Research paper

Simulating the Impacts of Wind Damage on Stand Structure and Dynamics of Plantations: a Case Study of Long-Term *Cryptomeria japonica* Experimental Plots with Two Spacing Trials

Ching-Peng Cheng,[1)] Chyi-Rong Chiou,[1,3)] Chiao-Ying Chou[2)]

【Summary】

Wind damage often causes unexpected risks and losses for forest managers. The impacts of catastrophic wind damage can lead to considerable disturbances in forest management plans. In this study, we analyzed the effects of wind damage on 2 long-term experimental plots of Japanese cedar (*Cryptomeria japonica* D. Don) with 2 spacing trials (CJ_{3000} with an original density of 3000 trees ha^{-1} and CJ_{5400} with an initial density of 5400 trees ha^{-1}) in 1944 (from Typhoon B174; T_1) and 1955 (from Typhoon Iris; T_2). These 2 experimental plots are located next to each other in the Xitou area of central Taiwan and were established via 2-yr-old seedlings in 1929. The objective was to simulate the impact of typhoons on the stand structure in terms of the present and long-term dynamics. First, the 3-parameter Weibull probability density function was used to fit and compare the diameter at breast height (DBH) distribution before and after wind damage occurred. Second, under an assumption of a self-thinning slope, a switching regression was used to simulate the number of trees between the 2 plots over time. Interventions by typhoons in 4 scenarios were assumed: plots suffered T_1, plots suffered T_2, plots suffered both T_1 and T_2, and simulated plots experienced no intervention. Results showed that (1) more trees with medium and smaller DBHs were removed than larger ones in both plots, (2) the 3-parameter Weibull probability density function effectively fitted and described the DBH-class structure of plots before and after the disturbance, with the patterns of DBH distribution after the interventions being more concentrated and similar to the consequences of low (or light) thinning, (3) the switching regression with dummy variables effectively estimated changes due to the typhoon intervention and reductions in the number of trees in the 2 plots, in particular, the number of trees in CJ_{3000} were higher than those in CJ_{5400} after 50 yr of age, and (4) the impact of wind damage could change the original density structure, which would lead to long-term changes in stand structure and stock.

Key words: wind damage, Weibull distribution, intervention analysis, switching regression.

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[1)] School of Forestry and Resource Conservation, National Taiwan University.

[2)] Biodiversity Research Center, National Taiwan University.

[3)] Corresponding author, e-mail:esclove@ntu.edu.tw 通訊作者。

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研究報告

風害對人工林的林分結構與動態影響之模擬：以兩個不同栽植距離的柳杉長期試驗地為例

鄭景鵬[1)] 邱祈榮[1,3)] 周巧盈[2)]

摘 要

風害通常會給林業管理人員帶來意料之外的風險和損失。而災難性風災的影響導致森林經營計劃受到相當大的干擾。在這項研究中，我們分析了1944年(T_1)和1955年(T_2)的兩次風害對柳杉的兩個栽植距離長期試驗地(CJ_{3000} and CJ_{5400})的影響，兩試驗地相鄰設置於臺灣中部的溪頭地區，於1929年栽植兩年生實生苗。首先使用三參數的韋伯機率密度函數擬合並比較風害前後的胸徑分佈變化。接下來在假設自我疏伐的前提下，使用轉換回歸來模擬兩個樣區之間的每公頃株數隨時間的變化。為藉由颱風在四種情況下的干預所假定的情境：兩樣區僅遭受T_1，兩樣區僅遭受T_2，兩樣區遭受T_1和T_2以及模擬兩樣區沒有任何風害干擾。結果顯示：(1)在兩個樣區中，胸徑屬於中型和較小的樹木都比較大的樹木容易被風害移除；(2)藉由韋伯函數能有效擬合並描述樣區干擾前後的徑級結構，受干擾後樣區的胸徑分佈模式更加集中，類似於下層(或輕度)疏伐的結果，(3)具虛擬變數的轉換回歸有效地估算了兩個樣區遭受颱風干擾後的林木株數變化，尤其是CJ_{3000}在50年生以後的林分株數比CJ_{5400}高。(4)風害的影響可能改變原始密度結構上的差異，導致影響長期的林分結構與蓄積量變化。

關鍵詞：風害、韋伯分佈、介入模型、轉換回歸。

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INTRODUCTION

Japanese cedar (*Cryptomeria Japonica* D. Don) originates from Japan, China, and South Korea, was introduced to Taiwan from Japan in the 19th century, and has become a vital timber resource in Taiwan's mountainous regions and in Japan more generally. Taiwan is situated on the Tropic of Cancer off China's southeastern coast in the northern Pacific Ocean, where it is hit by approximately 3.3 typhoons on average each year. Similar to Japan's Yakushima Island (Suzuki and Tsukahara 1987), typhoons are the main meteorological disaster in Taiwan. Wind-induced damage has always been a common cause of environmental and economic losses in Taiwan, especially in forest plantations (Wey and Chien 1989).

The impacts of catastrophic wind damage lead to considerable disturbances in forest management plans. In consequence, the costs of unscheduled thinning and harvesting are increasing, the losses of potential timber production are growing, and temporary timber may cause an oversupply in the market (Wey and Chien 1989, Quine 1995, Peltola et al. 2000, Zeng et al. 2004). In addition to economic losses, large numbers of wind-thrown trees reduce the stand density and variations in the stand structure (Mitchell 1995, Scott and Mitchell 2005). In the future, nonstop climate change would trigger more-frequent catastrophic typhoon events, with potential risks and impacts on individual trees and on the stand structure.

However, most of the literature has focused on the type of wind damage to trees, including branches blown off or broken, trees uprooted, trees leaning, and tops broken (Kuboyama et al. 2003, Yoshida and Noguchi 2009), windthrow risk modeling (Scott and Mitchell 2005), the structure and function of forest ecosystems (Lin et al. 2003, Lin et al. 2011), and modeling wind damage to forests (Hale et al. 2015, Hart et al. 2019).

In forest management plans, common growth models, i.e., self-thinning line slope (Reineke 1933, Yoda 1963), maximum size-density relationship dynamic thinning line (Cao and Dean 2008, VanderSchaaf and Burkhart 2008), and mortality analysis (Hiroshima 2014), are used to describe or predict stand density dynamics in different stages.

Very little research has explored typhoons' effects on the stand structure over time, not only the abrupt drop in the number of trees during a typhoon intervention, but also long-term stand density dynamics. According to records, Typhoon B174 in 1944 and Typhoon Iris in 1955 brought extreme rainfall, which resulted in severe flooding, landslides, and catastrophic wind disasters in Taiwan's central mountains. Thus, this study used wind disaster records from long-term Japanese cedar experimental plots with 2 different spacing trials. Data from these records were used to evaluate the impacts of wind damage on the stand structure before and after wind damage and the trend of the number of trees, in an investigation of whether wind damage helps or hurts forest plantations.

In this study, we mainly focused on changes and trends in the number of trees and applied a probability density function to simulate and describe changes in the diameter at breast height (DBH)-class structure of the plots before and after the disturbances. Therefore, the main objectives of this study were: 1) to address how the 2 typhoons in 1944 and 1955 influenced the DBH distribution, using the Weibull distribution (Bailey and Dell 1973) to evaluate changes in the stand structure before and after wind damage; and 2) to use the principle of intervention models (Box and Tiao 1975, Vujić et al. 2016) to simulate how the changing trends of trees per hectare were affected by multiple interventions, which were categorized into 4 scenarios with a switching regression.

MATERIALS AND METHODS

Study Site

The study site is located in the 3rd compartment (120°87'E, 23°60'N), Xitou Forest Management District (FMD) in the Experimental Forest of National Taiwan University (NTUEF) in central Taiwan. The Xitou FMD is surrounded by mountains (800~2000 m in elevation) to the east, west, and south, resulting in a concave-shaped terrain with a gap to the north. The annual mean temperature is 17.5℃, the annual precipitation is about 2698 mm, and the annual mean relative humidity is around 88.9%. (National Taiwan University Experimental Forest 2009).

Original Experimental Design

The site is at approximately 1270 m in elevation with a 20° slope facing west (Fig. 1). Two long-term experimental plots with 2 spacing trials were originally designed to monitor the long-term stand growth dynamics. In one plot, 213 trees were planted on 0.071 ha with a spacing of 1.9×1.9 m for a density of 3000 trees ha^{-1} (CJ_{3000}); in the other one, 351 trees were planted on 0.065 ha with a spacing of 1.5×1.5 m for a density of 5400 trees ha^{-1} (CJ_{5400}). Both plots were established in 1929 and were planted with 2-yr-old Japanese cedar seedlings.

The 2 plots are adjacent to each other (Fig. 1) and under the same stand conditions, including planting year, no pruning, and the same silvicultural treatments in the first 6 yr. Before 1959 (then a 31-year-old stand), the number of living trees, DBH, and tree height were recorded annually. After 1959, these data were recorded every 5 yr. In addition, the stand age of this study was calculated as the number of years minus the planting year plus 1.

Typhoon Records

Weather records were collected from a local agricultural meteorological station (23.67°N, 120.8°E, and 1150 m in elevation) at the Xitou Forest Nursery. The station was established in 1941. Typhoon B174 (August 14~16, 1944) and Typhoon Iris (August 22~24, 1955) swept across central Taiwan from east to west. They brought extremely heavy rainfall, of 300~600 mm d^{-1}, with maximum wind speeds of 50~55 m s^{-1} (Table 1). Both typhoons brought torrential rainfall, which washed away the soil and caused major landslides and debris flows, even partially changing the landscape in the mountains of central Taiwan.

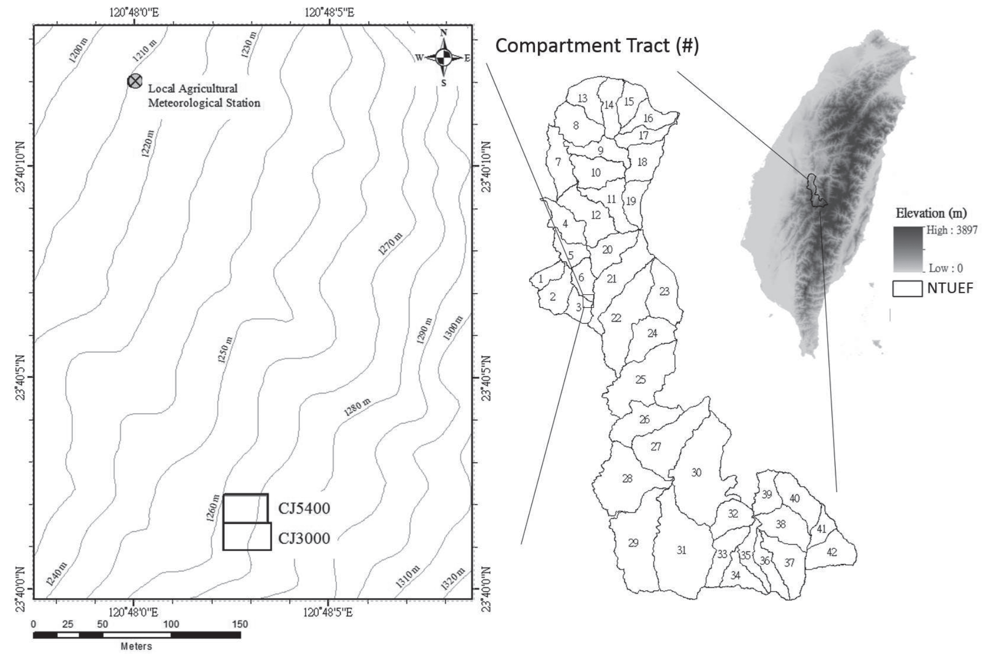

Fig. 1. Location of the study sites.

Table 1. Attributes of the typhoon interventions

Typhoon	Year of impact	Maximum wind speed at the center (kt)	Minimum central pressure (hPa)	Maximum wind speed (m s^{-1})	Maximum daily total precipitation (mm)
B174	1944	100	945	50	323.3
Iris	1955	90	960	55	581.5

Kt, knots; hPa, Hecto Pascal.

Analytical Methods

Weibull Distribution

Podlaski and Zasada (2008) showed that the Weibull distribution (Bailey and Dell 1973) was the most suitable distribution compared to the gamma, logistic, normal, exponential, and lognormal distributions, but only for single-storied stands and selected forests. Therefore, the three parameters of the Weibull probability density function (Weibull 3-pdf) were used to simulate the DBH distribution before and after the impacts of typhoons in the 2 plots (eq. 1). The maximum-likelihood estimation was adopted in this study to fit parameters of the Weibull distribution (Teimouri and Gupta 2013).

$$f(X) = \begin{cases} \frac{c}{b} \times \left(\frac{X-a}{b}\right)^{c\text{-}1} \times e^{-\left(\frac{X-a}{b}\right)^{c}}, \text{ where } (a \leq X) \\ 0, \textit{ otherwise} \end{cases} \quad \text{.......(1)}$$

The 3 parameters of the distribution are given by the set $f(X) = (a, b, c)$ with a (the Weibull location parameter) > 0, b (the scale parameter) > 0, c (the shape parameter) ≥ 0, and X is the DBH.

The cumulative distribution function calculated on the basis of DBH classes of each section, the theoretical frequency of which is calculated as shown in equation (2), provided L ≤ X < U, with a frequency of (L, U) range, is:

$$\mathrm{P(L \leq X < U)} = e^{-\left[\frac{\mathrm{L}-a}{b}\right]^{C}} - e^{-\left[\frac{\mathrm{U}-a}{b}\right]^{C}} ; \quad \text{.......(2)}$$

where L is the DBH-class lower bound, U is the DBH-class upper bound, and e is Euler's number.

The Kolmogorov-Smirnov (K-S) test (Sokal and Rohlf 1995) was chosen to test the different goodness-of-fit values between the 2 underlying 1-dimensional probability distributions, with critical value, D_α. The K-S test is a nonparametric test that compares the cumulative distributions of 2 datasets between the observed distribution and the simulated distribution of the Weibull 3-pdf. The assumptions are described as follows.

Null hypothesis (H_0): the simulated distribution is consistent with the observed distribution.

Alternative hypothesis (H_a): the simulated distribution is inconsistent with the observed distribution, when $D_{plus} > D_\alpha$.

The maximum value between the simulation and observations is subtracted after taking the absolute value of each DBH class as shown in equation (3):

$$D_{plus} = \text{Max of } \left| f(x) - f_0(x) \right| ; \quad \text{.......(3)}$$

where f(x) is simulated number of trees in each DBH class, $f_0(x)$ is the observed number of trees in each DBH class, and D_{plus} is the difference in the maximum value between the simulation and observations after taking the absolute value of each DBH class. D_α is defined in equation (4).

$$D_a = \sqrt{\frac{-\mathrm{In}\left(\frac{1}{2a}\right)}{2\mathrm{n}}} ; \quad \text{.......(4)}$$

where D_α is the threshold limit value of the K-S test, α is the significance level set to 0.05, and n is the number of trees.

Intervention Analysis

The procedure of the intervention analysis was introduced by Box and Tiao (1975) to study situations in which a significant intervention has interrupted the stable behavior of a time series of interest in the context of environmental and economic problems. Goh and Law (2002) and Chiou et al. (2013) indicated that the effects and time range of interventions can be observed based on the constructed model.

Before constructing an intervention model, it is necessary to know the starting time points and patterns of exogenous variables. The basic form of an intervention analysis uses dummy variables to represent the exogenous time series whose influence is of concern. The basic variable of the intervention analysis model is the dummy variable, and there are 2 common intervention variables. Both of these are dummy variables taking only the values 0 or 1 to respectively denote the nonoccurrence or occurrence of an intervention. One type represents the effects of an intervention that are expected to remain permanently after time T to some extent, given by equation 5:

$$S_t^{(T)} = \begin{Bmatrix} 0,\ t < T \\ 1,\ t \geq T \end{Bmatrix}. \qquad (5)$$

The other type represents the effects of an intervention that are temporary or transient and will disappear after time T, given by equation 6:

$$P_t^{(T)} = \begin{Bmatrix} 0,\ t \neq T \\ 1,\ t = T \end{Bmatrix}. \qquad (6)$$

Under the assumption of a self-thinning slope (Yoda 1963, Reineke 1993), the number of trees may have an exponential decreasing function in the time series in the 2 plots. On the record, wind damage caused abrupt decreases in the number of trees in both 1944 and 1955. Therefore, this study applied a logarithmic switching regression model to estimate changes in the number of trees. The typhoon was assumed to have impacted the trend of the number of trees, and this impact suddenly interrupted the original model, so a switching regression model was used to simulate the situation. Thus, a dummy variable was introduced into the model to take into account the effect of the exogenous interventions. The switching regression of the innervation analysis can be written as follows to simulate the number of trees over the years under the impacts of typhoons (eq. 7):

$$\mathrm{N} = m + n\ ln(age) + p\mathrm{T}_1 + q\mathrm{T}_2; \qquad (7)$$

where N represents the simulated number of trees; age represents the stand age; m represents the initial number of trees on the plot, when the age is 0 to 100 yr; n represents the slope; p and q represents the number of trees removed by wind damage; ln is the natural logarithm; and T_1 and T_2 are dummy variables equal to 0 or 1.

In this study, the 2 typhoon disasters were defined as permanent intervention variables, and the dummy variable in the years after the wind disaster was also set to 1. The beginning and ending points of the time series we set were from the year of establishment of the plots to 2015, and forecast to 2028 (when the trees will be 100 yr old). The permanent intervention variables, T_1, representing Typhoon B174 in 1944, and T_2, representing Typhoon Iris in 1955, are given by eq. 8 and eq. 9, respectively:

$$\mathrm{T}_1 = \begin{Bmatrix} 0,\ t < 1944 \\ 1,\ t \geq 1944 \end{Bmatrix} \text{ and} \qquad (8)$$

$$\mathrm{T}_2 = \begin{Bmatrix} 0,\ t < 1955 \\ 1,\ t \geq 1955 \end{Bmatrix}. \qquad (9)$$

Four scenarios of plots suffering both T_1 and T_2, plots suffering T_1, plots suffering T_2, and simulated plots with no intervention. (i.e., $T_1 \times T_2$, only T_1, only T_2, and $\emptyset$) were predicted by the switching regression to verify the effects of the typhoons on the 2 forest stands (i.e., CJ_{3000} and CJ_{5400}). The dummy variable equals 1 for the occurrence of an intervention and 0 for its nonoccurrence. Dummy variables are formed to represent the transition regime in the switching regression model. The occurrences of an intervention were set as dummy variables to evaluate their consequences.

By comparing the level of the post-intervention time series with that of the pre-intervention series, the statistical significance of the effect could be simulated. To evaluate the scope of the residual of the fit of the switching regression model and to compare the fitting results of the 2 plots, the root mean square error (RMSE) (eq. 10) was calculated, where obs_i is the number of observed trees ha^{-1}, and sim_i is the number of simulated trees ha^{-1}:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(sim_i - obs_i)^2} \text{ ....(10)}$$

RESULTS

Differences in DBH Distributions Before and After the Typhoons

Changes in the stand structures before and after the typhoon interventions in the 2 plots (CJ_{3000} and CJ_{5400}) are summarized in Table 2: the mean values of DBH increased, especially the minimum values which sharply increased, but the standard deviation decreased, and maximum values of DBH could not be differentiated by wind damage in either plot.

In this case, more trees were removed from CJ_{5400} than from CJ_{3000}. Figure 3 shows that the removed trees belonged to medium and small DBH classes, and the trees of larger than average DBH classes were not removed by wind damage (Table 2). In addition, the percentages of the number of trees lost were greater than those of the basal area lost in both plots, and percentages of both the trees lost and basal area lost were greater in the mature stand than in the younger stand.

Parameters *a*, *b*, and *c* in Table 3 fitted from the Weibull 3-pdf all passed the goodness-of-fit test ($D_\alpha > D_{plus}$). Meanwhile, the K-S tests failed to reject the null hypothesis that the observed and simulated DBH distributions came from the same population at the 5% level ($p < 0.05$).

Parameter *a*, the initial value of the probability density function, represents the simulated minimum DBH value in the stand. In CJ_{3000}, the values of parameter *a* increased from 5.91 to 10.18 after the T_1 intervention and from 10.84 to 13.25 after the $T_1 \times T_2$ interventions (Table 3). In CJ_{5400}, we discovered the same increasing pattern of values of parameter *a*: from 6.58 to 9.18 after the T_1 intervention and from 11.25 to 13.43 after the $T_1 \times T_2$ interventions. The values of parameter *a* obviously increased after the typhoon interventions in both plots, and the starting point of the curve was moved from left to right.

The simulation results show that parameter *b* of the two plots was reduced after wind damage occurred. The DBH-class distribution centralization (Fig. 2) could be represented by the decrease in parameter *b*, the coefficient of variation, and an increase in kurtosis. This means that the collective removal of the medium and small DBH-class trees led to a reduction in the discrete degree of the data.

For both plots, the values of parameter *c* tended to be positively skewed during the T_1 intervention, from 2.93 to 2.27 in CJ_{3000} and from 2.09 to 1.87 in CJ_{5400}. This indicates that the proportion of the larger DBH-class distribution relatively increased. However, they tended to be negatively skewed during the $T_1 \times T_2$ interventions (Table 3), and parameter *c* moved from 2.27 to 2.52 in CJ_{3000} and from 1.92 to 2.27 in CJ_{5400}. Cheng et al. (2017) pointed out that parameters of the Weibull 3-pdf have a regular trend in the change of stand age, and this will also be reflected in changes of the parameters after a disturbance occurs. In this study, parameter *c* was not positively skewed by the disturbance.

Although the kurtosis rose and the proportion of the larger DBH-class distribution relatively increased, the tail of skewness did not always move to the positive side. Perhaps this is related to the proportion of the distribution and percentile rank. In summary, changes in a single value sensitively reflected the interference of the stand, especially the minimum and maximum. By fitting the Weibull 3-pdf, it effectively described changes in the DBH distribution.

Dynamics of Stand Density Simulation

The fitted results are shown in Fig. 3. Overall, the number of trees in a density-stand age showed an inverted J-shaped distribution trend. It can be clearly seen that tree loss in CJ_{5400} after the wind damage was higher than that in CJ_{3000}. Table 4 shows the results of the switching regressions of the intervention analysis for the dynamics of stand density under the T_1 and T_2 interventions.

Adjusted R^2 values were 0.994 (p < 0.001) and 0.996 (p < 0.001) of the switching

Table 2 Forest stand dynamics before and after the intervention of typhoons in the 2 plots with different spacing trials

Plot	Intervention (Typhoon)		DBH (cm)			TPH (no. ha^{-1})		BA (m^2 ha^{-1})	
			Max	Mean±SD	Min	Total	Loss (%)	Total	Loss (%)
CJ_{3000}	T_1	Before	27.5	16.2±3.8	7.4	2479		54.51	
		After	27.5	17.3±3.3	11.1	2014		49.44	
		Loss				465	18.8	5.07	9.3
	$T_1 \times T_2$	Before	35.5	22.0±5.2	12.0	1662		66.48	
		After	35.5	23.9±4.6	14.6	1183		55.07	
		Loss				479	28.8	11.41	17.2
CJ_{5400}	T_1	Before	26.4	14.1±3.8	7.0	3615		60.77	
		After	26.4	15.2±3.3	9.4	2908		54.46	
		Loss				707	19.6	6.31	10.4
	$T_1 \times T_2$	Before	38.0	20.4±5.0	11.6	2092		71.84	
		After	38.0	22.5±4.4	14.5	1462		59.99	
		Loss				630	30.1	11.85	16.5

TPH, trees ha^{-1}; BA, basal area; SD, standard deviation; CJ_{3000}, *Cryptomeria japonica* plot with an original density of 3000 trees ha^{-1}; CJ_{5400}, *C. japonica* plot with an original density of 5400 trees ha^{-1}; T_1, Typhoon B174 in 1944; T_2, Typhoon Iris in 1955.

Table 3. Simulated 3-parameter Weibull distribution before and after the interventions of typhoons in the 2 plots

Plot	Intervention status	No. of trees in plot	Weibull Parameter					Kurtosis	Skewness	CV (%)
			a	b	c	D_0	D_{plus}			
CJ_{3000}	Before T_1	176	5.91	11.55	2.93	0.145	0.026	-0.17	0.17	23.68
	After T_1	143	10.18	8.00	2.27	0.161	0.019	0.04	0.38	19.19
	Before $T_1 \times T_2$	118	10.84	12.60	2.27	0.177	0.030	-0.42	0.32	23.83
	After $T_1 \times T_2$	84	13.25	12.03	2.52	0.211	0.185	-0.31	0.39	19.06
CJ_{5400}	Before T_1	235	6.58	8.44	2.09	0.125	0.055	0.13	0.56	26.77
	After T_1	189	9.18	6.73	1.87	0.140	0.083	0.46	0.76	21.93
	Before $T_1 \times T_2$	136	11.25	10.29	1.92	0.165	0.085	-0.11	0.48	24.37
	After $T_1 \times T_2$	95	13.43	10.26	2.27	0.197	0.058	0.70	0.45	18.89

CV, coefficient of variation; CJ_{3000}, *Cryptomeria japonica* plot with an original density of 3000 trees ha^{-1}; CJ_{5400}, *C. japonica* plot with an original density of 5400 trees ha^{-1}; T_1, Typhoon B174 in 1944; T_2, Typhoon Iris in 1955.

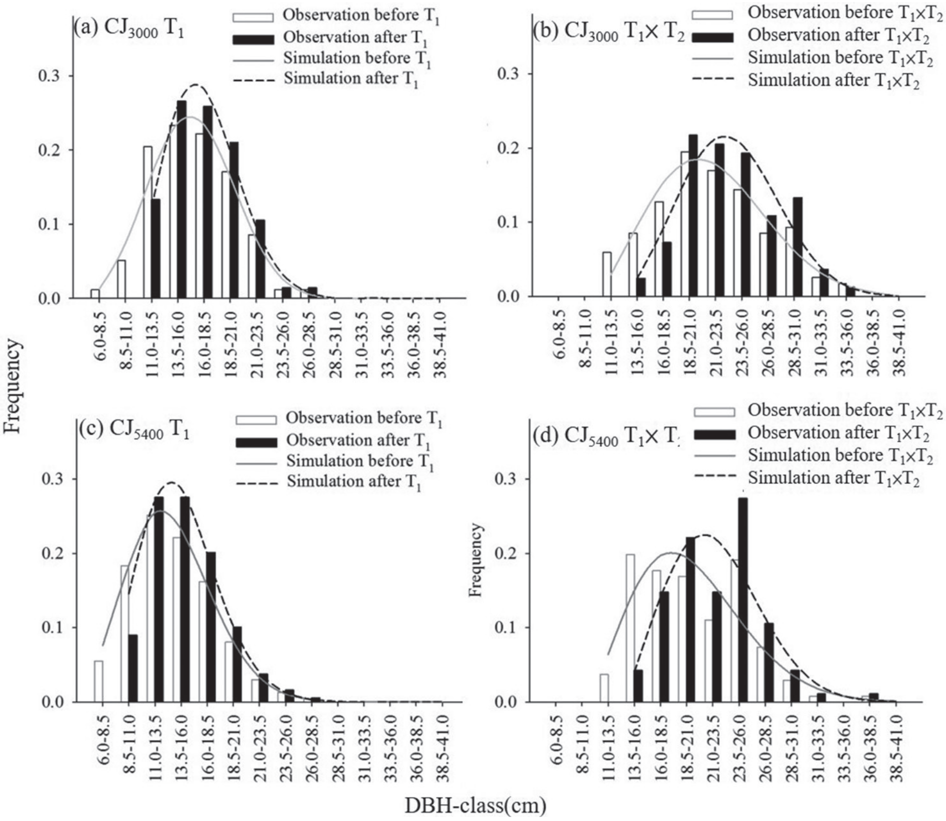

Fig. 2. Observed and simulated diameter at DBH-class distributions before and after the intervention of typhoons in the 2 plots with different spacing trials. (a) DBH distribution under the intervention of Typhoon B194 in 1944 (T_1) in a *Cryptomeria japonica* plot with an initial density of 3000 trees ha^{-1} (CJ_{3000}). (b)DBH-class distribution under the intervention of $T_1\times$Typhoon Iris in 1955 (T_2) in CJ_{3000}. (c) DBH-class distribution under the intervention of T_1 in a *C. japonica* plot with an initial density of 5400 tress ha^{-1} (CJ_{5400}). (d) DBH-class distribution under the intervention of $T_1\times T_2$ in CJ_{5400}.

regressions for CJ_{3000} and CJ_{5400}, respectively. Respective RMSEs were 78.09 and 127.99, and the variables were significant, indicating that switching regressions effectively fitted the changes in the number of trees after the interference. This indicates that the model was statistically significant.

The initial simulated numbers of CJ_{3000} and CJ_{5400} were 3525 and 6400, respectively, at a seeding age of 2 yr. Values of parameter n in CJ_{3000} and CJ_{5400} were -405 and -946, respectively, indicating that the trend of trees lost in the CJ_{5400} simulation was greater than that in CJ_{3000}. Numbers of trees removed in CJ_{3000} were 465 and 479, and simulated values were 412 and 576, respectively. Number of trees removed in CJ_{5400} were 707 and 630, and simulated values were 1017 and 664, respectively. The impacts of the 2 wind damage events show that losses of trees in CJ_{5400} were greater than those in CJ_{3000}.

In Fig. 3a, the simulated curves of number of trees in CJ_{3000} and CJ_{5400} intersected at a stand age of 57 yr under the T_1 and T_2 interventions, while the observed number of trees in both plots intersected at a stand age of 50 yr. There was only a 7-yr bias between the observed trend and the simulated curve.

In Fig. 3b, if plots only suffered the T_1 intervention, the simulated curves of number of trees in both plots intersected at a stand age of 61 yr, and the number of trees in both plots still remained > 1000 trees ha^{-1} as far as a stand age of 100 yr.

In Fig. 3c, if plots only suffered the T_2 intervention, the simulated curves of the number of trees in both plots gently decreased, they may intersect at some point beyond the simulated period, and the 2 plots retained > 1100 trees ha^{-1} as far as a stand age of 100 yr.

In Fig. 3d, if the plots had suffered no intervention, more than 1600 trees ha^{-1} at a stand age of 100 yr would have remained in the 2 plots, and the difference in the number of trees between the 2 plots would exceed 300 trees ha^{-1}.

From the simulated curve results, the numbers of trees in CJ_{5400} and CJ_{3000} intersected (Fig. 4). If the plots suffered both T_1 and T_2, the intersection occurred at a stand age of 57 yr. If plots suffered only T_1, intersection occurred at a stand age of 61 yr. If the plots suffered only T_2 or experienced no intervention, intersection did not occur in the age range of 100 yr.

As result, this case successfully demonstrated the trend of stand growth, i.e., the stand density (number of trees) under the effect of multiple interventions using switching regressions with dummy variables. The switching regressions effectively simulated trends of density dynamics under the interventions of typhoons through 4 simulated scenarios.

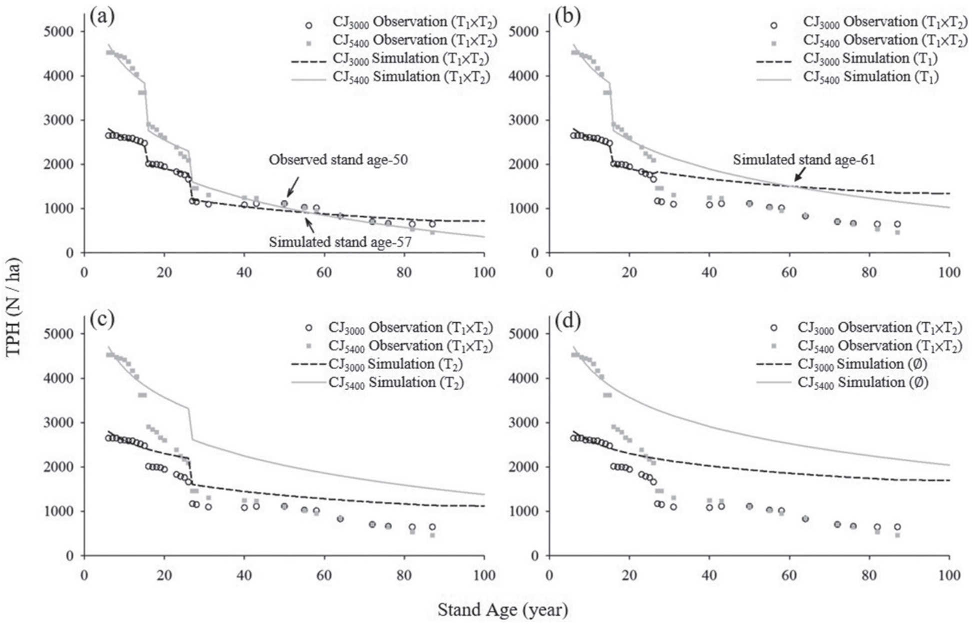

Fig. 3. Simulated trends of stand growth using switching regression of the intervention analysis in 4 scenarios. TPH, trees ha^{-1}.(a)The 2 plots suffered both Typhoon B174 in 1944 (T_1) and Typhoon Iris in 1955 (T_2) interventions. (b) The 2 plots suffered the T_1 intervention only. (c) The 2 plots suffered the T_2 intervention only. (d) The 2 plots experienced no intervention (Ø).

Table 4. Results of the switching regression model

Plot	Parameter				R^2	p value	RMSE
	m	n	p	q			
CJ_{3000}	3525.0*	-405. 1*	-412. 2*	-575.9*	0.994	< 0.001	078.09
CJ_{5400}	6400.3*	-946. 3*	-1017.0*	-663.6*	0.996	< 0.001	127.99

* $p < 0.001$. CJ_{3000}, *Cryptomeria japonica* plot with an original density of 3000 trees ha^{-1}; CJ_{5400}, *C. japonica* plot with an original density of 5400 trees ha^{-1}; RMSE, root mean square error.

DISCUSSION

Intervention Effect of Typhoons on DBH Distributions

In this study, more trees in CJ_{5400} were removed than were in CJ_{3000} (Fig. 2). As mentioned above, DBH-class structures changed due to the removal of small- and medium-sized trees more than large-sized trees after the typhoon interventions in both plots (Fig. 2). Wind-damaged trees in the 2 plots belonged to intermediate and suppressed trees. In this case, this study found the trees with a smaller DBH suffered greater impacts from the typhoon interventions.

However, this finding is contrary to some previous literature that claimed a positive relationship between the wind damage incidence and DBH. Kuboyama et al. (2003) and Lekes and Dandul (2000) indicated that wind damage was greater in mature and aged forests than in young stands and offered an explanation that may have been due to canopy closure, which served as a key to preventing wind damage. This indicates that a mature stand with a strong structure and closed canopy could better resist the risks of a typhoon. More specifically, intermediate-size trees had a high probability of stem breakage, and the risk of uprooting increased with the tree size (Wolf et al. 2004).

Another reason which was pointed out was that damaged trees might be similar to spindly trees, which are susceptible to wind damage (Cremer et al. 1982, Wonn and O'Hara 2001). Munishi and Chamshama (1994) and Wilson and Oliver (2000) demonstrated that trees in stands with wider planting distances have lower height-to-diameter ratios, which is conducive to reducing the incidence of wind damage. In our case, the spacing trials were inversely proportional to the wind damage incidence. Perhaps the height-to-diameter ratio is one of the characteristic factors of wind-damaged trees, and more survey records need to be researched in the future to evaluate this.

Statistics on destroyed woods after typhoons in Taiwan suggested that young trees and small-diameter trees suffered the most damage for both conifer and broadleaf trees (Wey and Chien 1989, Lin et al. 2009). It may be highly particular to the stand structural environment, climate, or topography (Gardiner and Quine 2000, Zachara 2014, Virot et al. 2016).

As previously mentioned, percentages of trees lost were greater than basal area losses in both plots. Characteristics of the DBH distributions after the interventions were similar to the consequences of low (or light) thinning (Smith et al. 1997, Mäkinen and Isomäki 2004). When the removed trees were of a smaller DBH class, the CV, standard deviation, and DBH distribution range accordingly decreased, but kurtosis increased. The DBH-class distribution was concentrated with the proportions of smaller DBH-class decreasing, since variations in parameter b were similar to variations in kurtosis.

The characteristic of parameter *c* is similar to the definition of skewness, which is the case for an asymmetrical distribution; it is influenced by variances in the distribution within the range. However, the effect of thinning on the skewness of the DBH distribution was not statistically significant in most cases (Versluis and Straetmans 2015). Although wind damage increased the proportion of the larger-DBH class distribution after the typhoon interventions in both plots, it was not positively skewed as we expected.

Intervention Effect of Typhoons on the Stand Density

Generally, the number of trees in a stand decreases along with the growth of the stand. Mortality caused by competition among trees within a crowded even-aged monospecific stand is so-called self-thinning (Reineke 1933, Yoda 1963). Overall, decreasing trends in the number of trees were similar to the pattern of a reverse J-shaped curve (Fig. 4d), when no intervention occurred. The number of trees decreases when a forest stand is aging and trees increase in size; it is also due to density-independent mortality and density-dependent mortality (VanderSchaaf and Burkhart 2008, Enquist et al. 2009, Deng et al. 2012), and disturbances could also impact density-dependent mortality (Nishizono and Tanaka 2012).

However, the limitation of this study is the lack of diversification in the number of trees in a single sample. Since the trend of the number of trees became more and more gentle among the three periods on the time series in the 2 plots, we assumed that wind damage was the main factor that changed the development of the forest stand structure. In order to verify the impact of wind damage, 4 types of simulations were fitted by a switching regression. From results of the aforementioned simulation, we inferred that Typhoon B174 in 1944 (T_1) had a greater impact on the development of stand structure than Typhoon Iris in 1955 (T_2). Although we reflected that wind damage caused changes to the stand structure of the 2 plots which led to future developments in the number of trees, there was no direct evidence or repeated samples to verify it. So we could only infer that it is 'possible'.

Cao and Dean (2008) and VanderSchaaf and Burkhart (2008) used a segmented regression to effectively estimate trajectories of the relationship between size and density. While most models use a nonlinear regression, logistical regression, exponential regression, or accumulative probability density function, these cannot sufficiently describe the trend of growth of a stand that suffers impacts of multiple interventions (Amateis et al. 1997, Antos et al. 2000, Antos and Parish 2002, Kleinbaum and Klein 2005).

Min et al. (2010) and Chiou et al. (2013) applied an intervention analysis to effectively fit the impact of disease and natural disasters on the number of tourists. In our case, we applied this feature to effectively fit the impacts of wind damage on the number of trees, and our results showed that Typhoon B174 in 1944 caused greater stand structural changes in the 2 plots than Typhoon Iris in 1955. As a result, the intervention analysis could overcome these problems and shed light on relationships between an intervention and the event of interest. As shown in Fig. 3, our simulation showed that the difference between plots with different spacing trials could have been modified by the effect of the intervention.

Long-Term Changes in Stand Structure and Dynamics

Long-term growth in the DBH, tree height, and number of trees can directly affect the stand structure and dynamics. After event T_2 in 1955, the number of trees showed a steadily decreasing trend in the 2 plots over the years. In particular, the basal area of CJ_{3000} at 40 yr old was more than that in CJ_{5400}, and the number of trees ha^{-1} of CJ_{3000} at 50 yr old was greater than that in CJ_{5400} (Fig. 4). Chiou et al. (2011) pointed out the initial volume and number of trees in plot CJ_{5400} was slightly higher than that in CJ_{3000}, but after 2 events with serious wind damage, the number of trees similarly trended in the 2 plots. Under the condition that there was no significant difference in tree height and large-diameter trees in CJ_{3000} were bigger than those in CJ_{5400}, but the volume in CJ_{3000} was higher than that in CJ_{5400} after 43 yr of age.

In this case, wind damage significantly decreased the BA and TPH with synchronous drops in 1944 and 1955. Although other typhoons have caused sporadic wind damage to trees as recorded in the ledgers, few events have caused such dramatic decreases in the number of trees. However, other typhoons caused different effects in the 2 plots after 1955 causing the BA and TPH to decrease due to other events, but most of those events lack detailed records. By comparing related references in the records, we inferred that Typhoon Wayne in 1986 and Typhoon Mindulle in 2004 caused decreases in the BA. Because of the limitation of a single sample, a small amount of dead trees could also have caused an apparent decrease in BA.

Nishizono and Tanaka (2012) indicated that thinning would change the density-size trajectory of a stand by affecting the density-dependent mortality period. Wind damage may be a form of natural selection, and its impacts might change the original density structure, which would affect the long-term stand structure and stock.

For long-term changes in stand structure and dynamics, there are many factors that affect stand development which may be jointly influenced by the site characteristics, silviculture treatments (Gardiner and Quine 2000, Zachara 2014), soil water content, root volume and shapes (Cremer et al. 1982, Gardiner 1994), typhoon disturbances, and forest dynamics (Lin et al. 2011). Although disasters may significantly change an area and lead to long-term impacts, wind damage does not necessarily cause negative effects. Particularly, stands with higher densities might suffer higher impact intensities from an intervention (Munishi and Chamshama 1994, Wilson and Oliver 2000). Perhaps, following past experience, we could evaluate the possible impacts of wind damage from Table 1, but they were not necessarily related to planting distances. In this study, it is possible that the impacts of wind damage were special events. Determining whether the 2 wind disasters were the main reasons for the impacts on stand development requires more evidence and samples.

CONCLUSIONS

In principle, an optimum planting density is key to achieving maximum yields of timber production. Planting distance or planting density is one of the silvicultural treatments for manipulating the forest structure in plantation management. Stand structure dynamics are greatly affected by typhoons, and wind-induced damage has always been a common cause of environmental and economic losses in Taiwan. In this study, we effectively and sufficiently examined the relationship between wind damage and stand structure dynamics (i.e., the number of trees, DBH distribution, etc.) by applying the Weibull distribution and an intervention analysis.

In this study, the Weibull 3-pdf was used to simulate the DBH distribution before and after typhoon interventions. Results showed that after the typhoon interventions (1) the trees with smaller DBH were more likely to be removed from the experimental plots, (2) the DBH distribution was more concentrated, and (3) the variance in the DBH distribution decreased. We concluded that patterns of DBH distribution after the typhoon interventions were similar to the consequences of low (or light) thinning. The characteristic of parameter *b* is similar to kurtosis, and the characteristic of parameter *c* is similar to skewness. Removing small-sized trees may lead to a reduction in the discrete degree of the DBH data, so that when the kurtosis rises, the skewness does not always move to a positive bias.

According to records of long-term studies, it is impossible to avoid interventions by natural disasters on stand growth. In results of this study, the typhoon intervention altered the stand density in long-term Japanese cedar experimental plots with 2 spacing trials. The typhoon interventions caused greater impacts (i.e., loss of trees) on the plot with the smaller planting distance (CJ_{5400}) than in the plot with a larger planting distance (CJ_{3000}). In this case, the switching regressions used dummy variables to deal with the effect of multiple interventions. As a result, the simulated curves of numbers of trees in the CJ_{5400} and CJ_{3000} plots were according to switching regressions. We inferred that Typhoon B174 in 1944 had a greater impact on the development of stand structure than did Typhoon Iris in 1955 through simulation of the intersection, removal of wind-damaged trees, and long-term stand development. Results demonstrated that switching regressions could efficiently evaluate the impacts of interventions from Typhoon B174 in 1944 and Typhoon Iris in 1955 in the 2 plots.

There is a limitation of this research that should be addressed. Use of a single sample for switching regression tests is a weakness

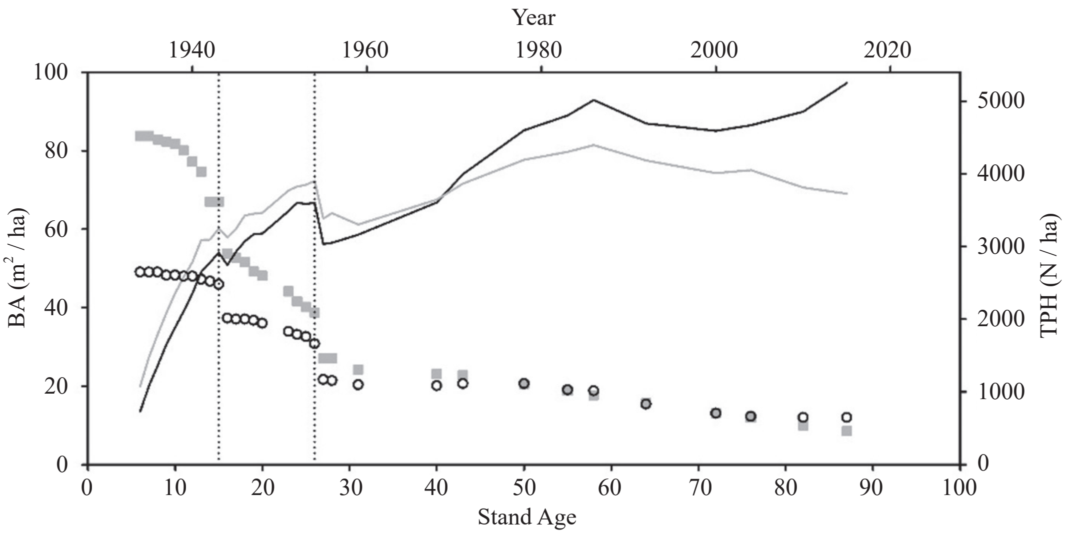

Fig. 4. Long-term changes in basal area (BA) and trees ha^{-1} (TPH).
Hollow black circle is TPH of a *Cryptomeria japonica* stand with an initial density of 3000 trees ha^{-1} (CJ_{3000}). Gray square is TPH of *C. japonica* stand with an initial density of 5400 trees ha^{-1} (CJ_{5400}). The black line is the BA of CJ_{3000}. The gray line is the BA of CJ_{5400}. A pair of dotted lines are event T_1 in 1944 and event T_2 in 1955.

for explaining general stand development. This study referred mostly to a single case in 2 long-term Japanese cedar experimental plots with 2 spacing trials. Regardless of whether the impact of the typhoon events caused a disaster, promoted stability, or had other effects on long-term forest development, we will prove the applicability of the method through evaluating additional stands with different conditions in the future.

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