Monitoring of Drought Condition and Risk in Bangladesh Combined Data From Satellite and Ground Meteorological Observations

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ABSTRACT

Drought is a very complex natural hazard and has a negative impact on the global ecosystem as a whole. Recently Bangladesh has been experiencing by different degree of dryness as a consequence of high climate variability, affecting the crop production to a great extent in the last couple of decades. In this context, the present study was made an effort to assess and analyse drought characteristics based on two drought indices, i.e., Standardized Precipitation Index (SPI) and Vegetation Condition Index (VCI), and model agricultural drought risk with Fast-and-frugal decision tree (FFT) model in Bangladesh from 2001 to 2016. We identified drought occurrence and its dynamics with three-time scale, i.e., SPI3J (November-January), SPI3A (February-April) and SPI6A (November-April), and three rice-growing seasons, i.e., Aus (March-July), Aman (June-November), and Boro (November-May) from TRMM (Tropical Rainfall Measuring Mission) and MODIS (Moderate Resolution Imaging Spectroradiometer) data. The results demonstrate that TRMM had good consistency with rain gauge measurement compared to CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) and PERSIANN-CDR (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record) data to derive SPI3J, SPI3A and SPI6A. Overall results confirmed that more drought frequency observed in SPI6A than SPI3J and SPI3A time scale, representing moderate to severe drought throughout the country. Regarding agricultural drought resulting from VCI demonstrated Boro rice-growing season as more vulnerable crop growing season affected by severe to extreme drought event. Validation results of VCI exhibited a high correlation with rice yield data than in-situ soil moisture data. Results of the FFT model show that out of ten predictor variables SPI3J and SPI6A caused agricultural drought with SPI value less than −1.08 and −1.21 respectively. Additionally, the model characterized SPI3J and SPI6A as the most critical driving factors with the highest balanced accuracy triggering agricultural drought risk in Bangladesh.

INDEX TERMS

Drought, SPI, VCI, TRMM, MODIS, Bangladesh.

I. INTRODUCTION

Drought is natural repetitive phenomena causing destructive disasters that considerably influence the environment, agriculture and economy of a country. Bangladesh has an agricultural-based economy and recently has made tremendous progress in agriculture, making the country self-sufficient in crop production and ensuring food security, which has a positive impact on poverty alleviation [1]. However, the agricultural sector is being exposed to more susceptible to climate change variability. The climate change variability is mainly due to its location in the tropics, low elevation above sea level, and high population pressure makes the country more prone to disaster. Drought, flood, cyclones, sea-level rise, etc. are major climatic disasters in Bangladesh affected by climate change variability. Among these disasters, Bangladesh has been affected by different degree of drought in the last couple of decades affecting...
2.3 million ha of cropland from April to September and 1.2 million ha during October to March in the dry season causing 1.5 million ton production loss per year [2], [3]. Though drought was not continuous events, every year Bangladesh has experienced dry season from November to May. Therefore, drought mainly happens during pre-monsoon (March-May) and post-monsoon (November-January) seasons in Bangladesh [4]. At present, the country uses the traditional method in monitoring and assessment drought that is based only on rainfall data. However, remote sensing technology needs to be incorporated to explain the anomaly in vegetation caused by drought, which provides a promising method for better understanding the spatial extent and intensity of drought.

Drought events were monitored by different indices (i.e., more than 100 indices currently available) developed by researchers and were applied in the areas of meteorology, hydrology, and agriculture [5], [6]. The Standardized Precipitation Index (SPI) is one of the most popular meteorological drought indices, which is estimated from rainfall frequency analysis [7]. Standardized Precipitation Evaporation Index (SPEI), more recently developed by Vicente-Serrano et al. [8], requires not only precipitation but also temperature to monitor drought. Using precipitation and temperature data, Palmer [9] determined the moisture supply into the soil layer, popularly recognized as the Palmer Drought Severity Index (PDSI) [6]. Also, Surface Water Supply Index (SWSI) [10] and Standardized Streamflow Index (SSI) [8] treated as hydrological drought indices. According to Alley [11], these indices lack appropriate technique to standardize it and only use the arbitrary rules to quantify it. Furthermore, the above-discussed indices mostly rely on historical data availability, which is very difficult to apply for those countries are lack of historical data record along with the limited meteorological stations. Under these circumstances, satisfactory spatial mapping of the index is complicated. However, we have used SPI for meteorological drought evaluation, which is a widely used index due to its simplicity, more easy computability on a different time scale, and require only one parameter. Sometimes the level of spatial precision for monitoring drought is hindered by discrete and point-based meteorological measurement [12], [13]. In this context, remote sensing data and tools offer substantial advantages for examining the drought in a place of scarce and inconsistency of in situ data related to drought [14], [15]. As a result, remote sensing-based drought indices: Vegetation Health Index (VHI) [16]; Temperature Condition Index (TCI) [17]; and Vegetation Condition Index (VCI) [18], [19] have been developed and widely used for drought monitoring. Several studies have also found using Temperature-Vegetation Dryness Index (TVDI) [20] and Vegetation Temperature Condition Index (VTCDI) [21] for drought evaluation which is time-dependent and region-specific. Furthermore, combined drought indices are new types of drought index which were developed in recent years [22], [23] and have good performance in drought monitoring. Recently the studies of drought propagation [24]–[26] help to understand unsaturated water, saturated groundwater, and surface water, that give a complete picture of drought mechanism in the hydrologic system. Finally for agricultural drought index VCI has been employed in this study because of its popularity and easily accessible at different spatial and temporal resolution.

Existing literature related to drought studies [27]–[29]; [3] in Bangladesh mainly focused on SPI based method with the historical data set. However, only few studies used remote sensing techniques for drought monitoring in Bangladesh [30], [31]. Recent study carried out by Rahman and Lateh [32] assessed spatio-temporal characteristics of meteorological drought in Bangladesh based on rainfall data and SPI method. In another study, Alamgir et al. [33] used SPI index for characterizing meteorological drought patterns during the various climatic seasons as well as cropping season. Drought analysis using SPEI index drought hazard map was created by Islam et al. [34] through probability distribution function. This study mainly emphasized the Boro rice growing season for drought evaluation in the north-western part of Bangladesh. However, Miah et al. [35] also used SPEI gridded data (0.5° resolution) data set of East Anglia’s Climate Research Unit (CRU) from 1901 to 2011 along with historical weather station data during 1995 to 2011 for meteorological drought assessment in Bangladesh. Therefore, we can confess that the use of vegetation indices for drought study derived from time-series remote sensing data set or satellite images are scarce in Bangladesh. Both meteorological and agricultural drought are characterized by precipitation as well as soil moisture deficit respectively, and it first starts with precipitation shortage which leads to soil moisture stress, and thus, limited vegetation growth. So, a better understanding of drought dynamics, we should consider both these parameters which have come from precipitation and vegetation. Therefore, we used Tropical Rainfall Measuring Mission (TRMM) data as a component of precipitation to calculate SPI as the first drought index. Then, we used Normalized Difference Vegetation Index (NDVI) from MODIS data as a component from vegetation to calculate VCI as second drought index to monitor the drought in the region over the last 16 years. In this study, we used ‘fast-and-frugal decision tree’ (FFT) model to trace agricultural drought, which has not been yet implemented in any other remote sensing studies for risk assessment. Hence, our main objectives are: firstly, to assess the severity and extent of drought using SPI and VCI in Bangladesh from 2001 to 2016; secondly, to evaluate the ability of VCI to represent agricultural drought for three rice-growing seasons using soil moisture and yield data; and finally, to model agricultural drought risk with FFT supervised machine learning model.

II. DATA AND METHOD
A. STUDY AREA

Bangladesh is situated in the South Asia region; geographically located between 20°34’ – 26°38’ N latitude and 88°01’ – 92°41’ E longitude covering, an area of
with a population of 160 million [36]. Being a country of high population density three-fourth of its total population has engaged in the agricultural activity [37]. India surrounds Bangladesh in its three sides (north, west, and east). The southern part of the country is exposed to the vast Bay of Bengal and southeastern part of the land bounded by Myanmar. Hill regions, Chittagong hills are seen in the southeast part of the country whereas, the largest mangrove forest is found in the southwestern part of the country. Administratively Bangladesh has eight divisions, 64 districts with a total population of 164,669,751 [38]. Land use land cover of Bangladesh with global vegetation classification scheme based on MODIS land cover type product (MCD12Q1) is shown in Fig. 1. It shows that most of the region is covered by crop. Bangladesh has climatically sub-tropical monsoon with wide cyclical distinctions in rainfall, moderate warm temperature, and high humidity [39]. These climatic characteristics differentiated the country’s climate into four seasons: i) dry winter continuing from November to February; ii) pre-monsoon or summer detected from March to May; iii) southwest monsoon noticed between June to September; and iv) post-monsoon ranging from October to November [40]. Maximum temperature in summer fluctuates from 35 to 41 °C throughout April and May. For rainfall, 75 % of the total rain occurred from June to October, 22% rainfall observed all over the hot summer season (March to May, and only 3% of the total rainfall noticed during winter season [32], [41]. At present, Bangladesh is facing higher temperatures, inconsistency in rainfall, more life-threatening weather events, and gradually rise in sea level [42]. Geographic location and physiography of the country along with more seasonal variability of temperature and rainfall patterns, make the country more vulnerable to drought [39], [43].

B. IN-SITU DATA AND SPEI CALCULATION

The monthly precipitation and temperature data of thirty-three weather stations for the period of 1970-2016, 47 years of historical records were collected from the Bangladesh Meteorological Department (BMD). This observed meteorological data were used as the real value to test the validity of the TRMM 3B43 precipitation data. Precipitation values of both station rain gauges and TRMM3B43 were examined using linear regression analysis in SPSS software. Station data were considered as independent variables, and corresponding grids were taken as the dependent variable to determine the regression determination coefficient $R^2$. We employed validity analysis of TRMM data with scatterplots and linear regressions equations for the period of 2001 to 2016 (Appendix A). Our results showed that the TRMM3B43 precipitation data were well correlated with those from meteorological station data with $R^2$ ranging from 0.72 to 0.91 in which 87.5 % of the data fit well with the meteorological station data (Table 1). The monthly precipitation from TRMM is slightly different from that of the meteorological station due to the changes between the spatial scales of the two kinds of rainfall data. This analysis confirmed the consistency of the two data sets is high with a clear linear correlation, allowing it appropriate for the calculation of the spatio-temporal distribution of drought.

We calculated SPEI using the long-term precipitation and temperature data. SPEI was calculated at different time scale...
TABLE 1. Validation results of TRMM precipitation data from 2001 -2016

| Year | Number of meteorological stations | Slope  | R²   | RMSE (mm/month) |
|------|-----------------------------------|--------|------|-----------------|
| 2001 | 33                                | 0.881  | 0.72 | 28.50           |
| 2002 | 33                                | 0.976  | 0.90 | 14.35           |
| 2003 | 33                                | 0.934  | 0.91 | 15.74           |
| 2004 | 33                                | 0.932  | 0.86 | 20.24           |
| 2005 | 33                                | 0.880  | 0.88 | 22.27           |
| 2006 | 33                                | 0.869  | 0.86 | 22.40           |
| 2007 | 33                                | 0.893  | 0.89 | 18.41           |
| 2008 | 33                                | 0.867  | 0.86 | 28.10           |
| 2009 | 33                                | 0.825  | 0.82 | 30.92           |
| 2010 | 33                                | 0.875  | 0.82 | 24.44           |
| 2011 | 33                                | 0.835  | 0.86 | 39.12           |
| 2012 | 33                                | 0.898  | 0.82 | 23.68           |
| 2013 | 33                                | 0.881  | 0.83 | 24.41           |
| 2014 | 33                                | 0.936  | 0.91 | 14.42           |
| 2015 | 33                                | 0.915  | 0.91 | 23.06           |
| 2016 | 33                                | 0.758  | 0.74 | 57.25           |

FIGURE 2. Methodological diagram of the overall workflow of the study.

(SPEI-3, SPEI-6, and SPEI-12) following Hargreaves [44] model using SPEI package in R software [45] to detect meteorological drought from 1970 to 2016. Here, we mainly focused SPEI revealed drought for last 16 (2001-2016) years as we mapped meteorological drought using SPI from TRMM (Tropical Rainfall Measuring Mission) data. We also used soil moisture from agro-meteorological station and yield data from Bangladesh Bureau of Statistics (BBS) from 2001 to 2016 to validate agricultural drought derived from MODIS data.

C. Method
The overall procedural steps used in this study is presented in Fig. 2. First, remote sensing-based data sets (Table 2) were acquired to initiate meteorological and vegetation-based indices. Second, the drought was detected based on time series analysis for the period of 2001-2016.

1) SATELLITE BASED PRECIPITATION DATA AND SPI CALCULATION
TRMM is a satellite-based estimate of precipitation (that has a spatial coverage that extends from 50°S to 50° N latitude) with land surface gauge analysis [46]. The TRMM 3B43 V7 monthly gridded rainfall data (mm/h) was download from Goddard Earth Science Data and Information Services (https://mirador.gsfc.nasa.gov/) website for the period of 2001-2016. In this study, TRMM rainfall data were used to calculate SPI.

In addition of TRMM data, we used two other satellite data such as CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) and PERSIANN-CDR (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record) to evaluate the performance with SPI estimate using gauge station data. CHIRPS is based on satellite precipitation blended with station data from GHCN (Global Historical Climate Network) and GSOD (Global Summary of the Data Set) data [47], [48]. CHIRPS data can be accessed at https://data.chc.ucsb.edu/products/CHIRPS-2.0/ for global landmass and a monthly temporal resolution. PERSIANN-CDR estimates precipitation from ANN algorithm using GridSat-B1 infrared data adjusted with GPCP (Global Precipitation Climatology Project) data. [49], [50]. This data provides daily, and monthly precipitation at 0.25° resolution can be found at https://chrsdata.eng.uci.edu/. Both these data sets are designed to monitor long term precipitation trend, flood and drought monitoring as well as for the study of climate evolution.

The SPI method proposed by McKee et al. [51] is a probability index to assess meteorological drought where observed rainfall probability is transformed into an index for any time scale (3, 6, 12, 24, 48-month time scale). Usually, SPI allows identification of drought condition at any time scale from long term precipitation data (≥30 years) [32], [51], [52]. However, using precipitation from TRMM data of moderate length records (at least ten years) improves the spatial and temporal characterization of drought [53]. Naumann et al. [54] also stated in his study that SPI with short-term time series of remote sensing data particularly from TRMM is feasible to

TABLE 2. Datasets and their properties employed in this study

| Dataset | TRMM 3B43 | CHIRPS and PERSIANN-CDR | MODIS MODIS L1C |
|---------|-----------|-------------------------|------------------|
| Variable | Precipitation rate (mm/h) | Precipitation (mm) | Surface reflectance |
| Source   | TRMM, gauge analysis | Rain Gauge and Satellite | MODIS MCD12Q1 |
| Temporal coverage | 1 January to 1 December 2016 | 1 January to 1 December 2016 | 1 January to 1 December 2016 |
| Spatial coverage | 50°S to 50°N | 50°S to 60°N | Global |
| Temporal resolutions | 1 month | 1 month | 16 days (composite) |
| Spatial resolutions | 0.25° × 0.25° | 0.05° × 0.05° | 500 m |
| Data format | Net CDF | TIF | HDF | HDF |
use because of its higher spatial resolution than other gridded data. Though other gridded data such as scpPDSI has the strength of high resolution, the scpPDSI was indicated to be very complex and difficult to interpret [6] compared to SPI from TRMM data. Here, we calculated SPI for 16 years with TRMM data at 3- and 6-month time scale from November to April (2001-2016), which is the dry period in Bangladesh. The rainfall of November-January is considered for 3-month SPI of January (SPI3J); February to April for 3-month SPI of April (SPI3A); and using November to April rainfall data 6-month SPI for April (SPI6A) was calculated. Cumulative TRMM rainfall distribution frequency (Fig. 3) from November to January, February to April and November to April indicate that February to April rainfall is more widespread than others representing more cluster rainfall for the period February to April. The Kolmogorov-Smirnov test (D = 0.523; \(p\)-value: 0.0001) also suggested that cumulative TRMM rainfall during these periods does not follow the same distribution pattern; rainfall distribution significantly varied with the time.

Due to the nature of rainfall distribution, a fitted normal distribution is required [55] done by the gamma probability distribution of each grid correspondence to thirty three weather stations of Bangladesh. Gamma distribution is essential in case of high rainfall variability where rainfall does not follow the same distribution pattern, and also it facilitates adjustable representation of a variety of distribution shapes (while considering two parameters, i.e., shape and scale) for precipitation. Subsequently, the parameters are applied to calculate the cumulative probability distribution for a specific grid and defined time scale [55]. We employed language and software environment R to calculate SPI with “SPEI” package [45]. This package allows gamma probability distributions for calculation of SPI for computation of the distribution function parameters. Continuous negative SPI values illustrate less than median rainfall causes drought events. The SPI value was extracted as a point from the grid cell which corresponds to the weather stations of the country. The widely used interpolation method inverse distance weighted (IDW) was used in ArcGIS software to the spatial extent of the point data [56]–[58].

2) MODIS DATA ACQUISITION AND VCI CALCULATION

In this study, 16-day composite MODIS vegetation indices product (MOD13A1 version 6) with 500 m spatial resolution was used. MODIS vegetation indices data were downloaded from NASA Level-1, and Atmosphere Archive & Distribution System (LAADS) Distributed Active Archive Center (DAAC) website (https://ladsweb.modaps.eosdis.nasa.gov). Time series Vegetation Condition Index (VCI) was derived from this data, which contains two tiles (h25v06 and h26v06) for the study area from 2001-2016.

Vegetation indices NDVI and VCI were computed utilizing two surface reflectance band red and NIR from the mosaicked tiles of MOD13A1 product. The tiles were mosaicked and re-projected to geographic projections of WGS84 datum with MODIS Conversion Toolkit (MCTK) [59]. Maximum Value Composite method was employed to extract time series VCI in this study. Because it is straightforward and fast and a good estimate of the whole period being maximum value assumed by the vegetation index. Time series maximum value composite of NDVI with Savitzky-Golay smoothing filtering method (Appendix B), seasonal average NDVI was computed to generate VCI value for each crop growing season. Here seasonal VCI value was given emphasized according to the rice crop growing season because in Bangladesh most of the crop area is dominant by rice. There is three rice growing season in Bangladesh namely; Aus, Aman, and Boro, each of this season, have distinct climatic characteristics. According to rice calendar (Appendix B), Aus season starts from March and end in July whereas, June-November period is for Aman season and finally Boro season last for November-May. The seasonal VCI for each rice growing season was obtained by collected average NDVI values of the months corresponding to each season. Finally, A total of 704 images were processed to derive time series VCI by computing maximum and minimum NDVI for each of 22 composites for each year with the following formula:

\[
VCI = \left(\frac{NDVI_j - NDV_{\text{min}}}{NDV_{\text{max}} - NDV_{\text{min}}}\right) \times 100
\]

where, \(NDVI_j\) is the average NDVI value of the pixels during a specific period, and \(NDV_{\text{max}}\) and \(NDV_{\text{min}}\) are the maximum and minimum values of NDVI during that particular time [60], [61]. Ecosystem and weather are two environmental parameters which characterize by NDVI where, the former one explains the long-term change in the environment, and the later one explains inter-annual variation in each ecosystem [62], [63]. Conceptually, the ecosystem impact influenced by climate, soils, and vegetation because
of weather condition, VCI improves this inter-annual variation of vegetation index (e.g., NDVI) [64]. Since the VCI value indicates the seasonal change of vegetation conditions by means of surface greenness, and low VCI means unfavourable growth condition or low vegetation cover [65]. The VCI value with below 50% indicate below normal condition of vegetation. VCI has established suitable for monitoring agricultural drought because of its large scale impact on vegetation [66]. SPI based drought classification as defined by World Meteorology Organization [67] and drought classification according to [66] and [68] for VCI is presented in Table 3.

3) PRINCIPAL COMPONENT ANALYSIS AND FAST-FRUGAL DECISION TREE (FFT) MODEL

The association among meteorological and agricultural drought along with the contribution of each variable to the SPI and VCI time series data, a multivariate technique named principal component analysis (PCA) was used in this study. PCA analysis was also done in this study with “prcomp” function in software R.

We modeled agricultural drought risk using a decision tree algorithm named FFT. Generally, a decision tree consists of a sequence of nodes based on conditional rules in the form of “if A, then B” [69]. Fast-and-frugal decision tree model described by Martignon et al. [70] a supervised machine learning algorithm usually solve the tasks and make a decision based on binary classification. The structure of binary classification is used a wide range of frameworks of the statistical analysis for making a judgment [71]. The algorithm evaluates the performance and makes comparison with other linear regression based on signal detection theory [72]. Here the binary criterion is the agricultural drought risk status which can either be true (having agricultural drought) or false (not having agricultural drought). For agricultural drought risk assessment, VCI considered as dependent variables which categorized as 1 (if the VCI value is less than 50) indicate agricultural drought risk and 0 (if the VCI value is more than 50) indicate no risk. The independent variables were taken into account were SPI3J, SPI3A, SPI6A, NDVI, and precipitation anomaly (PRCP_Anomaly), PC1 and PC2 (from PCA analysis), SPEI-3, SPEI-6, and SPEI-12 (from meteorological station data). A confusion table matrix was formed to assess the model accuracy of the decision algorithm. A confusion table contains algorithm decision and counts the observation with true criterion value for all four resulting cells. Positive criterion value correctly represents hits indicated by $hi$ cell, and negative criterion value correctly predicted to be negative describes by correct rejections indicated by $cr$ cell. Then again, false alarm represents by $fa$ cell for errors where negative criterion value erroneously predicted to be positive, and positive criterion value wrongly predicted to be negative indicated by misses represents by $mi$ cell. FFT analysis was done with “FFTress” package developed by Phillips et al. [69] in R software.

III. RESULTS AND DISCUSSIONS

A. TEMPORAL DROUGHT CHARACTERISTICS USING SPEI DURING 1970-2016

We calculated SPEI at three-time scale, such as SPEI-3, SPEI-6, and SPEI-12 by using monthly precipitation and temperature data of 33 meteorological stations from 1970-2016. These analyses showed the presence of wet and drought condition with positive and negative SPEI value respectively. Though SPEI analysis confirms the existence of both wet and dry periods during 1970-2016, we only investigated the drought period for last 16 years as one of our objectives to monitor drought during 2001-2016.

Fig. 4 representing SPEI analysis at different time scales demonstrated that drought is a frequent phenomenon and occurs at regular intervals in Bangladesh during 1970-2016.
but the magnitude of drought occurrence is more frequent during last 16 years though it varies from one-time scale to another time scale. It can also be seen that during the last 16 years more frequent negative SPEI values were found in the SPEI-3 time series during 2002-2016 while, at SPE-6 and 12 time scale negative SPEI was observed during 2009-2016. These droughts were related to recent changes in climate variability such as high temperature and erratic rainfall pattern during last 16 years.

### B. SPATIO-TEMPORAL PATTERN OF DROUGHT BASED ON SPI

Precipitation deficit was quantified in this study by SPI-3 and SPI-6-time scale using satellite data, which imitate the effect of drought on the availability of different water resources. To highlight the available moisture condition in an agricultural region, SPI-3 is more effective, whereas to detect a seasonal trend of precipitation anomalies SPI-6 is more useful in this context. Thus, precipitation anomalies with SPI-3 need to compare with SPI-6. The diversifications of temporal rainfall intensity together with the spatial consequence of time dimension make the variation of drought events at three-time scale. First we evaluated satellite estimate SPI with reference data (station data) then we characterized spatial patterns of drought events.

We compared the SPI (SPI3J, SPI3A, and SPI6A) derived from TRMM, CHIRPS, and PERSIANN-CDR with in-situ observations. The performance of satellite based SPI are evaluated based on R², R, and RMSE value against in-situ observation. The colored scatter plot are presented in Fig. 5 demonstrating comparable performance of satellite data with in-situ measurement for SPI values over 33 station in Bangladesh. The three satellites i.e. TRMM, CHIRPS, and PERSIANN-CDR give SPI estimates are in good agreement with those based on gauge observation with high R² value and low RMSE. This analysis suggested that all these three products are suitable for drought analysis. Among these three products TRMM (R² = 0.81 ~ 0.85; R = 0.902 ~ 0.922; RMSE = 0.40 ~ 0.42) shows slightly better performance compared to PERSIANN-CDR (R² = 0.81 ~ 0.83; R = 0.902 ~ 0.911; RMSE = 0.43 ~ 0.44), and CHIRPS (R² = 0.79 ~ 0.82; R = 0.887 ~ 0.906; RMSE = 0.43 ~ 0.46). This analysis indicate TRMM can be used for short-term drought analysis. Similar findings were reported by Zhao and Ma [47] where they claimed TRMM can be used for near-real-time drought monitoring whereas PERSIANN-CDR might be more suitable for long term drought monitoring. Finally, we analyzed spatial patterns of drought events with TRMM data.

Spatial pattern of drought based on SPI analysis suggested that frequent drought events were observed throughout the time though some years were found with the wet condition at SPI3J (Appendix C), SPI3A (Appendix C), and SPI6A (Fig. 6). Further, moderate to severe droughts were found prominently compared to extreme events which was consistent with the findings of Rafiuddin of Rafiuddin et al. [73]. Spatial distribution of SPI during SPI3J (Appendix C) time scale, demonstrated that 2013 and 2014 year were influenced by increased drought condition with more negative SPI value while at SPI3A (Appendix C) time scale more wet periods were observed with more positive SPI value. But the spatial extent of SPI6A gives the diverse distribution of SPI value ranging from −1.5 to < −2 that lead to diversified drought events in different parts of the country (Fig. 6). Results SPI6A also suggested that more negative SPI value was seen in the northern part of the country for most of the years compared to the south-central and southern part of the country except for the years of 2004, 2006, 2013, and 2014. In contrast, the country was found with wet periods by the years of 2003 and 2012 only at SPI6A.

Drought frequency was also analysed in high drought prone region based on drought events (moderate extreme, severe) occurrence at each time scale over Bangladesh (Table 4). The spatial pattern of Drought frequency gives an overview of the areas recurrently knock by drought at different time scale from 2001-2016. Moderate drought affected 66% of the total area in the high drought-prone area in SPI6A (Table 4). However, severe drought occupied 79.82% of the total area at SPI3A scale in the zone of the northern part and south-western part of the country. Extreme droughts found more prominent in SPI3J, which hit the north part, north-eastern and south-central part with an area of 73.35% of the country’s total area (Table 4).

Thus, from the above findings, it can be said that north-western, south-central, and south-western part of the country are more prone to drought. Diversification of drought events throughout the country is more prominent, due to the climate change and warming of the country [32]. Furthermore, oceanic circulation pattern is known as El Niño–Southern Oscillation (ENSO: which is periodic irregularity difference in winds and sea surface temperature over the Pacific region) creates an event of El Niño associated with the warming phase of sea surface temperature affects the monsoon rainfall in Bangladesh. In general, historical rainfall pattern reveals that Bangladesh received low rainfall during the moderate (2002-03 and 2009-10 years) and strong (2014-16 years) El Niño years [74], [75]. Therefore, long dry periods arise as sea surface temperature directly links to the rainfall pattern [76]. Bangladesh is also influenced by regional geographic position, i.e., the Indian Ocean in the south and Himalayan Mountain in the north have a significant effect on rainfall and drought in the country.

### C. SPATIO-TEMPORAL DISTRIBUTION OF DROUGHT BASED ON VCI

The spatial pattern of the drought was evaluated using VCI values for three rice-growing seasons, i.e., Aus, Aman, and Boro. The spatiotemporal pattern of VCI, which reflects the
FIGURE 5. Density-colored scatter plot between different satellite products and rain gauge measurement of SPI from 2001-2016: a) SPI3J_CHIRPS vs. SPI3J_Station data; b) SPI3A_CHIRPS vs. SPI3A_Station data; c) SPI6A_CHIRPS vs. SPI6A_Station data; d) SPI3J_TRMM vs. SPI3J_Station data; e) SPI3A_TRMM vs. SPI3A_Station data; f) SPI6A_TRMM vs. SPI6A_Station data; g) SPI3J_PERSIANN-CDR vs. SPI3J_Station data; h) SPI3A_PERSIANN-CDR vs. SPI3A_Station data; i) SPI6A_PERSIANN-CDR vs. SPI6A_Station data (The colored bars indicate the SPI value).
agricultural relevant drought events over Bangladesh for the period of 2001-2016, is discussed for Aus (Appendix D), Aman (Appendix D), and Boro (Fig. 7). Drought events are illustrated as mean VCI per pixel over the growing season period. Dynamics of drought pattern temporally and spatially revealed that the drought condition based on the growing season was located in the areas displayed for the inspected period. The spatial distribution of VCI demonstrating that moderate to severe drought was more frequent and found in the areas of northwestern and southwestern part of the country during Aus (Appendix D) and Aman (Appendix D) rice growing season. In contrast, vast area in the northern and south central regions were affected by severe to extreme drought events during Boro rice growing season. The overall results suggested that Boro season suffered more in terms of drought intensity than Aus and Aman season. This result might be the fact that around 80% rainfall comes during monsoon season (June-September) and rest 20% covers eight months, including the dry winter month in which Boro rice is grown. The historical rainfall trend also recommended that rainfall increases during the monsoon season and decreases in the winter month. This insufficient rainfall in winter leads to a moisture stress condition, which might affect the vigorous growth of rice crop and ultimately have a negative impact on VCI. Crop water requirement is also inclined by climate change, and according to the environmental condition, it reaches a peak in Boro season, which is characterized by hot, dry, and sunny condition (November - May). Besides Boro season, drought in Aus and Aman season is a consequence of rainfall deficiency, cumulative effects of dry days with high temperature (>35°C), and soil with low water holding capacity caused 27% reduction of Aus rice production and 1.5 million ton Broro Production loss [2].
We used yield and soil moisture data to verify the applicability and ability of VCI in monitoring agricultural drought. In this study, 33 agro-meteorological stations were selected to represent agricultural drought estimated from VCI at the examined station for validation with soil moisture (at 30 cm depth) and crop yield data. We performed regression analysis with scatter plot to detect the relationship of VCI with both cases of yield and soil moisture data at each site (Fig. 8). The scatter plots of VCI with both yield and soil moisture results presented in Fig. 8. The results showed that rice yield was closely related to agricultural drought in the rice-growing season ($R^2$ ranges 0.784, 0.742 and 0.906 in Aus, Aman and Boro season respectively). It is positively correlated indicates rice yield increase with an increase of VCI value and vice versa. The scatter plot of VCI with soil moisture also represents positive correlation with coefficient determination $R^2$ ranges from 0.21 to 0.25 which indicates VCI increase with an increase of soil moisture. Ultimately from this results it can be said that less soil moisture lead to agricultural drought in three rice-growing seasons. However, comparatively less strong correlation was observed in case of soil moisture compared to yield with VCI, this result is consistent with Park et al. [53]. This might be due to the variation of soil moisture at different depths for example top soil moisture (<10 cm) is more responsive for a short period to the total amount of rainfall reported by Zhang and Jia [77]. Moreover, complexity of plant physiology and high irrigation rate along with heterogeneous location of the ground station which made VCI less responsive to soil moisture. Overall, our validation analysis confirms that VCI derived drought better represents agricultural drought at the examined station in relation to yield than soil moisture.

D. AGRICULTURAL DROUGHT RISK ASSESSMENT

Before going to assess the agricultural drought risk, we evaluated the relationship of each variable between meteorological and agricultural drought with correlation analysis. In addition, contribution of the variables (drought indices) to the original SPI and VCI series was also evaluated by employing PCA analysis. The correlation between SPI and standardized VCI was computed and presented in Fig. 9. The correlation coefficient between SPI and VCI suggested that SPI and VCI were positively correlated. The strong correlation between SPI and VCI was found at SPI3J time scale with coefficient 0.87 whereas it was 0.45 for SPI6A. This positive relationship indicates that with an increase of SPI value, the VCI also increase and vice-versa. Finally, it can be concluded that agricultural drought increases with more negative SPI value.

To demonstrate the contribution of each variable in principal components, we employed biplot analysis. It is evident from Fig. 10 that all drought indices had a significant contribution to PC1, which accounts for 55.2% of the variance in the data set alternatively PC2 accounted for 24.5% variance. The loading values of each variable to principal components are shown in Table 5. PC1 represents the four variables with positive correlation among them where SPI3J responsible for highest loading contributed more thus considered
FIGURE 8. Scatter plot of VCI revealed drought with rice yield (Fig. a, b, and c) and soil moisture (Fig. d, e, and f) at each station in three rice growing season (The black line indicates fitted line; red line represents 0:1; and green dotted lines denote upper and lower confidence interval).
as the representative variable for PC1. SPI3A was found to be mostly contributed variables with positive loading in PC2 whereas SPI3J and VCI negatively correlated.

Agricultural drought risk was evaluated through fast-and-frugal decision tree model. Fast-and-frugal trees have exit branches either one or two on every node leading to an immediate decision and make the decision faster than other decision trees. The FFT( ) functions created six FFTs among these the FFT#1 is highlighted with the highest accuracy in training data set, including high sensitivity. The FFT tree presented in Fig. 11 indicates that the agricultural drought is being risked or not a risk for having a meteorological drought. To classify agricultural drought as risk or non-risk for the first node, if SPI value higher than $-1.08$ (SPI $>-1.08$) at SPI3J time scale there will be no agricultural drought risk whereas for SPI6A time scale if SPI value less than $-1.21$ (SPI $<-1.21$) there will be a change of agricultural drought events. The FFT also predicts for SPI3A time scale that if the SPI value higher than $>-0.60$ than no agricultural drought will happen; otherwise, there might be a risk of agricultural drought. Summary statistics of the FFT models with basic statistics, including the number of cases and metrics for accuracy, are presented in Table 6. The results in Table 6 shows the performance measure of the model in training and testing data set. The marginal accuracy of every cues or variable in the ROC (Receiver Operating Characteristics space) (Fig. 11) was presented in Fig. 12. Fig. 12 demonstrates the resulting plot for the agricultural drought risk reveals that the three cues or variables (such as SPI3J, SPI6A, and SPI3A) have the highest individual balanced accuracies. Besides these three cues, the figure also tells the next two important cues NDVI and PRCP Anomaly, which could be very helpful in guiding the top-down process of future FFT construction. The importance of each cue in the dataset was explored by using a forest of FFTs with FFTForest( ) function. Bootstrap simulation process conducted by FFTForest( ) functions to random subsets of the data creates a forest of many FFTs from a different set of cues. Cues importance is determined by particular cues selected for FFTs proportion in the forest. Network plotting of the cues from the results of random FFTs of agricultural drought risk data was presented in Fig. 13. This figure shows that most frequently occurring cues such as SPI3J, SPI6A, and SPI3A were considered as most important cues over the entire range of FFTs which is indicated by their node size. This results also indicate the cues (SPI3J, SPI6A, and SPI3A) which were most likely to co-occur by demonstrating the width of the connecting lines.

### E. UNCERTAINTIES AND LIMITATIONS OF THE STUDY

Remote sensing data and drought index used in this study may have some uncertainties affecting the results of the drought analysis. These uncertainties arise from the coarse resolution of MODIS and precipitation remote sensing products, cloud effects, data acquisitions, and grid data interpolation techniques [54]. We used SPI and VCI as drought index have some certain amount of subjectivity based on user’s analysis lead uncertainty of the results [63]. Moreover, we only used two indices in a row for drought monitoring is one of the limitations of the study. But the use of three or more indices for investigating drought is very significant for making an
Agricultural Drought Risk

FIGURE 11. A fast-and-frugal tree for classifying agricultural drought either as risk or non-risk based on up to three cues (drought indices). The information about the frequencies and base rates of positive and negative criterion classes presents in the top panel. The middle group represents the FFT arrays with the number and accuracy of the classes for each node. The lower group demonstrates the performance of FFT in the ROC curve with another algorithm (CART = classification and regression tree; RF = random forest; SVM = support vector machine and LR = logistic regression).

TABLE 6. Summary statistics of the FFT model with training and testing dataset

| Measure     | level | Dataset       | Training | Testing |
|-------------|-------|---------------|----------|---------|
| Cases       | n     |               | 152      | 75      |
| Hits        | hi    |               | 152      | 46      |
| Misses      | mi    |               | 54       | 11      |
| False alarms| fa    |               | 26       | 6       |
| Correct rejections | cr |               | 93       | 12      |
| Speed       | mcp'  |               | 1.75     | 1.80    |
| Frugality   | pfc'  |               | 0.70     | 0.70    |
| Accuracy    | acc   |               | 0.75     | 0.77    |
| Balanced accuracy | bacc |               | 0.75     | 0.73    |
| Sensitivity | sens  |               | 0.73     | 0.80    |
| Specificity | spec  |               | 0.78     | 0.66    |

mcp' = mean cue used; pfc' = percentage cues ignored

The FFT model with training and testing dataset

appropriate plan to reduce the severity of drought impacts on society. Further, one of the limitations of TRMM data that it is only available from 1998 to present date so this study lacks long term SPI calculation. However, TRMM is suitable for short term drought calculation [47]. Regarding VCI drought index, it has some disadvantages in its performance. Because VCI resulting from NDVI is very sensitive to dark and wet soil condition [60]. However, these data sets and drought index globally used for drought monitoring. In this study, TRMM data showed good agreements with reference data to derive SPI. Besides, VCI from MODIS data provided high consistency with statistical yield data. The high $R^2$ and low RMSE value resulting from validation analysis indicate these
FIGURE 12. Cue accuracies from the training data set calculated from each cue’s and its ranked accuracy across all cues based on balanced accuracy (bacc).

FIGURE 13. Network plot relationship between cues created by bootstrap simulation of 50 FFTs from a trained different random subset of agricultural drought data. How often each cue occurs across different FFTs and how often they co-occur within the individual FFTs is reflected by the size of the node and connection between the nodes respectively.
IV. CONCLUSIONS

This study was able to determine the significant drought years with the magnitude of different drought events and their severity in Bangladesh. Drought analysis based on SPI & VCI index detected dry and wet periods, which is very important to identify the meteorological and agricultural drought spatially and also for monitoring drought in future in the country. The findings of the study on spatial and temporal evaluation of SPI and VCI related drought identified the incidence of moderate to severe drought episode more visible in different parts of the country in case of both meteorological and agricultural drought. Regarding meteorological drought more drought frequency was observed in SPI6A time scale compared to SPI3J and SPI3A.

However, drought analysis based on VCI revealed that severe to extreme drought was more frequent during Boro season compared to Aus and Aman season. Further, the analysis of drought dynamics indicated that meteorological and agricultural drought has increased for a specific time and specific growing season, which is perhaps related to the natural response mechanism and changes in the variations of physical parameters of the ocean atmospheric system. Another significant feature of this study was to evaluate the factors causing agricultural drought based on a supervised ‘FFT’ machine learning model in Bangladesh. The model identified SPI3J and SPI6A as main activates triggering agricultural drought. Further, the model distinguished SPI3J and...
SPI6A as the most critical cues were most likely to occur of the entire range of FFT with highest balanced accuracy. The FFT model introduced in this study can be expanded in any crop growing areas to evaluate agricultural drought risk with remote sensing data to provide a better understanding concerning the spatial extent and severity of the drought.

The meteorological factors, especially the rainfall, impacts the agricultural drought to a great extent during Boro and Aus rice-growing season. Therefore, irrigation from groundwater or other sources, use of short duration variety, and finally drought-resistant variety need to be considered into the mitigation policy to combat drought effect. Ultimately, the applicability of SPI and VCI for monitoring both meteorological and agriculturally relevant drought established in this study on an interior Bangladesh. Thus, monitoring of drought with two indices in a row is very significant for making an appropriate plan to reduce the severity of drought impacts on society. Hence, a coping mechanism by the local and national level authority in time can eradicate extensive crop failure in the drought-affected area and makes the country away from food shortage.

**APPENDIX A**

**TRMM DATA VALIDITY ANALYSIS**

This section contains Figure 14 demonstrating the TRMM data validity analysis with scatter plots and linear regressions.

**APPENDIX B**

**NDVI VALUE**

This section contains Figure 15 representing the NDVI value of 16 days time interval for Bangladesh with seasonality parameters of start and end of the seasons determined by Savitzky-Golay fitted method of median filter process.

**RICE CALENDAR**

This section contains Figure 16 showing rice calendar with agro-climatic conditions of Bangladesh.

**APPENDIX C**

**SPATIAL ANALYSIS OF SPI**

This section contains Figure 17 representing drought events: SPI3J over Bangladesh from 2001 to 2016. This section also contains Figure 18 representing drought events: SPI3A over Bangladesh from 2001 to 2016.
This section contains Figure 19 representing drought intensity based on the seasonal distribution of VCI during Aus rice-growing season from 2001-2016.

**FIGURE 19.** Drought intensity based on the seasonal distribution of VCI during Aus rice-growing season from 2001-2016.

**FIGURE 20.** Drought intensity based on the seasonal distribution of VCI during Aman rice-growing season from 2001 to 2016.

**APPENDIX D**

**SPATIAL ANALYSIS OF VCI**

This section contains Figure 19 representing drought intensity based on the seasonal distribution of VCI during Aus rice-growing season from 2001 to 2016. This section also contains Figure 20 demonstrating Drought intensity based on the seasonal distribution of VCI during Aman rice-growing season from 2001 to 2016.

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