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Spatial-Temporal Variability of Vegetation Health During El Niño 2015/2016 and La Niña 2017/2018: A Case Study of Sarawak

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ABSTRACT

The El Niño incident in 2015/2016 resulted in a 30% decrease in Gross Domestic Product (GDP) mainly from the agricultural sector. This is due to the El Niño incident which contributed to the prolonged drought for 3 months. This prolonged drought disaster has caused the deterioration of plant health due to a decrease in the amount of rainfall. This study examines and analyzes the spatial-temporal dynamics to identify and delineate the vegetation stress zones in Sarawak. In achieving the objectives of this study Vegetation Health Index (VHI) has been used in studying the changes in monthly space due to changes in Oceanic Niño Index (ONI). This study only focuses on the two occurrences of El Niño in 2015/2016 and La Niña in 2017 and 2018 because the Visible Infrared Imaging Radiometer Suite (VIIRS) data only started operations in 2013 until now. The results of this study offer the discovery of the effect of La Niña on plant health compared to previous studies that only focus on the effects of El Niño (Drought) on plant health. Indirectly, this study can provide information on which areas of the district are severely affected by the occurrence of La Niña and El Niño on plant health.

Contribution/Originality: El Niño Oscillation Southern (ENSO) influences climate and weather in study areas. The effects of El Niño cause drought which indirectly influence plant health. However, there is still less study to provide spatial-temporal information effect of ENSO to plant health. Indirectly, this research provides insight into which areas of the county will be severely affected in terms of plant health by the La Niña and El Niño events.

1. Introduction

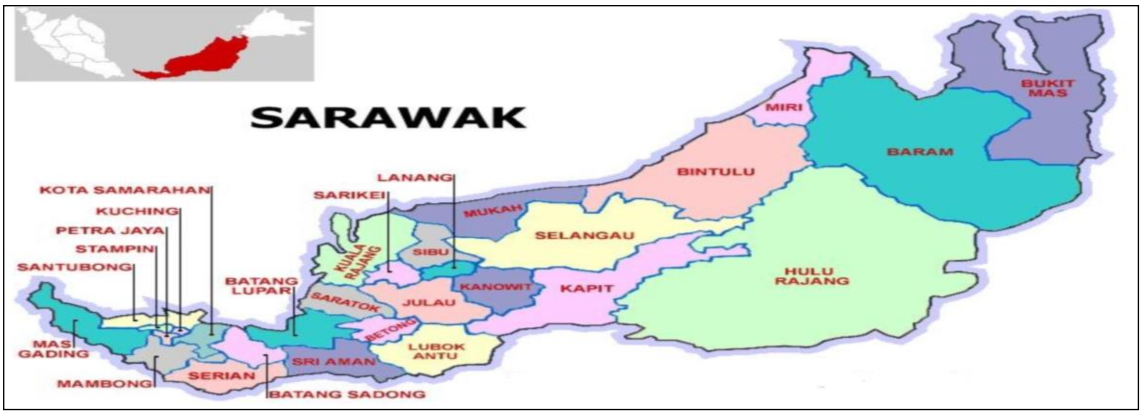
Plants play an important role in the global atmospheric, terrestrial ecosystem, hydrologic, carbon cycles, climate change, and drought monitoring (Measho et al., 2019; Winkler et al., 2017). In 2015/2016 the world experienced the highest hot, dry weather and drought recorded in human history that seemed to have the strength of the 1997/1998 El Niño. The occurrence of El Niño has the effect of heatwaves on the environment and humans. During the El Niño incident, the plants are under stress due to a lack of water supply which will reduce the length of the growing seasons. The El Niño incident is the biggest issue because it influences society and the economy, especially the agricultural sector. This study is a necessity in managing natural resources (Othman et al., 2016). This study will provide spatial information and continuous information on changes in human health. In Malaysia only, Othman et al. (2016) studied the effects of El Niño in 2015 in Kedah. However, his research is limited to El Niño. Othman et al. (2016) stated that the effects of El Niño will cause the death of animals, plants, and even humans due to the lack of rainfall. Mapping, monitoring, and managing this occurrence requires remote sensing technology. The following is a study of the use of remote sensing in studying the effects of drought on plant health. Vegetation indices are used in the study temporal remote sensing data were extensively used for identifying the periods of vegetative stress (Kogan, 1995; Rojas et al., 2011; Rhee et al. 2010; Logan et al., 2010; Skakun et al., 2016). All studies started to focus only on the effects of El Niño events on plants. To date, there has been no study studying the effects of La Niña on plant health. This raises the question of how the effects of the La Niña incident on the environment, especially plant health.

2. Method

The data used is VIIRS from 2013 to 2020. However, this study focuses on the two incidents of ENSO on La Niña in late 2017 and early 2018 and EL Niño in 2015/2016. Most past studies have used AVHRR data in studies on vegetative health products (Wenze et al., 2020). AVHRR data has expired in 2017 and will be replaced by VIIRS which started operations in 2013. This study was conducted to test the ability of VIIRS in observing the effects of ENSO on plant health. The data has been downloaded from the National Center for Applications and Research, the National Environmental Satellite Data and Information Service, NOAA, and its URL is https://www.star.nesdis.noaa.gov/smcd/emb/vci/VH / index.php.

Temperatures in the study area (Figure 1) are hot throughout the year, with average daily temperatures ranging from 23 degrees Celsius in the early morning to 32 degrees Celsius during the day (Sa'adi et al., 2017; Kottek et al., 2006).

Figure 1: Study Areas



The climate in Kuching is influenced by Madden Julian Oscillation, El Niño Southern Oscillation (ENSO), Indian Ocean Dipole (IOD), and Monsoon season (Sa'adi et al., 2019). In recent years, ENSO phenomena, climate change, and several incidents of heavy rainfall have been reported in Borneo Malaysia including in the study area, namely Sarawak (Sa'adi et al., 2017). On the other hand, 2009 was also recognized as the last year for Sarawak when two major rainfall events caused severe floods covering the whole of Sarawak including Kuching (Sa'adi et al., 2017). This phenomenon has raised concerns to encourage more research on meteorological data flow analysis to examine whether these changes are statistically significant or significant (Sa'adi et al., 2017).

2.1. Vegetation Index

The Vegetation Condition Index (VCI) is the best parameter for plants to respond to total rainfall. Refers to VCI capable of capturing water-related stress.

$$VCI = 100 \times (NDVI - NDVImin)/(NDVImax - NDVImin)$$

Where NDVImax and NDVImin are the maximum and minimum values of NDVI. Kogan (1995) stated that VCI is more sensitive to the value of dynamic rainfall than NDVI. It is also used in the Temperature condition Index (TCI) in measuring the effect of temperature on plant stress and the effect of excess moisture on plants (Kogan, 1995). Here is the formula for generating TCI.

$$TCI = 100 \times (BTmax - BT)/ (BTmax - BTmin)$$

where BT, BTmax, and BTmin are the Brightness Temperature, originally derived from AVHRR's fourth channel (10–11.5 μm), its multi-year absolute maximum, and minimum, respectively. By combining VCI and TCI through weighted averaging, one can obtain the Vegetation Health Index (VHI) as one can obtain the Vegetation Health Index (VHI) as:

$$VHI = \alpha \times VCI + (1 - \alpha) \times TCI,$$

where, in a general sense, the weight α is simply 0.5. All three indices have a value from 0 to 100. A value of 0 indicates the nature of the plant is the most stressful and the value of 35 to 65 is normal while 65 and above is very healthy. All three indices were developed for the study of food security problems including food availability, access to food, food utilization, and malnutrition. In addition, the above index is also used in drought studies, and crop yield estimation which is to identify and track drought in the planting area.

2.2. Oceanic Niño Indeks (ONI)

The ONI index shows the development and intensity of El Niño or La Niña events in the Pacific Ocean. ONI is a three-month Sea Temperature (SST) anomaly in the Niño region 3.4 5 ° N - 5 ° S, 120 ° - 170 ° W). The occurrence of El Niño is defined when the average value of three months at or above + 0.5 ° C anomaly, while the event of La Niña is defined as or under climate Anomaly −0.5 ° C (Kemarau & Eboy, 2021). ENSO value grade is classified into 5 classes Weak (with anomalies 0.5 to 0.9 SST), Medium (1.0 to 1.4), Strong (1.5 to 1.9), and Very Strong (≥ 2.0) for El Niño events and vice versa for La Niño events.

3. Result and Discussion

Referring to Figure 2 shows the pattern of ONI values from 2000 to 2019. Based on Kemarau and Eboy (2021) statement, El Niño representing ONI values starts from positive 0.5 and above and for La Niña its value starts from negative 0.5 and below. During the years 2000 to 2019 there were 6 La Niña incidents namely 2000, 2006, 2007 until January 2009, 2010/2012 and in July 2016 and end year 2017 until January 2018. While the El Niño incidents were from April 2002 until January 2003, October 2009, and 2015 / 2016. El Niño in 2015/2016 is the worst El Niño ever recorded in history that seems to have happened in 1997/1998. This is the same as stated by Tang (2019) and Tan et al. (2020).

Figure 2: The pattern of ONI values from 2000 to 2019.

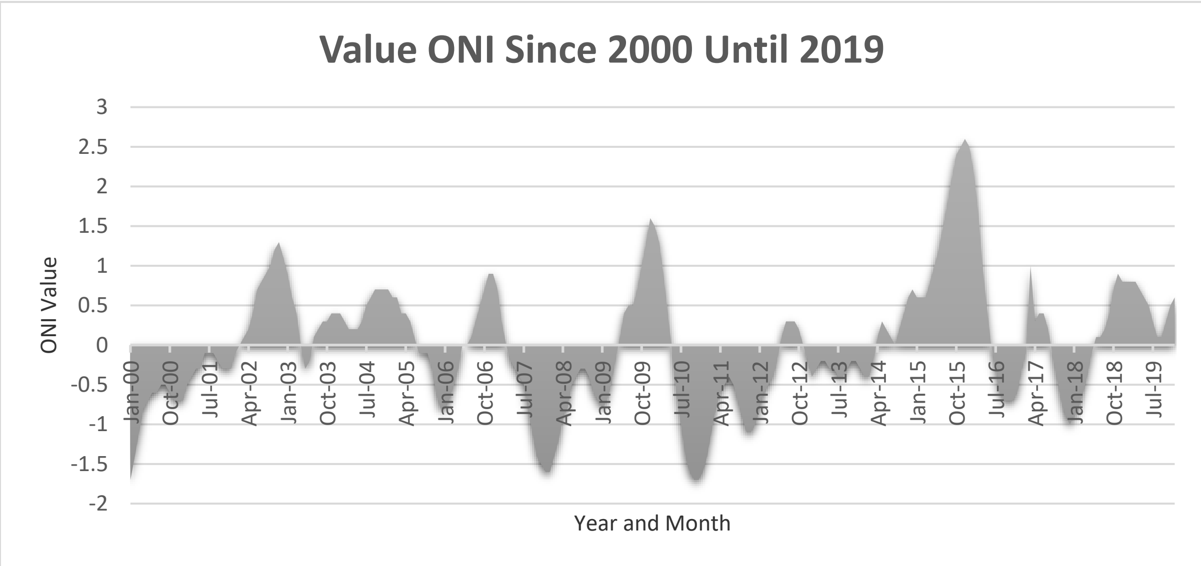
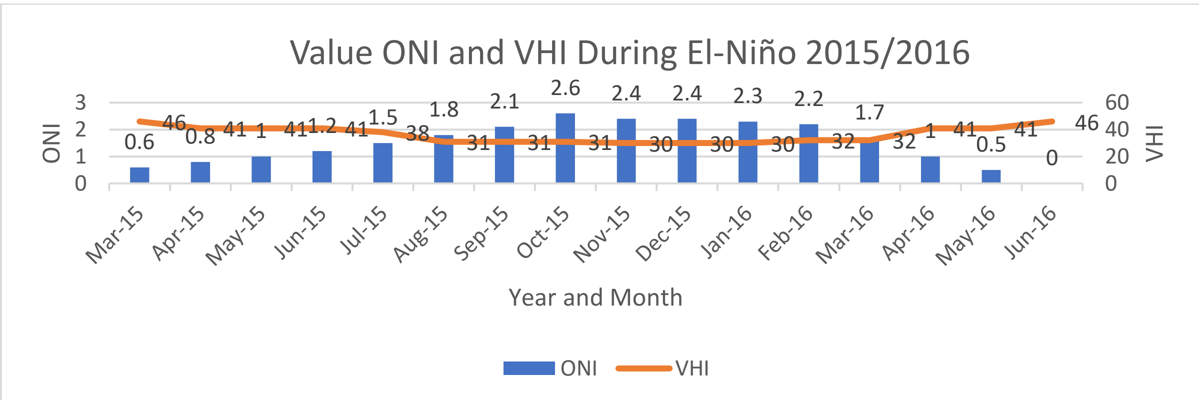


Figure 3 shows ONI and VHI values during El Niño 2015/2016. Based on the table above shows that the ONI value increases will cause the VHI value to decrease as described below.

Figure 3: The ONI and VHI values during the 2015/2016 El Niño incident.



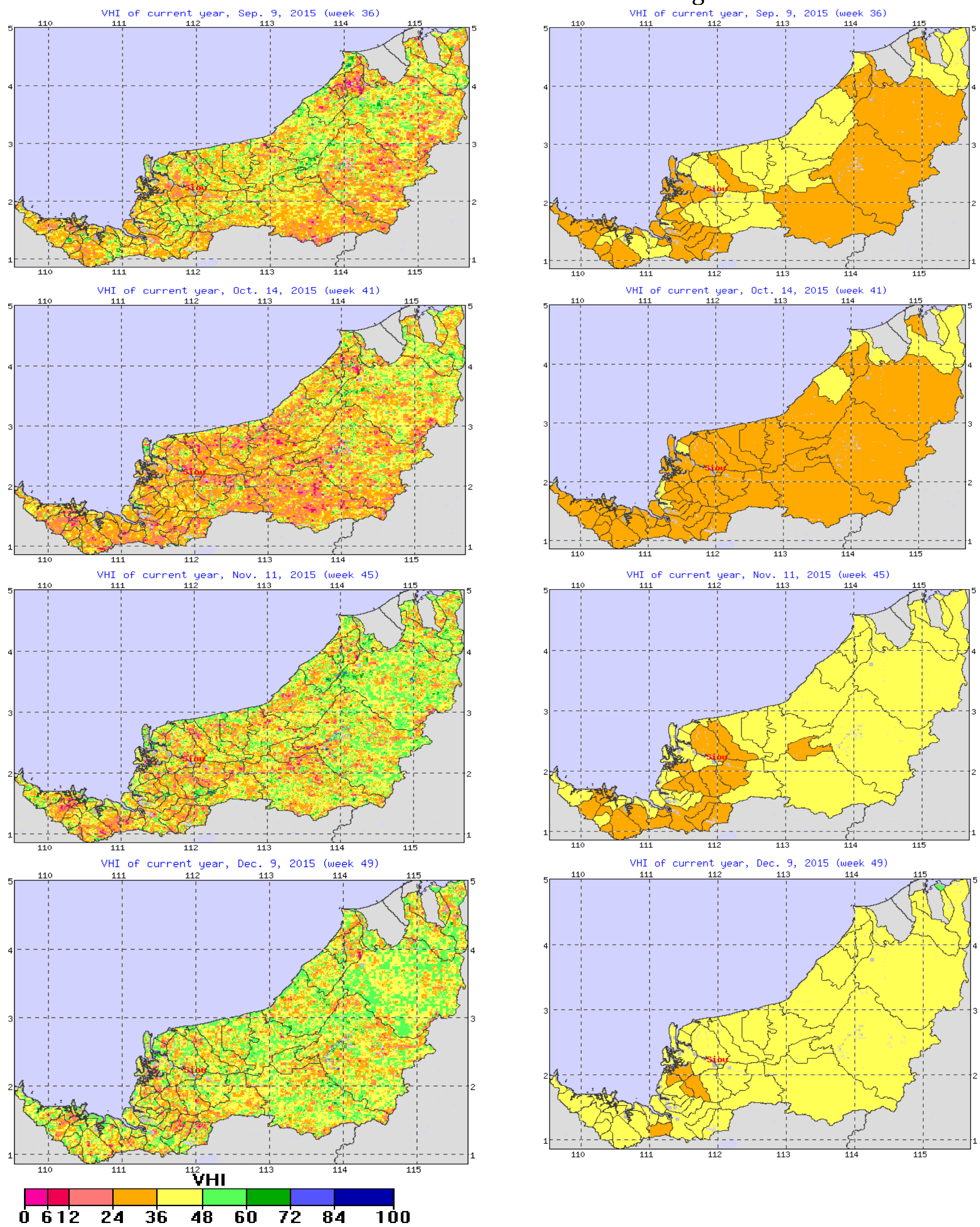
If the ONI Value is 1.2 then the VHI value is 41 and if the ONI value decreases to 2.1 then the VHI value is 31. An increase in the ONI value means an increase in temperature or an increase in the degree of El Niño strength. For El Niño, 2015/2016 events are found to start in March 2015 and increase until October 2015 and decrease in November 2016. The strength of El Niño depends on the value of ONI. The effect of El Niño on plant health depends on the value of ONI. The diagram below will explain more about the effect of ENSO on plant health in the form of space.

Figure 4 shows the spatial information for VHI during the El Niño incident in 2015/2016. The diagram on the left shows the distribution of VHI patterns and on the right shows the mean value for each district in Sarawak during the El Niño incident.

Figure 4: The spatial information for VHI during El Niño Incident in 2015/2016

VHI Spatial Pattern During El Niño Incident

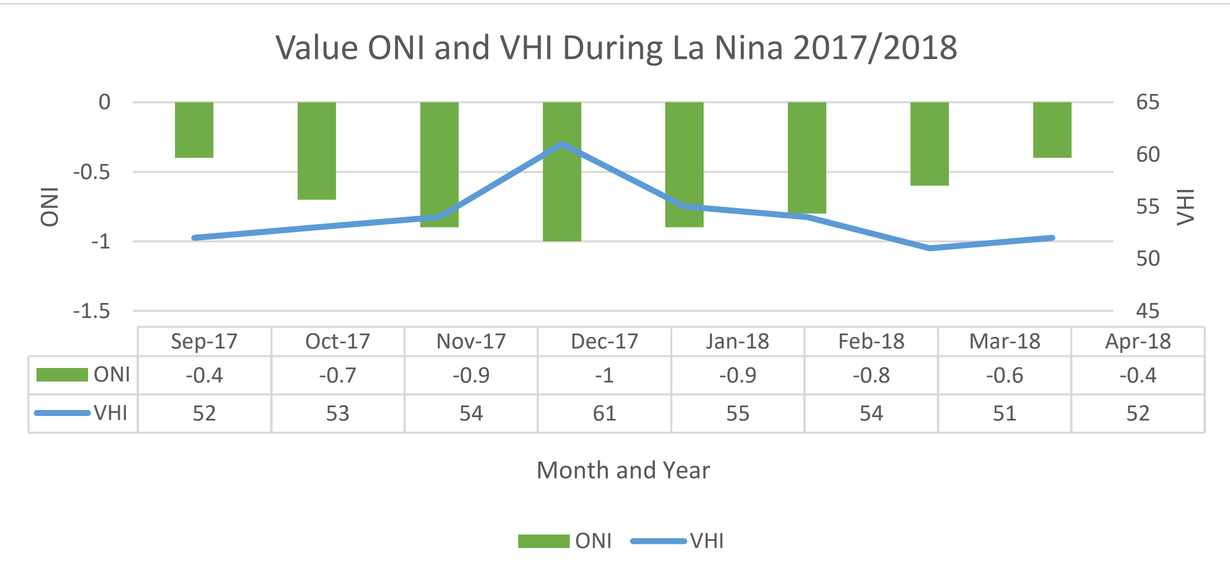
Spatial Pattern For VHI Value Mean districts During El Niño Events.



For example, the first diagram on the top left shows the distribution of VHI patterns on September 9, 2015, which is when the ONI value is 2.1. To facilitate an understanding of the effect of ENSO on the ONI scale 2.1 the average value map for each district is created as shown in the diagram on the left on the same day that is 9 September 2015 where most of the Sarawak area VHI value between 24-36 which is Miri, Baram, Kapit, Selangau, Sibu, Sri Aman Division, Serian, Lundu and including Kuching. Meanwhile, for areas of value 36 to 48 represented by yellow, many are in the coastal areas of Miri and Bintulu. The area of the yellow area where the value of 36 to 48 decreased in October 2015 where the value of ONI is 2.6 only in 4 parts such as Sibuti district, Belawai and the rest are in conditions 24 to 36. This clearly shows that the occurrence of ENSO is through the occurrence of El Niño caused the health of the plant to clear or deteriorate especially at the peak. However, the change in the VHI value column pattern decreased based on the ONI value as in December 2015 where the ONI value of 2.4 caused almost the entire area of Sarawak to be yellow which is the VHI value of 36 to 48 except for 4 parts as in the Sarikei area.

Figure 5 showed the patterns of the ONI and VHI values during the La Niña incident in late 2017 and early 2018. Based on the diagram above shows the decreased ONI value will cause an increase in the VHI value. For example, in October 2017 where the ONI value is negative 0.7 then the VHI value is 53. Whereas if the ONI value is negative 1 eat the VHI value is 61. Based on the evidence from Kemarau and Eboy (2021) classify if the negative ONI value of 0.5 and below is classified as La Niña. This explains why the La Niña incident also had a good effect on VHI. A more in-depth description of La Niña's impact on VHI will be explained through the VHI map below. ONI values have a significant effect on the distribution of VHI values.

Figure 5: The pattern ONI and VHI During La Niña Incident 2017/2018



Based Figure 6 shows the VHI distribution map above shows the map on the left shows the VHI value distribution during the La Niña incident. While on the right shows the average map of the district area in Sarawak. For example, the map on the top left shows the VHI exit map on 4 November 2017 where the ONI value is negative 0.9 and the map on the right is the average value distribution map of each district in Sarawak on the same day which is 4 November 2017. Based on observations on both the map found that almost the entire area of Sarawak has VHI 48 to 60 except 4 districts such as Kuching, Sri

Aman, Samarahan, and Serian. In contrast to El Niño, there is an increase in ONI value, but there is no increase in the green status area or VHI value higher than 60. On 16 December 2017 where ONI value is negative 1. The yellow area increases with yellow status. However, overall, the VHI area at La Niña was better during the El Niño incident. This is because plants react to a lack of water resources in carrying out the process of photosynthesis. As is well-known plants need water, sunlight, and carbon dioxide in the process of photosynthesis. An in-depth explanation will be explained in the next chapter through plant stress conditions during lack of moisture.

Figure 6: The map of VHI distribution during La Niña 2017/2018.

VHI Spatial Pattern During La Niña Incident

Spatial Pattern For VHI Value Mean districts During La Niña events.

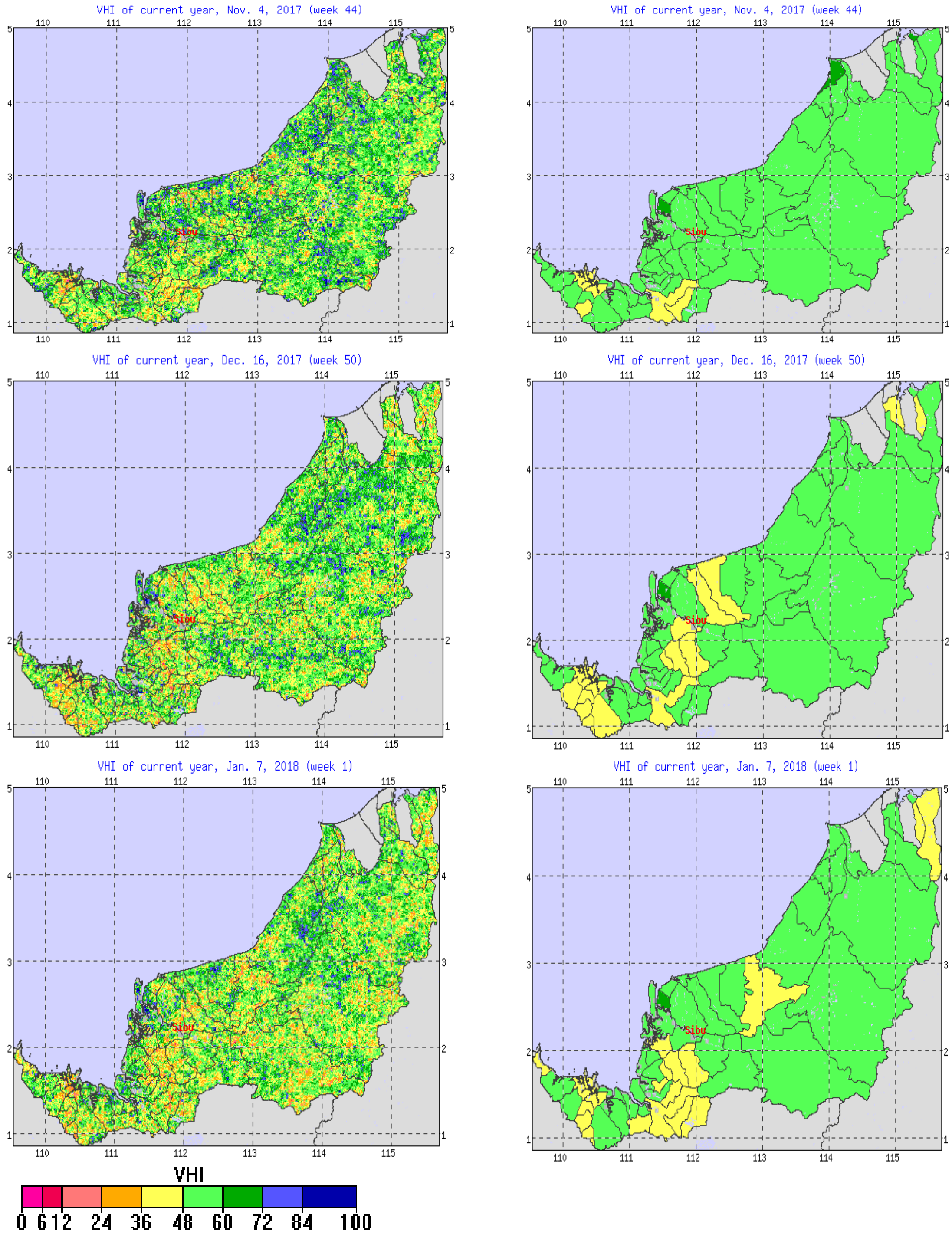
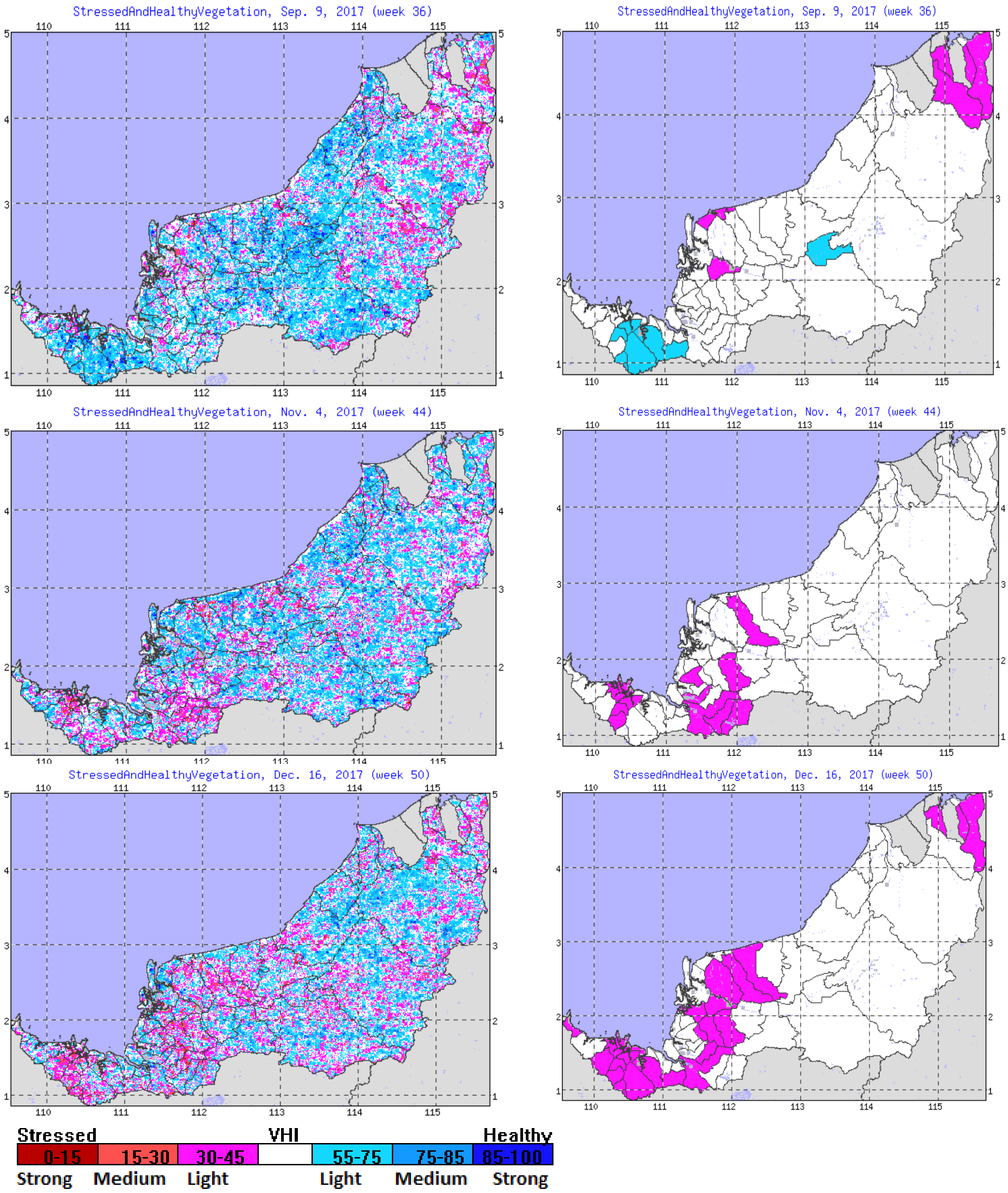


Figure 7 shows a map of the distribution of plant conditions during La Niña. Overall, most of the plants are in normal condition except on 9 September 2017, there are 5 districts in Sarawak. However, on 4 November 2017 and 16 December 2017 there are some areas of plants that are under stress at a value of 30 to 45 in western Sarawak. Overall, during the La Niña incident, the distribution of plants in Sarawak was normal.

Figure 7: The map of plant conditions that are stressed, normal or Healthy.

Stressed and Healthy Spatial Pattern During La Niña Incident	Spatial Pattern For Stressed and Healthy Value Mean districts During La Niña events.

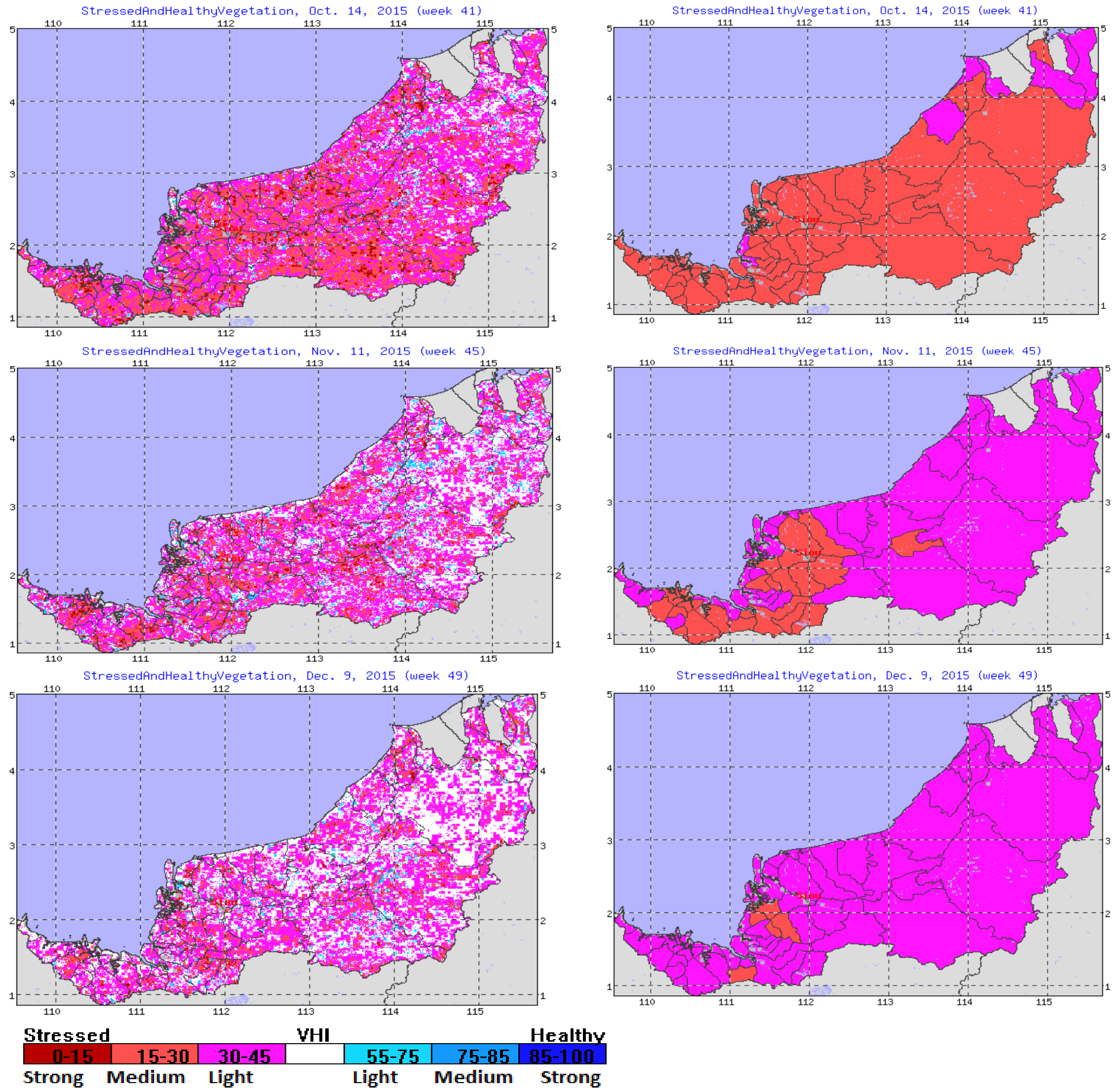


Referring to Figure 8 clearly explains the El Niño incident, especially on 14 October 2015 when the ONI value of 2.6 shows that 90 percent of plants are in a strong stress state except in the Sibuti district. On 9 December 2015 also showed that almost all areas are stressed light except in Sarikei and Engkili areas. This clearly shows that El Niño causes deteriorating plant health and stress due to lack of moisture and decreased amount of rainfall (Kemarau & Eboy, 2019).

Figure 8: The distribution of stressed and healthy conditions during the El Niño event in 2015/2016.

Stressed and Healthy Spatial Pattern During El Niño Incident

Spatial Pattern For Stressed and Healthy Value Mean districts During El Niño Events.

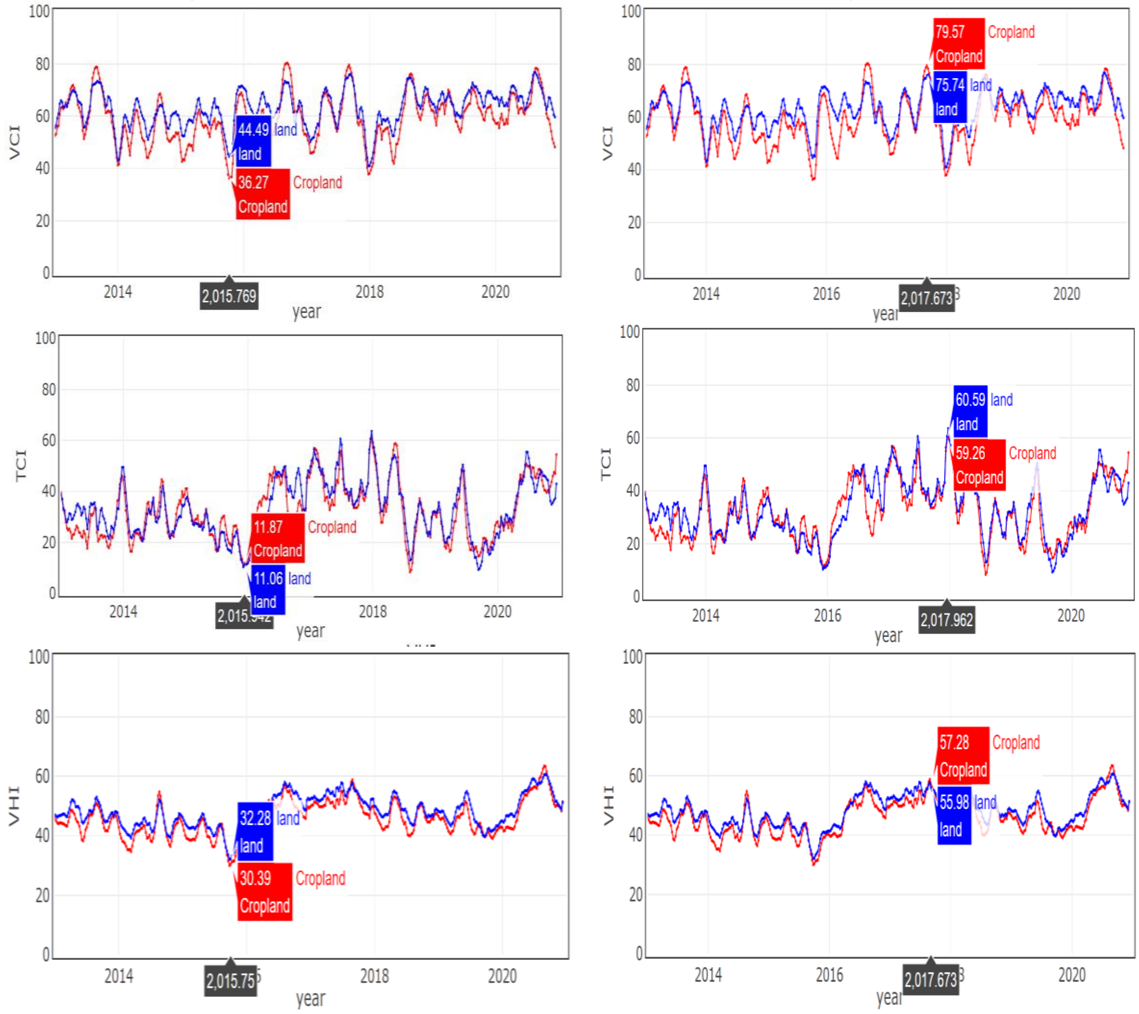


Based on Figure 9 it is found that the VCI value is 44.49 for natural plants and 36.27 for cropland in the El Niño incident compared to during the La Niña incident where the VCI values are 79.57 and 75.74. In addition, the TCI value in El Niño in 2015/2016 was found to be lower than the TCI value during the La Niña incident was 60.59 and 59.26 for land and cropland. For the last VHI found the current value of El Niño in 2015/2016 was 32.28 for land plants and 30.39 for cropland. VHI values were higher during La Niña incidence at 57.28 and 55.98 for each cropland and natural plant. This states very clearly that the occurrence of El Niño and La Niña has a significant impact on plant health. The use of this remote sensing technology can provide spatial information to the agriculture and plantation departments in taking appropriate action in reducing the impact of El Niño on their respective crops.

Figure 9: The difference in VCI, TCI, and VHI value patterns during the El Niño events in 2015/2016 and 2017/2018

The picture shows the difference in VCI, TCI, and VHI value patterns during the El Niño events in 2015/2016.

The picture shows the difference in VCI, TCI, and VHI value patterns during the La Niña events in 2017/2018.



Source: National Center for Applications and Research, NOAA (2020)

4. Conclusion

This study uses a new estimation methodology remote sensing to study the temporal-spatial El Niña and La Niña vegetation health. The study found clearly shows the diversity of VHI patterns based on ONI values. The result showed the higher the ONI will cause a decrease the level of plant health represented by VHI. VIIRS data successfully map the area conditions for each La Niña and El Niño incident. The El Niño incident is said to have caused the VHI distribution to be lower than during the La Niña incident. The ONI value plays an important role in determining the VHI value for each La Niña and El Niño event. The vegetation indices of VCI, TCI, and VHI derived from time series VIIRS data were found to be an effective approach to monitoring vegetation stress and drought conditions. The methodology adopted in the study provides reliable scientific information to the planners and policymakers to prepare drought mitigation plans and minimize the risk of droughts on agriculture and the livelihoods of people in the district.

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Conflict of Interests

The authors declare no conflict of interest in this study.

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