windthrow probabilities (ranging from 0 to 1) predicted for each grid cell by the random forest model.

Furthermore, the model depends on the effects of only one typhoon in a relatively small area, limiting generalizations to other situations. The relationships between windthrow occurrences and their explanatory variables are complex, differing in response to numerous factors, including typhoon tracks, wind direction against slopes, and forest types (Klaus *et al.*, 2011). For example, Hayashi *et al.* (2015) assessed the impact of Typhoon Songda (2004) in Tomakomai area of Hokkaido using satellite laser altimetry. They reported that the canopy height decreased (i.e. being disturbed by typhoon) most in artificial forests of Japanese larch (*Larix kaempferi* (Lamb.) Carr., Pinaceae), followed by Sakhalin spruce (*Picea glehnii* (F.Schmidt) Mast., Pinaceae) and Sakhalin fir. Hayashi *et al.* (2015) also found that serious damage occurred on gentle slope ($0-1^\circ$), which is consistent with the result of Nakagawa (2016), whereas little damage occurred on steep slope, which is inconsistent with Nakagawa (2016).

Therefore, a single case study is not enough to predict general trends in climate-change effects on windthrow risk in Japan. It may be of interest to future studies whether other typhoons will also decrease in intensity at high-latitude regions, as shown in the pseudo-global warming experiments of Typhoon Songda's impact on Japan (Ito *et al.*, 2016). Another potential area to explore is whether the proposed forest management in this study will be effective against windthrow in artificial forests from other regions, containing different tree species such as Japanese cedar (*Cryptomeria japonica*, Cupressaceae). To address these questions fully, it is necessary to accumulate case studies of windthrow events that include different localities and typhoons (e.g. Typhoon Mireille in 1991, see also Takemi *et al.*, 2016).

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