Assessing Agricultural Vulnerability to Drought in a Heterogeneous Environment: A Remote Sensing-Based Approach

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Abstract: Agriculture is one of the fundamental economic activities in most countries; however, this sector suffers from various natural hazards including flood and drought. The determination of drought-prone areas is essential to select drought-tolerant crops in climate sensitive vulnerable areas. This study aims to enhance the detection of agricultural areas with vulnerability to drought conditions in a heterogeneous environment, taking Bangladesh as a case study. The normalized difference vegetation index (NDVI) and land cover products from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite images have been incorporated to compute the vegetation index. In this study, a modified vegetation condition index (mVCI) is proposed to enhance the estimation of agricultural drought. The NDVI values ranging between 0.44 to 0.66 for croplands are utilized for the mVCI. The outcomes of the mVCI are compared with the traditional vegetation condition index (VCI). Precipitation and crop yield data are used for the evaluation. The mVCI maps from multiple years (2006–2018) have been produced to compute the drought hazard index (DHI) using a weighted sum overlay method. The results show that the proposed mVCI enhances the detection of agricultural drought compared to the traditional VCI in a heterogeneous environment. The “Aus” rice-growing season (sown in mid-March to mid-April and harvested in mid-July to early August) receives the highest average precipitation (>400 mm), and thereby this season is less vulnerable to drought. A comparison of crop yields reveals the lowest productivity in the drought year (2006) compared to the non-drought year (2018), and the DHI map presents that the north-west region of Bangladesh is highly vulnerable to agricultural drought. This study has undertaken a large-scale analysis that is important to prioritize agricultural zones and initiate development projects based on the associated level of vulnerability.

Keywords: agriculture; drought; NDVI; MODIS; remote sensing; Bangladesh

1. Introduction

Drought is one of the natural hazards characterized by a prolonged water shortage. The impacts of drought are multifaceted, ranging from the environment of a country to its economy and society [1–6]. Various components including agriculture, vegetation, ecosystem, and water resources can be affected by drought [7,8]. Agriculture is the backbone of the economy in many countries; however, this sector suffers from drought in many parts of the world [1,9]. Sound knowledge of the spatial variations in agricultural water stress is important for effective management of drought risk in agrarian countries.
Moreover, the determination of areas with agricultural vulnerability to drought is important to drought dynamic planning [7]. Various approaches have been developed and used to monitor different types of drought [5,10–15]. The traditional approach of drought monitoring has been based on meteorological observations, which lack continuous spatial data to monitor the detailed drought conditions [16]. Over the past decades, meteorological data have been used to improve the understanding of drought. Precipitation based drought indices e.g., the standardized precipitation index (SPI), rainfall anomaly index (RAI), Palmer drought severity index (PDSI), standard precipitation and evapotranspiration index (SPEI), national rainfall index (NRI) have been commonly used to monitor drought in various regions [17–22]. The meteorological drought indices have their own strengths and popularity; however, they are limited by the distribution of weather stations and provide only point data. In contrast, remote sensing (RS)-based drought indices have gained attention for drought monitoring as they provide repeatable information for broad regions [5,23,24].

The techniques used to monitor drought can be categorized as RS and empirical modelling. The use of RS based approaches to monitor vegetation and agricultural water stress in a large area is promising compared to other approaches [25]. Over the past decades, various RS based drought indices have been developed [9,13,14,26–29]. For example, the normalized difference vegetation index (NDVI) developed by Rouse et al. [30], has been used for vegetation classification and vegetation phenology study. The NDVI has also been used for the assessment of agricultural and vegetative drought [4,15]. Kogan [26] developed the vegetation condition index (VCI) for improving the analysis of vegetation conditions in non-homogeneous areas. The VCI has proved to be effective to provide accurate drought information and, therefore, this index has been applied to monitor vegetation water stress in various regions [1,31–33]. The temperature condition index (TCI), developed by Kogan [27], provided additional information on vegetation stress and facilitated the detection of stress whether it is caused by dryness or excessive wetness. Li et al. [28] developed the normalized temperature anomaly index (NTAI) and the normalized vegetation anomaly index (NVAI). These indices were applied to monitor drought and found a better measure of anomalies and evolution compared to the VCI and TCI. Sandholt et al. [29] developed the temperature vegetation dryness index (TVDI) using an empirical parameterization of the relationship between NDVI and land surface temperature (LST). The TVDI proved to be a potential indicator of understanding of the variations in soil moisture. Ghulam et al. [14] developed the perpendicular drought index (PDI) based on the spatial characteristics of moisture distribution in near infrared (NIR)–Red space. Their study concluded that PDI has potential in RS-based drought phenomenon analysis. The normalized multi-band drought index (NMDI) was proposed by Wang and Qu [13] for monitoring the moisture condition of soil and vegetation using RS data. Amri et al. [8] developed the vegetation anomaly index (VAI) and used it to assess the presence of vegetation stress. They found a satisfactory performance of the index; however, the VAI may be affected by the pattern of irrigation in agricultural areas, and evolutions of land use and its heterogeneity. The vegetation index has been widely used as one of the important parameters for understanding drought conditions, crop yield, and mapping of agricultural areas [34]. Gouveia et al. [35] applied correlation analysis between NDVI and SPEI to analyze the drought impacts on vegetation, and to determine the most sensitive vegetation types. Dutta et al. [36] used NDVI based VCI for monitoring agricultural drought and compared it with SPI, RAI and the yield anomaly index (YAI). They found a good agreement between the VCI and meteorological drought indices.

Although a great effort has been made to develop various drought indices [3,9,13,27,37], the previous studies rarely evaluated their performances to monitor and understand agricultural drought in a large heterogeneous environment. Various land cover types including cropland, wetland, waterbody, forest, urban built-up area, and tree cover can exist when analyzing a large territory. Land cover variability might influence the accurate detection of agricultural areas with vulnerability to drought. The purpose of this research is to improve the understanding of how the variations in land cover types affect the estimation of agricultural drought, and to identify the agricultural areas facing
high drought risk by combining multiyear RS-based drought indices. This study proposes a modified vegetation condition index (mVCI) suitable for the determination of agricultural drought in the areas of varied landscapes. This research uses the principle of NDVI based VCI [27], because it has been proven to be useful means for the detection of drought conditions around the world [2,33,38].

In this paper, Section 2 includes the study area profile and the experimental data. Section 3 elaborates in detail the approach of assessing the heterogeneity of landscape and improving the separation of agricultural drought from water-stressed vegetation. Section 4 demonstrates the results and discussion and, finally, concluding remarks are provided in Section 5.

2. Study Area and Experimental Data

This study selects Bangladesh as a research area. It is a South Asian country, which is situated between latitudes 20°34′ and 26°38′ N and longitudes 88°01′ and 92°41′ E. India borders Bangladesh along the north, west and northeast borders. It shares borders with West Bengal of India in the west, Meghalaya in the north and Tripura in the east. It also shares borders with Myanmar in the southeast, and the Bay of Bengal demarcates its southern border (Figure 1). Bangladesh consists of 64 administrative districts. Its topography is relatively flat, the great plain lies almost at sea level along the southern coast and rises gradually towards the north. Agriculture is the backbone of the country; it grows a wide variety of crops which are broadly classified as Kharif Crops (grown in the summer and harvested in early winter), and Rabi Crops (sown in winter and harvested in the spring or early summer). Rice and wheat are the major cereals of the country. The rice-growing seasons have been commonly classified into three categories e.g., Aus (sown in mid-March to mid-April and harvested in mid-July to early August), Aman (sown in early September and harvested in December to early January) and Boro (sown in mid-November to mid-January and harvested in April to May). Moreover, wheat is one of the most important winter crops, which is sown in November to December and harvested in March to mid-April [12,39,40].

Figure 1. Location of the study area. (a) Geographic location; (b) Bangladesh.
The country is characterized by a subtropical monsoon climate. The mean annual precipitation is nearly 2400 mm, with 70% occurring during the monsoon season. Figure S1 shows monthly and seasonal variations in the precipitation over a period of 13 years (2006–2018). The highest precipitation occurs between May and September. Note that the Aus rice-growing season receives the highest precipitation (72%), and the Boro rice-growing season is the driest season that receives only 7% of total precipitation. Bangladesh consists of four recognized seasons e.g., a hot, humid summer between March and May; a wet, monsoon season between June and September; autumn between October and November; and a dry winter between December and February [41]. Bangladesh regularly experiences natural hazards including droughts, floods and cyclones. In the past, Bangladesh experienced severe drought in the years 1951, 1961, 1975, 1989, 1997, 2006 and 2010. Most of these droughts occurred in pre- and post-monsoon seasons. It should be noted that drought is a periodic occurrence in many regions of Bangladesh; however, the northwest region is more vulnerable to drought compared to the other parts of the country. The mean annual precipitation in this dry zone ranges from 1250 to 1750 mm [41,42].

Over the past decades, RS data e.g., National Oceanic and Atmospheric Administration-Advanced Very High Resolution Radiometer (NOAA-AVHRR), Landsat, SPOT VGT NDVI, and Moderate Resolution Imaging Spectroradiometer (MODIS) satellite imageries have been commonly used to monitor drought conditions. This study uses NDVI products of MODIS (MOD13A3). For comparative analysis, and to evaluate the performance of the drought indices, this study uses data for both the drought and non-drought years. Moreover, precipitation and crop yield are used for evaluating the results. Precipitation data is collected from the Bangladesh Meteorological Department and crop yield from the yearbook of agricultural statistics of the Bangladesh Bureau of Statistics. This study uses the principle of VCI to assess agricultural drought, which requires long-term maximum and minimum NDVI values for each pixel, thereby a total of 156 NDVI images were collected from 2006 to 2018. This study reviewed related research on Bangladesh [41,42] and selected the typical years for assessing the agricultural drought. To understand the heterogeneity of the environment, this study also uses the MODIS land cover yearly product (MCD12Q1). It should be noted that MODIS land cover data consist of 17 land cover classes; however, the study area characterizes six major land cover types e.g., cropland, urban, tree cover, forest, wetland, and permanent waterbody. In contrast, other land cover classes are small in proportion. Note that small-scale changes in land cover would not affect drought monitoring [6], thus the six major land cover classes are considered in the analysis of the heterogeneity of the environment.

3. Improving Agricultural Drought Assessment in Heterogeneous Areas

In this research, first, the heterogeneity of the landscape is investigated. Second, land cover variability is considered in delineating the mVCI for separating the water-stressed croplands areas from other land covers and vegetation. Third, a comparative analysis is done between the mVCI and the traditional VCI, the result is evaluated using precipitation and crop yield. Lastly, multiyear mVCI maps are input to compute a composite map of areas indicating the levels of vulnerability to agricultural droughts. The composite map is important to the decision-makers to detect and prioritize the most vulnerable zones for initiating development projects and allocating funds to cope with drought in future.

3.1. Evaluation of Heterogeneity of the Landscape and Segregation of Agricultural Areas

A heterogeneous environment consists of various land covers including vegetation, which largely encompasses agricultural/cropland, rangeland, tree cover, and forest [43]. Various land cover classification approaches have been used to detect geographic features [44,45]. The NDVI has also been used as a good indicator for the classification of vegetation [30], and has been used to detect stressed or damaged crops [15,32,34]. This study evaluates the utility of NDVI in the segregation of agricultural land from other vegetation and land cover types. In this section, first, the influence of
seasonality and temporal variation on NDVI is evaluated. Second, yearly composite NDVI maps are
computed, and then representative sample patches of six major land cover types are collected from the
MODIS land cover maps. Third, the NDVI values are extracted by the sample patches, and the basic
statistics of NDVI for six land cover types are graphically presented to understand the heterogeneity of
the landscape. Fourth, to segregate agricultural land from other land cover types, a maximum and
minimum threshold value is defined. Faridatul and Wu [46] developed an approach of threshold
optimization and it proved to be efficient in the separation of land covers. Thus, this research used their
approach to determine threshold values of NDVI for the croplands. To avoid the influence of an outlier
or extreme values, this study uses the maximum and minimum threshold for the agricultural land
rather than using the maximum and minimum NDVI of the agricultural land. Finally, for evaluation
and comparison analysis overlay intersect is performed between NDVI-based agricultural land and
cropland as defined in the MODIS land cover map.

3.2. Assessment of Agricultural Drought using the Vegetation Condition Index

The NDVI based VCI as Equation (1) has been used as an indicator of the status of vegetation
cover. The conditions of vegetation are usually measured in percent. The VCI values close to 0% (zero)
indicate an extreme dry condition, whereas the VCI values between 50% and 100% indicate normal
vegetation conditions [32]. A VCI of less than 50% indicates drought conditions, and VCI ranges
between 0% and 35% indicate the severe drought condition [27].

\[ VCI = 100 \times \frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \] (1)

where \( NDVI_i \) is the NDVI value for a specific pixel in the month of \( i \), \( NDVI_{max} \) and \( NDVI_{min} \) are the
highest and lowest NDVI values of the same pixel for the period of 2006–2018.

It should be noted that the VCI has been used for assessing the spatial characteristics of
drought [7,33]; however, previous studies [32,47,48] rarely evaluated its performance in the detection
and separation of water stressed cropland from other vegetation. This study computes the VCI for
both the drought and non-drought years. The VCI values are extracted by sample patches of six major
land cover types as defined earlier, and the results are evaluated to understand the utility of this index
in the detection of agricultural drought in the areas of varied landscape.

3.3. Enhanced Estimation of Agricultural Drought and Comparison Analysis

For evaluating drought conditions in the heterogeneous environment, a land cover map could
be used to mask out non-agricultural lands. For example, Rulinda et al. [4] used a land cover map
to mask out non-vegetated areas and forest to separate vegetative areas. Note that this study uses
the threshold of NDVI to segregate cropland from other land cover types and applies Equation (2) to
measure and highlight agricultural drought conditions.

This study proposes an approach to make the VCI suitable for accurate assessment of agricultural
drought in a heterogeneous environment. First, yearly composite NDVI maps are computed and
analyzed for their spatial distribution in relation to land cover types. Secondly, the graphical and
statistical analysis is performed to compute the range of maximum and a minimum threshold of NDVI
values for the cropland. Finally, this research uses the principle of VCI and develops the modified
vegetation condition index (mVCI) as Equation (2).

\[ mVCI = \begin{cases} 
100 \times NDVI_{Ycom}, & \text{where } NDVI_{Ycom} > \text{measured maximum threshold of the cropland} \\
100, & \text{for } NDVI_{Ycom} < \text{measured minimum threshold of the cropland} \\
100 \times \frac{(NDVI_i - NDVI_{min})}{(NDVI_{max} - NDVI_{min})}, & \text{otherwise}
\end{cases} \] (2)
where NDVI_{Ycom} is the yearly composite NDVI, NDVI_{imax} is the maximum NDVI in the month of i, NDVI_i is the NDVI value for a specific pixel in the month of i, NDVI_{max} and NDVI_{min} are the highest and lowest NDVI values of the same pixel for the period of 2006–2018.

After deriving the traditional VCI and the proposed mVCI, this research performs a comparison analysis between them to improve the understanding of how the existence of heterogeneous land covers affect the estimation of agricultural drought using the traditional vegetation index. To demonstrate the competence of the modified drought index, the comparison is shown in maps. Moreover, the spatial distribution of the mVCI and VCI values are derived and shown by land cover types.

3.4. Detection of Agricultural Drought Vulnerable Regions

This study computes the agricultural drought hazard index to facilitate the investigation of the spatial distribution of drought-vulnerable regions. For each year, the seasonal mVCI maps are produced and reclassified. Then, the equally weighted sum overlay analysis is performed and a new drought vulnerable map is generated. This study applies an approach to detect drought hazard zones as used by Daneshvar et al. [49] and Yu et al. [6]. It should be noted that Daneshvar et al. [49] used the SPI and Yu et al. [6] both the SPI and VCI drought thematic maps to produce the drought hazard index (DHI). However, this study assigns weights to mVCI values (Table 1) and uses the drought thematic maps as in Equation (3). Finally, the drought vulnerable regions are defined as high, medium and low. Note that in this study, the highest and lowest DHI values indicate, respectively, high and low vulnerability of regions to agricultural drought. In contrast, the intermediate DHI values indicate medium-vulnerable regions.

\[
DHI = \sum_{ij=1}^{n} mVCI_{ij}
\]

where DHI is the drought hazard index produced by the sum overlaying of the mVCI drought thematic map of the i-th year and j-th season for a time of n = 13 years (2006–2018).

| mVCI Value | Cropland Condition | DHI Weight |
|------------|--------------------|------------|
| 0–25%      | Extreme dry        | 3          |
| 26–35%     | Severe dry         | 2          |
| 36–50%     | Moderate dry       | 1          |
| >50%       | Fair               | 0          |

4. Results and Discussion

In this section, first, the heterogeneity of the environment is investigated. Second, the drought indices that are derived using the VCI and mVCI and presented for visual interpretation and comparison analysis. Then, the DHI maps are computed for the investigation of the agricultural vulnerability to drought conditions.

4.1. Spatial Distribution of Land Cover Types and Detection of Agricultural Areas

This study assesses the heterogeneity of the landscape using the NDVI. It should be noted that the temporal and seasonal variations influence the characteristics of the land cover types [50]. Thus, the influence of their variations in the detection of land cover types is evaluated. Figure S2 shows that the NDVI values for the different land cover types including cropland, forest, tree cover, and other geographic features. The result confirms the variations in the NDVI values. To understand the spatial distribution of land cover types and detect cropland, this study uses yearly composite NDVI (Figure 2). The typical statistics of the NDVI show the lowest values for the non-vegetation land covers e.g., water, wetland, and urban. Forest and tree cover show the highest NDVI values. This study
computes and uses the threshold of NDVI to segregate cropland from other land cover types. Table 2 shows representative threshold values of the NDVI. To evaluate its performance an overlay analysis is performed between the cropland as defined in MODIS land cover product and threshold-based classified map. This study finds 91–95% agreement in the detection of cropland using the threshold of NDVI.

| Statistics | 2006 | 2010 | 2014 | 2018 |
|------------|------|------|------|------|
| Max        | 0.64 | 0.64 | 0.65 | 0.66 |
| Min        | 0.44 | 0.42 | 0.46 | 0.48 |

4.2. Evaluating Drought Conditions Using the VCI and mVCI

This study computes the vegetation conditions and investigates the seasonal and temporal variations in agricultural drought for 13 years. To be concise, this study presents the results from a representative drought year of 2006 [41] and a non-drought year of 2018. In contrast, the drought maps of other years are provided as supplementary material (Figures S3 and S4). Figure 3a–f shows the maps of the VCI and mVCI for the drought year. The index values range between 0 and 100. The drought conditions are highlighted, dividing the index values into four scales. The VCI and mVCI values of...
≤50% indicate the drought-prone areas and the values of greater than 50% indicate normal condition. Rice is one of the major cereals in Bangladesh, which grows in the three seasons. Moreover, based on broad crop growing season e.g., Kharif (May–October) and Rabi (November–April) the drought maps are produced and shown in Figures S5 and S6. The highest precipitation falls in Bangladesh in the Kharif/Aus rice-growing season and supports rain-fed agriculture [12] thus the highest index values are observed in these seasons. In contrast, the Boro and Rabi cropping seasons show the lowest index values.

![Vegetation Condition Maps](image-url)

**Figure 3.** Major cropping seasons and spatial distribution of vegetation conditions based on the VCI and mVCI in: (a–f) 2006, and (g–l) 2018.
Figure 3g–l presents the maps of the VCI and mVCI for the non-drought year of 2018. The results show overall higher index values than the drought year. Note that small areas contain the lowest values indicating drought conditions, and the influence of seasonal variations in the vegetation conditions is not significant in the normal year. The low index values indicate the development of vegetation with unfavorable weather. The vegetation phenology phases e.g., leaf coloring and unfolding, are driven by dry weather, which reduces the greenness in vegetation and enables the realization of drought conditions [32,51]. The lowest precipitation falls in the Rabi/Boro rice-growing season, and it is relatively dryer than the Kharif season, thus the highest drought condition is observed in this season.

4.3. Comparison Analysis

This study improves the VCI to estimate accurate drought conditions of cropland in a heterogeneous environment using the mVCI. Figure 4 presents a visual comparison between the maps of VCI and mVCI. It should be noted that both the VCI and mVCI require long-term maximum and minimum NDVI values for each pixel; thus, monthly NDVI images of 13 years, a total 156 images are used for estimating agricultural drought. However, to be concise, the comparative analysis is presented in detail for two representative years. The results reported in this study show that, without considering land cover types, the VCI yields the low index values for many non-vegetative areas that seem to be classified as drought-affected areas (Figure 4a,d) because the non-vegetative areas e.g., waterbodies, wetlands, and urban areas consist of low NDVI values compared to the cropland (Figure 2c,f). In contrast, consideration of land cover types in the mVCI minimizes the overestimation of drought areas (Figure 4c,f), thus improving the demarcation of actual agricultural drought areas. A large territory or an entire country consists of heterogeneous land covers, thus this study suggests considering land cover types in the mVCI.

Figure 5a–d show the differences in basic statistics of predicted drought conditions derived from the VCI and mVCI. The comparison analysis indicates the differences between the VCI and mVCI for cropland and other land cover types. The croplands show similar statistics in both models. It is worth noting that, without consideration of land cover types, the VCI yields very similar values of many land cover types (Figure 5a,c). Thus, it is challenging to estimate accurately the drought conditions of the cropland. In contrast, the consideration of land cover types in the mVCI facilitates the distinguishing of the actual conditions of cropland from other land cover types (Figure 5b,d).

Figure 5e,f presents the local spatial difference between vegetation conditions derived from the VCI and mVCI. The areas of water body, wetland, forest, tree cover and urban show strong deviations between the results of the VCI and mVCI in the prediction of drought conditions of 2006 (Figure 5e). In contrast, cropland shows low deviations between the models. The deviations in the estimation of drought condition in 2018 (Figure 5f) show similar findings to those for the dataset of 2006. Figure 6 also presents the differences in the mean temporal variations between the VCI and mVCI. The results demonstrate that the croplands yield relatively high index values in the wet months. The mVCI performs better that the VCI in separating agricultural drought conditions in the heterogeneous environment.

Monthly NDVI and its long-term maximum and minimum values are input into the computation of the indices and thus the variations in NDVI highly influence their values. Figure 2 confirms that the waterbody, wetland and urban areas have the lowest NDVI, thus resulting in the lowest VCI for these land covers. In contrast, the forest and tree covers may also suffer from water stress and result in low VCI. In a heterogeneous environment, the accurate estimation of the agricultural drought condition can be affected if these land covers are not considered in the estimation of VCI. Table 3 shows the differences in the estimation of drought conditions using the VCI and mVCI. The VCI overestimates the areas of extreme and moderate drought conditions. In contrast, the mVCI shows a lower proportion of areas of drought conditions than the VCI. In the estimation of mVCI, land cover types are considered, thus excluding the water-stressed vegetation and non-vegetation land covers in the calculation of agricultural drought.
Figure 4. Spatial distribution of land cover types and vegetation conditions derived from the VCI and mVCI in (a–c) 2006, and (d–f) 2018.
Figure 5. Comparison of typical statistics of the VCI and mVCI (a–d), and local spatial difference in the estimation of vegetation conditions (e,f).
Figure 6. Mean vegetation conditions as derived from the (a) VCI, and (b) mVCI.

### Table 3. Area (%) indicating different drought conditions.

| Yr2006 Index Range | Cropping Seasons | Yearly |
|--------------------|------------------|--------|
|                    | Aman VCI | mVCI | Boro VCI | mVCI | Aus VCI | mVCI |
| 0–30               | 32.1    | 25.0 | 43.0     | 31.5 | 12.0    | 6.8  |
| 30–50              | 32.2    | 24.7 | 30.9     | 22.9 | 28.5    | 21.6 |
| 50–70              | 21.9    | 17.8 | 16.5     | 15.8 | 37.7    | 28.0 |
| 70–100             | 13.7    | 32.5 | 9.6      | 29.8 | 21.9    | 43.7 |
|                    | 3.6     | 1.5  | 3.8      | 1.6  | 3.7     | 1.3  |
|                    | 17.8    | 13.1 | 15.6     | 10.4 | 17.9    | 11.4 |
|                    | 41.3    | 36.9 | 40.3     | 34.3 | 42.6    | 30.4 |
|                    | 37.3    | 48.5 | 40.3     | 53.7 | 35.8    | 56.9 |

### 4.4. Assessing Drought Hazard and its Impact on the Yield of Major Cereals

Figure S7 shows the cropping area of the major cereals, and Figure 7 shows the drought-vulnerable croplands. The results demonstrate that the regions located in the north-west are highly vulnerable to agricultural drought. In Bangladesh severe drought primarily occurred in the pre- and post-monsoon periods [42]. The results of this study also indicate a high drought occurrence in the pre-monsoon rice-growing season of Boro and post-monsoon rice-growing season of Aman (Figure 7b,c). In contrast, the rain-fed agriculture, Aus rice-growing season shows mild drought conditions (Figure 7a).
An evaluation of the drought impact on the yield of major cereals is shown in Figure 8. The results show the lowest yield in the drought year compared to the non-drought year. It is worthy of note that the Boro rice-growing season shows the lowest mean mVCI; however, the yield of Boro rice is highest (Figure 8a). It seems to be inconsistent because the low index value indicates higher drought conditions, thus it should have a high impact on the yield of Boro rice. The sown and harvesting times of Boro rice are between mid-November and April, which is the driest season in Bangladesh (Figure S1). Various factors including low precipitation, leaf unfolding, and coloring seem to have an impact on the vegetation conditions. In this study, the yield–mVCI relationship is shown graphically in Figure 8a. It shows a comparison between two representative years that limits the application of regression analysis to evaluate the impacts of drought on the crop yield. This study underlines the importance of using the long-term crop yield and mVCI for quantitative analysis in future work.

The NDVI-based VCI has been widely used to evaluate drought conditions \[^{[2,33,38]}\], and this study proposes the mVCI for the accurate estimation of agricultural drought. In the proposed approach, the thresholds of NDVI are used to segregate croplands from other land cover types, and Equation (2) is developed for the estimation of agricultural drought in the heterogeneous environment. This study finds 91–95% agreement in the detection of cropland using the threshold of NDVI. It is worthy of note that the heterogeneous environment consists of various land cover types, and non-vegetation land covers e.g., waterbody, wetland, and the built environment have low NDVI values compared to the cropland and other vegetation (Figure S2). Therefore, the use of the traditional vegetation index in the heterogeneous environment yields low VCI values in many areas of non-vegetation land covers and seems to include them as drought-affected areas (Figure 4). In contrast, the use of the NDVI threshold
and the consideration of separating croplands from other land cover types reduces the inclusion of misclassified drought areas thus improving the estimation of agricultural drought.

In this study, precipitation and crop yield have been used to verify the ability to detect drought conditions [32]. This study also uses these data to evaluate the performance of the drought hazard index. Figure S8 shows the temporal variations in the average precipitation and mVCI of the croplands between two representative years. The investigation indicates that the drought year yields low mVCI values compared to the non-drought year. It should also be noted that the mean mVCI values fall with a decrease in precipitation in 2006. In contrast, the influence of precipitation on the vegetation conditions is not noticeable in 2018. Temporal variations in precipitation present the dry and wet seasons, and can be used as an important indicator of meteorological drought.

Dutta et al. [36] used a yield-based drought index for comparison with the VCI and found a moderate coefficient of determination between VCI and yield of major rainfed crops (Sorghum). In this study, a comparison is shown between the yield of major cereals and the corresponding mean mVCI (Figure 8). The results demonstrate that mVCI is lowest in the rice-growing season of Boro but the yield rate is highest. In contrast, the mVCI is largest in the rice-growing season of Aus but the yield rate is lowest. The investigation of this research indicates that the vegetation condition is one of the important indicators of drought. However, several other influencing factors should be considered to find out the correlation between crop yield and the occurrence of drought.

It should be noted that this study selects a large territory for the assessment of agricultural drought. A large-scale analysis facilitates the detection and comparison of the levels of drought vulnerability (Figure 7) on a regional scale that are important to prioritize vulnerable croplands for initiating development projects and allocating funds accordingly. A large-scale analysis is also of importance for country-level decision making to withstand drought vulnerability.

5. Conclusions

Agricultural drought is one of the natural hazards occurring in many parts of the world. Various factors including reduction in precipitation and soil moisture, climate change, and the changes in water supply and demand cause drought. It is important to understand the factors of drought conditions and detect the vulnerable areas for effective planning and minimizing of the drought risk. Various indices are available to monitor drought conditions. For example, meteorological drought indices e.g., SPI, RAI, and SPEI have been commonly used but are limited by the distribution of weather stations and provide only point data. In contrast, RS based indices facilitate multi-temporal drought vulnerability mapping on a regional scale. The VCI is one of the popular RS-based indices that has been applied for drought analysis; however, existing studies rarely evaluate drought in a heterogeneous large territory. This study improves the traditional VCI and proposes the mVCI to make it suitable for investigating agricultural drought in a heterogeneous environment. The proposed mVCI uses MODIS earth observation data of NDVI and land cover. Note that the traditional VCI has been mostly used for small-scale analysis, and thereby land cover types have not been considered for evaluating drought. This study evaluates agricultural drought in an entire country and computes the mVCI considering the variations in land cover types.

In this study, the basic statistics of the NDVI for six major land cover types are enumerated. The results show the lowest NDVI values for the non-vegetation land cover types and the highest for the forest and tree cover. In contrast, the intermediate NDVI values indicate the cropland areas. This study computes a threshold of NDVI to segregate cropland from other land cover types and uses the threshold values in the algorithm of the mVCI. The proposed approach is compared with the VCI. The results reported in this study show that the use of the traditional vegetation index in the heterogeneous environment yields low VCI values in many areas of non-vegetation land covers thus overestimating the areas of agricultural drought conditions. In contrast, the use of the NDVI threshold and the consideration of separating croplands from other land cover types reduces the inclusion of misclassified drought areas thus improves the estimation of agricultural drought. The results
of seasonal variations in the drought conditions indicate that the Aus rice-growing season is less vulnerable to drought as the highest precipitation falls in this season. This study uses mVCI maps from multiple years and seasons to develop the DHI map. The result indicates the local spatial variations in the vulnerability to agricultural drought. The highly vulnerable agricultural areas are located in the north-west of Bangladesh. In contrast, the southeast hilly region consists of forest indicates less vulnerable to drought conditions.

It should be noted that most of the major cereals are cultivated in the north and north-west districts of Bangladesh. However, the north-west districts are highly vulnerable to drought conditions and thus care should be taken with dynamic drought planning for this region. The crops that withstand drought conditions could be selected for cultivation in the highly vulnerable regions. Note that this study assesses agricultural drought using s vegetation index. However, some other factors including hydrogeological characteristics, soil types and moisture conditions, air and land surface temperature, irrigation water demand and supply should be considered while estimating agricultural drought in future work. Climate change has varying impacts on global and local weather [42]. This study suggests climate change-induced drought assessment in future work. In this study, both the VCI and mVCI are generated by inputting the NDVI. However, NDVI-based vegetation indices commonly indicate the condition of vegetation in terms of greenness. High greenness indicates healthy vegetation, and low greenness indicates poor vegetation conditions. NDVI-based vegetation indices limit differentiation of the inherent causes (e.g., lack of water or nitrogen) of poor vegetation conditions, thus this research suggests considering the investigation of soil conditions in future work along with the vegetation condition.

Supplementary Materials: The following are available online at http://www.mdpi.com/2072-4292/12/20/3363/s1, Figure S1: Temporal variations in precipitation, Figure S2: Temporal variations of NDVI, Figure S3: Seasonal Multiyear VCI maps, S4: Seasonal Multiyear mVCI maps, Figures S5 and S6: Spatial distribution of vegetation conditions in 2006 and 2018, Figure S7: Cropping area of the major cereals, Figure S8: Temporal variations in the mean mVCI in relation to precipitation.

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