

## SPATIAL ANALYSIS OF VEGETATION DENSITY CLASSIFICATION IN DETERMINING ENVIRONMENTAL IMPACTS USING UAV IMAGERY

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#### ABSTRACT:

Along with remote sensing technology development, vegetation monitoring can be performed using satellite imagery or Unmanned Aerial Vehicle (UAV) data. UAV imagery with a high resolution, between 3 - 5 cm at an altitude <100 m, is able to present specific land conditions without being affected by the weather. Information related to vegetation density is one of the components in the Environmental Impact Analysis (EIA) study of a proposed project development due to vegetation removal. In this study, information from consumer-grade cameras of a low-cost UAV platform was explored to classify vegetation density using the potential of RGB imagery-based vegetation index (VI). The correlation coefficient ( $R^2$ ) between field observation data and the seven different values of VI demonstrated moderate to strong correlation. The highest liner correlation of 80.16% ( $R^2 = 0.64$ ) was performed by the Green Red Vegetation Index (GRVI). Classification of the vegetation density was established by applying the object-based image analysis method through the combination of supervised machine learning algorithm of Support Vector Machine (SVM) and the GRVI vegetation index. The vegetation density classification consists of very low, low, medium, high, and very high-density classes. The data can be utilized in determining vegetation management efforts from the presence of a proposed project in the EIA study. The use of UAV imagery is considered effective in identifying vegetation density.

## 1. INTRODUCTION

### 1.1 Background

The environment needs to be considered in planning activity. It is intended to minimize the impact of development on environmental components. For this reason, an Environmental Impact Analysis (EIA) is considered important to control the potential impacts that may arise from the implementation of the activity. EIA is a form of an effort to manage natural resources and the environment in development, where negative impacts can be reduced or eliminated by formulating impact resolution techniques based on an environmental approach (Kualita, 2007). Every activity that has a significant impact on the environment required an analysis of environmental impacts. There are types of activities that require an EIA. Internationally, the Food and Agriculture Organization of the United Nations issued an Environmental Impact Assessment Regulations in 2014. The regulation regarding the environmental impacts and proposed mitigation measures are outlined in section 8 and section 9, respectively. These sections are interrelated, environmental-related impacts that may happen in consequence the proposed project are represented in section 8, whereas section 9 signifies whether measures are being considered to mitigate against damage likely to be caused by the proposed project to human health and/or the environment. One of the components is vegetation analysis.

The percentage of land cover by vegetation and vegetation density are important parameters used in vegetation analysis. Vegetation data collection can be done through field surveys however, it is time-consuming and requires high cost. Remote sensing technology has been developed and widely applied for monitoring vegetation (Hardin and Hardin 2010; Rudianto, 2010; Colomina, 2014). One alternative technology for low-cost rapid

monitoring with real-time and detailed data is aerial photography using an Unmanned Aerial Vehicle (UAV) or a drone (Shofiyati, 2011; Colomina, 2014). Aerial photography with UAVs is carried out at an altitude below the clouds, thus avoiding images with high cloud cover and have sharper results compared to satellite images which are heavily influenced by atmospheric conditions (Hunt, et. al, 2013; Matese, et. al, 2014; Kushardono, 2014).

During recent years, RGB imagery-based captured by consumer-grade cameras of UAV has been studied to generate Vegetation Index (VI) by using the Visible Spectrum (VIS). The studies were able to demonstrate a good correlation of Visible Spectrum (VIS) based VI, i.e., Green Red Vegetation Index (GRVI) (Rouse, et. al, 1973); Excess Green Index (ExGI) (Woebbecke, et. al, 1995; Sonnentag, et. al, 2015); Green Chromatic Coordinate (GCC) (Woebbecke, et. al, 1995; Sonnentag, et. al, 2015; Rasmussen, et. al, 2017); Green Leaf Index (GLI) (Louhaichi, et. al, 2001), Visible Atmospherically Resistant Index (VARI) (Gitelson, et. al, 2002), Modified Green Red Vegetation Index (MGRVI) (Bendig, et. al, 2015) and Red Green Blue Vegetation Index (RGBVI) (Bendig, et. al, 2015). The visible band index of GLI and VARI have been tested in monitoring leaf chlorophyll content (Hunt, et. al, 2013). By applying a simple method with a consumer level UAV, processing result of four different index, e.g., GRVI, ExGI, GCC and VARI, using Digital Number (DN) of the VIS RGB-based images was able to produce a relatively high coefficient of determination of up to 60% (Larrinaga and Brotons, 2019). A comparative study of VIS index, e.g., ExGI, MGRVI and RGBVI, in modelling cotton canopy cover was obtained to be as accurate as Multi Spectral (MS) sensor-based canopy cover estimation using Normalized Different Vegetation Index (NDVI), with an average RMSE of less than three percent (Ashapure, et. al, 2019).

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In regard to the obtain classifications based on the information in each image pixel such as vegetation density classification, pixel-based method is one of the most frequently used digital classification method. However, the pixel-based method is less accurate when it is carried out on detailed scale remote sensing data such as UAV, especially on certain objects that have different coefficients (Kushardono, 2014). This method is usually used for medium or low scales. Therefore, it is necessary to conduct classification based on the object for UAV data. Object-based image analysis, such as SVM method, is conducted based on multiresolution segmentation into homogeneous areas with parameters such as scale, shape, compactness, and vegetation index information to separate objects from one another. This kind of segmentation will greatly underlie the advancement of image analysis and more efficient processing times as well as produce good vegetation classification map (Marpu, 2009).

A project of the development planning of tourist accommodation in Karangasem, Bali, Indonesia, is studied in order to estimate damages of vegetation as a result of a proposed project. The design of the tourism accommodation development in Karangasem, Bali is planned to be built on an area of 10 ha. In most countries, there is a national regulation regarding the types of activities and the implementation of EIA. According to the national regulation, EIA is compulsory for the proposed project. The magnitude of the impact is calculated from development activities on a land area of 10 ha, one of which is the amount and type of vegetation that may be lost. Thus, the EIA study must describe the biological aspect study, particularly the analysis of vegetation due to land clearing activities.

As a preliminary or feasibility study before establishing the project development plan, vegetation density classification is a

necessary information in the EIA study. A cost-effective approach, regardless the moderate accuracy, is certainly required in conducting the study. The use of this method can improve image analysis and time management, with good results. The data obtained can be used in an initial indication of land cover to be developed (Marpu, 2009). Furthermore, information on vegetation coverage and density can be used in the examination of biological aspects from the EIA study in the accommodation area development plan in Karangasem, Bali, Indonesia.

## 1.2 Research Objectives

The objective of this research is to evaluate different VIS-based VI and to conduct supervised classification method of SVM based on the vegetation index value information to extract vegetation density using UAV image data. The main purpose of the analysis is to enable related companies or agencies to perform a low-cost rapid vegetation analysis with high-accuracy results in conducting an EIA study for a proposed project.

## 2. METHODOLOGY

### 2.1 Research Scheme

The method used in this research is a classification with a combination of segmentation and classification based on objects with the supervised classification of SVM method and the VIS-based VI value in the vegetation density analysis using Quantum GIS (QGIS) software. The data processing process is described in Figure 1.

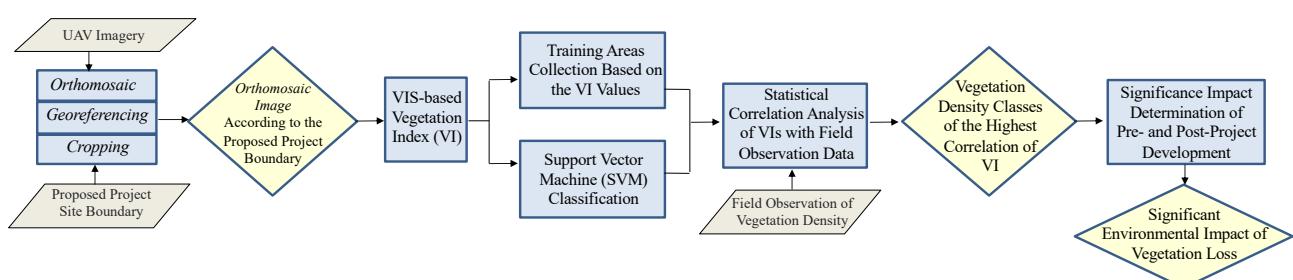


Figure 1. Flowchart of the research and data processing

### 2.2 Research Area

The research was conducted on the site of the development planning of tourist accommodation area in Karangasem Sub-District, Karangasem District, Karangasem Regency, Bali Province, Indonesia. The area of the development plan is 10 ha and geographically located at 8° 26' 14.11" S and 115° 36' 5.05" E to 8° 26' 34.31" S and 8° 26' 34.31" E. The surrounding vegetation in the plotted built-up area cover herbs, shrubs, trees and paddy field (see Figure 2.). The paddy field along the eastern part of the site is designed to be retained as a tourist attraction. The area that will be developed for tourism accommodation has an impact on the loss of the vegetation.

### 2.3 Data Collection

The data collection consists of field data collection of vegetation density and UAV images on the developed area. The UAV image used in the study was obtained by using DJI Phantom 4 Pro drone imaging with a flying height of 100 m on September 20, 2020. Aerial photos of the drone were then processed through the Orthomosaic process using Dronedeploy software, resulting in a map with a resolution of 5 cm per pixel, as shown in Figure 2.

The UAV image obtained has three bands, i.e., Red, Green, and Blue (RGB). The next process that needs to be applied is pre-processing on GIS analysis tools.

Field data collection of vegetation density was conducted through quadrat method. The method is able to be applied to any vegetation type to quantify the community of plantations in an observed area. A total of 265 transects with area size of 200 x 100 m along the site of development area were arranged for the sampling. The transects were determined based on a design of systematic random sampling to conform various types, canopy covers and aspects of vegetation. The existence of vegetation at every 40 m on the 200 m transect or every 20 m on a 100 m transect, was estimated via the point-quarter method (Bryant, et al, 2005; Humagin, et. al., 2017). Vegetation density of herbs, shrubs and trees was calculated as:

$$\text{Vegetation density} = \lambda = \frac{4n^2}{\left(\sum_{i=1}^n \sum_{j=1}^4 R_{ij}\right)^2} \quad (1)$$

where  $n$  is the sampling point number of transect (=5);  $4n$  is the total observation number in all transect (=20);  $i$  is a sampling

point observed in a transect ( $i = 1, \dots, n$ );  $j$  is a quarter at a point of transect ( $j = 1, \dots, 4$ ); and  $R_{ij}$  is the measurement of the tree distance at the point of transect  $i$  around the quarter  $j$  (Dick-Peddie, et. al, 1999).

The field data of vegetation density is categorized following the common EIA criteria for environmental quality of vegetation, i.e., scale 1 for very low density ( $\leq 20$  trees/ha), scale 2 for low density (21 – 50 trees/ha), scale 3 for medium density (51 – 100 trees/ha), scale 4 for high density (101 – 200 trees/ha) and scale 5 for very high density ( $>200$  plants/ha) (Fandeli, 1992).

#### 2.4 Data Analysis

The initial process is georeferencing to adjust the image according to the administrative area and geographical condition of Karangasem Sub-District, Karangasem District, Karangasem Regency, Bali Province, Indonesia. The correction process of image georeferencing is carried out by using a minimum of six reference points or Ground Control Points (GCP). Furthermore, the image can be cropped according to the boundary of the site plan for the analysis process. Data analysis in the form of a classification process applies the multispectral classification method. The method assumed that with high spatial resolution, the pixels that makeup one type of object have spectral similarities and each different object also has significant spectral differences (Phinn, et. al, 2002).

In this study, the vegetation density classification method was used based on the transformation of the vegetation index. The vegetation index is an important algorithm used to extract information related to vegetation conditions (Salas and Henebry, 2014). The RGB color composition of the image can be applied to produce a vegetation index in the image. This index is used to estimate the vegetation fraction in images with low sensitivity to atmospheric effects. The equation used in calculating the VIS-based VI is described in Table 1.

VIS-based VI	Equation	Reference
GCC	$\frac{G}{R + G + B}$ (2)	Rasmussen, et. al, 2017
VARI	$\frac{G - R}{R + G - B}$ (3)	Gitelson, et. al, 2002
GRVI	$\frac{G - R}{G + R}$ (4)	Rouse, et. al, 1973
ExGI	$2 \times G - (R + B)$ (5)	Sonnentag, et. al, 2015
RGBVI	$\frac{G^2 - R \times B}{G^2 + R \times B}$ (6)	Bendig, et. al, 2015
MGRVI	$\frac{G^2 - R^2}{G^2 + R^2}$ (7)	Bendig, et. al, 2015
GLI	$\frac{(G - R) + (G - B)}{(2 \times G) + (B + R)}$ (8)	Louhaichi, et. al, 2001

Table 1. The VIS-based VI calculation

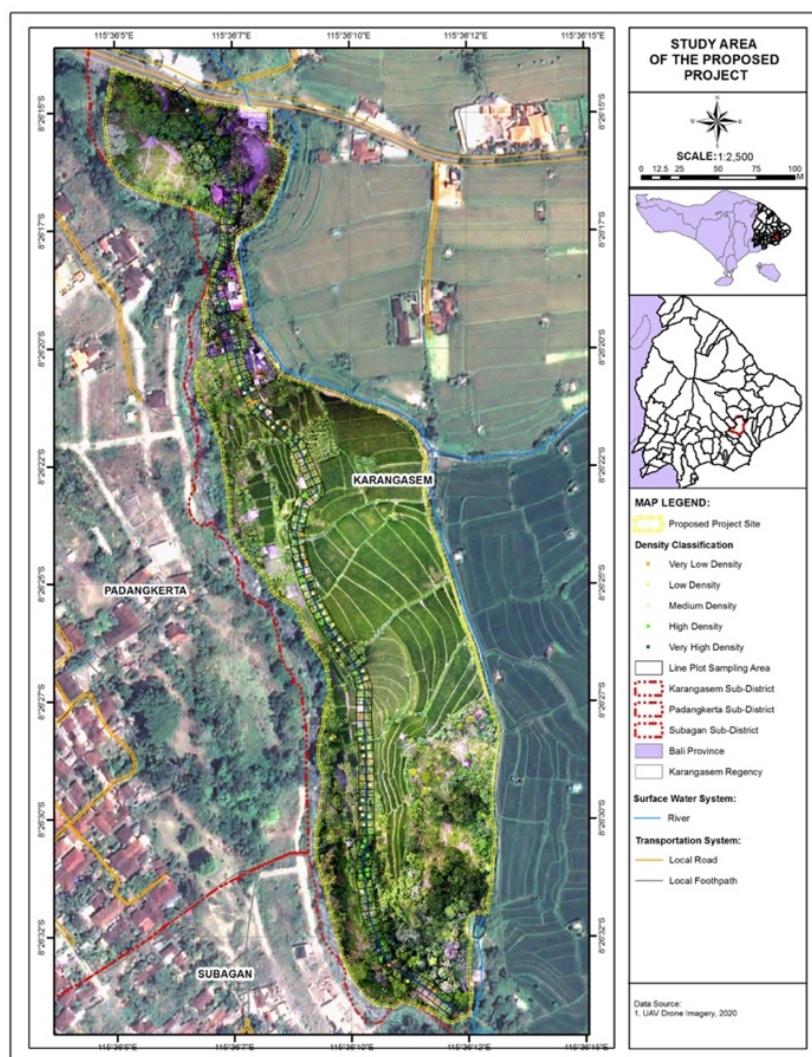


Figure 2. Study area of the proposed project

This study also used a supervised classification method. This method was applied due to the relatively simple algorithm with good classification results. In this method, the vector value of each Region of Interest (ROI) is calculated based on the average value of the vector for each ROI. Moreover, the supervised classification method used in the process is the Support Vector Machine (SVM) classification method. The SVM is a method based on machine learning algorithm used for classification. The input data for the SVM classifier is grids and training areas. The training areas are 265 data points collected from the field observation of vegetation density (see Figure 3.) that indicated very low, low, medium, high, very high density.

The SVM classification was conducted on QGIS application using the tool of SAGA. The tool was set to apply SVM calculation of 265 training areas as input on C-SVC with C (cost) value of 1.0 and linier kernel type. The other parameter was set

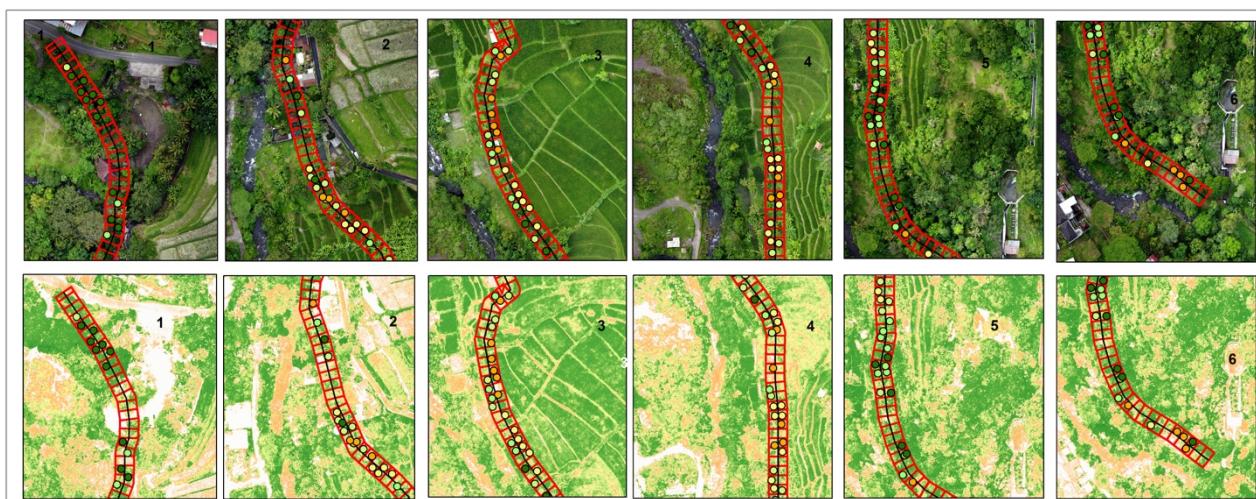
in default setting, i.e., 3 for the degree in kernel function, 0.5 for nu-SVR (parameter nu of nu-SVC, one-class SVM, and nu-SVR), 0.1 for epsilon in loss function of epsilon-SVR, 0.001 for the tolerance of termination criterion.

### 3. RESULTS AND DISCUSSION

The analysis of vegetation density using UAV images in the proposed project site for the construction of tourist accommodation in Karangasem Sub-District, Bali was carried out through spatial analysis of QGIS GIS application software. The correlation of the VIS-based VI was examined with field observation data was examined using a statistical linier regression analysis (see Table 2). Comparison of the field observation data points collected from field observation of vegetation density on the UAV imagery and GRVI image that indicate the highest correlation of VI described in Figure 3.

Statistics	GCC	VARI	GRVI	ExGI	RGBVI	MGRVI	GLI
Min. index value	0.0226	-0.7434	-0.9426	-0.9321	-0.9937	-0.9983	-0.9114
Max. index value	0.9565	0.9348	0.9556	1.8696	0.9990	0.9990	0.9556
Sum of index values	3205673	864725	1061883	2686502	3508102	2028604	1810236
Mean index value	0.4625	0.1248	0.1532	0.3876	0.5062	0.2927	0.2612
Std index value	0.0545	0.0753	0.0909	0.1634	0.1806	0.1646	0.1034
Sum of the squares	20554	39321	57266	184982	226033	187781	74130
R-squared value	0.4446	0.5653	0.6425	0.4776	0.4763	0.626	0.497
Correlation Coefficient	0.6668	0.7519	0.8016	0.6911	0.6901	0.7912	0.7050

**Tabel 2.** The correlation coefficient of VIS-based VI and field observation data



**Figure 3.** Comparison of the field observation data points of vegetation density on the UAV imagery and GRVI image result

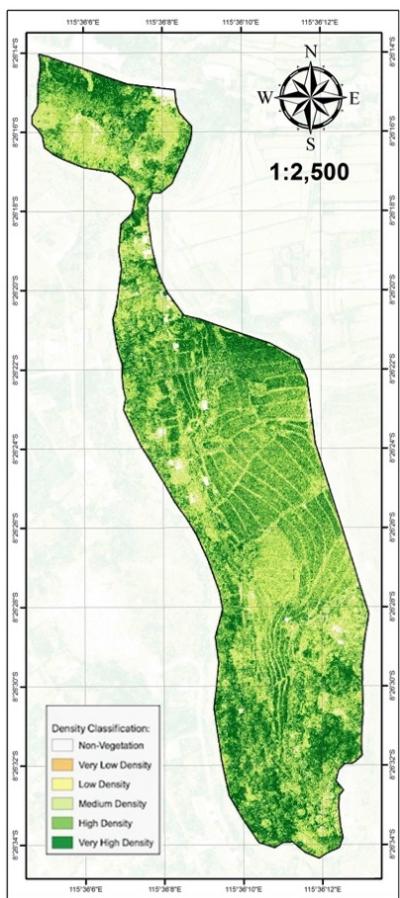
The method applied to GRVI is similar to the NDVI. The index corresponds to the senescence of leaves in deciduous forests. The GRVI has demonstrated good agreement in measuring crops and rangelands (Rouse et al., 1973). Therefore, the formula is beneficial for differentiating the aging condition of leaves.

The result of the vegetation density classification is described in Table 3. A UAV orthomosaic image according to the boundary of the development activity plan and the results of the vegetation density classification are presented in Figure 4. The classification of vegetation density in the UAV image analysis is indicated by five different color classes according to the level of vegetation density, i.e., orange (very low density, <10%), yellow (low density, 10 – 35%), light green (medium density, 35 – 60%), green (high density, 60 – 85%) and dark green (very high density, > 85%). In addition to the vegetation classes of the study area of the analysis, there was another class besides vegetation. The class

was an image interpretation of the built-up area located in the proposed project location. The result was compared with the field data that indicated 82 plots of very high density, 41 plots of high density, 66 plot of medium density, 45 plots of low density and 31 plots of very low density.

Vegetation Density Classification of	Element (Pixel)	GRVI Index	Vegetation Area (%)
Very Low Density	325791	0.0049	1.60
Low Density	3176668	0.0851	15.62
Medium Density	7919510	0.1652	38.95
High Density	3754467	0.2454	18.47
Very High Density	5154557	0.3255	25.35
Total	17929975	-	100.00

**Tabel 3.** Classification result of the vegetation density



**Figure 4.** Vegetation classification results of supervised SVM method and GRVI

In the EIA study, Environmental Impacts (EI) are commonly determined based on key criteria. In the case of Indonesia regulation, there are four criteria to evaluate Environmental Impacts (EI), i.e., (1) whether there is a burden on environmental components that are already high, (2) whether or not there are social, economic, and ecological values held by the environmental components, resulting in large changes in environmental conditions that will greatly affect people's lives and the integrity of the ecosystem, (3) whether or not there are high community concerns about these environmental components, and (4) whether there are rules or policies that will be violated and/or exceeded by these impacts (Kualita, 2007). In case that one or more criteria is identified on the potential impact, such as vegetation loss, the impact is classified as a hypothetical significant impact. Based on these criteria, vegetation removal as a component of the environment affects social, economic, and ecological values, thus it is determined as a hypothetical significant impact.

The hypothetical significant impact can be predicted as a significant EI by determining the magnitude of the impact and the important nature of the impact. In predicting the significant impact magnitude, the value of environmental quality of pre- dan post-development condition were categorized according to the vegetation density classes. The classes following the five level of vegetation density with scale of 1 to 5, i.e., very low vegetation density (1), low vegetation density (2), medium vegetation density (3), high vegetation density (4) and very high vegetation density (5). The result signified that the percentage of vegetation area classified as medium density, high density, and very high density was 82.77%. Therefore, the environmental quality can be

categorized in the scale of 4 or high density. As the evaluation, the post-development will reduce the percentage of the vegetation density. The environmental quality will be lower due to vegetation loss of the total area classified as medium density, high density, and very high density. The value of post-development was determined in the scale of 2 or low density according to the percentage of the remaining vegetation classified as very low and low density of 17.22%. The significance impact can be calculated as the reduction of the post- and pre-development scale of environmental quality (Fandeli, 1992). In this case, the pre- and post-development condition result in the negative impact of -2. The negative value of the impact magnitude can be categorized as low, medium and high with scale of 1 to 3. Therefore, the value of 2 can be categorized as a medium impact in negative influence.

Furthermore, the important nature of the impact can be analyzed using six criteria, i.e., (1) the size of the population that will be affected by the planned activities, (2) the area of impact distribution, (3) the intensity and duration of the impact, (4) the number of other environmental components that will be affected, (5) the cumulative nature of the impact, (6) reversal or non-reversal of impact. Each environmental component that is reviewed based on the six criteria of the nature of the impact has two classifications, i.e., important and not important. According to the criteria, if the impact signified as important for criteria (1) with impact magnitude  $\leq 1$  or indicated as important for one of the criteria or more with magnitude  $\geq 2$ , then the impact can be categorized as important or significant. In case of the vegetation loss, the impact was identified important for the criteria (4) and (5) due the absence of vegetation function for the environment, especially trees, to provide oxygen by absorbing carbon dioxide through the process of photosynthesis. Oxygen is used by other living things such as humans and animals. In addition, oxygen also makes the air fresher and help maintain the climate. Using the determination of the nature of the impact and the magnitude of the impact, i.e., important for two criteria with impact magnitude of 2, the impact of the vegetation loss can be eventually terminated as significant EI. In the EIA study, the significant EI should be taken into management and monitoring efforts.

The nature of the impact is determined based on changes in the Initial Environmental Baseline with the presence of a proposed project (Kualita, 2007). In this regard, information on vegetation density can be used to assess the pre-development quality as the Initial Environmental Baseline as well as the post-development quality. In the establishment of the proposed project, vegetation removal will be conducted therefore environmental management and monitoring efforts are required. Efforts that can be performed involve reforestation in the possible areas at the location of the proposed project development.

#### 4. CONCLUSION

The spatial analysis of seven different VIS-based VIs resulted in moderate to strong correlation with the field observation data of vegetation density. The highest VI, i.e., GRVI, signified the correlation of 80.16% with the vegetation density survey data. The GRVI values was utilized to create training samples in performing supervised classification method of SVM classification. The vegetation density classification in the proposed project of the tourism accommodation development in Karangasem, Bali, Indonesia demonstrated five density classes, i.e., very low, low, moderate, high and very-high density. The information can be utilized as an Initial Environmental Baseline to predict impact magnitude in the EIA study.

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