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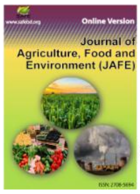

Original Article

Integrated Use of Remote Sensing and Climate Parameters to Explore Boro Rice (*Oryza sativa* L.) Cultivation Area and Driver of Expansion in Tangail Sadar Upazila

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A B S T R A C T

Crop area estimation and identification of drivers for land-use change are crucial for efficient crop management and decision-making in agriculture. Remote Sensing techniques are now being used to estimate crop area and production monitoring globally, including developing countries. In Bangladesh, rice area estimation has traditionally been done through location-based field visits or eye-estimation, which is tedious and time-consuming. The present study uses Remote Sensing (RS) and climate parameters to explore the cultivation area and driver of boro area expansion in Tangail Sadar Upazila. Multi-spectral Landsat imageries were obtained from 1999 to 2020 at the maximum growth stages of boro rice. Upazila's boundary was clipped over the images using a shape file created from Bangladesh map. The images were analyzed with QGIS, ArcGIS, and R software through the Random Forest (RF) supervised classification. Standardized Precipitation Evapotranspiration Index (SPEI) was calculated using monthly total rainfall; minimum and maximum temperature to observe drought impacts. The findings revealed that the boro rice cultivation gradually increased from 8104 ha (in 1999) to 12781 ha (in 2020). In 2009-20, the expansion rate (3.10 percent) of boro rice areas was much lower (11.49 percent) than in 1999-2009. It was due to relatively stable boro cultivation in the recent decade. The Overall accuracy was 93-96 percent with the kappa coefficient of 0.90-0.93. The study showed that there was a good relationship between satellite and traditionally estimated boro rice area. The expansion of boro rice areas has been driven mainly by the positive impacts of climate change. Long-term hydrological drought and a shorter wet spell have introduced boro rice cultivation to the lowlands and river basin areas. According to the benefit cost ration (BCR), growing mustard and boro rice in the same season was more profitable than growing any sole crop. The study revealed that remote sensing was effective for exploring boro rice cultivation area and driver of expansion.

Introduction

Human civilization developed with the development of agriculture which fulfils all basic needs, including food security. Among the seventeen Sustainable Development Goals (SDG), SDG-1 (no poverty), SDG-2 (zero hunger), SDG-12 (responsible consumption and production), SDG-13 (climate action), and SDG-15 (life on land) are directly related to agriculture (Ladha *et al.*, 2020). In contrast, others might be attained indirectly using agriculture. The role of the rice crop, in this case, is remarkable. Rice *(Oryza sativa* L.*)* belongs to the family Poaceae. It is the staple food for more than half of the world population, including many Asian countries (Mainuddin, 2021 and World Population Review, 2021). The demand and production of rice have been increasing gradually due to the ever-increasing population (Bhandari, 2019 and Titumir, 2021). Globally, rice paddy production was 746.55 million tonnes (Mt), with the third-highest position. China (220.05 Mt) and India (178.35 Mt) account for more than 50 percent of world rice production. Bangladesh ranked third (53.78 Mt) in rice paddy production globally (Statista, 2021 and Shahbandeh, 2021). Rice occupied the first position of the cereal crops produced in Bangladesh, where only boro rice contributed 54 % of 48.83 lakh hectares of land (BBS, 2020). Bangladesh's rice cultivation areas cover almost 75 % of cropped area and 97.26 % of the total food crop production (FPMU, 2021). Though rice paddy production in Bangladesh has become more than double in the last two decades, such a good increase in production sometimes cannot meet the demand (53.70 Mt)) of the country (Childs, 2021 and USDA, 2020). There are occasional crises with a shortage of rice, including the high market price. The crisis in our country is mainly due to the lack of real-time information on cultivation, storage, and impacts of climate drivers (Patchett L, 2019 and Islam Z., 2020). Traditionally, location-based field visits or eye-estimation methods are followed to predict rice area and production (Noureldin *et al.*, 2013).Thus, the perfect estimation and forecasting of the total rice production before harvesting is not available to policymakers for importing decisions. Because of these information limitations on rice cultivation and production, unscrupulous traders create a substantial artificial crisis in the market by stockpiling. So there is no substitute for improved monitoring techniques and effective management to solve the above problems (Asif, 2021; Irani, 2019; Zahid, 2020; Nabi & Mahmud, 2019, and Jahid, 2021).

According to recent reports, precision remote sensing might play an essential role in cultivation area monitoring (Abdullah *et al.*, 2019). The techniques may also alleviate the difficulties linked to rice production by giving real-time information on cultivating areas. Although remote sensing monitors agricultural data worldwide, it is still relatively new and limited in Bangladesh. As a result, Bangladeshi researchers need to do more in-depth studies in this area.

In the past, Bangladesh has used remote sensing, particularly MODIS NDVI, to estimate and predict crop area for a few essential crops such as aman rice and potato (Salam, 2014; Mosleh *et al.*, 2016 and Kalpoma *et al.*, 2019). Previous research on those crops indicated that accurate area assessment and forecast before harvesting are crucial for food security, long-term crop productivity, and farmer profitability (Faisal *et al.*, 2020 and Kalpoma *et al.*, 2020). As a result, comparative research on other vital crops, such as boro rice, should be done ahead of time to address any possible issues.

The first attempt was undertaken in Bangladesh using multi-decadal Landsat imagery and climatic parameters to estimate the boro rice area, to detect land use land cover (LULC) change, and to identify the climatic drivers influencing boro rice area expansion in the study location.

Materials and Methods

Study area

Tangail Sadar Upazila was selected as the study area, considering the suitability of boro rice production (Figure 1). The Upazila was located in between 24°10' and 24°22' north latitudes and in between 88°46' and 89°59' east longitudes. The total area of Upazila was 33426 ha. It was characterized by a low-lying floodplain near the *Jamuna, Dhaleshwari*, and *Lohajang* rivers. The average maximum temperature of the study site was 33.9 °C and the minimum was 11.4 °C. The annual average total rainfall was 2006.4 mm. The average elevation was 14 meters (49 feet) from sea level. The study area experiences a tropical savanna climate with a hot, humid tropical wet season (monsoon season) and warm, dry winter with high humid conditions year-round. Characteristically, the area's soil was sandy loam to loam due to the flood plain of the rivers, as mentioned above (BMD, 2020 and BBS, 2020).

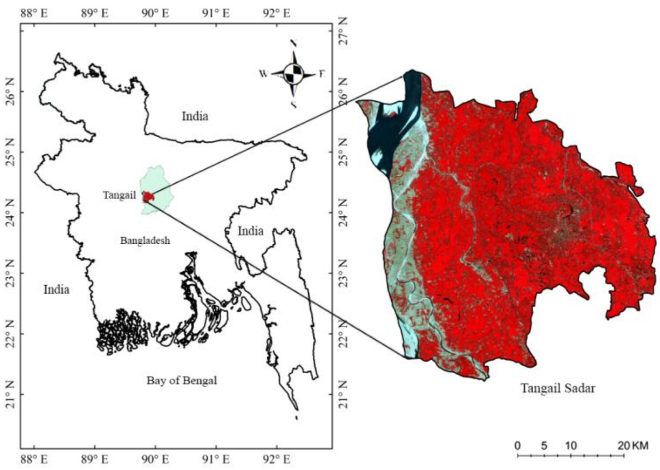

Figure 1. Map showing Tangail Sadar Upazila and the location in Bangladesh.

Crop selection

Generally, aman, aus, and boro rice crops were cultivated throughout the year. Mustard-Boro-Fallow-Fallow was the main cropping pattern in the study area. Boro rice was mainly cultivated in the winter season (February to June); however, it was transplanted after mustard harvesting in most areas. Since there were no clouds in the sky in winter, it was possible to get clear satellite images. Boro rice was the major crop grown in a large area at the time. That helped to get pure pixels in the case of proper satellite image classification. Boro rice also played a significant role in ensuring the country's food security (Nasim *et al.*, 2017). In view of the above, boro rice was selected for the present study.

Data collection and analysis

GPS data

From the boro rice field of the Tangail Sadar Upazila, the coordinates of the Global Positioning System (GPS) were recorded during April 2020. GPS is a constellation of more than 30 navigation satellites that orbit the earth. It is a US-based service that delivers positioning, navigation, and timing (PNT) services. A handheld GPS receiver, Google map, and GPS tracker mobile app were used to obtain the GPS coordinates. During the compilation of training data for satellite image classification, accuracy evaluation, and validation, these data were used to pinpoint the boro rice fields.

Climate parameters

Climate parameters such as daily total rainfall (mm), daily minimum, and daily maximum temperature (°C) were obtained from Bangladesh Meteorological Department (BMD). Daily climatic data were used to compute monthly total rainfall; monthly average, minimum, and maximum temperatures. The drought index, also known as the standardized precipitation evapotranspiration index (SPEI), was calculated using the following formula

SPEI<- spei * n (CWBAL, n).

Here, n = lag number, CWBAL<- (PRCP-PET),
PET<- hargreaves (TMIN, TMAX, lat=24.25)

These were then utilized to support or validate the findings of the study. The SPEI considers both precipitation and potential evapotranspiration (PET) (Katipoglu *et al*., 2020). The SPEI meets the criteria for a drought index because of its multi-scalar nature, which allows it to be utilized by various scientific fields to detect, monitor, and study droughts (Miah *et al*., 2017 and Abdullah, 2014).

Multi-spectral satellite imagery acquisition

Landsat satellite images were selected for this study due to long-term data availability. Time-series data were obtained from 1999 to 2020 when boro rice plants were at their maximum growth stage. Furthermore, there were cloud-free images available at the time. Attempts were made to take images at intervals of 5 years in the study, but it was impossible to take images at the same intervals as the cloud-free image was unavailable. The selected images were collected from the website of the United States Geological Survey (USGS). It should be mentioned that the dry season in Bangladesh is November-February, while the pre-monsoon season is March-May, and the rainy season is June-October. Table 1 lists the key characteristics of the imageries gathered.

Table 1. Main features of multi-spectral satellite imagery over Tangail Sadar Upazila.

Name of sensors	Path and Row number	Date of acquisition	Spatial resolution	Coordinate Reference System
Landsat 4-5 (TM)	138 and 043	28-03-1999	30 m	EPSG:32645
Landsat 4-5 (TM)	138 and 043	13-04-2005	30 m	EPSG:32645
Landsat 4-5 (TM)	138 and 043	24-04-2009	30 m	EPSG:32645
Landsat 8 (OLI)	138 and 043	24-03-2015	30 m	EPSG:32645
Landsat 8 (OLI)	138 and 043	06-04-2020	30 m	EPSG:32645

Satellite imagery processing

Atmospherically corrected surface reflectance (SR) imageries were required for long-term boro rice crop classification. The SR bands were obtained from the ESPA website for this purpose. The Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS), a specialized software initially developed by the National Aeronautics and Space Administration (NASA), was used to generate surface reflectance data for Landsat imageries. The software corrects the atmosphere using data from the Moderate Resolution Imaging Spectro-radiometer (MODIS), including water vapor, ozone, geo-potential height, aerosol optical thickness, and digital elevation. To generate top of atmospheric (ToA) reflectance, surface reflectance (SR), brightness temperature, and masks for clouds, cloud shadows, nearby clouds, land, and water, Landsat data were used in the second simulation of a satellite signal in the solar spectrum radiative transfer models. In addition, various vegetative indices (VIs) were gathered. To create multi-band images, the bands, including VIs, were blended using QGIS software. Tangail Sadar Upazila shapefile was served as a demarked study area border. Using QGIS software, multi-band pictures were clipped by the study area boundaries. The false-colored composite value was assigned to clipped images. RGB 4, 3, 2, and RGB 5, 4, 3 composites created false-color for Landsat 0-4 TM imagery and Landsat 8 OLI imagery, respectively. On false-colored images, objects showed distinct colors from which desirable classes may be identified. QGIS software was used to create accurate training inputs from composite images.

Image classification and area estimation

Following the generation of training input data with QGIS software, R Script was used to run selected images through the Random Forest (RF) algorithm. Random Forest is a well-known machine learning algorithm that uses the supervised learning method. Because of its simplicity and versatility are also among the most widely used algorithms (it can be used for both classification and regression tasks). The four classes used to categorize the images were the boro rice crop, other lands, vegetations, and water bodies. Other lands class included river char, fallow lands, built-up lands, homesteads, bricks fields, bare soil, etc. Non-boro rice crops, water hyacinth, trees, shrubs, grasses, green objects, and other greeneries were included in the vegetations class. The water class included river water, pond water, canal water, *beel* water, *boropit* water, lake water, etc. Reclassification of classified images was performed to re-assigning one or more values in a raster dataset to new output values. Reclassified images comprised pixel counts from which the cultivated area in hectares was calculated using ArcGIS software by the following equation.

$$Area\ (ha) = pixel\ number * 0.09$$

Here, Pixel size = 30 × 30 = 900 m^2 = 0.09 ha

Feature fields were added to each class after reclassification. Finally, the map was created and exported to be used elsewhere.

Spectral Reflectance Curve

From selected images, a spectral reflectance curve was created (Figure 4). QGIS software was used to generate training input data from false-colored composite imageries, and R software developed the signature curve using reflectance value. This curve illustrates the spectrum properties of various objects/ground features. The spectral curve suggests that accurate image classification is possible.

Crop statistical data collection and analysis

Time-series national statistical data on boro rice from 1999 to 2019 were gathered in the form of crop area (ha), yield (ton ha^{-1}), production (MT), production cost (Tk), and harvest time market price (Tk). The Bangladesh Bureau of Statistics (BBS), the Statistical Yearbook of Bangladesh (SYB), the Department of Agricultural Marketing (DAM), and the Yearbook of Agricultural Statistics (YAS) were used to compile the data. Crop data at the Upazila level was acquired from the office of Upazila Agriculture Officer under the Department of Agricultural Extension (DAE) in Tangail Sadar. Wheat, maize, potato, and mustard crop data were also collected for benefit-cost ratio (BCR) calculation. These results were validated and compared to remote sensing-estimated boro rice data and profitability estimates. The present value of the total revenue or benefit of the crops was divided by the present value of the total cost to determine the BCR. Because the data was gathered at various times, all collected values were converted to the current monetary value. The total revenue was calculated by multiplying the total production by the harvest time market price of the selected crop for that year. The overall production cost was calculated by multiplying the total area by the cost of production per hectare. The following formula was used for this.

$$FV = PV\ (1+r)^n$$

Here, PV = Present value is the value on a given payment date.
FV = This is the projected amount of money in the future
r = the periodic rate of return, interest, or the inflation rate
n = number of years.

Accuracy Assessment

Accuracy assessment is a vital task in the image classification process. It relates the classified image to ground truth data. It could be obtained from the field or attained from classifying high-resolution images or existing classified images. The general way to assess the accuracy of the classified image is to generate a set of random points from the ground truth data and relate it to the classified image in a confusion matrix. In this study, classification accuracy was assessed depending on the training sample. Training inputs were generated from satellite images using the GPS value of the boro rice field. Random points were obtained from the confusion matrix of the random forest (RF) model during image classification.

With those points user, overall and kappa accuracy were calculated. The accuracy of a map user, not the map developer, is measured by the user's accuracy. It refers to how accurate it is on the ground. Overall accuracy tells us what percentage of the reference sites are correctly mapped out of all of them. The kappa coefficient measures the agreement between classification and truth values. The Kappa Coefficient values remain between -1 and +1. The classification is not better than a random classification if the value is 0. The classification is much poorer than random if the number is negative (Abbas *et al.*, 2020). A close approximation to 1 suggests that the classification is much better than chance. The formulas for various accuracy assessments are given below:

$$\text{User's accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of classified pixels in that category}} \times 100$$

$$\text{Overall accuracy} = \frac{\text{Total number of correctly classified pixels}}{\text{Total number of referenced pixels}} \times 100$$

$$\text{Kappa Coefficient } (\acute{K}) = \frac{N \times \sum_{i=1}^{r} x_{i,i} - \sum_{i=1}^{r} (x_{i+} \times x_{+i})}{(N^2 - \sum_{i=1}^{r} (x_{i+} \times x_{+i}))}$$

Here,

N = Total number of classified values compared to truth values
i = The class number
$x_{i,i}$ = The number values found along the diagonal of the confusion matrix
x_{i+} = Total number of predicted values belonging to class i
x_{+i} = Total number of truth values belonging to class i

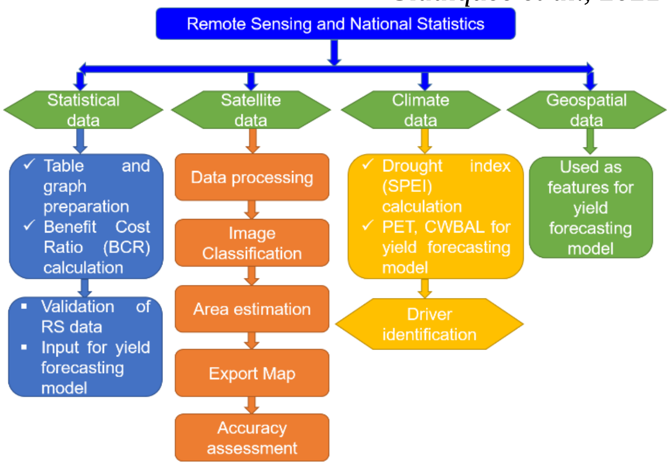

Figure 2. Overall process map of data collection and analysis of boro rice.

Results and Discussions

Identification and area estimation of boro rice

Classified map with identified land use land cover (LULC) classes have shown in Figure 3. Four land use land cover classes were boro rice, other lands, vegetations, and water bodies. In Figure 3, green indicates boro rice, yellow vegetations, light paste color other lands, and the deep blue water bodies. This research successfully identified the boro rice crop despite the challenges of assessing a single crop from satellite images. Zhang *et al.* (2019) described a few challenges of separating a single crop from satellite images: tropical cloud effects, mixed cropping, smallholder farmlands, etc. Although it was challenging to classify diverse crops cultivated in the fragmented fields in Bangladesh, boro rice has been proficiently separated using remote sensing techniques in this research study. This classification might be successful since cloud-free images were obtained since boro rice was cultivated during the winter. Another reason might be that, despite the small size of the rice fields, the boro areas were vast and continuous. As a result, pure pixels were obtained, the requirements for proper image classification. The results were supported by Su & Zhang (2021) and Roy *et al.* (2021).

The classification is also supported by the different spectral reflectance of land use land cover class features in the research area. The study area differed from the spectral reflectance of boro rice, other crops, trees, built-up, other lands, and water bodies (Figure 4). The findings of Sanchez *et al.* (2019) and Arias *et al.* (2020) supported these results. With spectral signature curves and satellite image processing, they were able to distinguish boro rice crops.

Based on classified imagery, the estimated area of land use land cover classes (LULC) has shown in Table 2. Table 2 shows that the highest boro rice areas were 12781 ha in 2020, followed by 12000 ha in 2015. While the lowest boro rice areas (8104 ha) were recorded in 1999, the second-lowest (10735 ha) was recorded in 2005. The highest area of other lands class (11066 ha) was observed in 1999, while the lowest (5222 ha) was found in 2020. According to the findings of this study, other lands gradually decreased with the increase in boro rice areas. Therefore, it is clear that other lands at one time came under vegetations and gradually converted into boro rice areas. It was possible due to the positive impacts of climate change and incorporating the boro rice in the existing cropping pattern of the study area.

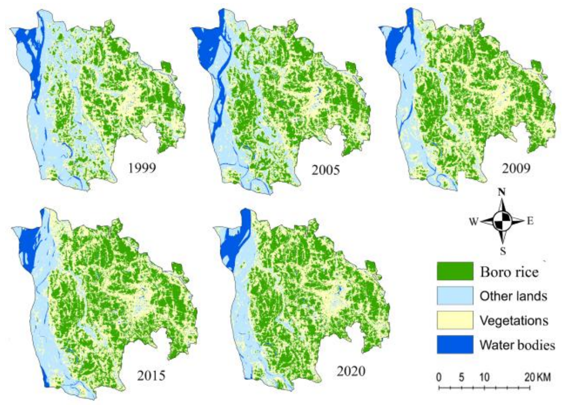

Figure 3. Classified map of Tangail Sadar showing LULC classes from 1999 to 2020.

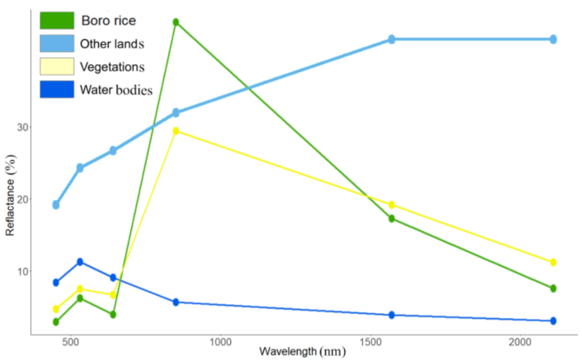

Figure 4. Spectral signature curve of Tangail Sadar showing the reflectance from LULC features in different spectral bands.

Table 2. Remote sensing estimated area of LULC classes in Tangail Sadar Upazila

Year	Area in hectares (%)				
	Boro rice	Vegetations	Other lands	Water bodies	Total
1999	8104 (25.30%)	11187 (34.92%)	11086 (34.54%)	1678 (5.24%)	32035
2005	10735 (33.51%)	11363 (35.47%)	7540 (23.54%)	2397 (7.48%)	32035
2009	11787 (36.79%)	12340 (38.52%)	6541 (20.42%)	1367 (4.27%)	32035
2015	12000 (37.46%)	12434 (38.81%)	6318 (19.72%)	1283 (4.00%)	32035
2020	12781 (39.89%)	12451 (38.86%)	5222 (16.30%)	1581 (4.94%)	32035

Image classification accuracy

A summary of the accuracy of Tangail Sadar Upazila has presented in Table 3. Table 3 shows the lowest user's accuracy (91%), overall accuracy (93%), and kappa coefficient (0.90) in 1999. In contrast, the highest user's accuracy (95%), overall accuracy (96%), and kappa coefficient (0.93) were observed in 2020. The study results revealed that large-scale homogenous boro rice areas were classified equally.

Table 3. Classification accuracy using RF confusion matrix of boro rice crop

Year	User's accuracy	Overall accuracy	Kappa coefficient
1999	91	93	0.90
2004	92	93	0.90
2009	93	94	0.91
2014	95	95	0.92
2019	95	96	0.93

Land use land cover (LULC) change detection

The masked boro rice class has shown in Figure 5 for better visualization. Figure 5 shows the limited boro rice-growing areas in 1999, which gradually increased up to 2020. Boro rice was mainly cultivated in the river flood plain and medium lands earlier. Later on, the adjacent area of the rivers and lowlands became suitable for cultivation due to prolonged drought spells.

Figure 6 depicts the transformation of LULC classes into one another. From 1999 to 2009, the most remarkable lands were converted to boro rice class from vegetations (3072 ha), followed by other lands (1579 ha). A small amount of boro rice was converted to vegetations (868 ha) and other lands (113), respectively. In contrast, the comparatively lower transformation happened from vegetations (2777 ha) to boro rice class in the decade 2009-2020, followed by other lands (310 ha) to boro rice class. During this decade, 1903 hectares were converted from boro rice to vegetations class. Mutual transformations were observed between boro rice and other classes, as shown in the Sankey diagram. Even though boro rice cultivation became widespread 15 years ago, stable or persistent boro rice fields became visible between 2009 and 2020. It shows that boro rice was becoming a common land use or farmer's preference.

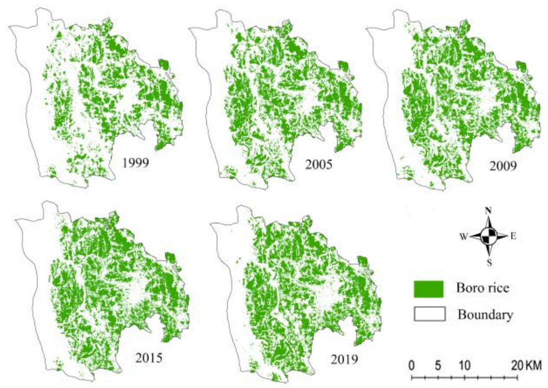

Figure 5. Map of Tangail Sadar showing the trend of boro cultivation from 1999 to 2019.

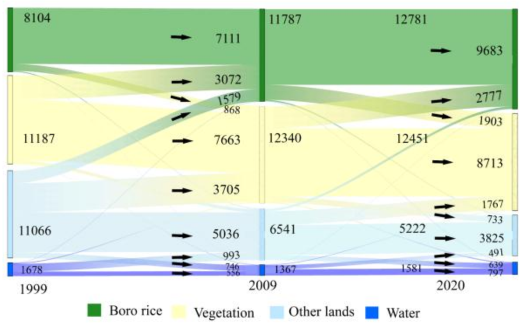

Figure 6. Sankey diagram showing the transformation of LULC classes of Tangail Sadar in two decades (1999 to 2020).

The rate of area expansion and shrinkage over the Thakurgaon Sadar is shown in Table 4. During the study period, the expansion rate of boro rice areas was found to be 14.59 %. But other lands and water bodies were shrunk at the rate of -18.24 % and -0.30 %, respectively. The highest rate of boro rice area expansion was observed at 11.49 % in 1999-2009. In 2009-20, the lowest rate of area expansion was found at 3.10 %. The study showed that boro rice areas were somehow stable or expanded slowly. Water bodies were marginally increased due to monsoon-induced wet spells at the end of the last decades, as seen in Table 4.

Table 4. Cultivation area changes under different classes from 1999 to 2020.

Land cover and land use classes	Area changes (%) in the decade 1999 to 2009	Area changes (%) in the decade 2009 to 2020	Area changes (%) within 20 years (1999 to 2020)
Boro rice	11.49	3.10	14.59
Vegetations	3.60	0.34	3.94
Other lands	-14.12	-4.12	-18.24
Water bodies	-0.97	0.67	-0.30

Comparison of remote sensing estimated area with traditional area

The study shows that the estimated boro rice area using remote sensing techniques was positively linked with the area estimated using traditional methods (Figure 7). In both remote sensing and traditionally estimated procedures, the boro rice cultivation areas were lowest in 1999, as shown in Figure 7. According to both estimation approaches, boro rice cultivation areas were increased gradually since 1999 and continued up to 2020. The R2 value of the regression was 0.96, indicating that the remote sensing and the traditionally estimated boro rice area were in good agreement.

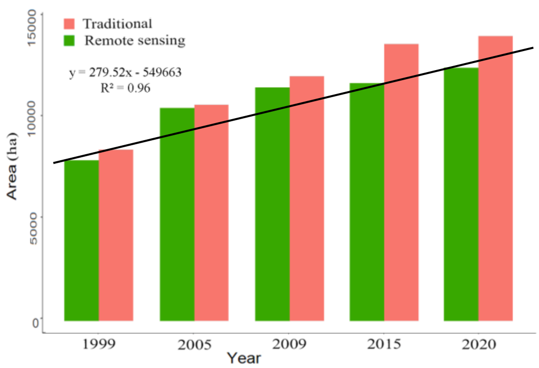

Figure 7. Bar graph showing the Boro rice area estimated by remote sensing and traditional techniques are well-matched.

Climatic drivers influencing the boro rice area expansion

Over 30 years, an analysis of climatic data revealed that rainfall decreased with increasing temperature in boro rice-growing areas. The drought index, or Standardized Precipitation Evapotranspiration Index, has been used to prove this point (SPEI). Figure 8 shows SPEI with a 12, 24, and 36-month lag from 1990 to 2019. Figure 8 shows that from 2007 to 2018, the hydrological wet spell became shorter and the dry spell became longer, affecting wetlands loss. Salimi et al. (2021) also found similar results for wetland shrinkage. As a result of the favorable impacts of climate change, fields that had water till the end of winter dried up 2-3 months ahead of time. Therefore, the lowland areas, particularly the *Khal*, *beel*, and river basin, dry-up earlier than in previous years. As a result, boro rice cultivation has been increasing and expanding to newly suitable areas.

Boro rice has been included in the study area's cropping pattern in the context of climate change. Due to the delay in drying water in low-lying areas, it was not possible to cultivate any crop other than boro rice. Mustard, wheat, maize, and onion could be cultivated after drying water in medium lowlands. However, if wheat and maize were cultivated, it was impossible to cultivate other crops or boro rice in those lands. But if mustard was cultivated, boro rice could be cultivated in those lands effortlessly. As a result, cultivating boro after mustard harvesting was more profitable (Table 5).Similar findings were observed by Haque et al. (2014) and Bapari et al. (2016). Additionally, the role of boro rice was more significant than that of all other crops in ensuring food security. For these reasons, farmers grew boro rice instead of onion, wheat, and other crops.

Table 5. The Benefit-Cost Ratio (BCR) value of major crops cultivated in the study site.

Year	Benefit-Cost Ratio			
	Boro rice	Mustard	Wheat	Onion
1999	0.744	1.043	0.599	1.601
2004	0.655	1.111	0.569	1.211
2009	0.639	1.669	0.5785	1.258
2014	0.717	1.999	0.983	1.577
2019	0.679	1.986	0.687	1.114

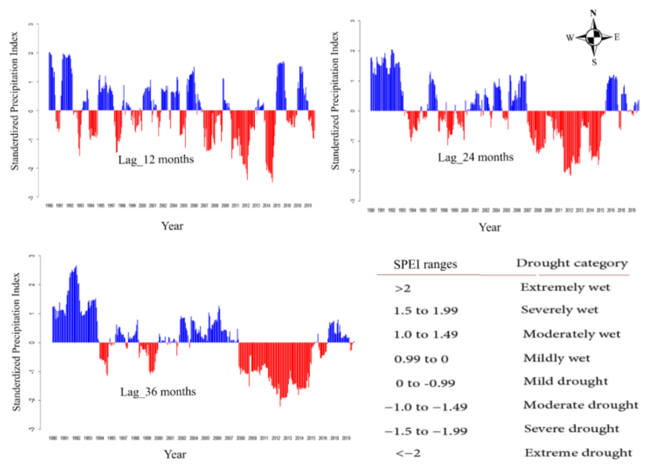

Figure 8. Standardized precipitation Evaporation Index in 12, 24, and 36 months lag from 1990 to 2019.

Conclusion

Exploring boro rice cultivation area and driver of expansion using remote sensing and climate parameters were efficient techniques. The study indicated that the boro rice cultivation area increased from 8104 ha (1999) to (12781 ha (2020). In the decade 1999-09, large quantities of vegetations (3072 ha) and other lands (1579 ha) were transformed into boro areas. However, this transformation was relatively less in 2009-20. The expansion rate of the boro cultivation (3.10 %) was much lower recent than previous (11.49 %). The main reason could be that boro rice cultivation has remained somehow stable over the last ten years. The study shows that the estimated boro rice area by remote sensing techniques agrees well with traditional. The key drivers for expanding the boro rice area could be the positive impacts of climate change and profitability. According to the standardized precipitation evapotranspiration index (SPEI) with 12, 24, and 36-months lag, hydrological drought impacts the shrinkage of wetlands. Lowland areas were drying up a few months earlier than usual due to the prolonged drought spell. As a result, the area near the river and lowland with *khal-beel* areas has become arable. It has been noticed that it was not possible to grow wheat, onion, and maize after mustard collection. On the contrary, it was impossible to cultivate boro rice after cultivating wheat, onion, and maize. But after mustard, it was possible to cultivate boro rice effortlessly. However, the profitability depends on the cropping pattern to be followed. According to BCR, boro rice cultivation after mustard was more profitable than any other single crop. Boro rice cultivation in lowland areas might be hampered if the monsoon-induced wet spell continues.

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References

Abbas Z., and Jaber H. S. (2020, March). Accuracy assessment of supervised classification methods for extraction land use maps using remote sensing and GIS techniques. In *IOP Conference Series: Materials Science and Engineering* (Vol. 745, No. 1, p. 012166). IOP Publishing.

Abdullah H. M. (2014, September). Standardized precipitation evapotranspiration index (SPEI) based drought assessment in Bangladesh. In Proceedings of 5th International Conference on Environmental Aspects of Bangladesh [ICEAB 2014]. Paper ID {Vol. 23, pp.40-42).

Abdullah H. M., Islam I., Miah M. G and Ahmed Z. (2019). Quantifying the spatiotemporal patterns of forest degradation in a fragmented, rapidly urbanizing landscape: a case study of Gazipur, Bangladesh. Remote Sensing Applications: Society and Environment, 13, 457-465.

Arias M., Campo-Bescos M. A., and Alvarez-Mozos, J. (2020). Crop classification based on temporal signatures of Sentinel-1 observations over Navarre province, Spain. *Remote Sensing*, *12*(2), 278.

Asif F. (2021, August 14). Millers, wholesalers trade blame for the rice price hike in Dhaka. *Bdnews24.Com*. https://bdnews24.com/business/2021/08/14/millers-wholesalers-trade-blame-for-rice-price-hike-in-dhaka.

Bapari M. Y., Chowdhury M. K. I., Haque M. E., and Al-Mamun A. (2016). Economic analysis of onion production in Sujanagar and Santhia areas of Pabna, Bangladesh. *International Journal of Humanities and Social Science Invention*, *5*(10), 5-12.

BBS. 2020. Yearbook of Agricultural Statistics. Bangladesh Bureau of Statistics. Statistics Division. Ministry of Planning. Govt. of the People's Republic of Bangladesh. Dhaka, p 377.

Bhandari H. (2019). Global rice production, consumption, and trade: trends and future directions. In *Proceedings of the Korean Society of Crop Science Conference* (pp. 5-5). The Korean Society of Crop Science.

BMD. (2020). *Bangladesh Meteorological Department*. Retrieved November 29, 2021, from http://live3.bmd.gov.bd.

Childs N. W. (2021). *Rice Outlook* (RCS-21B). Department of Agriculture, Economic Research Service. https://www.ers.usda.gov/publications/pub-details/?pubid=95900.

Faisal B. M., Rahman H., Sharifee N. H., Sultana N., Islam M. I., Habib S. M., and Ahammad T. (2020). Integrated Application of Remote Sensing and GIS in Crop Information System-A Case Study on Aman Rice Production Forecasting Using MODIS-NDVI in Bangladesh. *Agri-Engineering*, *2*(2), 264-279.

FPMU. (2021). *Bangladesh Food Situation Report* (No. 124). Food Planning and Monitoring Unit. http://fpmu.gov.bd/agridrupal/sites/default/files/FSR_124.pdf.

Hoque M .Z. and Haque M. E. (2014). Socio-economic Factors Influencing Profitability of Rice Seed Production in Selected Areas of Bangladesh. *The Agriculturists vol. 12(1): 33-40.*

Irani B. (2019, November 18). Rice prices are on the rise in Dhaka. *Dhaka Tribune*. https://www.dhakatribune.com/business/2019/11/18/rice-prices-on-the-rise-in-dhaka.

Islam Z. (2020, January 2). Farmers in 2020: Hit hard, yet resilient. The Daily Star. http://epaper.thedailystar.net.

Jahid S. P. A. A. M. (2021, July 14). Rice prices rise despite the bumper yield. *The Daily Star*. https://www.thedailystar.net/business/news/rice-prices-rise-despite-bumper-yield-2129621**.**

Kalpoma K. A., Ali R., Rahman A., and Islam A. (2020). Use of Remote Sensing Satellite Images in Rice Area Monitoring System of Bangladesh. In *IGARSS 2020-2020 IEEE International Geoscience and Remote Sensing Symposium* (pp. 4665-4668). IEEE.)

Kalpoma K. A., Arony N. N., Chowdhury A., Nowshin M., and Kudoh J. I. (2019, July). Boro rice model for haor region of Bangladesh based on MODIS NDVI images. In *IGARSS 2019-2019 IEEE International Geoscience and Remote Sensing Symposium* (pp. 7326-7329). IEEE.

Katipoglu O. M., Acar R., and Şengül S. (2020). Comparison of meteorological indices for drought monitoring and evaluating: a case study from Euphrates basin, Turkey. *Journal of Water and Climate Change*, *11*(S1), 29-43.

Ladha J. K., Jat, M. L., Stirling C. M., Chakraborty D., Pradhan P., Krupnik, T. J., and Gerard B. (2020). Achieving the sustainable development goals in agriculture: The crucial role of nitrogen in cereal-based systems. *Advances in Agronomy*, 163, 39-116.

Mainuddin M., Alam M. M., Maniruzzaman M., Kabir M. J., Mojid M. A., Hasan M. M., and Islam M. T. (2021). Yield, profitability, and prospects of irrigated Boro rice cultivation in the North-West region of Bangladesh. *PloS one*, *16*(4), e0250897.

Miah M. G., Abdullah H. M., and Jeong C. (2017). Exploring standardized precipitation evapotranspiration index for drought assessment in Bangladesh. *Environmental monitoring and assessment*, *189*(11), 1-16.

Mosleh M., Hassan Q., and Chowdhury E. (2015). Application of remote sensors in mapping rice area and forecasting its production: A review. Sensors, 15(1), 769-791.

Nabi S. M. and Mahmud N. (2019, January 14). What is causing the latest rice price hike? *Dhaka Tribune*. https://www.dhakatribune.com/bangladesh/nation/2019/01/15/what-is-causing-the-latest-rice-price-hike.

Nasim M., Shahidullah S. M., Saha A., Muttaleb M. A., Aditya T. L., Ali M. A., and Kabir M. S. (2017). Distribution of crops and cropping patterns in Bangladesh. *Bangladesh rice journal*, *21*(2), 1-55.

Noureldin N. A., Aboelghar M. A., Saudy H. S., and Ali A. M. (2013). Rice yield forecasting models using satellite imagery in Egypt. The Egyptian Journal of Remote Sensing and Space Science, 16(1), 125-131.

Patchett L. (2019, August 14). Bangladeshi rice growers suffer heavy losses. *The Chartered Institute of Procurement and Supply (CIPS)*. https://www.cips.org/supply-management/news/2019/august/bangladesh-rice-production-hit-by-flood-disaster/

Roy D., Murmu S., and Biswas S. (2021). Agricultural Crop Mapping Using MODIS Time-Series Data in DVC Command Area. In *Water Management and Water Governance* (pp. 167-178). Springer, Cham.

Salam M. A. (2014). Application of Remote Sensing and Geographic Information System (GIS) Techniques for Monitoring Boro Rice Area Expansion in Bangladesh. Asian Journal of Geoinformatics, 14(2).

Salimi S., Almuktar S. A., and Scholz M. (2021). Impact of climate change on wetland ecosystems: A critical review of experimental wetlands. *Journal of Environmental Management*, *286*, 112160.

Sanchez-Galan J. E., Barranco F. R., Reyes J. S., Quiros-McIntire E. I., Jiménez J. U., and Fabrega J. R (2019). Using Supervised Classification Methods for the Analysis of Multi-spectral Signatures of Rice Varieties in Panama.

Shahbandeh M. (2021, April 23). *Top countries based on the production of milled rice 2019/20*. Statista. https://www.statista.com/aboutus/our-research-commitment/1239/m-shahbandeh.

Statista. (2021, April 23). *Top countries based on the production of milled rice 2019/20*. https://www.statista.com/statistics/255945/top-countries-of-destination-for-us-rice-exports-2011/.

Su T., and Zhang S. (2021). Object-based crop classification in Hetao plain using random forest. *Earth Science Informatics*, *14*(1), 119-131.

Titumir R. A. M. (2021). Agriculture in Bangladesh. In *Numbers and Narratives in Bangladesh's Economic Development* (pp. 33-61). Palgrave Macmillan, Singapore.

USDA. (2020, July). *Rice* (July 2020). Foreign Agriculture Service. https://apps.fas.usda.gov/psdonline/app/index.html#/app/compositeViz.

World Population Review. (2021). *Rice Production By Country 2021*. https://worldpopulationreview.com/country-rankings/rice-production-by-country.

Zahid S. H. (2020, December 20). Time to pay attention to the rice market. *The Financial Express*. https://thefinancialexpress.com.bd/views/time-to-pay-attention-to-the-rice-market-1608481883.

Zhang T. X., Su J. Y., Liu C. J., and Chen W. H. (2019). Potential bands of sentinel-2A satellite for classification problems in precision agriculture. *International Journal of Automation and Computing*, *16*(1), 16-26.