Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model

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Improving Land Cover Classification Accuracy with UAV Images And YOLOv5 Deep Learning Model

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***Abstract*— Land cover is the appearance of the earth's surface covered by biological and non-biological diversity. Land cover can provide important information for modeling and understanding natural phenomena that occur on the earth's sur-face. Supervising land cover change is useful for designing and managing better actions to prevent or ameliorate loss-es resulting from land cover change activities. Types of land cover based on the ministry of environment and forestry and S.N.I. In the Liang Anggang protected forest area are primary swamp forest, secondary swamp forest, open swamp, wet bush, pure dry agriculture, mixed dry agriculture, open water, transmigration areas, plantation forest, and vacant land. The type of land cover in the Liang Anggang protected forest area can be classified into 3 types, namely bare, softly, and heavily. Land cover classification can be done from two types of data, namely satellite data and unmanned aerial vehicle (UAV). This research will use UAV data for better image detail. The model used is YOLOv5. The results of this study obtained mAP@.5 74.8%, mAP@.95 31.3%, precision 81.7%, recall 66.4% for bare class. mAP@.5 81.1%, mAP@.95 45.7%, precision 80.1%, recall 78.6% for "softly" class. mAP@.5 40.1%, mAP@.95 21.9%, precision 49.5%, recall 36.9% for "heavily" class. mAP@.25 72.8%, mAP@.5 65.6%, mAP@.75 53.6%, mAP@.95 33%, precision 70.4%, recall 60.7%, and accuracy 60% for all class.**

***Keywords*—Classification, Land Cover, YOLOv5, UAV**

I. Introduction

Land cover is the appearance of the earth's surface covered by biological and non-biological diversity. Land cover can provide important information for modelling and understanding natural phenomena that occur on the earth's surface. Land cover data can also be used to study climate change and understand the relationship between human activities and global change [1]. One type of land cover in South Kalimantan is peat land. One of the peatland areas in South Kalimantan is the Liang Anggang protected forest, Banjarbaru block 1 area which has an area of 494 hectares and is filled with land such as agriculture, plantations, roads, settlements, and shrubs. Apart from the fact that the location is peatland, the location in block 1 fulfils the characteristics and suitability of the needs in collecting data for the classification of peatland cover. So as the selection of this research location is in accordance with the data requirements.

Destructive changes in land use including on peatlands are the main cause of loss of biodiversity, damage to ecosystems and drastic climate change. Monitoring land cover change is useful for designing and managing better regulations to prevent or remedy losses arising from land cover change activities. Monitoring land cover changes can help in predicting and avoiding natural disasters or other hazardous events [1]–[3]. Monitoring and analysis of land cover can be carried out by classifying land cover, according to the

Ministry of Environment and Forestry and the National Standardization Agency, especially the Indonesian National Standard, land cover is classified into 23 classes, consisting of 6 forest classes, 16 non-forest classes, and 1 rehabilitation forest class [4]. The types of land cover based on the ministry of environment and forestry and the Indonesian National Standard (S.N.I.) found in the Liang Anggang protected forest area are primary swamp forest, secondary swamp forest, open swamp, wet shrub, pure dry agriculture, mixed dry agriculture, open water, transmigration areas, plantation forests, and bare ground. The types of land cover in the Liang Anggang protected forest area can be classified into 3 types, namely bare (surface that has no vegetation at all), Softly (surface covered with medium and high vegetation), and Heavily (surface covered with moderate vegetation). The data collection technique is carried out using the Unmanned Aeiral Vehicle (UAV) which can take pictures from a lower altitude so that the spatial resolution obtained is 1cm, more detailed than the satellite (30cm). And also, the UAV can take pictures in cloudy weather conditions because the UAV's height is lower than the clouds [5]–[8].

The technique that is highly favoured for classification is Machine Learning. Machine Learning is continually evolving and producing new fields such as Deep Learning. Deep Learning is popular in image analysis and intelligent image processing [9]–[12]. One of the popular models used in Deep Learning is You Only Look Once (YOLO).

The YOLO model is well-known for its use in object detection [13]. Several studies have used YOLOv5 for research purposes, such as Jun-Hwa Kim et al., who conducted a study on maritime object classification and optimized the Singapore Maritime Dataset (SMD) [14]. Nidhi et al. conducted a study on seed classification and quality using YOLOv5 and K-Means [15]. Linfeng et al. detected traffic signs using SSD300, Faster RCNN, YOLOv3, YOLOv4, and YOLOv5 to compare the accuracy of these models [16]. Daniel Padilla Carrasco et al. detected small vehicles in parking lots using YOLOv5 to manage parking spaces efficiently and achieve the goal of a smart city [17]. Tian-Hao Wu et al. used YOLOv5 to detect vehicles and their distances in real-time in a virtual environment to optimize autonomous vehicle technology [18]. Lastly, How Yong Chen et al. used YOLOv5 to detect defects in glove production [19].

II. LITERATURE REVIEW

A. *Land Cover*

Land cover refers to the surface features of the Earth that are covered by biotic and abiotic elements. Land cover provides important information for modeling and understanding natural phenomena occurring on the Earth's surface. Land cover data can also be used to study climate change and understand the relationship between human activities and global changes. Accurate land cover information is one of the determining factors in improving the performance of ecosystem, hydrology, and atmospheric models. One type of land cover found in South Kalimantan is peatland. Peatland is a water-saturated land composed of organic material (>12%) that occurs due to the accumulation of decomposing plant remains and tissues with a thickness of more than 50 cm. The accumulation is caused by the slow rate of decomposition compared to the rate of organic material accumulation inundated by water over a long period of time [1]–[3].

B. *Peatland*

Peatland is a water-saturated land composed of organic material (>12%). Peatland is formed by the accumulation of plant residues and decomposed plant tissues with a thickness of more than 50 cm. The accumulation is due to the slow rate of decomposition compared to the rate of organic material accumulation that is inundated with water for a long period of time [1]. Peat is classified as marginal land and is vulnerable to disturbances, so any increase in the productivity of peatland must be accompanied by efforts to prevent ecosystem damage. Peatland damage is caused by tree felling and forest conversion, fires, and reclamation. Peat can be considered a renewable resource only on a geological time scale. Peat growth estimates vary between 0.5 to 1 mm per year, and the subsidence rate of drained peatland is between 1.5 to 3 cm per year. Because the subsidence rate is 15-30 times that of the growth rate, peatland cannot be categorized as a renewable resource.

Several types of land cover based on the ministry of environment and forestry and S.N.I. located in the Liang Anggang area include:

1. Primary swamp forest: Forests growing in wet habitats include mangroves, sago, and peatlands.
2. Secondary swamp forest: Forests growing in wet habitats include mangroves, sago, and peat, often with human interventions such as logging and agriculture.
3. Open swamp: Open swamp with little vegetation.
4. Wet shrub: Wet area filled with shrubs.
5. Mixed dry agriculture: Areas used for agricultural activities and still have wild plants such as shrubs and trees scattered in the agricultural area.
6. Open water: Open water areas such as rivers and lakes.
7. Transmigration areas: The area surrounding the forest that is related to human activities such as houses, parks, and huts.
8. Pure dry agriculture: Areas used for agricultural activities.
9. Plantation forest: An area that has been planted with vegetation as part of forest rehabilitation efforts.
10. Bare ground: An area of empty land without vegetation.

Pictures of land cover types in the Liang Anggang protected forest can be seen in Table 1.

TABLE I
TYPES OF LAND COVER IN THE LIANG ANGGANG PROTECTED FOREST

Land Image	Land Type	Land Image	Land Type
	*Primary Swamp Forest*		*Wet Shrub*
	*Secondary Swamp Forest*		*Mixed Dry Agriculture*
	*Open Swamp*		*Open Water*
	*Plantation Forest*		*Transmigration Area*
	*Pure Dry Agriculture*		*Bare Ground*

C. Image Classification

Image classification is the process of arranging or grouping pixels into several classes based on object categories or certain criteria. Each pixel in each class is assumed to have homogenous characteristics. The goal of classification is to extract spectral patterns found within the image [20]–[22].

III. RESEARCH METHODOLOGY

A. Problem Identification

The first stage of this research is to identify the problem. Problem identification is carried out qualitatively by focusing on in-depth observation to discover a problem. The problem identified is the importance of classifying land cover using a reliable model to produce accurate land cover types with good accuracy results. The solution to this problem is to use the best object detection model for land cover classification and then observe the accuracy results of using the model. Good accuracy results in using the model can be a recommendation for the next researchers in land cover classification and object detection in general. And land cover classification information can be a further action by researchers or agencies related to land cover.

B. Image Acquisition

Image acquisition is carried out to collect the necessary data and to determine the digital image recording model to be used [23]. Land images were taken using a DJI Mavic Pro drone in November - December 2021 and July - August 2022. The drone is automatically controlled using the DroneDeploy application. The drone follows a predetermined path on DroneDeploy but can still be manually controlled with a remote. Image capture is done in clear or slightly cloudy weather conditions. The drone is set to fly at a height of 20 meters from the surface. Image capture is done between 8 am and 12 pm.

Because the Liang Anggang protected forest is located near the Syamsudin Noor airport, some areas cannot be captured with a drone because they are in a restricted fly zone with a maximum height of 60 meters in yellow areas and not allowed to fly at all in blue areas. Therefore, the area to be captured is located within a maximum of 60 meters with a drone capture height of 20 meters so that the drone can still capture images with sufficient coverage. The restricted fly zone in the Liang Anggang protected forest can be seen in Figure 1.

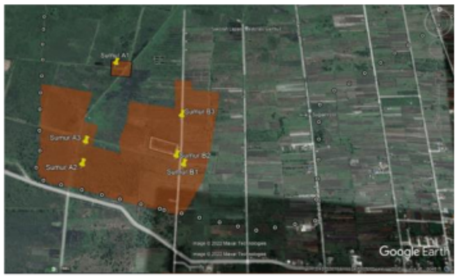
Figure 1. Restricted Fly Zone Around Liang Anggang Protection Forest

IV. RESULT

A. Image Capture Process

The first stage of taking images with a drone is determining the area to be photographed. Area capture settings are made in the Google Earth Pro application to determine the area to be captured. After the area marking has been completed, the results will be exported into a file with the .KML format. Then the file will be imported into the DroneDeploy application. From the DroneDeploy application, drones can be set to take pictures automatically according to the area that has been marked.

UAV image data obtained from the results of drone capture conducted in July - August 2022 collected 7437 images with an area of 22.6 hectares. The total image data collected after being combined with data taken in November - December 2021 collected 17,674 images with an area of 40.6 hectares. Areas that have been taken using drones are marked in orange which can be seen in Figure 2.



Class	Precission	Recall	mAP @.25	mAP @.5	mAP @.75	mAP @.95
All	0.704	0.607	0.728	0.656	0.536	0.33
Bare	0.817	0.664	0.688	0.748	0.418	0.313
Softly	0.801	0.786	0.841	0.811	0.661	0.457
Heavily	0.495	0.369	0.656	0.41	0.528	0.219

Figure 2. Territory That Has Been Taken by Drones

1. *Labelling*

   Labelling process is carried out to label objects in the image that will be detected. The label will assist the trained model to identify the objects to be detected.

   After all images have been preprocessed, the dataset construction is carried out to divide the dataset according to its usage in each stage. The dataset is divided into three folders, namely train, val, and test.

   The complete structure of the dataset can be seen in Figure 3.

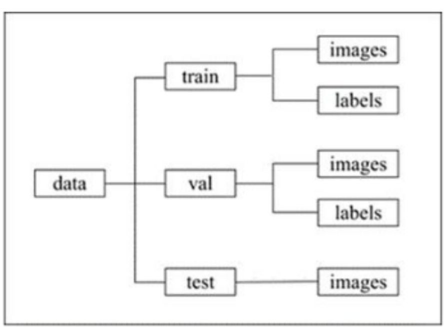


Figure 3. Complete Structure of Dataset

B. Training Model

Training is conducted using the Google Colab platform. The training stage of the YOLOv5 model is divided into 3 stages, namely the training, validation, and testing stages.

1. Training

   At the training model stage, the first step is to run the code to download the YOLOv5 file into the Google Colab project. After the download process is complete, the project will display the YOLOv5 folder. Then the next step is to connect the project with the dataset that has been stored on Google Drive and determine the location of the dataset from the coco128.yaml file.

   Model training is carried out by conducting training several times with different batch and epoch values to find out the optimal setting values to get the best precision, recall, and mAP values. The training results from the YOLOv5 training model for land classification for all classes obtained values of mAP@.25 0.728, mAP@.5 0.656, mAP@.75 0.536, mAP@.95 0.33, precision 0.704, recall 0.607. Complete values of training results for 100 epochs and 5 batches can be seen in table 2.

TABLE III
TRAINING RESULT VALUE

2. Validation

   After the training process is complete, the validation stage is carried out. The validation results of the YOLOv5 model for land classification for all classes obtained values of mAP@.25 0.728, mAP@.5 0.661, mAP@.25 0.536, mAP@.95 0.326, precision 0.696, recall 0.614. the complete value of the validation calculation can be seen in Table 3.

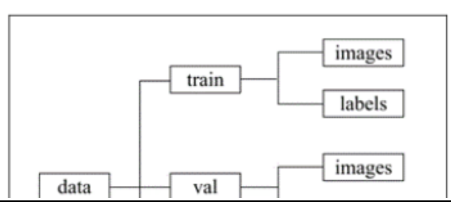


TABLE IIII
VALIDATION VALUE

3. Testing

The last stage is testing the model that has been trained in detecting objects. The mAP@.5 value of 0.65 indicates that the model can detect Softly land cover types quite well. However, it struggles to detect bare and heavily land cover types, as well as photos with more than one land cover type. Some test results can be seen in Figure 4.

Figure 4. Testing Result Image Examples

V. ANALYSIS

A. Training and Validation Result Analysis

Based on the precision-recall curve and the values of mAP, precision, and recall result can be seen in Figure 5 and Table 4.

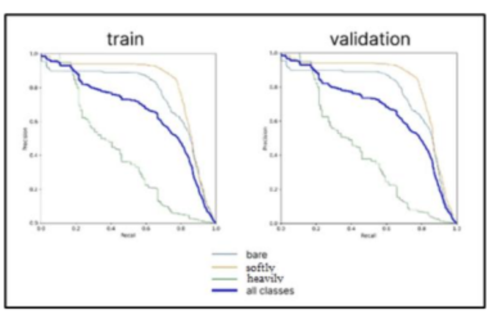


Figure 5. Precision-Recall Curve on Training and Validation

TABLE VI
COMPARISON OF MAP VALUE ON TRAINING AND VALIDATION

Stage \ mAP	**All**	**Bare**	**Softly**	**Heavily**
Train	65.6%	74.8%	81.1%	41%
Validation	66.1%	75%	81.5%	41.8%
Difference	0.5%	0.2%	0.4%	0.8%

Class	**Precission**	**Recall**	**mAP @.25**	**mAP @.5**	**mAP @.75**	**mAP @.95**
All	0.696	0.614	0.728	0.661	0.536	0.326
Bare	0.798	0.676	0.688	0.75	0.418	0.309
Softly	0.798	0.79	0.841	0.815	0.661	0.455
Heavily	0.492	0.376	0.656	0.418	0.528	0.213

The identical and quite good precision-recall graph and mAP values are above 70% and have a difference of less than 1% for the bare and Softly land cover types indicating the model's best fitting. However, the low precision-recall graph and mAP values below 70% for the Heavily land cover type indicate an underfitting model for that land cover type. The low value of the Heavily land cover type results in a low total mAP value for all classes, which is 65%, so it can be concluded that the model is underfitting.

B. Accuracy Analysis

The accuracy calculation was done using land photos that were not used in training the model and was calculated using Microsoft Excel. The resulting image for the accuracy calculation can be seen in Figure 6.

Figure 4. Example Used in Accuracy Calculation

The accuracy calculation was done using formula (5), Microsoft Excel, and images outside the training dataset to avoid bias with the training phase. The result of the calculation yielded an accuracy value of 0.6 or 60%. Based on the very small difference in values between the train and validation phases, below 1% (0.5% for all classes, 0.2% for the bare class, 0.4% for the Softly class, and 0.8% for the Heavily class), but having an mAP value below 70%, which is 65.6%, it can be concluded that the model is underfitting to classify land cover types.

C. *Model Performance Comparison*

This research will also use another deep learning model, YOLOv4, to compare its performance with the currently used YOLOv5 model. The comparison results between the performance of YOLOv4 and YOLOv5 can be seen in Table 5.

TABLE V
PERFORMANCE COMPARISON OF YOLOV4 AND YOLOV5 MODEL

Model / Value	**YOLOv4**	**YOLOv5**
mAP@.5	43.45%	65.6%
mAP@.95	0.0041%	33%
Precision	66%	70.4%
Recall	31%	60.7%

From the table above it can be seen that the performance of the YOLOv4 model is lower than that of the YOLOv5 model.

VI. CONCLUSIONS

A. *Accuracy Analysis*

The conclusions based on the research that has been done are as follows:

1. The YOLOv5 model obtained an mAP@.5 score of 75% and 81.5% for classifying bare and Softly land covers, but obtained a low mAP@.5 score of 41.8% for classifying Heavily land cover, indicating that YOLOv5 is good at classifying bare and Softly land covers but not as good for classifying Heavily land cover.

2. The YOLOv5 model obtained a precision of 70.4%, recall of 60.7%, mAP@.25 of 72.8%, mAP@.5 of 65.6%, mAP@.75 of 53.6%, mAP@.95 of 33%, and an accuracy of 60% for all classes.

B. *Recommendation*

The recommendations given in this study are as follows:

1. Using the pro version of the Google Colab account so that the training process on Google Colab becomes more effective.
2. Using special drones for industrial use, mapping, inspection and surveys so that the process of taking land images becomes more effective.
3. Using a dataset that has Heavily image quality and a larger number, especially for Heavily land cover types, so that the classification results, especially for Heavily land cover types, are better.
4. The YOLOv5 model gets a mAP@.5 value of 65.6% which is categorized as unfavorable. Therefore, the authors suggest using a model with a better architecture so that the value of the classification results becomes higher.

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