Assessment of December to May 1-month lead statistical drought hindcasts for the Philippines

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Abstract

We present the quantitative assessment of 1-month lead statistical hindcasts for detecting drought during the dry season in the Philippines using the Standardized Vegetation–Temperature Ratio (SVTR) drought index. The Oceanic Niño Index (ONI) and the satellite-derived measurements of land surface temperature (LST) and the Normalized Difference Vegetation Index (NDVI) from the Moderate Resolution Imaging Spectroradiometer are used as predictors for the hindcasts. We employ the Autoregressive Integrated Moving Average (ARIMA) model to generate 1-month lead SVTR hindcasts using the aforementioned predictors for 2011 to 2022. Nationwide hindcasts are accurate by (70±10)% across December to May. Areas with 100% hit rate tend to follow the monsoonal rains from December to February; however, the chance of false alarms increased as well. March to May had no chance of false drought warnings for nearly the entire country. Consolidating the different verification metrics, forecast reliability maps indicated ARIMA had high skill in predicting non-drought areas, particularly from February to May. Hindcasts were reliable in discriminating drought and non-drought areas in Maguindanao and Davao del Sur for January and select regions in Mindanao for May. Low reliability for forecasting drought elsewhere may partly be due to the infrequent drought occurrences, wherein we recommend using other forecasts and drought indices for these cases. The developments of this research will guide stakeholders and water managers in their drought mitigation and early warning response, more so in light of the anticipated El Niño.

Keywords: drought, tropical regions, remote sensing

1 Remote sensing of agricultural drought

Drought is a climate phenomenon resulting from prolonged lack of rainfall that may then affect crops, water reserves, and even the economy [1]. Although tropical cyclones pose persistent threats to the country, the Philippines is not immune to drought impacts, which reached nearly ₱8 billion worth of damages in the agriculture sector in 2019 [2–5]. Nationwide drought is linked to the El Niño climate event [3, 6] expected to recur this 2023 [7].

Perez, et al. estimated the severity of agricultural drought from satellites using the Standardized Vegetation Temperature Ratio (SVTR) for the Philippines [4]. The SVTR drought index is based on the changes in the temperature with the Land Surface Temperature (LST) and vegetation condition with the Normalized Difference Vegetation Index (NDVI):

$$X_{\mathrm{SVTR}}(t, m) \equiv \frac{R(t) - \mu_R(m)}{\sigma_R(m)}, \tag{1}$$

with NDVI-LST ratio $R \equiv X_{\mathrm{NDVI}}/X_{\mathrm{LST}}$ at time t, NDVI X_{NDVI}, and LST X_{LST}; alongside the mean $\mu_R(m)$ and standard deviation $\sigma_R(m)$ of R, respectively, for a given calendar month m across all years.

As predicting drought occurrences is crucial in early action responses, building confidence in the forecasting system is done by evaluating hindcasts, which are forecasts set in the past with complete observational counterparts. With the anticipated El Niño, this paper presents the quantitative assessment of short–term hindcasts in detecting drought in the Philippines using SVTR.

2 Confusion matrix analysis of statistical hindcasts

2.1 Hindcast setup

The mean μ_R and standard deviation σ_R in Eq. 1 were comprised of the monthly LST and NDVI at 0.05° (∼5.6 km) resolution from February 2000 to December 2022. All satellite products used were derived from the spectral measurements taken with the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor aboard the Terra satellite [8, 9]. The effect of the El Niño was introduced using the Oceanic Niño Index (ONI), which is a measure of the 3-month sea surface temperature (SST) changes over the central Pacific Ocean. ONI records were based on the Extended Reconstructed SST version 5 (ERSSTv5) and forecasts were taken from the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC) Consolidated Forecasts [7, 10, 11].

Using the Autoregressive Integrated Moving Average (ARIMA) model, LST and NDVI were separately forecasted, assuming there is a seasonal cycle repeating every 12 months. Hindcasts were produced by linear regression with ONI while the error was approximated by a first-order autoregressive model (i.e., the same timeseries with a 1–month lag).

Sets of 6-month hindcasts were generated using climatological data from February 2000 up to varying initialization months from January 2011 to October 2022, for a total of 142 hindcast sets. Within the 6 months of every hindcast run initialized in some month m, the second month (i.e., corresponding to month $m+2$) is defined to have the 1-month lead time, due to the latency in the data availability of the latest LST and NDVI. This lead time was expected to minimize the loss of skill experienced in longer lead times while having at least half a month.

2.2 Confusion matrix metrics

SVTR values were simplified to 0 and 1, representing no drought ($X_{\text{SVTR}} > -0.5$) and drought ($X_{\text{SVTR}} \leq -0.5$), respectively. All 1-month lead hindcasts for a given calendar month were compared with the actual recorded values using the confusion matrix convention (see Table 1). For example, if the forecast predicted drought for a given month but no drought was observed, we have a False Positive (FP) case.

Table 1: Confusion matrix table of drought detection of SVTR forecasts relative to observations.

Confusion matrix		**Observed SVTR**	
		Drought	**Non-drought**
Forecasted SVTR	**Drought**	True Positive (TP)	False Positive (FP)
	Non-drought	False Negative (FN)	True Negative (TN)

The performance of the forecasts in detecting the presence of drought was evaluated through the following skill metrics S based on the number n of TP, FP, FN, and TN for a given pixel:

$$\text{Accuracy}: \ S_{\text{Acc}} = \frac{n_{\text{TP}} + n_{\text{TN}}}{n_{\text{TP}} + n_{\text{FP}} + n_{\text{FN}} + n_{\text{TN}}} \tag{2}$$

$$\text{Hit rate}: \ S_{\text{Hit}} = \frac{n_{\text{TP}}}{n_{\text{TP}} + n_{\text{FN}}} \tag{3}$$

$$\text{Precision}: \ S_{\text{Prc}} = \frac{n_{\text{TP}}}{n_{\text{TP}} + n_{\text{FP}}} \tag{4}$$

$$\text{False Alarm Rate (FAR)}: \ S_{\text{FAR}} = \frac{n_{\text{FP}}}{n_{\text{FP}} + n_{\text{TN}}} \tag{5}$$

$$\text{Negative Predictive Value (NPV)}: \ S_{\text{NPV}} = \frac{n_{\text{TN}}}{n_{\text{TN}} + n_{\text{FN}}} \tag{6}$$

In addition, the skill metrics were consolidated into a single map to show the reliability of detecting drought ($S_{\text{Hit}} \geq 0.67$, $S_{\text{Prc}} \geq 0.67$) and non-drought ($S_{\text{FAR}} \leq 0.33$, $S_{\text{NPV}} \geq 0.67$) areas by filtering the cases detecting more than 50% (here arbitrarily set as 67%) of all drought or non-drought events while correctly classifying the presence or absence of drought.

3 Hindcast performance

Fig. 1 shows the pixelwise accuracy of the SVTR hindcasts for December to May, with the monthly mean ranging from (70±10)% with dips in performance during December and January. Higher accuracy is seen for the provinces along the western coastlines, with the exception of Palawan, away from the influence of the prevailing northeast monsoon from January to February [12]. Thereafter, at least 75% of the entire country had at least 67% drought detection accuracy.

The hindcast hit rate in Fig. 2 tends to reach 100% when accuracy was less than 50% and when the chance of false alarms was greater than 75% (see Fig. 3). These findings indicate probable drought overestimation during December and January. Cases with low hit rates and high accuracy may be attributed to high skill in predicting non-drought areas (i.e., large n_{TN}), as supported by the low FAR (see Eqs. 2 and 5), which occur from February to May, the driest months of the year [2].

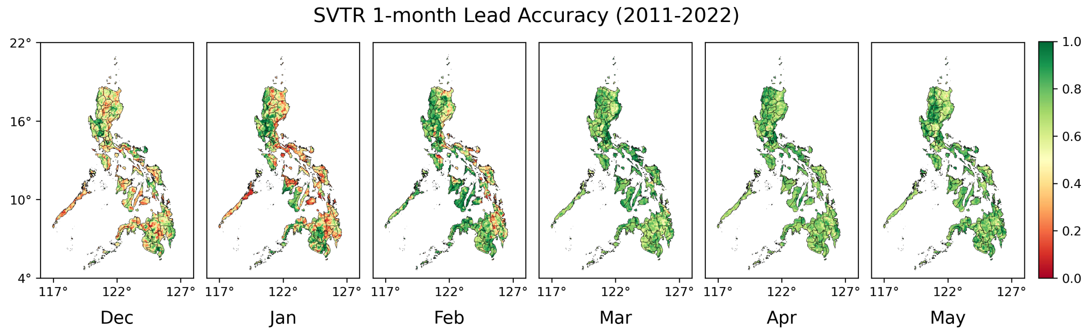

Figure 1: Nationwide accuracy S_{Acc} maps of lead-1 month SVTR ARIMA hindcasts for December to May.

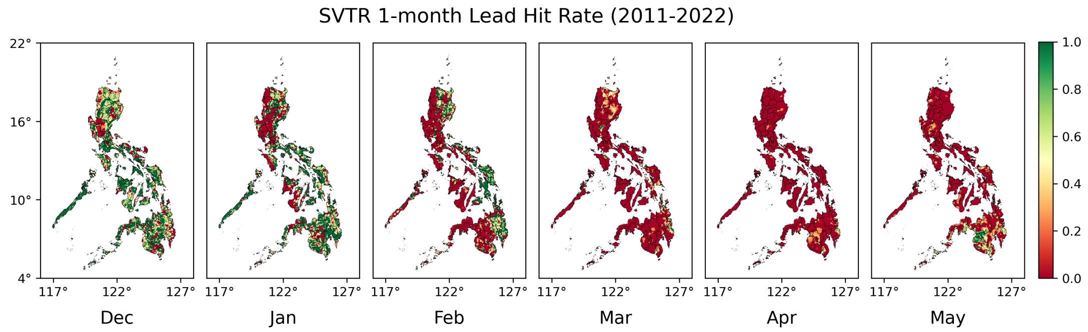

Figure 2: Nationwide hit rate S_{Hit} maps of lead-1 month SVTR ARIMA hindcasts for December to May.

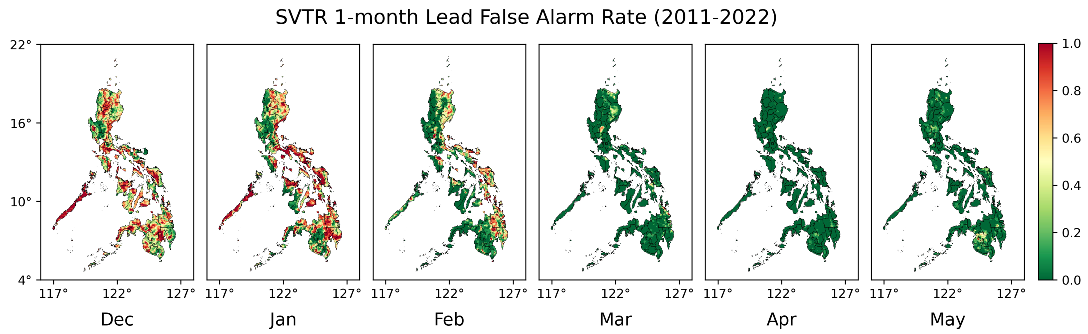

Figure 3: Nationwide FAR S_{FAR} maps of lead-1 month SVTR ARIMA hindcasts for December to May, with a reversed color scheme.

Determining the recommended applications of the hindcasts for operational drought early warning (as described in Subsec. 2.2), Fig. 4 shows the cases when and where the hindcasts can be used to detect non-drought (in sky blue), drought (in sand yellow), or either (in green). The hindcasts were skillful in detecting non-drought events across the country, particularly for February to May. Nearly all provinces recommended for drought detection were appropriate for detecting non-drought areas as well: Maguindanao and Davao del Sur in January; and Zamboanga del Sur, Maguindanao, South Cotabato, Sarangani, and Davao Oriental in May.

Low overall reliability in detecting drought may be due to the rare drought occurrences and formulation of the ARIMA model. The performance metrics employed were intended for balanced datasets which may not adequately describe the infrequent drought occurrences happening $(20\pm10)\%$ of the time [13]. By using ONI as a regressor, ARIMA predictions hinged on the El Niño recurrence for determining drought, although drought damage reports in the Philippines are not limited to El Niño years [6].

4 Conclusions and Recommendations

In conclusion, the satellite–based forecasts are appropriate for detecting non-drought areas across the Philippines from February to May. Drought detection from forecasts is high in Mindanao, particularly in January and May. Forecast verification may alternatively be done either with drought damage reports from the Department of Agriculture (DA) or changes in crop production from the Philippine Statistics

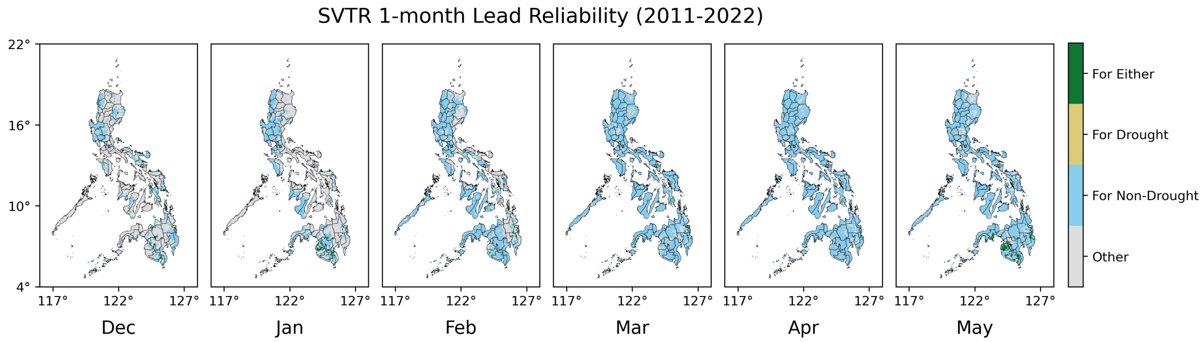

Figure 4: Nationwide reliability maps of lead-1 month SVTR ARIMA hindcasts for December to May.

Authority (PSA). For future work, metrics for imbalanced datasets such as the Area Under the Precision Recall Curve (AUPRC) will be used. Other statistical models will be explored as well as including rainfall and soil moisture as predictors. Subsequent analysis will look into the annual strength of the northeast monsoon and separate the hindcast assessment between El Niño and non–El Niño years. This quantitative assessment of the SVTR drought forecasts and improvements to the hindcast algorithm will act as the scientific basis for a national–level agricultural drought early warning system.

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