Onshore oil and gas reservoir detection through mapping of hydrocarbon microseepage using remote sensing

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Abstract. Remote sensing is one of an advance technology that can be used for detecting hydrocarbon microseepage onshore. One of the advantage is specialize in rapid and low cost detection. Remote sensing technique namely multispectral scanner can overview the characteristic of seepage system as an exploration indicator of subsurface hydrocarbon. Therefore, the objective of this study is to analyse the microseepage system as indication of subsurface hydrocarbon accumulation using a multispectral imagery. The hydrocarbon-induced surface alterations of soil and sediments (clay-carbonate, ferric iron, ferrous iron) and associated anomalous vegetation were used as parameters. This research used Sentinel 2 and Landsat 8 multispectral imagery combine with the Directed Principal Component Analysis method to detect mineral alteration also using vegetation normalization to detect vegetation anomalies. The results of this study indicate the distribution of hydrocarbon microseepage distributed in area around Sungai Kenawang and Pulau Gading field, and also linear distributed in Merang River and Lalan River.

1. Introduction
Remote sensing has been used as an advance technology of considerable interest to earth scientists in general and exploration geologists in particular [1], including of detecting hydrocarbon (here and after call as “HC”) accumulation as indication of onshore reservoir occurrence [2]. Remote sensing techniques can potentially be applied to onshore HC detection associated with the effects of microseepage on mineralogy or vegetation [3]. This approach holds a great promise for this aim because it is fast and cost-effective tool that can be applied to different operational scales for both direct and indirect seepage mapping [4]. HC micro seepage is a process of mass movement of light HC from its original place (reservoir) to the surface of the earth [5]. This phenomenon is a manifestation from HC migration that moves from the seal rock to the earth surface [6]. The detection of gaseous HC seepages (microseepages) plays a key role in oil and gas exploration and approximately 75 % of the world’s oil basins show HC seepage, excepting those with intact, unfractured seals [7].

The objective of this study was to detect the seepage system as indication of HC accumulation in the subsurface. A combination of multispectral imagery of Landsat 8 OLI and Sentinel 2 MSI were used for mapping the potential of HC micro seepage in X Block South Sumatera Province. In addition, this paper strives to compare the used of Sentinel 2 and Landsat 8 in order to detect HC microseepage. The detection of HC micro seepage area was conducted by detecting the anomalies of clay carbonate

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alteration, ferric iron alteration, and ferrous iron alteration. Thus, directed principal component analysis (DPCA) was utilized to minimize the vegetation effect on the surface [8]. Meanwhile, the vegetation normalization namely NDVI (Normalized Difference Vegetation Index), GNDVI (Green Normalized Difference Vegetation Index), SAVI (Soil Adjusted Vegetation Index), ARVI2 (Adjusted Resistant Vegetation Index 2), and Chlorophyll Index Green are used for detecting the geobotanic anomalies as indication of HC micro seepage occurrence. Then, all variables are integrated using fuzzy logic method for identifying the distribution of HC micro seepage potential area as indication of onshore reservoir occurrence.

2. The Study Area
The study area was performed in X Block that located in South Sumatera Basin. X Block is composed by the Formation of Air Bekanat (Tmk), Kasai Formation (QTk), Muara Enim Formation (Tmpm), alluvial sediment (Qa), and alluvium lacustrine / swamp (Qs) deposits. This basin has a great potency of HC especially as producer of coal, coal gas methane, and also oil and gas [9]. The potency of HC in this area is indicated by the presence of shale gas and HC seepage. The study area can be seen in Figure 1.

![Figure 1. The study Area located in South Sumatera Province. It is one of oil and gas onshore block in Indonesia.](image)

3. Method
This research is use two variables for detecting the HC micro seepage phenomenon. First, the mineral alteration anomalies data are obtained from Landsat 8 OLI (August 17th 2016) and Sentinel 2 (February 15th 2015) processing using directed principal component analysis (DPCA) method. Second, the geobotanic anomalies data that obtained from vegetation index data. Then, both of the data are combine and processed using fuzzy logic so as result the HC micro seepage potential area. Furthermore, several processing step was applied before extracting the information of mineral alteration anomalies and geobotanic anomalies, describe as follows. First, correction is performed by the ATCOR method to change the value of ToA (Top of Atmospheric) into the BoA (Bottom of Atmospheric) reflectance value searched by ground reflectance change. Second, the processing of HC microseepage anomaly is done by DPCA (Directed Principal Component Analysis) method. DPCA method performed on mineral alteration data obtained from the processing of band ratio. This method is appropriate to observe mineral alteration in tropical areas full of vegetation [8]. Third is calculating the vegetation index, by combine several ratio of visible and near-infrared band. Last, both processing anomalies are performed processing algorithm which can be seen in Table 1. Processed results with algorithmic function in Table 1 are further processed by fuzzy logic method. Determination of fuzzy logic process of minerals alteration anomaly value is conducted with special equation to know mineral anomaly threshold value. The equations used are:
\[ A_i = \bar{X} \pm \sigma \]  \hspace{1cm} (1)

where, \( A_i \) is anomaly threshold value of mineral \( i \), \( \bar{X} \) is the mean threshold value of mineral \( i \), \( \sigma \) is deviation standard threshold of mineral \( i \).

The HC micro seepage phenomenon can lead to the chemical change toward the passing mineral substance. Therefore, the presence of HC that seeps to the earth surface will be indicated by the occurrence of clay carbonate abundance, the reduction of ferric iron, and the abundance of ferrous iron. The symptoms of mineral alteration anomalies are conducted from the DPCA method processing, both in Landsat 8 and Sentinel 2 imageries. The principal of DPCA method is conducting the sharpening towards imagery information that separated from the intruder object, such as vegetation. Therefore, the information of each mineral that obtained from band ratio method in Table 1 will be corrected using the image with a dense vegetation characteristic. NDVI is used for choosing the image with vegetation dense information as input in DPCA coincide with mineral alteration information that obtained from band ratio method in Table 1. Then, each of image will be transformed so that resulting the eigenvector and eigenvalue which will be basic for choosing the right band. The DPCA can present several image selection containing different information based on the variance level of its eigenvector and eigenvalue. An image with a larger positive eigenvector (+) or smaller (-) than the image eigenvector value representing vegetation information (NDVI) can be selected as a vegetation corrected image [8].

### Table 1. Formula of data processing

| No | Anomalies                             | Algorithm                              | Method Input | Source                  |
|----|---------------------------------------|----------------------------------------|--------------|-------------------------|
| 1  | Ferric Iron Alteration                | SWIR 2/SWIR 1                         | DPCA         | Pour et al. (2013)      |
| 2  | Ferrous Iron Alteration               | SWIR 1/Vegetation Red Edge            | DPCA         | Pour et al. (2013)      |
| 3  | Clay Carbonate Alteration             | SWIR 1/SWIR 2                         | DPCA         | Pour et al. (2013)      |
| 4  | NDVI (Normalized Different Vegetation Index) | \( \frac{NIR - Red}{NIR + Red} \) | VI           | Arellano et al. (2015) |
| 5  | GNDVI (Green Normalized Different Vegetation Index) | \( \frac{NIR - Green}{NIR + Green} \) | VI           | Arellano et al. (2015) |
| 6  | SAVI (Soil Adjusted Vegetation Index) | \( \frac{NIR - Red}{NIR + Red + 0.5} (1 + 0.5) \) | VI           | Adamu et al. (2016)    |
| 7  | ARVI2 (Adjusted Resistant Vegetation Index 2) | \( \frac{(NIR - Red \times 1.17)}{NIR + Red} - 0.18 \) | VI           | Adamu et al. (2016)    |
| 8  | Chlorophyll Index Green                | \( \frac{NIR}{Green} - 1 \)           | VI           | Hunt et al. (2011)     |

### 4. Result and Discussion

#### 4.1 Mineral Alteration Anomalies

The result of DPCA transformation on Landsat 8 OLI imagery that is yield eigenvalue and eigenvector value can be seen in table 2. The selection terms of the image of the DPCA algorithm is that the eigenvector must be larger (+) or smaller (-) from the eigenvector of the vegetation image. Therefore, clay carbonate mineralization can be extracted from DPCA1 because the positive value (+) is higher than that of the NDVI eigenvector and other minerals. The value of clay carbonate eigenvector indicates that the mineralization information will be dominant in DPCA1 (+0.855386). Meanwhile, the eigenvector value for band ratio ferric iron is highest in DPCA4 with a value of +0.980684. Ferrous iron...
mineralization was obtained through DPCA2 extraction because it has a high eigenvector value of +0.892561 and higher than vegetation eigenvector of -0.03726. Furthermore, clay carbonate mineralization in DPCA transformation of Sentinel 2 imagery can be extracted on DPCA1 (0.9516) because its eigenvector value is less or more negative than the value of vegetation eigenvector. Furthermore, ferric iron mineralization can be extracted from DPCA4 because its eigenvector value is -0.8275. Meanwhile, ferrous iron mineralization was extracted from DPCA2 because it has eigenvector value of -0.9069 and more negative than vegetation eigenvector (0.2472), clay carbonate (0.0467), and eigenvector ferric iron (-0.3378).

**Table 2.** The Result of DPCA on Landsat 8 OLI

| Imagery  | DPCA  | NDVI  | Clay Carbonate | Ferric Iron | Ferrous Iron |
|----------|-------|-------|----------------|-------------|--------------|
| Landsat  | DPCA1 | 0.246961 | 0.855386      | -0.182515  | -0.417149   |
|          | DPCA2 | -0.03726  | 0.449148      | 0.014586   | 0.892561    |
|          | DPCA3 | 0.961577  | -0.218546     | -0.068805  | 0.15124     |
|          | DPCA4 | 0.113981  | 0.137182      | 0.980684   | -0.0803     |
| Sentinel | DPCA1 | 0.2804    | 0.9516        | 0.0817     | 0.0950      |
|          | DPCA2 | 0.2472    | 0.0467        | -0.3378    | -0.9069     |
|          | DPCA3 | 0.8470    | -0.292        | 0.4407     | 0.0516      |
|          | DPCA4 | 0.377     | -0.0809       | -0.8275    | 0.4071      |

The processing of mineral clay carbonate, ferric iron, and ferrous iron alteration anomalies was done by calculating the threshold of each channel. The anomalous threshold value is included in the highest threshold value of each channel measured by Equation 1. Avcioglu [10] used the calculation of mean (mean) and standard deviation values at the threshold to measure the threshold value of the anomaly used at the level of confidence 92%. The result of processing in each image can be seen in Table 3.

**Table 3.** The threshold of mineral alteration based on Landsat 8 and Sentinel 2 imagery processing

| The Imagery | Mineral Alteration | Mean   | SD    | Threshold of Anomalies Value |
|-------------|--------------------|--------|-------|-------------------------------|
| Landsat 8 OLI | Clay carbonate    | 164.789638 | 67.093271 | 231.88-255                    |
|             | Ferric iron       | 111.310726  | 45.89059  | 157.2-255                     |
|             | Ferrous iron      | 137.782104  | 47.732656  | 185.51-255                    |
| Sentinel 2  | Clay carbonate    | 64.65    | 53.9    | 118.55                        |
|             | Ferric iron       | 67.45    | 57.45   | 0-10                          |
|             | Ferrous iron      | 164.58   | 70.98   | 0-93.6                        |

4.2 Geobotanic Anomalies

The geobotanic anomaly states the phenomenon of crop damage due to the content and mass of HCs that damage the metabolic system of plants. Geobotanic anomalies can be characterized by changes in plant pigment photosynthesis, changes in leaf size, changes in leaf thickness, and changes in leaf structure [11,12]. Geobotanic anomalies were detected with Landsat 8 OLI and Sentinel 2 images through NDVI, GNDVI, SAVI, ARVI2, and Chlorophyll Index Green. This vegetation index will identify the geobotanic anomalies based on the low greenness or the vegetation dense value that obtained from NDVI, GNDVI, SAVI, and ARVI2, and the chlorophyll content that obtained from Chlorophyll Index Green.

The observed vegetation conditions through the normalization of NDVI index on Landsat 8 OLI image range from -0.55 to 0.99 and range -0.99 to 0.93 on Sentinel image 2. The GNDVI index mapped...
the vegetation conditions in the study area over the range of values -0.52 to 0.91 on Landsat 8 OLI image and range of values from -0.99 to 0.93 on Sentinel 2 image; the SAVI index on the Landsat 8 OLI image mapped the vegetation conditions of the study area in the range of values of -1.66 to 2.99 and on Sentinel 2 imagery detected in the range -2.98 to 2.80; lastly, the ARVI2 index mapped the vegetation condition from the range of values from -0.82 to 0.98 on Landsat 8 OLI and the range of values from -0.99 to 0.93 on Sentinel image 2. The lowest index value on each index stated the condition of the region with the lowest vegetation density or non-vegetation. In contrast, the highest index value states the condition of the region with very tight vegetation. Based on the processing with these vegetation indexes, the occurrence of geobotanic anomalies is found in the area with the low greenness or vegetation dense value. The condition of chlorophyll of plants obtained from Chlorophyll Green Index processing with Landsat 8 OLI and Sentinel 2 images shows the range of values -1 to 22.26. The range of values of each index quantitatively represents the condition of plant chlorophyll in the study area, where the higher the value the better the chlorophyll condition of the plant. Conversely, the lower the CGI value the lower the quality of plant chlorophyll.

4.3 Hydrocarbon Microseepage Potential Area
The potential area of HC microseepage is generated through fuzzy overlay gamma data of mineral alteration anomalies and geobotanic anomalies in each image. The result of fuzzy logic process on both images can be seen in Figure 2. The result of both that is represented by the threshold value of range 0-1. The closer is the value of 1, the higher the potential value of micro HC seepage in the study area. Conversely, the closer the value of threshold 0, the lower the potential value of seepage. The pattern of potential distribution of HC micro seepage in both relative images shows the same pattern in some area, especially in area around Merang River that across in the west of X Block. The distribution of HC micro seepage areas is mainly agglomerated in the eastern, southern and central regions of the X Block. Spatial pattern of micro HC seepage in Sentinel 2 image processing shows the distribution smaller and unvaried region rather than the spatial pattern of seepage of Landsat 8 image processing.

![Figure 2](image_url)

Figure 2. The visualization of HC microseepage potential area. The result on Landsat 8 imagery (left), the result on Sentinel 2 imagery (right).

The HC micro seepage area based on the Landsat 8 image processing shows the agglomeration in the middle of the X Block, mainly around Lalan River. This region is characterized by a large threshold value of fuzzy logic process compared to the surrounding areas. The distribution of HC micro seepage areas is also found in areas adjacent to oil and gas exploitation fields, namely Sungai Kenawang Field and Pulau Gading Field with the total extent of this category is 7.127.4 Ha. Meanwhile, the high potential of HC micro seepage based on Sentinel 2 which agglomerated in around Merang River, Sungai Kenawang Field, and Pulau Gading Field has the total extent 4,544.7 Ha.
5. Conclusion
This study shows that Landsat 8 OLI and Sentinel 2 images can be used to explore oil and gas resources through the detection of HC micro seepage in X Block. The detection of oil and gas resources is conducted by combining the DPCA method and vegetation index based on several multispectral imagery channels to identify the symptoms of mineral alteration anomalies and geobotanic anomalies. The results of this study indicate that the potential distribution area of HC micro seepage spreading in the area around the Merang River, Lalan River, Sungai Kenawang Field, and Pulau Gading Field with total extent 7,127 Ha based Landsat 8 processing, and 4,544 Ha based on Sentinel 2 processing.

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