Early Warning for Sugarcane Growth using Phenology-Based Remote Sensing by Region

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***Abstract*—It is crucial to know crop growing in order to increase agricultural productivity. In sugarcane's case, monitoring growth can be supported by remote sensing. This research aimed to develop an early warning for sugarcane growth using remote sensing with Landsat 8 satellite at a crucial phenological time. The early warning was developed by identifying regional sugarcane growth patterns by analyzing seasonal trends using linear and harmonic regression models. Identification of growth patterns aims to determine the crucial phenological time by calculating the statistical value of the NDVI spectral index. Finally, monitoring the sugarcane growth conditions with various spectral indices for verification: NDVI, NDBaI, NDWI, and NDDI. All processes used Google Earth Engine (GEE) as a cloud-based platform. The results showed that sugarcane phenology from January to June is crucial for monitoring and assessment. The value of the four corresponding indices indicated the importance of monitoring conditions to ensure a healthy sugarcane region. The results showed that two of the four regions were unhealthy during particular periods; unhealthy vegetation values were below 0.489 and vice versa, one due to excess water and the other due to drought.**

***Keywords*—Google earth engine; landsat 8; monitoring and assessment; sugarcane health**

I. Introduction

Sugarcane is a raw material for the sugar industry that plays a strategic role in Indonesia’s economy, with a crop area of 413.05 thousand ha in 2019 [1]. Sugar consumption in Indonesia continues to increase. In 2023, it will reach 7.15 million tons, in line with Indonesia's population growth rate [2]. However, domestic sugar production has not been able to meet Indonesia’s sugar needs [2]. In response to the increasing demand for sugar, Indonesia has declared the aim of self-sufficiency by increasing sugarcane production and productivity through policies and programs in the "on-farm" aspect [3]. In an effort to support the sugarcane production and productivity in Indonesia, it is essential to apply the proper technology, including remote sensing by satellite for early warning of sugarcane growing at crucial phenological times.

An early warning detects potential incidents and is beneficial in managing and preventing factors that cause crop loss, such as insufficient or excessive irrigation, disease, and pests. In addition, early warning at crucial phenological times helps identify and measure factors that affect plant growth, especially sugarcane. Through early warning, sugarcane regions experiencing stress can be identified and classified so that farmers can change their practices to increase sugarcane productivity and production. Then, knowing the condition of plants at the peak of phenology can also help in agricultural planning and management.

The application of remote sensing to sugarcane crop conditions has evolved in the last decade, for example, monitoring the growth phase of sugarcane by satellite in West Java, Indonesia [4]; the role of NDVI in mapping sugarcane conditions around oil and gas fields [5]; assessment of sugarcane conditions based on NDVI [6]; monitoring sugarcane growth [7]; sugarcane yield estimation and forecasting in smallholder farming conditions [8]; prediction of sugarcane yield based on NDVI and nutrient concentration [9]; and prediction of crop yields from MODIS relative vegetation health in Africa [10]. However, to monitor sugarcane growth, there has been no early warning during the crucial times of sugarcane phenology. In previous studies, plant growth was only through a cooperative data approach, not based on plant phenology knowledge. In addition, the method in the previous study was based on vegetation parameters only. Meanwhile, in this study, plant growth with several parameters based on satellite data was built with linear regression based on phenological knowledge.

On the other hand, available and open remote sensing data can now be analyzed with more affordable computing, and a free cloud platform can be used for geospatial analysis, namely Google Earth Engine (GEE). GEE, as a cloud platform, is efficient for geospatial analysis [11], which is helpful for precision agriculture, with its availability of comprehensive and open data, for example, for monitoring vegetation's current state and dynamics [12]. GEE applications have also been widely used to solve agricultural problems, for instance, mapping sugarcane by integrating multitemporal Sentinel-2 images [13]; rice mapping based on SNIC segmentation [14]; and object-oriented crop classification [15].

This research offers a solution to issues of production and productivity in building an early warning for sugarcane conditions at crucial phenological times through monitoring and assessment. The method of creating an early warning include several approaches: (1) analyzing seasonal trends in the region using linear regression and harmonic models to identify sugarcane growth patterns; (2) assessing the condition of sugarcane through statistical analysis of the Normalized Difference Vegetation Index (NDVI) spectral index at the crucial phenological phase; and (3) monitoring sugarcane conditions with various spectral indices, based on typical use, and having accurate results for condition interpretation, with

NDVI as the vegetation index, Normalized Difference Bareness Index (NDBaI) as the fallow land identification, Normalized Difference Water Index (NDWI) as a water content indicator, and Normalized Difference Drought Index (NDDI) as a drought indicator. The four spectral indices serve as a system of checks and balances to assess sugarcane conditions. All processes were performed on GEE as a cloud-based platform. Therefore, this research aimed to develop an early warning of sugarcane growth using remote sensing at a crucial phenological time. From the solutions offered, farmers can better anticipate particular practices, and the government can increase productivity and sugarcane production in a more sustainable manner through precision farming.

This paper is described in systematics: materials and methods used for early warning with several parameter indicators, building knowledge of plant phenology; and the results section to determine plant status using remote sensing data. The conclusions and recommendations section reports findings for future research.

II. Materials and Methods

A. Study Area

This study was carried out at sugarcane plantations of Djengkol Kediri, East Java Province, Indonesia, with a coordinate polygon of (Lat: 112.199, Long: -7.892). The area was selected because (1) East Java is the largest producer in Indonesia, with Djengkol Kediri as the second largest [2]; (2) the plantations in the area support the economy, and are the basis for the sugar self-sufficiency program; (3) it is a representation and model for other fields. As shown in Fig. 1.

In the study area (Fig. 1), the region was selected based on the sugarcane plantation and divided into four regions: (1) region A: relatively flat terrain with a mean elevation of 260 m above sea level; (2) region B: relatively flat terrain with a height of 264 m; (3) region C: sloping terrain (left to right) with a mean elevation of 267–272 m; (4) region D: sloping terrain (left to right) with a mean elevation of 273–276 m. The four regions are planted with the same sugarcane variety.

B. Maintaining the Integrity of the Specifications

The image data used in this study were sourced from the Landsat 8 satellite, available at GEE "LANDSAT/LC08/C01/T1_TOA". The public image collections were filtered with by using several timescales and criteria: (1) image collection from 2015 to 2020 was used to analyze seasonal sugarcane trends to obtain cropping patterns in the study region and to mask clouds; (2) cloud-free image data from 2014 to 2017 were used for the assessment of sugarcane conditions; (3) 2019–2020 was used for monitoring data on sugarcane health and cloud-free image collection. In addition, all image collection timescales used a resolution of 15 m, increasing the resolution shown in Fig. 2 through the Brovey transformation approach by blending the panchromatic [16] (Formula 1):

Fig. 1. The study area in the sugarcane plantation of Djengkol Kediri, Indonesia

$$R_{in} = R_{in} / (R_{in} + G_{in} + B_{in}) \times P_{in} \quad (1)$$

where R_{in} = Band 4, G_{in} = Band 3, B_{in} = Band 2, and P_{in} = Band 8 (panchromatic).

Fig. 2. RGB image 30 m (left) and the result of image sharpening through panchromatic blending, 15 m (right)

C. Sugarcane Phenology

Plant phenology can identify and obtain important information about vegetation [17]–[19]. Sugarcane (*Saccharum officinarum*) is a type of grass with unique characteristics. Sugarcane phenology has four phases: (1) germination—this phase lasts for 15–20 days while new shoots are growing; (2) tillering—the sugarcane plants grow tillers for 4–6 months during this phase, and up to 50% of each sugarcane stalk grows leaves; (3) grand growth during this phase, lasting for 5 months, sugarcane height elongates and plants grow to maturity; and (4) maturity: this phase, which occurs during the 3 months before harvest, includes vegetative decline and sucrose accumulation of up to 55% per dry weight of sugarcane [20]. The leaf area index (LAI) value reaches its maximum when the plant is 6 months old, decreasing slowly afterward [6], [20].

Sugarcane phenology generally lasts 10–12 months. In this study area, sugarcane phenology (Table I) proceeds as follows: from early October to November is seeding and budding, January to April is stem elongation, May to August is the period of sugar accumulation and ripening, and September is the harvest period.

TABLE I. TIME OF SUGARCANE PHENOLOGY IN STUDY AREA

Crop	Years/Month		Periods	
Sugarcane	2019	Oct	SE	
		Nov	SE	SL
		Dec		SL
	2020	Jan	ST	
		Feb	ST	
		Mar	ST	
		Apr	ST	
		May		SA
		Jun	MA	
		Jul	MA	
		Aug	MA	
		Sep		HA

Note: HA: harvest stage; SE: seeding stage; SL: seedling stage; ST: stem elongation stage; SA: sugar accumulation stage; MA: maturation stage.

D. Spectral Indices

Plants can absorb and reflect unique light waves. This phenomenon is carried out by chlorophyll in the mesophyll tissue of leaves (photosynthesis) [21]. As a basis for remote sensing using satellites, the brightness value received by satellite sensors in a particular band was used to identify plants. The spectral index works by calculating the wavelength of the band composition.

There are many types of indices, and only four were used in this study, namely (1) Normalized Difference Vegetation Index (NDVI), which describes the greenness of a plant. It is based on a mathematical combination of visible red light and near-infrared radiation (NIR) channels, which are used as indicators of the presence and condition of vegetation [22], as illustrated in Formula 2; (2) Normalized Difference Bareness Index (NDBaI) is used to separate fallow or open land from other types of cover using Landsat image data [23]. It is very sensitive for distinguishing between fallow, semi-fallow, and cultivated areas. The index uses the short infrared (SWIR) and thermal infrared (TIR) bands, as shown in Formula 3; (3) Normalized Difference Water Index (NDWI) is used to determine the water content of vegetation [24]. It is obtained from a combination of green and red bands, as presented in Formula 4; (4) Normalized Difference Drought Index (NDDI) aims to identify the presence of drought in vegetation [25] based on a comparison of the NDVI and NDWI index values, as illustrated in Formula 5.

$$NDVI = (NIR - RED) / (NIR + RED) \quad (2)$$

$$NDBaI = (SWIR - TIR) / (SWIR + TIR) \quad (3)$$

$$NDWI = (NIR - SWIR) / (NIR + SWIR) \quad (4)$$

$$NDDI = (NDVI - NDWI) / (NDVI + NDWI) \quad (5)$$

where NIR = Band 5, RED = Band 4, SWIR = Band B6, and TIR = Band 10.

The NDVI spectral index value was used as the primary reference for monitoring sugarcane conditions obtained from the assessment results, while the other three spectral indices (NDBaI, NDWI, and NDDI) were used for verification.

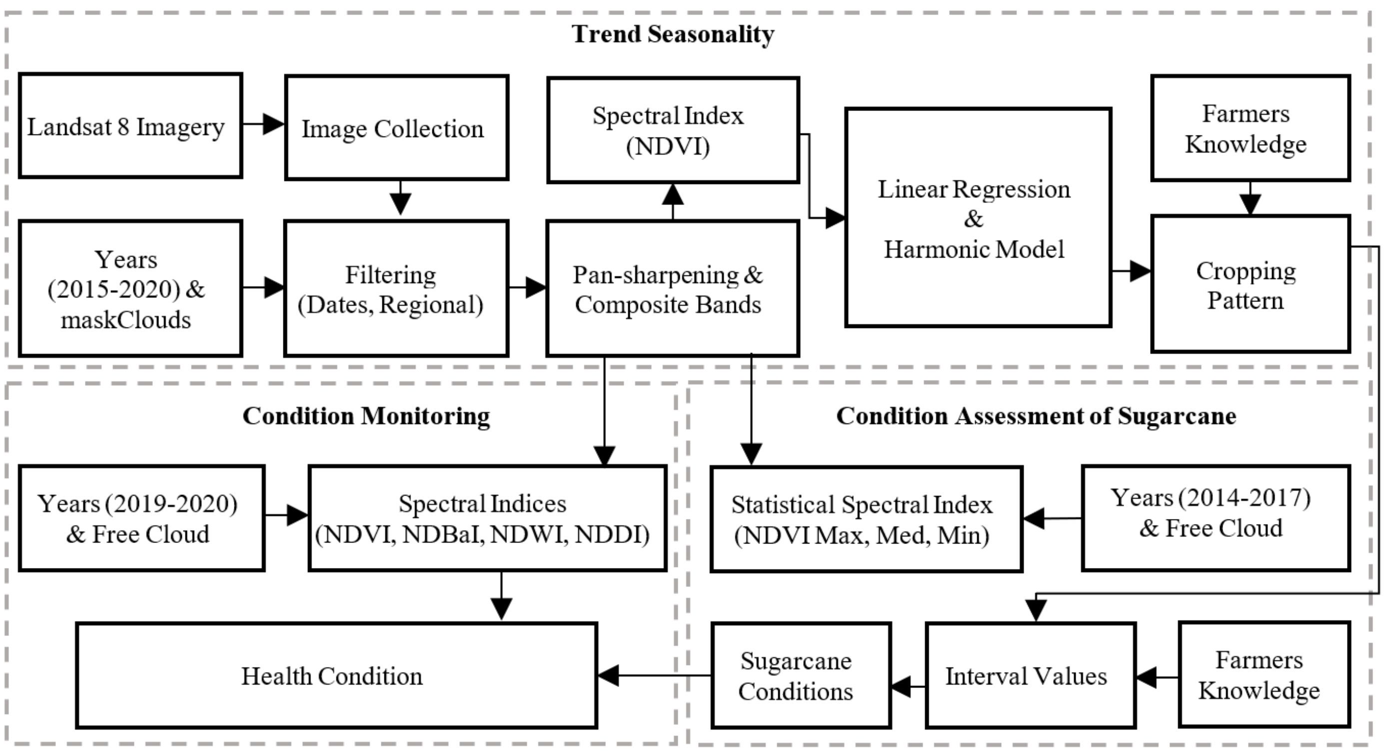

Fig. 3. The study area in the sugarcane plantation of Djengkol Kediri, Indonesia

E. Methodology

Three primary processes were carried out to create an early warning for sugarcane planting conditions (Fig. 3): (1) identification of sugarcane growing patterns by analyzing seasonal trends using a harmonic model (NDVI input); (2) assessing the condition of sugarcane using the NDVI spectral index; and (3) monitoring sugarcane condition with various spectral indices (NDVI, NDBaI, NDWI, and NDDI). All processes were performed on GEE as a cloud-based platform.

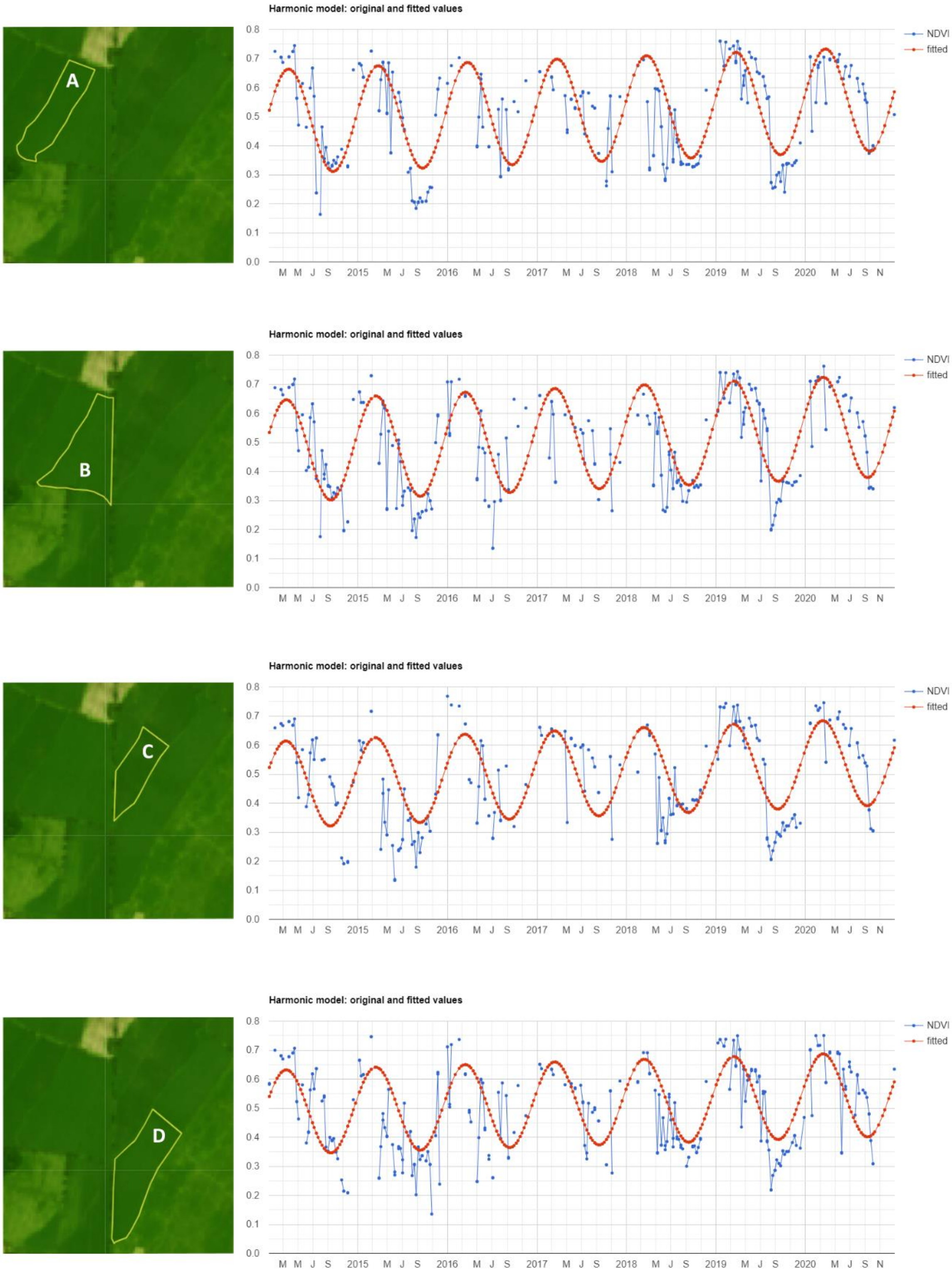

Fig. 4. The frequency of the sugarcane planting pattern based on NDVI values

F. Trend Seasonality

Monitoring seasonal changes in vegetation activity and plant phenology is very important in condition monitoring. In sugarcane, it is necessary to analyze seasonal trends based on phenology using multitemporal data. In GEE, a seasonal trend analysis can be constructed with time series data through temporal data (NDVI) with linear regression (Formula 6) [26]. The seasonal forecast is then built by combining the linear model with the harmonic model (Formula 7) [26].

NDVI values were integrated and used as the basis for seasonal trend analysis (Fig. 4) from image collection data for 2015–2020 in each region (A, B, C, D) by filtering out the masking clouds.

$$p_t = \beta_0 + \beta_1 t + e_t \quad (6)$$

$$p_t = \beta_0 + \beta_1 t + A\cos(2\pi\omega t - \varphi) + e_t$$
$$= \beta_0 + \beta_1 t + \beta_2 \cos(2\pi\omega t) + \beta_3 \sin(2\pi\omega t) + e_t \quad (7)$$

where A is the amplitude, ω is the frequency, e_t is the random error, and φ is the phase. $\beta_2 = A\cos(\varphi)$, and $\beta = A\sin(\varphi)$, implying $A = (\beta_2^2 + \beta_3^2)^{½}$, and $\varphi = A\tan(\beta_3/\beta_2)$. To fit this model to the time series, we set $\omega = 1$ (one cycle per unit time) and use ordinary least squares regression.

G. Sugarcane Assessment

The purpose of the assessment was to determine the condition of sugarcane. This was based on crucial phenology and used as a reference for an early warning of sugarcane conditions that could predict possible problems emerging in the sugarcane crop. This assessment was developed on phenological knowledge obtained from planting patterns (from analysis of seasonal trends). The results showed the importance of assessing the condition of sugarcane at intervals from January to June. There were several procedures included to assess sugarcane conditions: (1) image data were used for assessment of sugarcane conditions based on cloud-free image collection data from 2014 to 2017; (2) the locations used were the four regions (A, B, C, D); (3) NDVI spectral information was used as a parameter to determine the condition of sugarcane, then statistical calculations were performed (maximum, median, minimum); (4) the NDVI spectral value of the Landsat 8 image was verified with the farmers' knowledge on the current condition within the region (A, B, C, D) under prior normal conditions.

III. Results and Discussions

A. Sugarcane Cropping Pattern

Information on sugarcane cultivation patterns in the study area was obtained from the analysis of seasonal trends. The sugarcane cropping pattern was identified through the NDVI value by harmonic model analysis (Fig. 4). The planting pattern became the basis of knowledge for the monitoring and assessment of sugarcane. The sugarcane planting pattern in the study area follows: (1) the cropping pattern begins in October and ends in September of the following year, which applies to all regions (A, B, C, D), as verified with local farmers' knowledge of appropriate conditions (Table I); (2) the peak NDVI index value occurs six months after planting; (3) the crucial phenology occurs from January to June; therefore, this period was used as a reference for monitoring sugarcane conditions (from two months before peak plant growth to three months after, in preparation for harvest).

B. Assessment of Sugarcane Condition

Sugarcane conditions were assessed from the values of the NDVI spectral index. Based on statistical calculations of the NDVI value of the entire region (A, B, C, D) and the results of local knowledge of the planting pattern, the condition of sugarcane crops from January to June was the focus of the early warning. The interval value for each of those months was the reference for monitoring sugarcane conditions, as shown in Fig. 5.

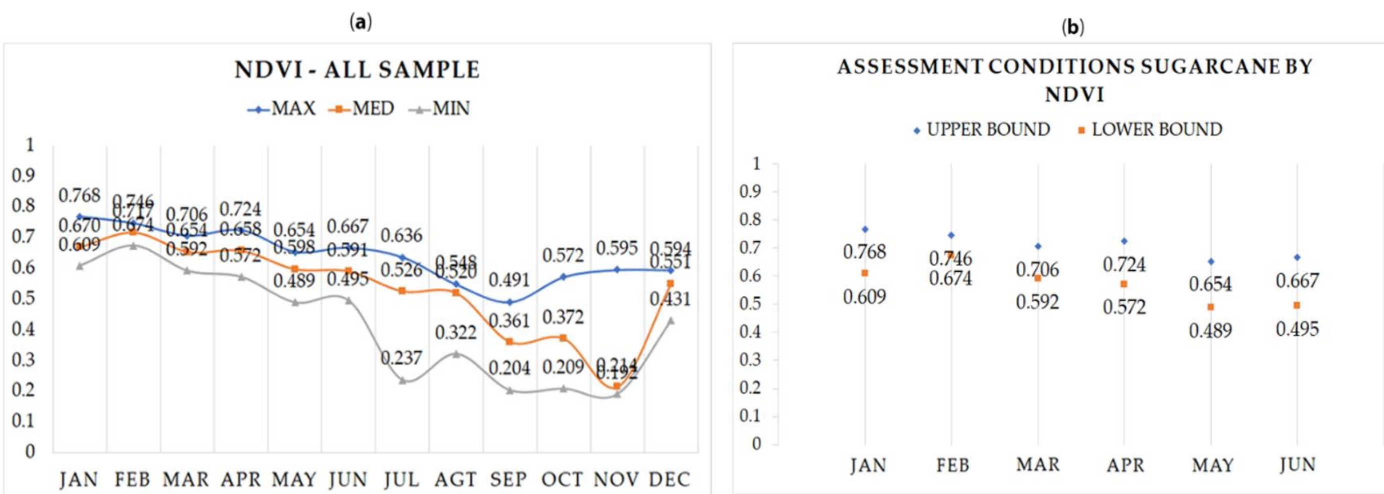

Fig. 5. Results of sugarcane condition assessment: (a) The statistical values from the combination of all sample regions; (b) Sugarcane conditions based on statistical calculations of NDVI values in the crucial months of January to June

C. Assessment of Sugarcane Health

The sugarcane plants were monitored from January to June in 2019–2020 (two periods of planting). The sugarcane condition was measured based on the NDVI spectral index value generated from the sugarcane condition assessment process. Furthermore, to verify the condition, comparisons were made through other spectral indices such as NDBaI, NDWI, and NDDI. The condition of healthy vegetation is the ability to absorb blue- and red-light energy to trigger photosynthesis and create chlorophyll.

Plants with more chlorophyll can reflect more near-infrared energy than the unhealthy variants [21], [27], hence, the spectra of absorption and reflection in visible. Thus, plant spectra of absorption and reflection in visible and infrared wavelengths can provide information about plant health and productivity.

From the results of monitoring the condition of sugarcane plants (Fig. 6), and verified by other spectral values (NDBaI, NDWI, and NDDI), sugarcane condition monitoring was categorized as follows:

- Regions A and B were in good health. The NDVI value belonged to the healthy condition interval value (results of the sugarcane assessment). In addition, the comparison of the other spectral index values (NDBaI, NDWI, and NDDI) was appropriate, as shown in Fig. 7.
- In region D, in April 2019, the NDVI value decreased, signaling an unhealthy condition (Table II). Compared with other spectral data, the value of the NDWI spectral index increased; this showed that region D in April was excessively moist. However, this condition normalized in the following month, as shown in Fig. 7.

TABLE II. NDVI VALUE IN THE MONITORING FOCUS PHASE. VALUES IN RED INDICATE AN UNHEALTHY CONDITION

Year/Month		Region A	Region B	Region C	Region D
2019	Jan	-	-	-	-
	Feb	0.749	0.730	0.709	0.728
	Mar	0.761	0.764	0.721	0.746
	Apr	0.733	0.727	0.698	0.451
	May	0.729	0.739	0.696	0.693
	Jun	0.713	0.716	0.672	0.664
2020	Jan	0.642	0.715	0.629	0.646
	Feb	0.675	0.719	0.711	0.696
	Mar	0.734	0.768	0.693	0.756
	Apr	0.636	0.706	0.702	0.679
	May	0.685	0.728	0.458	0.698
	Jun	0.663	0.659	0.368	0.667

- In region C, in May–June 2020, the NDVI value decreased until near the harvest period (Table II), indicating the sugarcane plants were in an unhealthy condition. Together with the other spectral index values (the NDWI values decreased, while the NDDI values increased), this showed that the unhealthy condition of region C sugarcane in May–June was due to lack of water, as shown in Fig. 7.

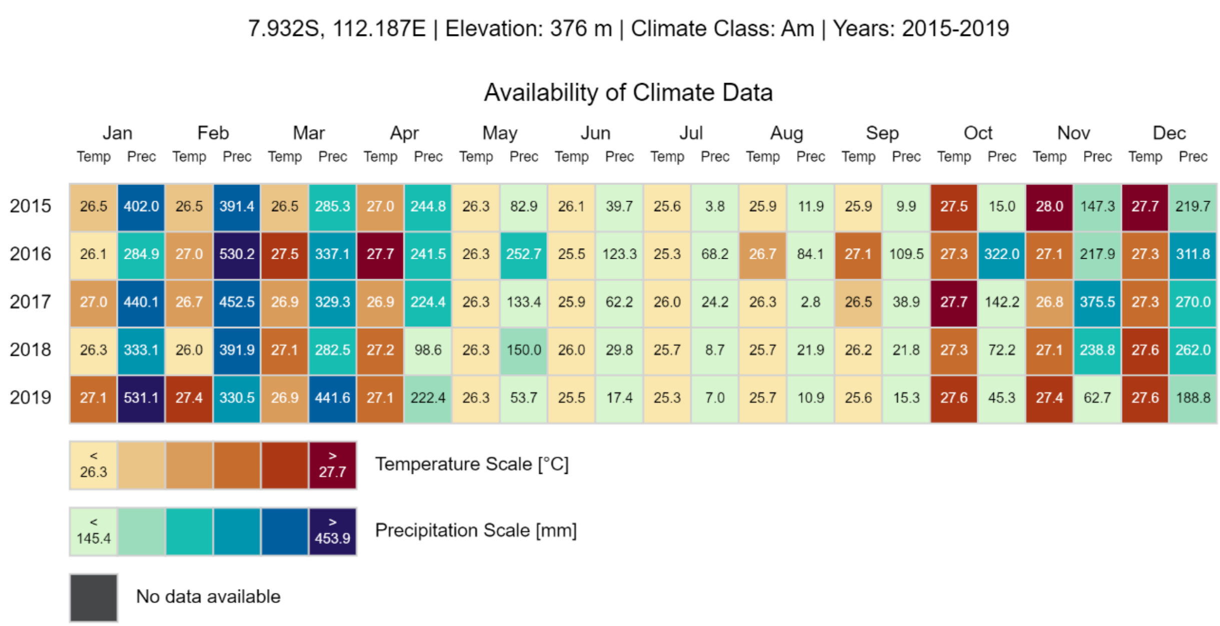

Fig. 6. Rainfall climate data in the study area from 2015 to 2019 [28]

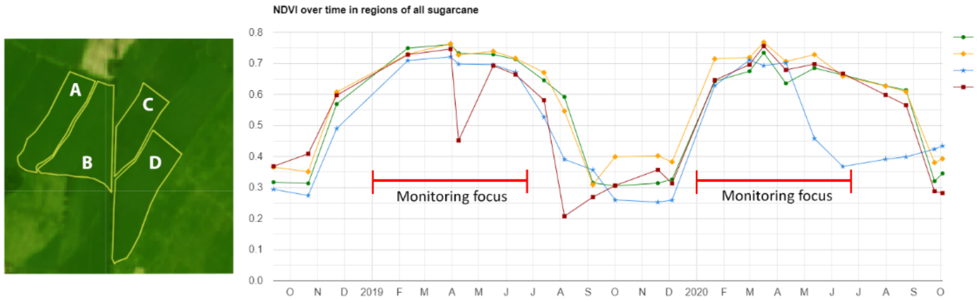

Fig. 7. The monitoring focus from January to June. The graph results of the sugarcane conditions are based on the NDVI value

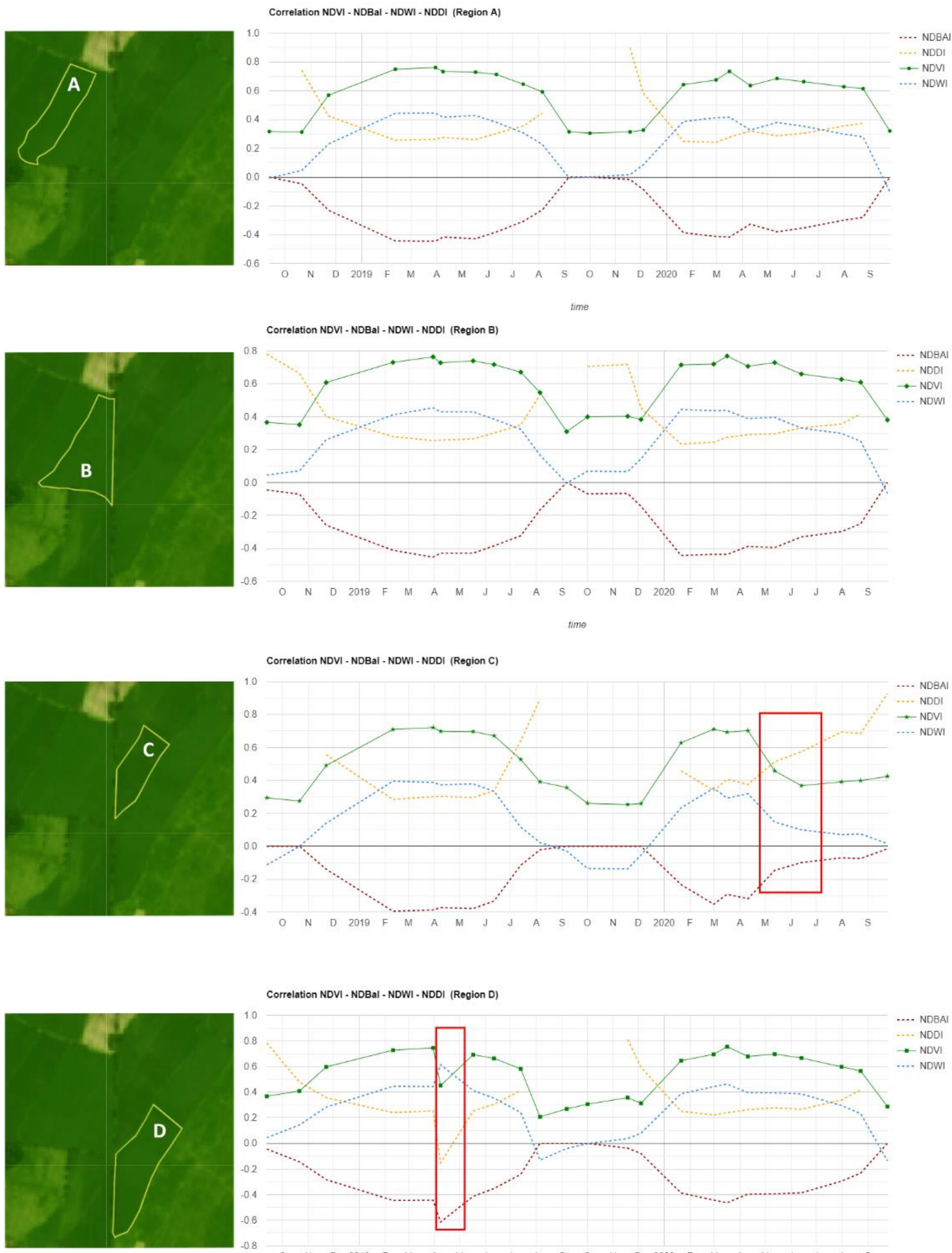

Fig. 8. Comparison of condition monitoring with several spectral index values of NDVI, NDBaI, NDWI, and NDDI from all regions. The red box is a marker showing when the planting phase was in an unhealthy condition

D. Discussions

The early warning was beneficial to find the factors that affected the growth of sugarcane plants. An early warning was developed based on a crucial phenological time. Phenology helps to obtain necessary information on plants, such as detecting, classifying, and monitoring plants [17]–[19], [28]–[30]. An early warning based on crucial phenology can anticipate problems with sugarcane crops and suggest practices to increase sugarcane productivity and production. In addition, early warning at crucial phenological times also provides knowledge concerning general sugarcane conditions. Although the primary index is only NDVI, it can describe the condition of sugarcane plantations when combined with other additional indices such as NDBaI, NDWI, and NDDI, unlike previous studies that only applied NDVI [5], [6], or estimates of sugarcane health conditions [8] that ignored sugarcane phenological time.

The early warning results based on phenological time show that the four regions (A, B, C, and D) had different challenges. Both regions A and B were in a healthy condition, while region D in April 2019 and region C in May–June 2020 were unhealthy. The four regions are in adjacent planting areas, but the four regions have different terrain. Regions A and B are on flat terrain, while regions C and D have sloping field characteristics.

Based on verification from other indices (NDBaI, NDWI, and NDDI), sugarcane in region D in April 2019 experienced a decrease in NDVI and NDDI value while NDWI rose, indicating that region D was waterlogged. To ensure the correct assessment of the sugarcane condition, we added a rainfall indicator in the study area [31], as shown in Fig. 8. In region D for April 2019, rainfall was still common, and in March 2019, the rainfall was relatively high. In region D, April 2019 had the potential to be waterlogged. However, this returned to normal by the following month.

In region C, May–June 2020, the sugarcane was in a drought condition. Rainfall data showed low rainfall duration and intensity, as shown in Fig. 8. Sloping terrain makes it essential for region C to apply early warning as a solution to anticipate adverse conditions. When discussed with farmers, sugarcane-growing regions need to improve water irrigation management, especially for regions characterized by sloping land. Irrigation improvement is in process with a trial of drip irrigation in August 2020.

This early warning showed factors that affected the condition of sugarcane crops. The practice of this approach to research helps early warnings become more considerate to ensure dynamic plant conditions. So solving the problem of early warning of plant growth becomes more certain against uncertain conditions. However, a drawback, namely the limited once-per-month data, results in the daily details of the sugarcane condition remaining unknown.

IV. Conclusion

Factors affecting sugarcane growth were identified using an early warning, which can help anticipate adverse conditions. In this study, it has been shown that monitoring the condition of sugar cane as an early warning, based on the phenology from January to June, describes the condition of the sugar cane using various indicators. The sugarcane conditions in each region were different. Regions A and B were in a healthy condition throughout the monitoring phase. In contrast, regions C and D were in unhealthy conditions for part of the time. Region D had excess water in April 2019, and Region C had a drought in May–June 2020. Conditions unhealthy are based on vegetation values below 0.489. As for health conditions, it is at the opposite vegetation value.

Suggestions for future research, early warning can be solved by sharp satellite, which has a sharper resolution with a range of data available daily. In addition, early warning indicators can be combined with data related to climate change.

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