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DIFFERENTIATION OF PINE STAND AGE CLASSES THROUGH DISCRIMINANT ANALYSIS

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ABSTRACT: Indonesia's forest ecosystems are essential for both ecological stability and economic productivity. Effective forest management relies on accurate data, with stand tables serving as key tools for understanding forest structure. Traditionally derived from field measurements, stand tables can now be developed using remote sensing data, including aerial photographs. This study explores the potential of photographic variables to distinguish forest age classes in pine plantations managed by Perum Perhutani. Using 40 observations of aerial imagery interpreted for qualitative and quantitative variables, non-hierarchical cluster analysis was applied to group forest stands into six age classes. Discriminate analysis was then conducted to identify significant variables and develop classification functions. The results show that quantitative variables—such as crown cover, crown diameter, and tree height—significantly differentiate forest age classes, while qualitative variables like tone and topography were less effective. The first two discriminant functions explained 98.5% of the variance, confirming their strong discriminatory power. This approach demonstrates that aerial photographic variables, particularly quantitative ones, offer a promising alternative for

forest age classification, enabling more efficient and large-scale forest inventory and planning.

Keywords: *Forest inventory; aerial photography; stand tables; cluster analysis; discriminant analysis; forest age classification; remote sensing; pine plantations; Perum Perhutani; quantitative variables.*

1. INTRODUCTION

Indonesia's forest resources are a vital component of the nation's natural wealth, playing a crucial role not only in generating national revenue but also in maintaining environmental balance. To ensure that forests continue to fulfill both their ecological and economic functions, sustainable and efficient management practices are essential. A fundamental requirement for such management is the availability of reliable data and information on forest resources, which is primarily obtained through forest inventory activities.

Among the standard tools used in forest inventory are tree volume tables and stand tables. Stand tables are particularly valuable because they provide detailed insights into the distribution of trees across diameter classes within a forest stand. These tables not only reflect the current structure of the stand but also serve as a basis for predicting future growth, mortality, and potential timber yield. Traditionally, stand tables are constructed using terrestrial measurements taken directly in the field, such as tree height, diameter, and basal area density.

However, recent advancements in remote sensing technology, especially aerial photography, have opened new opportunities for developing photographic stand tables. These methods are particularly advantageous in remote or inaccessible forest areas. Variables extracted from aerial images, including crown diameter, canopy density, texture, and spectral reflectance, can serve as proxies for field measurements and are increasingly used to estimate forest age, biomass, and structural parameters (Wulder et al., 2004[1]; Lu et al., 2016[2]). Despite their promise, the application of photographic variables in stand table construction is still limited and largely experimental, raising important questions about their accuracy and effectiveness.

To assess the potential of photographic variables, preliminary studies are necessary. One such study focuses on evaluating whether variables derived from aerial photographs can effectively distinguish between forest stand age classes using discriminant analysis. This is particularly relevant in plantation forests managed by Perum Perhutani—Indonesia's state-owned forestry company—where forest areas are typically categorized into 5-year age classes to reflect the interval from planting to harvesting.

The differentiation of age classes using aerial photographic data can be significantly improved by applying multivariate statistical methods, notably **discriminant analysis** and **cluster analysis**. Discriminate analysis is a supervised classification technique designed to distinguish predefined groups based on predictor variables. In forestry, it has gained wide use for classifying forest types, age classes, and structural conditions using both ground-based and remote sensing data (Cohen et al., 1995[3]; Hudak et al., 2008[4]). It identifies the optimal combination of variables that best separates different groups, making it particularly suitable for validating the discriminative power of aerial-derived indicators.

In parallel, cluster analysis—an unsupervised learning method—can be used to identify natural groupings within the data. Techniques such as K-means clustering are effective in grouping forest stands based on characteristics extracted from aerial imagery (Jin & Sader, 2005[5]). This method is useful during the exploratory phase of research and helps guide subsequent supervised classification.

Differentiating forest age classes is critical for effective forest management, as it supports the planning of harvesting rotations, monitoring of forest development, and estimation of ecosystem services such as carbon sequestration. Stratifying forests by age allows managers to allocate resources more efficiently and implement targeted strategies for conservation or timber production (FAO, 2012[6]).

Based on the above understanding, this paper aims to:

1. Group forest age classes from aerial photographs using non-hierarchical cluster analysis based on photographic variables.
2. Identify the aerial photographic variables that play significant roles in differentiating forest age classes through the discriminant analysis approach.

2. THEORETICAL REVIEW

2.1. Variables and Elements of Aerial Photo Interpretation

Aerial photographs, as a product of remote sensing technology, play a crucial role in forest resource inventory activities. Through aerial imagery, valuable information can be extracted, including topography, vegetation types, spatial location, land area, and forest potential. The three-dimensional depiction presented in aerial photography is particularly advantageous, as it allows for a clearer representation of terrain and site models, especially due to vertical exaggeration, and facilitates the creation of contour maps (Sutanto, 1986[7]).

Key variables used in interpreting aerial photographs include tree height, crown diameter, and crown cover percentage. Moreover, visual interpretation relies on several elements such as tone, shape, texture, topography, pattern, size, shadow, and site (Lillesand & Kiefer, 1990[8]; Campbell & Wynne, 2011[9]). These interpretation cues help analysts derive meaningful ecological and geographical information from aerial imagery, enhancing land-cover classification and resource assessment.

2.2. Cluster Analysis

According to Johnson and Wichern (2002)[10], cluster analysis is a statistical technique used to group observations or objects into clusters in such a way that objects within the same group are more similar to each other than to those in other groups. Similarity or dissimilarity is typically measured using specific indices such as Euclidean distance, probability-based indices, or other dissimilarity metrics. This process, also known as classification, often faces challenges in selecting appropriate criteria, as different classification rules may yield divergent outcomes depending on the nature of the observations and classification objectives (Kaufman & Rousseeuw, 2005)[11].

Clustering techniques are broadly categorized into graphical methods, hierarchical techniques, and non-hierarchical (partitioning) methods. Graphical methods include profile plots, Andrews plots, and modified Andrews plots. Hierarchical techniques use distance-based dissimilarity measures and include methods such as single linkage, complete linkage, centroid linkage, median linkage, and average linkage. In contrast, non-hierarchical techniques such as k-means clustering partition data into a pre-specified number of groups (Hair et al., 2010)[12].

Common distance metrics used to assess similarity and dissimilarity include:

- **Euclidean Distance**
- **Manhattan or City-block Distance (Minkowski Distance)**
- **Mahalanobis Distance**, which accounts for variable correlations and scale differences (Johnson & Wichern, 2002)[10].

2.3. Discriminant Analysis

Discriminant analysis is a statistical methodology used for describing and classifying individuals based on measured variables (Lebart, 1984)[13]. As Everitt and Dunn (1990)[14] explain, discriminant analysis is particularly relevant when there are two types of multivariate observations: (1) a training sample with known group memberships (a priori groups), and (2) a test sample where group membership is unknown and must be predicted.

The objectives of discriminant analysis include:

1. Determining statistically significant differences in means between known groups.
2. Establishing procedures for classifying statistical units (individuals or objects) into groups based on variable values.
3. Identifying the variables that contribute most to group separation (Hair et al., 2010)[12].

Common techniques include the **Fisher Linear Discriminant Function, Logistic Discriminant Analysis, Nearest Neighbor Rules, Classification Trees, Kernel Methods, and Minimum Mahalanobis Distance Classifier** (Everitt & Dunn, 1990[14]; Johnson & Wichern, 2002)[10]. Many of these approaches rely on F-tests and require careful attention to underlying assumptions and outliers (Karson, 1982[15]).

While discriminant analysis generally utilizes quantitative variables, categorical predictors can also be incorporated as discriminators (Johnson & Wichern, 2002)[10]. Rusolono (1995)[16] noted that ordination through discriminant analysis can provide clear grouping and separation of sampling units based on species composition and density within different land systems.

2.3.1. Linear Discriminant Function

Supranto (2004)[17] describes the linear discriminant function as a linear combination of predictor variables represented by the equation:

$$D_i = b_0 + b_1 X_{i1} + b_2 X_{i2} + \ldots + b_k X_{ik}$$

Where:

- D_i is the discriminant score for the i-th object,
- X_{ik} is the k-th variable for the i-th object,
- b_k is the discriminant coefficient for the k-th variable.

When the covariance matrices of k populations are equal and misclassification costs are uniform, the classification rule simplifies to a squared distance function:

$d_t^2(x) = (x - \mu_t)'\Sigma^{-1}(x - \mu_t) - 2In(\pi_t)$ An object x is classified into the population with the smallest discriminant distance. If μ_b $t = 1, 2, ..., k$ and Σ are unknown, they are estimated by their sample counterparts $\bar{x}$ and S (Johnson & Wichern, 2002)[10]. This yields a modified version of Fisher's discriminant function accommodating prior probabilities. Posterior probabilities guide the final classification decision, under the constraint that all posterior probabilities sum to one.

2.3.2. Error Rate Estimation

To evaluate classification accuracy in discriminant analysis, error rate estimation is essential. Johnson and Wichern (2002)[10] suggest splitting the dataset into two parts: a **training set** to derive the classification rule and a **test set** to evaluate its performance. The probability of misclassifying observations from population s into population t, denoted P(t|s), helps calculate the misclassification rate:

$$\hat{E}R(s) = \sum_{t=1, t \neq s}^{k} P(t \mid s)$$

The overall error rate for all populations is then defined as the weighted average of individual error rates. When sample sizes are limited, **cross-validation** (or leave-oneout validation) provides an alternative estimate by iteratively omitting one observation, fitting the model, and evaluating performance. However, this method may be sensitive to outliers. Posterior probability-based error estimates can also be used, whereby the posterior probability for the true population reflects the likelihood of correct classification. In linear discriminant analysis, observation xxx is classified into population Πt if: $d_t^2(x) \le d_s^2(x) \forall_s \neq t$

This simplifies to linear conditions involving the discriminant function coefficients, and classification is made into the group with the highest discriminant score.

2.3.3. Quadratic Discriminant Function

If the assumption of equal covariance matrices across groups does not hold, **quadratic discriminant analysis (QDA)** is more appropriate. Here, the classification rule depends on the distinct covariance matrices Σj of each group. The squared Mahalanobis distance becomes: $d_j^{\,2}(x) = (x - \bar{x}_j)' s^{-1} (x - \bar{x}_j) + In|s_j| - 2In(\pi_t)$; $j = 1, 2, ..., k$. The object is assigned to the group with the smallest distance. Although the posterior probability formula remains the same as in LDA, the discriminant function is now quadratic.

2.3.4. Variable Selection in Discriminant Analysis

A common issue in discriminant analysis involves determining the optimal number of variables that effectively explain group classification. This problem arises from multicollinearity or redundancy among predictor variables. Selecting an appropriate subset of variables is critical for model interpretability and performance. Stepwise selection techniques or principal component analysis can be employed to address this (Hair et al., 2010)[12].

3. METHOD

3.1. Data

The data used in this study were obtained from the interpretation and measurement of aerial photographs across various age classes. The variables include tone (X1), shape (X2), texture (X3), topography (X4), and pattern (X5), as well as percentage of crown cover (X6), crown diameter (X7), and tree height (X8) in pine stands located in the North Bandung Forest Management Unit (KPH Bandung Utara), West Java. These data were obtained from a study conducted by Adi (1998)[18].

The variables used in this research are as follows:

- **Tone** (expressed on a scale from 1 to 3, representing light gray, gray, and dark gray),
- **Shape** (expressed on a scale from 1 to 3, representing somewhat regular, regular, and irregular),
- **Texture** (expressed on a scale from 1 to 3, representing somewhat coarse, coarse, and fine),
- **Topography** (expressed on a scale from 1 to 3, representing flat, moderate, and steep),
- **Pattern** (expressed on a scale from 1 to 3, representing irregular, somewhat regular, and regular),
- **C** (crown cover percentage),
- **D** (crown diameter in meters), and
- **H** (tree height in meters).

These variables can be grouped into two categories: qualitative variables (tone, shape, texture, topography, and pattern) and quantitative variables (crown cover percentage, crown diameter, and tree height).

3.2. Data Analysis

The data analysis involved non-hierarchical cluster analysis using 40 different observations, combined with additional information on six age classes to determine which observations belong to each age class. Based on the observations within each age class, discriminant analysis was then conducted to derive discriminant functions for each age class. The reliability of the discriminant functions was tested through validation using 10 additional observations not included in the function development process.

The estimation of classification error rates was used to assess the reliability of the discriminant functions, by determining the rate of misclassification based on the 10 validation observations. An object is classified into a particular age class if it has the highest discriminant score (Johnson and Wichern, 2002)[10].

4. RESULTS AND DISCUSSION

4.1. Cluster Analysis Results

Based on the non-hierarchical cluster analysis using SPSS and assuming 6 clusters (representing age classes), a complete classification was obtained as shown in Appendix 1, while a summary of clusters and their members is presented in Table 1.

Table 1. Number of members in each cluster (age class)

No.	Cluster Members	Total
1	1, 2, 3, 4, 5	5
2	23, 24, 25, 38, 39, 47	6
3	20, 21	2
4	6, 7, 9, 11, 12, 13, 14, 17, 22, 27, 28, 30, 41, 42, 44, 45	16
5	8, 32, 33, 34, 35, 36, 37, 48	8
6	10, 15, 16, 18, 19, 26, 29, 31, 40, 43, 46, 49, 50	13

The choice of 6 clusters is consistent with the initial assumption based on the primary research data, which categorizes observation samples into six age classes. Therefore, each resulting cluster is interpreted as representing a specific age class.

The classification results in Table 1 differ from the initial classification derived from visual interpretation of aerial imagery. This discrepancy is likely due to the differing classification approaches. The original classification was qualitative and based on subjective interpretation of aerial photographs, while the non-hierarchical clustering approach applies objective mathematical analysis of variables extracted from the images. For subsequent analysis, the classification obtained via non-hierarchical cluster analysis was used.

4.2. Discriminant Analysis and Variable Testing

Before performing discriminant analysis, the classified data were split into two parts: 40 samples for constructing the discriminant function and 10 samples for validation, selected randomly. The discriminant analysis identifies which variables significantly differentiate clusters, as shown in Table 2 using Wilks' Lambda test.

Table 2. Wilks' Lambda test for equality of cluster means

Variable	Wilks' Lambda	F	p-value
Tone	0.746	2.312	0.065
Shape	0.520	6.287	0.000
Texture	0.685	3.127	0.020
Pattern	0.855	1.154	0.352
Topography	0.876	0.962	0.455
C	0.035	189.147	0.000
D	0.223	23.675	0.000
H	0.195	28.038	0.000

From Table 2, it is evident that almost all variables can significantly differentiate between clusters at the 5% significance level, except for tone, pattern, and topography. These variables are qualitative and rely heavily on the subjective skills of the interpreter. In contrast, the quantitative variables show stronger discriminative power, as reflected by higher F-values and lower Wilks' Lambda values. This supports previous research that shows quantitative metrics derived from remote sensing data (e.g., spectral, structural, or textural indices) often yield more objective classification results than purely visual interpretations (Lillesand et al., 2015[19]; Jensen, 2016[20]).

4.3. Discriminant Function Performance

Table 3 presents the percentage of variance explained by each discriminant function.

Table 3. Variance explained by discriminant functions

Function	Eigenvalue	% Variance	Cumulative %
1	59.482	91.4	91.4
2	4.601	7.1	98.5
3	0.583	0.9	99.4
4	0.296	0.5	99.9
5	0.129	0.2	100.0

The first two functions explain 98.5% of the total variance, indicating that most of the cluster separability can be attributed to these two functions. This is consistent with Fisher's Linear Discriminant principle, which seeks to maximize between-group variance relative to within-group variance (Klecka, 1980[21]).

4.4. Discriminant Function Formulas

The derived discriminant functions for each age class cluster using Minitab software are shown in Table 4.

Table 4. Discriminant functions based on aerial image variables

Labeling	Discriminant Function
1	-69.77 + 15 X1 + 23.93 X2 – 2.04 X3 + 15.15 X4 + 22.52 X5 + 1.36 X6 + 6.31 X7 – 1.26 X8
2	-389.79 + 30.21 X1 + 65.22 X2 – 16.26 X3 + 30.77 X4 + 48.84 X5 + 4.75 X6 + 21.17 X7 – 2.57 X8
3	-316.49 + 22.33 X1 + 65.31 X2 – 14.29 X3 + 26.80 X4 + 46.22 X5 + 4.53 X6 + 19.14 X7 – 3.65 X8
4	-543.12 + 30.05 X1 + 72.91 X2 – 17.14 X3 + 31.85 X4 + 55.09 X5 + 6.66 X6 + 24.31 X7 – 4.32 X8
5	-552.70 + 30.74 X1 + 74.84 X2 – 18.49 X3 + 32.30 X4 + 55.13 X5 + 6.51 X6 + 25.88 X7 – 3.93 X8
6	-431.51 + 26.27 X1 + 71. 52 X2 – 17.62 X3 + 30.68 X4 + 50.73 X5 +5.58 X6 + 22.70 X7 – 3.65 X8

(Note: X1 to X8 represent the respective aerial photo variables such as tone, shape, texture, etc.) (Refer to the original table for formulas.)

These functions allow the assignment of new observations to specific clusters based on discriminant scores, where the highest score determines cluster membership.

4.5. Validation and Cross-Validation Results

To test the reliability of the discriminant functions, a validation was performed using 10 samples. All were correctly classified, indicating 100% classification accuracy (Table 5).

Table 5. Discriminant function testing

Label	X1	X2	X3	X4	X5	X6	X7	X8	Classification	Discriminant Score (Di)					
										1	2	3	4	5	6
1	2	1	1	2	3	0	0	0	1	**80**	-72	-29	-198	-205	-112
2	3	3	3	3	3	40	8.45	29.39	2	225	**380**	358	320	334	361
4	3	2	1	2	2	95	4.29	13.13	4	236	483	478	**530**	523	515
4	3	3	3	2	3	85	3.6	16.56	4	256	493	489	**525**	520	518
4	3	3	3	1	3	9	3	18.2	4	24	47	46	**50**	49	49

						0				2	0	8	**5**	8	6
5	2	3	4	1	3	90	10.72	32.16	5	256	551	528	585	**594**	576
5	3	3	4	2	2	80	8.69	28.65	5	242	481	460	491	**498**	494
6	2	3	4	3	3	60	7.41	19.36	6	241	432	429	424	428	**442**
6	3	3	3	1	3	65	5.91	16.78	6	228	416	415	416	416	**428**
6	3	3	4	1	3	65	5.34	22.33	6	215	373	370	361	361	**377**

Table 6. Cross-validation results (selected view)

Original Class	**Observations**	**Classification by Function**					
		1	2	3	4	5	6
1	4	4 (100%)	0	0	0	0	0
2	5	0	5 (100%)	0	0	0	0
3	2	0	0	2 (100%)	0	0	0
4	13	0	0	0	12 (92,3%)	1 (7,7%)	0
5	6	0	0	0	0	6 (100%)	0
6	10	0	1 (10%)	0	1 (10%)	1 (10%)	7 (70%)

Cross-validation, a more stringent method especially with smaller sample sizes, showed an overall misclassification rate of 10%. The highest misclassification was observed in Cluster 6, possibly due to internal variability within this group or overlap in variable characteristics with other clusters. Nevertheless, the general performance of the discriminant functions was satisfactory and aligns with findings from other forestry or ecological classification studies that used discriminant analysis with remote sensing data (Foody, 2002[22]; Franklin, 2001[23]).

5. Discussion

This study successfully applied a non-hierarchical cluster analysis followed by discriminant analysis to classify forest stand age using remote sensing data, particularly aerial imagery. The results highlight the strengths of quantitative variables in distinguishing age classes of forest stands, which is consistent with the growing body of literature emphasizing the importance of objective metrics for land use and vegetation classification.

5.1. Cluster Analysis and Age Class Identification

The cluster analysis results, where six distinct age classes were identified, reflect the efficiency of non-hierarchical methods in handling large-scale and complex datasets. The classification of the samples into six clusters was consistent with the initial hypothesis based on field observations, underscoring the reliability of this analytical approach in ecological studies. Recent studies have similarly demonstrated the power of non-hierarchical clustering techniques for managing diverse forest data. For example, Xu et al. (2018)[24] utilized k-means clustering to differentiate land cover types in temperate forests, reporting significant improvements in classification accuracy compared to traditional hierarchical methods.

5.2. The Role of Quantitative Variables

The discriminant analysis showed that quantitative variables, such as shape and texture, provided a higher discriminatory power than qualitative variables, such as tone and pattern. This observation is supported by recent advancements in remote sensing and image classification techniques, where quantitative metrics derived from spectral bands, texture features, and other image-derived indices have consistently been found to outperform subjective visual interpretation (He et al., 2019[25]; Gislason et al., 2014[26]). For example, He et al. (2019)[25] demonstrated the superior performance of texture-based variables in differentiating forest stand structures, aligning with our findings where texture played a significant role in classifying classes.

Moreover, the discriminative power of quantitative variables aligns with the advancements in machine learning and deep learning approaches for classification tasks in ecological studies. Recent literature highlights the integration of machine learning algorithms with remote sensing data to enhance the classification of vegetation types (Zhang et al., 2021)[27]. These techniques automatically extract relevant features from images, reducing the reliance on human interpretation and offering more scalable solutions for large datasets.

5.3. Discriminant Function Accuracy and Cross-Validation

The discriminant functions derived in this study achieved a high level of classification accuracy during both initial testing (100%) and cross-validation (90%), suggesting that the discriminant analysis method used is reliable for classification tasks in forest monitoring. The cross-validation results, although slightly less accurate, are in line with other studies that have examined the robustness of discriminant analysis in land cover classification. For instance, Gislason et al. (2014)[26] reported similar cross-validation performance in their study on forest structure classification, with some misclassifications arising due to inherent variability in forest data and overlap between certain class features.

The misclassification rate of 10% in cluster 6, observed in the current study, may be attributed to the intrinsic heterogeneity within that particular class. Similar findings were reported by Liang et al. (2020)[28], who used discriminant analysis on forest canopy types, noting that certain canopy types exhibited significant internal variability, which resulted in misclassifications despite high overall accuracy. This suggests that further refinement of classification methods, such as incorporating additional variables or hybridizing techniques with machine learning models, could reduce the misclassification rates in future studies.

5.4. Literature on Remote Sensing and Discriminant Analysis

Recent research has increasingly focused on combining discriminant analysis with other statistical or machine learning methods to improve classification performance. Studies by Li et al. (2016)[29] and Zhang et al. (2021)[27] highlight the complementary use of discriminant analysis with random forests and support vector machines (SVM) for more accurate land cover classification. These hybrid approaches leverage the strengths of both traditional statistical methods and advanced machine learning algorithms, offering promising results for future applications in forest management and ecological studies.

Furthermore, the importance of multispectral and hyperspectral data in forest stand classification has been extensively documented in recent literature. Gislason et al. (2014)[26] emphasized the value of spectral diversity in distinguishing various forest types and age classes, a concept that aligns with the approach taken in this study, where texture and shape were critical features derived from the aerial images. Advances in remote sensing technology, such as the development of higher resolution imagery and better spectral bands, are further enhancing the capabilities of remote sensing in ecological studies (Zhang et al., 2021)[27].

5.5. Implications for Forest Management

The results from this study offer significant implications for forest management and ecological monitoring. By accurately classifying forest stands into age classes, forest managers can better understand stand dynamics, structure, and biodiversity. Age-class distribution is a key indicator of forest health, influencing decisions on sustainable logging, regeneration practices, and biodiversity conservation (Germino et al., 2013)[30]. The ability to classify forest stands using objective, automated methods also improves the efficiency of monitoring efforts, particularly in large, inaccessible forest areas.

Recent literature further underscores the relevance of this approach to sustainable forest management. For example, Ferraz et al. (2021)[31] highlighted the potential of remote sensing techniques, combined with machine learning, for monitoring forest regeneration and health at a landscape scale. These methods can provide real-time data on forest dynamics, helping to predict changes in forest structure due to climate change or human intervention (Xu et al., 2018[24]). In this context, the methods employed in this study can be seen as a step toward integrating remote sensing-based monitoring systems into broader forest management frameworks.

6. Conclusion

The application of non-hierarchical clustering and discriminant analysis in forest stand classification is a promising approach for enhancing forest management practices. This study's results contribute to the growing body of literature advocating for the use of quantitative metrics and advanced statistical techniques in ecological classification tasks. Further refinement of these methods, particularly through the integration of machine learning and multi-source data, could provide even more accurate and scalable solutions for forest monitoring.

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