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Evaluating diameter distribution models for coniferous forests in the northwestern Himalayas

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ABSTRACT

Accurate modeling of tree diameter distribution is crucial for sustainable forest management, biomass estimation, and ecological conservation. This study evaluates the effectiveness of four probability distributions viz., Normal, Log-normal, Weibull, and Gamma in characterizing the diameter at breast height (DBH) distributions of Cedrus deodara, Pinus wallichiana, and Abies pindrow in the Shopian and Roamshi forest ranges of the North-Western Himalayas. A total of 750 trees were sampled using a stratified random approach, and their DBH measurements were analyzed using maximum likelihood estimation. Model performance was assessed using Kolmogorov–Smirnov (KS) tests, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and log-likelihood (LogL) values. Results indicate that the Gamma distribution provides the best fit across all species, outperforming other models in terms of statistical goodness-of-fit. The study encountered standard Himalayan field challenges, including rugged terrain and sites with restricted access, as well as the requisite truncation of diminutive stems (10 cm DBH), which may affect the lower tail of empirical DBH distributions. Even with these problems, we offer a species-resolved, multi-criteria benchmarking that shows the Gamma distribution gives the best overall fit for all species (by AIC/BIC/LogL) and points out species-specific differences that can be seen in KS diagnostics. These findings underscore the ecological importance of species-specific diameter distributions and provide a robust statistical framework for forest inventory, carbon stock assessments, and sustainable silvicultural planning.

Keywords: *Tree diameter modeling, probability density functions, tree diameter, volume estimation, forest ecosystems, DBH distribution, gamma distribution, silviculture, biomass and carbon stock assessment, north-western himalayas.*

Introduction

The sustainable management of forest resources at the local, regional, or national levels hinges upon a comprehensive understanding of both the size and structure of these resources. Such knowledge enables forest managers to devise strategies that ensure the sustained longevity of forest ecosystems[1]. Tree diameter distribution is pivotal in guiding forest stand management decisions among the various structural parameters. This parameter offers rich insights into timber assortments, carbon stock estimations, and biodiversity considerations [2]. The modeling of tree diameter distribution provides a scientific foundation for determining stand structure, quantifying forest resources, and planning silvicultural interventions. Typically, diameter distribution models describe the frequency of tree diameters, offering a basis for calculating stand volume through equations that incorporate diameter at breast height (DBH) and height [3,4,5]. Diameter distributions are essential tools for assessing forest sustainability by determining whether the younger trees are sufficiently abundant to replace mature ones [6].

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A range of probability density functions (PDFs) has been utilized in forestry to model tree diameter distributions. These include the log-normal distribution [7], gamma distribution [8], Weibull distribution [9], and beta distribution [10,11], among others. The three-parameter Weibull distribution, along with beta and SB models, is widely used due to their flexibility in fitting skewed distributions [12]. However, comparative studies [13], have shown that the gamma distribution is often more suitable for modeling tree diameters, outperforming others like the exponential distribution.

The North-Western Himalayan region of Kashmir, home to ecologically significant conifer species such as *Cedrus deodara*, *Pinus wallichiana*, and *Abies pindrow*, represents a vital part of the Himalayan ecosystem. These forests are integral to regional biodiversity, carbon sequestration, and timber production. Despite their importance, there has been limited research on the application of advanced statistical models to assess tree diameter distributions in this region. This gap highlights the need for refined modeling techniques to inform sustainable forest management and conservation practices.

The main aim of this study was to conduct a detailed evaluation of four statistical PDFs, viz., Normal, Log-normal, Weibull, and Gamma to evaluate their effectiveness in modeling the diameter distributions of both basal area and stem counts in forest stands located in the Roamshi and Shopian regions of Shopian Forest Division in the North-Western Himalayas. This comparative analysis not only fills a significant research gap but also offers valuable insights into the structural composition of these coniferous forests. By identifying the most suitable distribution for characterizing diameter distributions, this study provides essential knowledge for improving forest management strategies, conservation efforts, and policymaking in this understudied yet ecologically crucial region.

Materials and Methods

Study Area

The study was conducted in the forested areas of Shopian and Roamshi ranges within the Shopian Forest Division, focusing on three key conifer species: *Cedrus deodara*, *Pinus wallichiana*, and *Abies pindrow*, which are naturally occurring or cultivated through plantations. These regions are in the North-Western Himalayan Pir Panjal area of Kashmir, between 33° - 30' and 33° - 48' North latitude and 74° - 30' and 74° - 50' East longitude, as illustrated in Fig. 1. The Pir Panjal Mountain Range forms the western boundary, defining the southern edge of the Kashmir Valley, with the Nallah Veshav marking its southern limit. Elevations in this tract range from 1,900 meters (at the lowest contour of Yarwan Karewa) to 4,745 meters (at the summit of Romshi Thung), with the principal forest belt occurring between 1,950 meters and 3,200 meters.

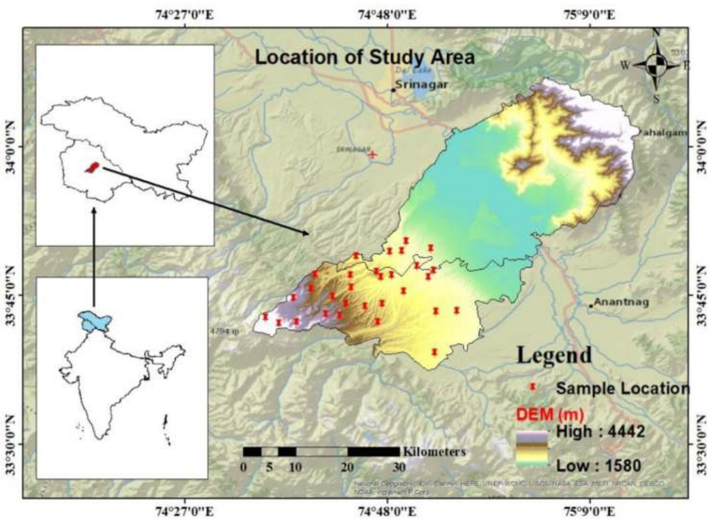

Fig. 1. Study area with sampling locations

Data collection and sampling methodology

750 trees, representing three coniferous species (*Cedrus deodara*, *Abies pindrow*, and *Pinus wallichiana*), were sampled, with 250 trees per species. A stratified random sampling approach with a multi-stage cluster sampling design was employed to improve representativeness across varying ecological conditions. In the first stage, forest blocks were deliberately selected based on the presence of the target conifer species. Within these blocks, strata were established based on elevation gradients and forest types to ensure adequate coverage of different growth conditions. Subsequently, systematic random sampling was applied within each stratum to select 15 plots per range, with each plot measuring 100 meters × 100 meters [14,15]. This multi-stage approach helped minimize spatial autocorrelation and capture variations within the study region.

Although efforts were made to achieve a robust sampling design, potential biases may still arise from site accessibility constraints, which might have limited the inclusion of extremely remote or inaccessible areas. Additionally, species dominance in certain elevation bands could have influenced the sample representation across different forest compositions. However, these biases were minimized by employing a stratified approach and ensuring adequate sample distribution, enhancing the study's reliability and reproducibility.

Tree measurements and data collection

For each selected tree within the designated plots, key biometric parameters were measured, ensuring consistency with standard forestry measurement protocols.

Girth measurement and DBH calculation

The girth at breast height (GBH) was first measured using a flexible measuring tape at 1.3 meters above the ground level. This method ensures accuracy in cases where trees have irregular diameters or buttress formations at the base. The recorded girth measurements were then converted to diameter at breast height (DBH) using the formula:

$$DBH = \frac{GBH}{\pi}$$

Where π ≈ 3.1416. This approach provides a standardized diameter over bark (DOB) in centimeters, which is widely used in forestry research.

DBH measurement

Direct DBH measurements were also taken using a vernier caliper and measuring tape at the same 1.3-meter height to validate the converted DBH values. To improve precision, measurements were recorded from two perpendicular directions, and the average DBH was calculated to account for any variations in tree shape. This ensured consistency with forestry measurement standards [16].

Height measurement

The total height of each standing tree (in meters) was meticulously measured using a Ravi Multimeter, a field instrument designed for precise tree height assessment. This method aligns with the standard methodologies for forest inventory and tree height estimation [17]. The use of this device helped minimize observer errors and provided reliable height data for all sampled trees. These measurements ensured accurate biometric data collection, essential for evaluating tree growth patterns, forest stand structure, and species-specific differences in DBH and height distribution.

Probability distributions

Modeling the DBH is essential in forestry to understand stand structure, tree growth patterns, and biomass estimation [18,19]. The selection of an appropriate probability distribution is crucial, as DBH data often exhibit skewness and non-negative values. Different forest conditions, species compositions, and stand management practices influence the shape of DBH distributions, necessitating the use of flexible probability models [20].

The Normal, Log-Normal, Gamma, and Weibull distributions are commonly applied in forestry research due to their ability to model various shapes of DBH distributions [18,21]. The Normal distribution is used for symmetrical diameter distributions but is often less suitable for raw DBH data due to the typical right skewness observed in forest stands. The Log-Normal and Gamma distributions effectively capture right-skewed data, commonly observed in uneven-aged forests and natural stands where smaller trees dominate [21,22]. The Weibull distribution is particularly versatile, accommodating different skewness levels and providing accurate representations of DBH structures across forest types [23]. These distributions have been extensively evaluated in forestry studies for their effectiveness in modeling tree diameter distributions and predicting stand dynamics [18,21]. The choice of these four distributions ensures a comprehensive assessment of DBH variations, allowing for statistical inference in tree diameter modeling. Their mathematical formulations and theoretical properties provide a foundation for evaluating forest stand characteristics and guiding sustainable forest management.

Normal distribution

Normal distribution is a crucial probability distribution in statistics, as it accurately represents many natural phenomena. It was initially introduced by the English mathematician [24]as a limiting case of the binomial distribution. It was later derived in 1809 by Kark Friedrich Gauss [25], and he was given the credit of normal distribution and was thus also called the distribution of Gaussian.

A random variable X is said to be normally distributed if its PDF is expressed as:

$$f(X;\mu,\sigma)=\frac{1}{\sigma\sqrt{2\pi}}exp\left\{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right\};-\infty<x<\infty,-\infty<\mu<\infty,\sigma>0$$

where

X = Continuous random variable

μ =Mean

The mean of normal distribution $\bar{X}=\frac{1}{n}\sum_{i=1}^{n}X_i$ is an estimate ofμ.

The variance of normal distribution $S^2=\frac{1}{n}\sum_{i=1}^{n}(X_i-\bar{X})^2$is an estimate of σ^2

Log-normal distribution

A log-normal distribution is a statistical distribution of values whose logarithms follow a normal distribution. It can be transformed into a normal distribution and vice versa through appropriate logarithmic calculations.A continuous random variable X is considered to follow a log-normal distribution if the logarithm of X is normally distributed. The PDF of X is given by:

$$f(X;\mu,\sigma^2)=\frac{1}{x\sigma\sqrt{2\pi}}exp\left\{-\frac{(log\,x-\mu)^2}{2\sigma^2}\right\},\sigma>0$$

where

Mean = $exp\left(\mu+\frac{\sigma^2}{2}\right)$

Variance = $[exp(\sigma^2)-1]\,exp(2\mu+\sigma^2)$

Gamma distribution

The gamma distribution is a family of continuous probability distributions that are right-skewed. A positive random variable X is said to follow a gamma distribution with parameters α and β if its PDF is defined as:

$$f(X;\alpha,\beta)=\frac{1}{\beta^\alpha\Gamma(\alpha)}e^{\frac{-x}{\beta}}x^{\alpha-1};x>0$$

where

Mean = $\alpha\beta$

Variance = $\alpha\beta^2$

Weibull distribution

The Weibull distribution is a continuous probability distribution named after the Swedish mathematician Wallodi Weibull [26], who extensively described it in 1951. A continuous random variable X has a weibull distribution with parameters β and α if its PDF is given by:

$$f(x;\beta,\alpha,)=\frac{\beta}{\alpha}\left(\frac{x}{\alpha}\right)^{\beta-1}exp\left\{-\left(\frac{x}{\alpha}\right)^{\beta}\right\};x\geq 0,\beta>0,\alpha>0$$

where,

Mean = $\alpha\Gamma(1+1/\beta)$

Variance = $\alpha^2\left[\Gamma\left(1+\frac{2}{\beta}\right)-\left(\left(1+\frac{1}{\beta}\right)\right)^2\right]$

Goodness of fit measures

Kolmogorov-Smirnov (K-S) test

The K-S test is a non-parametric statistical test used to compare an empirical distribution with a theoretical probability distribution. It evaluates the maximum absolute difference between the empirical cumulative distribution function (ECDF) of observed data and the cumulative distribution function (CDF) of the reference distribution [27,28]. The test statistic is defined as:

$$D=sup|F_o(x)-F(x)|$$

where

$F_o(x)$ = the CDF of hypothetical distribution,

$F(x)$ = the empirical distribution function of observed data.

The null hypothesis for the test is:

Null hypothesis, H_0: The data follows the specified distribution.

Alternate hypothesis H_1: The data does not follow the specified distribution.

If D exceeds the critical value, the null hypothesis is rejected. Critical values for D can be obtained from the K-S test p-value table [29].

Akaike Information Criterion (AIC)

The AIC is a metric used to compare and select the best-fitting statistical model based on goodness of fit while penalizing for model complexity [30]. It is calculated as

$$AIC=2k-2\ln(\hat{L})$$

where

k = no. of model parameters

$\hat{L}$= maximum value of the likelihood of the model

Lower AIC values indicate a better trade-off between model fit and complexity.

Bayesian Information Criterion (BIC)

The BIC, like AIC, evaluates model fit while incorporating a stronger penalty for the number of parameters to prevent overfitting [31]. It is given by:

$$BIC=kln(n)-2\ln(\hat{L})$$

where

k = no. of model parameters

$\hat{L}$= maximum value of the likelihood of the model

n = sample size

Lower BIC values suggest a more parsimonious model that best explains the data.

Log-Likelihood (LogL)

The LogL measures how well a statistical model explains the observed data by computing the logarithm of the likelihood function. It is expressed as:

$$\log L=\sum_{i=1}^{n}\log P(x_i/\theta)$$

where $P(x_i/\theta)$ represents the probability of observing data points x_i with model parameter as θ. A higher Log-Likelihood value indicates a model with better explanatory power.

Results

This rigorous data collection process, combined with the systematic sampling approach, was implemented to ensure the acquisition of a robust and representative dataset for the study, minimizing potential biases in the selection of trees for analysis. The overall descriptive statistics for species growth parameters presented in Table 1 show that the average tree has a diameter of 0.53 meters, a height of 27.91 meters, and a volume of 6.12 cubic meters. The data has moderate variability, with the highest standard deviation for height (6.89 meters) and volume (3.29 cubic meters).

The ranges indicate a significant spread in values, particularly for volume, which spans from 0.64 to 16.94 cubic meters. The median and mode are close to the mean for all parameters, suggesting relatively symmetrical distributions, though the positive skewness values indicate a slight right-tailed distribution, especially for diameter and volume. Kurtosis values near zero suggest the data distributions are not heavily peaked or flat, with height having the flattest distribution (kurtosis of -0.06). Overall, the data indicates a wide range of growth among the species, with some skew towards larger trees in terms of diameter and volume.

Table 1: Overall descriptive statistics for species growth parameters

	Diameter (m)	Height (m)	Volume (m^3)
Mean	0.53	27.91	6.12
Std Dev	0.16	6.89	3.29
Min	0.16	8	0.64
25%	0.43	23	3.57
Median	0.51	28	5.41
75%	0.61	32	8.07
Max	1.18	47	16.94
Variance	0.03	47.41	10.83
Skewness	0.52	0.3	0.9
Kurtosis	0.41	-0.06	0.55

Fig. 2 illustrates the relationship between tree height and diameter for various species and ranges. Analyzing the scatter plot, we can observe a positive correlation between tree height and diameter, indicating that taller trees tend to have larger trunk diameters. Additionally, the scatter plot allows us to identify species-specific patterns and variations in this relationship.

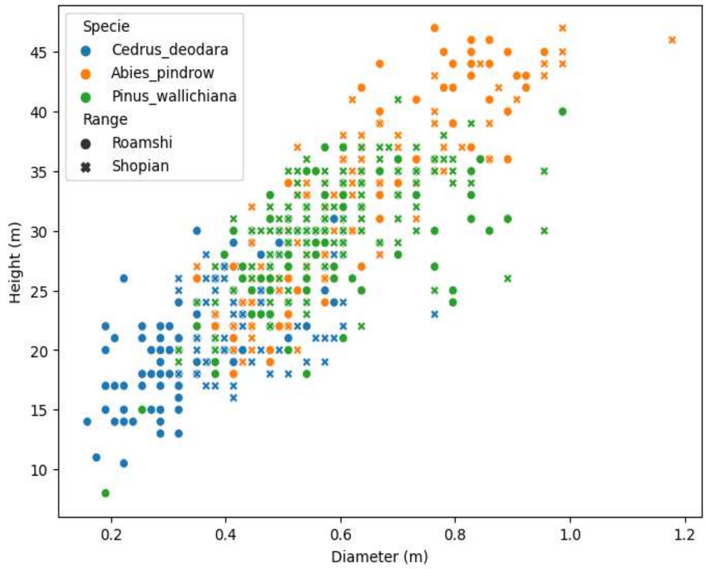

Fig. 2. Species- and range-wise scatterplot of tree height (m) versus diameter (m)

Table 2: Key statistics for diameter and height of three conifer species in Roamshi and Shopian ranges

Range	Type	Species	Mean	Std. Dev.	Median	Variance	Skewness	Kurtosis
Roamshi	Diameter	*Cedrus deodara*	37.23	11.53	35.03	133.05	0.33	-0.64
		Abies pindrow	62.71	15.40	60.51	237.17	0.33	-1.03
		Pinus wallichiana	57.40	13.70	55.73	187.70	0.49	0.67
	Height	*Cedrus deodara*	21.78	4.87	21.00	23.73	0.04	-0.64
		Abies pindrow	32.55	7.72	33.00	59.55	0.08	-1.04
		Pinus wallichiana	28.56	5.12	29.00	26.19	-0.77	1.68
Shopian	Diameter	*Cedrus deodara*	45.65	8.35	44.59	69.70	0.92	0.97
		Abies pindrow	60.78	16.14	57.32	260.41	1.09	0.83
		Pinus wallichiana	57.89	12.66	57.32	160.26	0.48	0.31
	Height	*Cedrus deodara*	23.44	3.39	24.00	11.51	-0.02	-0.69
		Abies pindrow	31.76	6.65	30.50	44.22	0.26	-0.67
		Pinus wallichiana	30.30	4.53	30.00	20.55	-0.41	-0.24

Table 2 summarizes key statistics for the diameter and height of three conifer species—*Cedrus deodara*, *Abies pindrow*, and *Pinus wallichiana* across two distinct forest ranges. In the Roamshi range, mean diameter values indicate that *Cedrus deodara* (37.23 cm) is notably smaller than both *Abies pindrow* (62.71 cm) and *Pinus wallichiana* (57.40 cm). Among these three, *Abies pindrow* not only shows the greatest diameter but also the highest variance (237.17), reflecting pronounced size variability within its population. *Cedrus deodara* exhibits a moderate standard deviation of 11.53 cm, while *Pinus wallichiana* is slightly more variable (std = 13.70) and displays a higher skew (0.49), suggesting a longer right tail. In terms of height, *Abies pindrow* again dominates (mean = 32.55 m), followed by *Pinus wallichiana* (28.56 m) and the shorter *Cedrus deodara* (21.78 m). Skewness in height is minimal for *Cedrus deodara* (0.04) and *Abies pindrow* (0.08), yet *Pinus wallichiana* shows a left-skew (−0.77) coupled with a high positive kurtosis (1.68), implying a strong central peak with fewer extremely tall or short individuals.

In the Shopian range, *Cedrus deodara* increases its mean diameter to 45.65 cm, surpassing its Roamshi value by a notable margin, though *Abies pindrow* (60.78 cm) remains the largest-diameter species overall. *Abies pindrow* also retains the highest variance (260.41), reaffirming its wide size spread, while *Pinus wallichiana* remains in the same approximate diameter band (57.89 cm). The skewness of *Cedrus deodara* (0.92) and *Abies pindrow* (1.09) in Shopian reveals strongly right-tailed distributions, whereas *Pinus wallichiana* (0.48) is moderately skewed. A similar trend emerges for height, where *Cedrus deodara* rises modestly to 23.44 m (showing near symmetry with skew = −0.02), and *Abies pindrow* (31.76 m) still leads in overall stature. *Pinus wallichiana* (30.30 m) is close behind, though its skewness (−0.41) and kurtosis (−0.24) contrast with the positive skew found in *Abies pindrow*, suggesting a less right-biased distribution.

Taken together, these data corroborate that *Abies pindrow* achieves the greatest diameters and heights across both Roamshi and Shopian, aligning with its established status as a climax fir that accommodates a broad range of size classes [32]. *Cedrus deodara*, meanwhile, displays more pronounced site-dependent variation, particularly in diameter, consistent with studies indicating that local environmental conditions and past disturbance strongly influence its growth potential [33,34]. By contrast, *Pinus wallichiana* maintains moderate average sizes but exhibits notable shifts in distribution shape, especially in height, a pattern often attributed to the species' flexible regeneration strategies and susceptibility to stand-level disturbance dynamics [33,35].

Parameter Estimation

For each species, a total of 250 trees were categorized into six diameter groups, ranging from 10-25 to 85-100, and the count of trees within each diameter class was recorded. Statistical models for diameter distribution were applied to investigate the distribution pattern of these trees. Specifically, four probability distributions, namely normal, log-normal, gamma, and Weibull, were employed for *Cedrus deodara, Pinus wallichiana,* and *Abies pindrow*. The parameters of these PDFs were estimated using the maximum likelihood method, and this analysis was conducted using the MASS package [36] and the fitdistrplus package [37] in R software, version 4.0.2.

In Fig. 3, all three species exhibit their highest counts within the 40–55 cm diameter class, suggesting that this mid-range diameter may serve as a particularly favorable ecological niche. Nonetheless, a closer look reveals distinct species-specific patterns. *Cedrus deodara* shows a stronger presence in the lower diameter classes (10–25 cm and 25–40 cm), indicating that it often occupies stands with comparatively smaller tree sizes. In contrast, *Abies pindrow* and *Pinus wallichiana* extend into the larger diameter categories, with some individuals reaching up to 100 cm. These differing distributions underscore the importance of considering individual species' ecological requirements and growth patterns when devising forest management and conservation strategies.

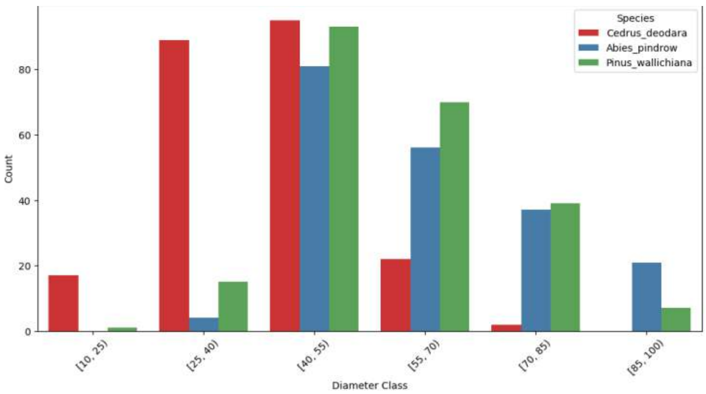

Fig. 3. Count of trees in each diameter class for the three species

Table 3 reports the estimated parameters for four candidate distributions (normal, log-normal, gamma, and weibull) fitted to the diameter data of three species: *Cedrus deodara*, *Pinus wallichiana*, and *Abies pindrow*. These parameter estimates provide insights into both the central tendency and dispersion of tree diameters, which are critical for forest growth modeling and management.

For the Gamma distribution, the shape parameter (α) for *Cedrus deodara* is 8.82, which is considerably lower than the values for *Pinus wallichiana* (α = 12.59) and *Abies pindrow* (α = 12.12). In the context of the Gamma distribution, a lower α suggests a flatter, less peaked distribution, indicating that *Cedrus deodara* exhibits a more uniform diameter spread. The scale parameter (β) is similar across species (0.20 for *Cedrus deodara*, 0.22 for *Pinus wallichiana*, and 0.20 for *Abies pindrow*), implying that although the central concentration differs, the relative dispersion remains comparable. The Normal distribution's parameters further differentiate these species. *Abies pindrow* has the highest mean diameter (μ = 61.2) and variability (σ = 17.2), suggesting that its trees tend to be larger and more variable in size. In contrast, *Cedrus deodara* has a lower mean (μ = 43.98) and smaller standard deviation (σ = 14.85), indicating a more concentrated diameter distribution. This quantitative difference highlights species-specific growth patterns where *Cedrus deodara* consistently maintains smaller, more uniform diameters. For the Log-normal distribution, the location parameter (μ) on the logarithmic scale is lowest for *Cedrus deodara* (μ = 3.73), which reflects a lower median diameter on the original scale. The scale parameter (σ) is nearly identical for all species (0.34 for *Cedrus deodara*, 0.30 for both *Pinus wallichiana* and *Abies pindrow*), indicating that the relative dispersion around the median is similar among them.

The Weibull distribution parameters reveal differences in skewness and spread. The shape parameter (β) is lower for *Cedrus deodara* (β = 3.12) than for *Pinus wallichiana* (β = 4.04) and *Abies pindrow* (β = 3.88), suggesting a less pronounced right skew in *Cedrus deodara*. Additionally, the scale parameter (α) is highest for *Abies pindrow* (α = 67.6), followed by *Pinus wallichiana* (α = 62.53) and lowest for *Cedrus deodara* (α = 49.13). In Weibull terms, a higher α indicates a larger characteristic diameter, confirming that *Abies pindrow* tends to have larger trees with a broader spread. Overall, these parameter estimates quantitatively demonstrate that *Cedrus deodara* tends to have smaller, more consistent diameters, while *Abies pindrow* and *Pinus wallichiana* display larger diameters with greater variability and right-skewness. These distinctions are critical for accurately modeling forest structure and informing species-specific management strategies.

Tables 4–6 present the observed and expected cumulative frequencies for each diameter class of *Cedrus deodara*, *Pinus wallichiana*, and *Abies pindrow*, along with the Kolmogorov–Smirnov (KS) deviations for the Normal (N), Log-Normal (LN), Gamma (G), and Weibull (W) distributions. The critical KS value was 0.086 (α=0.05), meaning any model with a maximum deviation below this threshold could not be rejected at the 5% level. For *Cedrus deodara*, the Gamma distribution exhibited the smallest maximum deviation (0.02), closely followed by Log-normal (0.03), with Normal and Weibull registering 0.05 and 0.06, respectively. Although Normal and Weibull remained acceptable by staying below the critical KS cutoff, Log-Normal provided the strongest overall fit for this species. In contrast, the Gamma distribution produced the most accurate representation of *Pinus wallichiana*, showing a 0.03 KS difference compared to 0.04 for Log-Normal, 0.05 for Normal, and 0.06 for Weibull. Such an outcome reinforces the conclusion that Gamma can be better suited when diameter data display particular skewness patterns [38]. For *Abies pindrow*, Log-Normal again yielded the best fit (0.04), while Gamma showed a higher KS value of 0.06, and Normal and Weibull both measured 0.07. These results align with other findings demonstrating that Log-Normal tends to excel in distributions with a pronounced right-skew and diverse diameter classes [39].

Overall, Log-Normal described the diameter distribution most accurately for *Abies pindrow*, whereas Gamma was preferable for *Cedrus deodara* and *Pinus wallichiana*. Even though Normal and Weibull also satisfied the 5% significance criterion, their larger deviations suggest relatively weaker performance, which is consistent with previous studies emphasizing the importance of testing multiple models to find the most suitable fit for each species [40,41]. Consequently, the Log-Normal or Gamma distributions appear to be the more appropriate choices for modeling conifer diameter classes in these Himalayan stands, depending on the species in question.

Table 4. Kolmogorov-Smirnov test statistic for Cedrus deodara

Diameter Class (cm)	Cumulative distribution function					D=max $\|F_{exp} - F_{obs}\|$			
	Observed frequencies	**Expected frequencies**				**N**	**LN**	**G**	**W**
		N	**LN**	**G**	**W**				
10-25	0.08	0.09	0.07	0.08	0.11	0.01	0.01	0.00	0.03
25-40	0.43	0.38	0.45	0.43	0.41	0.05	0.02	0.00	0.02
40-55	0.81	0.76	0.78	0.79	0.75	0.05	0.03	0.02	0.06
55-70	0.93	0.94	0.93	0.94	0.94	0.01	0.00	0.01	0.01
70-85	0.99	0.98	0.98	0.99	0.98	0.01	0.01	0.00	0.01
85-100	1.00	0.98	0.99	1.00	0.99	0.02	0.01	0.00	0.01
D $statistics$ $(Critical$ $value) = 0.086$, N = Normal, LN = Log-Normal, G = Gamma, W = Weibull									

Table 5. Kolmogorov-Smirnov test statistic for Pinus wallichiana

Diameter Class (cm)	Cumulative distribution function					D=max $\|F_{exp} - F_{obs}\|$			
	Observed frequencies	**Expected frequencies**				**N**	**LN**	**G**	**W**
		N	**LN**	**G**	**W**				
10-25	0.02	0.02	0.00	0.01	0.02	0.00	0.02	0.01	0.00
25-40	0.11	0.13	0.15	0.14	0.15	0.02	0.04	0.03	0.04
40-55	0.50	0.45	0.52	0.49	0.44	0.05	0.02	0.01	0.06
55-70	0.78	0.81	0.81	0.81	0.79	0.03	0.03	0.03	0.01
70-85	0.96	0.97	0.94	0.96	0.96	0.01	0.02	0.00	0.00
85-100	1.00	1.00	0.98	0.99	1.00	0.00	0.02	0.01	0.00
D $statistics$ $(Critical$ $value) = 0.086$, N = Normal, LN = Log-Normal, G = Gamma, W = Weibull									

Table 6. Kolmogorov-Smirnov test statistic for Abies pindrow

Diameter Class (cm)	Cumulative distribution function					D=max $\|F_{exp} - F_{obs}\|$			
	Observed frequencies	**Expected frequencies**				**N**	**LN**	**G**	**W**
		N	**LN**	**G**	**W**				
10-25	0.01	0.02	0.00	0.00	0.02	0.01	0.01	0.01	0.01
25-40	0.06	0.11	0.10	0.10	0.12	0.05	0.04	0.04	0.06
40-55	0.43	0.36	0.42	0.41	0.36	0.07	0.01	0.02	0.07
55-70	0.69	0.70	0.72	0.73	0.68	0.01	0.03	0.04	0.01
70-85	0.88	0.92	0.89	0.91	0.91	0.04	0.01	0.02	0.03
85-100	1.00	0.99	0.96	0.98	0.99	0.01	0.04	0.02	0.01
D $statistics$ $(Critical$ $value) = 0.086$, N = Normal, LN = Log-Normal, G = Gamma, W = Weibull									

In addition to evaluating the quality of distribution fits using the KS test, statistical criteria such as the AIC, BIC, and LogL values were utilized for further evaluation. The results consistently showed that the Gamma distribution provided the best fit across all tree species, achieving the lowest KS test statistic values, AIC and BIC values, and log-likelihood values. Table 8 presents a detailed comparison of different probability distributions (Gamma, Log-normal, Normal, and Weibull) across three conifer species—*Cedrus deodara*, *Pinus wallichiana*, and *Abies pindrow*—based on AIC, BIC, and log-likelihood values. The Gamma distribution consistently outperformed the other distributions across all species:

- For *Cedrus deodara*, the Gamma distribution yielded the lowest AIC (2042), BIC (2049), and the highest log-likelihood (-1019).
- For *Pinus wallichiana*, the Gamma distribution showed the best performance with an AIC of 2087, a BIC of 2094, and a log-likelihood of -1041.
- Similarly, for *Abies pindrow*, the Gamma distribution achieved the lowest AIC (2032), BIC (2140), and the highest log-likelihood (-1064).

Conversely, the Weibull distribution exhibited the poorest fit, demonstrating the highest KS test statistic, AIC, and BIC values and the lowest log-likelihood values across all species. These results affirm that the Gamma distribution is the most appropriate model for tree diameter distribution in the studied conifer species. This contrast highlights that the KS test, which focuses on the maximum distance between observed and expected cumulative distributions, can sometimes rank distributions differently than likelihood-based criteria that account for the entire distribution shape and penalize model complexity.

By integrating both goodness-of-fit (KS) and information-theoretic (AIC, BIC, LogL) metrics, the present findings suggest that Gamma may be the most robust choice overall for modeling diameter distributions across the studied conifer species, even though Log-normal may appear optimal under a purely KS-based assessment in certain cases.

Table 8. Comparison of probability distributions based on AIC, BIC and LogL values for different species

Distributions	Species								
	Cedrus deodara			*Pinus wallichiana*			*Abies pindrow*		
	AIC	BIC	LogL	AIC	BIC	LogL	AIC	BIC	LogL
Gamma	**2042**	**2049**	**-1019**	**2087**	**2094**	**-1041**	**2032**	**2140**	**-1064**
Log-normal	2046	2053	-1021	2090	2095	-1046	2143	2150	-1069
Normal	2063	2070	-1029	2092	2098	-1050	2135	2142	-1065
Weibull	2061	2068	-1028	2107	2114	-1052	2137	2144	-1066

Discussion

The results highlight distinct growth patterns and ecological strategies among the three conifer species. Across the dataset, tree height and diameter were positively correlated, reflecting fundamental allometric relationships in forest trees [42]. However, species-specific deviations in the height–diameter scatter suggest different growth forms or strategies. For example, *Abies pindrow* consistently achieved the greatest diameters and heights [43] in both the Roamshi and Shopian ranges, aligning with its status as a late-successional "climax" fir that occupies a broad range of size classes.

In contrast, *Cedrus deodara* showed more site-dependent growth performance. In the Roamshi range *C. deodara* had a markedly smaller mean diameter and height than in Shopian, where its mean diameter was much larger (45.6 cm vs 37.2 cm). This suggests that *C. deodara*'s growth is strongly influenced by local environmental conditions and stand history [44]. Such sensitivity is consistent with studies indicating that factors like soil depth, moisture, and past disturbance events can constrain or promote *C. deodara* growth [45]. Our findings of a smaller mean size in one range but significantly larger in another corroborate that *C. deodara* responds plastically to site quality and disturbance regime. Notably, *C. deodara* also had a stronger presence in lower diameter classes (e.g. 10–25 cm) than the other conifers.

Pinus wallichiana exhibited intermediate characteristics, maintaining moderate average sizes in both ranges but notable shifts in distribution shape between sites. In Roamshi, the blue pine's height distribution was left-skewed with a high kurtosis, indicating many trees of an intermediate height and a few shorter individuals. This suggests an even-aged stand structure where most pines have reached canopy height and few recruits are present beneath them [46]. Such a pattern can arise if regeneration has been episodic – for example, if a past disturbance created a cohort that grew up together, with little subsequent recruitment. In Shopian, *P. wallichiana* had a more symmetric height distribution (skew ~−0.4, kurtosis ~−0.2), hinting at a more equilibrated stand with a mix of size classes. The presence of *P. wallichiana* individuals reaching the largest diameter classes (up to ~100 cm) in our study indicates this species can persist long enough to attain impressive sizes, but the relative paucity of seedlings/saplings in some stands implies reliance on disturbance-created openings for continuous regeneration. This is supported by prior findings that *P. wallichiana* population structures are heavily shaped by stand-level disturbance dynamics and flexible regeneration strategies [47].

The dominance of mid-sized (40–55 cm) diameter classes across all three species further suggests that many of these stands are in a mid-successional stage. Few trees have reached the extreme upper sizes, possibly due to past harvesting of the largest timber, and in some cases, a shortage of very small trees points to limited recent recruitment. Ecologically, this scenario might reflect secondary forests recovering from logging several decades ago, now comprised mostly of maturing trees, with future regeneration contingent on gap formation. Overall, the species-specific diameter and height distributions we found are consistent with each species' life-history strategy [48].

It is noteworthy that the Gamma distribution outperformed the Weibull distribution for these Himalayan conifers, as the Weibull is often regarded as a flexible, go-to model for tree diameter distributions. Traditionally, forest biometricians have favored the Weibull function to model diameter frequency because of its adaptability to various shapes (from reverse-J to bell-shaped) by tuning its parameters [49]. Our results, however, underscore that the best-fitting model can be context-dependent. The diameter distributions of all three species in our data were moderately right-skewed with a single central mode (peaking around mid-sized trees), and the Gamma distribution was apparently better at capturing. By contrast, in forests with a strong *reverse-J* distribution (many small stems and exponentially fewer large ones – a hallmark of an uneven-aged, regenerating stand), Gamma distributions may perform poorly. For example, a study in a Nigerian reserve found a two-parameter Gamma model yielded fits "far from the reverse J-shaped" distribution of the natural stand, making it an inappropriate choice for that scenario. In such cases, Weibull or Beta distributions, or even composite models, might be more suitable [20]. In our study area, however, the scarcity of very small diameter trees (due in part to our minimum diameter of ~10 cm for sampling) and the predominance of intermediate sizes mean the diameter distribution is unimodal rather than reverse-J [50]. The Gamma model, with its shape and scale parameters, was flexible enough to match this unimodal, right-tailed distribution for each species. This illustrates a key methodological consideration: one should not assume a particular statistical distribution a priori for all forest types but rather test candidates and use criteria like AIC to determine the best fit empirically for the data at hand. Our use of multi-criteria validation strengthens the validity of selecting the Gamma model as the basis for further analysis and interpretation.

Several potential limitations and biases should be acknowledged. First, the significant site differences observed for *C. deodara* suggest that a stratified analysis (fitting distributions per range) might have revealed nuances, though our sample size in each range might then have been marginal for four-model comparisons. Second, our inventory did not include seedlings or saplings below 10 cm in diameter. This truncation means our distributions start at the sapling/pole stage, omitting the youngest regeneration. Therefore, our modeled distributions do not capture the full regeneration curve (the steep rise from numerous seedlings to fewer small trees). Inferences about regeneration must be made cautiously, since a lack of sub-10 cm stems in the data could be due to sampling protocol rather than true absence. If a management goal is to assess regeneration status, additional data on seedlings would be needed. Third, the K-S test, while useful, has limitations: with large sample sizes it can detect very small deviations as significant, and it focuses on the maximum deviation of cumulative distributions, which might not reflect overall fit as sensitively as AIC does. We mitigated this by relying more on AIC/BIC and log-likelihood for model selection, which provide a global measure of fit across all diameter classes. Another consideration is the assumption of independent, identically distributed data for model fitting – in reality, trees are spatially clustered and competition can induce local correlations in sizes. Our analysis does not explicitly account for spatial autocorrelation or stand dynamics (e.g. whether some diameters come from dense thickets vs. gaps). However, given the broad scale and mix of conditions in the sample, such effects likely average out and are of secondary importance for the broad distribution shape.

The estimated Gamma shape parameters (α) were around 12 for *Pinus wallichiana* and *Abies pindrow*, but lower (~8.8) for *Cedrus deodara*, indicating a slightly flatter distribution for cedar (more uniform representation across mid-sizes). These quantitative differences support the earlier ecological observation that cedar has a more even spread (and some smaller trees) compared to the other species [51]. The Weibull shape parameters showed a similar trend, with *C. deodara*'s shape < 3.5 versus ~4.0 for pine, again reflecting cedar's less right-skewed distribution. These statistical findings lend credence to our ecological interpretations, demonstrating internal consistency between the data modeling and field observations. In summary, the methodological approach – from sampling design to model selection – is robust, but care was taken to recognize its constraints. Future studies could build on this by incorporating longitudinal data (to see how diameter distributions evolve), including smaller size classes, or exploring advanced models (e.g., mixture distributions or size–density relationships) for an even deeper understanding of stand dynamics. Also, incorporating seedlings and saplings to capture full regeneration curves, test mixture/hierarchical models that accommodate spatial autocorrelation, and integrate repeated measurements and remote-sensing (e.g., LiDAR) to link stand dynamics with terrain and disturbance history. These advances would refine yield, carbon, and silvicultural planning for Himalayan conifer forests.

Practical Implications

The insights from this study have practical implications for forestry management, conservation, and ecological planning in Himalayan conifer forests. A key finding is that all three species concentrate around mid-size classes, with comparatively fewer young recruits and not many very old giants. From a sustainable forestry perspective, this suggests that many stands are middle-aged and may not be regenerating at a rate to replace the largest trees as they age out. Forest managers should consider interventions to ensure balanced age structures, especially for *Pinus wallichiana* and *Abies pindrow*. In stands dominated by mature *P. wallichiana* with little natural regeneration underneath, management could mimic natural disturbances to create the conditions this pine needs for regeneration. In contrast, *Abies pindrow*, being shade-tolerant, can regenerate under its own canopy to some extent. The presence of multiple size classes of fir in our data (albeit skewed towards larger trees) indicates potential for continuous recruitment if conditions are right.

Management for fir might focus on protecting seedlings from browsing by livestock and ensuring that there are occasional small gaps for those seedlings to be released from suppression. Given *A. pindrow*'s dominance in old-growth conditions, maintaining a population of younger firs is critical for long-term stand persistence.

For *Cedrus deodara*, the management approach might differ between sites. In the Roamshi range, cedar had smaller diameters on average, possibly indicating younger stands or sites where cedar is not reaching its full growth potential. Here, management could aim to improve site conditions for cedar – for instance, through soil conservation measures or by reducing interspecific competition to allow these stands to develop larger trees. Given cedar's higher presence in smaller size classes, these stands might benefit from a "release" of young cedars by removing overtopping competitors or safeguarding them from damage. In the Shopian range, where cedars attained much larger sizes, the priority might be conservation of these veteran trees and ensuring their reproduction. *C. deodara* is a highly valued timber species and has cultural significance in the region, so past exploitation pressures have been high. The fact that we found considerably larger cedars in one range suggests that where cedars have been less disturbed and environmental conditions are favorable, they can flourish. Protecting such stands from logging will allow them to serve as seed sources and carbon reservoirs. Additionally, in a climate change context, *C. deodara*'s sensitivity to frost and moisture implies that managers should monitor these stands for climate-driven stress (such as increased droughts or unseasonal frosts) and possibly assist migration or planting in new areas if current habitats become less suitable (assisted migration could be considered for lower elevations where cedar might gain a competitive edge as conditions warm) [52].

Across all species, the identification of the Gamma distribution as the best fit provides a useful tool for management modeling. Since the Gamma model accurately represents the current diameter structure, its parameters can be used to forecast future stock and yield under various scenarios. For instance, forest planners can use the shape and scale parameters to simulate how the diameter distribution will shift if a certain number of mid-sized trees are harvested or if a disturbance removes a fraction of the canopy. The ability of the Gamma distribution to describe the stand structure means silvicultural prescriptions can be tailored to maintain or steer the distribution towards a desired shape. If a goal is to achieve an uneven-aged stand with continuous regeneration (often visualized as a reverse-J diameter curve), managers now know that the current structure deviates from that, and deliberate measures (like shelterwood cuts for pine or selective thinning for fir) may be needed to introduce more small stems while retaining enough canopy. On the other hand, if the objective is timber production, the concentration of trees in the 40–60 cm range in our study indicates a substantial volume that could be sustainably harvested if done selectively. Our volume data (mean tree volume ~6 m^3, max ~16.9 m^3) suggest that the standing biomass is considerable; thus, carbon stock management is another angle. Conservation planners should note that these conifer forests hold significant carbon in mid-sized and large trees. Protecting the largest individuals (especially those of *Abies pindrow* and *Cedrus deodara,* which live the longest) is important for carbon storage and for preserving the ecological legacy of old trees (e.g., habitat for cavity nesters and substrate for epiphytes).

At the same time, ensuring younger cohorts are coming up will maintain carbon sequestration rates as old growth eventually senesces.

Another implication relates to forest policy in the region. In Jammu & Kashmir and Himachal Pradesh, policies like bans on green felling (enacted in the 1980s) have left many forests effectively unmanaged except for protection [53] . While this has allowed recovery of tree cover and the development of mature stands, it might also result in stagnating regeneration for species like pine that need disturbances. The discussion [33] notes that after decades of no silvicultural intervention, deodar stands showed structural irregularities and potential productivity decline. Our findings echo that concern: a lack of ongoing management can lead to forests packed with mid-sized trees but lacking the dynamism of a truly sustainable uneven-aged forest. Therefore, forest departments could consider a nuanced approach that continues to protect these forests from destructive exploitation but reintroduces carefully controlled silvicultural treatments to enhance structural diversity. For example, a series of small patch cuts or group selection harvests in a *Pinus wallichiana* stand could regenerate pine while minimally impacting the overall forest cover. In an *Abies*-dominated stand, selective removal of a few mature trees might open space for fir saplings that are otherwise languishing in deep shade. Importantly, any management should be evidence-based and adaptive. Long-term monitoring of diameter distributions should guide interventions if we see, say, an increase in sapling counts after a treatment, which indicates success; if not, strategies must be adjusted.

In summary, the study provides a scientific basis for managing these conifer forests. By understanding each species' size distribution and ecological role, managers can tailor actions: promoting regeneration of pine, facilitating growth of cedar in suboptimal sites, and conserving the structural complexity brought by fir. The alignment of our findings with other regional research (e.g., the dominance of *A. pindrow* in high-altitude forestsand the known disturbance-mediated regeneration of *P. wallichiana*) gives confidence that these recommendations are grounded in a broader context. Ultimately, integrating such data-driven insights into forest management plans will help balance multiple objectives like timber production, biodiversity conservation, and climate resilience, ensuring the long-term sustainability of Himalayan temperate conifer forests.

Conclusion

This study reveals distinct growth patterns and ecological strategies among *Cedrus deodara*, *Pinus wallichiana*, and *Abies pindrow* in the North-Western Himalayan Kashmir region, with each species showing characteristic distributions of diameter and height. Consistent with earlier work on conifer allometry [42,43], we found that larger diameters tend to accompany taller trees, though local site conditions and stand history clearly modulate growth performance [44,45]. The contrasting structure and skewness of *P. wallichiana* in Roamshi versus Shopian highlight the role of disturbance-mediated regeneration and episodic recruitment for pine [46,47], while *A. Pindrow*'s ability to persist in multiple size classes underscores its status as a shade-tolerant climax fir occupying a broad ecological niche. *C. deodara* displayed more site-dependent variation, aligning with evidence that factors like soil, moisture, and past logging events strongly shape its growth [45].

Across all species, the Gamma distribution consistently provided the best statistical representation of the diameter data, as demonstrated by its lower AIC, BIC, and KS statistics compared to the Normal, Log-normal, and Weibull distributions [37,49]. This finding contrasts with the common perception that Weibull can flexibly model most diameter distributions; in our case, forests containing predominantly mid-sized trees in unimodal distributions were better captured by Gamma. Although our sampling excluded seedlings below 10 cm diameter and thus did not represent the full regeneration curve, the results still provide robust insights for management. The identification of mid-successional stands with limited small-size recruitment calls for targeted interventions, such as releasing *C. deodara* juveniles in poorer sites or creating canopy gaps for *P. wallichiana* regeneration [33]. For *A. pindrow*, preserving large firs while protecting understory saplings can enhance multi-aged stand structure. Because site quality and disturbance history differ among the two ranges, it may be necessary to adapt silvicultural strategies for each species and locality [53].

Overall, these conclusions emphasize the ecological heterogeneity of Himalayan conifer forests and the importance of verifying distribution models with both Kolmogorov–Smirnov tests and information-theoretic criteria. By confirming that Gamma offers the most accurate depiction of current diameter structures, managers can use Gamma's parameter estimates to forecast future stand development, assess biomass and carbon stocks, and design interventions that promote balanced age distributions. The robust fit of Gamma in this context highlights the need to avoid a one-size-fits-all assumption about diameter models, thus reinforcing the value of empirical model testing [54]. Future studies could expand on these findings by incorporating seedlings, adding spatial analyses of stand structure, or exploring how climatic variations and management regimes interact to shape diameter distribution patterns over time.

Authorship Contributions

Aqib Gul, Imran Khan, Nageena Nazir: Conceptualization, Methodology, Formal analysis, Resources, Writing - review & editing the original draft, work administration. **Aqib Gul, Nageena Nazir, Ume Kulsum**: Methodology, Formal analysis, Resources, Visualization, Validation, Writing - review & editing the original draft. **Aqib Gul, Nageena Nazir, Ume Kulsum, Arif Bashir**: Resources, Validation, Writing - review & editing. **Aqib Gul, Nageena Nazir, Ume Kulsum, Arif Bashir, Masroor Majid, Uzma Majeed, Sheikh Aadil Mushtaq:**Resources, Validation, Writing - review & editing, read and approved the final manuscript. The authors confirm that all individuals involved in the research have thoroughly read and given their consent to the final version of the manuscript that is to be published.

Competing interest: All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Data availability

The datasets generated and analyzed during the current study are not publicly available due to restrictions imposed by the forest department, which provided the data under specific conditions of use. However, the data are available from the corresponding author on reasonable request, subject to approval by the forest department and relevant university authorities.

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