The Dhaka University Journal of Earth and Environmental Sciences, Vol. 8, 2019

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Relationship between *Boro* Rice Production and MODIS Derived NDVI for Rice Production Forecasting: A Case Study on Bangladesh

Manuscript Received: 15 May 2019
Accepted: 1 November 2019

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Abstract: *The present investigation illustrates an inclusive approach to extract remotely sensed Normalized Difference Vegetation Index (NDVI) from Moderate Resolution Imaging Spectroradiometer (MODIS) (AQUA/TERRA) imageries to find out a relationship with Boro rice production for forecasting crop production in the context of Bangladesh. This study utilizes AQUA/TERRA MODIS reflectance data (250 m resolution) for the month of March (Peak-greenness period) to calculate the average NDVI values by following MODIS based algorithm at district level during 2011-2016. The linear regression analysis of calculated average NDVI and BBS estimated Boro rice production statistics reveals a significant positive relationship due to maximize photosynthetic activities. Among the regression equations from (2011-2016), the highest regression coefficients $R^2=0.87$ and $R^2=0.85$ for AQUA and TERRA MODIS data have been found respectively in 2015. Therefore this regression equation can be used for future estimation of Boro rice production at country scale. However, further testing and simulation of this regression model is required to generate Boro rice production forecasting dataset on timely basis. Hence this study summarizes that, NDVI based regression equation may be an effective process to forecast the Boro rice production which can play an important role in decision-making process relevant to the food security issues of Bangladesh.*

Keywords: *Boro Rice, MODIS (AQUA/ TERRA), NDVI, Rice Production Forecasting, Food security*

Introduction

Bangladesh is one of the major rice producing countries in the world with an average annual production of 40 million tons and is the most significant provider of national development (BBS, 2016). Among the three rice producing-seasons of Bangladesh, *Boro* rice is grown over the dry season which generally lasts from December/January to April/May (Rashid, 1991). In respect of volume of production, the *Boro* rice is the most important and single largest crop in Bangladesh and has been obstinately contributing to higher rice production in last decades (BBS, 2016). Currently, the cropped areas of Bangladesh are single (29%), double (52%) and triple (19%) with an average cropping intensity of 191% (BBS, 2013).

However, the agriculture sector is already under pressure for increasing population and food demand, excessive urbanization, decreasing of agricultural land and depletion of water resource and most importantly the changing pattern of climatic condition. Therefore, timely and accurate estimation and prediction of rice crop yield/production could allow more precise assessment of food production and better crop management strategies to provide solutions to the challenges of food sovereignty. In Bangladesh, the traditional methods of rice yield estimation and prediction usually depend on field sampling measurements that are costly and time-consuming (Son et al., 2016) and generally have large errors due to incomplete ground observations (Reynolds et al., 2000). Therefore, traditional methods based yield estimation and production statistics are usually available after several month of crop harvesting which creates dilemma for the decision makers to take appropriate action on the food security issues of country. On the other hand, satellite images can provide information on spatial variability and allow more efficiency in field reconnaissance (Schuler, 2002). Therefore, remote sensing can be used for crop growth monitoring, yield estimation (Mohd et al., 1994) and crop production because of its capability to provide spatial information of features and earth phenomena at a global scale on an almost real-time basis.

The crop yield estimation studies are generally established on empirical regression methods that relate crop yield to remotely sensed data, such as Leaf Area Index (LAI) and Normalized Difference Vegetation Index (NDVI) (Son et al., 2016; Bala and Islam, 2009; Inoue et al., 2002; Mkhabela et al., 2011). Studies using vegetation indices derived from coarse satellite sensors (e.g. MODIS and AVHRR) have proved to be successful for crop yield/production estimation during the leaf constant cropping period (Salazar et al., 2007; Bala and Islam, 2009) due to high plant growth and biomass during this period (Le-Toan et al., 1997). However, remote sensing data has the potentiality and capacity to be used extensively as a tool to assess and monitor vegetation parameters, yield estimation, and crop production. Many studies notably Groten (1993), Rasmussen (1997), Gat et al.(2000), Liu and Kogan (2002) have found relationship between the NDVI calculated from remote sensing images and the green biomass, land surface temperature (Faisal et al., 2017) as well as yield (Nuarsa et al., 2012). Earlier in the context of world, several research works have been done to find out the relationship between satellite-based NDVI with ground-based crop statistics for forecasting of rice yield and production (Huang et al., 2013). However, Mosleh and Hassan (2014) have found good resemblance between forecasted (i.e., MODIS-based NDVI) and ground-based *Boro* and *Aman* rice yield i.e., R^2 (0.76 and 0.86) over Bangladesh. Nevertheless, the study on the relationship between remotely sensed data and crop production of *Boro* rice is yet to be conducted at country scale for Bangladesh.

In view of above, the objective of this research are to a) develop a methodological framework to derive the satellite based rice crop information, and b) to find relationship between the satellite images derived Normalized Difference Vegetation Index (NDVI) and ground-based (BBS estimated) *Boro* rice crop production at country scale for rice production forecasting to improve the food security information of Bangladesh.

Materials and Methods

Geographical Context of the Study

The study area was bounded between 20°34′and 26°38′ North latitude and 88°01′ and 92°41′ East longitude and the territory is situated on one of the largest as well as complex deltas in the world where the Ganges, Brahmaputra, and Meghna rivers enter the Bay of Bengal. The climate of Bangladesh is sub-tropical warm, wet and humid and experiences natural disasters frequently such as excessive rainfall (floods), droughts and tropical cyclones; which creates a negative impact on agricultural yield and production. Bangladesh has three seasons: a hot or summer (March to June), a warm and humid monsoon (June to September) and a cold and dry (October to February) (Ahmed, 2006). The annual average rainfall varies from 1,500 mm to 5,000 mm; temperature and humidity ranges from 12-30 °C and 65-90% (Rahman et al., 2006), respectively. In recent years, the weather pattern has become erratic as the cool and dry season have been noticeably decreased which is probably attributable to the climate change (World Bank, 2011).

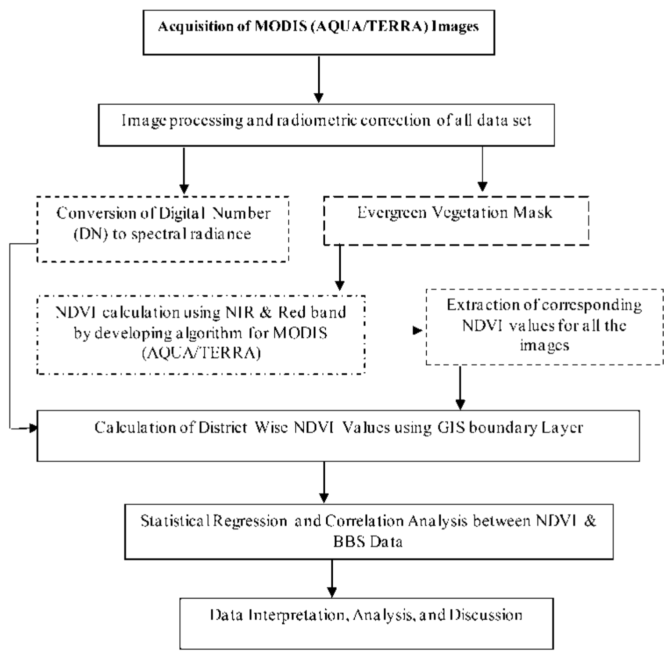


Figure 1: Schematic Showing Remote Sensing Based Crop Information Extraction Process

Geospatial Data Selections

The satellite images of MODIS (AQUA/TERRA) have been selected for this study over the period of (2011-2016) at the month of March (peak greenness period) as it is the *Boro* cropping seasons in Bangladesh. These imageries have been selected as it provides daily global imagery at spatial resolutions of 250-m (red and NIR1) and 500-m (blue, green, NIR2, SWIR1, SWIR2) and has improved atmospheric correction (Vermote and Vermeulen, 1999). These MODIS (AQUA and TERRA) imageries have been downloaded and processed by following the standard procedure in

ERDAS Imagine software (ERDAS, 2017). Therefore, NDVI has been calculated for the stipulated time period by following specific Equation-1. On the other hand, the country scale ground-based *Boro* rice production statistics from (2011-2016) have been collected from Bangladesh Bureau of Statistics (BBS) published documents.

Normalized Difference Vegetation Index (NDVI)

The NDVI index is widely used for environmental monitoring because it relates well with vegetation biomass; leaf area index and crop yield (Kogan et al., 2012). The NDVI is a dimensionless ratio between surface reflectance from the near-infrared and red bands of the spectrum as follows in Equation-1 (Xiangming et al., 2006; Ali and Mohammed, 2013).

$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \quad \text{..........} \quad (1)$$

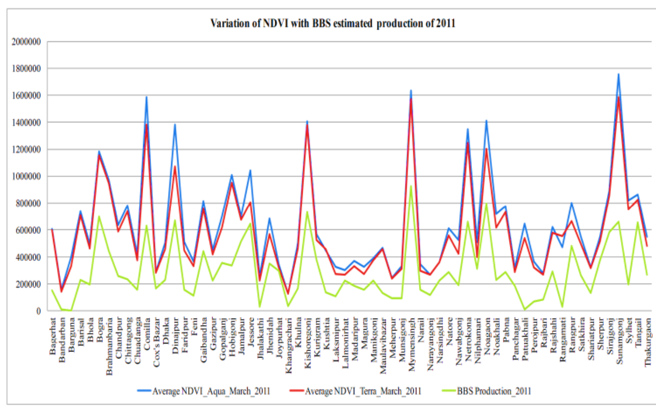
Because of the high reflectance of infrared light and a relatively low reflectance of red light the healthy plants shows high NDVI value. According to Bala and Islam (2009), the areas of consistently healthy and vigorous crop appear uniformly bright whereas the stressed vegetation appears dark amongst the brighter and healthier crop areas. In order to minimize the influence of non-agricultural land cover types, a country scale vegetation mask layer has been applied to calculate NDVI values at district level. Therefore, necessary statistical analysis has been performed for data interpretation and discussion. A schematic in Figure 1 illustrates the district wise average NDVI calculation process from MODIS imageries with complete study design.

Results and Discussion

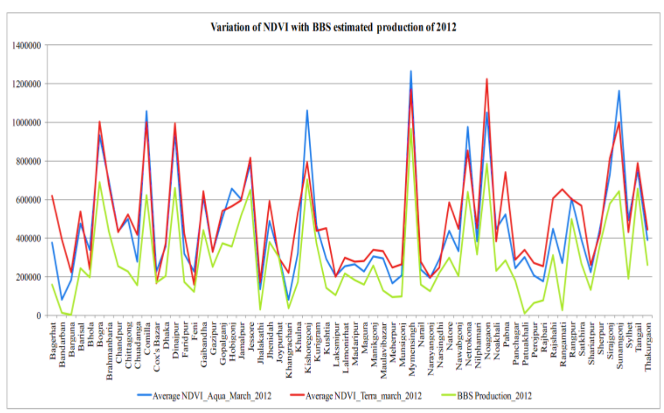
This following section presents the relationship between MODIS (TERRA/AQUA) satellite-derived NDVI and ground-based (BBS) estimated *boro* rice production from (2011-2016).

Variations of NDVI with ground-based (BBS estimated) production

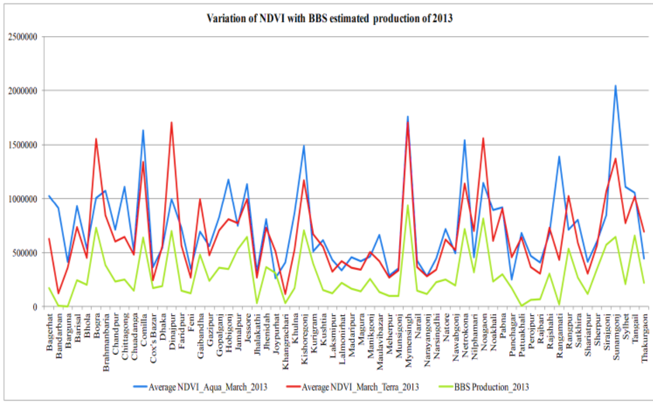
The average NDVI indices have been computed at country scale over the period (2011-2016) from MODIS (TERRA/AQUA) images. The average NDVI values have been calculated at district level. The average NDVI of March in respective years have been considered to find out relationship as this is the peak of the rice-growing season. The average NDVI of March for AQUA and TERRA MODIS imageries in respective years are frequently changing and the variations are noticeable with respect to the estimated BBS statistics. The changing pattern of NDVI values tells that, with the changes of average NDVI for respective years, the production of *Boro* rice also varies in most of the cases (Figure 2-a, b, c, d, e and f). According to Tucker (1979), the NDVI values may have an impact on the production of rice as NDVI divides the difference between reflectance values in the visible red and near-infrared wave lengths by overall reflectance in those wavelengths to give an estimate of green vegetation abundance. However, the extensive use of NDVI values over the world for measuring the vegetation cover characteristics, crop assessment studies and monitoring of crops and vegetation changes have been reported by Bausch (1993) and Wanjura and Hatfield (1987). Therefore, it can be said that the MODIS (AQUA/TERRA) derived average NDVI may have a strong relationship with the production of *Boro* rice crops and can be an effective tool for crop condition monitoring and estimation of production.



(a)



(b)



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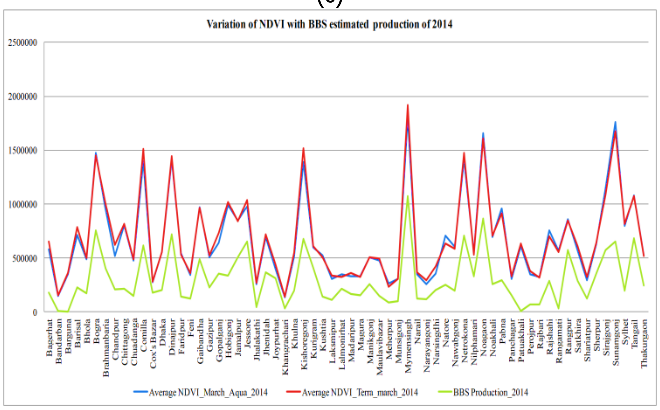

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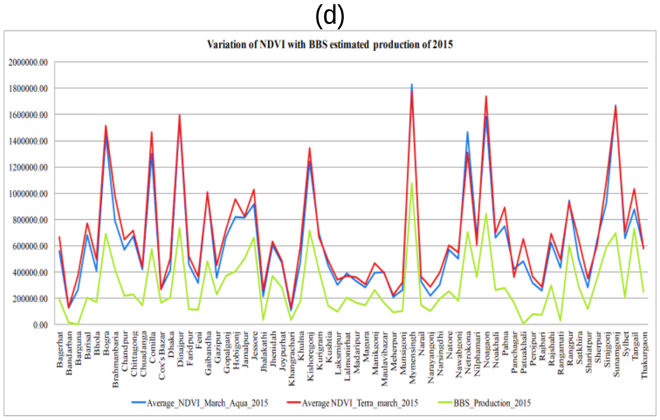
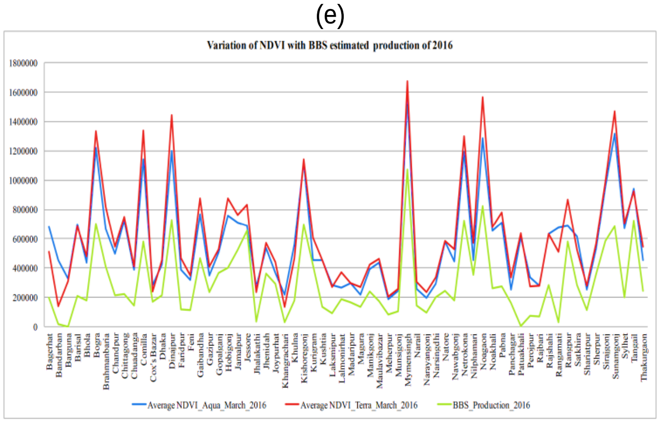


(e)



(f)

Figure 2: Variations of NDVI with BBS Estimated Production of a) 2011; b) 2012; c) 2013; d) 2014; e) 2015 and f) 2016

Correlation between NDVI and B*oro* Rice Estimated Production Statistics

In order to find the correlation, scatter plots have been drawn between BBS estimated *Boro* rice production and average NDVI for the month of March at respective years. Relevant articles summarize that, the peak greenness period (March) is generally related to the *Boro* crop production (Becker-Reshef et al., 2010; Rojas, 2007). The scatter plots have been presented in Figure 3 to Figure 8. The scatter plots show the strong positive relationship and have been presented with correlation coefficient value individually. In 2011, the correlation coefficient R^2=0.78 and R^2=0.77 have been found for the AQUA MODIS and TERRA MODIS, respectively (Figure 3). A fair significant correlation coefficient R^2=0.85 and R^2=0.77 have also been found in 2012 for AQUA MODIS and TERRA MODIS, respectively (Figure 4). Nevertheless, in 2013, the regression coefficient of R^2=0.46 was not significant for AQUA MODIS derived NDVI but found highly significant for TERRA MODIS (Figure 5). These may happen due to the unavailability of the cloud-free image in the respective time. The positive significant regression coefficients of R^2=0.83 and R^2=0.84 in 2014 and R^2=0.77 and R^2=0.84 in 2016 have found for the AQUA and TERRA MODIS data respectively, which tells that they are strongly correlated between them (Figure 6 and Figure 8). Among all the year from 2011 to 2016, the highest significant positive relationships with a coefficient determination of R^2=0.87 and R^2=0.85 have been found in 2015 for AQUA and TERRA MODIS data, respectively (Figure 7). In this study, the NDVI values have been derived without considering the angular effects and atmospheric corrections of the satellite imageries. However, the results show a good agreement between the NDVI and ground based BBS estimated crop statistics at the country scale.

Based on the highest regression coefficient, a model can be established to estimate the *Boro* rice crop production as the potentiality of regression models to estimate crop yield more accurately under variable management conditions have been clearly mentioned previously. Moreover, the studies of Haig (2003) and Murthy et al. (1994) reported the validity of crop yield models with satellite-derived NDVI but clouds, atmospheric perturbations, and variable illumination and viewing geometry can contaminate the signals and may reduce the NDVI values. Therefore, the present correlation regression analysis reveals that, *Boro* rice production and the satellite image (AQUA/TERRA

MODIS) derive NDVI values have significant positive relationship which may mean that increase in NDVI values during the peak greenness period is generally related to the *Boro* crop production.

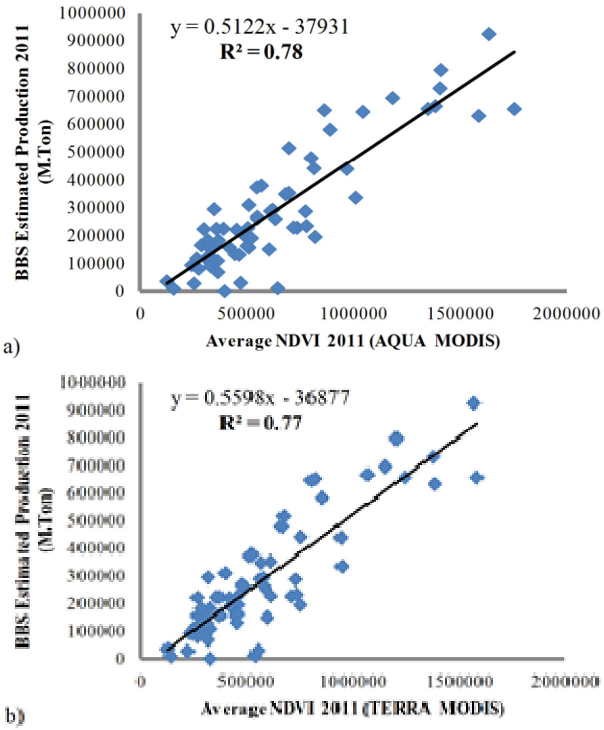


Figure 3 (a-b): Relationship between Average NDVI and BBS Estimated Production in 2011

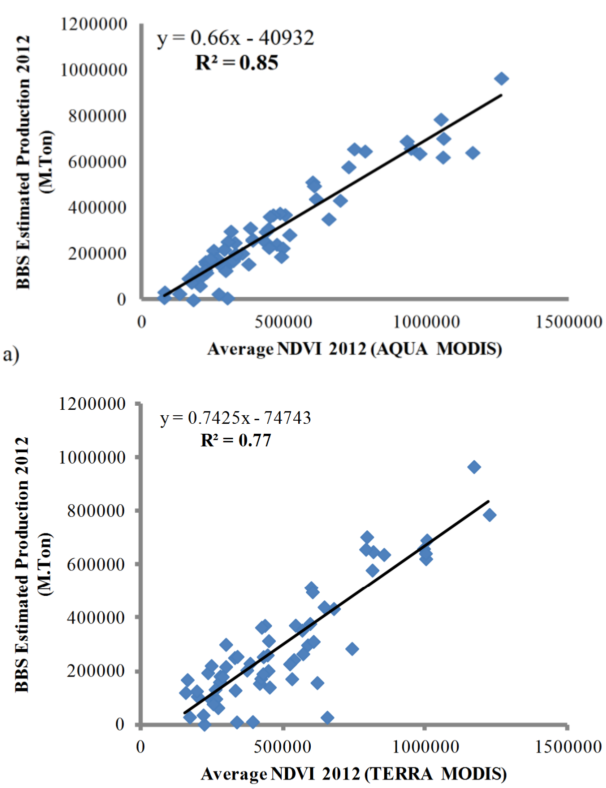


Figure 4 (a-b): Relationship between Average NDVI and BBS Estimated Production in 2012

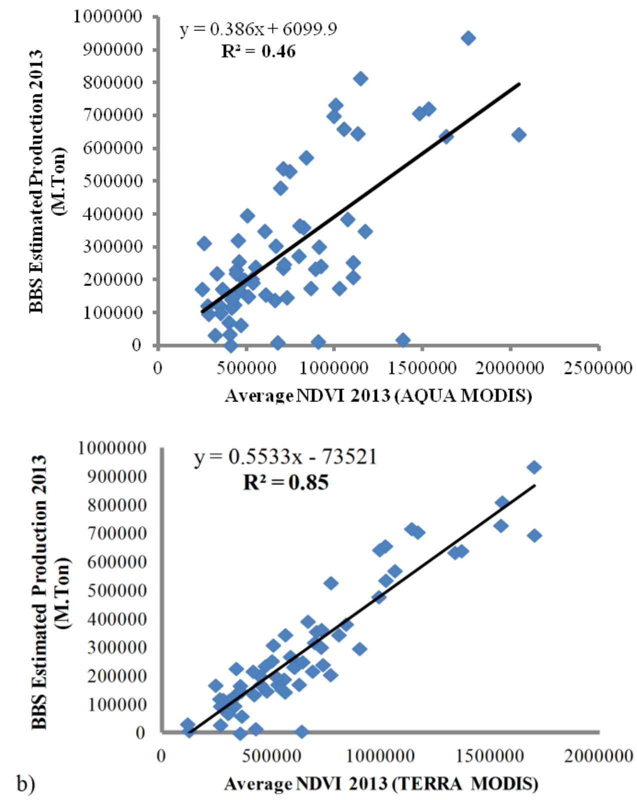


Figure 5 (a-b): Relationship between Average NDVI and BBS Estimated Production in 2013

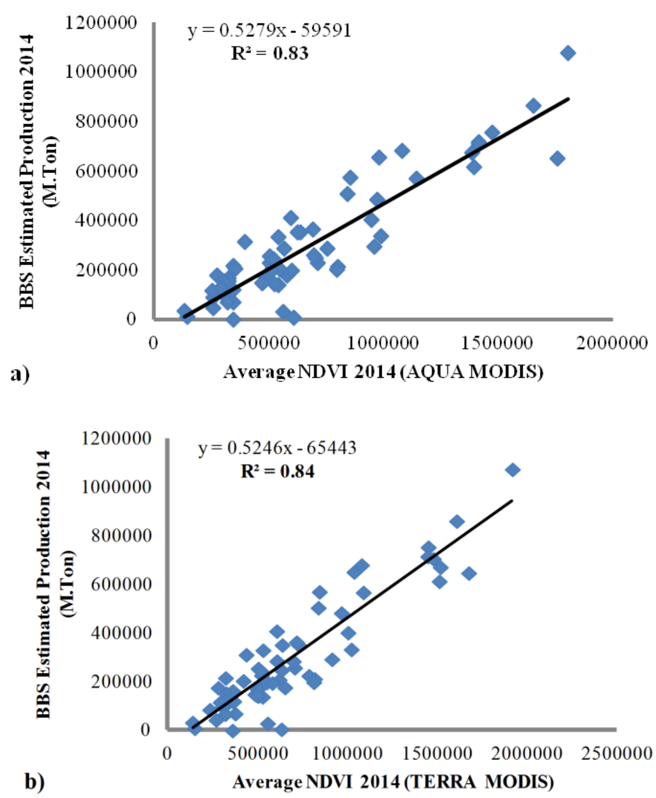


Figure 6 (a-b): Relationship between Average NDVI and BBS Estimated Production in 2014

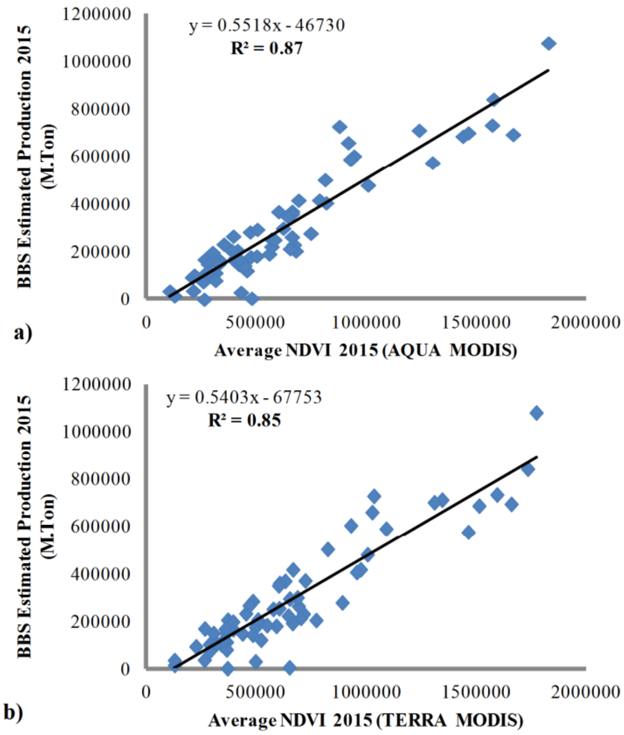


Figure 7 (a-b): Relationship between Average NDVI and BBS Estimated Production in 2015

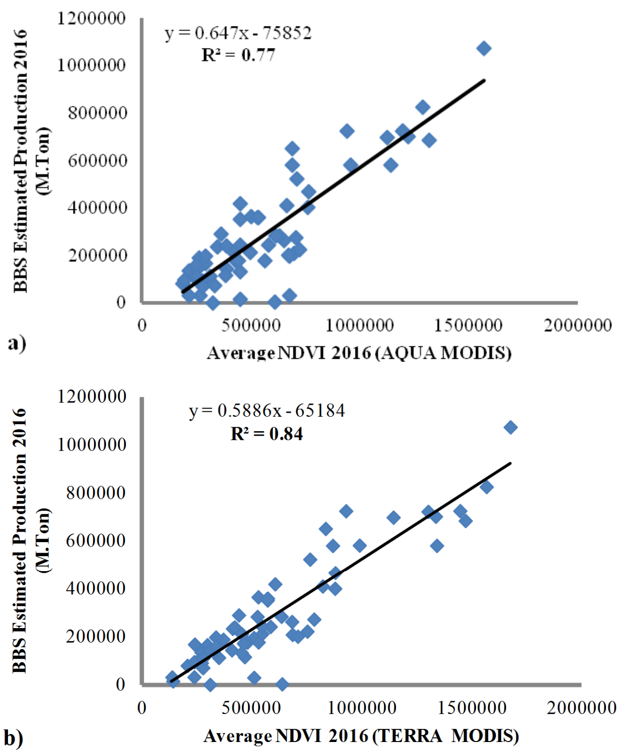


Figure 8 (a-b): Relationship between Average NDVI and BBS Estimated Production in 2016

Discussion

The regression coefficients for AQUA and TERRA MODIS data have been changing positively over the years (2011-2016). The correlation coefficient values for AQUA and TERRA MODIS data from 2011-2016 have been plotted in Figure 9 to show its variation during peak-greenness period. The correlation value varies from 0.46-0.87 and the highest values of 0.87 and 0.85 have been found in 2015. The regression coefficient value for TERRA MODIS in 2013 may become low due to the presence of cloud or noise in the acquired image. Nevertheless, the regression analysis and variation pattern of regression coefficient indicates that the strong relationship exists between the satellite image derive NDVI and *Boro* rice crop production. These findings have been supported by study of Nessa (2004), who used NDVI for monitoring rice growth and its production in Bangladesh with NOAA satellite data. Furthermore, simple linear regression models based on spectral index are often used to predict crop yield before harvest as the spectral indices have significant correlation with crop biomass (Ren et al., 2008, Labus et al., 2002).

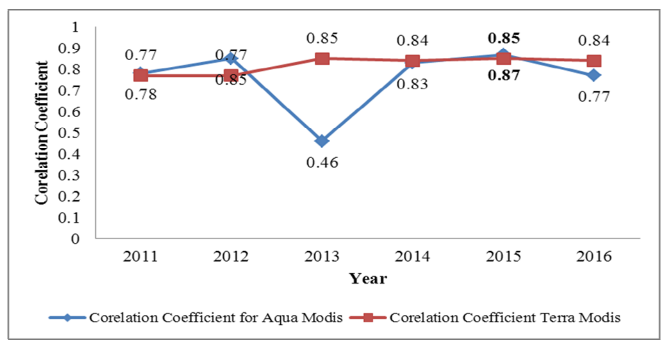


Figure 9: Yearly Scale Correlation Coefficient of *Boro* Rice (2011-2016)

Therefore, the regression equation of 2015 for AQUA MODIS (Equation 2) and TERRA MODIS (Equation 3) can be used for future estimation of the *Boro* crop production as this has shown the highest positive regression coefficient over the years 2011-2016. However, the present regression model mentioned in Equation-2 and Equation-3 requires simulation and extensive validation for ultimate forecasting of the *Boro* rice production statistics at country scale.

$$\text{(AQUA MODIS) Boro Crop Production } (Y)_{(M.Ton)} = 0.5518\times\sigma - 46730 \quad (2)$$

$$\text{(TERRA MODIS) Boro Crop Production } (Y)_{(M.Ton)} = 0.5403\times\sigma - 67753 \quad (3)$$

Where, the dependent variable *Boro* Crop Production (Y) has been expressed in absolute values (m. tons) for each district, 0.5518 and 46730; 0.5403 and 67753 are the coefficient, and σ is the average NDVI values for each district.

Conclusion

This research work focuses on the development of MODIS-NDVI based effective methods to estimate *Boro* rice production from remote sensing based regression equation. This study concludes that, significant positive relationship exists between the MODIS derived NDVI and *Boro* rice production. Hence, (TERRA/AQUA) MODIS-NDVI based regression models can be used to estimate the *Boro* rice production at the country scale. Hereafter, the crop production can be estimated earlier than official crop statistics which can play a vital role in the food security issues of Bangladesh. Though the regression equation needs to be simulated and validated prior to use it for crop forecasting purpose. However, more studies are required on times series analysis of MODIS-NDVI and ground-based estimated statistics based regression model to test its suitability and crop production forecasting capacity.

Acknowledgements: The authors are grateful to the NASA for MODIS imageries and BBS for ground based district wise crop production statistics. SPARRSO is also gratefully acknowledged for technical support to complete the study.

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