Drought Assessment of Rice in the Philippines using Enhanced Vegetation Index based Agricultural Drought Indices

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Abstract

Agricultural drought has a considerable impact on agricultural productivity in the Philippines. This study evaluates the performance of agricultural drought indices: Standardized Vegetation and Temperature Ratio (SVTRe) and Vegetation Health Index (VHIe) derived from the Enhanced Vegetation Index (EVI) of the Moderate Resolution Imaging Spectroradiometer (MODIS) to assess drought conditions across the Philippines from 2000 to 2024. Using run theory, we quantified drought frequency, duration, and intensity, identifying drought-prone regions such as Cagayan Valley, Western Luzon, and Western Visayas. SVTRe recorded 15 to 20 incidents, and was more sensitive to moderate droughts, while VHIe recorded 15 to 30 events, capturing more extreme conditions. Both indices revealed consistent spatial and temporal drought patterns, with Mann-Kendall trend analysis indicating increased severity throughout the study period. SVTRe demonstrated higher overall accuracy (58.25%), whereas VHIe, achieved a higher hit rate (90.14%). Taken together, these indices offer complementary tools towards improving drought monitoring and enhancing agricultural resilience in the Philippines.

1. Introduction

Drought is a natural hazard characterized by prolonged periods of below-average rainfall, which can severely affect agriculture, ecosystems, industries, and economies (Perez et al., 2016). It is typically categorized into four stages: meteorological, hydrological, agricultural, and socio-economic. Agricultural drought occurs when insufficient soil moisture damages crops, causing reduced yield. The progression of drought begins with meteorological drought, leading to agricultural drought as soil moisture declines, followed by hydrological drought, affecting water supply in various economic sectors and causing adverse impacts such as food insecurity and economic losses. Hence, monitoring agricultural drought is critical for minimizing its impacts on crop productivity.

Various drought indices have been developed to monitoring agricultural drought characteristics, progression, and impacts to help prevent significant crop losses. Commonly used indices include Palmer's Drought Severity Index (PDSI; Palmer, 1965), which measures long-term drought by analyzing precipitation, soil moisture, and temperature; the Crop Moisture Index (CMI; Palmer, 1968) which tracks short-term changes in soil moisture; and the Standardized Precipitation Index (SPI) which provides flexible precipitation anomaly assessments (McKee et al, 1993). However, traditional data collection methods have limited spatial and temporal coverage. This has led to the development of satellite-derived indices such as Standardized Precipitation Evapotranspiration Index (SPEI), Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Vegetation Health Index (VHI), and Temperature-Vegetation Difference Index (TVDI) to aid in assessing agricultural drought and plant health.

In the Philippines, the Philippine Atmospheric, Geophysical, and Astronomical Services Administration (PAGASA) utilizes ground-based monitoring indices such as SPI and Percent Normal Precipitation (PNP) for operational drought monitoring. The Standardized Vegetation Temperature Ratio (SVTR) has been effective for localized drought assessments, especially during the 2015-2016 El Niño (Macapagal, 2017; Perez, et al., 2016). Recent efforts have introduced refined drought indices to better capture vegetation stress and agricultural impacts. For example, Rojas (2020) enhanced VHI integration into a comprehensive Agricultural Stress Index (ASI) to evaluate dry periods and the extent of arable land affected. Perez et al. (2022) demonstrated that SVTR and VHI detected vegetation stress affecting nearly 50% of the country during the 2019 El Niño event. Valete et al. (2022) proposed the Combined Drought Index (CDI) which combines NDVI, Land Surface Temperature (LST), and SPI to monitor the transition from meteorological to agricultural drought.

EVI measures vegetation greenness with improved sensitivity over the NDVI in densely vegetated regions by reducing atmospheric interference and reducing canopy background noise (Didan and Muñoz, 2019). This enhanced sensitivity of EVI allows for better assessment of vegetation health under drought conditions and captures extreme drought events closely aligned with meteorological drought indicators. Studies have shown that EVI outperforms NDVI-based indices like VCI and VHI in detecting severe droughts (Xie and Fan, 2021). Despite its advantages, EVI remains underutilized in the Philippines for agricultural drought monitoring. Traditional indices, while common, show limitations in local drought monitoring due to spatial constraints of ground-based methods. NDVI, while widely used, struggles with short-term vegetation stress detection, while EVI exhibits superior sensitivity (National Aeronautics and Space Administration, n.d.).

This study aims to address this gap by developing and evaluating the performance of EVI-derived drought indices—the Standardized Vegetation and Temperature Ratio (SVTRe) and Vegetation Health Index (VHIe) for agricultural drought monitoring in the Philippines. Specifically, this study aims to develop SVTRe and VHIe using EVI, characterize drought occurrences with MODIS-derived data, investigate the spatial and temporal progression of drought, and determine the correlation between these drought indices and quarterly rice yield.

2. Materials and Methods

2.1 Study Area

This study focused on the Philippines, a tropical archipelago in Southeast Asia that is highly vulnerable to climate-related hazards. Drought is one of the major hazards affecting the country, resulting to significant damage to agriculture, particularly rice production.

Rice is a staple crop and a key contributor to national food security and agricultural output. Around 32% of the country's terrain is devoted to farming, with rice and corn as the two most widely cultivated crops (PSA, 2024). Rice covers approximately 30% of cultivated land and goes through a growth cycle consisting of vegetative, reproductive, and ripening phases, typically lasting 100 to more than 160 days, depending on the variety. In 2023, national rice production totaled 7.24 million metric tons, a slight increase from the previous year. The Ilocos Region led in production, followed by Central Luzon and Cagayan Valley. Although there was a 1.5% reduction in harvested area, yield per hectare rose from 4.06 to 4.13 metric tons, with Central Luzon having the highest yield at 4.96 metric tons (PSA, 2024).

2.2 Datasets and pre-processing

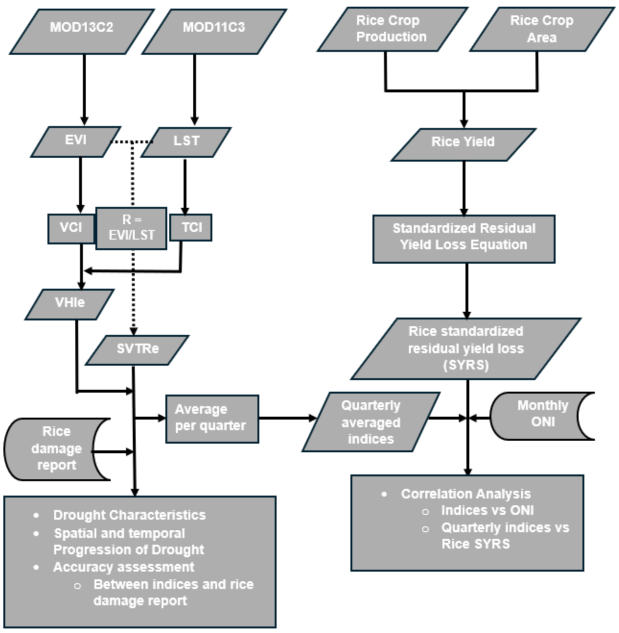

Figure 1. Process flowchart of the study.

In this subsection, we describe how we calculated SVTRe and VHIe, and then how these indices will be used to characterize drought. Figure 1 shows the process flowchart, which starts with data collection and continued with pre-processing to obtain monthly satellite data and quarterly crop yield. We then processed the data using the appropriate equations to obtain the SVTRe, VHIe, and Rice standardized yield residual series (Rice SYRS). Following that, various analyses were conducted to achieve each of the study's specific objectives.

2.2.1 Satellite data

EVI and LST datasets were derived from MODIS land products Version 6 Level 3 (https://modis.gsfc.nasa.gov/data/dataprod/). MOD13C2 and MOD11C3 represent EVI and LST, respectively. Both datasets contain monthly data with a spatial resolution of 0.05° or 5.6 km, covering from February 2000 to the present. For this study, data were extracted for the Philippine domain from February 2000 to February 2024.

2.2.2 ENSO data

The Oceanic Niño Index (ONI) for the same period was obtained from the NOAA Climate Prediction Center (https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php). ENSO has two phases: warm phase (El Niño) that causes delayed rainy season and triggers drought, and cool phase (La Niña) that brings more rain, especially in the Western Pacific Region. The use of ONI in this study is motivated by previous findings that droughts in the Philippines are strongly linked with ENSO variability (Hilario et al., 2009).

2.2.3 Rice production, Harvest, and Damage Statistics

Rice production and harvested area statistics were obtained from the Philippine Statistical Authority's (PSA) OpenSTAT platform (https://openstat.psa.gov.ph/PXWeb/pxweb/en/DB/DB__2E__CS/?tablelist=true&rxid=bdf9d8da-96f1-4100-ae09-18cb3eaeb313). These are quarterly data, aggregated at the provincial level. For this analysis, data from the second quarter of 2000 through the fourth quarter of 2023 were used to match the coverage of SVTRe and VHIe, which began in February 2000.

The rice crop damage report from the Department of Agriculture – Food and Agriculture Organization (DA-FAO) during 2018-2019 El Niño was used for accuracy assessment. Additionally, a rice map from the Philippine Rice Information System (PRISM) of the Philippine Rice Research Institute (DA-PhilRice) was used to mask the satellite data, isolating the rice areas, to correlate with the rice yield and evaluate the indices' performance against rice damage reports.

2.2.4 Data pre-processing

The downloaded MODIS EVI and LST values were pre-processed by multiplying it with the appropriate scale factors: 0.001 for EVI and 0.02 for LST. LST values are also converted from K to °C from the scaled LST. The outcome would be monthly EVI and LST values, with EVI being unitless and LST being in degrees Celsius. To match the satellite dataset to the quarterly rice dataset's temporal resolution, the values were computed as three-month averages.

For the rice datasets, rice yield was computed using the crop yield equation:

$$Crop\ yield = \frac{crop\ production}{area\ harvested} \tag{1}$$

where crop production = amount of rice paddy harvested
area harvested = area where the rice paddies are harvested.

2.3 Data processing

SVTRe was computed per pixel using pre-processed MODIS EVI and LST, as defined by the equation:

$$\text{SVTRe} = \frac{R_i - \bar{R}_i}{\sigma_R} \tag{2}$$

where R_i = quotient of NDVI over LST for month i,
$\bar{R}_i$ = mean of EVI-LST ratio for month i,
σ_R = standard deviation of EVI-LST ratio for month i.

SVTRe values are classified based on severity: Normal, Mild, Moderate, and Severe (Table 1), where drought occurrence using SVTRe will start if SVTRe < -0.50.

SVTRe Values	Drought Severity
≥ 0.50	Normal
-1.00 to -0.51	Mild
-2.00 to -1.01	Moderate
< 2.00	Severe

Table 1. SVTRe drought severity classification. Adapted from Macapagal (2017).

VHIe was also derived from the pre-processed MODIS EVI and LST data. The Vegetation Condition Index (VCI) and Temperature Condition Index (TCI) were first calculated using Equations 3 and 4 below.

$$\text{VCI} = 100 \text{ x } \frac{EVI - EVI_{min}}{EVI_{max} - EVI_{min}} \tag{3}$$

$$\text{TCI} = 100 \text{ x } \frac{LST_{max} - LST}{LST_{max} - LST_{min}} \tag{4}$$

where VCI = vegetation condition index
TCI = temperature condition index
EVI = monthly enhanced vegetation value
EVI_{min} = minimum EVI value from the series
EVI_{max} = maximum EVI value from the series
LST = land surface temperature value
LST_{min} = minimum LST from the series
LST_{max} = maximum LST from the series

VHIe values ranged from 0 to 100, with lower values indicating vegetation stress or drought conditions, and higher values representing healthier vegetation.

$$\text{VHIe} = \alpha\text{VCI} + (1-\alpha)\text{TCI} \tag{5}$$

where VHIe = Vegetation Health Index using EVI as vegetation index
$\alpha = 0.5$
VCI = vegetation condition index
TCI = temperature condition index

Similarly, VHIe values can be classified into five categories: Normal, Mild, Moderate, Severe, and Extreme (Table 2), where drought occurrence using VHIe will start if the values drop at VHIe = 40. The drought severity classification for VHIe follows the same drought severity classification for VHI.

The VHI threshold of 40 has been widely used in the literature to indicate the onset of drought stress, where VHI ≤ 40 denotes drought conditions and values above this threshold indicate no drought (Ghaleb, et al., 2015; Kogan, 2001; Kogan, 1995). This criterion is based on empirical studies linking VHI values to vegetation stress and agricultural yield reduction in various climatic regions, including tropical and subtropical areas.

Drought Severity	Values
Extreme	<10
Severe	<20
Moderate	<30
Mild	≤40
Normal	>40

Table 2. VHIe drought severity threshold. Adapted from Ghaleb, et al. (2015).

For the crop yield, crop yield anomalies were first calculated to determine the deviation from the long-term mean and then standardized to generate the standardized yield residual series (SYRS) following the method described by Waseem, et al., 2022 and Potopová , et al., 2015:

$$\text{SYRS} = \frac{Y_i - \mu}{\sigma} \tag{6}$$

where Yi = residual from the detrended yield for month i,
μ = mean of residuals
σ = standard deviation of the residuals.

2.4 Data Analysis

To characterize drought occurrences using SVTRe and VHIe, drought events were identified when their values are below the threshold values of -0.50 for SVTRe and 40 for VHIe. Each drought episode was described using run theory (Yevjevich, 1967) metrics according to duration (DD), defined as the number of months the index remained below the threshold; severity (DS) calculated as the cumulative index deficit; and intensity (DI), the ratio of severity to duration. To determine the spatial extent of the drought, the proportion of impacted areas was computed.

Spatial and temporal progression of drought was conducted to investigate the patterns during the weak (2018-2019), moderate (2009-2010), and strong (2014-2016) El Niño events. We then evaluated the drought events during El Niño events by conducting correlation analysis for SVTRe and VHIe for the period February 2000 to February 2024. The Mann-Kendall test was performed to detect temporal trends. Pearson correlation analysis was performed to examine the relationship between the drought indices, and other parameters such as SYRS for rice, and ONI. These analyses provided insights into the ENSO-driven drought dynamics across the country.

To evaluate the reliability of SVTRe and VHIe in detecting agricultural drought, we evaluated these indices against rice damage reports from DA-FAO during the 2018-2019 weak El Niño event. We define drought event periods where the values of the calculated indices were less than index thresholds for at least two months (-0.5 for SVTRe and 40 for VHIe). Both datasets were transformed into binary classifications (drought or no drought), where 440 of the 1,267 towns identified with farm rice reported damage from the drought. Model performance was evaluated using accuracy metrics, including accuracy, precision, recall, and specificity. By confirming the indices' usefulness in identifying the effects of drought, this validation helped to develop systems for drought prediction and response.

3. Results

3.1 Drought Characterization using SVTRe and VHIe

Both indices identified drought-prone areas, including Cagayan Valley, western Luzon, Western Visayas, and western Mindanao. Figure 2 showed that SVTRe identified 15 to 20 drought events (Figure 2a), with VHIe identifying 15 to 30 (Figure 2b). Moreover, VHIe detected more extreme drought events, while SVTRe showed a more balanced detection of moderate droughts.

Drought duration analysis shows regions classified under Type I climate (e.g., Western Luzon, Visayas, Zamboanga Peninsula), experienced mean drought durations of 9 to 14 months or longer. These regions are more susceptible due to factors like El Niño, rain-shadow effects, and weak monsoonal influences. In contrast, eastern areas like Eastern Visayas and Bicol experienced shorter droughts due to exposure to moist trade winds and typhoons.

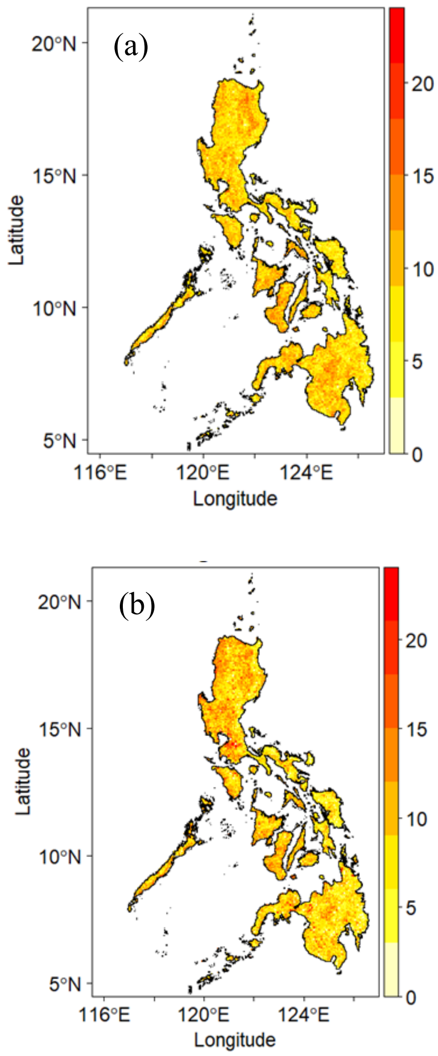

Figure 2. Spatial distribution of the number of drought events based on (a) SVTRe and (b) VHIe.

When looking further in terms of percent area damage shown in Figure 3, both SVTRe and VHIe showed similar trends in percentage areas affected by agricultural drought, highlighting their potential for rapid and initial assessment of the extent of damage during drought. Furthermore, when evaluating the spatial coverage affected based on severity, SVTRe has more percentage area affected due to moderate drought. On the other hand, VHIe has more percentage area affected due to extreme drought. These results suggest that the indices were able to identify the affected area, but with difference in severity of the drought. Hence, further field validation is recommended for verification on the severity of the drought in the affected areas.

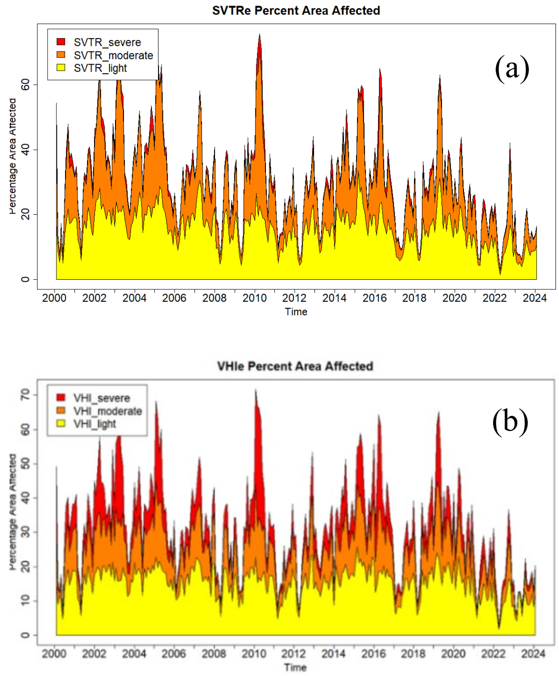

Figure 3. Total percentage area affected per drought severity using (a) SVTRe and (b) VHIe.

3.2 Spatial and temporal distribution of drought

The spatial and temporal progression of agricultural drought was analyzed using both indices during the strong El Niño event from November 2014 to April 2016.

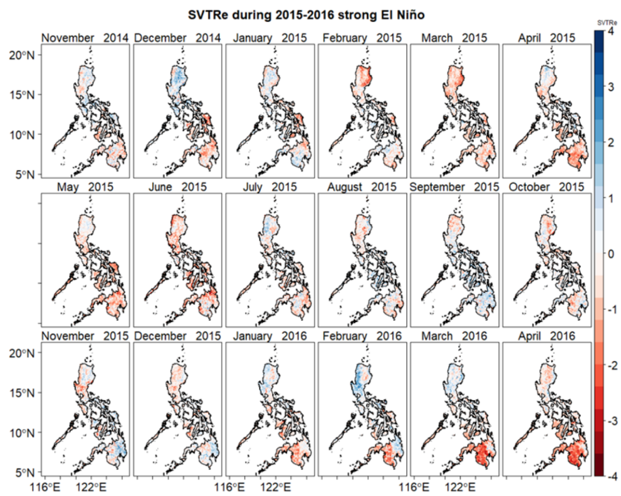

Figure 4. Spatial extent and progression of drought based on SVTRe. As both SVTRe and VHIe showed similar patterns, only SVTRe is displayed in this paper.

Severe drought conditions were highlighted in red and wetter-than-normal conditions in blue (Figure 4). Mild drought occurred initially, but conditions intensified in mid-2015 (panels 6 to 8 in Figure 4), particularly in central and southern regions. By late 2015 (panels 12 to 15 of Figure 4), severe drought was widespread in Mindanao and western Visayas, reaching its height from March to April 2016, coinciding with the peak phase of the 2015–2016 El Niño, showing significant vegetation stress. After the event ended in May 2016, some recovery was noted.

3.3 Spatial distribution of drought trends using SVTRe and VHIe

To assess long-term trends in agricultural drought, the Mann-Kendall trend test was applied to the SVTRe and VHIe time series from 2000 to 2024. Autocorrelation was first applied using the Durbin-Watson statistics to ensure validity in regions where autocorrelation was detected, the time series were first detrended using linear and polynomial regression models before applying the Mann-Kendal test. This preprocessing ensured that observed trends were not artifacts of serial correlation.

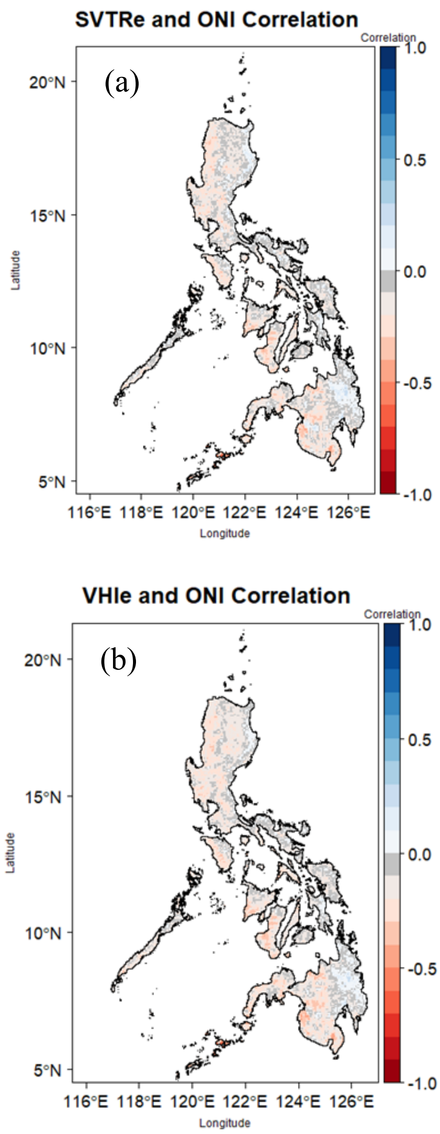

Figure 5. Correlation between (a) SVTRe and ONI, and (b) VHIe and ONI.

The results showed that key-drought-prone areas, particularly Northern Luzon and parts of the western region of the country, experienced slight but statistically significant declines in index values, suggesting drought severity over time during the study period. Sen's slope values are relatively low (-0.084 for SVTRe and -0.087 for VHIe), which implied gradual increase of drought intensity over the past 24 years. Although the results showed that this change is not abrupt, it highlights that conditions for these regions are increasingly drought prone.

3.4 Relationship between drought indices and ENSO

We explored the correlation between ONI and agricultural drought indices which relates the intensity of droughts with the El Nino Southern Oscillation (ENSO) phases. The results in Figure 5 showed positive results indicating that the drought regions did have some correlation, albeit moderate negative correlations, with the drought indices and ONI (drought correlation index lower than -0.35). SVTRe showed having 82% and 5% of the spatial extent being weak and moderate negative correlations respectively. VHIe showed weaker correlations with 84% and 0.2% of the spatial extent being considered weak and moderate negative correlations respectively. Lag relationship may be further explored using lag correlation analysis. Nonetheless, results show the potential of drought indices to delineate regions where significant drought impacts are expected during the El Niño phases

When looking at the correlation per month as seen in Figure 6, the months of January to April showed to have the most areas with moderate to high negative correlation for both SVTRe and VHIe. Interestingly, the mentioned months were within the dry season of the country (November to May) according to DOST-PAGASA (n.d.). Thus, the months of January to April would be considered critical periods for drought impact during El Niño, especially to the areas vulnerable to drought.

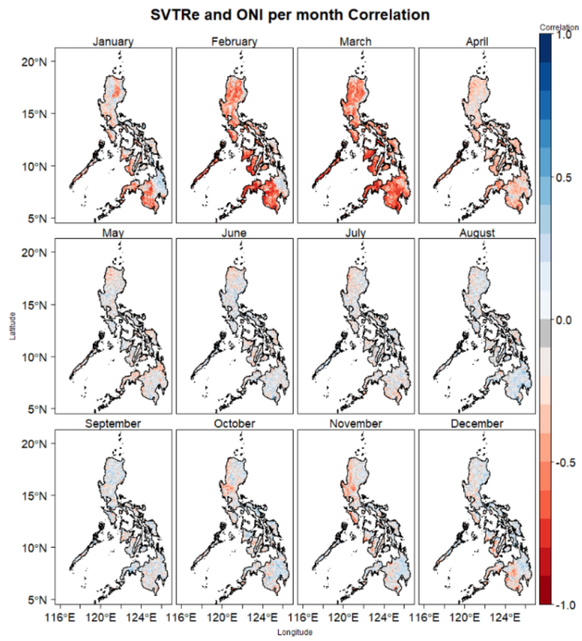

Figure 6. Spatial extent and progression of drought based on SVTRe. As both SVTRe and VHIe showed similar patterns, only SVTRe is displayed in this paper.

3.5 Relationship between drought indices with rice yield

The study analyzed the correlation between quarterly rice yield per province and average vegetation temperature (VT) indices.

Figure 7 showed a weak to moderate yet significant positive correlation in drought-affected areas, indicating that higher VT values correlate with higher rice yields and vice versa. Moderate correlations emerged in Northern Luzon, the western regions, and western Mindanao, with maximum correlations of 0.427 for SVTRe and 0.457 for VHIe.

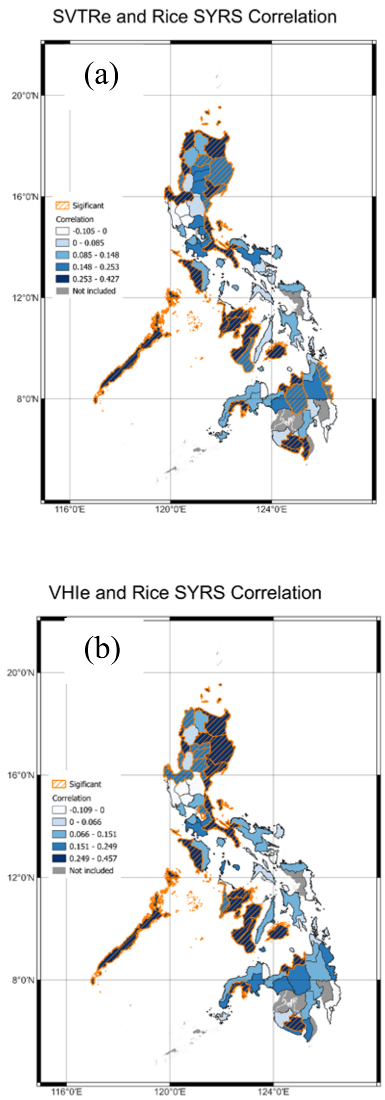

Figure 7. Correlation between standardized yield residual series for rice and VT indices for SVTRe (a) and VHIe (b).

Many provinces exhibiting moderate positive correlations with rice yield were statistically significant ($p < 0.05$), suggesting a weak to moderate causal relationship between EVI-based VT indices and rice yield. The analysis showed SVTRe had more significant correlations with rice yield in Mindanao while VHIe showed more significance in Luzon. Despite these correlations, the indices alone may not fully account for yield variability, as other factors like climate extremes and irrigation practices also play a crucial role. Additionally, spatial variability in farming systems and the timing of satellite observations could weaken this relationship. The study recommends integrating meteorological data and ground-based observations to enhance the predictive accuracy of these indices for rice yield forecasting and suggests further research on their applicability to other crops in the country.

3.6 Accuracy assessment of the drought indices during 2018-2019 Weak El Niño

The performance evaluation of the EVI-derived indices during the 2018-2019 Weak El Niño was done using the reported affected rice area data as a reference. The confusion matrix was used to determine the number of places affected by the drought. Table 3 showed the value of the different performance metrics to both indices on rice.

Performance Metrics (%)	SVTRe	VHIe
Accuracy	58.25	36.15
Precision	27.10	29.25
Hit Rate (Sensitivity)	29.01	90.14
Miss Rate	70.98	9.86
False Alarm Rate	30.37	84.87
True Negative Rate (Specificity)	69.63	15.13

Table 3. Performance score metrics from the use of confusion matrix in relation to the agricultural drought indices on rice.

The result from Table 3 showed that SVTRe demonstrated a higher accuracy of 58.25% compared to VHIe's 36.15%, primarily due to more true negatives (TN) and fewer true positives (TP). In regions like Northeastern Luzon and Western Visayas during the weak El Niño, there were more false negatives (FN), indicating SVTRe's inability to capture drought-affected areas accurately. This may be attributed to drought severity remaining above the detection threshold for many months.

Although SVTRe is more accurate in identifying non-drought conditions, its lower hit rate suggests a need for enhancement in detecting actual drought events, particularly in moderately affected regions. Conversely, VHIe had lower accuracy due to fewer TP and significantly fewer TN, yet a higher hit rate of 90.14% was observed. This implies VHIe was effective in identifying true drought occurrences, evidenced by more TP relative to FN. However, the higher number of false positives led to increased false alarm rates (FAR), with some areas incorrectly categorized as drought-affected despite no reported rice damage. This may result from pre-peak rice harvests in drought areas, leading to increased temperature readings in VHIe. Thus, while VHIe is advantageous for early drought detection, the elevated FAR indicates a requirement for refinement to enhance precision and reduce unnecessary alerts for effective mitigation efforts.

Low precision from both indices is likely due to insufficient differentiation between irrigated and rain-fed rice fields, alongside limited calibration of parameters such as constant (α) in VHIe. The confusion matrix was applied regionally across Luzon, Visayas, and Mindanao, with consistent results indicating that SVTRe outperformed VHIe in terms of accuracy. Both indices exhibited relatively low precision; however, VHIe showed a higher hit rate and a lower miss rate. In contrast, SVTRe demonstrated a high true negative rate.

4. Discussion

Drought-prone areas identified by both indices are primarily croplands that rely on irrigation or rainfall, rendering them susceptible to agricultural drought (Perez, et al., 2016). VHIe indicated more frequent droughts, whereas SVTRe provided accurate geographical mapping of impacted areas. Areas with high drought duration were mostly under Type I of Modified Corona's Climate Classification, notably in western parts like Ilocos and Zamboanga, which rely heavily on agriculture. They are known to be climatologically drier or more exposed to drought-inducing weather phenomena, such as the El Niño, which disrupts rainfall patterns and intensifies dry spells. Additionally, the rain-shadow effect caused by mountain ranges may contribute to localized drying (Bagtasa, 2020), further influencing drought duration. Southern Mindanao has varied exposure due to intertropical convergence and weak monsoon flows, but eastern coastal areas receive more moisture, resulting in shorter droughts (Olaguera and Manalo, 2024). Both indices revealed comparable patterns, but their severity levels differed, highlighting the necessity for field validation and focused agricultural planning to successfully manage drought impacts.

Both indices had the same spatial extent throughout the El Niño events, including the strong (November 2014 – April 2016), moderate (August 2009 – March 2010), and weak (October 2018 – June 2019). The similarities in terms of spatial extent may be attributed to the same variable used in calculating the indices. However, they differed with the severity of the drought in the affected area. This is because of the standardization done when computing the SVTRe, whereas the VCI and TCI for VHIe was based on the difference between the maximum and minimum EVI and LST, making the ratio in the Eq. 4 and Eq. 5 for distinction when it comes to being extremely low and high. Another factor could be attributed to their own drought severity range. Thus, the result suggested that EVI-derived indices are found to be sufficient in mapping drought spatially, assisting local governments in planning preventive measures to mitigate crop damage, especially for rice.

A low, but significant decrease in values of both indices throughout the study period indicated a gradual increase of severity. This gradual increase in severity might be attributed to the changing land cover, where some areas were converted for residential/commercial use, resulting to possible increase in LST. And with the increase of LST, it will cause stress to the crops, especially rice during vegetative stage. These findings are important in the context of early warning systems and drought mitigation strategies as they can provide an opportunity for policymakers and farmers to prepare for worsening conditions and take measures to protect agricultural output.

One of the challenges encountered was the rice yield and map data used in this study where it did not differentiate the rain-fed and irrigated type due to unavailability of their spatial maps for spatial analysis. The correlation between drought indices and ENSO provided an insight on the influence of ENSO as cited by Hilario, et al (2009), however, it was not done per ENSO phase. Hence, a need for further investigation on these relationships per ENSO phase as well as applying the lag correlation analysis. The correlation between drought indices and rice yield was done in a quarterly time series. However, each area has different planting seasons for rice, which could be another reason for weak to moderate correlations. Hence, a separate study on a smaller scale (regional, provincial, or municipal) using high-resolution satellite data is recommended. While SVTRe has higher accuracy than VHIe, its low hit rate and high miss rate during 2019 Weak El Niño suggested that SVTRe is more sensitive to non-drought areas. VHIe, on the other hand, could be used as early warning due to its high hit rate. Thus, accuracy assessment using these indices during moderate and strong El Niño events is recommended to identify their over-all performance.

Despite the challenges and limitations arose from this study, SVTRe and VHIe were able to perform in identifying drought-affected areas, though they differ with the severity of drought. Moreover, the spatial and temporal progression of drought using these indices provided to be useful in assessing the impact of drought. Furthermore, its moderate correlation to the ENSO and rice yield would help in predicting possible damages during drought events. While comparing EVI-derived indices with other local indices is not within the scope of this study, the results show that these indices are sufficient for drought assessment and can serve as an alternative way of measuring drought. This would help local government units (LGU) in providing the farmers the necessary preventive measure to avoid further loss. Lastly, this will provide the policy makers evidence for their policy decision-making, strengthening the urgent need for disaster preparedness.

5. Conclusion

In this study we evaluated agricultural drought indices using Enhanced Vegetation Index (EVI) for rice in the Philippines. We found that drought occurrences are prevalent in Cagayan Valley and the western regions, with SVTRe indicating 15 to 20 events and VHIe showing 15 to 30 events during the 24-year period of study. Both indices showed similar patterns during El Niño, with SVTRe identifying more moderate drought and VHIe indicating severe drought. A low to moderate negative correlation between indices and ONI was noted, intensifying from January to April during dry seasons. A decreasing trend in drought indices was observed in Northern Luzon and Western Visayas. Weak to moderate positive correlations were found in rice field provinces, with maximum correlations of 0.427 for SVTRe and 0.457 for VHIe against quarterly rice yield. During the 2018-2019 Weak El Niño, SVTRe showed higher accuracy (58.25%) than VHIe (36.15%) due to capturing more non-drought areas. VHIe, on the other hand, is recommended for identifying drought areas due to its high hit rate, capturing more affected areas with a higher false alarm rate.

Agricultural drought indices developed from EVI, have been shown to identify drought-affected areas; however, further research will be required to understand vegetation response using EVI. Moreover, further refinement of indices' time series using smoothing techniques may be applied. While both indices show similar geographical drought patterns during El Niño episodes, discrepancies in intensity and duration highlight the need for more detailed studies at regional or provincial levels to accurately estimate damage. Although there are low to moderate negative correlations with the Oceanic Niño Index (ONI), many correlations are statistically significant, making them useful for early El Niño evaluations and requiring further research by event. Using long-term satellite data to study seasonal crop yields, particularly rice, and applying the indices to different crops and other El Niño events (weak and moderate) can enhance accuracy and widen their agricultural applicability. Lastly, a comparative analysis between these indices with the other local indices is recommended for further research.

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agricultural production and harvest area data for rice per province is provided by the Philippine Statistical Authority through https://openstat.psa.gov.ph/PXWeb/pxweb/en/DB/DB__2E__CS/?tablelist=true&rxid=bdf9d8da-96f1-4100-ae09-18cb3eaeb313.

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