forests

MDPI

Article

Effects of Plot Design on Estimating Tree Species Richness and Species Diversity

Chenhao Zhao [1], Yan Zhu [2] and Jinghui Meng [1,*]

[1] Research Center of Forest Management Engineering of National Forestry and Grassland Administration, Beijing Forestry University, Beijing 100083, China
[2] State Key Laboratory of Vegetation and Environmental Change, Institute of Botany, Chinese Academy of Sciences, Beijing 100093, China
* Correspondence: jmeng@bjfu.edu.cn; Tel.: +86-10-6233-8133

Abstract: Species richness and diversity substantially affect forest structures and function and are critical indicators of sustainable forest management. Sampling surveys are widely used in forest inventories because they efficiently assess forest characteristics. However, an appropriate sample plot design is required. The objectives of this study were to evaluate the effects of plot design on estimating species richness and species diversity using a simulation. A 20 ha census plot was established in a temperate forest to obtain the true values of species richness and species diversity. One single plot design and nine cluster plot designs were evaluated. The results indicated significant differences in forest species richness and species diversity for different plot designs. The cluster plot design with a square subplot configuration (SCONFIG) and extent of ground area covered by a cluster (EGROUND) of 500 m^2 exhibited the best performance (accuracy, precision) in estimating forest species richness. In contrast, a rectangular cluster plot with an EGROUND of 1000 m^2 was more suitable for assessing species diversity. This study demonstrates that cluster plots outperform a single plot for evaluating species richness and species diversity in temperate forests.

Keywords: plot design; species richness; species diversity; sampling survey

check for updates

Citation: Zhao, C.; Zhu, Y.; Meng, J. Effects of Plot Design on Estimating Tree Species Richness and Species Diversity. *Forests* **2022**, *13*, 2003. https://doi.org/10.3390/f13122003

Academic Editors: Olga Viedma and Takuo Nagaike

Received: 9 October 2022
Accepted: 24 November 2022
Published: 26 November 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Forest ecological functions, such as water conservation, biodiversity conservation, and carbon sequestration, have received increasing attention due to increasing ecological and environmental problems, e.g., global warming, biodiversity loss, and landscape degradation [1–4]. Biodiversity refers to the variety of organisms (animals, plants, microorganisms, etc.) within a certain time and space [5]. It is crucial to maintain the flow of energy, material, and information in an ecosystem that significantly affects forest ecological functions [5,6].

Species richness and species diversity represent the core of biodiversity. They are critical for forest conservation and management and are closely related to ecosystem stability and forest structure and function [7–9]. According to the niche complementarity theory, communities with a variety of species are better able to obtain and exploit scarce resources because they have species with a wide range of ecological characteristics [10]. For instance, Huang, et al. [11] argued that species diversity is a key theoretical predictor of ecosystem function. Liang, et al. [12] also reported that the positive correlation between species diversity and productivity was dominant in global forests, and the loss of biodiversity would lead to an accelerated decline in global forest productivity. Therefore, it is of great significance to protect diversity and improve and restore ecosystem function [13].

Sustainable forest management requires monitoring species richness and species diversity to prescribe a strategy for preserving and maintaining the integrity of ecosystems [14]. Many studies [13,15,16] have documented the importance of species diversity information in forest management. For example, Zhu, et al. [13] analyzed the relationship between tree species diversity and productivity and found that species diversity had a positive

correlation with productivity, suggesting that forest productivity could be increased by increasing species diversity. Pedro, et al. [17] found that increasing tree species diversity could mitigate the effects of intensifying disturbance regimes on ecosystem functioning and improve the robustness of forest carbon storage and the role of forests in climate change mitigation. Furthermore, some studies [10,18] have shown a relationship between species diversity and stand structural attributes, such as forest growth, tree recruitment, and mortality, suggesting that species diversity indirectly influences forest structures and species composition. Therefore, monitoring biodiversity has become an indispensable aspect of forest inventories, especially for forests with a complex structure and species composition.

It is often impossible to conduct a census survey to derive forest attributes because it is rather difficult, expensive, and time-consuming. On the other hand, a sampling survey has high efficiency, low cost, and is widely applicable [19–21]; therefore, it is a promising alternative to obtain forest attributes. Sampling surveys have been widely used for estimating forest biodiversity [22,23], stand characteristics [24–27], forest productivity [28,29], and forest mortality [30]. A sampling strategy has three design components: sampling design, plot design, and estimation design [22,25,27,31]. Many studies have extensively explored different plot designs in assessing forest attributes [22,23,25,31,32]. Two common plot designs are single plot and cluster plot designs. A cluster plot consists of several subplots located at a specific distance and with a specific configuration; this plot design has been widely used [33]. A cluster plot is considered more efficient than a single plot for capturing forest stand attributes, especially in heterogenous forest stands [22,32,34,35].

In this study, we assume that (1) a cluster plot will outperform a single plot under the same conditions, and (2) different cluster plot designs are suitable for estimating different forest attributes. Our objectives are to investigate how a cluster plot design, i.e., the subplot configuration (SCONFIG) and the extent of ground area covered by a cluster (EGROUND), affects the estimation of species richness and species diversity. We recommend potentially best-suited plot designs for estimating species richness and species diversity within our study site.

2. Materials and Methods

2.1. Study Site

Our study was conducted on Dongling Mountain (39°48′~40°00′ N, 115°24′~115°36′ E) in the Mentougou District of Beijing, China (Figure 1). Dongling Mountain is located in the Yanshan subsidence zone in the central part of the North China plateau [36]. The area has a warm temperate continental monsoon climate. The average annual temperature is 4.8 °C, the average temperature in July is 18–25 °C, and the average temperature in January is −4–10 °C. The annual precipitation is 500–650 mm. The terrain is undulating with valleys and ridges [37,38]. The soils are alfisols [39,40]. The vegetation is warm temperate deciduous broad-leaved secondary forest, and the stands are well developed with complex vertical stratification [41]. The deciduous broad-leaved forest in the warm temperate zone of northern China, represented by the forest ecosystem of Dongling Mountain in Beijing, is an important part of the forest ecosystem in the middle latitude of the northern hemisphere.

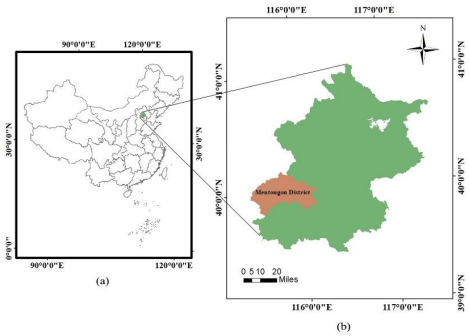


Figure 1. The geographical location of the study area. (**a**) Beijing in China, (**b**) Mentougou District in Beijing, China.

2.2. Data

The census dataset was collected in a 20 ha plot (400 m × 500 m) on Dongling Mountain, Mentougou District, Beijing, China. It is a permanent plot established in 2010 to monitor long-term forest dynamics. The vegetation at the experimental site is well preserved with high species diversity and distinct layers. The data obtained in 2010 were used in this study. All trees with a DBH ≥ 5 cm in the plot were mapped, measured, and the species identified. The plot had 16,249 trees belonging to 46 species, 27 genera, and 18 families, and the most common species were *Quercus mongolica* Fisch. ex Ledeb, *Betula dahurica* Pall., and *Acer pictum* subsp. *mono* (Maxim.) H. Ohashi (Table 1).

Table 1. Forty-six plant species in the 20 ha plot in Dongling Mountain.

Family	Genera	Species	Relative Frequency (%)
Adoxaceae	Sambucus	*Sambucus williamsii*	0.0123
Araliaceae	Eleutherococcus	*Eleutherococcus senticosus*	0.0062
Betulaceae	Betula	*Betula chinensis*	0.0062
		Betula dahurica	14.8132
		Betula platyphylla	4.4803
	Corylus	*Corylus mandshurica*	0.2400
Caprifoliaceae	Abelia	*Zabelia biflora*	2.3448
	Lonicera	*Lonicera hispida*	0.0246
		Lonicera chrysantha	0.0308
Cornaceae	Cornus	*Cornus bretschneideri*	0.2216
Ericaceae	Rhododendron	*Rhododendron micranthum*	0.1292
		Rhododendron mucronulatum	0.0246
Fagaceae	Quercus	*Quercus mongolica*	27.0417
Hydrangeaceae	Deutzia	*Deutzia parviflora*	0.0123
	Hydrangea	*Hydrangea bretschneideri*	0.5354
Juglandaceae	Juglans	*Juglans mandshurica*	3.1140
Lamiaceae	Vitex	*Vitex negundo*	0.0062
Malvaceae	Tilia	*Tilia amurensis*	0.1723
		Tilia mandshurica	1.5755
		Tilia mongolica	2.0494
		Tilia tuan	0.0369
Oleaceae	Fraxinus	*Fraxinus bungeana*	0.2216
		Fraxinus chinensis	4.0002
	Syringa	*Syringa reticulata*	0.0615
		Syringa tomentella	1.0955
Pinaceae	Larix	*Larix gmelinii*	0.7139
Rhamnaceae	Rhamnus	*Rhamnus davurica*	1.3601
		Rhamnus globosa	0.0492
		Rhamnus parvifolia	0.1108
Rosaceae	Malus	*Malus baccata*	0.0800
	Padus	*Prunus padus*	0.1477
	Prunus	*Prunus davidiana*	0.8431
		Prunus sibirica	0.0985
	Sorbus	*Sorbus discolor*	3.4648
	Spiraea	*Spiraea dasyantha*	0.0062
Salicaceae	Populus	*Populus cathayana*	0.9970
		Populus davidiana	8.3205
		Populus tomentosa	0.0185
	Salix	*Salix babylonica*	0.0369
		Salix caprea	0.0062
		Salix pseudotangii	0.0985
		Salix schwerinii	0.8801
Sapindaceae	Acer	*Acer pictum*	15.4533
Ulmaceae	Ulmus	*Ulmus laciniata*	0.9416
		Ulmus macrocarpa	2.0247
		Ulmus pumila	2.0924

2.3. Methods

2.3.1. Plot Design

We considered the following three plot design factors: (1) plot configuration (PCONFIG), i.e., single plot versus cluster plot; (2) subplot configuration (SCONFIG); (3) extent of ground area covered by a cluster (EGROUND) [33,42]. The combinations of the design factors and their levels are shown in Figure 2. We used a circular plot in this study because it is a standard shape most suitable for comparing species composition and diversity [43]. Additionally, the layout of the circular plot is convenient and has low labor costs [44]. Many countries used circular plots in their national forest inventory (NFI), e.g., the United States, Canada, France, and Switzerland [45].

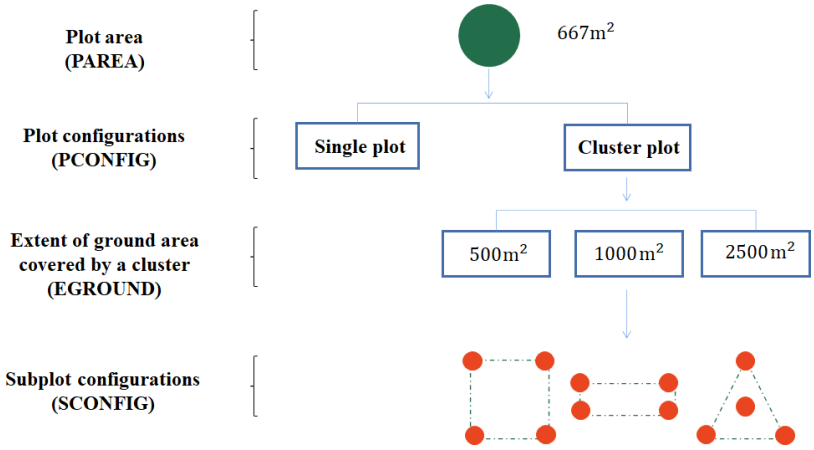


Figure 2. One single plot design and nine cluster plot designs. The locations of subplots are depicted by solid red circles and EGROUND refers to the area of the geometric figure drawn by the blue dotted line.

The sample location was in the center of the single circular plot and the cluster center of the cluster plot. We used four subplots in a cluster plot, following the plot design used in the NFIs of most countries [46]. The plot area (PAREA) was 667 m^2; this size has been extensively used in forest inventories in China, e.g., the Chinese NFI. In the cluster plot, the PAREA was the total area of the four subplots. SCONFIG and EGROUND are parameters of the cluster plot (Figure 2). We considered three types of SCONFIG, i.e., a square, an equilateral triangle, and a rectangle with a length-to-width ratio of 3:1. Quon, et al. [22] found that a rectangular subplot layout with an aspect ratio of 3:1 provided the optimum performance for estimating species diversity. The sample location was in the cluster center, and the four subplots were placed at the vertices in the square and rectangular design. In the equilateral triangle design, three subplots were located at the vertices and one at the cluster center [47]. The EGROUND could significantly affect the sampling efficiency and survey cost because of the distance between the four subplots [22,48]. A larger EGROUND means that the subplots are further apart. In this study, three EGROUND levels were considered, i.e., 500, 1000, and 2500 m^2. Quon, et al. [22] recommended that EGROUND should be $\leq$1000 m^2 in tropical forests, which are far more complex than our warm temperate forests. Therefore, an EGROUND of 2500 m^2 was sufficient for our forests. We had 10 plot designs, including 1 single plot design and 9 cluster plot designs.

2.3.2. Species Richness

The number of species observed in the sample (S_{obs}) typically underestimates the actual number of species (S) [32]. Nonparametric extrapolation methods are the most efficient for reducing bias. The first- and second-order *Jackknife* indicators [49] and the *Chao* estimator [50], i.e., *Jack1*, *Jack2*, and *Chao1*, have been extensively used to estimate species richness. These nonparametric estimators correct the S_{obs} in different methods with regard to rare species. *Jack1* and *Jack2* used the number of one-cluster species and two-cluster

species. In comparison, *Chao1* corrects the S_{obs} using the number of one-individual species and two-individual species [50,51]. These indices are calculated as follows:

$$Chao1 = S_{obs} + \frac{a^2}{2b} \quad (1)$$

$$Jack1 = S_{obs} + s_1\left(\frac{f-1}{f}\right) \quad (2)$$

$$Jack2 = S_{obs} + \left[\frac{s_1(2f-3)}{f} - \frac{s_2(f-2)^2}{f(f-1)}\right] \quad (3)$$

where S_{obs} is the number of species observed in the sample, a is the number of one-individual species, b is the number of twoindividual species, s_1 is the number of one-cluster species, s_2 is the number of two-cluster species, and f is the number of sampling plots.

2.3.3. Species Diversity

Species diversity indices reflect the different types of species in a population. The Shannon-Wiener and Simpson's indices have been extensively used to quantify species diversity [52,53].

$$Shannon - Wiener = -\sum_{i=1}^{S} \pi_i \log_2(\pi_i) \quad (4)$$

$$Simpson = 1 - \sum_{i=1}^{S} {\pi_i}^2 \quad (5)$$

where S is the species richness of the population, π_i is the frequency of the ith species.

2.3.4. Simulation and Analysis Methods

Systematic sampling has been widely used in forest surveys because of its high efficiency and representativeness of estimated results; moreover, researchers can easily analyze and conduct samples using this method due to its structure [46]. We employed systematic sampling (SS) to estimate species richness and species diversity. The initial sample location was determined by randomly selecting x- and y-coordinates. Based on the initial point, 500 sample locations were systematically generated at equal intervals. Lin, et al. [23] used 1000 sample locations in one iteration and repeated the sampling 100 times to assess the effect of the plot design on species diversity and other attributes in tropical and subtropical forests. Quon, et al. [22] conducted a simulation study to evaluate species composition in tropical and subtropical forests in 25 ha and 50 ha census plots; 500 sample locations were selected in one iteration, and the simulation was repeated 100 times. Yang, et al. [31] randomly generated 100 sample locations to study the effects of plot size and shape on plant species composition in 50 ha and 25 ha census plots in tropical and subtropical forests. Therefore, we assumed that 500 sample locations were sufficient for our temperate forest, which has less species richness and diversity and a simpler structure than tropical forests. We applied the reflection method to correct the boundary slopover if a sample location was near to the boundaries of the study area [54]. At each sample location, all the plot designs were laid out, and the species richness and species diversity were quantified. This approach ensured that we could compare the forest attributes derived from the 10 plot designs at a single sample location. Additionally, the simulation was repeated 100 times to derive the prediction interval.

Let θ_{ijk} be an estimate of the forest structure indicator for the k-th plot design at the j-th sample location in the i-th iteration, where $k = 1, \ldots, 10$, $j = 1, \ldots, 500$, and $i = 1, \ldots, 100$. Specifically, $k = 1$ refers to the single plot, and $k = 2, \ldots, 10$ refers to the cluster plot designs. The mean ($\bar{\theta}_{ik}$) and standard error ($SE(\theta)_{ik}$) were calculated for each indicator θ and the k-th plot design in the i-th iteration. The relative standard error ($rSE(\theta)$) is the ratio of the standard error to the mean. The efficiency ($Efficiency_{ik}$) of the k-th cluster plot design in

comparison to the single plot design was defined as the ratio of the rSE of the k-th cluster plot design to the rSE of the single plot design. The equations are as follows:

$$\overline{\theta}_{ik} = \sum_{j=1}^{n=500} \frac{\theta_{ijk}}{500} \tag{6}$$

$$SE(\theta)_{ik} = \sqrt{\left[\frac{\sum_{j=1}^{n=500}\left(\theta_{ijk} - \overline{\theta}_{ik}\right)^2}{499}\right]/500} \tag{7}$$

$$rSE(\theta) = \frac{SE(\theta)_{ik}}{\overline{\theta}_{ik}} \tag{8}$$

$$Efficiency_{ik} = \frac{rSE(\theta)_{ik}}{rSE(\theta)_{i1}} \tag{9}$$

where n is the number of sample locations, $rSE(\theta)_{i1}$ is the rSE of the single plot design.

For each indicator θ and the k-th plot design, the 100 iterations produced 100 estimates of $\overline{\theta}_{ik}$ and $Efficiency_{ik}$. The mean and the 2.5% and 97.5% quantiles of the 100 estimates were calculated. The interval between the 2.5% and 97.5% quantiles was defined as the empirical 95% confidence interval (95%).

A one-sample t-test was performed on estimators with the null hypothesis that the estimated values of the indicator θ from a cluster plot design were not significantly different from those of the single plot design, and otherwise for the alternative hypothesis. For the j-th sample location in the i-th iteration, $d(\theta)_{ijk1} = \theta_{ijk} - \theta_{ij1}$, for $k = 2, \ldots, 10$, which represented the difference in the estimated results of the indicator θ between the k-th cluster plot design and the single plot design. $d(\theta)_{ijk1}$ was calculated for the 500 sample locations. The one-sample t-test with $\alpha = 0.05$ was carried out and the p-value extracted. With the 100 iterations, the 100 p-values were averaged and reported. The above procedure was carried out in R 3.6.3.

3. Results

3.1. Species Richness

The true number of tree species with a DBH $\geq$ 5 cm in the 20 ha plot was 46. The estimated tree species richness obtained from the 10 plot designs is shown in Figure 3.

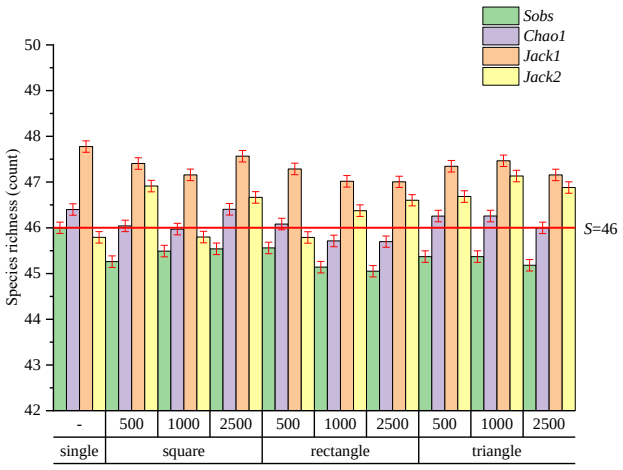


Figure 3. Species richness estimates obtained from 10 plot designs derived from systematic sampling. Depicted means are calculated as the average of 500 means from the 100 iterations, while empirical 95% confidence intervals depicted by red error bars are constructed from 2.5% and 97.5% quantiles of the 500 means.

Regardless of the PCONFIG and the SCONFIG and EGROUND of the cluster plots, *Chao1* showed the best performance in estimating the true value (46), whereas *Jack* 1 exhibited the worst performance, significantly overestimating the value. *Sobs* underestimated the species richness.

Figure 3 showed that *Chao1* was much closer to the true value for the cluster plots than the single plot, regardless of SCONFIG and EGROUND, suggesting that cluster plots outperform single plots in estimating species richness (Figure 3; Table 2). Additionally, we observed that the measure of efficiency (*rSE*) was less than 1 in the cluster plots, regardless of SCONFIG and EGROUND, suggesting that the cluster plot designs were more efficient in estimating species richness (Table 3). For example, the efficiency increased as the EGROUND increased, and the *rSE* of the cluster plot designs decreased to 85.5% of that of the single plot, suggesting that increasing EGROUND could improve efficiency. However, we did not observe any difference in efficiency for different SCONFIG with the same EGROUND.

Table 2. *p*-value of t-test for the species richness estimate results of cluster plots and single plots.

Plot Design			*p*-Value			
PCONFIG	**SCONFIG**	**EGROUND (m^2)**	***Sobs***	***Chao1***	***Jack1***	***Jack2***
cluster	square	500	<0.001 ***	0.0258 *	0.0132 *	0.0156 *
	rectangle	500	<0.001 ***	0.0204 *	0.0819 **	0.0286 *
	triangle	500	<0.001 ***	0.0416 *	0.0532	0.0182 *
	square	1000	<0.001 ***	0.0115 *	0.0501	0.0149 *
	rectangle	1000	<0.001 ***	0.0039 **	0.0034 **	0.0018 **
	triangle	1000	<0.001 ***	0.0128 *	0.0474 *	0.0276 *
	square	2500	<0.001 ***	0.0115 *	0.0227 *	0.0076 **
	rectangle	2500	<0.001 ***	0.0247 *	0.0445 *	0.0340 *
	triangle	2500	<0.001 ***	0.0114 *	0.0134 *	0.0011 **

* *p*-value shows the difference between the estimated species richness result of different cluster plot designs and that of a single plot. Difference: *p*-value < 0.05 (*); significant difference: *p*-value < 0.01 (**); strikingly significant difference: *p*-value < 0.001 (***).

Table 3. Efficiency of cluster plot designs compared to the single plot design for estimating species richness.

Plot Design		Efficiency (Species Richness)			
SCONFIG	**EGROUND (m^2)**	***Sobs***	***Chao1***	***Jack1***	***Jack2***
square	500	0.930	0.902	0.796	1.035
rectangle	500	0.899	0.894	0.802	1.051
triangle	500	0.921	0.891	0.801	0.971
square	1000	0.887	0.888	0.797	1.038
rectangle	1000	0.860	0.854	0.763	0.869
triangle	1000	0.880	0.850	0.762	0.869
square	2500	0.842	0.820	0.740	0.925
rectangle	2500	0.797	0.787	0.706	0.781
triangle	2500	0.830	0.812	0.732	0.802

As the EGROUND increased for different SCONFIG, *Chao1* exhibited different responses. For the square SCONFIG, *Chao1* decreased and then increased with an increase in EGROUND, and the lowest *Chao1* occurred at EGROUND = 1000 m^2. For the rectangular SCONFIG, *Chao1* showed a decreasing trend, and the estimated value closest to the true value occurred at EGROUND = 500 m^2 rather than at EGROUND = 2500 m^2. For cluster plots with a triangular SCONFIG, the estimated species richness reached the maximum at EGROUND = 1000 m^2 and the minimum at EGROUND = 2500 m^2 (Figure 3). However, the *rSE* showed a decreasing trend with the increasing EGROUND, regardless of SCONFIG, suggesting that increasing EGROUND could improve sampling efficiency.

When EGROUND = 500 m^2, *Chao1* obtained from the cluster plot with a square SCONFIG was the closest to the true value, whereas the triangular SCONFIG resulted in the worst performance. In addition, the *Chao1* values obtained from the cluster plots with a rectangular SCONFIG and an EGOUND of 500 m^2 were accurate. However, when the EGROUND value was fixed, the highest efficiency was obtained for the triangular plot using the *Chao1*. Interestingly, the EGROUND affected the estimated species richness derived from the rectangular cluster plot. However, the estimated species richness derived from a triangular cluster plot showed a stable trend, suggesting that increasing EGROUND did not improve the accuracy of species richness estimation. *Chao1* had the smallest deviation from the true value. In general, the optimum estimates were obtained for a square subplot with EGROUND = 500 m^2.

3.2. Species Diversity

The true values of the Shannon and Simpson indices derived from the census data were 1.99 and 0.76, respectively. The estimated species diversity (Shannon and Simpson) obtained from the cluster plots was higher and closer to the true values than that derived from the single plot, regardless of the SCONFIG and EGROUND. The estimated Shannon and Simpson indices obtained from the cluster plots were 11.84% and 9.00% higher than those obtained from the single plot (Figure 4; Table 4). In summary, the Shannon and Simpson indices were underestimated, regardless of plot design. The cluster plots were also more efficient than the single plot (Table 5). Table 5 shows that the sampling efficiency improved with an increase in EGROUND. It was also found that the precision of a rectangular cluster plot was higher than that of other SCONFIG.

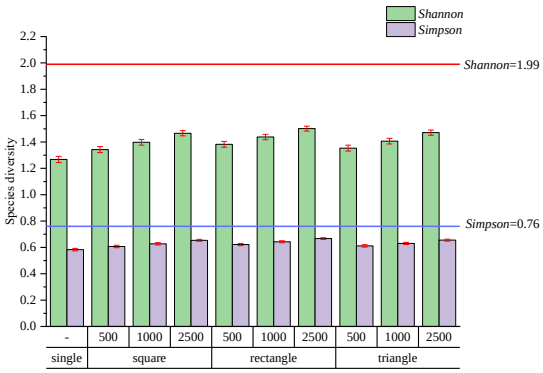


Figure 4. Species diversity estimators obtained from 10 plot designs derived from systematic sampling. Depicted means are calculated as the average of 500 means from the 100 iterations, while empirical 95% confidence intervals depicted by red error bars are constructed from 2.5% and 97.5% quantiles of the 500 means.

Table 4. *p*-value of t-test for the species diversity estimate results of cluster plots and single plots.

Plot Design			*p*-Value	
PCONFIG	**SCONFIG**	**EGROUND (m^2)**	**Shannon**	**Simpson**
cluster	square	500	0.0031 **	<0.001 ***
	rectangle	500	0.1230	0.0084 **
	triangle	500	0.0075 **	<0.001 ***
	square	1000	0.0324	0.0340 *
	rectangle	1000	0.0439	0.0567
	triangle	1000	0.0500	0.0753
	square	2500	0.0477 *	0.4074
	rectangle	2500	<0.001 ***	0.0106 *
	triangle	2500	0.0233 *	0.3073

* *p*-value shows the difference between the estimated species diversity result of different cluster plot designs and that of a single plot. Difference: *p*-value < 0.05 (*); significant difference: *p*-value < 0.01 (**); strikingly significant difference: *p*-value < 0.001 (***).

Table 5. Efficiency of cluster plot designs compared to the single plot design for estimating species.

Plot Design		Efficiency (Species Diversity)	
SCONFIG	**EGROUND (m^2)**	**Shannon**	**Simpson**
square	500	0.918	0.902
rectangle	500	0.860	0.830
triangle	500	0.903	0.883
square	1000	0.839	0.804
rectangle	1000	0.775	0.727
triangle	1000	0.829	0.794
square	2500	0.730	0.673
rectangle	2500	0.662	0.598
triangle	2500	0.723	0.669

For a constant SCONFIG, the estimated species diversity increased with an increase in EGROUND, approaching the true value. When EGROUND was fixed, the rectangular cluster plot had the largest species diversity estimate and was closest to the true value (Figure 4). A rectangular cluster plot with EGROUND = 2500 m^2 had the largest estimated Shannon and Simpson values and the lowest deviation from the true value. However, it had a high cost.

4. Discussion

4.1. Effect of Plot Design on Sampling Performance

Many authors [22,32] have examined the effects of different sampling strategies on estimating species richness and diversity in subtropical and tropical forests. For instance, Quon, et al. [22] used a 25 ha plot in subtropical submontane evergreen broad-leaved forests in Fushan, Taiwan Island. Gimaret-Carpentier, et al. [32] also employed a 25 ha plot in the western part of the tropical primary-lowland rainforest of Pasoh in Malaysia. These authors found that a 25 ha plot size provided the suitable estimates of species richness and species diversity. As the warm-temperate deciduous broad-leaved forest in our study has less species richness and a simpler structure than tropical forests, we assumed that a 20 ha plot would be suitable for estimating species richness and diversity and investigating the performance of different sampling strategies, including plot design. To the best of our knowledge, no similar studies have been conducted in northern China, although they are needed for biodiversity conservation.

Due to cluster plots' complex design, it has been assumed that the parameters of interest for quantifying diversity could be accurately estimated with data obtained from a cluster plot [22,32,34,35]. Our result supported this assumption and confirmed that cluster plots had higher accuracy and precision than single plots for estimating species richness and species diversity. Many authors [33,55] have drawn the same conclusion. For instance, Yim, et al. [33] demonstrated that a suitable cluster plot design enabled the estimation of growing stock, basal area, and plant species richness in different forest types in South Korea. Green, et al. [55] also demonstrated the advantage of cluster plots and found that small subplots with a larger distance captured more unique plant species than a single large plot. Half of 36 countries with an NFI system use SS with cluster plots rather than single plots [46].

The performance of cluster plots is highly dependent on the spatial heterogeneity of forest stands [56]. Many authors [31,56,57] have demonstrated that cluster plots are highly efficient in heterogeneous forest stands. The reason is that a cluster plot provides more information on forest characteristics. Seidler, et al. [57] also observed that cluster plots were more sensitive to spatial heterogeneity and efficiently captured spatial changes in forest characteristics, resulting in higher performance than single plots. Ma, et al. [58] investigated plant species distribution in our study area and found that conspecific individuals tended to clump on a relatively small spatial scale, suggesting high spatial heterogeneity. Additionally, Ye, et al. [56] investigated the effects of environmental gradients and forest heterogeneity on

α-diversity in our study area. It was observed that species richness and diversity depended on the scale, suggesting high spatial heterogeneity. Therefore, the high performance of the cluster plot design could be explained by the high heterogeneity of forest characteristics in our study area.

Furthermore, it was noteworthy that increasing the EGROUND improved the performance of the cluster plots. The reason is that spatial autocorrelation between subplots decreases as the EGROUND increases [33,59], suggesting that more information on species composition was derived from cluster plots than from a single plot. Our study confirms our expectations. The same finding was reported by Quon, et al. [22] and Thompson [35], who observed that increasing the distance between subplots, i.e., EGROUND, increased the accuracy and precision of the estimated species richness.

This spatial compactness of the cluster plot is defined as the ratio of EGROUND to the perimeter of the geometric figure formed by the lines between the centers of subplots [22]. The compactness of plots has been extensively used to evaluate sampling performance. For instance, Kleinn [60] found that a less compact cluster provided more information because of the larger area. The square SCONFIG has the highest compactness, followed by the triangle and rectangle, indicating that a rectangular cluster plot provides the most information [22]. Our result confirms the effect of compactness on sampling performance. A rectangular cluster plot with EGROUND = 500 m^2 provided more information on species composition and had higher efficiency.

Interestingly, we observed that the accuracy of the estimated value obtained from the rectangular cluster plot decreased with the increasing distance between the subplots. The likely reason may be the limited dispersal of plant seeds. Similarly, Ma, et al. [58] also found that species information between two sites might not be captured when the distance between subplots is large and attributed this result to the limited dispersal ability of plant seeds. It is noteworthy that Ye, et al. [56] investigated forest diversity in our study area using transect sampling; they demonstrated that the estimated species diversity reached the maximum value when the transect was 60 m, and the estimated value fluctuated as the transect continued to increase.

The increase in EGROUND generates an increase in the corresponding survey cost. Although the EGROUND = 2500 m^2 results were closest to the true value when we investigated species diversity, we would highly recommend the EGROUND = 1000 m^2 cluster plot because the estimated results obtained from those did not differ much from those obtained from the cluster plot with larger EGROUND. The perimeter of a square is smaller than a rectangle of the same area, so when EGROUND is the same, the SCONFIG = square cluster plot costs less, and the estimated results are not significantly different. So, when estimating species richness, we would highly recommend a cluster plot with SCONFIG = square and EGROUND = 500 m^2, instead of a cluster plot with SCONFIG = rectangle.

We found that S_{obs} generally underestimated the true values (Figure 3), which is consistent with previous studies [32]. The negative bias can be explained by the species–area relationship. Condit, et al. [61] examined species-individual curves in a tropical forest and found that the number of observed species was highly correlated with the sample plot area. Additionally, the underestimation might be attributed to rare species, which are difficult to quantify [32].

Many authors [49,50,62] have demonstrated that nonparametric extrapolation methods are the most efficient for predicting population richness from samples. In this study, three corrected estimators were used (*Chao1*, *Jack1*, and *Jack2*) to estimate species richness. Although all three corrected estimators overestimated species richness in some plot designs, *Chao1* showed the best performance (Figure 3). *Chao1* was corrected by the numbers of one-individual and two-individual species [50,51]. Some authors [32,62] have reported the same results. For example, Gimaret-Carpentier, et al. [32] investigated the forest vegetation species richness in Uppangala and Pasoh and found that the *Chao* provided accurate estimates of species richness using a small sample. They observed that the *Chao* had a lower bias than the *Jackknife* estimators. In contrast, the *Jackknife* estimators, especially *Jack1*,

exhibited the lowest performance in estimating species richness in this study (Figure 3). The *Jackknife* estimators were corrected by the number of one-cluster and two-cluster species [49,50], and they were more sensitive to rare species. Furthermore, some studies have suggested that *Jackknife* estimators only perform well when the proportion of rare species is relatively small [63,64]. Chazdon, et al. [62] defined rare species as those with 10 or fewer individuals when all quadrats were pooled. In our study area, 15 tree species had less than 10 individuals, accounting for 32.6% of all tree species, suggesting a large proportion of rare species. As a result, the *Jackknife* estimators had relatively low performance.

The Shannon and Simpson indices had a negative bias, regardless of the plot design (Figure 4). The underestimation might be attributed to the sample size, the spatial heterogeneity, and the characteristics of the species diversity indices. Gimaret-Carpentier, et al. [32] found that the Simpson and Shannon indices were positively correlated with the sample size. Lande [65] attributed the underestimation of the Shannon index to the frequently occurring underestimation of species richness. The heterogeneity or variation in α-diversity might also account for the biased estimation. For example, Ye, et al. [56] observed that species composition varied significantly in forests with environmental gradients and low spatial heterogeneity, making it difficult to prevent bias, even at a large sampling size. Thus, Heltshe and Forrester [66] stated that numerous small subplots were preferable to a few large ones with the same total area. Therefore, in future studies, we can try to change the sampling method, such as stratified sampling, to reduce the impact of environmental gradients on the estimation of species diversity; or, try to change the sample size.

4.2. Study Limitations and Future Perspectives

Although we observed that cluster plots with a large EGROUND had the best performance for estimating species richness and diversity, this cluster plot design has higher sampling costs [22]. It is highly recommended to quantify the relationship between the sampling cost and accuracy/precision of the sampling results to determine the optimum sampling design.

Although our study provided information on the optimal sampling plot design, the plot design must also consider the survey objective, terrain, and heterogeneity of the study area. Some studies [33,60] demonstrated the difficulty of determining the optimum cluster plot design because of forest conditions, spatial structure, and cost. Further studies of other types of forests are required to assess the influence of species composition and environmental gradients on estimating species richness and species diversity [67].

Studies of forest structural diversity provide detailed information on forest stands and have been extensively used to inform forest management [26,68–70]. In addition to tree species diversity, forest structural diversity includes tree size and tree position, which can be quantified by the Gini index, species intermingling index, and neighborhood pattern [71,72]. Thus, investigating optimal sampling strategies is suggested for these indices. Additionally, future studies on plot design using other SCONFIG, e.g., L-shaped, T-shaped, and linear configurations, are highly recommended.

5. Conclusions

In this study, we investigated the influence of different plot design factors on estimating species richness and species diversity in a warm temperate deciduous broad-leaved secondary forest on Dongling Mountain in the Mentougou District of Beijing, China. A significant advantage of the cluster plot was observed in this simulated sampling, and different plot design combinations were required according to specific survey objectives, indicating that SCONFIG and EGROUND had great influence on the estimated results. Based on the estimated values of the species richness and species diversity, we drew the following conclusions: (1) the cluster plot design with SCONFIG = square and EGROUND = 500 m^2 exhibited the best performance in estimating forest species richness; (2) the rectangular cluster plot with an EGROUND of 1000 m^2 was more suitable for assessing species diversity.

This study is one of few studies to comprehensively examine the effects of plot design on species richness and species diversity in northern China. Importantly, our study was conducted in a 20 ha plot to derive the true values of species richness and species diversity. This strategy ensured the reliability of our results, providing a theoretical basis for sampling forest species richness and diversity. Our results suggest that cluster plots are more suitable than a single plot for estimating species richness and diversity. A larger EGROUND provides more species information in forests with high spatial heterogeneity.

Author Contributions: All authors made significant contributions to the manuscript: J.M., Y.Z. and C.Z. conceived, designed, and performed the experiments; C.Z. analyzed the data and results; Y.Z. contributed materials/analysis tools; J.M. and C.Z. are the main authors who developed and revised the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Strategic Priority Research Program of Chinese Academy of Sciences, grant number XDB31000000; the National Key Research and Development Program of China grant number 2017YFA0605103; and the NSF-China grant number 32271614 and 31870408.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to confidentiality.

Acknowledgments: We thank our colleagues at the Dongling Mountain dynamic monitoring plot for their support during fieldwork.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Xie, S. Philosophical Thinking and Analysing on the Practice of China's Forest Resouces Classification Management. Ph.D. Thesis, Beijing Forestry University, Beijing, China, 2006.
2. Crow, T.R.; Buckley, D.S.; Nauertz, E.A.; Zasada, J.C. Effects of management on the composition and structure of northern hardwood forests in Upper Michigan. *For. Sci.* **2002**, *48*, 129–145.
3. Larson, B.C. Thoughts on the development of new, appropriate measures of complexity. In *Complex Stand Structures and Associated Dynamics: Measurement Indices and Modelling*; Ontario Forest Research Institute: Sault Ste. Marie, ON, Canada, 2007; p. 54.
4. Bonan, G.B. Forests and climate change: Forcings, feedbacks, and the climate benefits of forests. *Science* **2008**, *320*, 1444–1449. [CrossRef]
5. Chiarucci, A.; Bacaro, G.; Scheiner, S.M. Old and new challenges in using species diversity for assessing biodiversity. *Philos. Trans. R. Soc. Lond. B Biol. Sci.* **2011**, *366*, 2426–2437. [CrossRef]
6. Yang, Y. A Study on Quantity and Sampling Optimization of Wetland Plant Species Diversity Based on UAVRS. Master's Thesis, Jiangxi Normal University, Nanchang, China, 2020.
7. Wang, K.; Wang, C.; Feng, X.; Wu, X.; Fu, B. Research progress on the relationship between biodiversity and ecosystem multifuctionality. *Acta Ecol. Sin.* **2022**, *42*, 13.
8. Haas, S.E.; Hooten, M.B.; Rizzo, D.M.; Meentemeyer, R.K. Forest species diversity reduces disease risk in a generalist plant pathogen invasion. *Ecol. Lett.* **2011**, *14*, 1108–1116. [CrossRef] [PubMed]
9. Fan, X.; Zhang, B.; Fan, C. Effects of species diversity and structural diversity on productivity in different succession stages of typical natural forest in Changbai Mountains of northeastern China. *J. Beijing For. Univ.* **2021**, *43*, 1–8.
10. Lei, X.; Wang, W.; Peng, C. Relationships between stand growth and structural diversity in spruce-dominated forests in New Brunswick, Canada. *Can. J. For. Res.* **2009**, *39*, 1835–1847. [CrossRef]
11. Huang, L.; Yu, Y.; An, X.; Yu, L.; Xue, Y. Leaf functional traits, species diversity and functional diversity of plant community in Tiankeng forests. *Acta Ecol. Sin.* **2022**, *42*, 1–12.
12. Liang, J.; Crowther, T.W.; Picard, N.; Wiser, S.; Zhou, M.; Alberti, G.; Schulze, E.-D.; McGuire, A.D.; Bozzato, F.; Pretzsch, H. Positive biodiversity-productivity relationship predominant in global forests. *Science* **2016**, *354*, aaf8957. [CrossRef]
13. Zhu, J.; Wu, A.; Zou, S.; Xiong, X.; Liu, S.; Chu, G.; Zhang, Q.; Liu, J.; Tang, X.; Yan, J.; et al. Relationships between tree diversity and biomass/productivity and their influence factors in a lower subtropical evergreen broad-leaved forest. *Biodivers. Sci.* **2021**, *29*, 1435–1446. [CrossRef]
14. Pan, C.; Shi, R. Sustainable forest management: From timber to biodiversity. *J. Beijing For. Univ.* **2006**, *6*, 133–138.
15. Bastow Wilson, J.; Lee, W.G.; Mark, A.F. Species diversity in relation to ultramafic substrate and to altitude in southwestern New Zealand. *Vegetatio* **1990**, *86*, 15–20. [CrossRef]
16. Tilman, D.; Downing, J.A. Biodiversity and stability in grasslands. *Nature* **1994**, *367*, 363–365. [CrossRef]

17. Pedro, M.S.; Rammer, W.; Seidl, R. Tree species diversity mitigates disturbance impacts on the forest carbon cycle. *Oecologia* **2015**, *177*, 619–630. [CrossRef]
18. Kant, S. The marginal cost of structural diversity of mixed uneven-aged hard maple forests. *Can. J. For. Res.* **2002**, *32*, 616–628. [CrossRef]
19. Li, L.; Wang, J. Spatial sampling model of geographic data. *Prog. Nat. Sci.* **2002**, *12*, 99–102.
20. Shi, J.; Lei, Y.; Zhao, T. Research progress in sampling survey techniques of forest resources. *For. Res.* **2009**, *22*, 101–108.
21. Sun, H.; Lin, H.; Shi, J.; Mo, D.; Zhu, G.; Zang, Z. Comparative study of remote sensing sampling technique in national forest inventory of Hunan provinc. *J. Cent. South Univ. For. Technol.* **2010**, *30*, 26–31. [CrossRef]
22. Quon, C.; Lam, T.-Y.; Lin, H.-T. Designing cluster plots for sampling local plant species composition for biodiversity management. *For. Syst.* **2020**, *29*, e002. [CrossRef]
23. Lin, H.-T.; Lam, T.Y.; von Gadow, K.; Kershaw, J.A. Effects of nested plot designs on assessing stand attributes, species diversity, and spatial forest structures. *For. Ecol. Manag.* **2020**, *457*, 117658. [CrossRef]
24. West, P. Tamm review: Sampling to estimate the frequency distribution of tree diameters or ages across large forest areas. *For. Ecol. Manag.* **2021**, *488*, 118939. [CrossRef]
25. Carrer, M.; Castagneri, D.; Popa, I.; Pividori, M.; Lingua, E. Tree spatial patterns and stand attributes in temperate forests: The importance of plot size, sampling design, and null model. *For. Ecol. Manag.* **2018**, *407*, 125–134. [CrossRef]
26. Peck, J.; Zenner, E. Structure area curves in Eastern Hardwoods: Implications for minimum plot sizes to capture spatially explicit structure indices. *Ann. For. Sci.* **2021**, *78*, 16. [CrossRef]
27. Wagner, F.; Rutishauser, E.; Blanc, L.; Herault, B. Effects of plot size and census interval on descriptors of forest structure and dynamics. *Biotropica* **2010**, *42*, 664–671. [CrossRef]
28. Metcalfe, D.; Meir, P.; Aragao, L.E.O.; da Costa, A.; Almeida, S.; Braga, A.; Gonçalves, P.; Athaydes, J.; Malhi, Y.; Williams, M. Sample sizes for estimating key ecosystem characteristics in a tropical terra firme rainforest. *For. Ecol. Manag.* **2008**, *255*, 558–566. [CrossRef]
29. Lin, D.; Lai, J.; Mi, X.; Ren, H.; Ma, K. Spatial variation in community structure of a subtropical evergreen broad-leaved forest: Implications for sampling design. *Chin. Sci. Bull.* **2013**, *58*, 1181–1186. [CrossRef]
30. Gray, A. Monitoring stand structure in mature coastal Douglas-fir forests: Effect of plot size. *For. Ecol. Manag.* **2003**, *175*, 1–16. [CrossRef]
31. Yang, T.-R.; Lam, T.Y.; Su, S.-H. A simulation study on the effects of plot size and shape on sampling plant species composition for biodiversity management. *J. Sustain. For.* **2019**, *38*, 116–129. [CrossRef]
32. Gimaret-Carpentier, C.; Pélissier, R.; Pascal, J.P.; Houllier, F. Sampling strategies for the assessment of tree species diversity. *J. Veg. Sci.* **1998**, *9*, 161–172. [CrossRef]
33. Yim, J.-S.; Shin, M.-Y.; Son, Y.; Kleinn, C. Cluster plot optimization for a large area forest resource inventory in Korea. *For. Sci. Technol.* **2015**, *11*, 139–146. [CrossRef]
34. Bowering, R.; Wigle, R.; Padgett, T.; Adams, B.; Cote, D.; Wiersma, Y.F. Searching for rare species: A comparison of Floristic Habitat Sampling and Adaptive Cluster Sampling for detecting and estimating abundance. *For. Ecol. Manag.* **2018**, *407*, 1–8. [CrossRef]
35. Thompson, S.K. *Sampling*; John Wiley & Sons: Hoboken, NJ, USA, 2012; Volume 755.
36. Li, Z.; Chen, W.; Wei, J.; Kirim, M.; Zhang, Y.; Zhang, S.; Wang, X. Tree-ring growth responses of Liaodong Oak (*Quercus wutaishanica*) to climate in the Beijing Dongling Mountain of China. *Acta Ecol. Sin.* **2021**, *41*, 27–37.
37. Gu, H.; Li, J.; Qi, G.; Wang, S. Species spatial distributions in a warm-temperate deciduous broad-leaved forest in China. *J. For. Res.* **2020**, *31*, 1187–1194. [CrossRef]
38. Ding, Z.; Xu, G.; Zhang, S.; Zhang, Y.; Ma, K. Altitudinal pattern of soil fauna-plant interaction in Dongling Mountain, Beijing. *Acta Ecol. Sin.* **2022**, *42*, 2741–2750.
39. Liu, H.; Li, L.; Sang, W. Species composition and community structure of the Donglingshan forest dynamic plot in a warm temperate deciduous broad-leaved secondary forest, China. *Biodivers. Sci.* **2011**, *19*, 232–242.
40. Shi, X.; Yu, D.; Sun, W.; Wang, H.; Zhao, Q.; Gong, Z. Reference datum for Chinese and American soil classification Systems: A reference between soil classes and American soil classes. *Chin. Sci. Bull.* **2004**, *13*, 1299–1303.
41. Gu, Y.; Lv, X.; Tao, Q.; Yu, Z.; Wang, L.; Li, Y. Effects of temperature and precipitation on litter decomposition in Donglingshan Mountain broad-leaved forest. *Quat. Sci.* **2021**, *41*, 1156–1168.
42. Kleinn, C.; Corrales, L.; Morales, D. Forest area in Costa Rica: A comparative study of tropical forest cover estimates over time. *Environ. Monit. Assess.* **2002**, *73*, 17–40. [CrossRef]
43. Güler, B.; Jentsch, A.; Apostolova, I.; Bartha, S.; Bloor, J.M.; Campetella, G.; Canullo, R.; Házi, J.; Kreyling, J.; Pottier, J. How plot shape and spatial arrangement affect plant species richness counts: Implications for sampling design and rarefaction analyses. *J. Veg. Sci.* **2016**, *27*, 692–703. [CrossRef]
44. Yang, F. Study on Sampling Scheme Based on Annual Monitoring of Circular Cluster Plot Stock. Master's Thesis, Beijing Forestry University, Beijing, China, 2017.
45. Lei, X.; Hong, L.; Lu, Y.; Tang, M. Design of ground sample for national forest resources inventory. *World For. Res.* **2008**, *21*, 35–40. [CrossRef]

46. Tomppo, E.; Gschwantner, T.; Lawrence, M.; McRoberts, R.E.; Gabler, K.; Schadauer, K.; Vidal, C.; Lanz, A.; Ståhl, G.; Cienciala, E. National forest inventories. In *Pathways for Common Reporting*; European Science Foundation: Strasbourg, France, 2010; Volume 1, pp. 541–553.
47. Bechtold, W.A.; Patterson, P.L. *The Enhanced Forest Inventory and Analysis Program—National Sampling Design and Estimation Procedures*; USDA Forest Service, Southern Research Station: Asheville, NC, USA, 2005; Volume 80.
48. Magurran, A. *Measuring Biological Diversity*, 1st ed.; Blackwell: Oxford, UK, 2004; 264p.
49. Zahl, S. Jackknifing an index of diversity. *Ecology* **1977**, *58*, 907–913. [CrossRef]
50. Chao, A. Nonparametric estimation of the number of classes in a population. *Scand. J. Stat.* **1984**, *11*, 265–270.
51. Burnham, K.P.; Overton, W.S. Estimation of the size of a closed population when capture probabilities vary among animals. *Biometrika* **1978**, *65*, 625–633. [CrossRef]
52. Simpson, E.H. Measurement of diversity. *Nature* **1949**, *163*, 688. [CrossRef]
53. Shannon, C.E. A mathematical theory of communication. *Bell Syst. Tech. J.* **1948**, *27*, 379–423. [CrossRef]
54. Valentine, H.T.; Ducey, M.J.; Gove, J.H.; Lanz, A.; Affleck, D.L. Corrections for cluster-plot slop. *For. Sci.* **2006**, *52*, 55–66.
55. Green, R.H.; Young, R.C. Sampling to detect rare species. *Ecol. Appl.* **1993**, *3*, 351–356. [CrossRef]
56. Ye, W.; Ma, K.; Ma, K.; Sang, W.; Gao, X. Studies on Plant Community Diversity in Dongling Mountain, Beijing, China IX. The Influence of Scale on α-diversity. *Acta Ecol. Sin.* **1998**, *18*, 12–16.
57. Seidler, T.G.; Plotkin, J.B. Seed dispersal and spatial pattern in tropical trees. *PLoS Biol.* **2006**, *4*, e344. [CrossRef]
58. Ma, F.; Wang, S.; Feng, J.; Sang, W. Spatial distribution patterns of snag and standing trees in a warm temperate deciduous broad-leaved forest in Dongling Mountain, Beijing. *Acta Ecol. Sin.* **2018**, *38*, 5717–5725.
59. Kleinn, C. Comparison of the performance of line sampling to other forms of cluster sampling. *For. Ecol. Manag.* **1994**, *68*, 365–373. [CrossRef]
60. Kleinn, C. Ein Vergleich der Effizienz von verschiedenen Clusterformen in forstlichen Großrauminventuren. *Forstwiss. Cent. Ver. Tharandter Forstl. Jahrb.* **1996**, *115*, 378–390. [CrossRef]
61. Condit, R.; Hubbell, S.P.; Lafrankie, J.V.; Sukumar, R.; Manokaran, N.; Ashton, F.P.S. Species-area and species-individual relationships for tropical trees: A comparison of three 50-ha plots. *J. Ecol.* **1996**, *84*, 549–562. [CrossRef]
62. Chazdon, R.L.; Colwell, R.; Denslow, J.; Guariguata, M. Statistical methods for estimating species richness of woody regeneration in primary and secondary rain forests of northeastern Costa Rica. *Man Biosph.* **1998**, *20*, 285–309.
63. Smith, E.P.; van Belle, G. Nonparametric estimation of species richness. *Biometrics* **1984**, *40*, 119–129. [CrossRef]
64. Liu, C.; Ma, K.; Yu, S.; Wang, W. Plant Community Diversity in Dongling Mountain, Beijing, China VI. Estimation of The Numbers of Species in Several Types of Plant Communities. *Acta Ecol. Sin.* **1998**, *18*, 138–150.
65. Lande, R. Statistics and partitioning of species diversity, and similarity among multiple communities. *Oikos* **1996**, *76*, 5–13. [CrossRef]
66. Heltshe, J.F.; Forrester, N.E. Estimating species richness using the jackknife procedure. *Biometrics* **1983**, *39*, 1–11. [CrossRef]
67. Pitkänen, S. The use of diversity indices to assess the diversity of vegetation in managed boreal forests. *For. Ecol. Manag.* **1998**, *112*, 121–137. [CrossRef]
68. Meng, J.; Li, S.; Wang, W.; Liu, Q.; Xie, S.; Ma, W. Estimation of forest structural diversity using the spectral and textural information derived from SPOT-5 satellite images. *Remote Sens.* **2016**, *8*, 125. [CrossRef]
69. Hui, G. The Neighbourhood Partten: A New Structure Parameter for Describing Distribution of Forest Tree Position. *Sci. Silvae Sin.* **1999**, *35*, 37–42.
70. Bettinger, P.; Tang, M. Tree-level harvest optimization for structure-based forest management based on the species mingling index. *Forests* **2015**, *6*, 1121–1144. [CrossRef]
71. Ozdemir, I.; Karnieli, A. Predicting forest structural parameters using the image texture derived from WorldView-2 multispectral imagery in a dryland forest, Israel. *Int. J. Appl. Earth Obs. Geoinf.* **2011**, *13*, 701–710. [CrossRef]
72. Pommerening, A. Approaches to quantifying forest structures. *For. Int. J. For. Res.* **2002**, *75*, 305–324. [CrossRef]