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MODELLING SILVICULTURAL THINNING USING UNSUPERVISED MACHINE LEARNING: EVIDENCE FROM *PTEROCARPUS SANTALINUS* TRIAL PLOTS OF ODISHA, INDIA

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Abstract. Silvicultural thinning is essential for regulating stand density, yet conventional prescriptions rely on fixed rules and subjective judgment that may not fully account for stand heterogeneity. This study applies unsupervised machine learning to support silvicultural thinning decisions in *Pterocarpus santalinus* trial plots across Odisha, India. Tree-level girth and height data from six plots were analysed using k-means and hierarchical clustering to classify trees for retention or felling. Across all six plots, k-means produced better-separated clusters than hierarchical clustering, with higher silhouette scores (0.53–0.62 versus 0.46–0.61) and higher Caliński–Harabasz index values (approximately 538–2504 versus 200–2334). The clustering approach offers an objective, reproducible, and quantitative framework for characterising intra-stand variability that can complement traditional rule-based thinning and support more consistent, data-informed silvicultural management.

Keywords: K-means clustering; Hierarchical clustering; *Pterocarpus santalinus*; Silvicultural thinning; Silhouette score; Caliński–Harabasz index.

1 Introduction

In recent years, the adoption of data-driven technologies alongside ecological priorities has driven a significant transformation in the monitoring and management of forest resources. Silviculture, central to this evolution, relies on thinning as a key intervention to regulate stand structure and enhance forest health, productivity, and biodiversity. Traditionally guided by expert judgment and empirical rules, thinning decisions can now be strengthened through machine learning, enabled by expanding data availability and computational capacity. By integrating biophysical and socio-economic datasets, machine learning supports adaptive, objective, and data-driven decision-making, enabling the identification of environmental risks and the reconciliation of multiple management objectives. As such, machine learning offers a robust pathway toward more efficient, resilient, and holistic forest management.

The richness and reliability of forest datasets available for machine learning analysis can be enhanced by resources such as remote sensing, LiDAR, and ground-based sensors (Abbas et al. 2020). Techniques that interpret machine learning model estimates and quantify prediction uncertainties can, in turn, increase transparency in decision-making processes (Cattaneo et al. 2024). The incorporation of real-time monitoring and feedback loops within machine learning-based forest management systems further supports robust, evidence-driven decision-making. This approach promotes interdisciplinary collaboration and expedites the application of machine learning within silvicultural practice (Mosin et al. 2019).

Machine learning algorithms enable the effective analysis of extensive and diverse datasets, supporting the extraction of valuable insights, the creation of predictive models, and the provision of accurate information for management decision-making (Zhou et al. 2017).

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These applications span a broad spectrum of forestry operations, such as species classification, forest inventory estimation, yield prediction, and habitat modelling (Maxwell et al. 2018). By integrating species distribution, habitat attributes, and landscape connectivity data, machine learning can inform thinning prescriptions and help align productivity goals with biodiversity conservation and ecosystem resilience (Stupariu et al. 2022). Machine learning is also useful for assessing the susceptibility of forest ecosystems to climate change and for formulating adaptive management strategies. By combining climate projections with soil moisture data and species-specific physiological characteristics, such models can forecast changes in forest structure and composition. This capability supports the planning of thinning interventions, thereby mitigating climate-related risks and enhancing forest resilience under future environmental uncertainty (Seidl et al. 2017).

Through the systematic extraction of complex patterns and interdependencies within forest datasets, machine learning algorithms facilitate the prediction of stand dynamics, tree mortality, and species composition. This capability supports data-driven thinning decisions, reducing avoidable timber loss and promoting overall stand health (Goodbody et al. 2019).

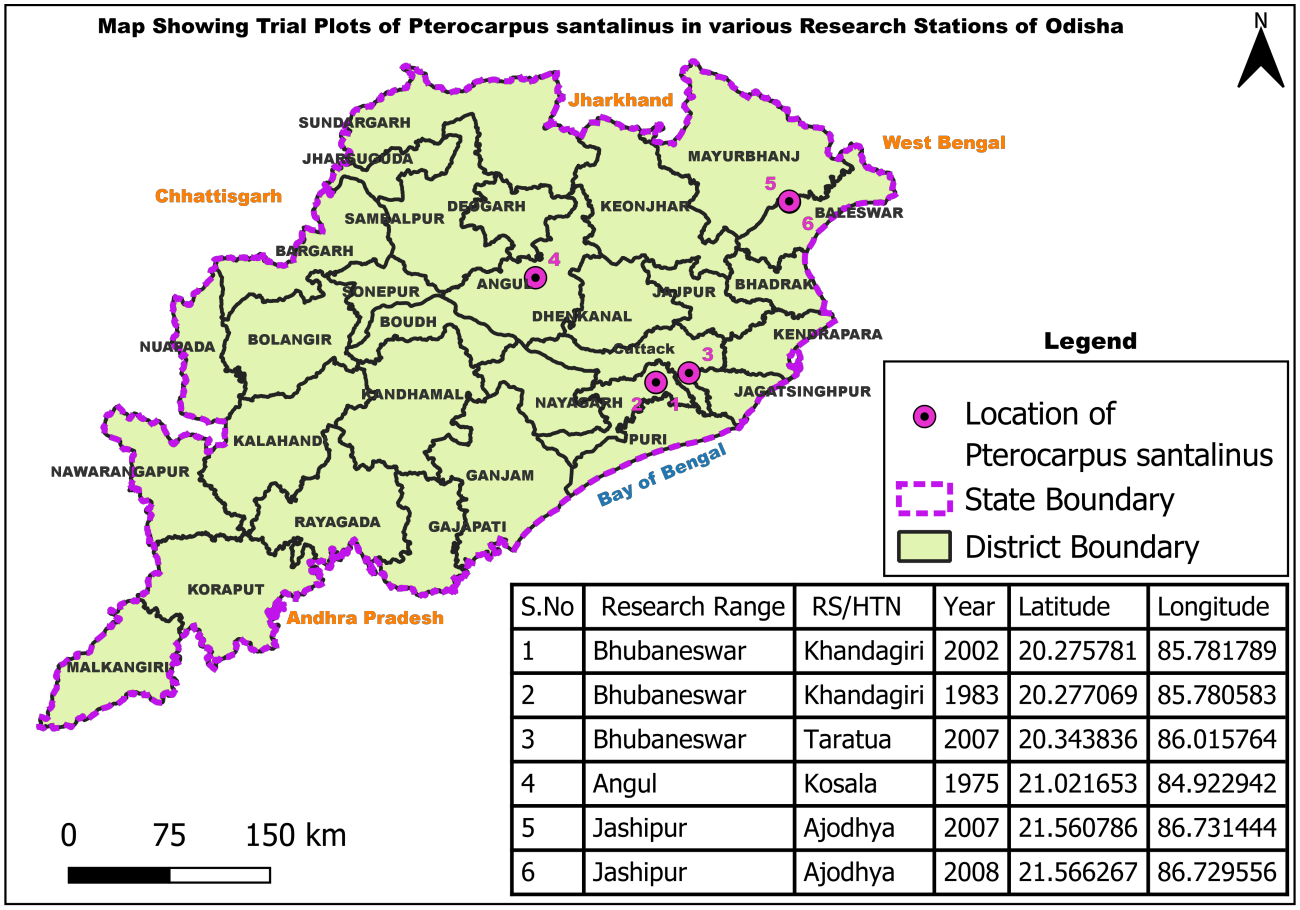
Silvicultural thinning, as a strategic intervention, can effectively modulate stand density and structure. Thinning involves the selective removal of individual trees to achieve specific spatial arrangements and growth characteristics, ultimately enhancing the attributes and value of the remaining stand (Pommerening and Grabarnik 2019). As a management intervention, thinning is fundamental to achieving multiple objectives, including timber production, biodiversity conservation, carbon sequestration, and ecosystem resilience. Machine learning offers considerable potential for optimising silvicultural thinning across these objectives. To support the development of predictive models of stand dynamics, these algorithms can analyse historical growth data, environmental variables, and management interventions. Such models enable forest managers to evaluate diverse thinning options and identify management approaches that enhance sustained forest productivity (McAdam 2015).

The integration of machine learning into silvicultural thinning represents a substantial shift in forest management methodology. Historically, silvicultural practice has relied predominantly on general guidelines and expert assessment (Hanewinkel et al. 2013), which can lead to less-than-ideal results or the inefficient allocation of resources. Foresters typically evaluate site conditions visually and then prescribe thinning intensities based on traditional guidelines or individual professional experience.

The integration of machine learning into silvicultural thinning is explored here to improve forest productivity and uphold ecological integrity through the identification of appropriate thinning regimes, informed by historical stand, growth, and environmental data. The integration of remote sensing data and field-based observations can further facilitate adaptive management by enabling thinning strategies to respond to environmental stressors, including drought, pest infestations, and invasive species.

Nevertheless, incorporating machine learning into silvicultural thinning introduces several challenges and constraints. A primary requirement is the availability of high-quality, reliable data for effective algorithm training. Forestry datasets often exhibit sparsity, incompleteness, or inconsistent quality, which can hinder algorithm development and validation (Banskota et al. 2014). Consequently, close collaboration among researchers, forest managers, and data providers is essential, because compiling comprehensive datasets that accurately reflect the complexity of forest ecosystems is itself a significant challenge. A further challenge concerns the interpretability of machine learning models, particularly for sophisticated algorithms such as deep learning, whose predictive outputs can be difficult to interpret or empirically validate. Understanding the processes that govern model predictions is critical for building stakeholder confidence and supporting sound decision-making (Zhang et al. 2021). Addressing these challenges requires sustained interdisciplinary collaboration, methodological advances, and continuous improvement of best practice. An additional constraint is the limited transferability of models trained on particular forest types or geographic areas to novel environments. Ensuring the scalability and transferability of machine learning solutions across diverse forest ecosystems therefore remains a critical research priority (Blanco et al. 2020).

This research investigates the application of unsupervised machine learning techniques to silvicultural thinning and examines their potential to strengthen forest management practice. The study uses machine learning algorithms to generate actionable insights from field datasets, thereby supporting evidence-based, data-driven decision-making. This responds to key challenges facing contemporary silviculture, such as raising forest productivity, supporting ecosystem stability, and buffering the effects of climate change. Accordingly, unsupervised classification methods were systematically applied to support silvicultural thinning in *Pterocarpus santalinus* trial plots dis-



S.No	Research Range	RS/HTN	Year	Latitude	Longitude
1	Bhubaneswar	Khandagiri	2002	20.275781	85.781789
2	Bhubaneswar	Khandagiri	1983	20.277069	85.780583
3	Bhubaneswar	Taratua	2007	20.343836	86.015764
4	Angul	Kosala	1975	21.021653	84.922942
5	Jashipur	Ajodhya	2007	21.560786	86.731444
6	Jashipur	Ajodhya	2008	21.566267	86.729556

Figure 1: Map showing trial plots of *Pterocarpus santalinus* at various research stations of Odisha.

tributed across diverse agroclimatic zones of Odisha, India.

2 Materials and Methods

2.1 Study area

Six red sanders (*Pterocarpus santalinus*) trial plots were selected in different agroclimatic regions of Odisha (Figure 1), a state situated between 17°49′ and 22°34′ N latitude and 81°27′ and 87°29′ E longitude, India (Hota 2024). The average elevation of the trial-plot districts is about 600 m a.s.l. The plots lie within an "Aw" (tropical savanna) climate according to the Köppen classification (Köppen 1936). The rainy season extends from June to September, and the mean annual rainfall is approximately 1500 mm. Temperatures range from 15°C to 35°C in winter and from 30°C to 45°C in summer.

Pterocarpus santalinus (red sandalwood) is a species of high cultural, economic, and ecological value. For this species, the study applies a machine learning-based framework to support silvicultural thinning in trial plots across Odisha by reducing resource competition, enhancing stand productivity, and supporting biodiversity and ecosystem functions.

2.2 Methodology

2.2.1 *Data collection and preprocessing*

Data were collected from December 2024 to April 2025 from six red sanders trial plots (Figure 1), which had been raised between 1975 and 2008. The girth and height of individual trees were recorded within each trial plot. Tree height was measured with a Nikon Forestry Pro II laser range finder, and girth was measured at breast height with a measuring tape. These two parameters served as the input variables for the subsequent clustering analyses (k-means and hierarchical clustering).

Before the clustering algorithms were applied, the data were checked for consistency and completeness. The dataset contained complete girth and height records for all trees, so no imputation or record removal was required. Girth and height were analysed in their original units of measurement (cm and m, respectively) without standardisation. All analyses were performed in R version 4.4.2 (R Core Team 2024).

2.2.2 Clustering analysis

Two clustering methods, k-means and hierarchical clustering, were applied. For k-means clustering, the number of clusters must be specified in advance. In this study the number of clusters was set to two in most cases, and to three for the two trial plots at Ajodhya (raised in 2008) and Taratua (raised in 2007). K-means clustering was applied iteratively to partition the trees in each plot into groups based on the similarity of their girth and height measurements. The algorithm minimises the within-cluster sum of squares, separating trees into homogeneous groups with minimal intra-cluster variance.

Two clusters were used in the majority of plots because trees generally need to be divided into two groups: those to be retained and those to be felled. Where two well-defined groups did not adequately represent the stand structure, three clusters were used instead. Unlike k-means, hierarchical clustering follows an agglomerative approach, building a hierarchical structure by iteratively merging observations or clusters according to their similarity. Here, hierarchical clustering was used to construct a dendrogram representing the hierarchical structure of tree groups within each plot; the dendrogram supports the determination of cluster delineations and thus helps distinguish trees designated for felling from those to be retained. Dissimilarity between observations was measured using the Euclidean distance metric, and average linkage was used to determine inter-cluster dissimilarity as the mean distance between clusters.

After the clustering algorithms were applied, the resulting clusters were analysed to identify a suitable thinning strategy for each plot. Trees in the cluster characterised by substantially smaller girths and heights were identified as candidates for removal, whereas those in the cluster characterised by larger girths and heights were prioritised for retention. This interpretation is consistent with established silvicultural principles for optimising stand structure and growth dynamics while maintaining timber yield and ecosystem resilience.

2.2.3 Validation and refinement

The robustness and reliability of the clustering outcomes were assessed using multiple validation methods: silhouette analysis, the Caliński–Harabasz index, and visual analysis of the cluster distributions. Silhouette analysis measures cluster compactness and distinctiveness and provides a widely recognised metric for assessing clustering quality. The Caliński–Harabasz index, also known as the variance ratio criterion, evaluates clustering performance as the ratio of between-cluster dispersion to within-cluster dispersion, with higher values indicating more well-defined clusters. Both indices were computed for the k-means and hierarchical clustering results across all plots. The clustering outcomes were then reviewed in light of practical considerations to ensure alignment with silvicultural objectives and site-specific stand conditions.

2.2.4 Implementation and monitoring

Once thinning strategies have been established for each plot, the trees identified for removal can be selectively harvested while those intended for retention remain undisturbed. Subsequent monitoring and assessment of stand dynamics, growth patterns, and ecosystem responses can then be conducted to evaluate the efficacy of the thinning interventions. This iterative process of implementation and monitoring supports adaptive management and the ongoing refinement of silvicultural practice based on observed outcomes and field-based feedback.

3 Results

3.1 K-means clustering

K-means clustering partitioned the trees in each trial plot into groups based on their girth and height. The results are shown in Figures 2–7 for the six trial plots of *Pterocarpus santalinus*. The algorithm separated trees into a cluster of smaller girths and heights, indicative of suppressed or less vigorous individuals, and a cluster of larger girths and heights, representing dominant or healthier trees. The cluster centres and sizes are reported in Table 1. The trial plots at Ajodhya (2008) and Taratua (2007) were divided into three clusters, whereas the remaining plots were divided into two. K-means clustering therefore provided a workable grouping of trees into two or three classes, supporting the identification of individuals suitable for felling or retention on the basis of girth and height. A limitation is that methods relying on predefined cluster centroids may be less able to capture more complex patterns within the data.

3.2 Hierarchical clustering

Hierarchical clustering produced dendrograms showing the hierarchical structure of tree groupings in each trial plot (Figures 2–7). For example, Figure 2 shows the dendrogram for the Ajodhya (2007) plot, in which the green rectangles indicate the aggregation of the data into two groups. The dendrograms enable the identification of cluster divisions and thus help distinguish trees slated for felling from those selected for retention, based on their placement within the hierarchical structure. The remaining dendrograms correspond to the other five trial

Table 1: Comparison of k-means and hierarchical clustering results for silvicultural thinning in *Pterocarpus santalinus* trial plots ($k = 2$ or $k = 3$).

Sl. No.	Trial site	Year	Total trees	k	K-means cluster size	Centroid height (m)	Centroid GBH (cm)	Hierarchical cluster size
1	Ajodhya	2007	1228	2	581	11.3	55.5	781
					647	8.5	31.6	447
2	Ajodhya	2008	499	3	107	9.4	59.1	385
					254	8.8	43.9	101
					138	6.8	27.4	13
3	Kosala	1975	260	2	160	16.1	59.8	232
					100	20.2	99.8	28
4	Khandagiri	1983	623	2	333	6.5	25.4	407
					290	13.4	78.4	216
5	Khandagiri	2002	881	2	474	11.6	60.4	530
					407	6.9	25.5	351
6	Taratua	2007	240	3	59	11.0	58.2	142
					68	4.9	17.8	94
					113	8.7	39.3	4

Note: GBH = girth at breast height. For each plot, k-means cluster sizes and centroids are listed in the same order; hierarchical cluster sizes are given for the same plot but represent an independent partition.

Table 2: Quantitative comparison of clustering methods.

S. No.	Trial plot	Year of formation	Silhouette score		Caliński–Harabasz index	
			K-means	Hierarchical	K-means	Hierarchical
1	Ajodhya	2007	0.5658	0.5280	2504.56	1992.54
2	Ajodhya	2008	0.5263	0.4615	924.43	413.92
3	Kosala	1975	0.5651	0.5128	537.91	200.10
4	Khandagiri	1983	0.5977	0.5694	1517.93	1307.27
5	Khandagiri	2002	0.6249	0.6123	2504.17	2334.05
6	Taratua	2007	0.5354	0.5102	595.21	299.53

plots. Hierarchical clustering provides a systematic representation of tree partitioning and supports detailed analysis of stand structure.

As with k-means, the clusters produced by hierarchical clustering were analysed to determine a suitable thinning approach for each plot: trees in clusters with smaller girths and heights were identified as candidates for felling, and those in clusters with larger girths and heights were recommended for retention.

The clustering results were validated using the silhouette score and the Caliński–Harabasz index to assess their robustness and reliability (Table 2). Silhouette analysis measures intra-cluster cohesion and inter-cluster separation, with higher scores indicating well-defined clusters with minimal overlap. The silhouette score for k-means clustering was higher than that for hierarchical clustering in all six trial plots. Similarly, the Caliński–Harabasz index was higher for k-means clustering than for hierarchical clustering across all plots. These validation results indicate that, for the present dataset, k-means clustering produced better-separated clusters than hierarchical clustering.

4 Discussion

The unsupervised clustering algorithms provide a data-driven approach to supporting thinning decisions, with quantitative validation indicating that k-means clustering produced more well-defined and compact clusters than hierarchical clustering for these trial plots. This provides an objective basis for categorising trees into "felled" and "retained" groups, which can inform management decisions. As a strategic intervention, silvicultural thinning can regulate stand density and structure (Pommerening and Grabarnik 2019).

Silvicultural thinning is important for achieving diverse objectives, and machine learning holds considerable promise for optimising thinning across multiple dimensions. By supporting the development of predictive models of stand dynamics, these algorithms can help foresters simulate different thinning scenarios and identify effective management options (McAdam 2015).

Silvicultural thinning plays a critical role in the health, productivity, and sustainability of *Pterocarpus*

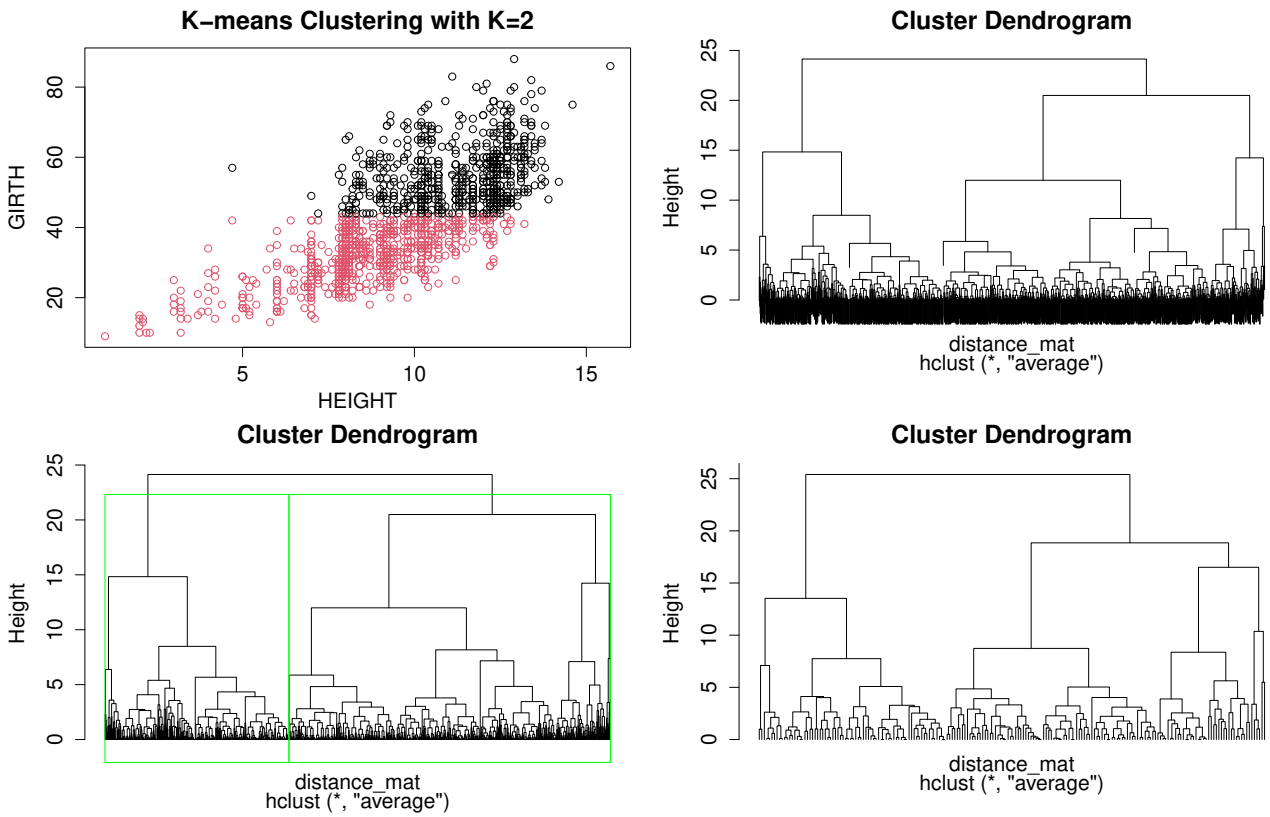


Figure 2: K-means cluster plot and hierarchical-clustering dendrograms for the Ajodhya (2007) trial plot.

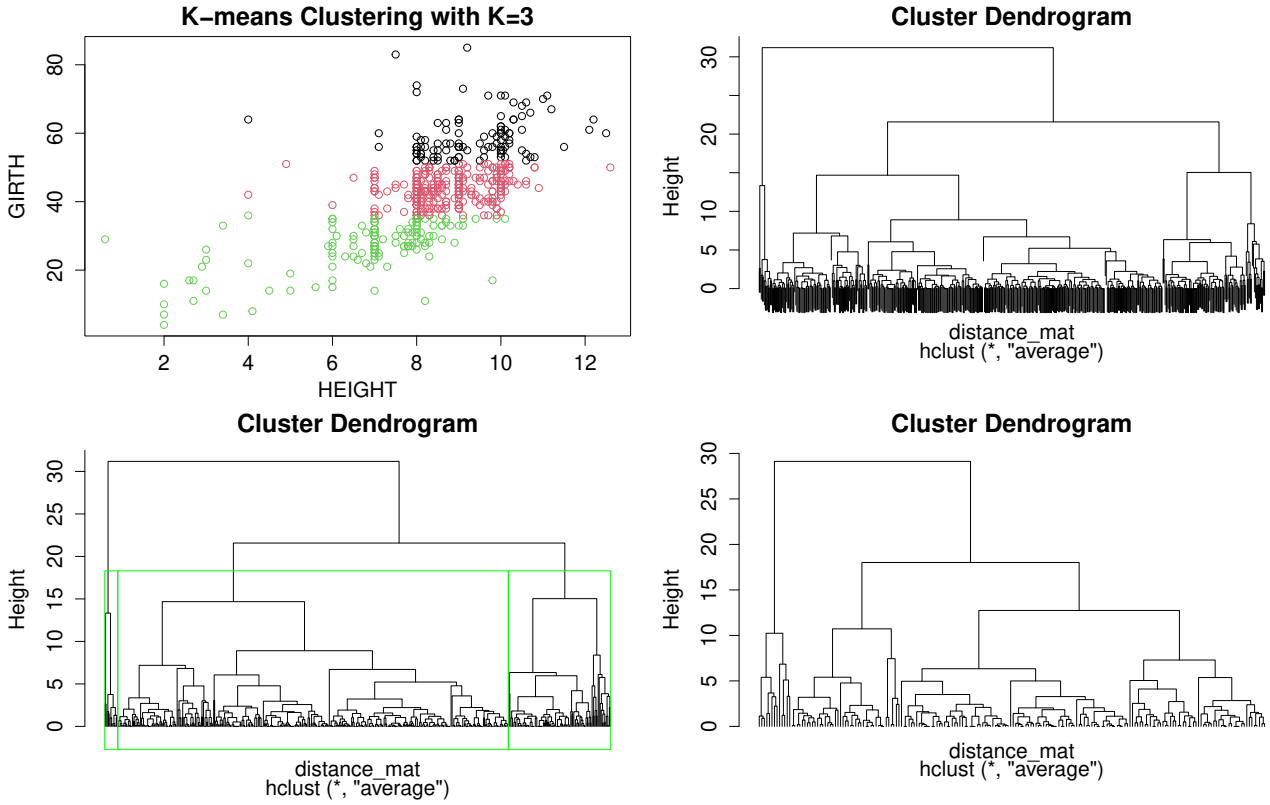


Figure 3: K-means cluster plot and hierarchical-clustering dendrograms for the Ajodhya (2008) trial plot.

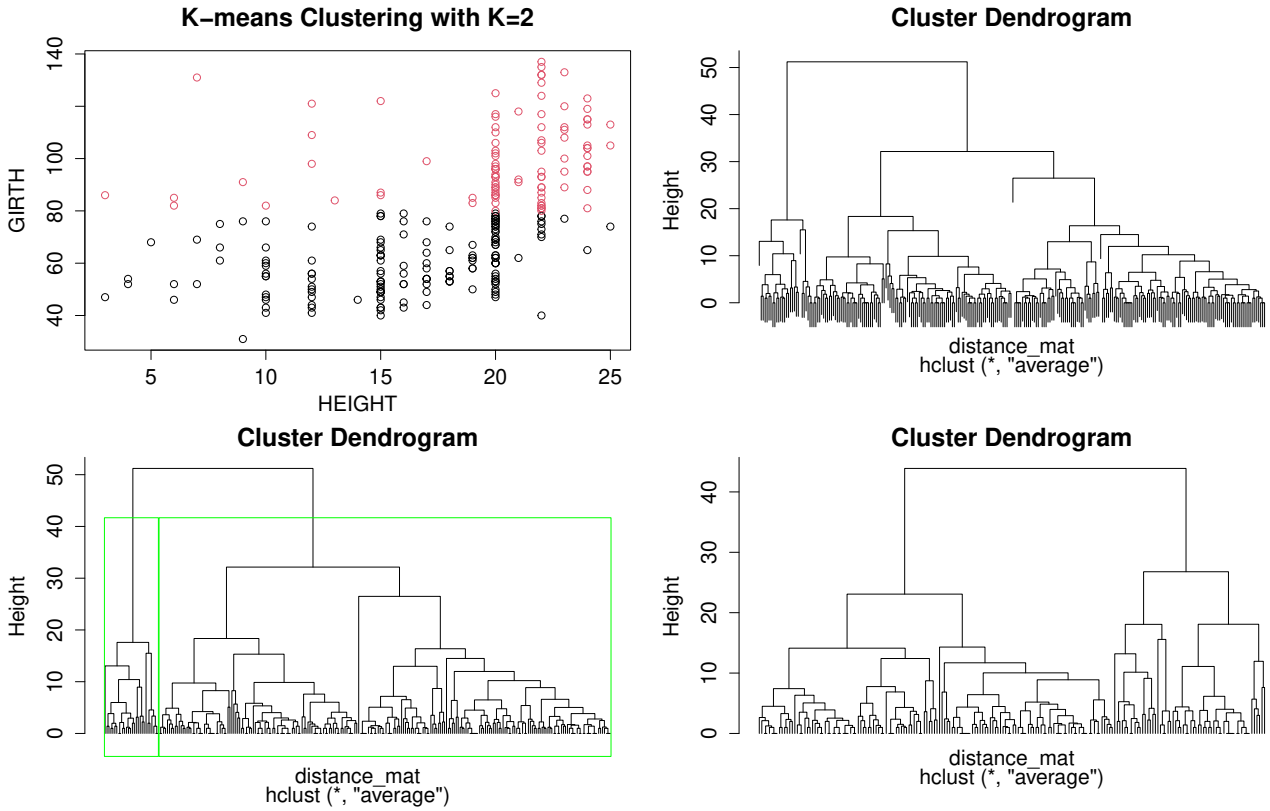


Figure 4: K-means cluster plot and hierarchical-clustering dendrograms for the Kosala (1975) trial plot.

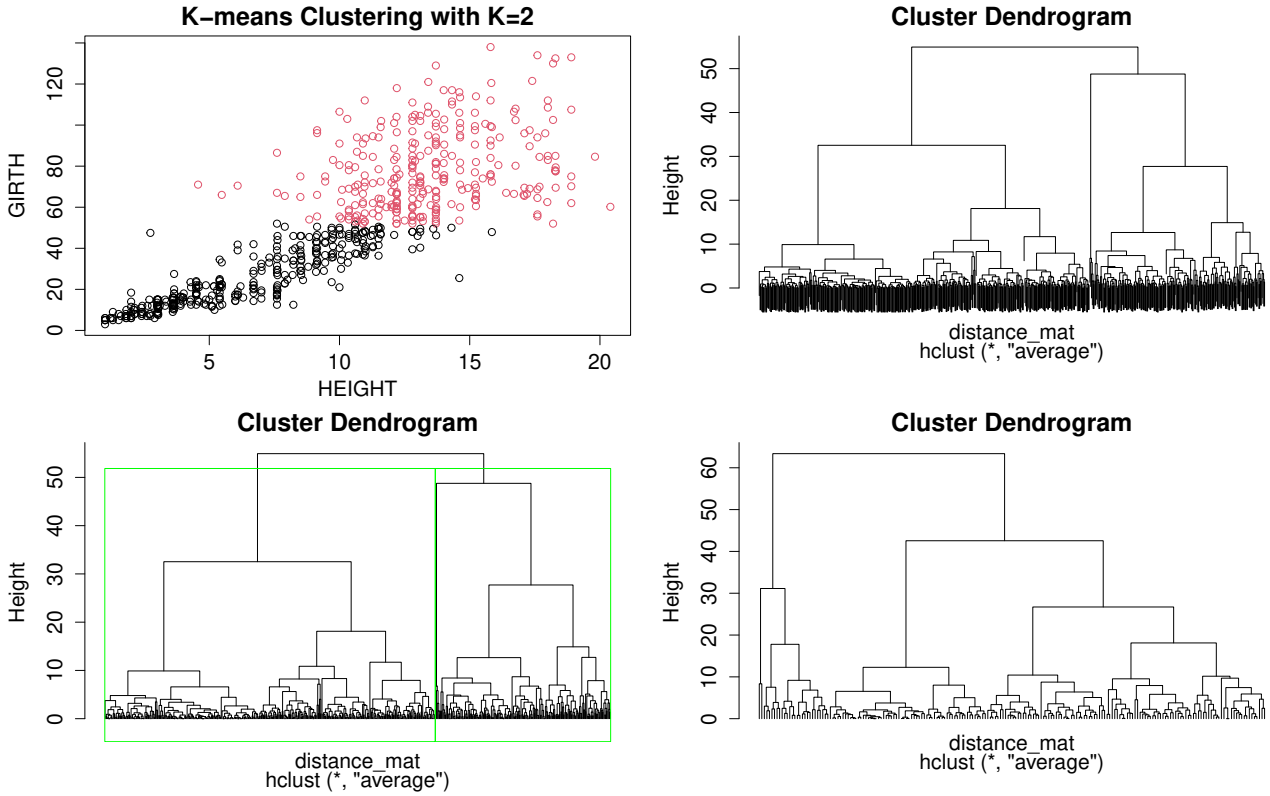


Figure 5: K-means cluster plot and hierarchical-clustering dendrograms for the Khandagiri (1983) trial plot.

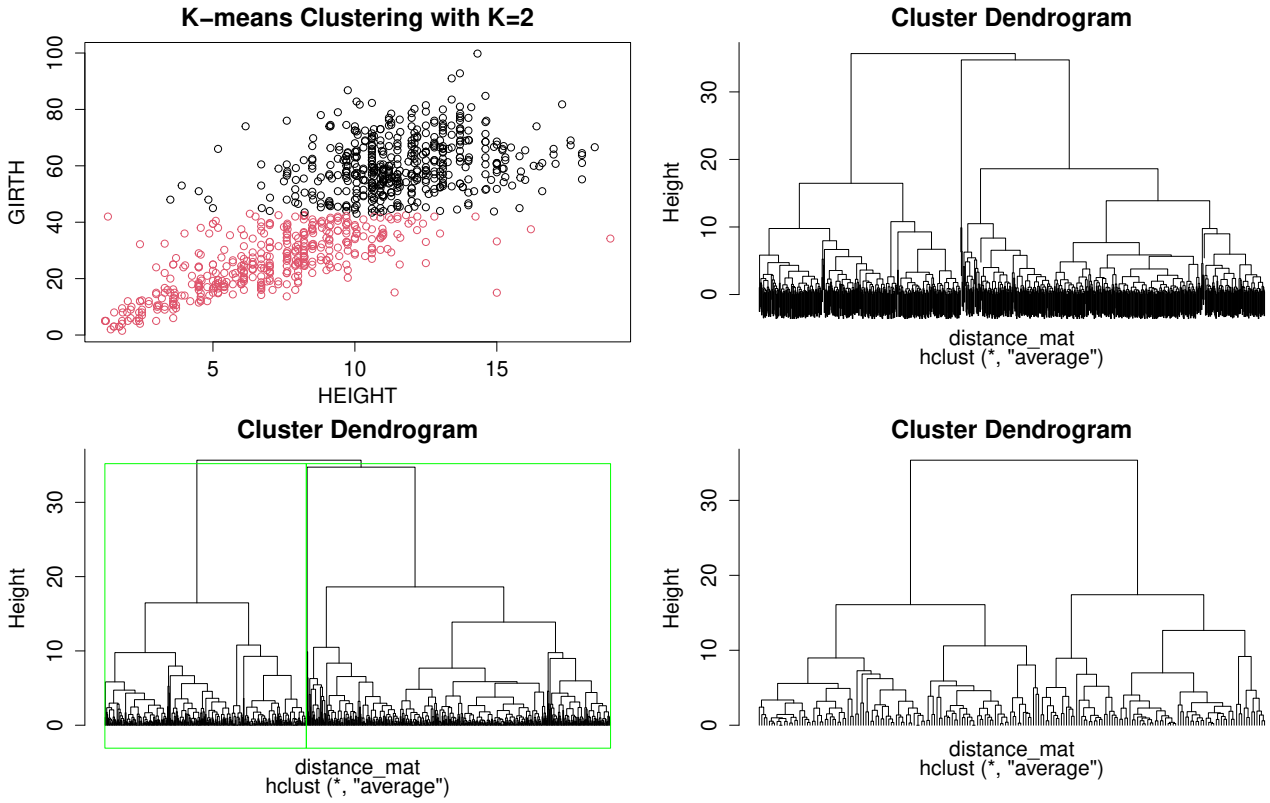


Figure 6: K-means cluster plot and hierarchical-clustering dendrograms for the Khandagiri (2002) trial plot.

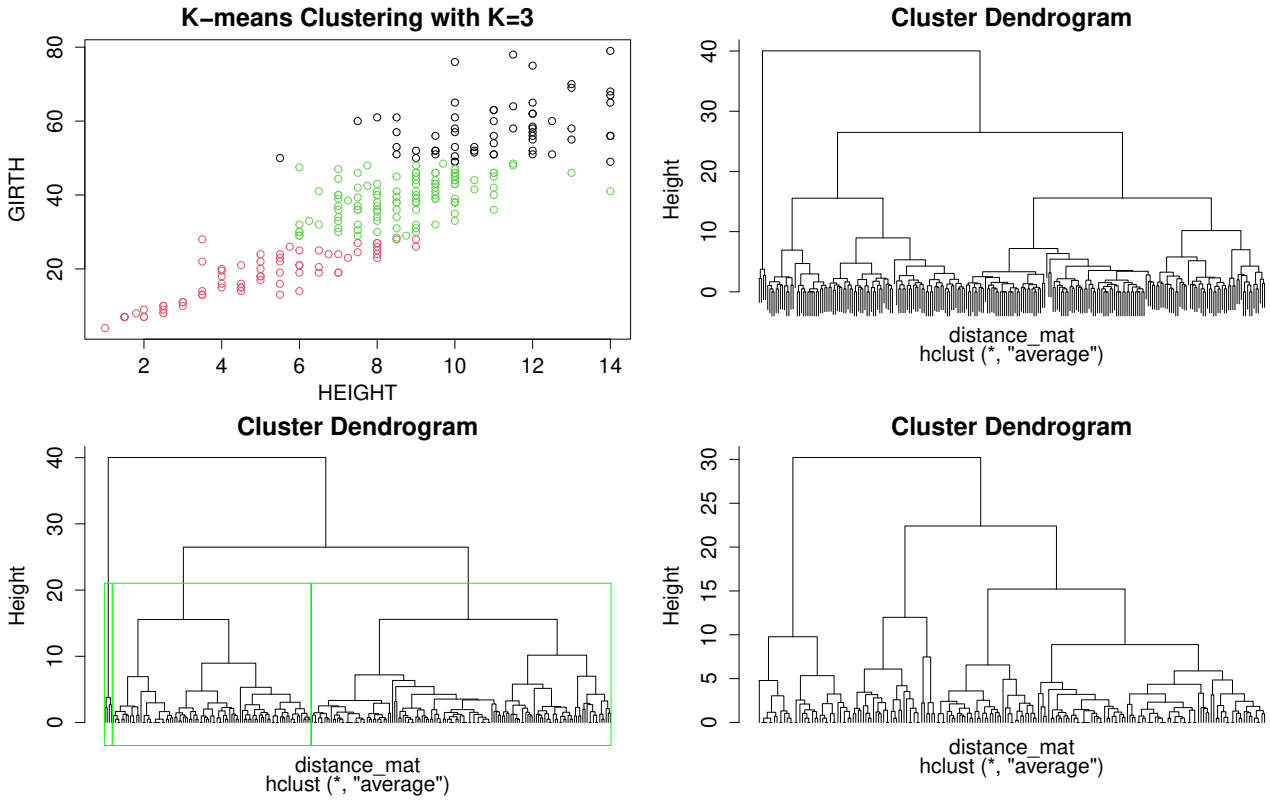


Figure 7: K-means cluster plot and hierarchical-clustering dendrograms for the Taratua (2007) trial plot.

santalinus plantations. It involves the selective removal of trees to optimise stand density, promote individual tree growth, and enhance timber quality. Adaptive and sustainable management options can be used to enhance forest productivity while balancing timber production with biodiversity conservation (Stupariu et al. 2022). By dividing trees into two or three classes according to height and girth, k-means clustering can facilitate thinning prescriptions that reconcile timber production objectives with biodiversity conservation, thereby supporting ecosystem integrity and forest resilience.

Unsupervised machine learning can help characterise tree attributes objectively and categorise individual trees for thinning. This represents a shift from reliance on general guidelines toward a data-driven approach to regulating stand density, with the potential to increase productivity, improve timber quality, and enhance ecosystem resilience. Predictive models can also support the analysis of factors such as species composition, stand growth dynamics, and tree mortality. By incorporating data on tree characteristics, environmental conditions, and stressors, machine learning models can help assess the likelihood of individual tree mortality; this information can be used to prioritise trees for removal during thinning, reducing the loss of valuable timber and supporting overall stand health (Goodbody et al. 2019).

The silhouette score and the Caliński–Harabasz index provide quantitative insight into clustering quality. Silhouette analysis measures cluster compactness and separation: higher scores indicate distinctly delineated clusters with minimal overlap, corresponding to the conventional notion of a well-defined cluster, and thus indicate stronger clustering performance. On this basis, k-means clustering performed better than hierarchical clustering in this study. It should be noted, however, that the outputs of complex algorithms can be challenging to interpret or empirically validate (Zhang et al. 2021), and continuing developments in interpreting model outputs and quantifying prediction uncertainties will improve transparency and confidence in decision-making (Cattaneo et al. 2024). It should also be recognised that these indices assess the geometric quality of the partitions (compactness and separation in girth–height space), not the silvicultural merit of the resulting prescriptions.

The unsupervised algorithms were effective in deriving a data-driven partition from the tree-level measurements. Such algorithms can analyse extensive and diverse datasets to derive insights, build predictive models, and guide management decisions (Zhou et al. 2017). The adoption of machine learning in silvicultural thinning reflects a broader shift in forest management: whereas foresters have traditionally assessed stands visually, in the present study unsupervised machine learning proved effective for partitioning trees and thereby supporting stand management. Thinning can regulate stand density and structure (Pommerening and Grabarnik 2019).

In *Pterocarpus santalinus* plantations, silvicultural thinning can alleviate intra-stand competition for light, water, and nutrients, thereby enhancing diameter growth and heartwood quality in retained trees. As a management intervention, thinning is central to achieving multiple objectives, including sustainable timber production, biodiversity conservation, and ecosystem resilience (McAdam 2015).

By objectively classifying trees from growth data, unsupervised machine learning may reduce the subjectivity inherent in conventional C-grade thinning and better capture stand heterogeneity, with the potential to produce statistically validated, site-specific thinning decisions. A direct, quantitative comparison with C-grade thinning was beyond the scope of the present study and is identified as an important direction for future work. Such a comparison would require, at a minimum: (i) an explicit statement, with its source, of the operative C-grade thinning prescription for these plantations; (ii) marking of the trees to be removed under that prescription in the same six plots, independently of the cluster labels; (iii) quantification of the agreement between the rule-based and cluster-based removal sets (for example, the proportion of trees selected by both methods, or Cohen's kappa), together with the number and proportion of trees removed by each; (iv) comparison of the residual stands produced by the two alternatives in terms of stem density, the mean and distribution of girth and height, and basal area; and (v) evidence of subsequent stand response, either from re-measurement of the plots after thinning or from projection with a suitable growth model. Only with such evidence could the clustering approach be said to outperform conventional thinning in its silvicultural outcomes, rather than in the internal consistency of its partitions.

Future research could incorporate additional features to improve the predictive performance of the models, including multivariate models, improved model interpretability, empirical validation, and formal performance assessment.

5 Conclusion

This study illustrates the potential of unsupervised machine learning as a data-driven framework for supporting silvicultural thinning in *Pterocarpus santalinus*. The objective classification of trees for felling and retention across six trial plots, validated using silhouette scores and the Caliński–Harabasz index, provides a consistent and reproducible description of stand structure.

These insights can facilitate the development of targeted, site-specific thinning strategies intended to improve productivity while preserving ecological integrity. The proposed framework combines field-derived measurements with quantitative analytical methods to support transparent and adaptive forest management, balancing timber production with biodiversity conservation and ecosystem resilience. These findings indicate that unsupervised machine learning-based clustering is a promising and scalable decision-support tool for silvicultural thinning; a direct comparison with conventional practices remains an important next step to confirm its operational advantages.

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