INVESTIGATION OF CORELATION BETWEEN OIL PALM AGE AND CROWN PROJECTION AREA (CPA) BASED ON UNMANNED AERIAL VEHICLE (UAV)

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ABSTRACT

Monitoring of oil palm age is very important for estimating production, diseases and tax estimation. One of the technic for monitoring of oil palm age is based on unmanned aerial vehicle (UAV). UAV technologies is promissing technology can be detected Crown Projection Area (CPA) of oil palm plantation. The aim of this study is to investigate correlation between oil palm age and crown projection area (CPA) based on unmanned aerial vehicle (UAV) The study area is in Oil palm Plantation of PTPN III Sei Dadap, Asahan Regency, North Sumatra, Indonesia. The methodology includes oil palm UAV acquisitions, pre-processing, orthophoto, estimating CPA by using object-based image analysis (OBIA) and correlating with oil palm age. The result show for CPA estimation using OBIA classification with multiresolution segmentation technique with various parameters includes parameter scale from 100 to 300, shape 0.4 to 0.5, and compactness 0.4 to 0.5. The correlation of CPA with oil palm age having quadratic model $y=-0.0353x^2+1.0288x+4.0366$ with $R^2=0.74$.

Keywords: Oil palm, UAV, OBIA, and CPA.

1. INTRODUCTION

Oil palm is a palm tree species that grows in over 43 tropical nations, typically between 10° N and 10° S at the equator (Darmawan et al., 2021). Oil palm is a plantation crop product that is an essential foundation of industry in Indonesia (Carolita et al., 2017). Oil palm also helps to improve the community's quality of life, especially in the economic, social, and environmental domains (Darmawan et al., 2021). The entire land area of oil palm plantations is around 14.62 million hectares, with a total CPO production of 45.12 million tons (Carolita et al., 2021). The national oil palm industrial sector and the palm oil plantation sector have become one of key components of the Indonesian economy due to their large area and high CPO production (Carolita et al., 2019). The climate, soil and topography of the region are the main environmental factors that influence the success of oil palm growth, in addition to other factors such as plant materials and technical cultural treatment given (Chemura et al., 2015).

The planting and phenology of the oil palm (Figure 1) is a significant factor that affects the growth of fruit bunches. It has a major role in estimating the production of oil palms since their growth follows a certain pattern and their morphological features may be used to identify their phenology (Hernawati et al., 2022). The oil palm has the potential for commercial cultivation for a period ranging from 20 to 25 years. The plant shows significant height and offers challenges in terms of harvesting when it reaches the age of 25 years (Lubis, 2008). Additionally, the yield of fruit bunches is significantly limited, making the cultivation of such plants not profitable beyond this age.

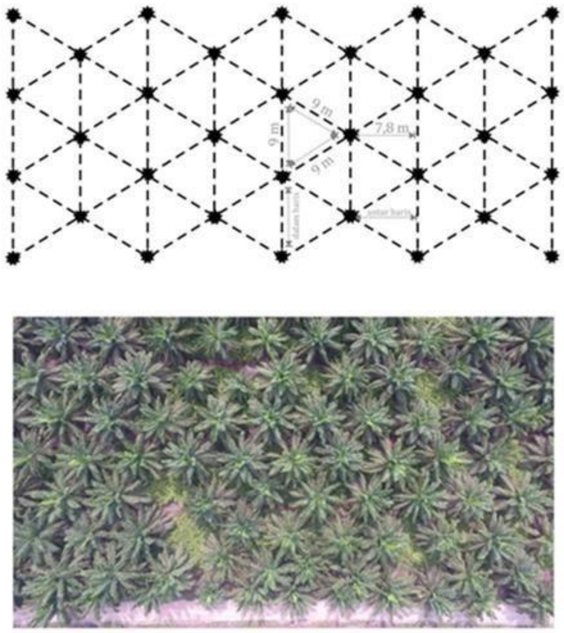

Figure 1. Planting pattern of Oil Palm (Lubis, 2008)

The oil palm cultivation has an economic life cycle that covers around 20 to 25 years, starting from a beginning planting phase in nurseries for 11 to 16 months. The first harvest is usually produced within 32 to 38 months after planting, while peak production is reached between 5 to 10 years after the first planting. The number of trees per hectare, ranging from 128 to 148, is based upon factors such as plant material, soil type, and present climatic conditions. The recommended planting configuration requires a triangular arrangement with a spacing of 9 meters by 9 meters, with an average of 143 trees per hectare (Tinker, 2016). All these trees are based on the morphological or physical caracteristics of oil palm. The morphological of oil palm can be monitored by studying the biophysical parameters such as height, crown size, and vegetation vigor (Chong et al., 2017). Spectral reflectance based vegetation indices are effective in monitoring vegetation vigor and phenological parameters (Suab et al., 2019). Several biophysical parameters such as leaf area index (LAI), crown diameter, crown projection area (CPA), vigor, and tree height are positively correlated with the plant growth stage (Avtar et al., 2020).

The height of oil palm stems increases by around 45 cm per year, depending on the age of the tree, nutritional availability, soil conditions, climate, and plant genetics (Chemura et al., 2015). Fruit of various hues follows, ranging from black to purple to red. The fruit grows in bunches from each stalk. The fruit produces oil, and the oil content increases as the fruit matures. As a result, it is important to determine the width of the oil palm canopy based on age. Considering the size of Indonesia's oil palm plantation, it is important to have technologies that can measure canopy width based on age on a large scale. The Crown Projection Area (CPA) is a biophysical measure that has been found to have a correlation with age, as demonstrated by Chong et al. (2017) (Chong et al., 2017). McMorrow (2001) observed a positive linear correlation between oil palm crown projections and age during the early growth phase of oil palm trees, which is between the age range of 2 to 13 years (McMorrow, 2001). Avtar et al (2020) has explores the use of UAV derived NDVI and CPA of young oil palm to detect the health conditions (Avtar et al., 2020).

The utilization of unmanned aerial vehicles (UAVs) for remote sensing purposes has led to significant innovations in the actual field. This technological advancement has enabled more accurate detection of variations in biophysical parameters as compared to observations conducted by satellite-based methods (Avtar et al., 2020). The aim of this study is to investigate correlation between oil palm age and crown projection area (CPA) based on unmanned aerial vehicle (UAV) The study area is in Oil palm Plantation of PTPN III Sei Dadap, Asahan Regency, North Sumatra, Indonesia.

2. MATERIAL AND METHOD

2.1 Data

This study uses data including the orthophoto data was acquired using the operation of an Unmanned Aerial Vehicle (UAV) during field acquisition conducted from November 17th to 20th, 2022. The UAV aircraft was flown at an altitude of 100 meters from the takeoff location. As a result, the Ground Distance value

Sampling (GSD) was determined to be 3 centimeters. The oil palm plantation block data, and field measurements of oil palm planting year.

2.2 Methodology

The methodology (Figure 2) includes oil palm UAV acquisitions, pre-processing, orthophoto, the method to estimate CPA by using object-based image analysis (OBIA) and correlating with oil palm age.

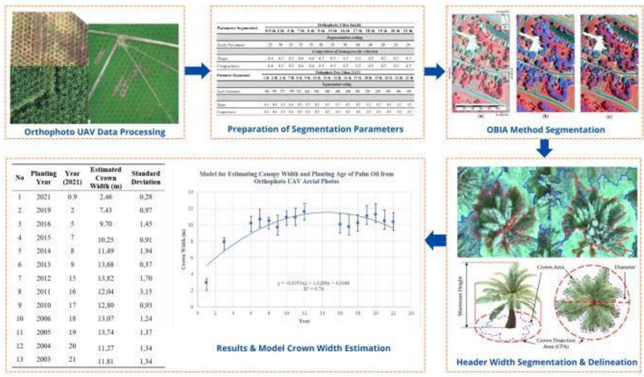

Figure 2. Methodology

2.2.1 Processing

Processing (Figure 3) is performed on aerial photo data obtained from Unmanned Aerial Vehicle (UAV) processing, beginning with aligning the acquired aerial photos, searching for the camera position and orientation for each photo, and then building a sparse point cloud model, followed by the point dense cloud stage, where the aerial photo results are displayed (Dubois et al., 2017). The camera depth information is combined and calculated, and then the point cloud results, which are already point dense clouds, are carried out by solving Structure Form Motion (SfM), followed by the filtering process to carry out orthomosaic processing, followed by the geometric correction process and point cloud classification.

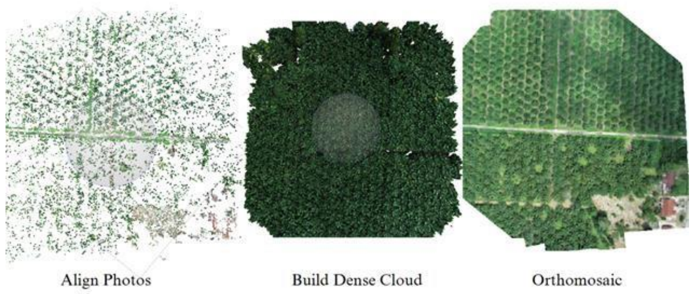

Figure 3. Processing of UAV orthophoto

2.2.2 OBIA Classification

Object-Based Image Analysis (OBIA) classification is a classification methodology that includes both spectral and spatial characteristics of objects (Thenkabail, 2015).

The application of OBIA involves a segmentation process that aims to create homogenous objects (Rizeei et al., 2018). This method combines pixels with based on their spectral values, creating the formation of areas with similar or identical spectral characteristics (Blaschke, 2010). Subsequently, the orthophoto data needs processing with the aim of estimating the width of the palm oil canopy. This can be done by using multiresolution segmentation algorithms to group pixels collectively and generate individual objects. The multiresolution segmentation approach involves the adjustment of parameters such as scale, shape, and compactness. Once the parameters have been determined, a segmentation of the canopy width is created according to the age of the oil palm (Figure 4).

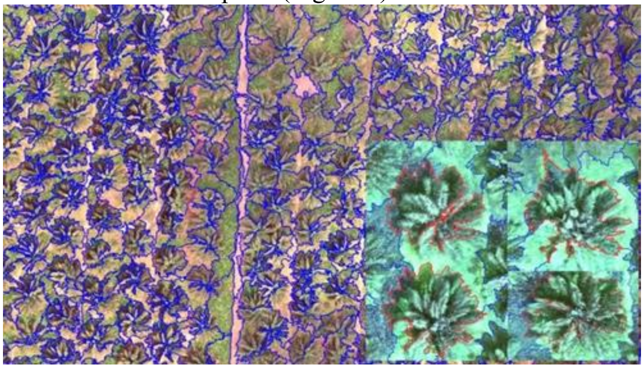

Figure 4. Segmentation the Caopy of Oil Palm

The segmentation results of the orthophoto data were obtained by measuring the crown width, which was determined by measuring the diameter of the crown projection area. This projection area was generated based on the outer boundary of the crown region as identified in the segmentation findings. The measurement of canopy (Figure 5) width has been collected for a sample of 10 trees at various stages of oil palm plantation growth.

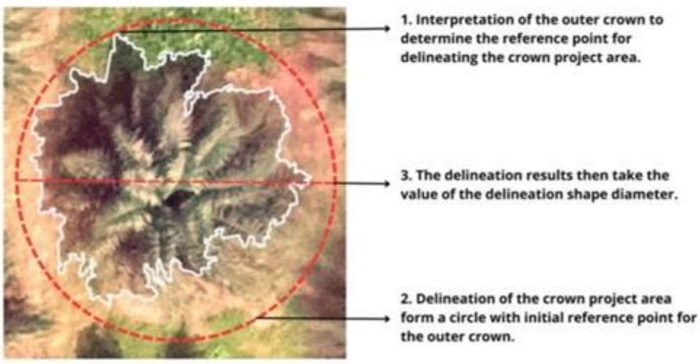

Figure 5. Estimation of Canopy Crown

3. RESULT AND DISCUSSION

Based on the results of estimating the width of the palm oil canopy from the Umaned Aerial Vehicle (UAV) Aerial Photo orthophoto, it was found that the lowest crown width value was at the age of 1 year with a value of 2,979 meters, while the highest canopy width was at the age of 12 years with a value of 11,621 meters (Figure 6 and Table 1). with the second order polynomial regression model, the coefficient of determination (R^2) is 0.74 (Figure 7)

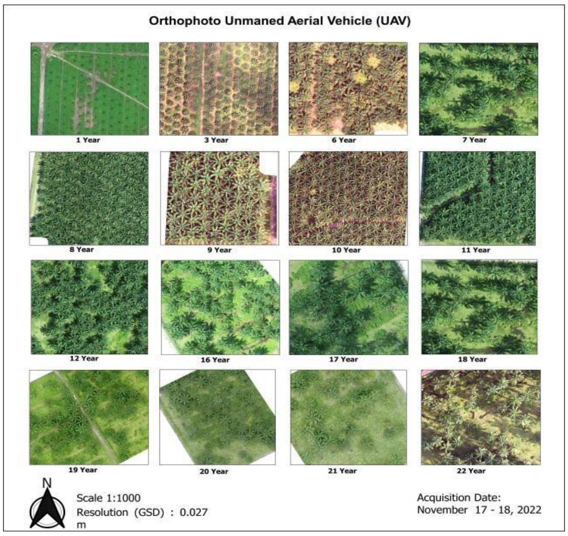

Figure 6. Oil palm crown for various age

Table 1. Crown Width Estimation

Planting Year	Age (year)	Crown Width (m)	rmse
2021	1	2,98	0,45
2019	3	7,92	0,51
2016	6	10,19	0,85
2015	7	10,68	1,21
2014	8	10,50	0,43
2013	9	9.73	1,45
2012	10	10,96	0,73
2011	11	10,90	1,15
2010	12	11,62	0,97
2006	16	10,03	1,30
2005	17	9,76	1,51
2004	18	10,24	1,01
2003	19	11,08	1,27
2002	20	11,28	1,30
2001	21	10,48	1,33
2000	22	10,32	1,17

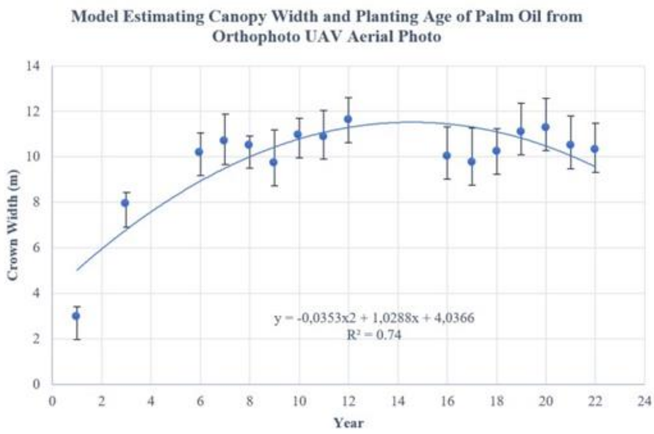

Figure 7. Correlation Crown Width with Oil Palm Age

4. CONCLUSSION

The estimation of CPA (Change Point Analysis) is performed utilizing the OBIA (Object-Based Image Analysis) classification methodology, specifically employing the multiresolution segmentation method. This approach involves the utilization of several factors, namely the scale parameter ranging from 100 to 300, the shape parameter varying between 0.4 and 0.5, and the compactness parameter ranging from 0.4 to 0.5. The relationship between CPA (Crude Palm Oil) and the age of oil palm trees may be described by a quadratic model, represented by the equation $y = -0.0353x^2 + 1.0288x + 4.0366$, where y represents the CPA and x represents the age of the oil palm trees. The coefficient of determination (R^2) for this model is 0.74.

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