Selection of vegetation indices for mapping the sugarcane condition around the oil and gas field of North West Java Basin, Indonesia

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Abstract: Selection of vegetation indices in plant mapping is needed to provide the best information of plant conditions. The methods used in this research are the standard deviation and the linear regression. This research tried to determine the vegetation indices used for mapping the sugarcane conditions around oil and gas fields. The data used in this study is Landsat 8 OLI/TIRS. The standard deviation analysis on the 23 vegetation indices with 27 samples has resulted in the six highest standard deviations of vegetation indices, termed as GRVI, SR, NLI, SIPI, GEMI and LAI. The standard deviation values are 0.47; 0.43; 0.30; 0.17; 0.16 and 0.13. Regression correlation analysis on the 23 vegetation indices with 280 samples has resulted in the six vegetation indices, termed as NDVI, ENDVI, GDVI, VARI, LAI and SIPI. This was performed based on regression correlation with the lowest value $R^2$ than 0.8. The combined analysis of the standard deviation and the regression correlation has obtained the five vegetation indices, termed as NDVI, ENDVI, GDVI, LAI and SIPI. The results of the analysis of both methods show that a combination of two methods needs to be done to produce a good analysis of sugarcane conditions. It has been clarified through field surveys and showed good results for the prediction of microseepages.

1. Introduction
The vegetation indices is an important algorithm used to extract the information of vegetation condition [1]. Many vegetation indices have been published but only small of them have the important biophysical fundamental for plant monitoring and have been tested systematically [2]. Vegetation indices are employed to enhance the vegetation conditions and they represent a single value for converting the reflectance spectrum for measuring vegetation characteristics [2]. Vegetation characteristics, in general, can be distinguished into three categories: structure, biochemistry and plant physiology or stress condition [2].

For the past two decades, the normalized difference vegetation index (NDVI) is used as the important algorithm to analyze and map the spatial distribution of vegetation. Generally, NDVI is calculating based on the ratio of the near-infrared reflectance and red reflectance [4]. NDVI is the
popular index that corresponds to the photosynthetic rate and the capability to absorb energy in the vascular plants [5]. NDVI also is related to the plant cover linearly [6] and has a significant positive relationship to the Landscape function analysis (LFA) [7].

Similar to NDVI, many vegetation indices were developed to analyze the vegetation characteristics successfully. These indices include EVI which was designed to optimize the vegetation signal in regions of leaf area index [8], GARI is demonstrated to sense the concentration of chlorophyll, to measure the rate of photosynthesis and to monitor plant stress [9], GNDVI is calculating based on the ratio of near-infrared and green spectrum. This index was found more sensitive to the chlorophyll concentration in wide range variation and enabled precise assessment of pigment concentration [10], GRVI tested showed significant linear relationships with biomass [11]. The purpose of this study is to select the related vegetation indices for mapping the sugarcane conditions around the oil and gas field. The results of the vegetation indices selection are expected to identify vegetation anomalous due to the impact of hydrocarbon seepages.

2. Data and Methods

2.1 Study sites
The study site is located at Jatituhu sugarcane plantation in Indramayu and Majalengka Regency. Jatituhu sugarcane plantation area is the largest sugar producer in West Java Province. Jatituhu plantation has been operating since 1975 based on Agriculture Minister Decree No. 795/Mentan/VI/1975 regarding Principle License of Establishment of Jatituhu Sugar Company [12]. This area also covers active oil and gas fields operated by Pertamina. Several wells have been drilled since 1979 [13]. Hence we choose this site for our study. The study site is located approximately ±32 km from Indramayu and Majalengka [14]. The study site can be seen in figure 1.

![Study site map overlay with oil and gas wells in red dot and boundary of oil and gas field in brown lines.](image)

**Figure 1.** Study site map overlay with oil and gas wells in red dot and boundary of oil and gas field in brown lines.

2.2 Data and Processing
To choose and select the vegetation indices for mapping of sugarcane conditions around oil and gas field, we employed Landsat 8 with an acquisition date on September 25, 2015, and path/row 121/165.
Landsat 8 started recording of the earth surface changes after Landsat 5 discontinued and Landsat 7 has the SLC problem [15]. Comparing with Landsat 7 ETM+, Landsat 8 has higher near-infrared band values in the vegetation land cover and lower values in non-vegetation cover. Landsat 8 also has lower values for shortwave infrared (2.11-2.29) and had higher values in shortwave infrared (1.57-1.65) in all land cover types [17].

Radiometric calibration is a multi-step process to convert 8-bit digital numbers to satellite reflectance [18]. The atmospheric radiometric correction is conducted by using the FLAASH. This correction is based on the MODTRAN4 model. It is one of the most accurate preprocessing for remote sensing data in atmospheric radiometric correction [19]. The geometric correction is conducted using an image to image correction. The process of registration converts each pixel of Landsat 8 into a new coordinate system. Landsat 8 is corrected and registered using Universal Transverse Mercator (UTM) projection Zone 49 South. The process of registration is following the cubic convolution technique. The root means squares (RMS) error of this registration is 0.345 pixel.

2.3 Analysis

For the purpose of this research, 23 vegetation indices were evaluated. The spectral band combination and vegetation indices used in the analysis are in table 1. These vegetation indices have been used extensively in the vegetation properties studies. The vegetation indices were evaluated using the standard deviation and the linear regression to select the vegetation indices. The analysis to select the vegetation indices was conducted to map sugarcane conditions in three stages. In the first stage, the vegetation indices were selected using standard deviation. The standard deviation is a measure of spreading a set of data from its mean. In this research, we used 27 samples that had similar vegetation features near the oil and gas field (figure 2). The high values indicated that the data points are spread out over a wider range of values. Its mean there was an anomaly in the vegetation.

| Vegetation Indices | Formulas | Ref. |
|--------------------|----------|------|
| Enhanced Vegetation Index | EVI = 2.5 x (NIR - Red)/(NIR + (6 x Red) - (7.5 x Blue) + 1) | [8] |
| Green Difference Vegetation Index | GDVI = NIR - Green | [11] |
| Green Ratio Vegetation Index | GRVI = NIR/Green | [11] |
| Atmospherically Resistant Vegetation Index | ARVI = (NIR - (Red - γ(Blue-Red)))/(NIR + (Red - γ(Blue-Red))) | [20] |
| Difference Vegetation Index | DVI = NIR - Red | [21] |
| Global Environmental Monitoring Index | GEMI = \( \eta \times (1 - 0.25 \times \eta) + \frac{(\text{Red} - 0.125)}{(1 - \text{Red})} \) | [22] |
| GNDVI = \( \eta = \frac{2(NIR^2 - \text{Red}^2) + 1.5 \times \text{NIR} + 0.5 \times \text{Red}}{\text{NIR} + \text{Red} + 0.5} \) | [10] |
| Green Normalized Difference Vegetation Index | GARI = (NIR-[Green-γ(Blue-Red)])/(NIR+[Green-γ(Blue-Red)]) | [10] |
| Green Atmospherically Resistant Index | GVI = (-0.2848xTM\(_1\)) + (-0.2435xTM\(_2\)) + (-0.5436xTM\(_3\)) + (0.7243xTM\(_4\)) + (0.0840xTM\(_5\)) + (-0.18xTM\(_7\)) | [23] |
| Infrared Percentage Vegetation Index | IPVI = NIR/(NIR+Red) | [24] |
Table 1. Continued

| Vegetation Indices                  | Formulas                                         | Ref. |
|------------------------------------|--------------------------------------------------|------|
| Leaf Area Index                    | LAI = 3.618 x EVI – 0.118                        | [25] |
| Modified Non Linear Index          | MNLI = (((NIR^2-Red) x(1+L))/(NIR^2+Red+L))      | [26] |
| Modified Simple Ratio              | MSR = ((NIR/Red)-1)/(√(NIR/Red)+1)               | [27] |
| Non Linear Index                   | NLI = (NIR^2 – Red)/(NIR^2 + Red)                | [28] |
| Normalized Difference Vegetation   | NDVI = (NIR-Red)/(NIR + Red)                     | [29] |
| Index                              |                                                  |      |
| Optimized Soil Adjusted Vegetation | OSAVI = (NIR-Red)/(NIR+Red+0.16)                 | [30] |
| Index                              |                                                  |      |
| Renormalized Difference Vegetation | RDVI = (NIR-Red)/√(NIR+Red)                     | [31] |
| Index                              |                                                  |      |
| Soil Adjusted Vegetation Index     | SAVI = (1.5 x (NIR-Red))/(NIR+Red+0.5)           | [32] |
| Simple Ratio                       | SR = NIR/Red                                     | [33] |
| Visible Atmospherically Resistant  | VARI = (Green – Red)/(Green + Red - Blue)         | [34] |
| Index                              |                                                  |      |
| Transformed Difference Vegetation  | TDVI = √(0.5 + (NIR-Red)/(NIR+Red))              | [35] |
| Index                              |                                                  |      |
| Structurally Independent Pigment   | SIPI = (NIR-Blue)/(NIR – Red)                    | [36] |
| Index                              |                                                  |      |
| Enhanced Normalized Difference     | ENDVI = ((NIR+Green)-(2xBlue))/((NIR+Green)+(2xBlue)) | [37] |
| Vegetation Index                   |                                                  |      |

Figure 2. Samples of vegetation indices values for standard deviation analysis in red dot and linear regression analysis in yellow lines overlaid with Landsat 8 OLI/TIRS 432 RGB.

In the second stage, the method employed to select the vegetation indices is the linear regression. In this research, we used 280 samples to create the linear regression. The samples on the image of vegetation indices are taken out continuously cross the oil and gas field with the south-north direction (figure 2). The correlation analysis between vegetation indices is done by the coefficient of determination (R^2) method on linear regression results of each vegetation indices. The coefficient of
determination ($R^2$) is a statistical calculation showing of how well the regression line approaches the real data points. The limit of $R^2$ in this research is 0.8. The correlation results between vegetation indices are expected to obtain the indices used for this research.

In the third stage, the final analysis is done by combining the standard deviation analysis results and the linear regression correlation to choose the vegetation indices employed. This analysis is done based on the role of each index to map the effect of oil and gas field on sugarcane conditions. The result of its combination is expected to obtain the vegetation indices that can map the sugarcane plantation conditions due to the influence of oil and gas fields.

3. Results and Discussion

The results of standard deviation analysis of 23 vegetation indices algorithm showed the values range from 0.03 to 0.47 (figure 3). The standard deviation is a description of the spread of data and how widely it spreads from the mean. Smaller standard deviations show the data clustered near the mean. A larger one indicates that the data are scattered. This indicates that the vegetation indices can differentiate vegetation conditions in more detail. So it can illustrate the health of vegetation and the changes that occur in leaf structure. Based on these results, the vegetation indices used for the next analysis are GRVI, SR, NLI, LAI, SIPI and GEMI. The standard deviation values are 0.47, 0.43, 0.30, 0.18, 0.17 and 0.16. The vegetation indices are used with large standard deviation values as to map anomalous sugarcane conditions that are influenced by the oil and gas seepages.

| NO | VEGETATION INDICES | STANDARD DEVIATION |
|----|---------------------|-------------------|
| 1  | GRVI               | 0.47              |
| 2  | SR                 | 0.43              |
| 3  | NLI                | 0.30              |
| 4  | LAI                | 0.18              |
| 5  | SIPI               | 0.17              |
| 6  | GEMI               | 0.16              |
| 7  | OSAVI              | 0.12              |
| 8  | ENDVI              | 0.10              |
| 9  | ARVI               | 0.10              |
| 10 | TDVI               | 0.09              |
| 11 | NDVI               | 0.09              |
| 12 | GARI               | 0.09              |
| 13 | ENNDVI             | 0.09              |
| 14 | GSAVI              | 0.08              |
| 15 | RNDVI              | 0.07              |
| 16 | MSR                | 0.07              |
| 17 | GDVI               | 0.07              |
| 18 | DVI                | 0.06              |
| 19 | EVI                | 0.06              |
| 20 | MNLI               | 0.05              |
| 21 | JPVI               | 0.05              |
| 22 | VARI               | 0.04              |
| 23 | GVI                | 0.04              |

Figure 3. Standard deviation values of 23 vegetation indices.

The impact of oil and gas below the earth has resulted anomalous in the surface conditions. This phenomenon occurs due to the hydrocarbon seepages reaches the surface. This has an impact on the health conditions of vegetation, changes in clay mineral content, iron oxide, carbon delta and soil gas [38]. The condition occurs because of oil and gas seepage either in the form of microseepage and macroseepage [39]. Vegetation anomalies that occur are usually by vegetation stress characterized by slow growth and reduced chlorophyll [40]; low vegetation density and reduced oxygen in the soil [42]; the leaves tend to be yellowish [43]. In the internal leaf, there will be an increase in carotenoids [44].

The regression correlation results on 23 vegetation indices with the coefficient of determination limit ($R^2$) = 0.8 obtained NDVI, GDVI, ENNDVI, VARI, LAI, SIPI. The results of correlation based on the coefficient of determination are as follows:
1. NDVI correlates with TDVI \((R^2 = 1)\), SAVI \((R^2 = 0.8619)\), RDVI \((R^2 = 0.8829)\), MSR \((R^2 = 0.9976)\), MNLI \((R^2 = 0.8497)\), IPVI \((R^2 = 1)\), GNDVI \((R^2 = 0.8002)\), GARI \((R^2 = 0.9467)\), EVI \((R^2 = 0.8715)\), ARVI \((R^2 = 0.9585)\), GRVI \((R^2 = 0.8308)\), SR \((R^2 = 0.9244)\), LAI \((R^2 = 0.8715)\) and OSAVI \((R^2 = 0.9518)\).

2. GDVI correlates with GVI \((R^2 = 0.8564)\), DVI \((R^2 = 0.9202)\), GEMI \((R^2 = 0.8475)\) and, NLI \((R^2 = 0.9384)\).

3. ENVI correlated with SAVI \((R^2 = 0.8516)\), RDVI \((R^2 = 0.8394)\), GVI \((R^2 = 0.8348)\), GNDVI \((R^2 = 0.8244)\), DVI \((R^2 = 0.8226)\), GRVI \((R^2 = 0.8074)\), NLI \((R^2 = 0.8526)\) and OSAVI \((R^2 = 0.8114)\).

4. LAI correlated with TDVI \((R^2 = 0.8715)\), SAVI \((R^2 = 0.9909)\), RDVI \((R^2 = 0.9925)\), NDVI \((R^2 = 0.8715)\), MSR \((R^2 = 0.8836)\), MNLI \((R^2 = 0.8903)\), IPVI \((R^2 = 0.8715)\), GVI \((R^2 = 0.9634)\), GNDVI \((R^2 = 0.8108)\), EVI \((R^2 = 1)\), DVI \((R^2 = 0.9441)\), GRVI \((R^2 = 0.9076)\), SR \((R^2 = 0.8840)\), NLI \((R^2 = 0.9057)\) and OSAVI \((R^2 = 0.9719)\).

5. VARI and SIPI are not correlated well with other vegetation indices on the \(R^2 = 0.8\).

The results of selecting the vegetation indices based on the standard deviation and the linear regression obtained the 10 vegetation indices, namely GRVI, SR, NLI, SIPI, GEMI, LAI, NDVI, GDVI, ENDVI dan VARI. Further analysis is needed to minimize the number of vegetation indices used for mapping. The combination of the regression analysis and the Standard deviation showed that GRVI correlated with NDVI, ENDVI and LAI; SR correlated with NDVI and LAI; NLI correlated with GDVI, ENDVI and LAI; and GEMI correlated with GDVI. Based on these correlations, GRVI, SR, NLI and GEMI can be represented with NDVI, GDVI, LAI and ENDVI. Based on the final analysis result, the mapping of sugarcane vegetation condition can be done with 6 vegetation indices, that is NDVI, ENDVI, GDVI, VARI, LAI and SIPI. Although LAI correlates well with NDVI, it is still used in this study. LAI is required for analyzing the leaf area index. It is important to know the influence of hydrocarbon microseepages in the leaf cover.

Visual analysis showed that NDVI, ENDVI and GDVI were used to assess vegetation anomalies suspected to be in the south to the east of the study site. The anomaly is described as lower index values around the oil and gas field area. It is confirmed using LAI and SIPI results. The LAI results provide the information that at the location of the anomalous vegetation results still have vegetation with the rare condition. The SIPI results indicate that the location of the suspected vegetation anomaly has a higher SIPI value compared to its vicinity. These SIPI values indicate that the carotenoids in sugarcane vegetation increase, while the chlorophyll of leaves is reduced as a sign of stress vegetation [45]. VARI is less able to provide a significant picture of anomalies in sugarcane crops. A low standard deviation score (0.04) is thought to cause the result of VARI value in relatively uniform, so the anomalous does not appear well.

Survey results in March 2017 provide the confidence in the existence of microseepages in the south to the east of the oil and gas field. In this site, the sugarcane plant is not growing well. This indication is clearly visible with the small number of sugarcane clumps, ie between 2 - 7 trees and the height of the trees are less than 2 meters including leaves. This is a very different to the normal vegetation, where the clumps of sugarcane range from 11 to 20 trees. Surveys in August 2017 showed that sugarcane crops died at the site of the anomalous vegetation. NDVI, ENDVI, GDVI, LAI, SIPI and VARI images showed in figure 4.
Figure 4. Maps of vegetation indices were extracted from Landsat 8 as the selection results for mapping sugarcane condition around of oil and gas field, (a) NDVI; (b) ENDVI; (c) GDVI; (d) LAI; (e) SIPI and (f) VARI.

4. Conclusion
The selection of vegetation indices to map the sugarcane conditions around the oil and gas field can be done with the combination of the standard deviation and the linear regression methods with the value of the coefficient of determination of ($R^2$) > 0.8. The combination of both obtained six vegetation indices for mapping the sugarcane vegetation conditions around the oil and gas field, namely NDVI, ENDVI, GDVI, LAI and SIPI. The NDVI, ENDVI and GDVI provide an overview of vegetation conditions around the oil and gas fields. The vegetation anomalies in the oil and gas fields are characterized by the low value of the three vegetation indices. The LAI describes the vegetation cover conditions while the SIPI describes the stress vegetation conditions with increasing index values as an illustration of increased carotenoids and decreased chlorophyll.

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