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Assessing Agricultural Drought Conditions in Bangladesh Using Vegetation Indices Derived From Remote Sensing

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Abstract: Drought evaluation is essential for food security and sustainable resource management in the face of changing climatic patterns and agricultural production. This study analyzes Bangladeshi agricultural drought patterns using multiple indices, such as Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation Health Index (VHI) to detect drought stress and assess their ability to capture drought conditions of different intensities. Secondary data have been used to carry out this research. Spatial Analyst tools in ArcGIS and Pearson correlation analysis in SPSS were used to analyze and represent data. This study shows that "Extreme Drought" declined from 2005 to 2020. VCI drought class shows that "Extreme Drought" declined from 57.05% in 2005 to 83.28% in 2020, and VHI shows that it declined from 75.67% in 2005 to 4.57% in 2020. However, "Moderate drought" shows an increasing trend from 2005 to 2020 in the VHI drought class, which accounted for 6.29% in 2005 to 7.62% in 2020. Results from the study revealed fluctuations in drought severity in the Rabi season over the examined years, reflecting the dynamic nature of climate impacts on vegetation. This research helps stakeholders reduce drought's detrimental effects on crop productivity and rural livelihoods by providing policy-making, resource allocation, and adaptive agricultural strategies.

Keywords: Drought, Crop yield, Rabi season, Vegetation health, Land surface temperature

1. Introduction

Drought is a very detrimental natural calamity that manifests in diverse climatic regions, exhibiting fluctuations in occurrence rates and intensities. There are typically four categories of droughts, which are categorized as follows: meteorological, agricultural, hydrological, and economical. The terms "meteorological drought" and "hydrological drought" refer to conditions that occur on the earth's surface, whereas "agricultural drought" describes the effects that those two types of drought have on the nation's crop production (Mishra and Singh, 2010). In Bangladesh, drought was divided into three categories by Mirza and Pal (1992) and Das (1997) based on the effect it had on human habitat and the surrounding environment; a. Agricultural drought- a shortage of moisture in the soil for crop growth, b. Hydrological drought- a falling of the surface and subsurface water levels and a decrease in stream flow eventually affecting soil moisture, c. Economic

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drought- a condition that has a negative impact on the overall economy (Habiba et al., 2011).

According to Thomas and his colleagues (2016), Drought has a significant global impact on the security of food and water resources, while the extent of its effects depends on the ability to address its social, economic, and environmental implications (Marengo et al., 2021). Being an agriculture dependent country, Bangladesh particularly has extremely susceptibility to drought damage. Agriculture has been damaged, and the water supply is already under stress. The country's socioeconomic environment and development attempts are also impacted by the drought (Kamruzzaman et al., 2022). Droughts during the Rabi season occur more frequently in the north and northwest of Bangladesh (Alamgir et al. 2015). The rabi season is one of the most prone to droughts, which significantly decrease the number of crops that can be harvested from agricultural land. As a result of this, it is essential to keep track of droughts and create maps so that decisions can be taken, resources can be distributed, and people can be prepared for natural disasters.

To assess and monitor the spatiotemporal distribution characteristics of drought, it is required to utilize a wide variety of different metrics and indicators in order to keep track of the situation. Drought indices are commonly used (Zhang et al., 2022a).The Standardized Precipitation Index (SPI), which was established by McKee et al. in 1993, and the Palmer Drought Severity Index (PDSI) was initially published by Palmer in 1965, are two indices that find widespread application in the fields of meteorology and hydrology. But, the techniques for calculating these indicators can be difficult at times or need the gathering of large datasets, which may not be easily accessible in all scenarios. It is possible to obtain an image processing and analysis interface that is both effective and streamlined in a cost-effective and reliable way because of the widespread availability of satellite imagery, GIS, and remote sensing technologies. By using the potentiality of these available advance technologies in monitoring the drought conditions would be a great development. Remote sensing drought indices that are frequently used for the purpose of monitoring the effects of drought on vegetation include the Normalized Difference Vegetation Index (NDVI), the Land Surface Temperature Index (LST), the Temperature Condition Index (TCI), the Vegetation Condition Index (VCI) and the Vegetation Health Index (VHI) (Kogan, 1990, 1995). Also, these indices are utilized to evaluate agricultural output and locate regions with insufficient growth of vegetation.

The fundamental purpose of this research project is to carry out an investigation of the severity of the drought conditions that existed in agricultural settings during the duration of the rabi season. The agricultural drought will be investigated based on five indicators including state of vegetation, thermal state of vegetation, vegetation condition, moisture, and vegetation health.

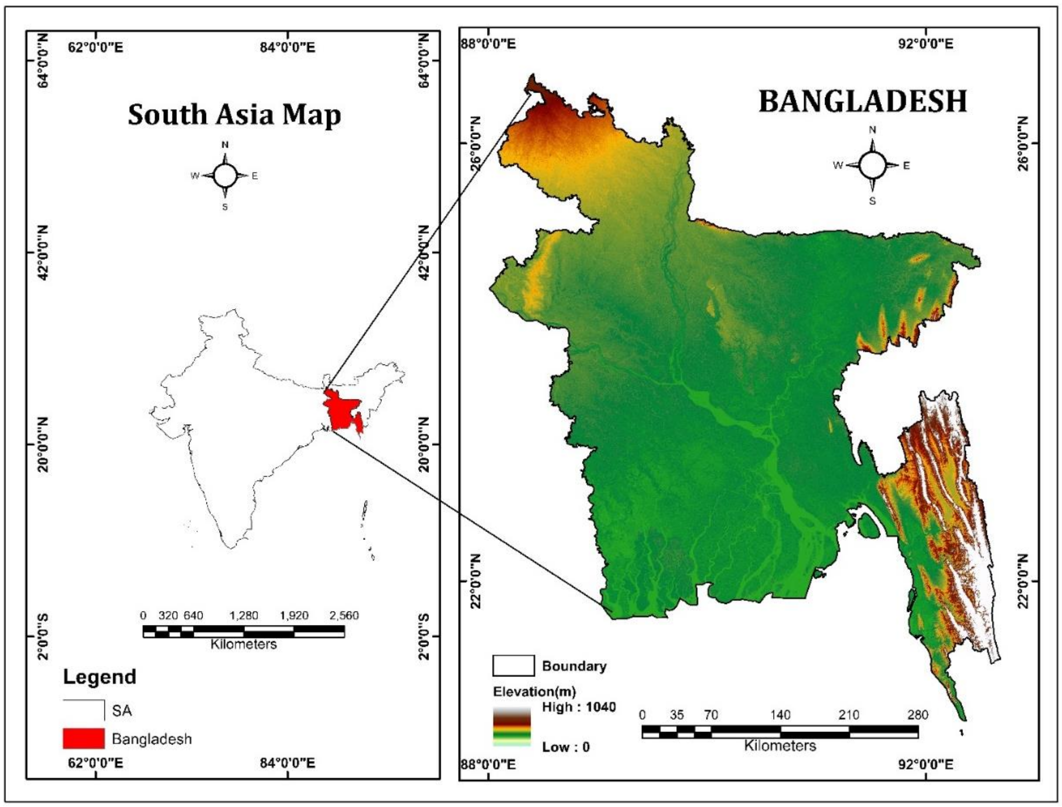
2. Materials and Methods

2.1 Study Area

Bangladesh is characterized by its low-lying and flat topography, with the majority of the country being part of the Ganges-Brahmaputra Delta. The delta is formed by the confluence of the Ganges, Brahmaputra, and Meghna rivers. Besides, it exhibits a tropical monsoon climate, distinguished by distinct wet (June to October) and dry (November to March) seasons. According to Islam and Miah (1981), the temperature fluctuations in this region are particularly noticeable during the hot summer months (March to May) due to its subtropical geographical positioning. The temperature exhibits a range of 30° to 40 °C during the months of April and May, which are considered the hottest months. In contrast, the temperature ranges from 8 °C to 25 °C in the period spanning December to January. The research region experiences an average annual rainfall ranging from 1400 to 1900 mm, with 92.7% of the total precipitation occurring between the months of May and October (Biswas et al., 2017). At now, Bangladesh is equipped with a total of 35 meteorological stations, with 6 of these stations located in the northwestern region of the country.

The vast majority of Bangladesh's population works in agricultural occupations, making this sector an essential component of the country's economy. Rice is the most important crop for subsistence, but jute is a significant cash crop. Extreme weather conditions, such as droughts and floods, can have a negative impact on the agricultural industry.

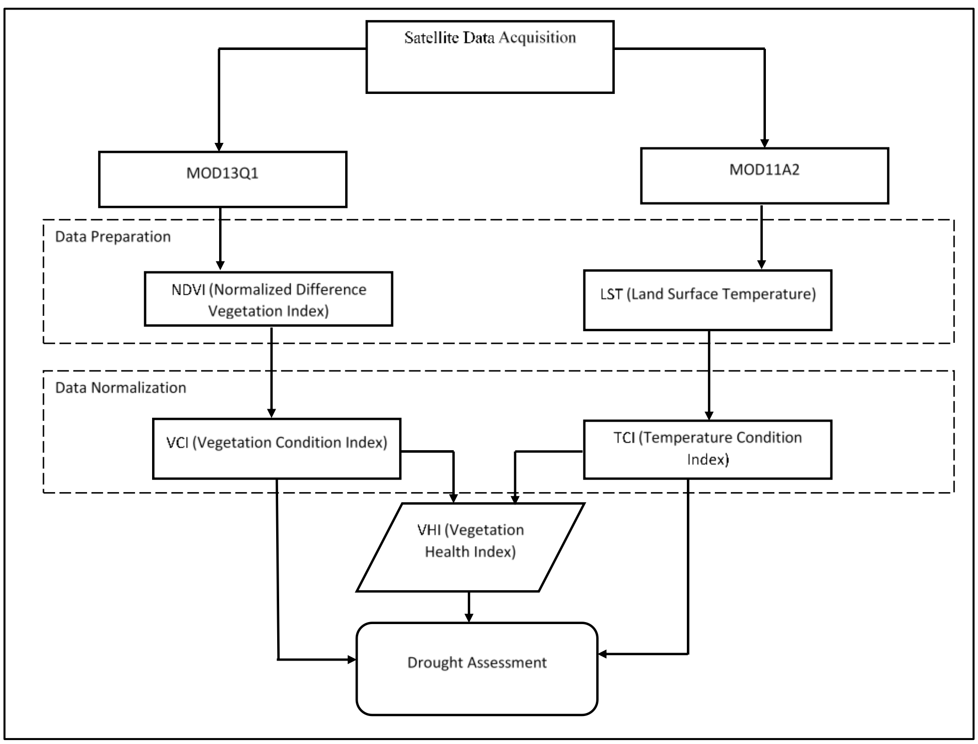
Figure 1: Study area map (data source: https://SRTM.csi.cgiar.org)



2.2 Data Sources

In this particular field of study, the Moderate Resolution Imaging Spectroradiometer, or MODIS, was utilized so that measurements of both the Normalized Difference Vegetation Index (NDVI) and the Land Surface Temperature (LST) could be obtained and examined. According to the findings of the research that was carried out by Tucker and his colleagues in 2005, it was concluded that MODIS offers a method of evaluating surface vegetation that is more sophisticated and accurate in terms of radiometric, spectral, and spatial aspects (Tucker et al., 2005). The MODIS sensor imageries were obtained from the official website of NASA Earth Data (https://www.earthdata.nasa.gov/learn/find-data/near-real-time/modis) for the period spanning from February, encompassing the years 2005, 2010, 2015 and 2020 due to the availability of data. The MOD13Q1 and MOD11A2 datasets were utilized to monitor the 16-day Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) at a spatial resolution of 1 kilometer. These two data were individually gathered over the month of February. The investigation focused on analyzing the time series data of Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation Health Index (VHI) by examining the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) measurements.

Figure2: Methodological workflow diagram



For the purposes of data processing, analysis, and visualization, this study made use of two types of software: the geospatial software ArcGIS 10.8 and the statistical software SPSS. The MODIS NDVI and LST data can be retrieved using a variety of tools (Data management tool, the Spatial Analyst tool) and processes that are carried out by ArcMap 10.8 and to construct the cartographic representations. The calculations of VCI, TCI, and VHI are performed using the Map algebra tool found under the Spatial Analyst tool. These calculations are based on the LST and NDVI datasets. The SPSS statistical package was used to carry out the Pearson correlation analysis between NDVI and LST.

2.3 Data analysis

2.3.1 NDVI Estimation

The Normalized Difference Vegetation Index (NDVI) was calculated using the formula proposed by Rouse and his colleagues in 1973, which involves subtracting the red radiation from the near-infrared radiation and dividing the result by the sum of the near-infrared radiation and red radiation (Rouse et al., 1973). This method was initially established in the 1970s and has since been utilized by researchers such as Karnieli et al., 2010 and Sultana et al., 2021. The Normalized Difference Vegetation Index (NDVI) was normalized in order to provide a standardized value ranging from -1 to +1, as described by Huang and his colleagues in 2021 (Huang et al., 2021). According to Kogan (1995), a higher value of NDVI is indicative of healthier and denser vegetation, as well as a reduced vulnerability to drought. Conversely, a negative NDVI value suggests the presence of stressed vegetation and a deficiency in precipitation. The index proposed by Kogan (1990) can be utilized to identify instances of food shortages that are associated with weather conditions. The equation for the normalized difference vegetation index (NDVI) can be expressed as follows:

$$NDVI = (NIR - RED) / (NIR + RED)$$

In this context, NIR refers to the near-infrared reflectance band, while Red denotes the visible red reflectance band. The calculation of Normalized Difference Vegetation Index (NDVI) from MOD13Q1 dataset involved the utilization of following Equation, which is expressed as

$$NDVI = NDVI_i \times 0.0001.$$

In this context, $NDVIi$ represent the Normalized Difference Vegetation Index (NDVI) for the i-th month, and 0.0001 be the scaling factor. NDVI values ranges from (-1 to 1). Elevated NDVI values, approximately 0.61 to 1, are indicative of healthy vegetation, while 0.31-0.60 indicate moderate density values, 0.01-0.30 indicate slightly density vegetation and typically below 0, suggest either moisture stress or no vegetation (Laksono et al., 2020).

2.3.2 LST Estimation

The Land Surface Temperature (LST) data generated from the Moderate Resolution Imaging Spectroradiometer (MODIS) is utilized. The MODIS Land Surface Temperature and Emissivity (LST/E) products offer temperature and emissivity measurements at a per-pixel level. The level-3 MODIS global Land Surface Temperature (LST) and Emissivity data are derived from the daily 1-kilometer LST product (MOD11A1). This dataset has a spatial resolution of 1km and a temporal resolution of 8 days. The data is presented in sinusoidal projection and represents the average values of clear-sky LSTs over an 8-day period.

LST values are initially stored as Digital Numbers (DN) in the MODIS data. To convert DN to radiance, the following formula are used:

$$L = (DN - 1) * \text{scale factor}$$

Here, **L** is radiance, **DN** is the digital number from MODIS data, and **scale factor** (0.02) is a value specific to the MODIS product.

For both bands 31 and 32 of MODIS LST product, the Planck's law formula was used to convert radiance to brightness temperature:

TB = K2 / ln ((K1 / L) + 1)

To calculate the Land Surface Temperature (LST), researchers used the brightness temperatures from bands 31 and 32,

LST = (TB31 + TB32) / 2

Here, **TB31** and **TB32** are the brightness temperatures from bands 31 and 32, respectively.

2.3.3 Vegetation Condition Index (VCI)

Kogan (1997) is acknowledged with developing the Vegetation Condition Index (VCI), which is used to analyse the impact of various climatic conditions on plant cover. This measure is also universally approved for use while researching the drought conditions in a particular location. In order to calculate VCI, one of the necessary parameters is the normalized difference vegetation index (NDVI), which is a well-known measure that distinguishes between good and unhealthy forms of vegetation. Even though the NDVI has been successful in identifying crops that are well-grown and crops that are stressed, interpretation problems frequently develop owing to variations in the amounts of vegetation and natural resources in a given location, such as the climate, the soil, and the vegetation. For example, the NDVI may make a clear distinction between a single crop in an area with an abundance of resources and a crop in an area with scarce resources. It is therefore conceivable to identify the two components in NDVI as ecological and climatic, and it is difficult to see variations between the two components for the intense or high vegetation zone. When used on its own, the NDVI value makes it difficult to identify the climatic component of crops. As a result, researchers developed the VCI index in order to more easily determine the impact of the weather on crops (Kogan, 2001). Calculating the Vegetation Condition Index (VCI) can be done using the following equation-

$$VCI = 100 * (NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min})$$

Where the highest possible value of the VCI index is in the range of 100, and the lowest possible value is 0. This value is close to 100 when conditions are good for crop production, and it is close to 0 in environments that are unfavorable for crop production.

2.3.3 Temperature Condition Index (TCI)

The VCI is not sufficient on its own as a monitoring tool for drought in agricultural contexts, as the findings of various research have found. Because of this, a completely new index was devised and given the name the TCI. The primary data source for this index was the land surface temperature (LST) and it was published by Kogan in 1997. The TCI is a thermal stress indictor, and it is utilized in the analysis of drought periods that are related to temperature. LST will be derived from MOD11A2 so as to do this following equation-

$$LST\ (\circ C) = (\delta \times 0.02) - 273.15$$

LST (°C) = land surface temperature in degrees Celsius and "δ" indicates row scientific data (SDS) in this context. The TCI for the time period under investigation was determined with the use of the following equation:

$$TCI = 100 * (LST_{max} - LST_{i}) / (LST_{max} - LST_{min})$$

Here, LST_i equals the LST value for the i^{th} month, LST_{max} and LST_{min} represent the maximum and minimum LST values for the years, 2005, 2010, 2015, 2020 respectively. The values of the TCI can range from 0% to 100%, with higher values being greater than 40% and lower values being less than 40%. According to Cong and his colleague, different values for the TCI indicate conditions that are either beneficial (no drought) or unfavorable (drought) (Cong et al. 2017).

2.3.4 Vegetation Health Index (VHI)

Several researchers have been making use of the VHI index for the better part of the past three decades to identify agricultural droughts, the length of time they last, and the influence they have on various locations across the world. The VHI is an integrated index that represents the state of the vegetation and is comprised of both the VCI and the TCI. It provides an indication of the soil moisture availability as well as the soil temperature in order to provide an idea about the status of the vegetation's health (Kogan, 1997, 2012). In order to calculate VHI, following equation was utilized-

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

In this context, α represents a contributing factor for both VCI and TCI, with a specific value of 0.5 (Bento et al., 2018b; Du et al., 2018). In this case, the value is 0.5, and it serves as a contributing factor to both the VCI and the TCI. VHI that is lower than 40 percent suggest an increased likelihood of agricultural drought, and vice versa.

Table 1: Drought severity classes for VCI, TCI, and VHI

Severity Class	Values (%)
Extreme Drought	< 10
Severe Drought	10-20
Moderate Drought	20-30
Mild Drought	30-40
No Drought	> 40

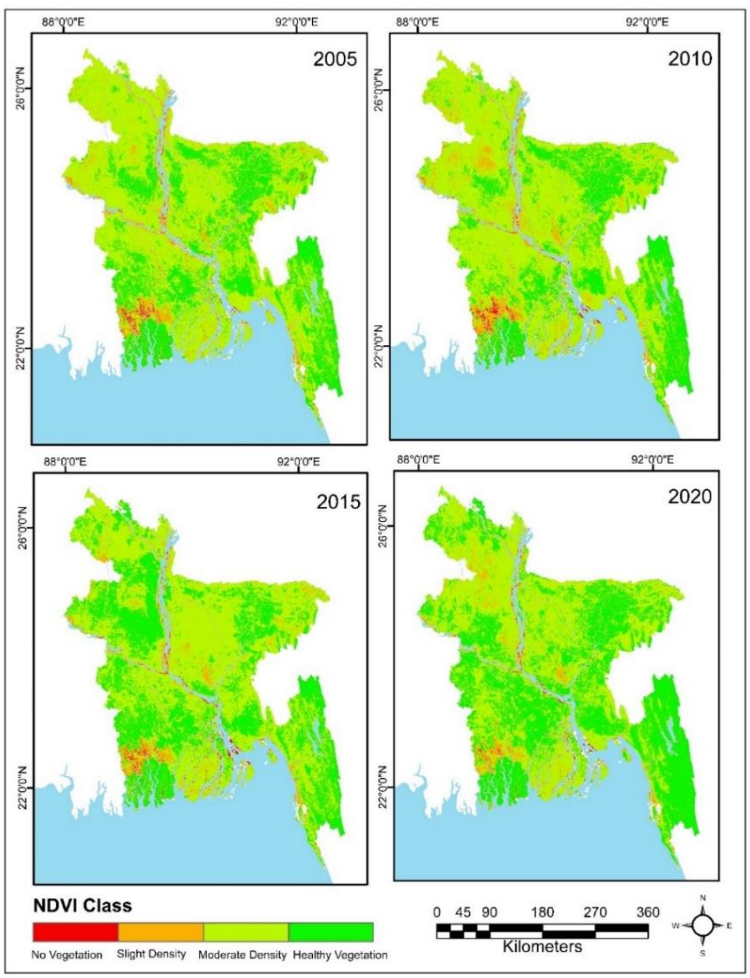
Source: Kogan, 2002

3 Result and Discussions

3.1 Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) possesses the capability to identify the state of vegetation, which in turn might impact the environmental conditions of certain regions. The NDVI value serves as an indicator of the overall health condition of vegetation. According to Faridatul and Ahmed (2020), areas with high NDVI values are indicative of healthy vegetation, while low greenness suggests vegetation that is stressed or in poor condition due to insufficient moisture or water availability in a certain region. The results show that NDVI values during the Rabi season (November to March) were detected to estimate the extent of agricultural drought in the study area from 2005 to 2020. A previous study demonstrated a favorable correlation between the Normalized Difference Vegetation Index (NDVI) and precipitation (Ghebrezgabher et al., 2020). Several significant researchers have employed NDVI drought monitoring as a method of investigation (Ji and Peters, 2003; Rojas et al., 2011; Kaushalya et al., 2014; Faridatul and Ahmed, 2020; Xie and Fan, 2021). As can be seen in figure 3, there was an indication of vegetation stress in the northwestern part of Bangladesh in the years 2005 and 2010, and this was followed by findings in additional central and some eastern regions in the years 2015 and 2020. In the year 2020, the overall values of the NDVI are relatively high. The NDVI analysis reveals that the regions of the research area located in the southeast had higher NDVI values than the other parts of the research area. According to the findings of the study, there was a discernible shift in the conditions of the vegetation over the course of the investigation. The variation in the severity of the drought has a temporal and spatial influence.

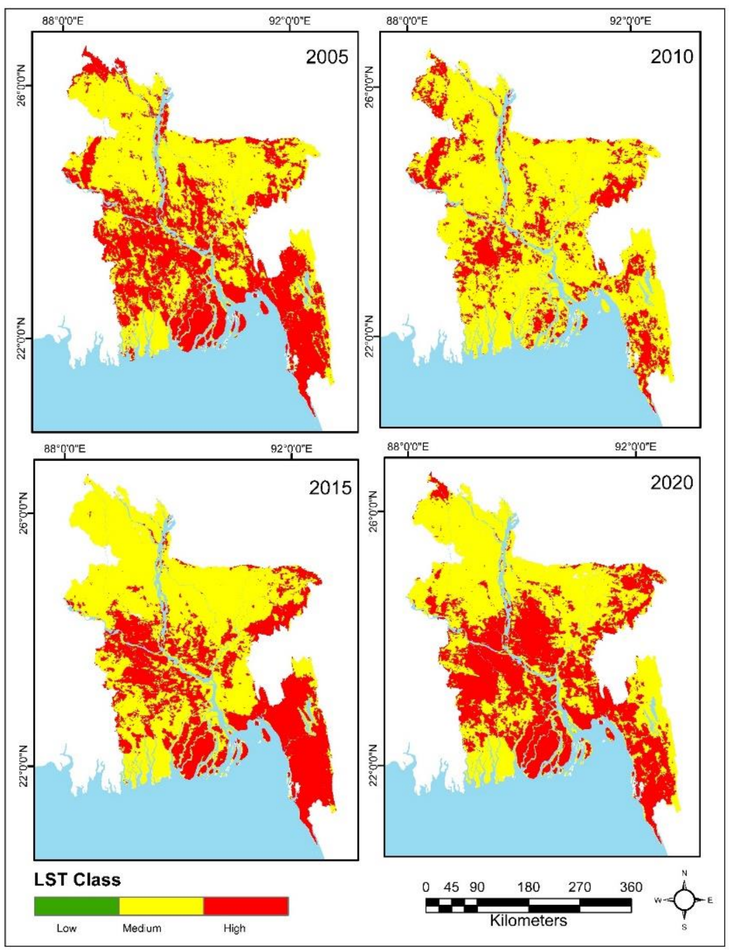
Figure 3: NDVI value classes during the rabi season (mid-October to mid-March) from 2005 to 2020.



3.2 Land Surface Temperature (LST)

The researchers employed the Land Surface Temperature (LST) technique to assess the thermal state of vegetation (Kogan et al., 2003). Additionally, it presents a chance to assess the impact of drought caused by thermal influences on the well-being of vegetation, which occurs when high temperatures coincide with a deficiency in moisture (Bhuiyan et al., 2017). Elevated Land Surface Temperature (LST) values often indicate arid environmental conditions characterized by little precipitation (Li et al., 2021) and reduced soil moisture content. The Land Surface Temperature (LST) analysis method is able to provide an assessment of the present state of agricultural crops. A higher temperature value, as a consequence, is indicative of the presence of the most severe form of drought that is currently taking place. A lower temperature value, as a result, is indicated by the presence of a mild or nonexistent drought. As shown in (figure 4), increased LST values were discovered in various locations across Bangladesh in the years 2005 and 2010. In addition, information gathered in 2015 suggests that the south and southeast regions of the country are associated with high LST values.

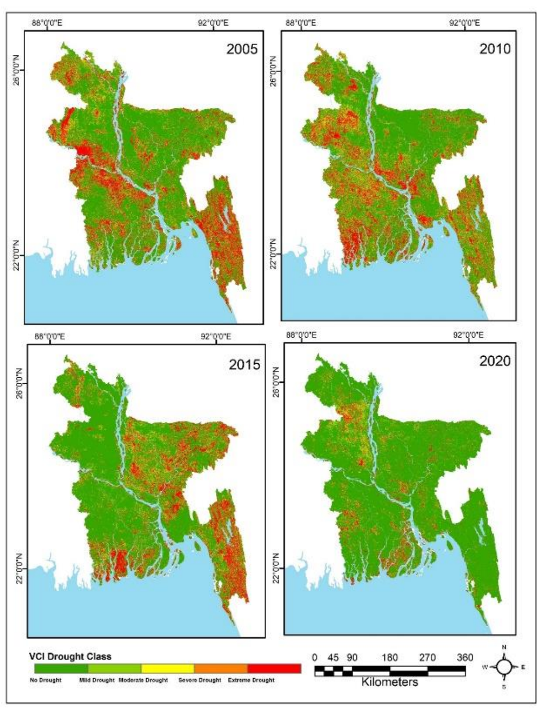
Figure 4: LST values during the rabi season (mid-October to mid-March) from 2005 to 2020.



3.3 Vegetation Condition Index (VCI)

The identification of drought occurrence throughout the Rabi season was determined using the Vegetation Condition Index (VCI). The Vegetation Condition Index (VCI) has been widely recognized as a suitable tool for monitoring agricultural drought, as evidenced by several studies (Kogan, 1995, 1997; Wang et al., 2001; Singh et al., 2003; Quiring, 2009; Quiring and Ganesh, 2010; Barrett et al., 2020; Bento et al., 2020). The Vegetation Condition Index (VCI) for the year 2005 exhibits a notable decrease, notably in the north-western and southeastern regions, hence exerting a detrimental impact on the overall health of vegetation. According to Kogan (1995), low values of the Vegetation Condition Index (VCI) can serve as an indicator of drought. Drought has been classified into five classes based on the VCI values such as extreme, severe, moderate, mild, and no drought areas. In 2005, 2010 and 2015 shows that north-western and south-eastern areas are affected by extreme drought and 2015 shows that the eastern side of the country is affected by extreme drought. In 2020, VCI shows comparatively less drought-affected areas. The area covered by no drought class gradually decreased from 79821.117 in 2005 to 77927.136 in 2010, then increased to 91586.255 in 2015, and further to 117254.04 in 2020. The percentage of area covered by no drought also exhibited a similar trend. The area under mild drought increased from 11980.976 in 2005 to 14422.335 in 2010, then decreased to 11190.068 in 2015, and even further to 6757.0585 in 2020. The percentage of area covered by mild drought followed a similar pattern. The area within the moderate drought category also showed some fluctuations over the years, with slight variations in both absolute area values and percentages. The area covered by severe drought experienced some changes as well, with fluctuations over the years in both the absolute area values and the corresponding percentages. The area under extreme drought displayed variations from 27817.37 in 2005 to 25392.594 in 2010, then increased to 21404.516 in 2015, and further to 7906.1228 in 2020. The percentages of the area covered by extreme drought followed a similar pattern.

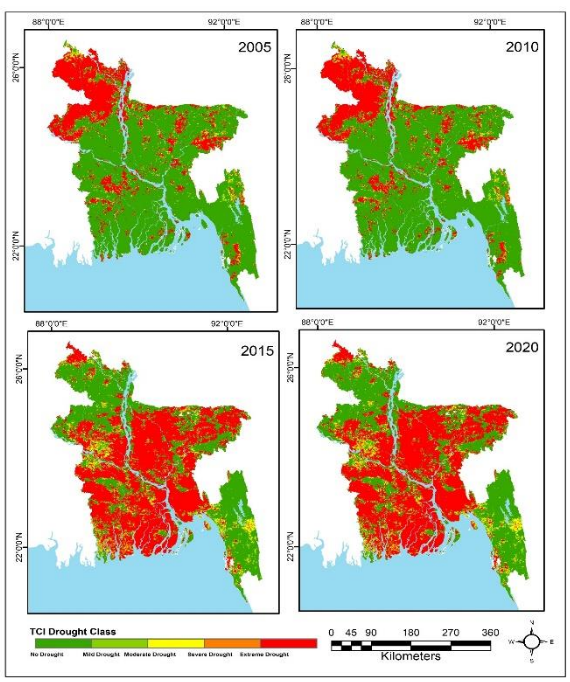
Figure 5: VCI drought Category during the rabi season (mid-October to mid-March) from 2005 to 2020.



3.4 Temperature Condition Index (TCI)

Because of the high temperatures and absence of precipitation, the vegetation in many different parts of the area under investigation was subjected to stress. According to Jiao et al. in 2016, the Land Surface Temperature (LST) has a direct influence on the TCI value. This influence can be seen in a variety of ways. According to Kogan (1995), the TCI exhibits greater accuracy than the VCI in the monitoring of agricultural drought, particularly in connection to dryness or excessive wetness. This is one of the conclusions that may be drawn from this comparison. Therefore, the Thermal Condition Index (TCI) has the ability to recognize and evaluate the presence of both excessive moisture and aridity over a certain geographical region. This is the case because of the TCI's ability to distinguish between the two. According to the values of the TCI, drought has been categorized into five different classes. These classes include extreme, severe, moderate, mild, and no drought areas at all. The percentage of the total area that was classified as having "No Drought" was around 71.38% overall years, with the "No Drought" class covering a total area of 101177.98 square kilometers. Additionally, the area categorized as "Mild Drought" stayed the same every year at 3237.0498 square kilometers, which corresponds to around 2.28% of the total land area. The area that was classified as having a "Moderate Drought" remained the same throughout all years at 3054.1607 square kilometers, making up around 2.15% of the total area each time. Throughout all four years, both the area and the percentages for the category "Severe Drought" remained the same: 2800.0051 square kilometers and 1.97%, respectively. The amount of land that was affected by an "Extreme Drought" stayed the same from year to year, coming in at 31468.932 units, and the accompanying percentages were the same each time as well.

Figure 6: TCI drought category during the rabi season (mid-October to mid-March) from 2005 to 2020.



3.5 Vegetation Health Index (VHI)

The Vegetation Health Index (VHI), which is developed from the Normalized Difference Vegetation Index (NDVI), is able to easily detect agricultural drought. Gebrehiwot et al. (2011), Essa et al. (2016), Sholihab et al. (2016), Liou et al. (2019), and Bento et al. (2020) are only few of the researchers who have made substantial use of the VHI in drought assessment. The weighted average of the VCI and TCI is what makes up the VHI. Crop yields have been evaluated with the help of this indicator (Salazar et al., 2008; Kogan et al., 2012). The region that is considered to be in a "No Drought" class has expanded throughout the years, going from 8828.4737 square kilometers in 2005 to 105131.13 square kilometers in 2010, then going down to 85231.435 square kilometers in 2015, before expanding once more to 101635.63 square kilometers in 2020. The corresponding percentages of the landmass that were not affected by drought followed a pattern that was very similar. Both the area and the percentages that fell into the "Mild Drought" category experienced some minor shifts over the course of the years, with the areas experiencing more movement than the percentages. The area affected and the proportion of the total affected by "Moderate Drought" varied slightly from year to year, very much like the case with the "Mild Drought" category. The area affected and the proportion of the total that was classified as "Severe Drought" also showed some change over the years. The region impacted by "Extreme Drought" went through a series of shifts beginning with a value of 104870.97 in the year 2005, down to 8450.6748 in the year 2010, rising to 15785.984 in the year 2015, and then falling to 6393.3879 in the year 2020. The matching percentages of the land that had been severely affected by drought followed a pattern that was very similar.

Figure 7: VHI drought category during the rabi season (mid-October to mid-March) from 2005 to 2020.

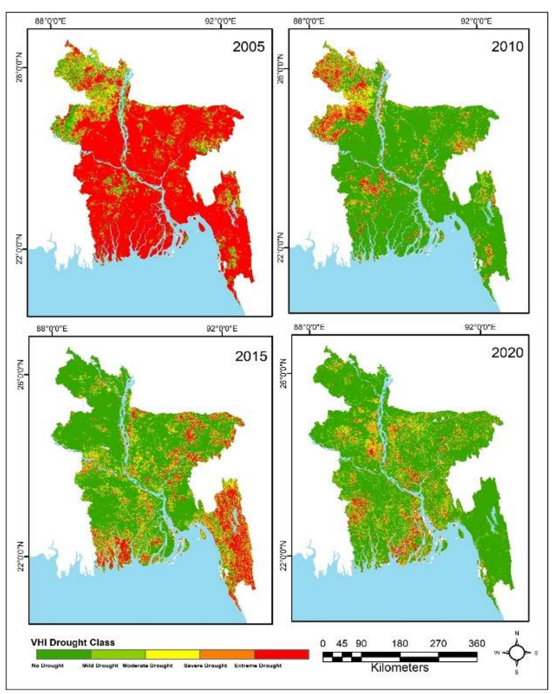


Table 2: Summary table of VCI, TCI and VHI

Drought Index	Drought Severity Class	Area (2005)	Area(%)	Area(2010)	Area(%)	Area(2015)	Area(%)	Area(2020)	Area(%)
VCI	No Drought	79821.117	57.04	77927.136	55.44	91586.255	64.83	117254.04	83.28
	Mild Drought	11980.976	8.56	14422.335	10.25	11190.068	7.92	6757.0585	4.79
	Moderate Drought	10919.921	7.81	12593.341	8.95	9514.9309	6.74	5163.9741	3.66
	Severe Drought	9388.229	6.71	10243.212	7.28	7594.2784	5.37	3701.8847	2.63
	Extreme Drought	27817.37	19.81	25392.594	18.06	21404.516	15.15	7906.1228	5.62
TCI	No Drought	101177.98	71.38	101177.98	71.38	53320.306	37.65	53320.306	37.65
	Mild Drought	3237.0498	2.28	3237.0498	2.28	6187.3158	4.36	6187.3158	4.36
	Moderate Drought	3054.1607	2.15	3054.1607	2.15	6690.4753	4.73	6690.4753	4.73
	Severe Drought	2800.0051	1.97	2800.0051	1.97	6447.4819	4.55	6447.4819	4.55
	Extreme Drought	31468.932	22.21	31468.932	22.21	68949.16	48.69	68949.16	48.69
VHI	No Drought	8828.4737	6.37	105131.13	75.33	85231.435	60.82	101635.63	72.79
	Mild Drought	7842.762	5.65	8934.0856	6.41	13761.325	9.82	14118.517	10.12
	Moderate Drought	8726.2962	6.29	9137.5819	6.55	13728.697	9.79	10631.605	7.62
	Severe Drought	8323.5969	6.01	7914.8872	5.67	11641.358	8.31	6833.0085	4.89
	Extreme Drought	104870.97	75.66	8450.6748	6.05	15785.984	11.26	6393.3879	4.57

3.6 Relationship between NDVI and LST

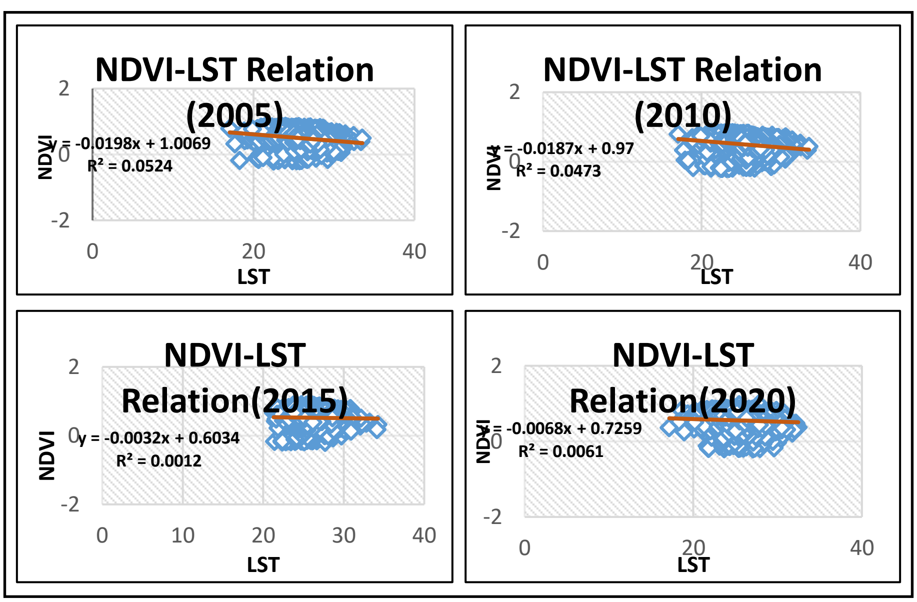
As the Land Surface Temperature (LST) increases, there is a tendency for the Normalized Difference vegetative Index (NDVI) values to fall. This decrease in NDVI values might potentially result in vegetative stress, ultimately leading to agricultural drought. The NDVI value has a negative connection with the Land Surface Temperature (LST) as reported by previous studies (Yue et al., 2007; Tran et al., 2017; Han et al., 2020). Previous research has indicated an inverse relationship between Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) (Nemani and Running, 1989; Shashikant et al., 2021). Consequently, there exists an inverse relationship between the Land Surface Temperature (LST) and the minimum Normalized Difference Vegetation Index (NDVI) values. The inverse correlation between Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) can be attributed to the elevated moisture levels found in vegetation during the wet season. Additionally, this relationship can be influenced by variations in land cover types (Guha & Govil, 2020).

Table 3: NDVI-LST Correlation Analysis

Correlation						
	LST(2005)	**NDVI(2005)**			**LST(2010)**	**NDVI(2010)**
LST(2005)	1	-.229**	***Pearson Correlation***	**LST2010**	1	-.217**
		.000	***Sig. (2-tailed)***			.000
	4324	4324	***N***		4358	4358
NDVI(2005)	-.229**	1	***Pearson Correlation***	**NDVI2010**	-.217**	1
	.000		***Sig. (2-tailed)***		.000	
	4324	4324	***N***		4358	4358
	LST(2015)	NDVI(2015)			LST(2020)	NDVI(2020)
LST(2015)	1	-.035*	***Pearson Correlation***	**LST(2020)**	1	-.078**
		.022	***Sig. (2-tailed)***			.000
	4354	4354	***N***		4341	4341
NDVI(2015)	-.035*	1	***Pearson Correlation***	**NDVI(2020)**	-.078**	1
	.022		***Sig. (2-tailed)***		.000	
	4354	4354	***N***		4341	4341

*Correlation is significant at the 0.05 level (2-tailed).
**Correlation is significant at the 0.01 level (2-tailed).

Figure 8: NDVI-LST relation



The findings indicate a substantial negative correlation between NDVI and LST which is statistically significant (Table.3). An examination of the LST data revealed a trend in the direction of an increase at consistent intervals of five years for the period spanning 2005–2020 (Fig. 8). The substantial negative correlation between normalized difference vegetation index (NDVI) and temperature that we detected during all five years of our research suggests that this increase in temperature is having a significant detrimental effect on the vegetation. This association was found to exist across all five years of our investigation.

4 Conclusion

The establishment of a generally appropriate approach for identifying agricultural drought remains complex. This study utilized a variety of satellite-derived indicators to evaluate the occurrence and intensity of agricultural droughts in Bangladesh. The study employed various indices, such as NDVI, VCI, VHI, LST, and TCI, to assess the incidence of agricultural dryness throughout Rabi crop cultivation period, which spans from mid-October to mid-March. All of these indices demonstrated statistically significant occurrences of drought during the rabi season of crop cultivation. The results of this study show the spatio-temporal pattern of drought in the agriculture sector in the studied area at 5-year intervals for the period 2005 to 2020. The results of VHI indicate that Bangladesh experienced extreme and severe drought. In 2005, extreme drought was detected in the maximum region of Bangladesh. Notably, the research highlights a positive development in drought severity, with a decline in the occurrence of "Extreme Drought." However, with RS indices, some other factors including hydrogeological characteristics, soil types, irrigation water demand and supply should be considered while estimating agricultural drought in future work. However, the results from the multiple drought indices can contribute to monitoring the onset of agricultural drought as an early warning system.

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