THE USE OF AERIAL PHOTOGRAPHS FOR PADDY RICE PHENOLOGY ESTIMATION

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ABSTRACT: In the world of traditional paddy rice cultivation, the farmers need the assistant to enhance both yield production and paddy rice growth. The aerial photograph of UAVs exists as one of the solutions. This contribution will help farmers to estimate the time requires for harvesting and also predict the yield. Several aerial photographs used to estimate the paddy rice phenology using object-based image analysis (OBIA) and the minimum distance classification techniques. In contrast, the estimated paddy leaves chlorophyll obtained based on the model, namely UAV chlorophyll regression (UCR). Both results must be inline. The phenology stages and estimated chlorophyll has increased together before it must decrease before harvested. The classification result has given the paddy field into nine classes of phenology stages. Besides that, the UCR unable to detect chlorophyll properly, and it becomes the sources of error.

1. INTRODUCTION

Besides that, several methods have used for determining the chlorophyll content from the plant. It started from the empirical data obtained in the laboratory, performing field survey for direct measurement using handheld chlorophyll equipment (Ghazali et al., 2020), and the used of multi-sensor of satellite data (Mainly, optical data) have become a great choice (Ying et al., 2016). Some technique offers efficiency, high accuracy and simplicity, and considering the possibilities of satellite and data field integration are significant in raising those parameters.

Generally, the application of UAV’s in vegetation monitoring has widely used. The broad application started from burn monitoring (Fernández-Guisuraga et al., 2018), tundra coverage (Riihimäki et al., 2019), soil moisture (Hassan-Esfahani et al., 2015), plant height and canopy cover (Bendig et al., 2015), and related to the study crops like potatoes (Li et al., 2019), (Liang et al., 2018), banana (Harto et al., 2018), to paddy monitoring (Ghazali et al., 2020).

Specifically, to study plant phenology, the variation occurs as a climatic influence which is possible to monitor individually (Park et al., 2019). In the subtropical region, this variation exists as the colour change of tree canopy (Berra et al., 2016; Yingying et al., 2018), besides that, it also describe the invasion of the plant (de Sá et al., 2018), and in crops, it appears like the function of plant growth that in line with yield production. Such as in paddy rice, wheat and sugar cane trees (Kyratzis et al., 2017; Rokhmatuloh et al., 2020; Zul Fahmi, L.P. and Widartono, 2019). Moreover, precisely, Hailemichael et al. (2016) stated that in crops, the phenological stage has a relationship with water status and chlorophyll content. But in paddy rice, it very close to flowering and grain yield (Ramesh et al., 2002). According to Mandal et al., (2019), the paddy rice development from flowering to grain filling describes the entire stages of paddy rice phenology.

Enhancing the previous study conducted by Ghazali et al., (2020), this study has successfully integrated the spectral reflectance of paddy rice canopy, with an aerial photograph to estimate the chlorophyll. The Modified Chlorophyll Absorption Ratio Index named MCARIspectrometer and multiple linear regression for the chlorophyll in paddy field level named UAV Chlorophyll regression (UCR). This study aimed to explain the estimation of paddy phenology, based on the estimated chlorophyll content distribution the aerial photograph of UAV's still used in the whole processed.

2. METHODS

2.1 Study location

The study of phonological stage estimation based on the estimated chlorophyll content conducted in a paddy field in Sukoharjo villages, Sukoharjo sub-district, in Pringsewu residence, Lampung Province (Figure 1). The paddy field covers the area 4.368 hectare produces 23.799 tonnage paddy rice per year. So, this place becomes one of the primary paddy rice sources that supply many people lives in Lampung (Asmoro, 2020).

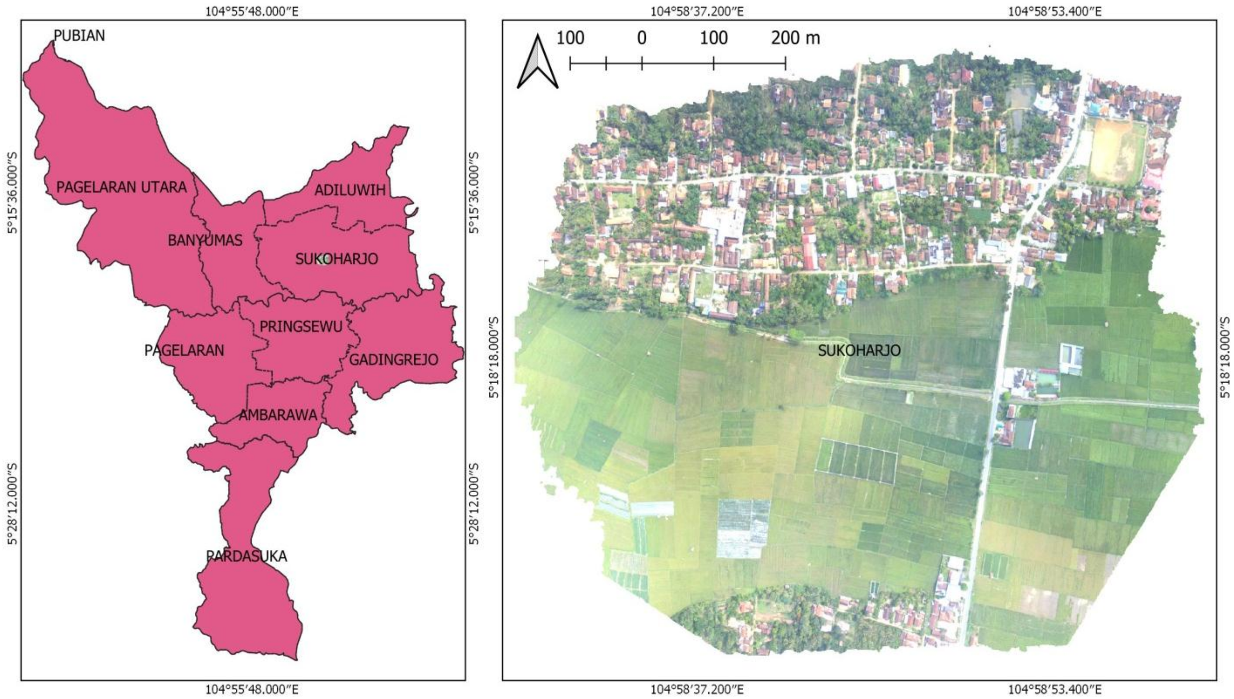

Figure 1. Study location of paddy field in Sukoharjo village, Pringsewu residence

2.2 Data

An RGB orthophoto image of UAV's is the only one data used at this study. It obtained from the DJI Phantom 4 that flight at 200 meters above the surface, with pixel size 2 cm has successfully collected 30 pieces of aerial photos. The orthophoto itself was generated using agisoft software. As complementary data, some of the area in study location has assigned with day after planting (DAP) information to indicate the general stage of it planting time

2.3 Data processing

In order to generate the chlorophyll content using the UCR formula (Eq.1), the orthophoto must be corrected by doing a conversion. Since this study used the formula proposed by Ghazali et al., (2020) that built based on the linear relation of spectral reflectance and digital number (DN) of UAVs. The conversion formula is expressed below (Eq.2).

$$\text{UCR} = 1.954 - 0.963 \times \text{Red} + 1.589 \times \text{Green} - 0.217 \times \text{Blue} \quad (1)$$

$$\text{Reflectance (\%)} = [(\text{DN} - 0) / (225 - 0)] \times 100 \quad (2)$$

The corrected orthophoto image that has converted to UAV reflectance based on the Eq. 2 has masked out to separate paddy rice field area from the non-paddy field. This step, a digitation on-screen has applied to perform this process. Finally, the UCR formula has used to generate the chlorophyll content in only paddy field areas. Besides this process, the object-based image analysis (OBIA) procedure using SAGA GIS software has implemented to gain a segmented image. Then a supervised classification with a minimum distance method has used to classify the paddy field area based on the phenology stage describe in (Mandal et al., 2019).

The function of the estimated chlorophyll of UCR has appeared in this process. The classification result image of OBIA is needed to overlay over the UCR image. It gave the information that the chlorophyll content increase from the early stages named seeding to the flowering stage. However, it decreases gradually from the stage of dough or grain filling and mature.

3. RESULTS AND DISCUSSION

3.1 Chlorophyll distribution based UCR formula

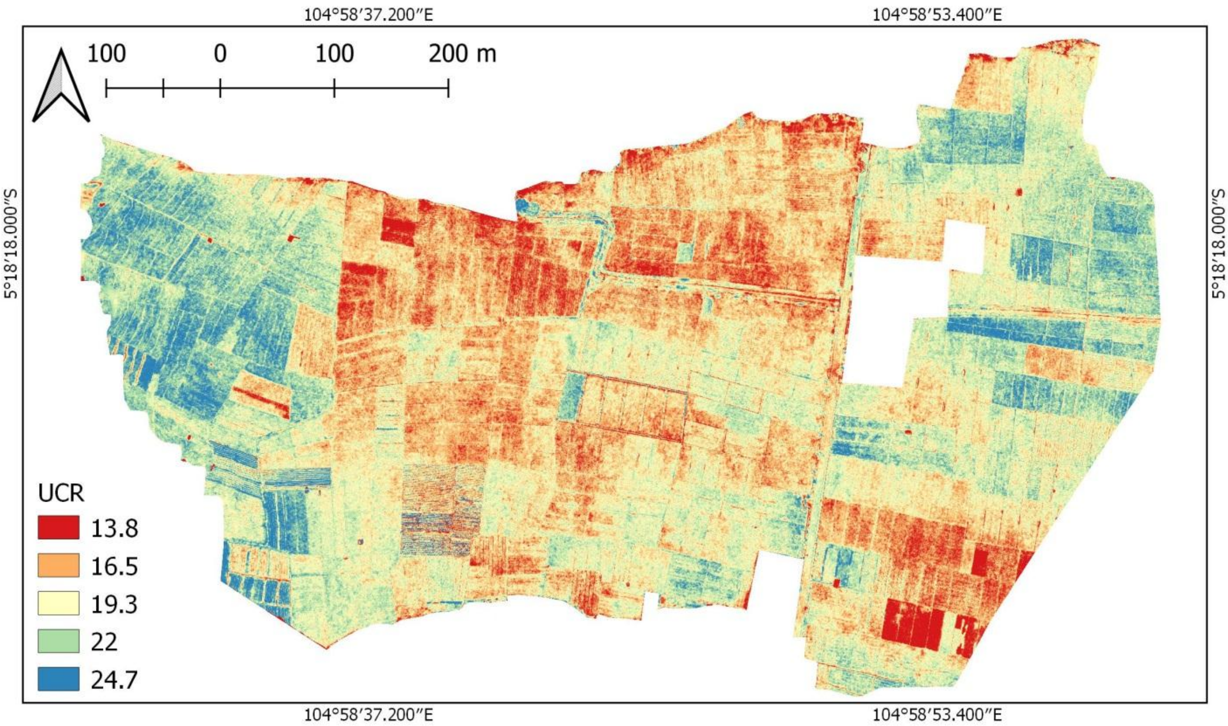

Figure 2. Estimated chlorophyll content in paddy field in Sukoharjo village, Pringsewu residence

The estimated chlorophyll based on the UCR shown in the map (Figure 2). In entire the paddy field, it ranges from 13.8 to 24.7 ml/6.5 m2. Generally compared with the map in Figure 1, the lowest chlorophyll content corresponds with the green paddy rice, while the highest described the yellow paddy rice. It seems these variations occur as influences of the different day after planting (DAP). In other hands, the farmers have started to grow paddy plant at a different time. Nevertheless, outside this factor, The effect of adaptation capability to environment condition like weather condition includes the rainfall, soil moisture, and temperature also give the harmful effect. As described by Liu et al., (2013), the chlorophyll variation on plant especially in paddy plant caused by higher temperature led to a significant loss in rice grain yield.

3.2 Phenology estimation of paddy rice

There are classified nine classes of phonological stages, includes preparation, seeding, tillering, elongation, booting, heading, flowering, dough and grain filling, and mature. These stages are located randomly in the entire study location. The maps below show the relative position of each class, in the entire stages of phenology (Figure 3). The spatial distribution of phonological stages

After the land preparation (Figure 3.1), the vegetative stages also named preparation, seeding, tillering, elongation, booting, and heading have mostly occurred in the north (Figure 3.2 to 3.6). In the same time, the next stages, namely reproductive phases shown in the middle, indicates the flowering and grain filling (Figure 3.7 to 3.9). The third phases namely dough and grain filling, and mature stages, mostly occur in the south.

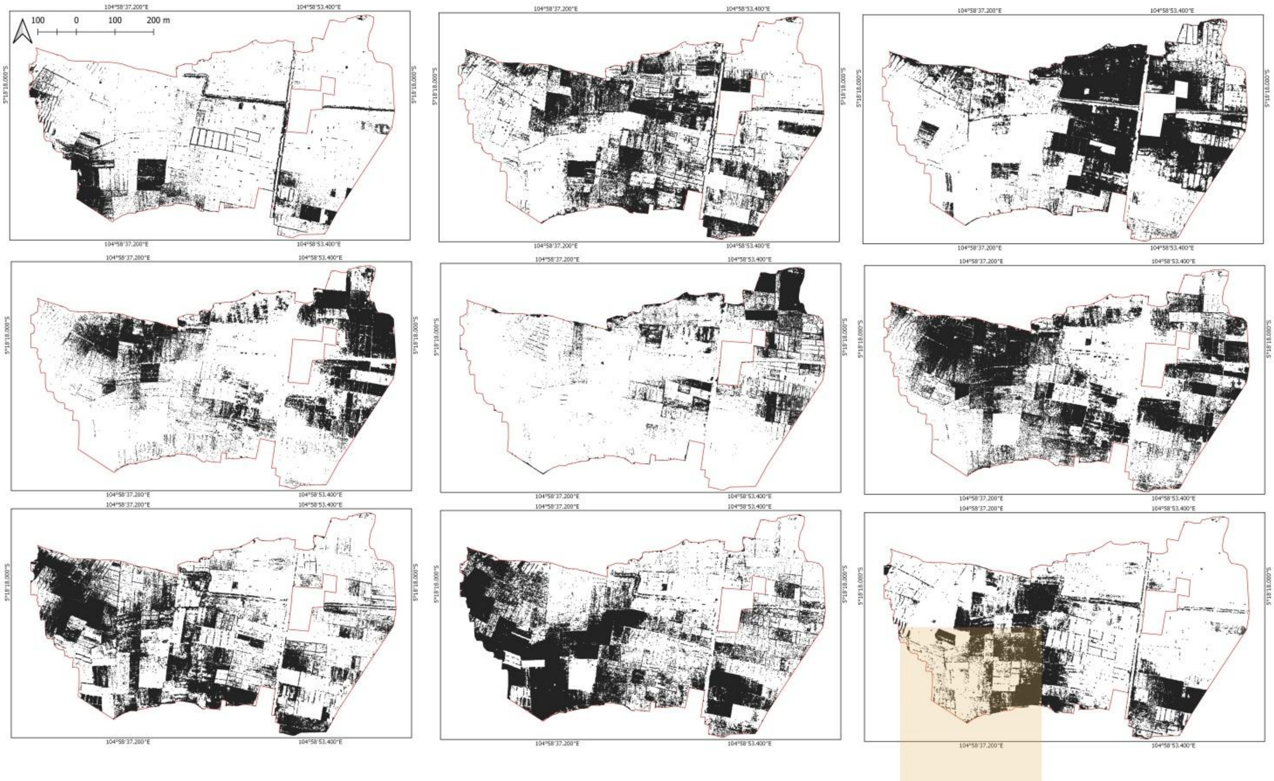

Figure 3. Estimated paddy rice phenology stages. Clockwise, from left to right preparation, seeding, tillering, elongation, booting, heading, flowering, dough and grain filling, and mature (bottom right corner).

3.3 The anomaly presence and occurs in paddy field based on the estimated phenology

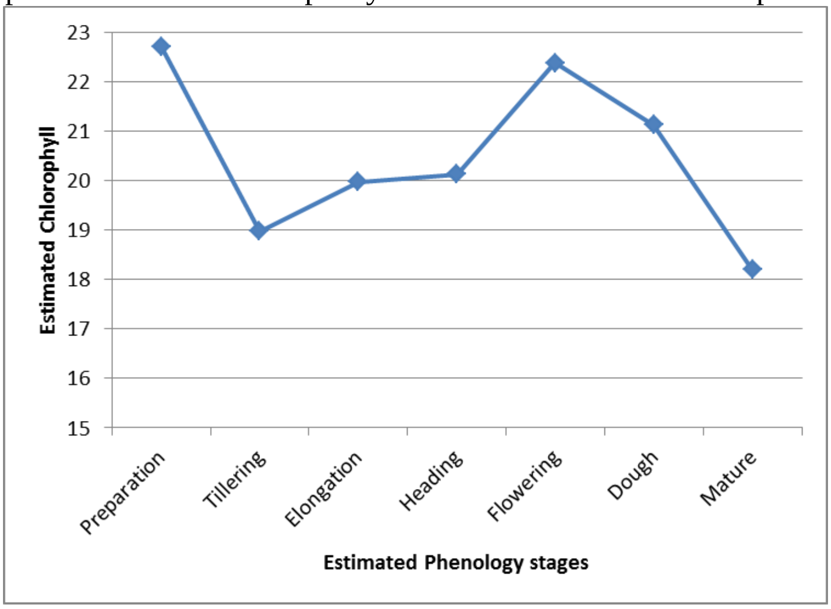

Figure 4. The relation and trends of estimated chlorophyll and phenology stages

The conversion process was applied to convert the DN to reflectance. However, this process did not look good enough to remove vegetation outside the paddy rice plant. For example, grasses have grown in rice field embankment. This situation occurred and documented very well in the preparation stage (Fig. 3.1). one of them is an irrigation channel and rice field embankment. Another anomaly appears in the trends of estimated chlorophyll. In the position of preparation stages, the value seems higher than other. The ideal condition must follow the rules that these values should be lower than the tillering stages (Fig. 4). This condition must be considered as the sources of error.

4. CONCLUSION

The study explains the potential of an aerial photograph of UAV for estimation paddy rice phenology. Mainly this study is the integration between OBIA and minimum distance classification methods. These procedures have successfully created nine classes of phenology stages. The performance of the UCR formula is capable of detecting entire phenology stages. However, it may losses the detection capability since the objects outside the paddy plant exist in the test area. This evidence has to consider for future study.

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