



Article

# Integrated Application of Remote Sensing and GIS in Crop Information System—A Case Study on Aman Rice Production Forecasting Using MODIS-NDVI in Bangladesh

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**Abstract:** This research work studies the integrated application of satellite Remote Sensing (RS) and Geographic Information System (GIS) for the monitoring and forecasting of rice crop (Aman) production in Bangladesh. Normalized Difference Vegetation Index (NDVI) images of Terra MODIS products MOD13A1 (h25v06 and h26v06) with 500 m spatial resolution, composed using Maximum Value Composite (MVC) techniques, were used to cover Bangladesh for the period of 2011–2017. Country scale NDVI (district-wise summation) was calculated pixel-by-pixel to draw a regression curve while using Bangladesh Bureau of Statistics (BBS) estimations of Aman production for the months of September–November. The regression study of district-wise pixel-based summation of MODIS-NDVI and ground-based BBS-estimated Aman production shows a strong correlation ( $R^2 = 0.54\text{--}0.78$ ); for the months of September and October, most of the regression coefficient indicates significant correlation due to maximum photosynthetic activities. Therefore, based on the highest regression coefficient value of September and October, Aman Crop Production (ACP) models were developed and the ACP Model-2 was exploited (from the derived set of coefficient values) to acquire year-wise rice production for all the years (2011–2017). The simulated ACP Model-2 demonstrates good agreement between the estimated and predicted yearly Aman rice production for the 2011–2017 time period with Mean Bias Error (MBE) = (−9435 to 23,156) M.Ton; Root Mean Square Error (RMSE) = 253–4426 M.Ton; Model Efficiency (ME) = (0.89–0.93); and, Correlation Coefficients = (0.72–0.94). Hence, the MODIS–NDVI-based regression model seems to be effective for Aman crop production forecasting in the context of food security issues in Bangladesh. The applied system is simple, rationally accurate, and fit for the generation of nationwide crop statistics.

**Keywords:** RS\_GIS; Aman crop; MODIS-NDVI products; ground-based estimates; regression model; simulation; forecasting

## 1. Introduction

Rice production is of essential importance in Bangladesh and in the context of economy and food security issues [1], where the grain solely occupies 76.7% of total area under cultivation [2]. Aus, Aman, and Boro are the three major types of rice cultivated in Bangladesh; where Boro or winter rice is grown from January to June under irrigated conditions, while the Transplanted Aman (T. Aman or monsoon rice) is grown from July to December, mostly under rain-fed conditions [3]. Presently,

in Bangladesh, Aman rice accounts for about 50% of the total rice production in the country [4]; nevertheless, the yield gaps between the Boro and Aman seasons are about 0.9 tons ha<sup>-1</sup> and 1.3 tons ha<sup>-1</sup> due to biotic and socio-economic constraints. Monsoon rains are very important for the Aman crop, which is harvested in November/December. However, Aman rice requires a special habitat of prolonged flooding. A maximum amount of Aman is transplanted between the end of June to mid-August, although planting can occur as late as the last week of September and harvested in November/December [5]. In view of the above, early assessment of Aman crop production in the context of Bangladesh is very important due to food security issues.

Crop production assessment in Bangladesh is done by considering the crop acreage estimates and corresponding crop yield estimates, which are often subjective, costly, and prone to large errors, thus leading to poor crop assessment [6]. Besides, the collected information might become available too late for appropriate action to be taken by the decision-makers or planners in the country. On the contrary, remote sensing can help obtain surface information macroscopically, periodically, and economically; and, has many advantages in agricultural monitoring—great success has been achieved in the recent past [7–10]. In this context, Normalized Difference Vegetation Index (NDVI) is a key signifying factor for vegetative growth conditions and degree of vegetative cover study [11]. Ref. [12] It is to be noted that, if an area is covered by vegetation, then the NDVI value of that area is a positive number, and it increases along with an increase in vegetative cover. A few studies have attempted to estimate rice yield using high-resolution remote sensing data (such as Quickbird; 0.65 m, WorldView; 0.31 m and IKONOS; NIR 3.2 m, PAN 0.82 m) in the past two decades [13]; however, their approach has encountered problems with swath width and high costs [14,15]. Similarly, the use of Landsat imagery has encountered problems with obtaining cloud-free images due to temporal resolution, which makes it impossible to obtain phenology information during the relevant crop period.

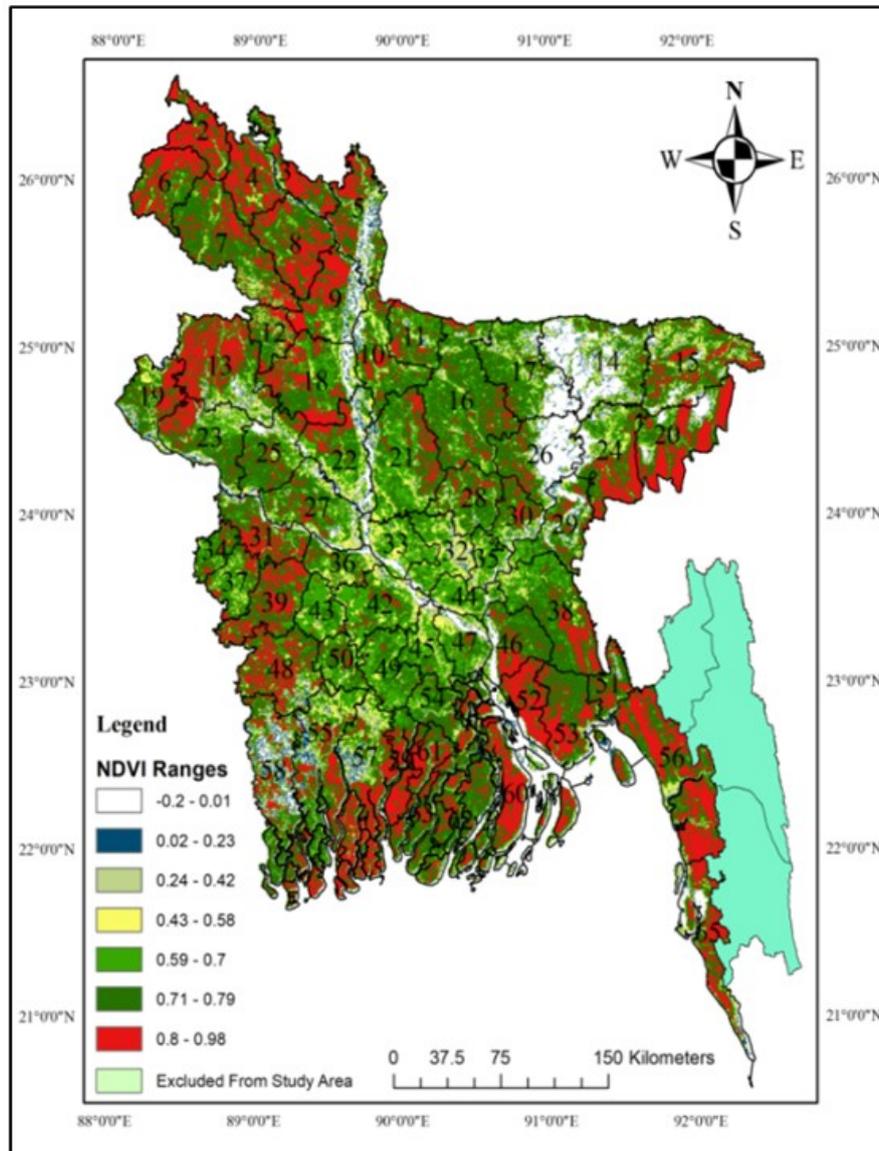
However, MODIS constellations have been used in retrieving agricultural crop information and they are mostly used due to their larger regional scale, smaller dataset, and faster revisiting time [16,17]. Moreover, the dynamics of MODIS-derived NDVI products is representative of crop growth and biomass changes that are closely related to crop yield and it has a direct relationship with Leaf Area Index (LAI), biomass, and vegetation cover [18–20]. The suitability of using MODIS-derived NDVI data for crop yield estimation prediction, crop production, and monitoring has been recommended by several studies [21–24]. Therefore, the MODIS-derived NDVI product is used in this study. The present study focuses on NDVI, because it is widely used in phenological works [25–27] and it is known to be more sensitive to small increases in the amount of photosynthetic vegetation [28,29]. In view of the above, the objectives of this study are to forecast seasonal crop (Aman) production estimates based on the developed methodology for potential use in tackling the country's food security issues.

## 2. Materials and Methods

### 2.1. Study Area

The study area is located between 20°34' to 26°38' North latitude and 88°01' to 92°42' East longitude, except for the southeastern three hilly districts (Rangamati, Khagrachari, and Bandarban) of Bangladesh. Figure 1 shows the NDVI distribution in the study area. The three hilly districts mentioned above are not considered in this study, because surface reflectance from the hilly terrain might be influenced by adjacent areas, as has been stated in several studies [30–32]. In Bangladesh, the mean annual rainfall is about 2300 mm; however, annual rainfall ranges from 1200 mm in the extreme west to over 5000 mm in the east and north-east [33]. Regional variability in agricultural production pattern and a diverse landscape in the country has resulted in temporally and spatially fragmented rice production areas [34,35]. Among the three rice-producing seasons, the primary production season generally lasts from July to November, depending on the region; the dry (Boro) irrigated rice is generally planted in December or January and harvested in March or April; and, the early summer season (Aus) is a short rice season, which precedes Aman in a few areas [36]. The geomorphological characteristics

of Bangladesh imply that the Aman crop has to experience dry and wet climatic conditions due to a longer growing season. With respect to the Aman crop, early rainfall is negatively correlated, whereas monsoon rainfall is important for the maturity of rice grains.



**Figure 1.** Normalized Difference Vegetation Index (NDVI) distribution in Bangladesh derived from MODIS NDVI imageries.

### 2.2. Phenology of Aman Crop in Bangladesh

The Aman rice crop phenology is divided into three distinct phases: (1) vegetative phase, (2) reproductive phase, and (3) ripening phase. The vegetative phase starts out by germination and ends with the initiation of a panicle (Table 1). The vegetative phase lasts from 55 to 85 days, depending on the Aman crop varieties. The Aman crop yield largely depends on the reproductive phase that persists from panicle initiation to flowering. The ripening phase lasts from the flowering of the plants to the maturity of grain. The rainy days with low temperatures may lengthen the ripening phase while sunny and warm days may shorten it. Usually, the most of the Aman crop varieties take 30 to 35 days for the completion of their reproductive and ripening phase each [37]. The phenological changes of the crops life cycle are demonstrated in Figure 2 using MODIS derived NDVI distribution of four different times.

Table 1. Phenological stages of Aman crop.

Phases (Days)			
Vegetative Phase	Reproductive Phase	Ripening Phase	Total
55–85 days	30–35 days	30–35 days	115–155 days

Source: [37].

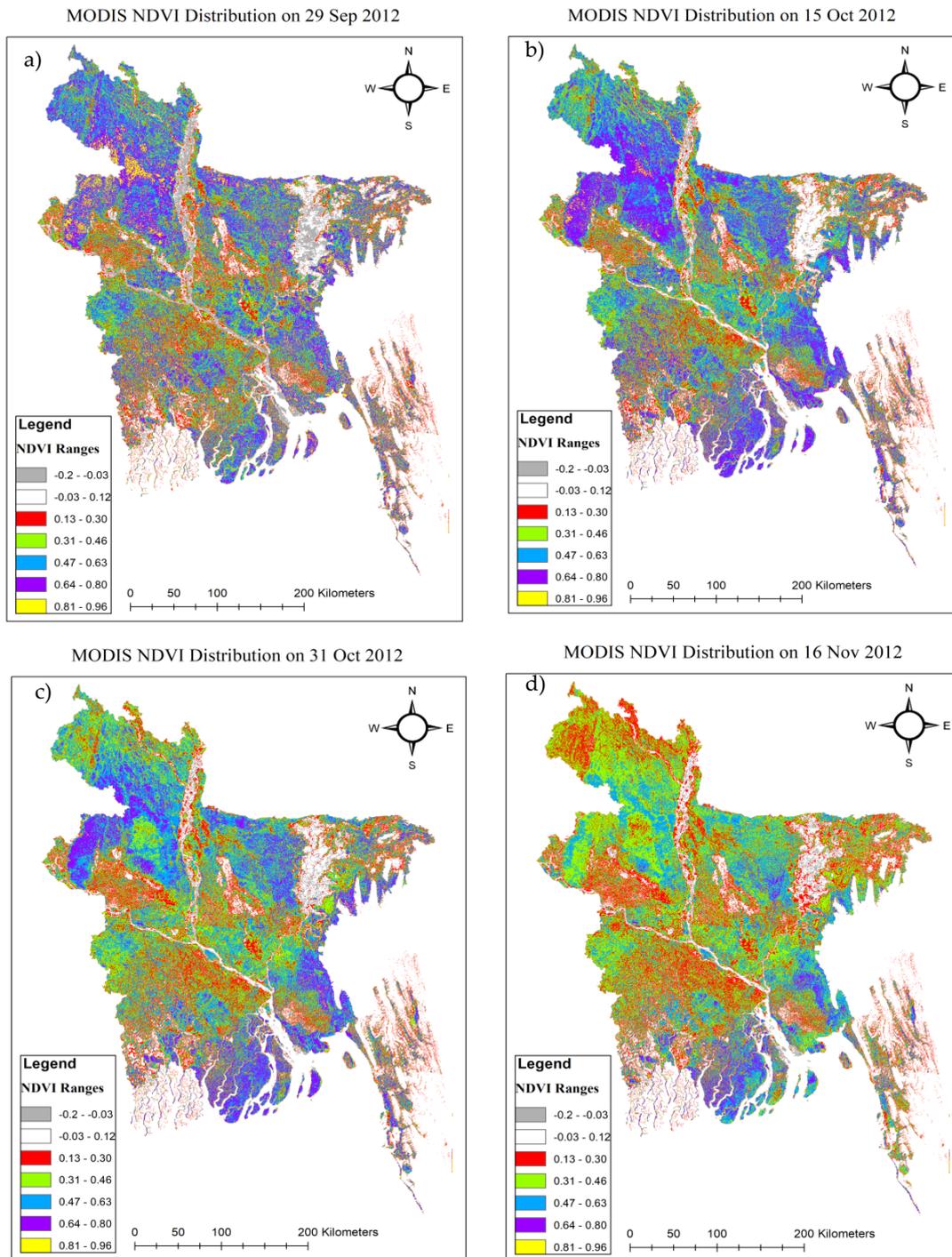


Figure 2. (a–d): Phenological changes of crops based on MODIS NDVI distribution at different dates in a year (2012).

### 2.3. Geospatial Data Used

The two MOD13A1 scenes (MOD13A1: h25v06 and h26v06) have been accessed from the website of the US National Aeronautical Space Agency (NASA) Earth Observing System (EOS) in Hierarchical Data Format (HDF-EOS) to serve the purpose of the present study [38]. The applicability of MODIS VI products (MOD13A1) for the crop production forecasting in Bangladesh has already been proven by [24]. Therefore, the Terra MODIS 16-day Maximum Value Composite (MVC) NDVI image products (MOD13A1) of 500 m resolution have been utilized in the present study in order to gather Aman crop information in the context of Bangladesh. The pixel-by-pixel cloud-free quality images can be obtained from MVC NDVI images, which can effectively identify the major changes in crops phenology. Accordingly, the growth of the Aman crops at different stages of its life cycle can be monitored by MVC NDVI images. The utility of MVC products for generating Boro crop information in Bangladesh has been tested and well documented in [24]. On the basis of the phenology of the Aman crop lifecycle in Bangladesh, the study period is accounted from September to November of 2011 to 2017. Eventually, each image of MODIS MVC products corresponding to each month as obtained is based on the selection of the best pixel value from a total of 16 images of 16 consecutive dates of the same pixel. Tables 2 and A1 summarize the detailed specifications of used MODIS NDVI products and satellite image acquisition date, respectively.

**Table 2.** MODIS NDVI products (MOD13A1) description.

Data Source	Data Description	Data Type	Pixel Size	Composite Technique	File Format
Terra MODIS	500 m 16 days NDVI	16-bit signed integer	500 m	MVC (Maximum Value Composite)	HDF-EOS

Source: [38].

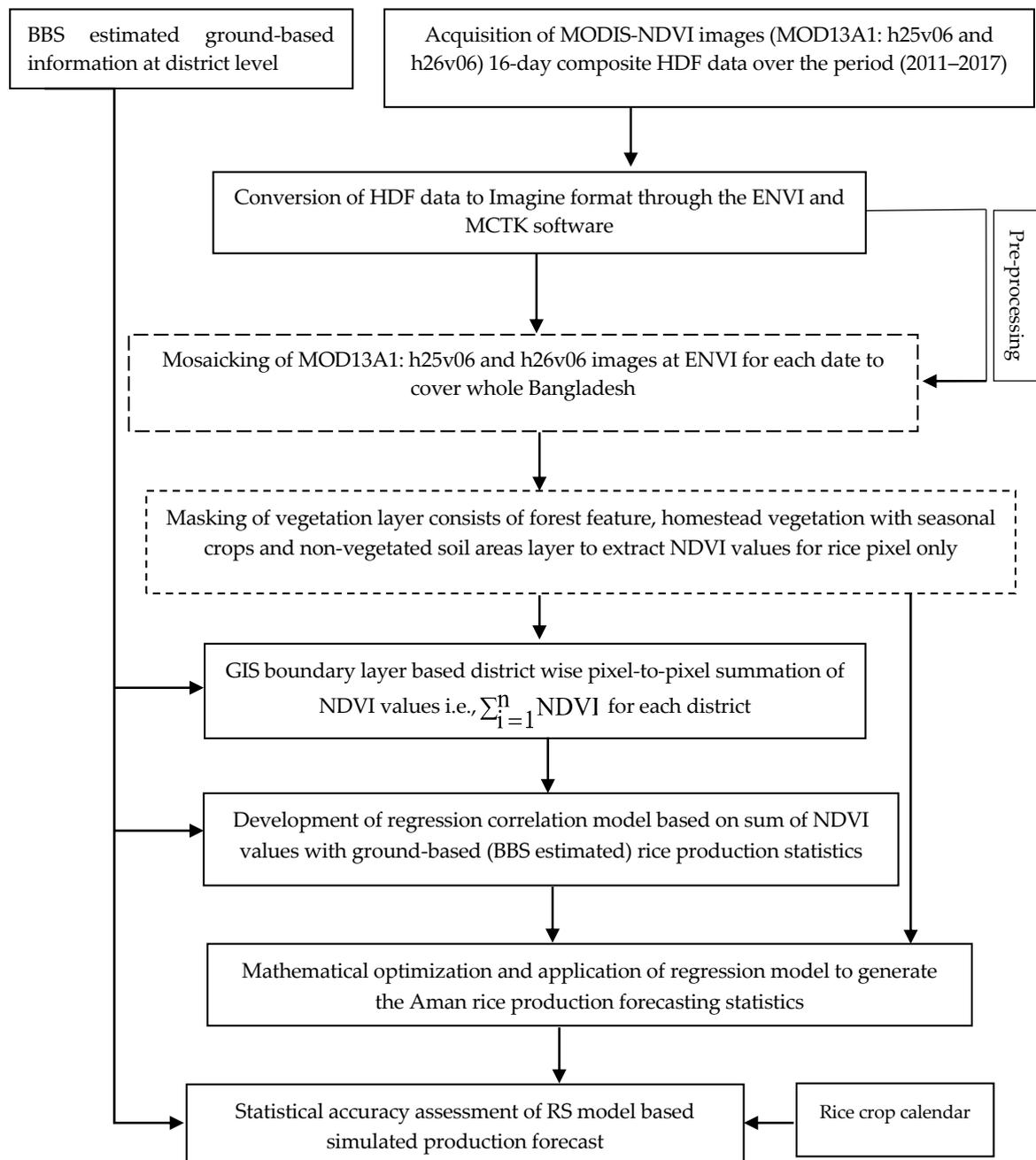
The ground-based estimated Aman rice crop production statistics from 2011–2017 have been collected from the Bangladesh Bureau of Statistics (BBS). For yield/production estimation information, BBS follows the Food and Agriculture Organization (FAO) guided conventional methods (direct observation and measurement) and collects data from 10,348 numbers of clusters, where each cluster averaging five acres of land as a sample frame. The detailed procedure of yield/production estimation information of BBS has been described in [24] and in [39].

### 2.4. Methodological Framework

Figure 3 illustrates a methodological framework for this study. After acquisition of satellite data multiple steps of pre-processing likely (a) conversion of Hierarchical Data Format (HDF) dataset into image compatible format through MODIS Conversion Tool-kit (MCTK) and ENVI software; (b) digital mosaicking of converted images (MOD13A1: h25v06 and h26v06); (c) re-projection of the NDVI images into Transverse Mercator; and, (d) necessary geometric correction have been performed in order to develop rice production forecasting methods.

After the necessary pre-processing of satellite imageries, the country scale vegetation layer has been used to mask out the non-crop vegetation cluster using Erdas Imagine software. The prime objective of using country scale vegetation mask layer is to screen out the part of vegetation that was mostly stable or having unchanged cover for relatively longer time period. The used country scale vegetation mask layer consists of (i) forest features, (ii) homestead vegetation together with (iii) seasonal crops, and (iv) mostly non-vegetated soil areas. These vegetation mask layers have been generated from high-resolution satellite data (RapidEye/Landsat) and they have been utilized to find the district-wise rice pixel only in present study. The regular updating of these vegetation layers every 3-4 years can give satisfactory updated surface features at the country scale. The detailed procedure for preparing this vegetation mask layer has been stated in [24]. The Pixel-wise spatial summation of NDVI values for all of the individual pixels covering each individual district area in the MVC NDVI image provides a single value for each district. Hence, a district-wise pixel-to-pixel addition operation has been carried out to provide NDVI summation of all pixels i.e.,  $\sum_{i=1}^n$  NDVI for each district areas

based on MODIS NDVI raster layer properties supported by the GIS boundary layer. Here,  $n$  is the total number of data points (pixels) under a district.



**Figure 3.** Schematic illustration of remotely sensed Aman rice production forecasting methodology (Note—RS: Remote Sensing; NDVI: Normalized Difference Vegetation Index; BBS: Bangladesh Bureau of Statistics; MCTK: MODIS Conversion Toolkit).

Therefore, the district-specific sum of NDVI values has been extracted from September to late November over the years 2011–2017. Ultimately, the derived summed NDVI is the resultant of all the pixels within each district area and it is assumed to be proportional to the presence of vegetation therein. Hereafter, based on MODIS derive district wise sum of MODIS-NDVI values with ground-based (BBS estimated) Aman rice crop production statistics, the regression analysis has been performed for the period of 2011–2017. Subsequently, based on the highest regression (Monthly Scale) coefficient value, the regression model of October 2012 (ACP Model-2) has been applied to independently

generate crop production statistics at the country scale (Table A1). After that, the Remote Sensing (RS) model-based simulated results have been compared with ground-based BBS estimated Aman crop production statistics for testing or validating the model, which were not used to retrieve the values of the parameters. After the model simulation, necessary statistical parameters, like (a) Mean Bias Error (MBE); (b) Root Mean Square Error (RMSE); and, (c) Model Efficiency (ME), have been derived for suitability assessment by applying the Equations (1)–(3).

$$MBE = \frac{\sum_{i=1}^n (P_i - O_i)}{n} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (O_i - P_i)^2}{n}} \quad (2)$$

$$ME = \frac{[\sum_{i=1}^n (O_i - \bar{O})^2 - \sum_{i=1}^n (P_i - O_i)^2]}{[\sum_{i=1}^n (O_i - \bar{O})^2]} \quad (3)$$

where  $n$  is the number of data points,  $P_i$  is the  $i$ 'th model predicted data point,  $O_i$  is the  $i$ 'th observed data, and  $\bar{O}$  is the mean of the observed data.

### 3. Results

This section illustrates the research outcomes, limitations, and way forward for future study.

#### 3.1. Remotely-Sensed Aman Rice Production Model

The potentiality of regression model derived from remote sensing NDVI and ground-based crop statistics to estimate the crop yield [40–42] and crop production [24,43] under different land management has been notified. Generally, the Aman season in Bangladesh continues from the month of August/September to November/December. Consequently, the maximum NDVI values can be found during peak greenness period of crop life cycle, which is around the month of October. A linear regression model has been developed between the sum of MODIS-NDVI and ground-based (BBS estimated) crop production from September to November of 2011 to 2017 (Table A1). The regression coefficient value ranges from (0.54–0.78) among the individually developed twenty-eight (28) regression coefficients (Table A1). The highest ( $R^2 = 0.78$ ) and lowest ( $R^2 = 0.54$ ) regression coefficient values have been found for the month of September of 2012 and November of 2015, respectively. Besides, the highest regression coefficient for the month of October ( $R^2 = 0.76$ ) has been found in 2012 over the time period 2011–2017, which is also considered as a peak greenness period in context of Bangladesh. Accordingly, the regression coefficient shows the higher regression value for the month of September/October among the entire regression coefficient. Several studies [44–49] depict that the peak greenness period represents the highest NDVI values and it is related to crop production.

The developed regression equation illustrates the distinctive relation between Aman rice crop productions with sum of MODIS-NDVI values, which depicts that the increases of sum of MODIS-NDVI during the peak greenness period are generally related to Aman crop production. Other studies support the observed strong positive relationship between the sum of MODIS derived NDVI and ground-based Aman crop production in the present study [24,50]. In the present study, it is found that the regression coefficient becomes low in late November in all cases (Figure 4), which indicates the harvesting period of Aman crop and results in low NDVI values during this time. Therefore, based on the highest regression coefficient, month-wise regression models have been derived to simulate Aman crop production that is likely for the month of September (ACP Model-1) and October (ACP Model-2).

$$\text{(Sep) Aman Crop Production (ACP)}_{(M.Ton)} = 0.2596 \times \sigma - 21,026 \quad (\text{ACP Model-1})$$

$$\text{(Oct) Aman Crop Production (ACP)}_{(M.Ton)} = 0.2605 \times \sigma - 29,779 \quad (\text{ACP Model-2})$$

where the dependent variable (ACP) is expressed in absolute values (M.Tons) for each district; 0.2596 and 21,026; 0.2605 and 29,779 are the regression coefficients; and,  $\sigma$  is the sum of NDVI values for each district.

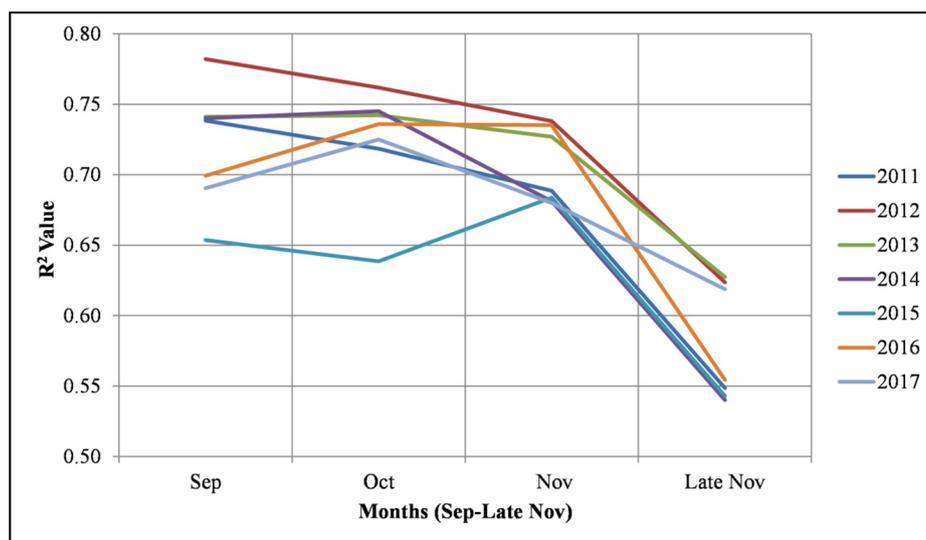


Figure 4. Variations of monthly derived remote sensing regression models (2011–2017).

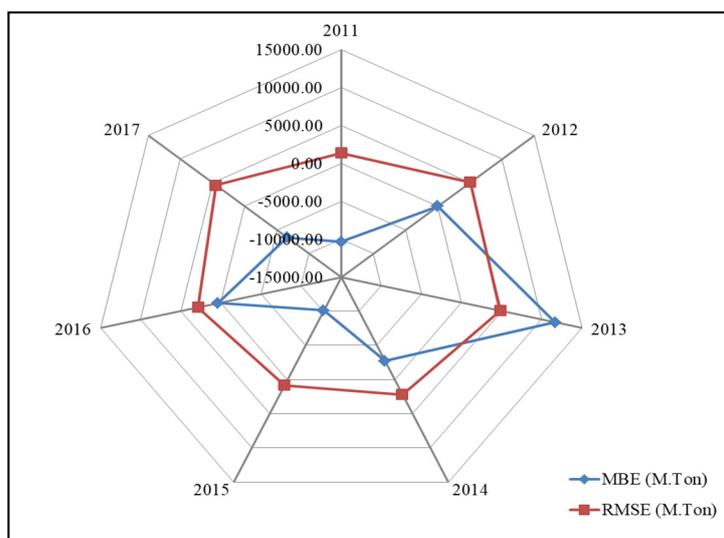
### 3.2. Simulation of Remotely Sensed Rice Production Model

The derived remote sensing regression models (ACP Model: 1 and 2) have been applied to simulate the Aman crop production for each of the years of 2011 to 2017. The difference between the predicted and estimated production is found to be larger in the ACP Model-1 as compared to the ACP Model-2. The simulation result of ACP Model-2 might become closer to the estimated production, because high NDVI values indicate enhanced photosynthetic activities towards the peak growth stage of Aman rice crop. However, RS-derived ACP Model-1 can also be used, but ACP Model-2 is more applicable and suitable, as October is the peak greenness month in the context of Bangladesh.

A simulation result of ACP Model-2 has been summarized over the time period of 2011 to 2017 in this section. The coefficient values of the regression model have been derived through mathematical optimization of the model against a single year data of October 2012. Subsequently, using the same set of derived model coefficient values (that of October 2012), data for the other years 2011 to 2017 have been independently generated. For training the model, only one year (2012) has been exploited and the remaining years have been evaluated. Table A2 provides statistics of Aman rice production over the years (2011–2017) according to RS Model-based (ACP Model-2) estimation along with ground-based BBS estimation. The RS Model-based observation versus BBS estimated production statistics (Table A2) shows relatively high correlation ( $R^2 = 0.72$  to  $0.94$ ) for each of the years from 2011 to 2017. The differences between the predicted and official statistics demonstrate the potential of a remotely sensed MODIS-NDVI based Aman rice production estimate at the country scale. Therefore, necessary statistical measures, like MBE, RMSE, and ME, have been employed to analyze the suitability of developed ACP models [51]. Several studies relevant to crop yield forecasting, notably [24,45,48,52,53] have also found good relationship between estimated and predicted rice yield for different countries.

### 3.3. Suitability Assessment of Developed ACP Model

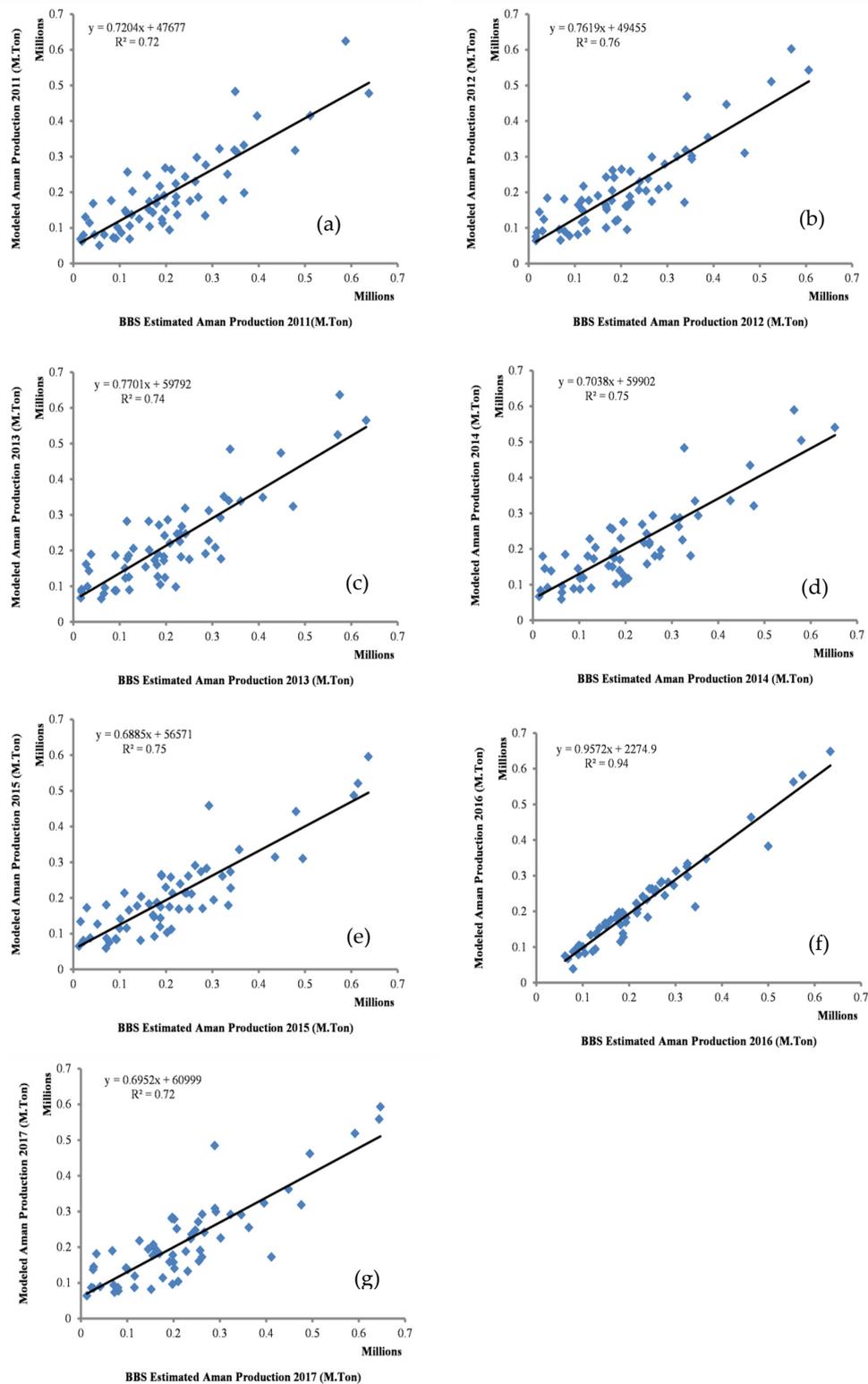
Based on the relevant study [53], the accuracy assessments of derived Aman crop production forecasting models have been mathematically performed [54], as described in Equations (1)–(3). The regression model based estimated crop statistics from ACP Model-2 has been assessed with statistical parameters MBE and RMSE presented in Figure 5 with a radar chart. Besides, Figure 6 also shows a strong relationship ( $R^2 = 0.72$  to  $0.94$ ) between predicted and estimated value of Aman crop in Bangladesh for the year 2011 to 2017. The MBE for applied Aman forecasting model ranges from  $(-10,353$  to  $11,691)$  M. Ton, which reveals that the applied model underestimates the Aman production for the year 2011, 2014, 2015, and 2017, whereas overestimates for the year 2012, 2013, and 2016 as the positive MBE gives the average amount of overestimation in calculated value and vice versa [54]. The RMSE value for the applied model ranges from  $(842-5067)$  M. Ton, which is a positive value, and also the use of RMSE in model validation has been appreciated by [53,55]. Model Efficiency (ME) is also used to assess the potentiality of model and, here, the ME ranges from  $(0.90-0.92)$  for the applied Aman crop forecasting model. The relevant literature clarifies, ME of 1 is a perfect match of modeled data to forecasted data whereas closer value of ME to 1 demonstrates its better accuracy [56]. Hence, the present ME over the period of  $(2011-2017)$  shows potentiality for using this model for Aman crop production forecasting at the country scale. Therefore, the MBE, RMSE, and ME values in this study indicate close prediction results for Aman crop forecasting estimates during 2011–2017 for Bangladesh (Table A2). The forecasted and estimated Aman production shows strong relationship, but this model-based forecasting methodology does not consider the unexpected weather condition [16,56].



**Figure 5.** Radar chart shows statistical accuracy of Remote Sensing (RS) model simulation for each year.

However, the inaccuracies in the model can be found due to the presence of cloud [57] and atmospheric-moisture contamination in the NDVI signals, methodological drawbacks and ground data collection procedure, heterogeneous characteristics of fragmented landscapes [51], climatic variability of different meteorological parameters over the season, as well as the frequency of natural disasters [58–60]. Based on the graphic inspection and statistical suitability test i.e.,  $R^2$ , RMSE, and ME of RS modeled and ground-based estimates of BBS it can be inferred that the remote sensing-derived Aman rice-cropped production can be predicted from the MODIS-NDVI based regression model. This proposed model provides a flexible way of generating Aman crop production statistics at the country scale in the heterogeneous landscape of Bangladesh. This model shows promising results in predicting Aman crop production, though there may have some limitations in its present form, but there are ways to improve

in the future implications. Moreover, the developed satellite remote sensing-based model needs to be assessed before implementing it in other geographical locations.



**Figure 6.** Correlation between RS model-based forecasted and ground-based (BBS estimated) production estimates at 61 district-levels during (a) 2011; (b) 2012; (c) 2013; (d) 2014; (e) 2015; (f) 2016; and, (g) 2017.

#### 4. Conclusions

The necessity of effective rice crop production estimation in the context of Bangladesh under the consequences of climate change phenomena is well documented. This research work solely looks forward to apply the satellite remote sensing-based Aman crop production forecasting in advance where MODIS-MVC data product MOD13A1 appears to be effective. This methodological framework directly calculates the district-wise rice production statistics based on pixel-by-pixel NDVI summation. A strong correlation is found between the district wise pixel-based summation of MODIS derived NDVI and ground-based BBS estimated Aman production. The time series analysis of NDVI products over the time period 2011–2017 implies that MODIS NDVI and BBS estimated statistics based regression models can estimate and predict the crop production effectively, as the predicted estimation shows resemblance to national crop statistics with reasonable statistical accuracy. Nevertheless, the developed models do not consider the pest invasion. Furthermore, this model needs to be validated from ground-based observation in order to enhance its forecasting ability. Beyond this limitation, the present research findings can add important value to the country’s national food security issues.

**Author Contributions:** All authors contributed systematically to the research work presented in this paper. B.M.R.F. comprehensively processed satellite data, described research findings, and wrote the manuscript. H.R. conceptualized the research theme and provided instruction in all the process of completing the article. N.H.S., N.S., M.I.I., S.M.A.H. and T.A. explore the study outcome and positively modified the manuscript at all stages of preparing the article. All authors have read and agreed to the published version of the manuscript.

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**Conflicts of Interest:** The authors declare no conflict of interest.

#### Appendix A

**Table A1.** Satellite remote sensing based monthly scale regression models for Aman crop production (2011–2017).

Input Variables	Month	Day	Year	Satellite-Based Aman Crop Production Model		R <sup>2</sup> : Determination Coefficient
MODIS NDVI (MOD13Q1) Versus Ground-based Estimated Production of 2011	Sep	30	2011	$y = 0.2517$	$x = (-23,193)$	0.74
	Oct	16	2011	$y = 0.2598$	$x = (-18,833)$	0.72
	Nov	1	2011	$y = 0.2911$	$x = (-24,592)$	0.69
	Nov	17	2011	$y = 0.3142$	$x = (-10,619)$	0.55
MODIS NDVI (MOD13Q1) Versus Ground-based Estimated Production of 2012	Sep	29	2012	$y = 0.2596$	$x = (-21,026)$	0.78
	Oct	15	2012	$y = 0.2605$	$x = (-29,779)$	0.76
	Oct	31	2012	$y = 0.2776$	$x = (-24,748)$	0.74
	Nov	16	2012	$y = 0.3118$	$x = (-19,556)$	0.62
MODIS NDVI (MOD13Q1) Versus Ground-based Estimated Production of 2013	Sep	30	2013	$y = 0.2431$	$x = (-28,042)$	0.74
	Oct	16	2013	$y = 0.2511$	$x = (-32,388)$	0.74
	Nov	1	2013	$y = 0.3003$	$x = (-31,778)$	0.73
	Nov	17	2013	$y = 0.3318$	$x = (-23,808)$	0.63
MODIS NDVI (MOD13Q1) Versus Ground-based Estimated Production of 2014	Sep	30	2014	$y = 0.2657$	$x = (-38,250)$	0.74
	Oct	16	2014	$y = 0.2757$	$x = (-41,011)$	0.75
	Oct	31	2014	$y = 0.298$	$x = (-35,704)$	0.68
	Nov	17	2014	$y = 0.3439$	$x = (-14,072)$	0.54

Table A1. Cont.

Input Variables	Month	Day	Year	Satellite-Based Aman Crop Production Model		R <sup>2</sup> : Determination Coefficient
MODIS NDVI (MOD13Q1) Versus Ground-based Estimated Production 2015	Sep	30	2015	y = 0.2622	x = (-34,210)	0.65
	Oct	16	2015	y = 0.1754	x = (-26,854)	0.64
	Nov	1	2015	y = 0.3107	x = (-35,090)	0.68
	Nov	17	2015	y = 0.3157	x = (-16,129)	0.54
MODIS NDVI (MOD13Q1) Versus Ground-based Estimated Production of 2016	Sep	29	2016	y = 0.2562	x = (-11,222)	0.70
	Oct	16	2016	y = 0.2602	x = (-29,813)	0.74
	Oct	31	2016	y = 0.2601	x = (-29,783)	0.74
	Nov	17	2016	y = 0.3352	x = (-20,508)	0.55
MODIS NDVI (MOD13Q1) Versus Ground-based Estimated Production of 2017	Sep	30	2017	y = 0.2558	x = (-8147.3)	0.69
	Oct	16	2017	y = 0.2716	x = (-33,632)	0.72
	Nov	1	2017	y = 0.2878	x = (-31,295)	0.68
	Nov	17	2017	y = 0.3209	x = (-20,336)	0.62

Table A2. Comparative statistical analysis of RS Model and BBS estimated Aman production (2011–2017).

Year	Aman Rice Production (M.Ton)		R <sup>2</sup>	MBE (M.Ton)	RMSE (M.Ton)	ME
	RS Model Estimated	BBS Estimated				
2011	12,029,108	12,660,663	0.72	-10,353	1374	0.90
2012	12,663,105	12,661,584	0.76	24	5067	0.92
2013	13,473,504	12,760,304	0.74	11,691	4831	0.92
2014	12,729,610	12,895,079	0.75	-2712	2191	0.91
2015	12,442,664	13,060,239	0.75	-10,124	842	0.90
2016	13,372,820	13,352,668	0.94	330	2818	0.91
2017	13,125,570	13,528,734	0.72	-6609	4449	0.90

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