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## Influence of slope, aspect and competition index on the height-diameter relationship of *Cyclobalanopsis glauca* trees for improving prediction of height in mixed forests

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### Highlights

- In this study, the effects of slope, aspect and competition index (CI) on the H-DBH relationship were explored and an improved CI was developed and included to improve predictions of *Cyclobalanopsis glauca* tree height.
- It was found that the effects were statistically significant and considering slope, aspect and CI for developing the H-DBH models significantly increased the H prediction accuracy.

### Abstract

Diameter at breast height (DBH) and height (H) of trees are two important variables used in forest management plans. However, collecting the measurements of H is time-consuming and costly. Instead, the H-DBH relationship is modeled and used to estimate H. But, ignoring the effects of slope, aspect and tree competition on the H-DBH relationship often impedes the improvement of H predictions. In this study, to improve predictions of *Cyclobalanopsis glauca* (Thunb.) Oerst. tree H in mixed forests, we compared eleven H-DBH models and examined the influence of slope and aspect on the H-DBH relationship using 426 trees. We then improved Hegyi competition index and explored its effect on the H predictions by including it in the selected models. Results showed 1) There were statistically significant effects of slope and aspect on the H-DBH relationship; 2) The log transformation and exponential model performed best for sunny- and shady-steep, respectively, and the Gompertz's model was optimal for both sunny- and shady-gentle; 3) Compared with the whole dataset, the division of the data into the slope and aspect sub-datasets significantly reduced the RMSE of H predictions; 4) Compared with the selected models without competition index, adding the original Hegyi and improved Hegyi\_I into the models improved the H predictions but only the models containing the improved Hegyi\_I significantly increased the prediction accuracy at the significant level of 0.1. This study implied that modeling the H-DBH relationship under different slopes and aspects and including the improved Hegyi\_I provided the great potential to improve the H predictions.

**Keywords** effect; improved Hegyi\_I; secondary forest; topographic feature; tree height estimation

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## 1 Introduction

The diameter at breast height (1.3 m above ground) (DBH) and total height (H) of trees are often used to estimate tree volume and biomass and thus are two important variables that are used in forest management planning and measured in forest inventories. Generally, DBH is relatively easily and accurately measured and an accuracy of greater than 95% is achievable. However, measuring H is usually time-consuming and costly, and an average accuracy of about 80% is often obtained (Larjavaara et al. 2013; MacPhee et al. 2018). This is especially true in the forests that have dense canopies and are located in the areas of complex topography. In order to reduce the cost of data collection in the field, H-DBH models are usually developed by sampling and measuring DBH and H of trees and then used to account for the H-DBH relationship and predict H values for the un-measured trees (Rupsys et al. 2015; Mensah et al. 2018).

Substantial research has been conducted to explore the H-DBH relationship. Various linear and nonlinear models such as logarithmic, exponential and logistic models have been developed (Huang and Titus 1992; Larsen and Hann 1987; Amaro et al. 1998; de Mendonca et al. 2011; Fekedulengn et al. 1999; Fast et al. 2011; Phillimon et al. 2019; Sharma 2009; Yuancai and Parresol 2001). In the models, when DBH is used as the only independent variable to predict tree H, the percentage error of predicted H values often varies from 10% to 20% and the prediction accuracy is acceptable. In order to further improve the prediction accuracy of tree H, standard height curves are used to account for the H-DBH relationship by adding stand variables such as dominant tree height and average DBH of basal area into the models (Krumland et al. 1978; Parresol et al. 1992).

However, various factors and variables including topographic features (elevation, slope and aspect), site quality, tree density and competition environment, tree species composition of mixed forests, etc., affect the growing of tree H and DBH and thus the H-DBH relationship (Sharma 2016; Temesgen et al. 2014). For example, at different elevations the H-DBH relationship may differ due to different growth rates of H and DBH caused by the gradient characteristics of climatic and soil properties (Mensah et al. 2018). Given the similar elevations, different slopes and aspects lead to different H-DBH relationships. Variable site quality may also result in different H-DBH relationships. Given the same elevation, slope, aspect and site quality, the H-DBH relationship may differ due to different tree density and competition of neighboring trees, which leads to the trees that have same values of DBH have a great range of H. However, the existing H-DBH models cannot well capture the heterogeneity of the H-DBH relationship caused by topographic features and tree competition, and the interactions between them.

In order to account for the heterogeneity of the H-DBH relationship, most of the commonly used approaches are to introduce dummy variables into the H-DBH models and use nonlinear mixed-effect models to fit the H-DBH relationship (Calama and Montero 2004; Kalbi et al. 2018; Kearsley et al. 2017; Lappi 1997; Robinson and Wykoff 2004). The studies take into account the effect of site quality on the H-DBH relationship but focus on tree species in pure forests. There are few reports that deal with modeling the H-DBH relationship for tree species in mixed forests (Zang et al. 2016).

Inter-tree competition has been considered as an important variable that affects the relationship of H with DBH. A tree competition index (CI) is defined as the ability of trees to obtain space and resources for growth in the same environment (Peet and Christensen 1987; Pickett et al. 1987). Various CIs have been employed to quantify the degree of competition among trees (Bella 1971; Burkhart and Tome 2012; Lorimer 1983; Biging and Dobbertin 1995; Ledermann 2010; Martin and Ek 1984) and can be divided into relative CIs and absolute CIs. Relative CIs reflect the dominance of individuals in a stand rather than the actual level of competition because they are not associated with growth space of trees (Daniels et al. 1986; Alder 1979; Tome and Burkhart

1989). Absolute CIs reveal the actual competition degree among adjacent trees by quantifying the growth space of trees.

Burkhardt and Tome (2012) divided tree CIs into distance-independent and distance-dependent. The former are simple functions of stand level variables and/or dimensions of a target tree related to the average or maximum value of a stand. Distance-independent CIs can be easily obtained with less demand of data due to location information not required. However, they lack the ability of accurately accounting for the space a target tree needs for growing.

In distance-dependent CIs, it is assumed that each tree has a neighboring overlapped area of influence expressed as a function of its size and competitive stress is measured as the impact of the neighbors on the target tree (Burkhardt and Tome 2012; Opie 1968). Distance-dependent CIs vary depending on selection of competitors and determination of an index that measures the degree of the target tree to share resources with its competitors. Competitors include the uses of a fixed area or a fixed number of trees, angle based sampling, etc. (Daniels 1976; Hegyi 1974; Lorimer 1983; Rival et al. 2005). The commonly used CIs consist of point density indices (Spurr 1962), area overlap indices (Opie 1968), and those based on the size and distances of the neighbors within a search radius, estimation of shading or light interception, etc. (Daniels 1976; Daniels et al. 1986).

Tree CIs have been also computed according to symmetric and asymmetric, and one-sided and two-sided competition for resources sharing (Brand and Magnussen 1988; Burkhardt and Tome 2012; Weiner 1990). In the models of CI with two-sided and symmetric competition, resources are shared by all competitors surrounding the target tree. In the models of CI with one-sided and asymmetric competition, the growth of a larger tree is less affected by smaller neighbors (Brand and Magnussen 1988; Weiner 1990). Moreover, there are models of CI that account for competition for light (Canham et al. 2004; Pretzsch et al. 2002) and spatial distribution of competitors and effect of their directions (Pukkala 1989).

Various variables that account for tree competitive effect, including tree DBH, H, crown width and distance of competitors to the target tree, have been widely used to develop CIs. However, tree competition varies depending on tree sizes, canopy structures, species and composition, topographic features, etc. Especially, both the distances of a target tree to competitors and the height of the target tree in relation with the neighbors form a 3-dimensional space in which the target tree competes with its neighbors for resources. However, the 3-dimensional space needs the measurements of tree H.

Compatibly, the distance-dependent CIs provide better performance of quantifying the degree of tree completion than the distance-independent CIs and are also required by the spatially-explicit forest growth models and forest management (Burkhardt and Tome 2012). This is especially true for mixed forests. Traditionally, the shortcoming of the distance-dependent CIs is the difficulty to obtain spatially-explicit measurements of distance among trees and their height in a study area. As remote sensing technologies develop, the disadvantage of the distance-dependent CIs and the gain of a CI in a 3-dimensional space can be, to some extent, overcome by using a photogrammetric method based on high spatial resolution stereo images and LiDAR data. This implies that the development of the spatial-explicit distance-dependent CIs is promising. However, so far there have been no reports that deal with the development of the 3-dimensional space based CIs using remote sensing technologies.

Hegyi CI is one of the most widely used distance-dependent CIs (Burkhardt and Tome 2012; Hegyi 1974), in which the DBH values of the target tree and competitors and their distances to the target tree are taken into account. However, the effects of tree H from the competitors related to the target tree is ignored because tree H is often not easily obtained. In this study, we explored the improvement of Hegyi CI and its application to quantify the competitive degree of *Cyclobalanopsis glauca* (Thunb.) Oerst. trees that mostly exist in mixed forests of Southern China. The *C. glauca* is

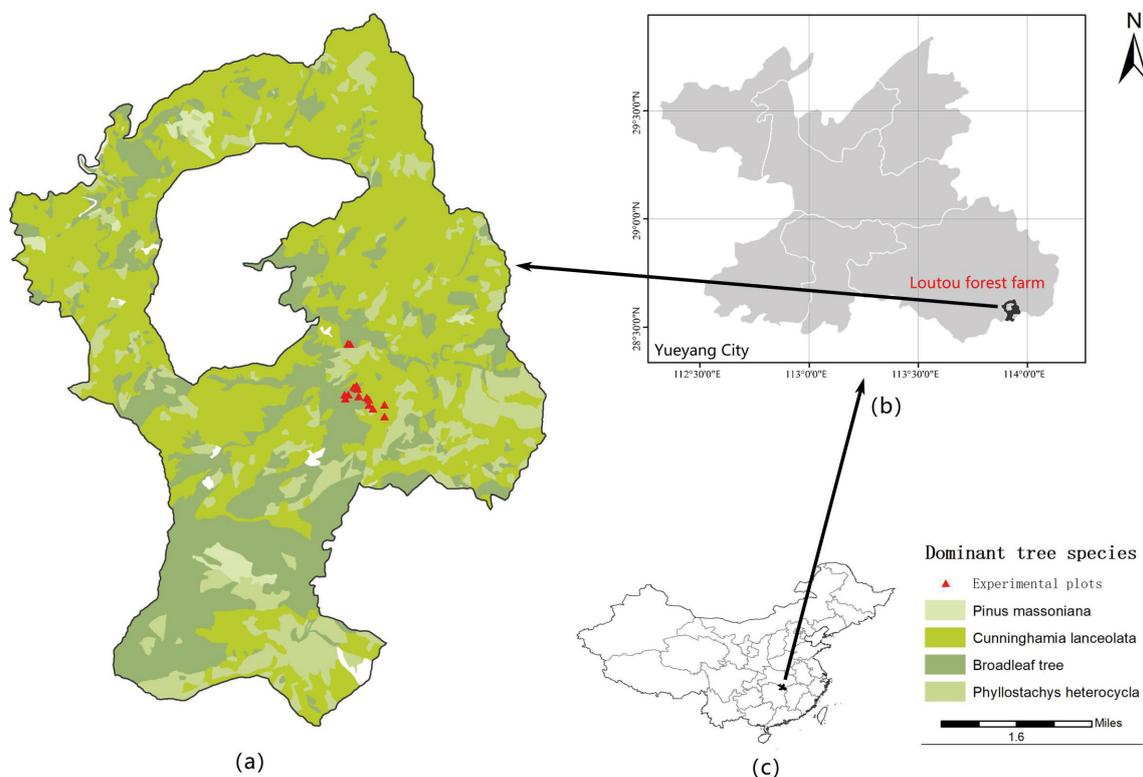
one of the major tree species in the secondary natural oak mixed forests that occupy 16.1 million hectares and account for 13.7% of the total natural forest area in China. Owing to the strong adaptability, *C. glauca* is widely distributed in evergreen broad-leaf forests in the provinces of Hunan, Hubei, Guangdong and Sichuan. The mixed forests are often distributed in the regions with elevations of 2600 m and lower. The *C. glauca* is a valuable timber tree species in China because of its high stress resistance and solid wood. The development of substantial root systems and a long time of growth make *C. glauca* important in water and soil conservation and ecological protection in China. However, only few studies on the H-DBH relationship for *C. glauca* have been conducted.

The overall objective of this study was to improve the predictions of tree H in the *C. glauca* secondary forests by taking into account the influence of slope, aspect and tree competition on the H-DBH relationship. The specific objectives included 1) analyzing the influence of different slopes and aspects on the H-DBH relationship of *C. glauca* trees based on the widely used H-DBH models; and 2) developing an improved Hegyi CI and assessing its effect on the improvement of modeling the H-DBH relationship by adding it into the selected H-DBH models.

## 2 Materials and methods

### 2.1 Study site

The study site is located in the Loutou forest farm of Yueyang city, Hunan Province of southern China, with the longitude and latitude range of 113°51'52"–113°58'24"E and 28°31'17"–28°38'00"N (Fig. 1). The study area has an average slope of about 25°. It is located in the northern end area of Luxiao mountains in China with a continental monsoon climate. The mean annual temperature is 16.8 °C and the mean annual precipitation is 1624.8 mm. The soil types vary depending on eleva-



**Fig. 1.** The location of a) the study area – Loutou forest farm in b) Yueyang of Hunan Province, c) southern China.

tion in this study area with red soil located in the areas below the elevation of 600 m, mountainous yellow soil in the areas with the elevations of 600–1200 m and mountainous yellow brown soil in the areas above the elevation of 1200 m. The dominant tree communities consist of Fagaceae, Lauraceae, Theaceae, Magnoliaceae, Aquifoliaceae, Elaeocarpaceae, Hamamelidaceae and Symplocaceae. The study area is dominated by natural secondary forests after being damaged. The dominant tree species are composed of *Rhododendron latoucheae* Franch., *Alniphyllum fortune* (Hemsl.) Makino, *Castanopsis sclerophylla* (Lindl.) Schottky, *Symplocos sumuntia* Buch.-Ham. ex D. Don and *Castanopsis eyrei* (Champ. ex Benth.) Tutcher. In the secondary natural and mixed forests, *C. glauca* is distributed.

## 2.2 Data

The used data were obtained from a total of 16 plots in the secondary mixed forests in the Lutou forest farm (Fig. 1a). All the plots were established in 2015 each with the area of 20 m × 20 m. The plots had different topographic features with 8 plots in the areas of sunny slopes and 8 plots in the areas of shady slopes. In the plots, the dominant tree species was *C. glauca* with mixed tree species including *C. eyrei*, *C. sclerophylla*, *Cunninghamia lanceolata* (Lamb.) Hook., *A. fortune* and *R. latoucheae*. Within each of the plots, the values of tree DBH and H were obtained and plot position (X and Y coordinates), elevation, slope, aspect, slope position and canopy density were recorded. Tree DBH and H were measured using a diameter tape and a Blume-Leiss hypsometer, respectively. Plot slope and aspect were measured at four corners of each plot using a compass theodolite and their average values were used as the plot slope and aspect. Plot elevation and slope position were measured using a global positioning system. The information of the plots and trees was shown in Table 1. The statistics of tree variables were given based on different slopes and

**Table 1.** The information of the measured variables for the 16 sample plots (Note: DBH: diameter at breast height; H: tree height; Cg: *Cyclobalanopsis glauca*; Rs: *Rhododendron simsii*; Cs: *Castanopsis sclerophylla*; Ce: *Castanopsis eyriei*; Lc: *Loropetalum chinense*; Cl: *Cunninghamia lanceolata*; Af: *Alniphyllum fortune*; Ca: *Canarium album*; Mr: *Myrica rubra*; Ss: *Symplocos sumuntia*).

Sample plot number	Altitude (m)	Slope (degree)	Slope aspect	Slope position	Crown density	Tree composition	Number of trees	Mean DBH (cm)	Mean H (m)
1	324	19	sunny	medium	0.9	4Cg 3Rs 1Cs 1Ce 1Lc	63	15.4	11.1
2	340	17	sunny	medium	0.7	4Cg 3Rs 2Lc 1Cl	54	12.9	9.5
3	312	22	sunny	below	0.8	4Cg 3Rs 2Cl 1Ce	41	14.6	10.0
4	310	34	shady	medium	0.8	4Cg 4Rs 1Lc 1Ca	54	12.5	9.3
5	330	20	sunny	below	0.7	3Cg 2Ce 2Cl 2Rs 1Mr	30	14.9	9.7
6	312	32	sunny	below	0.8	4Cg 3Rs 2Ce 1Lc	51	12.1	9.1
7	315	33	sunny	below	0.7	3Cg 3Af 3Rs 1Cl	53	13.1	9.0
8	320	35	shady	medium	0.8	4Cg 3Cs 3Lc	46	15.1	8.8
9	314	35	shady	medium	0.7	4Cg 2Cs 2Rs 1Af 1Lc	29	14.3	11.3
10	318	32	shady	upper	0.7	5Cg 3Rs 2Af	45	13.2	9.9
11	302	15	shady	medium	0.7	4Cg 2Af 2Cl 2Lc	48	12.8	9.6
12	305	20	shady	medium	0.7	5Cg 2Rs 2Af 1Cl	81	12.7	9.5
13	310	16	shady	upper	0.6	5Cg 2Rs 2Cs 1Lc	50	12.3	12.5
14	325	27	sunny	medium	0.8	6Cg 2Cs 1Rs 1Cl	52	14.6	9.5
15	308	30	sunny	medium	0.6	3Cg 3Cs 2Rs 1Ce 1Af	40	9.5	9.6
16	285	20	shady	below	0.8	4Cg 3Cl 1Ce 1Af 1Rs	100	12.1	10.3

**Table 2.** Characteristics of *Cyclobalanopsis glauca* tree height and diameter at breast height (DBH) measurements for the total, modeling and validation datasets based on sunny-gentle, sunny-steep, shady-gentle and shady-steep (Max: maximum; Min: minimum; SD: standard deviation).

Subsets	Sample type	Number	Height (m)				DBH (cm)			
			Mean	Max	Min	SD	Mean	Max	Min	SD
Sunny-gentle	Total	96	11.5	17.3	5.6	2.9	14.6	42.5	5.2	6.9
	Modeling	77	11.5	17.3	5.6	3.0	14.7	42.5	5.2	7.3
	Validation	19	11.6	16.3	6.1	2.8	14.3	22.7	7.3	5.1
Sunny-s teep	Total	86	10.3	15.4	6.5	2.2	12.9	26.0	5.0	5.1
	Modeling	69	10.2	15.4	6.5	2.3	13.0	26.0	5.0	5.4
	Validation	17	10.5	14.4	7.8	1.8	12.4	18.6	6.1	4.1
Shady-gentle	Total	139	10.4	14.9	3.5	2.5	12.8	29.0	5.1	4.9
	Modeling	111	10.4	14.8	3.5	2.5	12.9	27.2	5.1	4.9
	Validation	28	10.4	14.9	5.8	2.5	12.0	29.0	5.8	4.7
Shady- steep	Total	105	10.6	15.0	6.4	2.0	15.2	41.6	5.1	7.0
	Modeling	84	10.7	14.7	6.4	1.9	14.8	33.4	5.1	6.3
	Validation	21	10.2	15.0	6.7	2.4	16.4	41.6	5.1	9.4

aspects in Table 2. There were a total of 426 *C. glauca* trees. Considering the slope and aspect, the dataset was randomly split into two parts: 80% (341 trees) for modeling and 20% (85 trees) for validation. The modeling and validation datasets were further divided into sub-datasets of sunny gentle, sunny steep, shady gentle and shady steep with the number of sample trees varying from 77 to 111 for the modeling dataset, and from 17 to 28 for the validation dataset. The sample means of tree height and DBH measurements among the whole, modeling and validation datasets did not statistically significantly differ from each other at the significant level of 0.05 for all the sub-datasets. Thus, the random divisions were acceptable.

### 2.3 Modelling of H-DBH relationship and selection of models

A large number of models have been developed to model the relationship of tree H with DBH for different tree species and different regions of same tree species. In this study, a total of 11 commonly used tree H-DBH equations including linear, logarithm linear, exponential, Hyperbolic, Quadratic model and those proposed by Gompertz (1825), Yoshida (1928), Schumacher (1939), Richards (1959), Näslund (1937) and Wykoff et al. (1982), were selected to fit the tree H-DBH relationship of *C. glauca* secondary forests (Table 3). Because the H-DBH relationship may be different depending on topographic features and also affected by the competition among trees, modeling the H-DBH relationship was conducted under the different slopes and aspects including sunny-steep, sunny-gentle, shady-steep and shady-gentle and also by introducing a tree competition variable into the models in this study. The differences in the growth of H and DBH due to different slopes and aspects and the corresponding growth process were analyzed using Chow's F-test based on the sums of square residuals of H predictions. If the growth between the sunny and shady slope was different significantly, the differences of the growth process among sunny-gentle, sunny-steep, shady-gentle and shady-steep slope were further tested. A statistical test result of no significant difference implied that the tree H-DBH relationship of *C. glauca* trees was basically consistent under different slopes and aspects.

**Table 3.** The basic models used for comparison of modeling the relationship of tree height (H) with diameter at breast height (DBH) (Note: D is DBH; a, b, c and d are model parameters; M#: model numbers).

M#	Model	References	M#	Model	References
M1	$H = a \times D + b$	Linear	M7	$H = \frac{a}{(1 + b \times D^{-c})} + d$	Yoshida (1928)
M2	$H = a \times \ln(D) + b$	Log	M8	$H = a \times e^{-\frac{b}{D}}$	Schumacher (1939)
M3	$H = a \times D^b$	Exponential	M9	$H = a \times (1 - e^{-c \times D})^b$	Richards (1959)
M4	$H = a - \frac{b}{D + c}$	Hyperbolic curve	M10	$H = D^2 / (a + b \times D)^2$	Huang and Titus (1992)
M5	$H = a \times D^2 + b \times D + c$	Quadratic	M11	$H = e^{a+b/(D+1)}$	Wykoff et al. (1982)
M6	$H = a \times e^{-b \times e^{-c \times D}}$	Gompertz (1825)			

## 2.4 The improved Hegyi competition index

As a famous and simple index, Hegyi CI has been widely used for quantifying competition degree among trees in forest stands (Vanclay et al. 2013; Timilsina and Staudhammer 2013). Hegyi CI is defined based on the DBH values of a target tree and its competitors and the horizontal distances of the competitors to the target tree and easy to obtain because the values of tree H are not taken into account. That is, Hegyi CI ignores the impact of tree H from the competitors. However, in a forest, because trees grow with biomass accumulated by absorbing light, water and nutrients, a 3-dimensional space is needed, in which trees compete with each other for gaining the resources. Thus, Hegyi CI should be improved by defining it in a 3-dimensional space. Considering the values of tree H are often difficult to gain, in this study the relative relationships of tree H between competitors and a target tree were taken into account. The widely used methods of selecting competitors include the uses of crown overlap, nearest neighbors and Thiessen polygon. Moreover, previous studies show that four trees closest to the target tree often have obvious effects on the growth of the target tree because the four nearest neighbors are most likely competing with the target tree for the resources needed for growing (Hui et al. 2018). In addition, this method is simplest. Therefore, four nearest trees from the target tree were regarded as competition trees in this study. The original Hegyi CI is calculated as follows:

$$CI = \sum_{j=1}^N \frac{D_j}{D_i \times L_{ij}}, \quad (1)$$

where  $i$  is the target tree,  $j$  represents the competing tree  $j$ ,  $D_i$  is the DBH of the target tree,  $D_j$  is the DBH of the competing tree  $j$ ,  $L_{ij}$  is the distance between the target tree  $i$  and competing tree  $j$ , and  $N$  is the number of the competing trees. Considering the impact of tree H from the competitors, given a distance and DBH a competition tree taller than the target tree should have a greater impact on the growing of the target tree than the one shorter than the target tree. This is mainly because the former occupies more space vertically and may have a strong root system than the latter. Moreover, the former often shades the target tree. Thus, the improved Hegyi CI focused on the adjustment of competition effect by changing the contributions of the diameters of the competing trees. The adjusted diameter of the competitor  $j$  was calculated as follows:

$$D_j = D_j^k, \quad (2)$$

where  $k$  is a generalized parameter and functions to reflect the contribution from the height  $H_j$  of the competing tree  $j$  by modifying its value of DBH. When the target tree is taller than a competing tree (that is,  $H_i > H_j$ ), the impact of the competing tree on the growth of the target tree is assumed to be weaker and thus  $k$  could be smaller than 1. When the target tree is equal to and shorter than a competing tree (that is,  $H_i \leq H_j$ ), the impact of the competing tree on the growth of the target tree is assumed to be stronger and thus  $k$  could be equal to or larger than 1. Theoretically, the  $k$  could be any value and determined by the ratio of the height of a competing tree to the height of the target tree. For simplification, in this study we only tested two values, that is,  $k = 0.5$  for  $H_i > H_j$ , and  $k = 1$  for  $H_i \leq H_j$ .

The improved Hegyi CI is accounted for by Eq. 1 and Eq. 2 together and denoted with Hegyi\_I. When the height of the target tree is higher than that of the competition tree, the effect of the  $H_j$  on the target tree is indirectly accounted for by reducing the contribution from its DBH to  $\sqrt{D_j}$ , that is, weakening the impact of the competitor. When the target tree is shorter than the competing tree, the contribution from the DBH of the competing tree is not adjusted, which means that the impact of the taller competitor is relatively enhanced compared with that of the shorter competitor. Moreover, the improvement does not lead to the need to accurately measure the heights of trees. Instead, the relative relationships between the height of the target tree and the heights of the competing trees can be easily and visually determined.

The original Hegyi CI is defined in a 2-dimensional space. The improved Hegyi CI indirectly takes into account the effect of tree H from competitors and quantifies the impacts of four nearest competing trees on the target tree from both horizontal and vertical directions. In this study, the effects of these two CIs on the H-DBH relationship were compared by analyzing their correlations with tree H and DBH and assessing the prediction accuracies of tree H using the H-DBH models in which the original and improved, Hegyi and Hegyi\_I, were added as a predictor, respectively.

## 2.5 Model assessment

In this study, the whole modeling dataset was first used to develop the models and make the predictions of tree H. The modeling dataset was then divided into sunny and shady slope sub-datasets and the two sub-datasets were respectively utilized to build the models and predict the tree H. The residuals of the tree H predictions from the models using the whole modeling dataset and two sub-datasets respectively were calculated and Chow's F-tests were conducted to examine if the corresponding parameters of the same models obtained using the sunny and shady slope sub-datasets were statistically significantly different from that of the whole dataset (Chow, 1960). The tests were carried out based on the sums of the squared residuals. The Chow's F-test equation was:

$$F = \frac{SSR_5 / m}{SSR_4 / (n_1 + n_2 - 2m)} \sim F(k, n_1 + n_2 - 2k), \quad (3)$$

where given a model, let  $SSR_T$ ,  $SSR_1$  and  $SSR_2$  be the sums of squared residuals from the H-DBH models using the whole modeling dataset and the sunny and shady slope sub-datasets, respectively.  $SSR_4 = SSR_1 + SSR_2$ ,  $SSR_5 = SSR_T - SSR_4$ ,  $n_1$  and  $n_2$  are the numbers of the observations for the sunny and shady slope sub-datasets and  $m$  is the number of the arguments. In Chow's F-test, the hypothesis is given as follows: given a model, aspect does not affect the H-DBH relationship. If the whole modeling dataset is divided into two sub-datasets corresponding to the sunny and shady slope and these two sub-datasets are fit using the same model, the sums of the squared residuals

from two models that have the same structure should have the same normal distribution. If the model structures are the same, the total sum of the squared residuals from two sub-datasets,  $S_1 + S_2$ , should not statistically significantly different from that,  $S_R$ , obtained using the whole modeling dataset. Therefore, the coefficients of the models, that is, the model structures, are statistically the same. If F statistics is greater than the critical value of F at the significance level of 0.05, the hypothesis is rejected, implying that the division of the sunny and shady slope sub-datasets led to significant difference of sums of the square residuals, that is, different coefficients of the models. If so, the further divisions of the sunny slope into sunny-steep and sunny-gentle and the shady slope into shady-steep and shady-gentle, and the corresponding Chow's F-tests were conducted.

Moreover, a total of eleven basic models were compared to fit the H-DBH relationship of *C. glauca* trees (Table 3). The H-DBH models were evaluated using the coefficient of determination ( $R^2$ ) and root mean square error (RMSE) between the observed and predicted values of tree H, and Akaike information criterion (AIC). Through the assessment results, the optimal model was selected. Finally, the original Hegyi and the improved Hegyi\_I were respectively introduced into the selected models as a predictor and the resulting models were used to predict tree H. For the same model, the prediction results from the model without CI and the models with Hegyi and Hegyi\_I were compared to verify whether or not the introduction of Hegyi and Hegyi\_I significantly improved the predictions of tree H.

### 3 Results

#### 3.1 The effects of slope and aspect on the H-DBH relationship

In Table 4, the H-DBH relationship of *Cyclobalanopsis glauca* trees was fit using the eleven models (M1 to M11) and the whole modeling dataset. The relationship was further fit using the sub-datasets of sunny-slope, shady-slope, steep-slope and gentle-slope and the optimal model was selected for each of the sub-datasets in Table 5. The results of Chow's F-test showed that the division of the modeling dataset into sunny and shady slopes, and steep and gentle slopes led to the different structures of the H-DBH relationship because there were statistically significant differences of the

**Table 4.** The results of eleven basic models (M1 to M11) used for fitting the H-DBH relationship using the whole modeling dataset (H is tree height; DBH is diameter at breast height; a, b, c and d are model parameters; RMSE and  $R^2$  respectively are root mean square error and coefficient of determination between the observed and estimated values of H; and SSR is the sum of squared residuals).

M#	Model parameter				Model evaluation		
	a	b	c	d	$R^2$	SSR	RMSE
M1	0.321	6.241			0.624	972.654	1.511
M2	4.735	-1.323			0.683	821.522	1.389
M3	3.529	0.043			0.670	854.983	1.417
M4	19.897	216.848	10.988		0.685	816.203	1.384
M5	-0.0097	0.6517	3.8716		0.679	831.126	1.397
M6	15.02	1.471	0.116		0.686	813.143	1.382
M7	10.672	156.574	2.024	5.169	0.686	811.589	1.380
M8	16.936	5.552			0.676	839.931	1.404
M9	15.949	0.764	0.071		0.685	814.723	1.383
M10	0.874	0.235			0.682	821.891	1.389
M11	2.87	-6.62			0.681	826.471	1.393

**Table 5.** The results of the optimal models selected from the eleven basic models (M1 to M11) used for fitting the H-DBH relationship for each of the sub-datasets including sunny, shady, steep and gentle slope, and sunny-steep, sunny-gentle, shady-steep and shady-steep (a, b and c are model parameters; RMSE and  $R^2$  respectively are root mean square error and coefficient of determination between the observed and estimated values of H; SSR is the sum of squared residuals; and AIC is Akaike information criterion).

Dataset	Model #	Model parameter			Model evaluation			
		a	b	c	$R^2$	SSR	RMSE	AIC
Sunny slope	M6	16.704	1.416	0.094	0.695	394.29	1.472	146.7
Shady slope	M6	13.945	1.597	0.140	0.702	379.41	1.247	113.7
Steep slope	M2	3.922	0.451		0.714	232.83	1.104	85.4
Gentle slope	M6	15.816	1.757	0.124	0.720	492.06	1.447	130.3
Sunny-steep	M2	4.253	-0.249		0.622	154.55	1.341	54.4
Sunny-gentle	M6	16.817	1.591	0.109	0.754	200.08	1.444	76.5
Shady-steep	M3	4.094	0.359		0.818	73.03	0.834	-34.1
Shady-gentle	M6	14.119	2.184	0.169	0.706	255.58	1.356	92.7

sums of square residuals from the H predictions of all the models at the significant level of 0.05. Similarly, when the modeling dataset was divided into sunny-steep, sunny-gentle, shady-steep and shady-gentle slope, Chow's F-test also indicated that the sums of square residuals from the H predictions of all the models significantly differed from each other, implying the significantly different H-DBH relationship structures for almost all the models obtained by the sub-datasets.

### 3.2 Selection of optimal H-DBH models

In Table 4, when the whole modeling dataset was used, the values of  $R^2$  and RMSE obtained using all the models statistically were not significantly different from each other at the significant level of 0.05 except for M1 led to poorer performance. With the division of the sunny, shady, steep and gentle slope sub-datasets, the optimal model M6 was obtained based on the smallest RMSE and AIC and the largest  $R^2$  for all the sub-datasets except for the steep slope in which the model M2 performed best (Table 5). With the division of the sunny-steep, sunny-gentle, shady-steep and shady-gentle slope plots, overall the values of  $R^2$  or RMSE were similar among the non-linear models (M2 to M11), while the linear model M1 led to smaller  $R^2$  and larger RMSE (Table 5). Based on the smallest AIC, however, M2 was selected for the sunny-steep and M6 was selected for the sunny-gentle and shady-gentle, while M3 was chosen for the shady-steep (Table 5).

### 3.3 Effect of competition index

The correlation coefficients of the original Hegyi and the improved Hegyi\_I with tree H and DBH showed similar trends (The coefficients omitted due to the limited space). The improved Hegyi\_I had the absolute coefficients varying from 0.37 to 0.65 with H and from 0.37 to 0.67 with DBH for the whole modeling dataset and all the sub-datasets. The corresponding values of the original Hegyi ranged from 0.25 to 0.53 with H and from 0.26 to 0.55 with DBH. This implied that the improved Hegyi\_I increased the correlation and enhanced the effect of tree H from the competitors.

The Hegyi\_I and Hegyi as an independent variable were respectively added into each parameter of the same H-DBH model selected for each of the sunny-steep, sunny-gentle, shady-steep and shady-gentle sub-datasets. The fittings led to different structures of the models and the optimal model structure was then selected based on the largest  $R^2$  and smallest RMSE. In Table 6, compared with those without CI, overall, adding the original Hegyi into the models increased the

**Table 6.** The comparison of the results using the optimal models without and with the original Hegyi and improved Hegyi\_I involved for sunny-steep, sunny-gentle, shady-steep and shady-gentle slope forests (a, b, c, f and g are model parameters; STE is the standard error of the estimated parameter; RMSE and R<sup>2</sup> respectively are root mean square error and coefficient of determination between the observed and estimated values of H; SSR is the sum of squared residuals; and the symbol \* implying the model parameter statistically is significantly different from zero at the significant level of 0.05).

Model characteristics	Model parameter			Model evaluation				
	a (STE)	b (STE)	c (STE)	f (STE)	g (STE)	RMSE	SSR	R <sup>2</sup>
Sunny-steep slope								
$H = a \times \ln(D) + b$	*4.253(0.362)	-0.249(0.908)				1.341	154.550	0.622
$H = (a + f \times Hegyi) \times \ln(D) + b$	*10.198(0.906)	-0.921(1.083)		0.071(0.063)		1.330	152.192	0.628
$H = (a + g \times Hegyi\_I) \times \ln(D) + b$	*3.693(0.463)	1.712(1.367)			*-0.182(0.086)	1.312	148.219	0.638
Sunny-gentle slope								
$H = a \times e^{-b \times e^{-c \times D}}$	*16.817(0.924)	*1.591(0.178)	*0.109(0.019)			1.444	200.078	0.754
$H = a \times e^{-(b+f \times Hegyi) \times e^{-c \times D}}$	*16.858(0.981)	*1.542(0.283)	*0.107(0.022)	0.006(0.026)		1.443	199.967	0.754
$H = a \times e^{-b \times e^{-(c+g \times Hegyi\_I) \times D}}$	*17.259(0.967)	*1.119(0.130)	*0.093(0.016)		*0.015(0.004)	1.348	174.524	0.786
Shady-steep slope								
$H = a \times D^b$	*4.094(0.195)	*0.359(0.017)				0.834	73.031	0.818
$H = (a + f \times Hegyi) \times D^b$	*4.415(0.245)	*0.339(0.018)		*-0.022(0.009)		0.811	69.059	0.828
$H = a \times D^{(b+g \times Hegyi\_I)}$	*4.864(0.279)	*0.316(0.018)			*-0.017(0.004)	0.759	60.472	0.849
Shady-gentle slope								
$H = a \times e^{-b \times e^{-c \times D}}$	*14.119(0.581)	*2.184(0.355)	*0.169(0.026)			1.356	255.579	0.706
$H = (a + f \times Hegyi) \times e^{-b \times e^{-c \times D}}$	*14.301(0.645)	*1.928(0.402)	*0.162(0.029)	-0.298(0.250)		1.363	258.098	0.703
$H = a \times e^{-(b+g \times Hegyi\_I) \times e^{-c \times D}}$	*13.906(0.504)	*2.850(0.569)	*0.191(0.027)		*-0.044(0.021)	1.341	249.868	0.712

R<sup>2</sup> values and reduced the RMSE values for all the sub-datasets. The improvements were further enhanced by introducing the improved Hegyi\_I into the models (Table 6).

For the sunny-steep, compared with the optimal model M2 without the CIs, the additions of both the original Hegyi and improved Hegyi\_I into M2 increased the prediction accuracy of tree H but the parameter corresponding to the original Hegyi was not significantly different from zero at the significant level of 0.05, while the parameter corresponding to the improved Hegyi\_I significantly differed from zero. The similar results were obtained for the sunny-gentle and shady-gentle sub-datasets in which the model M6 was selected. For the shady-steep, the model parameters corresponding to the original Hegyi and the improved Hegyi\_I in the model M3 were statistically significantly different from zero. This implied that introducing the improved Hegyi\_I into the selected models statistically resulted in significantly different model structures of the H-DBH relationship for all the sub-datasets and increased the prediction accuracy of tree H compared with the models with and without the original Hegyi, while the effect of adding the original Hegyi into the models was significant only for the shady-steep.

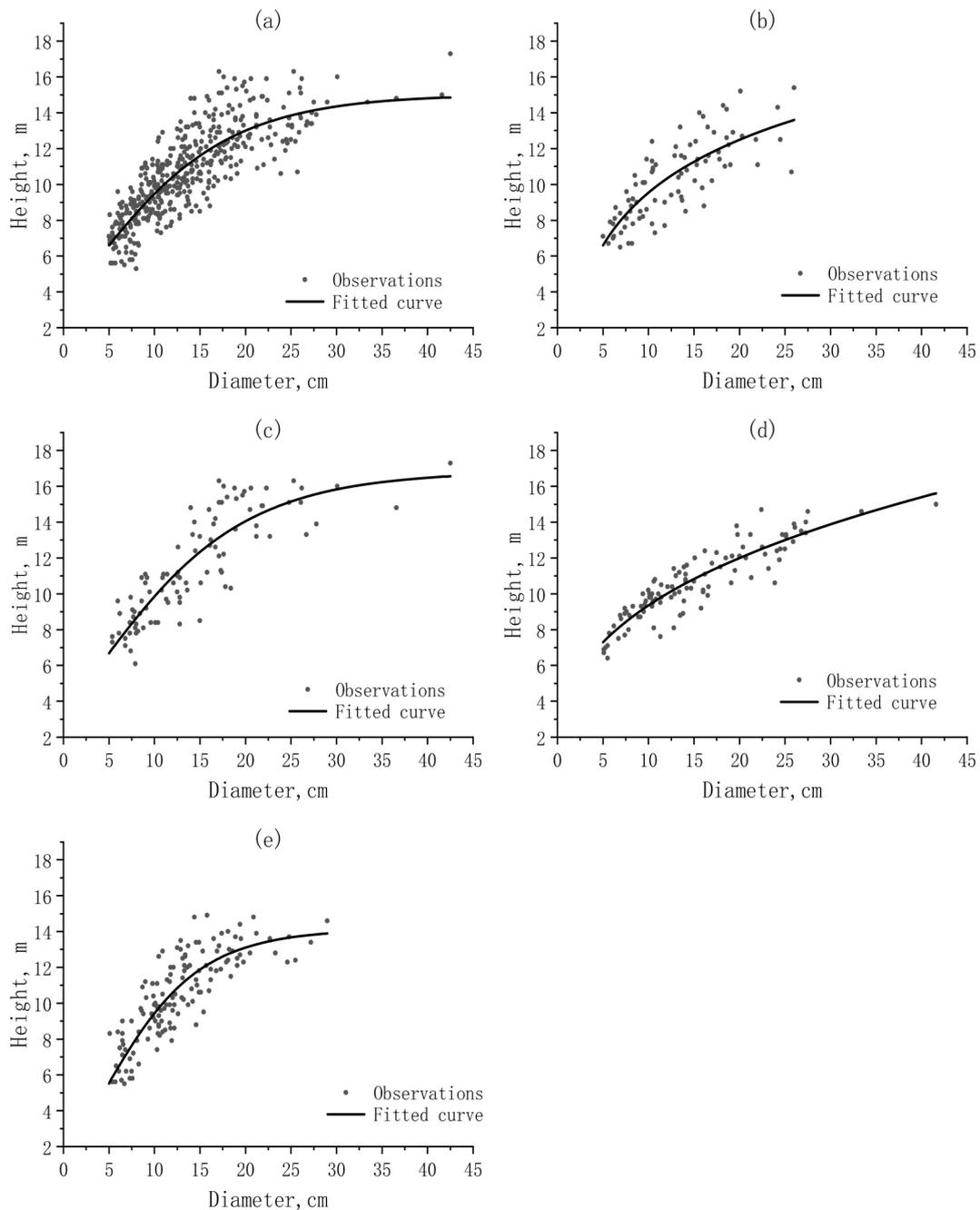
In Table 7, significant difference tests of the average absolute residuals of the H predictions from zero using the models without and with the original Hegyi and the improved Hegyi\_I were conducted using the student-T distribution. The test results showed that at the significant level of 0.05 the average absolute residuals were not significantly different from zero for all the sub-datasets and all the models without and with the original Hegyi and the improved Hegyi\_I. However, the absolute average residuals of the predictions decreased due to the inclusions of the original Hegyi and the improved Hegyi\_I in the models. This indicated that compared with the models without the CIs, the models with the original Hegyi increased the prediction accuracy of tree H and the accuracy was further increased by the models with the improved Hegyi\_I.

In Table 7, given a sub-dataset the significant difference between any two average absolute residuals of the H predictions from the models without and with the CIs was also examined. When the models without the original Hegyi were compared with the models that contained the original Hegyi, the P-values for all the sub-datasets were greater than 0.1, indicating that adding the original Hegyi into the models did not significantly reduce the average absolute residuals. Compared with the models without the improved Hegyi\_I, the models with the improved Hegyi\_I led to the P-values of smaller than 0.05 for both the sunny-steep and shady-steep and smaller than 0.1 for the sunny-gentle and shady-gentle. This suggested that at the significant level of 0.1, the models with the improved Hegyi\_I significantly increased the prediction accuracy of tree H. Moreover, when the models with the original Hegyi were compared with the models containing the improved Hegyi\_I, all the P-values were greater than 0.1 except for the shady-steep sub-dataset that led to the P-value smaller than 0.1 but greater than 0.05.

**Table 7.** Significant difference test of the average absolute residuals from zero using the models without and with the competition indices Hegyi CI and Hegyi\_I CI involved ( $\delta_1$  is the average of the absolute residuals for the model without competition index,  $\delta_2$  is the average of the absolute residuals for the model with the original Hegyi and  $\delta_3$  is the average of the absolute residuals for the model with the improved Hegyi\_I).

Sub-datasets	Model	$\delta_1$	$\delta_2$	$\delta_3$	$\delta_1$ vs. $\delta_2$		$\delta_1$ vs. $\delta_3$		$\delta_2$ vs. $\delta_3$	
					T value	P value	T value	P value	T value	P value
Sunny-steep	M2	1.10*	1.05*	0.98*	1.635	0.106	2.310	0.023	1.578	0.118
Sunny-gentle	M6	1.18*	1.12*	1.09*	0.405	0.686	1.748	0.084	0.303	0.763
Shady-steep	M3	0.65*	0.62*	0.57*	1.292	0.199	2.386	0.019	1.903	0.060
Shady-gentle	M6	1.11*	1.09*	1.05*	0.676	0.500	1.906	0.059	1.495	0.137

In Fig. 2, the observations of tree H were graphed against the observations of DBH together with the fit curves for the whole dataset and sub-datasets. When the whole dataset was used, the fit curve obviously led to the overestimations and underestimations for the small and large values of tree H. The divisions of the whole dataset into the sub-datasets reduced the overestimations and underestimations.



**Fig. 2.** The scattered distributions and fitted curves of the observed height (H) against the observed diameter (DBH) for a) the whole dataset and different sub-datasets: b) sunny-steep; c) sunny-gentle; d) shady-steep; and e) shady-gentle.

**Table 8.** The improvement of tree H predictions using separate models at different slopes and aspects by comparison with the whole model based on root mean square error (RMSE) between the predicted and observed values of the validation dataset (W is the whole model, S<sub>1</sub> is the separate models without competition index, S<sub>2</sub> is the separate models with the original Hegyi and S<sub>3</sub> is the separate models with the improved Hegyi\_I).

Datasets	RMSE				Percentage of reduced error (%)			
	W	S <sub>1</sub>	S <sub>2</sub>	S <sub>3</sub>	W vs. S <sub>1</sub>	W vs. S <sub>2</sub>	W vs. S <sub>3</sub>	S <sub>2</sub> vs. S <sub>3</sub>
Sunny-steep slope	1.366	1.341	1.33	1.312	1.83	2.64	3.95	1.35
Sunny-gentle slope	1.635	1.444	1.443	1.348	11.68	11.74	17.55	6.58
Shady-steep slope	1.064	0.834	0.811	0.759	21.62	23.78	28.66	6.41
Shady-gentle slope	1.412	1.356	1.363	1.341	3.97	3.47	5.03	1.61

In Table 8, the RMSE values of the predicted H from the whole model and the separate models without and with the CIs were compared based on the validation dataset. Compared to the whole model, the separate models from the sunny-steep, sunny-gentle, shady-steep and shady-gentle slope reduced the RMSE values by 1.83% to 21.62% depending on the sub-datasets. All the decreases were significantly different from zero except for the model for the sunny-steep sub-dataset. This implied that the H-DBH relationship varied with the slopes and aspects and showed different structures. Thus, separately developing the H-DBH relationship at different slopes and aspects significantly improved the predictions of tree H. Moreover, compared with the whole model, all the separate models with the original Hegyi and the improved Hegyi\_I, respectively, led to the significant reduction of RMSE for the predictions of tree H (Table 8). In addition, compared with the separate models that contained the original Hegyi, the separate models with the improved Hegyi\_I further reduced the values of RMSE for the predictions of tree H but the significant decreases happened only for the sunny-gentle and shady-steep sub-datasets.

## 4 Discussion

There are many factors and variables affecting the growth of tree H and DBH and thus the H-DBH relationship, such as elevation (Scaranello et al. 2011), soil (Gauthier et al. 2018), slope and aspect (Rohner et al. 2013), etc. Slope and aspect cause the differences of light trees need for growing and thus are the most important variables that have effects on the H-DBH relationship of trees and forest productivity (Kravkaz et al. 2018). Light intensity and time of illumination on sunny slopes and shady slopes are quite different, which leads to different survival rates and growth rates of trees on sunny slopes and shady slopes (Motsinger et al. 2010). On the other hand, steep slope areas often have poorer soil nutrients and less water supply than gentle slope areas and the different amounts of resources trees need for growing would affect the H-DBH relationship of trees (Scharnweber et al. 2011). Rohner et al. (2013) found that oak trees grow faster in diameter at lower elevation and gentler slope areas than at higher elevation and steeper slope areas. The results of Chow's F-test based on the sums of square residuals in this study showed that the slope and aspect had significant effects on the H-DBH relationship of *C. glauca* trees and the H-DBH relationship should be modelled by considering different slopes and aspects, which supported the conclusion of previous studies for other tree species. Thus, the H-DBH relationship should be modeled based on sunny-steep, sunny-gentle, shady-steep and shady-gentle slope forests.

Various nonlinear equations with high accuracy and strong ability of predicting H have been widely used to model the H-DBH relationship of different tree species at different conditions (Ozcelik et al. 2014; Sancheza et al. 2003). However, because the H-DBH relationship varies depending

on different tree species and different site conditions, the selection of nonlinear equations is necessary and critical to optimize modeling the H-DBH relationship for *C. glauca* trees at different site conditions including the sunny-steep, sunny-gentle, shady-steep and shady-gentle slopes. In this study, it was found that the linear model had significantly poorer performance than the nonlinear equations. When the whole modeling dataset was used, the nonlinear equations resulted in only slight differences of accuracy for predicting H of the trees based on RMSE and  $R^2$ . However, the log transformation equation (M2) and exponential equation (M3) were optimal to model the H-DBH relationship for the sunny- and shady-steep slope forests, while the Gompertz's equation (M6) had best performance to explain the H-DBH relationship for the sunny- and shady-gentle slope forests. This implied that the H-DBH relationship had different structures due to different site conditions caused by the aspects and slopes.

Tree competition for obtaining resources (light, water and nutrients) is a complicated process and various CIs have been developed to quantify the degree of tree competition (Burkhardt and Tome 2012). However, the performance of CIs is often site-specific and varies depending on forest types and site conditions (Contreras et al. 2011). Because of being defined in a 2-dimensional geographic space, distance-dependent CIs are usually superior compared with distance-independent CIs (Burkhardt and Tome 2012). However, trees grow and compete for obtaining the resources in a 3-dimensional space, the distance-dependent CIs often ignore the impact of tree H from competitors mainly due to the difficulty for measuring tree H (Burkhardt and Tome 2012).

Because of its simplification and effectiveness, Hegyi CI has been most commonly utilized to quantify the competitive impact (Saha et al. 2014; Vanclay et al. 2013; Timilsina and Staudhammer 2013). However, Hegyi is defined based on tree DBH values and distances among trees in a 2-dimensional geographic space and ignores the impacts of H from competitors on a target tree. In this study, an improved Hegyi\_I was developed by taking into account into the original Hegyi the relative relationships of H for competitors to the target tree and representing the impacts of tree H from the competitors through adjusting the contributions of DBH to the CI when the heights of competitors were different from the target tree H. Thus, the improved Hegyi\_I was indirectly defined in a 3-dimensional space to quantify the competition degree. The correlation analysis showed that the improved Hegyi\_I, to some extent, reflected the effects of tree H from competitors in addition to their DBH values and distances to the target tree and was more appropriately used as a CI than the original Hegyi. Moreover, although, compared with the models without the original Hegyi and improved Hegyi\_I, the inclusions of both CIs in the H-DBH models increased the prediction accuracy of tree H for all the sub-datasets, the accuracy increases by the improved Hegyi\_I were statistically significant at the significant level of 0.1 but not by the original Hegyi. The improved Hegyi\_I is generalized in which, theoretically, the  $k$  quantifies the contribution of height from each competing tree to the improved competing index and should be determined using the ratio of the height from the competing tree to the height of the target tree. However, this requires the measurements of tree heights and makes the improved index hardly applicable. For simplification, in this study only  $k=0.5$  for  $H_i > H_j$  and  $k=1$  for  $H_i \leq H_j$  were examined and the obtained results showed promising. The simplification would not weaken the generalization of the improved Hegyi\_I. In the future study, optimal  $k$  values should be explored.

The objective of developing the improved Hegyi\_I is to improve the estimation of tree H. That means that the heights of the target tree and its competitors are unknown. However, the calculation of the improved Hegyi\_I still requires the information of the relative relationship of the target tree H to the H values of its competitors. The information of the relative relationship does not need accurate measurements of the tree heights and can be obtained by approximate or visual estimation. However, currently there have been rare cases in which relative heights of four nearest trees for each target tree in a plot were obtained or the heights of the trees were visually estimated.

Tree heights are often measured with a hypsometer instead of visual observations, which could give an overly positive view of the accuracy. The proposed index could still be used, especially in forests where visual estimation of height is feasible. In the future, the approximate values of tree heights can be yielded using high spatial resolution stereo images by photogrammetric measurements or using airborne or terrestrial laser scanning LiDAR data. Thus, the improved Hegyi is promising for its application.

In addition, the mixed-effect models have been commonly applied in practice for their advantages in the application of repeated and multi-level data and accounting for random effects. This is especially true for mixed forests. In this study, the mixed-effect models were not used mainly because the site conditions of the plots in the study area were similar except for slope and aspect. Thus, we would like to focus on the influence of slope and aspect on the H-DBH relationship. Moreover, the mixed-effect models are relatively complex and computation-intensive, while the influence of slope and aspect on the H-DBH relationship could be clarified by using simple regression models to be easily and separately developed based on different categories including sunny-steep, sunny-gentle, shady-steep and shady-gentle. Therefore, our research objectives could be easily achieved by using the relatively simpler and applicable method. In the future study, the mixed-effect models should be explored.

Finally, considering the slope and aspect, the dataset was randomly split into modeling and validation datasets. How the random division influences the results of the analysis is not clear. This can be achieved by repeatedly conducting the random divisions and corresponding modeling and analyses with a reliable number of runs such as greater than 30 times. But, this will lead to a huge amount of work. Due to the limited time and space, we did not carry out the analyses in this study. In the future study, the simulations can be done.

## 5 Conclusions

In this study, in order to improve the predictions of *Cyclobalanopsis glauca* tree H, the effects of slope and aspect on the H-DBH relationship were investigated using Chow's F-test based on the sums of square residuals and assessment of H predictions from models. A total of eleven equations were compared and selected to optimize modeling the H-DBH relationship. Moreover, an improved Hegyi\_I was developed and the effects of both the original Hegyi and the improved Hegyi\_I on the H-DBH relationship were analyzed by separately introducing them into the selected models. The results showed that 1) The effects of slope and aspect on the H-DBH relationship of *C. glauca* trees were significant at the significant level of 0.05; 2) The H-DBH relationship varied depending on different slopes and aspects, which led to different optimal models, including the log transformation model (M2) and exponential model (M3) for the sunny- and shady-steep slope forests and the Gompertz's model (M6) for both the sunny- and shady-gentle slope forests. Compared with the model from the whole dataset, the division of the dataset into the sub-datasets of the sunny-steep, sunny-gentle, shady-steep and shady-gentle slope significantly reduced the RMSE values; 3) Compared with the selected models without the CIs, adding the original Hegyi and the improved Hegyi\_I into the H-DBH models increased the prediction accuracy of tree H for all the sub-datasets but the significant improvements were achieved only by the models that contained the improved Hegyi\_I at the significant level of 0.1. This indicated that the improved Hegyi\_I, to some extent, more accurately quantified the competition degree of trees in the *C. glauca* mixed forests than the original Hegyi. This study implied that modeling the H-DBH relationship under different slopes and aspects, coupled with the inclusion of the improved Hegyi\_I, provided the great potential to improve the prediction accuracy of tree H in the *C. glauca* mixed forests.

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