

UAV-based spatial analysis for modelling pine resin yield and assessing land potential in South Sulawesi, Indonesia

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Abstract

This study aims to map land potential and estimate pine resin yield in Abulo Sibatang Forest Farmers Group (KTH), Laiya Village, Cenrana Subdistrict, Maros Regency, using drone technology and field data. The research method was carried out by aerial photography using UAV to produce orthomosaic and land cover maps which were then combined with dendrometric data, specifically trunk diameter and tree height. Data analysis was performed using a regression model and testing the classification accuracy through a confusion matrix. The inventory data showed 12,590 pine trees with a height distribution of 25–27 m (29.5 %), 28–30 m (54.6 %) and ≥ 30 m (15.9 %). The estimated resin yield from the tall class reached 51,034 kg·yr⁻¹, or more than half of the total production. Factors affecting production included tree morphometric characteristics, particularly diameter at breast height and tree height, supported by spatial and site-related factors. The combination of UAV and field data proved successful in identifying priority tapping areas and improving resource management efficiency. This finding confirms the positive correlation between tree dimensions and resin yield and demonstrates the great potential of UAV technology to support non-timber forest products.

Key words: estimating, potential mapping, resin production, UAV mapping.

Introduction

Pine resin production has attracted increasing interest in recent years due to its high economic value and wide range of industrial applications, including rosin, turpentine, adhesives, paints, and pharmaceutical products. As a high-value non-timber forest product, pine resin also plays an important role in supporting forest conservation and rural livelihoods, as it provides a continuous source of income

without requiring tree harvesting (Imanuddin et al. 2020). Indonesia is one of the world's leading producers of pine resin, with *Pinus merkusii* Jungh. & de Vriese as the main species widely planted in Java, Sumatra, and Sulawesi. For example, Perum Perhutani manages more than 1.6 million ha of tapping land and produced more than 90,000 t of resin annually between 2015 and 2018, representing a significant contribution to the national forestry economy (Imanuddin et al. 2020).

Despite its significant role at the national level, local-scale research in developing regions such as South Sulawesi remains limited, particularly in areas with high potential, such as Abulo Sibatang Community Forest in Maros District.

Pine resin production is strongly influenced by species-specific characteristics, including resin canal structure, growth patterns, and physiological responses to tapping. Previous studies have shown that resin yield varies significantly among pine species, such as *Pinus merkusii*, *Pinus pinaster* Aiton, and *Pinus elliotii* Engelm., and is closely related to tree morphometric attributes, site conditions, and tapping techniques (Rodríguez-García et al. 2015, Lukmandaru et al. 2021, García-Méijome et al. 2023). In Indonesia, *P. merkusii* is the primary resin-producing species, and its productivity has been reported to be strongly associated with diameter at breast height and stand conditions (Suhartati and Attoric 2021, Irawan et al. 2024).

This study introduces the integration of UAV-based spatial analysis with resin yield modelling as an innovative approach to improve the efficiency and spatial accuracy of land potential assessment in pine forests. The use of drone imagery for land suitability mapping has increased due to its ability to produce high-quality spatial data that surpass those obtained using traditional methods. UAV-based remote monitoring enables detailed analysis of topography, plant health, and other environmental factors that are essential for identifying the most suitable areas for pine cultivation (Wang et al. 2023). In South-east Asia, the use of UAV technology is growing for ecological mapping and crop health monitoring due to its cost-effectiveness and improved accuracy (Gohari et al. 2024).

However, the integration of spatial data from UAVs with resin yield modelling remains limited, particularly in Indonesia, where detailed production databases are often unavailable. In addition, variations in tapping methods and management practices contribute to inconsistencies in resin productivity, even under similar environmental conditions (Mukhlisa and Dwi-yanti 2021). These limitations highlight the need for an integrated approach that combines spatial analysis with production modelling to support more accurate and efficient resource management.

Abulo Sibatang Community Forest in Maros Regency has favourable environmental conditions for pine growth, with elevations ranging from 500 to 800 m above sea level and an average annual rainfall of approximately 2,000 mm. These conditions indicate strong potential for resin production; however, without accurate spatial mapping, this potential cannot be optimally utilised. UAV-based mapping enables the identification of suitable planting locations, reduces the risk of suboptimal land allocation, and improves overall land productivity.

Furthermore, most previous studies have relied on conventional field-based approaches, which are often time-consuming and limited in spatial coverage. In this context, the integration of UAV-based spatial analysis with resin yield modelling offers a transferable framework that can be applied to other pine-growing regions worldwide, particularly in areas lacking detailed forest inventory data. This approach supports precision forestry by enabling efficient resource assessment and site-specific management.

This study aims to analyse the relationship between land potential and pine resin yield in Abulo Sibatang Community Forest, Maros Regency, South Sulawesi.

Specifically, it seeks to identify key factors influencing resin production, including tree morphometry (diameter and height), environmental conditions (climate and topography), and tapping methods. The study also integrates UAV-based spatial data with dendrometric measurements to develop a regression model for yield estimation. The results are expected to support more accurate mapping of productive areas and contribute to the sustainable management of non-timber forest resources, particularly pine resin.

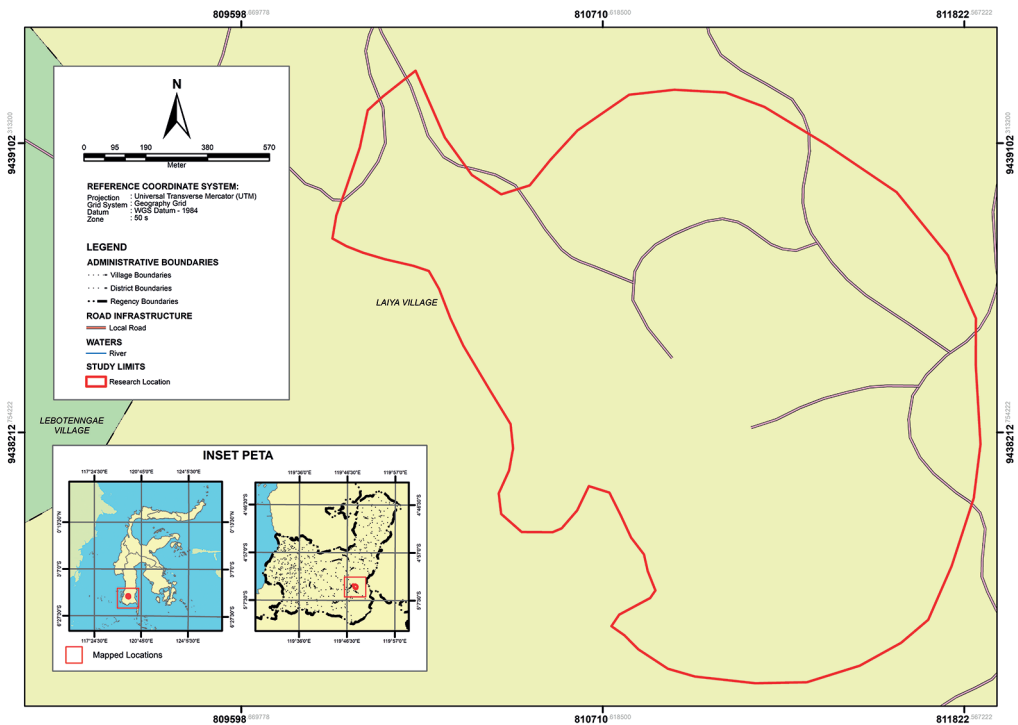
Study Area

Abulo Sibatang Forest Farmers Group (KTH) is located in Laiya Village, Cenrana Subdistrict, Maros Regency, South Su-

lawesi, Indonesia (Fig. 1). Geographically, the area occupies a strategic position bordering Gowa and Bone regencies. It functions as a buffer zone with distinctive topographical features and considerable biodiversity potential. Based on its geographical coordinates, KTH Abulo Sibatang lies at approximately 5°04'29.42" S and 119°48'16.51" E. Administratively, the area is bordered by Limampocoe and Cenrana Baru Villages to the north, Bontomanai and Bontosomba Villages to the south, Lebbottangae and Semangki Villages to the west, and by Bone and Gowa Regencies to the east.

Tools, Materials and Methods

This study employed an integrated approach combining UAV-based spatial



analysis with field-based dendrometric measurements to estimate pine resin production. The methodological framework comprised three main stages: (1) acquisition and processing of UAV imagery to generate orthomosaics and land-cover maps; (2) field inventory to collect tree-level dendrometric data; and (3) statistical modelling to estimate resin yield and analyse its relationship with land potential.

To clarify the methodological flow, the study was conducted in a sequential manner. First, UAV flights were carried out to acquire high-resolution aerial imagery, which was processed to produce orthomosaic and land-cover maps of the study area. Field inventory was then carried out within the mapped pine stands to collect dendrometric data, including diameter at breast height (DBH) and total tree height. Subsequently, spatial information derived from UAV products was integrated with field measurements to classify tree height classes and to delineate potential zones for pine resin tapping. Finally, multiple regression analysis was applied to estimate pine resin yield and to examine the relationships between tree morphometric variables and land potential.

Tools and materials

The tools and materials used in this study included a DJI Mavic 2 Pro drone, a GPS receiver, a spirit level, a digital camera, a measuring tape, and standard field recording instruments. Supporting data consisted of drone imagery, topographic base maps (RBI), climatic data, and a digital elevation model (DEM).

Data collection

The sampling unit in this study was individual pine trees. Sampling points were

selected based on the spatial distribution of pine stands identified from UAV-derived land-cover maps. Field inventory was conducted throughout the study area to ensure representative coverage of different tree height classes. Each sampled tree was georeferenced, and dendrometric measurements, including DBH and total tree height, were recorded for subsequent analyses.

Spatial data were obtained through aerial photography using drones at an altitude of 120 m, with 80 % forward overlap and 70 % side overlap. Aerial photographs were processed into orthomosaics and land cover maps. An orthomosaic is a geometrically corrected aerial image generated by combining multiple overlapping photographs into a single spatially accurate map with a uniform scale. These products were used to improve the reliability of stand volume estimation, following approaches similar to those reported by Yahya et al. (2019). Their study combined UAV imagery with NDVI data derived from Landsat 8 to estimate stand productivity potential using a linear regression model, with spatial accuracy verified through field validation.

Similar approaches have been applied in Indonesia, where UAV-derived imagery has been successfully combined with field measurements to estimate forest stand potential. For example, Yahya et al. (2019) demonstrated that UAV-derived orthomosaics combined with regression analysis can reliably estimate stand potential at the management-unit level. Building upon this principle, the present study extends the application of UAV-based spatial analysis to non-timber forest products by integrating canopy height information with dendrometric data to estimate pine resin production.

Sampling adequacy and classification

accuracy were evaluated using a confusion matrix-based approach. The sample size was determined by the extent of the field inventory and the spatial distribution of pine stands identified from UAV-derived land-cover maps. Given the large number of inventoried trees ($n = 12,590$), the dataset was considered sufficient for robust statistical modelling.

Data analysis

Spatial data were processed to generate orthomosaics and land-cover maps and to estimate potential areas for resin production. The classification accuracy was evaluated using a confusion matrix. A confusion matrix is a statistical tool used to assess classification performance by comparing predicted classes with actual field observations, allowing the calculation of metrics such as overall accuracy and the kappa coefficient. UAV-derived spatial products were used to map pine stand distribution and classify trees into height classes. Field validation was conducted by cross-checking UAV-based classification results with field-measured dendrometric data collected during the forest inventory. The consistency between UAV-derived spatial information and field data confirmed the reliability of the spatial analysis and supported its integration with dendrometric measurements for regression modelling and the delineation of potential resin tapping zones.

Pine resin production was estimated using regression models. The general form of the regression Equation (1) was:

$$Y = b_0 + b_1 \cdot X + \alpha_0 \cdot Z + \alpha_1 \cdot (X \cdot Z) + \varepsilon, \quad (1)$$

where: Y is the predicted resin yield; X is the independent variable; Z is the supporting variable; $(X \cdot Z)$ is the interaction term between X and Z ; b_0 is the intercept; b_1 , α_0 , and α_1 are regression coefficients; and

ε is the error term.

Multiple regression analysis was then applied to estimate pine resin production based on DBH and tree height. The full regression model is given in Equation (2):

$$Y = b_0 + b_1 \cdot DBH + b_2 \cdot H + b_3 \cdot DBH \cdot H, \quad (2)$$

where: Y represents the estimated pine resin yield ($\text{kg} \cdot \text{tree}^{-1} \cdot \text{yr}^{-1}$), DBH is the diameter at breast height (cm), and H is the tree height (m). The interaction term between DBH and H was included to capture potential synergistic effects. b_0 is the intercept, b_1 , b_2 , and b_3 are regression coefficients, and ε denotes the random error term.

The multiple regression model applied in this study follows approaches commonly used in previous research to estimate pine resin yield based on tree morphometric variables. Similar models incorporating DBH and total tree height have been widely applied to analyse resin production in pine species (Rodríguez-García et al. 2015, Suhartati and Attoric 2021, Widjaya and Pradinda 2021). The regression analysis quantified the relationship between resin yield and tree morphometrics, with an interaction term included to capture potential synergistic effects of DBH and tree height. Model performance was evaluated using the coefficient of determination (R^2), which indicates the proportion of variance explained by the model.

Results and Discussion

The reliability of the results in this study is supported by methodological validation. The agreement between UAV-derived spatial analysis and field-measured dendrometric data confirms the accuracy of tree height classification and resin yield estimation. This validation ensures that the observed patterns of resin production

across different height classes reflect actual field conditions rather than artifacts of spatial analysis.

Stand characteristics and height class distribution

Based on the results of field mapping conducted in KTH Abulo Sibatang, Laiya Village, Cenrana Subdistrict, Maros Regency, there are 12,590 recorded pine trees. Field data shows significant variation in tree size, both in terms of DBH and tree height. Table 1 presents the distribution of the number of trees grouped according to tree height class.

Tree height was classified into three classes: low (25–27 m), medium (28–30 m), and high (≥ 30 m). Based on height classification, stands are dominated by the 28–30 m class, which is generally appropriate for stands planted in the 1980s. Relative height growth remains constant after the mature phase, while diameter growth has a greater impact on resin productivity (Audina et al. 2020, García-Méijome et al. 2023).

Estimation of pine resin production based on regression models

Multiple regression analysis indicated that all variables significantly contribute to resin production. The intercept coefficient was negative value (-2.04), indicating that under conditions of nearly zero DBH and

height, resin production practically does not occur. DBH variable has a positive effect with a coefficient of 0.00055, while the tree height variable has a positive effect with a coefficient of 0.227. The interaction between DBH and height was significant, although its value was very small ($1.55 \cdot 10^{-8}$). The coefficient of determination R^2 was 0.88, indicating that the model explained 88 % of the variation in resin production. This study is in line with previous studies showing that diameter has a significant effect on resin productivity in *P. merkusii*, while tree age does not always have a significant effect (Suhartati and Attoric 2021). Another study in Gunung Walat Educational Forest also showed that the best model included diameter and height with an R^2 value of approximately 66 % (Widjaya and Pradinda 2021).

As a result, these estimates support the evidence that DBH and tree height can be used as reliable indicators for predicting pine resin production. In practice, this model can be used for quick estimates of production potential in stands without the need to measure resin per tree. However, it is important to note that the data used in this study are derived from a combination of field data and model estimates. Estimated pine resin production based on the multiple regression model is presented in Table 2.

Production estimates based on multiple regression models with DBH and tree height variables are dominated by the me-

Table 1. Distribution of tree numbers and estimated resin production based on height class.

Height class	Average height, m	Area, ha	Number of trees	Estimated total production, kg·yr ⁻¹	Production, kg·ha ⁻¹ ·yr ⁻¹
Low (25–27 m)	25.98	25.30	3,708	11,124	439.7
Medium (28–30 m)	28.99	33.77	6,878	28,888	855.5
High (≥ 30 m)	37.46	14.20	2,004	11,022	776.1
Total			12,590	51,034	

Table 2. Estimation pine resin production based on the multiple regression model.

Height class	Number of trees	Average DBH, cm	Average height, m	Estimated production, kg·tree ⁻¹ ·yr ⁻¹	Total production estimate, kg·yr ⁻¹
Low (25–27 m)	3,708	42.14	25.98	471.04	11,917.37
Medium (28–30 m)	6,878	47.00	28.99	778.65	26,295.16
High (≥30 m)	2,004	42.14	37.46	781.62	11,098.97
Total	12,590				49,311.51

Note: DBH values in this table represent proportional adjustments from the regression model to maintain data consistency. The regression coefficients for DBH and DBH·Height interaction were rescaled ($\beta_1' = 0.01533$; $\beta_3' = 4.32 \cdot 10^{-7}$).

dium class. The model used in estimating pine resin production demonstrates a pattern consistent with tree physiology theory, in which both diameter and height simultaneously influence a tree's potential to produce resin (Suhartati and Attoric 2021).

Comparison of production estimates based on height class and regression model

A comparison of the estimation results shows a difference in method between classification based on tree height and estimation using a regression model. Estimates from height classes show that forests with medium heights (28–30 m) contribute to total production because they have the largest number of trees. In contrast, estimates using regression models show a more biologically consistent pattern in which production per tree tends to increase in the tall class (≥30 m), although total production is still dominated by the medium class. These results are in line with previous studies that emphasise the importance of dendrometric variables as predictors of resin production, both in *P. merkusii* in Indonesia and *P. pinaster* in the Mediterranean region (Suhartati and Attoric 2021, Widjaya and Pradinda 2021).

In comparing resin yield estimation based on tree height classes and regression models, statistical validation is a crucial component to ensure that the regression model provides accurate predictions and good generalisability. Yates et al. (2022) emphasise that, in ecological modelling, cross-validation is an essential method for evaluating model predictive performance beyond the training dataset, recommending approaches such as leave-one-out or k-fold cross-validation to reduce bias and improve the reliability of predictions.

Furthermore, studies assessing cross-validation strategies for UAV-based yield prediction indicate that the choice of validation protocol – such as random cross-validation, spatial cross-validation, or leave-one-field-out – can significantly influence a model's ability to generate predictions transferable across different domains or regions (Habibi et al. 2024). This highlights the importance of selecting and implementing appropriate validation strategies when developing regression model for forest yield estimation.

Another study by Babakos et al. (2024) further demonstrates that the application of random cross-validation in predictive regression can result in more robust regression coefficients and more realistic error estimates compared to reliance solely

on traditional training-based performance metrics. This indicates that cross-validation not only improves estimation accuracy but also enhances the overall reliability and stability of regression models.

Accordingly, previous studies have emphasised the importance of cross-validation and residual analysis in enhancing the robustness and generalisability of regression-based yield estimation models. Such approaches highlight the need for careful model evaluation to prevent overfitting and ensure reliable prediction across varying forest conditions.

Relationship between land potential and pine resin production

Potential mapping was conducted by integrating field data (DBH, tree height, and tree diameter) and remote sensing products (drones and DEM) to obtain canopy height. Recent studies have shown that height estimates from UAV/CHM can achieve high accuracy when compared to field height, making them effective in mapping spatial variations in stands (Wu et al. 2023).

Statistically, the amount of resin produced per tree increases in taller classes. This is in line with the latest analysis that tree dimensions determined by DBH and height, season, and tapping techniques are the main factors affecting resin variation. Based on the analysis, a positive relationship was found between tree height and estimated resin yield. Trees in the tall

class have a higher average production compared to the low class. Estimated resin production by height class is presented in Table 3.

The dominance of this class makes this group the main contributor to resin production, accounting for more than 50 % of total production (Fig. 2). This finding confirms the positive correlation between tree size and resin production. Diameter at breast height is the most widely studied dendrometric variable, and there is generally a positive relationship between it and resin production. In addition, pine tree stem diameter and number of taps have a positive effect on resin production. With an average diameter of approximately 42.68 cm and 7 taps, they reported a maximum production of 448 grams per tree. This reinforces the finding that tree morphometry (including diameter) is an important predictor in estimating resin production (Rodríguez-García et al. 2015, Febriani et al. 2024).

Factors influencing resin production

a) Tree morphometry

DBH as a key indicator correlates positively with resin yield in various pine species and growing locations. In *P. pinaster*, production increases with DBH, while in *P. elliottii* Engelm. × *P. caribaea* Morelet, DBH correlates with higher resin content. In a study of *P. merkusii* in Indonesia, diameter was reported to affect resin production (Garcia et al. 2023). These find-

Table 3. Estimated pine resin production based on height class.

Height class	Estimated production, kg·tree ⁻¹ ·yr ⁻¹	Number of trees	Total production estimate, kg·yr ⁻¹
Low (25–27 m)	3.0	3,708	11,124
Medium (28–30 m)	4.2	6,878	28,888
High (≥30 m)	5.5	2,004	11,022
Total		12,590	51,034

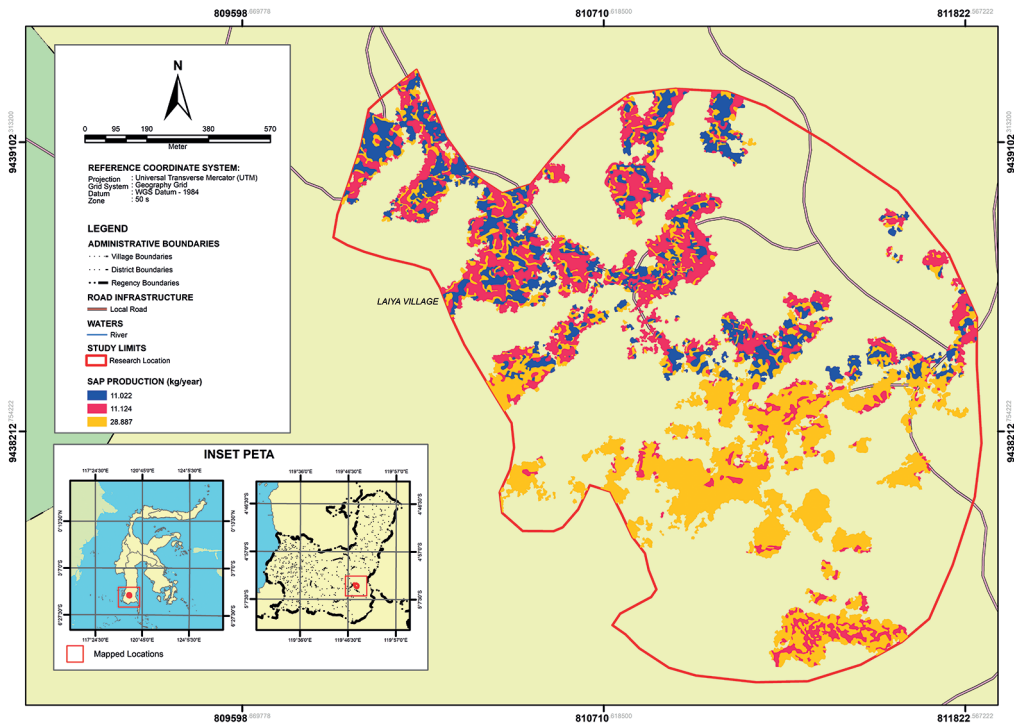


Fig. 2. Map of potential pine resin tapping locations.

ings support those of Irawan et al. (2024), who showed that the resin productivity of *P. merkusii* increases with tree diameter. In their study in the Gunung Manglayang Protected Forest, trees with a diameter of 50–55 cm produced an average of 30.89 g of resin per tree over a period of 7 days, higher than the 20–25 cm diameter class, which only produced 18.55 g per 7 days. These findings are in line with the regression model in this study, which shows that trees with large DBH tend to have higher production.

b) Environment and location

Weather conditions and landforms also influence production variations. *P. merkusii* located in areas with moderate rainfall ($<2,000 \text{ mm}\cdot\text{yr}^{-1}$), temperatures of 22–

28 °C, and altitudes of 400–700 m a.s.l. produce more resin than trees in locations with high rainfall or altitudes $>700 \text{ m a.s.l.}$ (Lukmandaru et al. 2021). Conditions in Maros District, which fall within this range, are quite conducive to optimal pine resin production potential.

Although Lukmandaru et al. (2021) stated that the optimal potential for pine resin production is at an altitude of 400–700 m a.s.l. with moderate rainfall conditions, research by Haryani (2023) in KPH Kedu Utara found that the highest productivity was obtained at an altitude of 700–999 m a.s.l., especially in age class V. This difference indicates that the influence of the environment on resin production is not linear but is also influenced by age and stand conditions, meaning that locations above 700 m a.s.l. can still pro-

duce optimal yields when combined with the appropriate age class and season.

c) Tapping techniques

Variations in tapping height, wound size, and the use of stimulants affect the volume of resin produced. At the research site, tapping was relatively uniform, but differences in individual tree conditions still caused variations in yield. The results of the study by Gustawan and Nugroho (2024) show that resin productivity is not only influenced by physiological factors of the tree, such as diameter and height, but is also greatly determined by human factors, particularly the skills of the tapper, work intensity, and tapping methods. These findings are consistent with the regression results in this study, which emphasise the importance of dendrometric variables in production estimation, while also reminding us that external factors in the field can strengthen or weaken the production potential predicted mathematically. Several other studies, such as the research by Evayanti et al. (2019), mention that resin production increases with the number of taps up to a certain limit, but begins to decline if the number of taps is too high.

Management implications

The results of this study indicate that the application of UAV technology combined with regression-based resin yield estimation at KTH Abulo Sibatang can significantly improve the efficiency of non-timber forest resource management, particularly for pine resin production. Methodological validation through consistency checks between UAV-derived spatial analysis and field-measured dendrometric data supports the reliability of resin

yield estimation. In line with Mukhlisa and Dwiyantri (2021), UAV-based spatial mapping supports more efficient management of non-timber forest products by optimising tapping practices across forest landscapes in Indonesia.

The implementation of a more rigorous validation process provides more reliable estimates of resin productivity, with direct implications for sustainable forest management. The validated model enables forest managers to identify and map highly productive tapping zones more effectively, while reducing pressure on less productive trees and minimising the risk of overexploitation. This is particularly relevant in pine forest systems, where resin represents a high-value non-timber product that contributes significantly to local livelihoods. As explained by Febriani et al. (2024), the use of precise spatial mapping technologies can improve both the quantity and quality of resin production in a controlled manner, thereby reducing ecological disturbance and supporting environmentally sound management practices.

Beyond the local scale, the results indicate strong potential for transferring the proposed approach other regions with comparable pine species and ecological conditions. As noted by Gavilan-Acuna et al. (2025), precision forestry approaches based on UAV-derived spatial data provide robust, data-driven tools for improving forest management and optimising non-timber forest product yields at broader spatial scales.

Furthermore, previous studies, such as Rodríguez-García et al. (2015), have shown that the integration of UAV-based spatial data into pine forests management can enhance resin productivity while reducing ecosystem impacts through more measurable and controlled interventions. Overall, the use of UAV technology cou-

pled with a regression-based estimation model for resin yield estimation not only supports sustainable management at the local level but also presents a scalable approach for improving non-timber forest resource management in pine-dominated forests worldwide.

Conclusions

This study demonstrates that pine resin yield is primarily determined by tree morphometric characteristics, particularly DBH and tree height. Results from the multiple regression analysis indicate that these variables account for a substantial proportion of the variation in estimated resin production. The predominance of the medium height class in total resin yield further emphasises the importance of stand structure in determining production potential. These findings, supported by both spatial analysis and field-measured dendrometric data, confirm that the conclusions drawn are directly underpinned by the applied methods and observed data.

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