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RESEARCH ARTICLE

Effect of bin width on variogram model accuracy: a case study of teak tree volume specific to Solomon clone in Tawau, Sabah, Malaysia

Johannah Jamalul Kiram[a,b], Rossita Mohamad Yunus[b], Yani Japarudin[c], Mahadir Lapammu[c], Olivier Monteuuis[d] and Doreen Kim Soh Goh[e]

[a]Preparatory Centre for Science and Technology, Universiti Malaysia Sabah, Jalan UMS, Kota Kinabalu, Sabah, Malaysia; [b]Institute of Mathematical Sciences, Faculty of Science, Universiti Malaya, Kuala Lumpur, Malaysia; [c]Sabah Softwood Berhad, Tawau, Sabah, Malaysia; [d]CIRAD-BIOS Department – UMR AGAP, TA A-108/03, Avenue Agropolis, F-34398Montpellier, Cedex 5 France; [e]YSG Biotech Sdn Bhd, Yayasan Sabah Group, Voluntary Association Complex, Mile 2½, off Tuaran Road, Kota Kinabalu, Sabah, Malaysia

ABSTRACT

The volume of teak trees (*Tectona grandis* Linn. f.) was analyzed using data from a teak plantation managed by the research and development team at Sabah Softwood Berhad in Brumas Camp, Tawau, Sabah, Malaysia. To fit the exponential model to the experimental variogram, various bin widths were used to obtain different variogram models. These models were plotted for comparison, and the root mean square error (RMSE) was calculated. Additionally, cross-validation was performed to assess the predictive accuracy of each model for the unseen data. The analysis indicated that a bin width of 0.003—that was approximately 333 m apart—was ideal for fitting the exponential model. This width demonstrated the lowest RMSE and ideal graphical observations. This study confirms that selecting the optimal bin width significantly affects the accuracy of model predictions, regardless of the sample size.

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spatial; variogram; bin width

1. Introduction

The estimation of tree volume helps to access the biomass which is essential for determining the status and flux of biological materials (Bisht et al 2022) in an ecosystem and for understanding the dynamics of the ecosystem (Andersson, 1971; Bargali & Singh, 1997; Bisht et al., 2023). The quantity of tree biomass per unit area of land constitutes the primary inventory data needed to understand the flow of materials and water through forest ecosystems (Bargali & Singh, 1997; Bisht et al., 2023; Camargo García et al., 2023; Swank & Schreuder, 1974; Tavares Júnior et al., 2021). The current study gains importance when forest or plantation biomass and volume are measured and analyzed, as these metrics are fundamental to understanding and managing productivity, which is central to ecosystem functioning and sustainability (Awasthi et al., 2022; Lieth, 1975). This study assesses the spatial modeling of teak tree volume, which is known as a variogram model. However, before constructing a variogram model of the teak tree volume, selecting an optimal bin width is crucial because it affects sampling. Although numerous georeferenced teak trees were collected, the optimal bin width was crucial in selecting an accurate model to represent the data. It determines the range of lag distances over which pairs of sample points are grouped for variogram calculations (Oliver and Webster 2015). The lag distance represents the distance between a pair of sampled trees, and the number of possible pairs increases when the trees are far apart. However, if the sampling lacks adequate spatial coverage, the results may be affected. The accuracy of a variogram depends on adequate data density rather than the sample size, specifically if the samples do not vary in the lag interval. Therefore, to ensure reliability, comparisons should be made for each lag interval to enhance the estimation of variogram models (Oliver and Webster 2015).

Teak trees (*Tectona grandis* Linn. f.) planted in Brumas Camp, Tawau, Sabah Malaysia, specifically Solomon Island-derived clones, demonstrated ideal growth in this study. Teak is one of the most valuable tree species of the world and considered as king of timbers(Sasidharan & Ramasamy, 2021). The teak tree is significant in research, both in situ or in vitro, across natural stands or plantations. Studies on this species can be observed in most tropical regions, including India, Nepal, Thailand, and Brazil (Ghosh et al., 2019; Kenzo et al., 2020; Koirala et al., 2021; Pelissari et al., 2017; Sasidharan & Ramasamy, 2021; Tewari & Singh, 2018). Despite its prominence in research, studies focusing on spatial aspects remain limited (Pelissari et al. 2017; Kiram et al. 2022, 2023). Studies focusing on the volume of teak trees include research on the

CONTACT Johannah Jamalul Kiram johannah612@ums.edu.my Preparatory Centre for Science and Technology, Universiti Malaysia Sabah, Jalan UMS, Kota Kinabalu, Sabah, Malaysia

effects of different spacings in Brazil (Vendruscolo et al. 2022), a study estimating the volume of the stems of teak trees using artificial neural networks and regression (Tavares Júnior et al. 2021), models of growth and yield in Nigeria using linear and multiple linear regression (Popoola & Ude, 2024), and a study focusing on the growth, biomass accumulation, carbon storage, and energy production in clonal teak plantations of different ages in Central Java (Wirabuana et al. 2022).

This study is based on research conducted in 1994 by Innoprise Corporation Sdn Bhd (ICSB) for the mass cloning of teak trees in partnership with the CIRAD Forestry Department (Goh and Galiana 2000). The success of their 1997 research and investment in a monoclonal block (Goh and Monteuuis 2005) inspired two other provenance and progeny trials that same year. Detailed reports of its field performances have been published (Goh and Monteuuis 2005; Goh et al. 2013; Monteuuis and Goh 2015, 2017). However, its spatial statistical research has not been previously explored in depth, nor has its effects on growth been studied thoroughly.

Small bin widths create detailed but noisy variograms because of limited number of sample pairs. However, a large bin width produces smoother variograms that may obscure significant spatial patterns, thereby raising questions regarding optimal bin widths. The objective of this study was to determine the optimal bin width for an ideal variogram model of the volume of *Tectona grandis* Linn. f. specific to the Solomon Island-derived clone. It was hypothesized that an optimal bin width would minimize prediction error by effectively capturing the spatial structure and variability of this specific clone. Previous studies have identified the relationship between physical parameters and spatial data of the trees (Kiram et al. 2022, 2023). This study used existing experimental variogram models, specifically the exponential model, to assess the effects of bin widths. Subsequently, these models were graphed for comparison, and the root mean square error (RMSE) was calculated. Additionally, cross-validation was performed to assess the predictive accuracy of each model for the unseen data. This study focused on small plantation sites because it provides insights into how spatial dependence affects larger plantations (Kiram et al. 2022).

2. Materials and methods

2.1. Data

This study continues the work of Kiram et al. 2022 by focusing on the *Tectona grandis* Linn. f. block managed by the research and development team of Sabah Softwood Berhad, at Brumas Camp, Tawau, Sabah, Malaysia. The data from this site have been observed over 12 years, located on the coordinates 4°37'23.85"N and 117°47'05.12" E. Figure 1 illustrates the topological features of the site, provided by the Sabah Softwood Berhad research team.

These plots were designed as a randomized complete block with four contiguous replications, each containing two rows of 30 plants from 15 different genotypes. The plots were spaced at 4 x 4 m with 625 stems per hectare, resulting in over 4000 trees. Plants

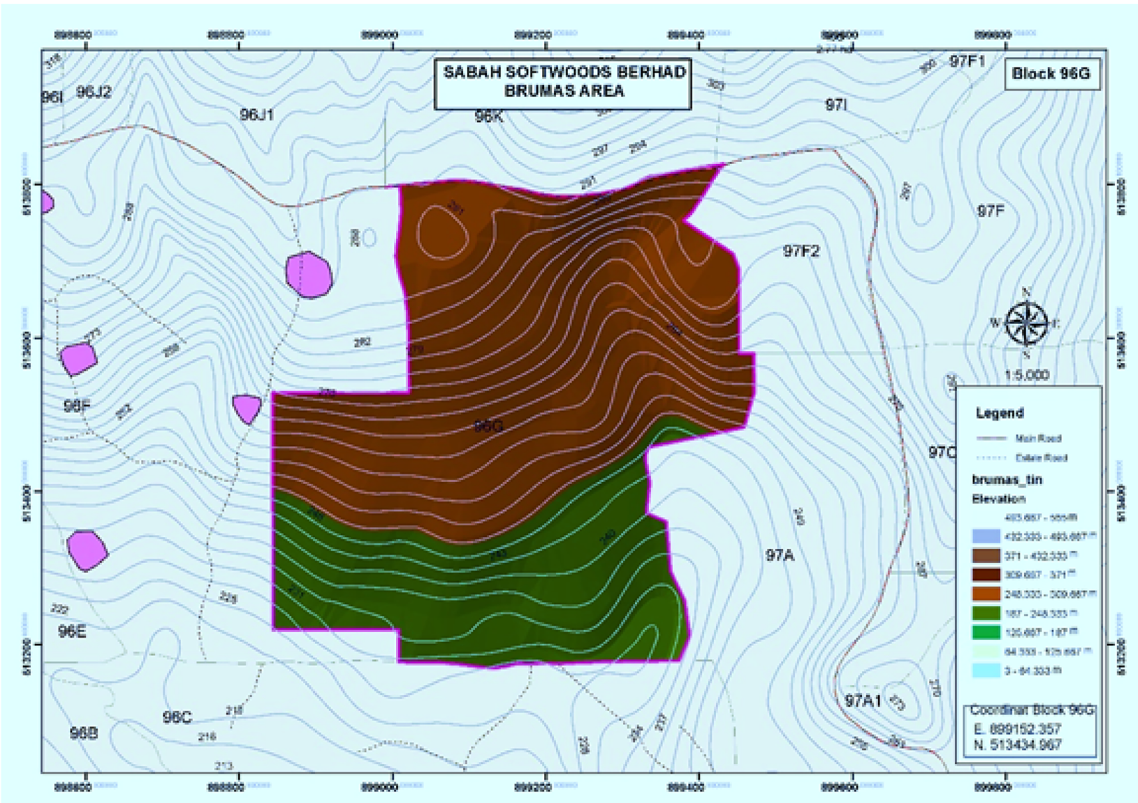

Fig. 1. Topologic map of block 96G at Brumas Camp, Tawau, Sabah.

11–20 in each row were assessed, resulting in 80 plants per clone. Block 96G was situated on slopy land at an altitude ranging from 180–370 m above sea level. The climate of the region was classified as tropical rainforest (Köppen), whereas its soil is classified as Tanjung Lipat with low levels of nitrogen, potassium, and magnesium.

The sample data of 1200 trees, including height and diameter at breast height were collected and used to calculate the volume based on equation (1). However, for Solomon Island-derived clones, excluding undergrown and fallen trees, a total of 451 samples were collected. Statistical analyses were conducted using R Studio 4.0.5 and Microsoft Excel. Of these samples, 432 georeferenced individual tree points were obtained for the 6^{th}-year plot. The georefencing points were accurate up to six decimals. Further geostatistical analyses were performed using ArcGIS 10.8.1 and R Studio 4.0.5.

The bole volume of the teak trees was derived from previous studies (Goh et al. 2013; Monteuuis and Goh 2015) with similar objectives, as presented in equation (1)

$$V = \frac{1}{10}\left[\left[1.3\pi\left(\frac{D}{2}\right)^2\right] + \left[\pi\left(\frac{D}{2}\right)^2\left(\frac{H-1.3}{3}\right)\right]\right] \quad (1)$$

where V represents the volume, D represents the diameter at breast height (1.3 m above the ground), and H represents the tree height. This collaboration expanded their research and established numerous teak plantations across different districts in Sabah for research purposes and yielding. Therefore, the data for this study were provided by a teak plantation managed by a research team at Sabah Softwood Berhad in the Brumas Camp, Tawau, Sabah, East Malaysia. Spatially continuous data are crucial for decision-making in all ecological systems, including forests (Karahan and Erşahin 2018).

2.2. The experimental variogram

The semivariogram, or variogram, is a statistic that assesses the average of how the similarity between two random variables reduces as the distance between them increases, with applications in exploratory data analysis (Olea 1999). The variogram model assumes that samples in nearby locations behave similarly to those farther apart. In this study, we assessed two random variables, $Z(x_i)$ and $Z(x_i+h)$, representing the volume of the two trees. We calculated the difference in volume between these two trees for $N(h)$ number of pairs and subsequently obtained the average. In this context, x_i and $x_i + h$ represent the spatial positions separated by vector h, indicating the spatial dependence between two observations as a function of distance. The distance h between two points cannot be zero because the two trees cannot occupy the same spot. Therefore, the variogram function varies from above zero to its maximum value of h, where the points are farthest from each other. For variogram analysis, the data should be approximately normal, and anisotropy should be checked before assuming isotropy to reduce errors. In Table 1, $y(h)$ represents the semivariance of the $Z(x_i)$ variable and $N(h)$ represents the number of plot pairs for each lag distance h (Olea 1999).

Subsequently, the experimental variogram predicted the value of the target variable at the unsampled locations within the study area. When modeling spatial autocorrelation using spatial data, the experimental model is developed. This study focused on an exponential theoretical variogram to assess the effect of bin width on model accuracy. The variogram models are listed in Table 1.

The bin widths compared were 555, 333, 277.5, and 222 m apart. This is based on latitude conversion, where 1° latitude is approximately 111 km. Therefore, we used bin widths of 0.005, 0.003, 0.0025, and 0.002, with the fit.variogram command in the 'gstat' package in Rstudio.

Subsequently, cross-validation was conducted to ensure reliability, with the variogram accurately representing the spatial structure. Graphical observations were made, and the RMSE of each model was calculated.

3. Results

Figures 2a, 2b, 2c, and 2d illustrate the fitted exponential variogram applied to the empirical variogram with various bin widths. The graph with a bin width of 0.002 (Figure 2d) demonstrates the smoothest fit, whereas that with a bin width of 0.005 (Figure 2a) demonstrates a clear and concise fit. However, relying solely on graphical observations is challenging because the primary objective of modeling remains reliable and precise.

Subsequently, cross-validation was conducted, as illustrated in Figures 3a, 3b, 3c, and 3d. The prediction errors for all four bin widths were relatively symmetric near zero, indicating balanced errors without systematic bias. The narrow histograms in all four graphs indicate small errors. However, detailed observations of the histogram with a bin width of 0.003 (Figure 3b) revealed a higher concentration of errors near zero,

Table 1. Empirical and theoretical variograms.

Model	Variogram	
Empirical	$\gamma(h) = \frac{1}{2N(h)}\sum_{i=1}^{N(h)}\left[Z(x_i) - Z(x_i+h)\right]^2$	
Theoretical- Exponential	$\gamma(h) = C_0 + C\left[1 - e^{(\frac{-h}{a})}\right]$	if, $0 \le h \le a$. Otherwise, $C_0 + C$.

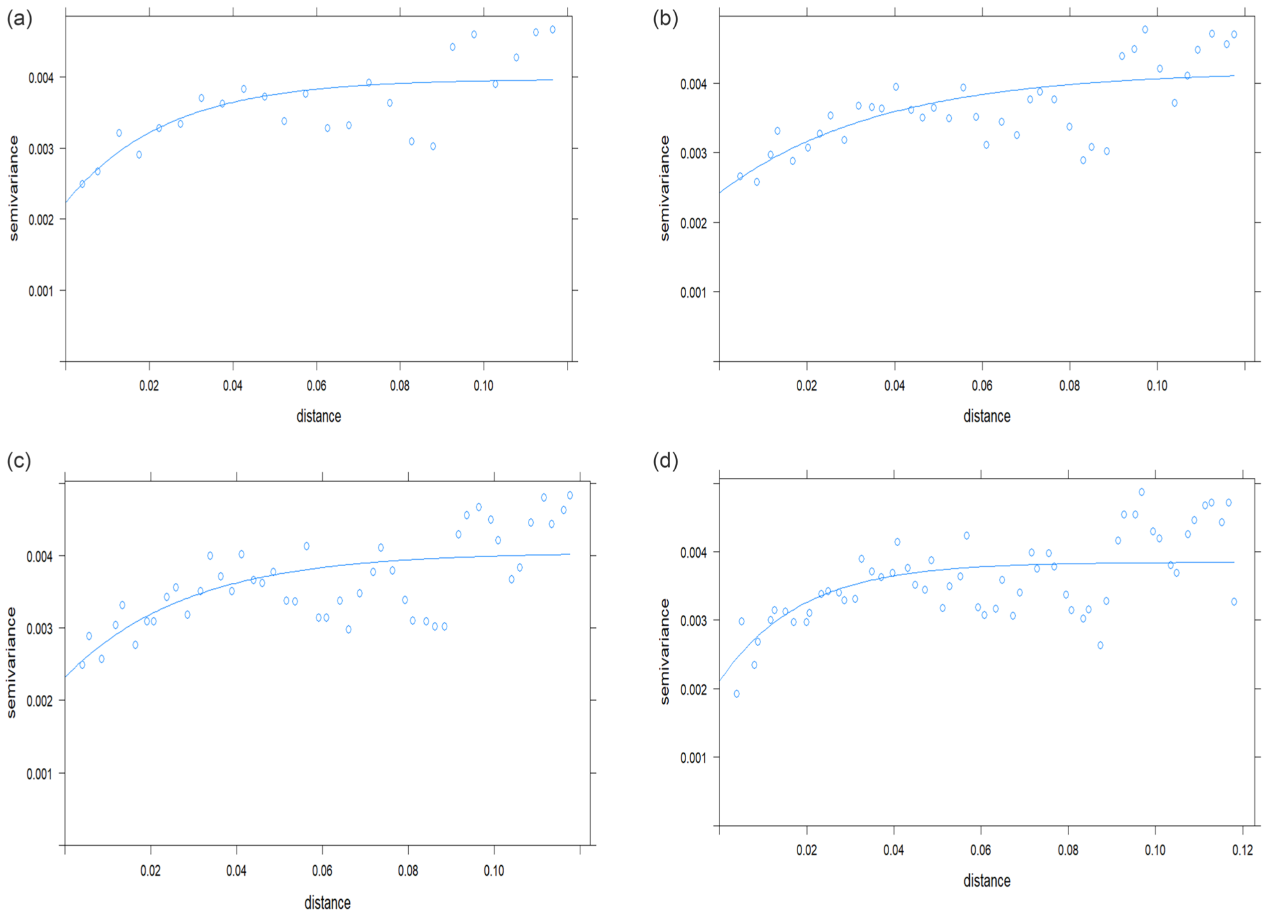

Fig. 2. a. Bin width (0.005). b. Bin width (0.003). c. Bin width (0.0025). d. Bin width (0.002).

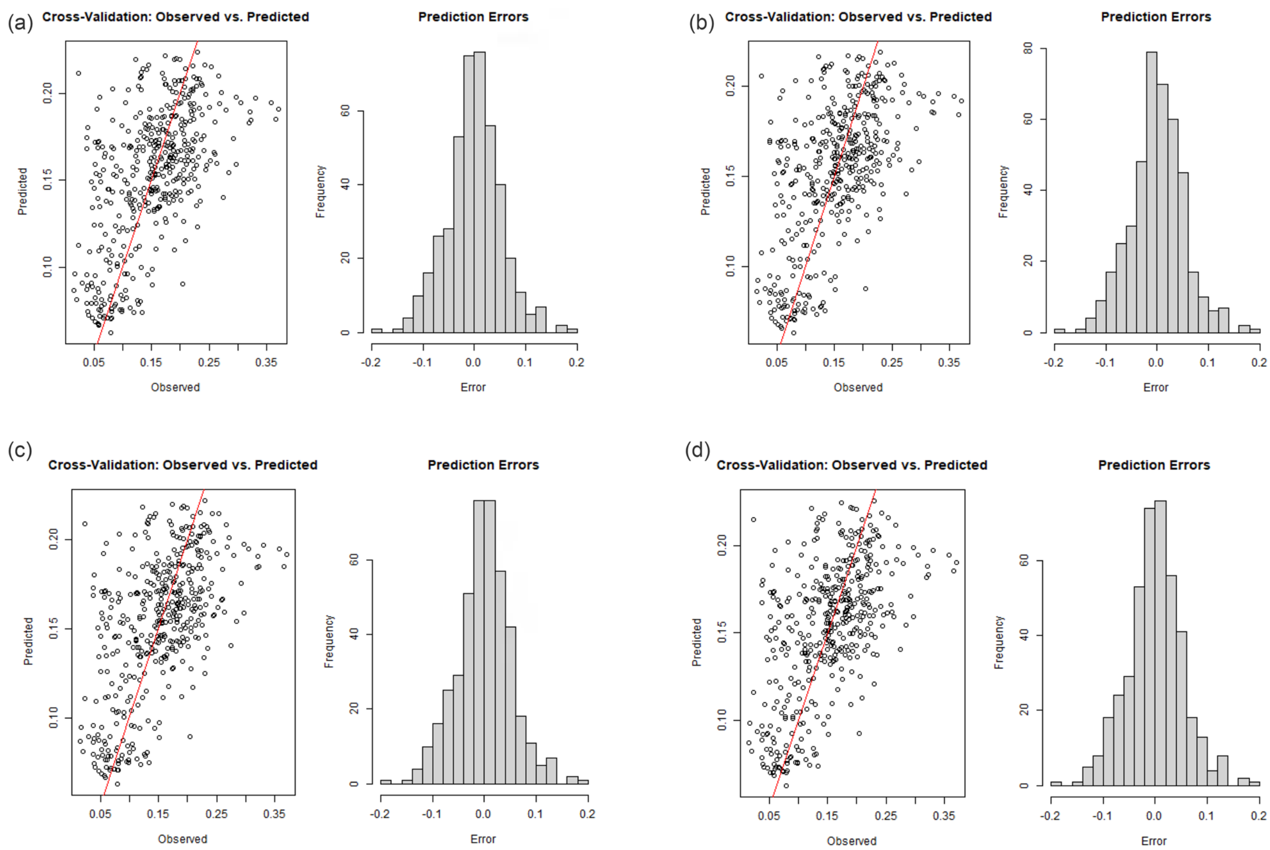

Fig. 3. a. cross-validation of the model with a bin width of 0.005. b. Cross-validation of the model with a bin width of 0.003. c. validation of the model with a bin width of 0.0025. d. validation of the model with a bin width of 0.002.

Table 2. Calculated RMSE, Nugget, psill, and range for all models.

Bin Width	pairs	RMSE	Nugget	Psill	Range
0.005	24	0.05383854	0.002230198	0.001740518	0.02396327
0.003	39	0.05361541	0.002424124	0.001753697	0.03648523
0.0025	47	0.05372381	0.002320105	0.001727215	0.02840659
0.002	59	0.05404312	0.002111044	0.001736450	0.01845881

which implies enhanced prediction accuracy, thereby indicating that it may represent a more accurate model.

The final calculations of RMSE, nugget, psill, and range presented in Table 2 indicate that the model with a bin width of 0.003 (333 m apart) is the most accurate—with the lowest RMSE of 0.05361541—making it the ideal model compared to that of the others. This lower RMSE value suggests that the chosen bin width of 0.003 effectively balances smoothness with precision, avoiding overfitting or underfitting the empirical variogram. Specifically, a narrower bin width such as 0.002 might lead to more noise and less stability in the variogram fit, while a wider bin width such as 0.005 might oversimplify spatial relationships. The balance achieved with a bin width of 0.003 resulted in a better fit, reflected by the lower RMSE.

4. Discussion and Conclusion

This study accentuates the critical role of selecting the optimal bin width in enhancing the spatial model accuracy. Spatial models, particularly in forestry applications, are highly sensitive to the chosen bin width as it determines the resolution at which spatial relationships are assessed (Journel & Huijbregts, 1976). Through a systematic comparison of various bin widths, this study identified an ideal bin width of 0.003—equivalent to approximately 333 m lag distance between tree pairs. This bin width yielded 39 tree pairs per lag, producing the lowest prediction error, as indicated by the concentration of prediction errors near zero (Figure 3). This outcome highlights the importance of calibrating bin width to optimize model accuracy.

However, the optimality of the 333 m bin width is highly context-specific and should not be assumed to generalize across different datasets or ecological contexts. For instance, spatial relationships in tropical teak plantations, such as those in Sabah, Malaysia, are characterized by distinct patterns of variability that this bin width effectively captured. In contrast, forest types with different ecological and structural attributes, such as temperate coniferous forests or mixed deciduous forests, may require distinct bin widths to accurately model spatial variation (Isaaks, 1989). Consequently, researchers are strongly advised to perform a thorough bin width analysis tailored to their specific datasets before proceeding to variogram computation.

Although numerous statistical models indicate that larger sample sizes enhance model performance (Hastie, 2009; Kuhn, 2013; Tanaka, 1987), spatial modeling presents a more nuanced scenario. Bin width and lag distance are crucial in determining the reliability and accuracy of the spatial model. The selected bin width of 0.003 is not universally optimal, as different forestry settings or climates have unique spatial patterns and variability. For instance, while this bin width effectively captures spatial relationships in tropical teak plantations in Sabah, it may not be appropriate for other forest types, such as temperate coniferous forests, which therefore requires a different approach to accurately model spatial variation. If the data are sampled in all directions with various lag distances adequate to represent the intact research site, larger sample sizes may be beneficial. Larger sample sizes may enhance spatial modeling in cases where spatial data comprehensively represent the study site's heterogeneity and are collected across multiple directions and adequate lag distances. This is inline with previous findings that have demonstrated that spatial models rely heavily on appropriate lag distances, bin width, and data density to capture spatial dependence accurately, often outweighing the benefits of simply increasing sample size (Bivand, 2008; Diggle & Ribeiro, 2007; Hengl et al., 2018). However, ensuring that the collected spatial data sample is adequately comprehensive can be costly, challenging, and potentially hazardous. Therefore, spatial modeling is crucial because it enables predictions without the need for challenging and hazardous sampling tasks, specifically in forested areas that serve as habitats for diverse wildlife.

Spatial modeling serves as a crucial tool in addressing these challenges by enabling predictions without involving extensive field data collection. This capability is especially vital for forested regions where ecological conservation, biodiversity protection, and accessibility constraints are its concerns. Future studies should aim to evaluate how bin width selection interacts with other factors, such as sampling directionality, lag structure, and spatial autocorrelation, to refine predictive accuracy further (Brenning, 2005; Hengl et al., 2018). Additionally, integrating adaptive binning strategies or automated bin width selection methods could enhance the efficiency of spatial modeling in forestry applications (Cressie, 2015; Li & Heap, 2011).

In conclusion, while this study demonstrates the efficacy of a 333 m bin width for spatial modeling in tropical teak plantations, this finding is not universally applicable. Researchers must adapt their methodological choices to the unique characteristics of their datasets and ecological contexts to ensure robust spatial modeling outcomes.

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Disclosure of interest

The authors declare no conflict of interest in this study.

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