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A COMPARATIVE ANALYSIS ON MAIZE YIELD PREDICTION USING SENTINEL 2A AND LANDSAT 8 SATELLITE IMAGE IN SUNDARGANJ, GAIBANDHA, BANGLADESH

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Abstract

Maize is an important cereal crops in Bangladesh. Over the last two decades, its cultivation has increased promisingly, especially in the Northern part of Bangladesh. The effective estimation of crop yields at a regional scale holds significant importance in facilitating decision-making within the agricultural sector, thereby ensuring grain security. The traditional ground-based measurement techniques suffer from inefficiencies, and there exists a need for a reliable, precise, and effective method for estimating regional crop yields. This study used remote sensing (RS) techniques for forecasting pre-harvest maize yield to improve the management system. Currently, the normalized difference vegetation index (NDVI) is widely used to predict crop yield including maize. However, the present study used Landsat 8 (~ 30 m) and Sentinel 2A (~ 10 m) high resolution data for 2018-2019 and 2019-2020 to predict maize yield based on the year 2020-2021 at Sundarganj Upazila in Gaibandha district. The single cloud free image acquisition date based on maximum NDVI for both satellite images was used for each maize growing period to develop a yield prediction model. A regression model was performed between NDVI values and 20 farmers field-level maize yields. The absolute mean error of prediction was about 10.30% for Landsat 8 and 6.70% for Sentinel 2A compared to the actual maize yield during 2020-2021. The study revealed that NDVI data extracted from Sentinel 2A high resolution satellite images can be successfully used to predict the maize yield with appreciable accuracy. Finally, this study has demonstrated the efficacy of combining multi-temporal remote sensing data for accurate maize yield estimation, aiding agricultural authorities and production enterprises in the timely formulation and refinement of cropping strategies and management policies for the ongoing season.

Key words: Maize, NDVI, Landsat 8, Sentinel 2A, Remote sensing and Yield prediction

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Introduction

Maize (*Zea mays L.*) is the second most widely grown cereal food crop in the world. It is one of the most important cereal crops in Bangladesh, as well as the third-largest crop after rice and wheat in the world. Maize is the highest yielding grain crop having multiple uses. The average production of maize in 2019 in the world was 5.82 tons per hectare as compared to 3.55 and 4.66 tons per hectare for wheat and rice, respectively (FAO, 2021). Its position is the first among the cereals in terms of yield [maize: 9.12 mt/ha, wheat: 3.69 mt/ha and rice: 3.36 mt/ha)] but in terms of area and production, it ranks the second just after rice (BBS, 2024). Maize cultivation has increased rapidly in the northern part of Bangladesh. Currently crop statistics in Bangladesh are generally gathered by the accumulation of representative field sampling data which is time-consuming and misses information on the spatial distribution of field variability. Large-scale research cannot employ traditional field-based surveys due to the substantial labour and material costs (Khan et al., 2024). Yield estimation is then carried out on ground-based field visits and reports. These are often subjective, costly, time consuming and mostly have huge errors due to incomplete ground observations (Reynolds *et al*., 2000). Crop yield estimation has been transformed by satellite remote sensing technology, which provides a broad-coverage, reliable, and non-destructive method (Wang *et al*., 2020; Lyu *et al*., 2024). The precise and timely monitoring of potential yields is crucial for decision making as it influences markets, export–import decisions and farm income budgeting (Zhao *et al*., 2020). Nonetheless, it is important to get precise predictions on time for the food security of a country (Shen *et al*., 2022). Many crop yield estimation techniques are being applied; nevertheless, the most effective one is based on using geospatial data and technologies like remote sensing. Though, the remote sensing data that are required to estimate crop yields are inadequate most of the time due to numerous problems like climate conditions (% of clouds), and low temporal resolution (Awad, 2019). In addition, yield estimations with conventional methods are no longer beneficial for planners as they take too much time. As satellite-based remote sensing is one of the best tools to provide vital information about the distribution of crops and their growing conditions over large areas, it can be applied for maize growth monitoring and yield forecasting. Currently, satellite data with higher spatial resolution (e.g. Landsat, 30m; Sentinel-2, 10m) has become freely available and offers an opportunity to improve the identification of smaller crop fields and estimation of their yield, yet to be evaluated (Bitelli *et al*., 2016).

Now-a-days, several methods are used for the prediction of crop yields at a range of scales such as observed equations, remote sensing and simulation models. Remote sensing data from satellites is more often applied as input data in crop models for grain yield predictions. AVHRR and MODIS are the most popular satellite sensors to obtain within-season information to predict final yield at the regional scale (Becker-Reshef *et al*., 2010; Zhang *et a*l., 2016 and French *et al*., 2017), while for smaller areas, the most generally applied data are extracted from Landsat and Sentinel satellites (Skakun *et al*., 2017; Mirasi *et al.,* 2019 and Fieuzal *et al*., 2020).The yield predictions can be prepared at several spatial levels, from forecasts for particular crop fields to regional forecasts for all countries or even on a worldwide scale (Basso *et al*., 2019). Researchers used crop models to predict crop growth and yields at a regional scale. Landsat 30m 16-day cloud-free imagery and Sentinel-2 10m 10-day processed satellite images were downloaded for crop yield estimation (Gumma *et al*., 2021). Several studies have been carried out on the correlation of normalized difference vegetation index (NDVI) with yield (LiuWT *et al*., 2002). Recent studies took advantage of Landsat and Sentinel 2 data to approach crop yield forecasting at a moderate spatial resolution. Landsat and Sentinel-2 data were used in recent studies to measure crop yields at a moderate spatial resolution. Lambert *et al*. (2018), for example, used Sentinel-2 data and a peak LAI technique to estimate cotton, maize, millet, and sorghum yields in Mali. Lai *et al*. (2018) applied time-integrated Landsat NDVI for wheat yield estimation in Australia. Lima et al. (2019) observed that both satellites showed the same performance in terms of accuracy for Sentinel-2 and Landsat 8, respectively. However, Landsat 8 mapped 36.9% more area of selective logging compared to Sentinel-2 data for mapping small-scale logging in the Brazilian Amazon.

In Bangladesh, Bala and Islam (2009) expanded potato yield estimations models by using NDVI, LAI (leaf area index), and fraction of photosynthetically active radiation (fPAR) vegetation indices for Munshiganj district of Bangladesh by applying Moderate Resolution Imaging Spectroradiometer (MODIS) data and noticed that an average error of estimation is about 15% for the study location. Rahman *et al.* (2012) utilized NOAA-AVHRR data for prediction of potato yields in Bangladesh. Newton *et al*. (2018) improved a potato yield prediction model by Landsat 8 data to identify the maximum NDVI value of a potato growing season in the Munshiganj district of Bangladesh. The maximum coefficient of determination (R^2) was found to be 0.81 between the mean NDVI and potato yield and revealing that the difference between predicted and actual filed yield is approximately 10.4%. Rahman *et al.* (2024) developed a potato yield prediction model based on the maximum NDVI values combined use of Landsat 8 and Sentinel 2A. The predicted percentages of the mean yield gap for Sentinel 2A were 8.58%, while for Landsat 8, these were 9.56%, respectively, at Shibganj Upazila, Bogura. Mohammad et al. (2024) generated a maize yield model and found the percentage of yield gap was 8.82% for Sentinel 2A and 10.15% for Landsat 8 at Kaharole in Dinajpur district.

However, very few studies have been conducted on the relationship between high-resolution (~ 30 m) Landsat 8 and Sentinel 2A (~ 10 m) satellite data and maize yield in Bangladesh. The objective of the present study was to construct a maize yield estimation model and forecast maize yield using satellite based remote sensing technique using high-resolution Landsat 8 and Sentinel 2A surface reflectance data at Sundarganj Upazila in Gaibandha district of Bangladesh. The high spatial resolution of both images has been used in this study to predict maize yield in the study area.

Study Area

The study was conducted at Sundarganj Upazila in Gaibandha district especially in the *Rabi* season which was a promising maize growing area of Bangladesh. Especially in char lands, the area and production of maize have been increasing rapidly over the last decades in this location. Maize grew on a project basis most of unions of Sundarganj Upazila like Kapasia, Belka, Candipur, Haripur, Tarapur and Sripur. It covered 7.34% and 3.99% maize cultivation areas in the northern part and all over Bangladesh respectively (BBS, 2020). Sundarganj Upazila lies between 25° 24′ to 25° 39′ N latitude and 89° 24′ to 89° 43′ E longitude respectively (Fig. 1). It covers 426.52 km^2 where 65% of the areas is cultivable land. The climate condition of this area is hot and humid from April to October (summer) and cool and dry from November to March (winter). This Upazila receives an annual average rainfall of 2417 mm, where 90% of rainfall occurs between May and October. The maximum and minimum mean temperature during the winter varies between 23.6 to 16.8°C and 24 to 16.8°C, respectively in the study area. During summer, the maximum and minimum mean temperatures vary between 33.2 to 26.0°C and 29.8 to 25.6°C, respectively. The average monthly minimum and maximum humidity vary from 68 to 86%, where the maximum humidity observed during the summer and the minimum humidity observed during the dry season. The agricultural pattern of this area is categorized by two growing seasons, *Rabi* and *Kharif*. *Rabi* is the main growing season, which is dominated by maize, rice and wheat that starts in late October or early November and ends in April. Again, *Kharif* is dominated by rice and jute, which starts in May and ends in September. Other food crops which include potato, pepper, onion, pulses, sugarcane, and oilseed are also cultivated in the study area. Sundarganj occupied major part of the Teesta Flood Plain. The soil condition of those areas has prevailed by non-calcareous brown floodplain soils and grey floodplain soils.

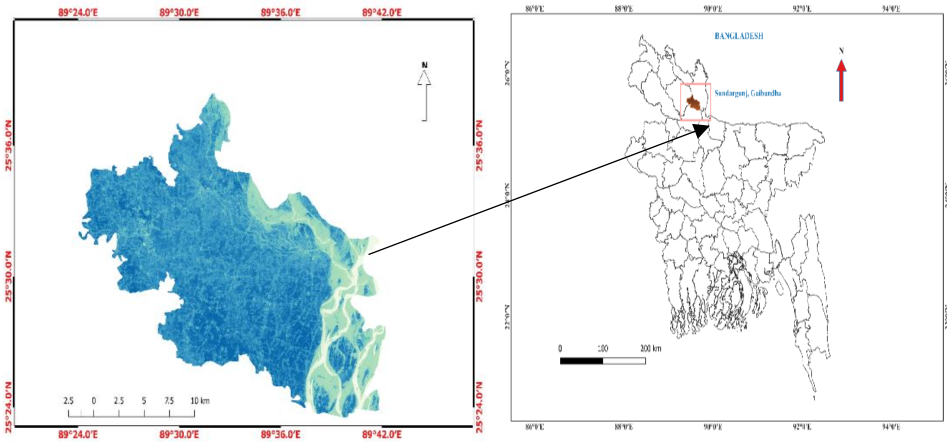


Fig. 1. Map of the study area.

Materials and Methods

Yield data collection from farmer's fields

Twenty maize fields were selected randomly from Sundarganj Upazila, Gaibandha district for the three maize growing seasons 2018-2019, 2019-2020 and 2020-2021 with the agreement of the farmers (Fig. 2). Ground truth points (GTPs) were collected from those 20 maize fields for each season. Crop information data such as field GPS locations, planting and harvesting time and yield were collected from these selected Upazilas farmers' fields.

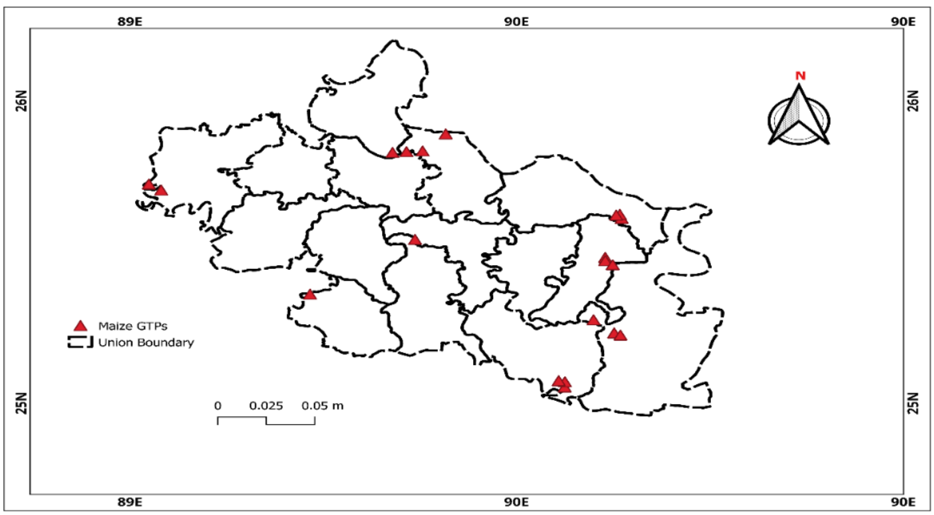


Fig. 2. GTPs of maize fields over Sundarganj, Gaibandha.

Landsat-8/OLI and Sentinel-2A /MSI Datasets

Remote sensing images adopted by the Operational Land Imager (OLI) instrument aboard Landsat-8 satellite and by the Multi-Spectral Instrument (MSI) aboard Sentinel-2A satellites were used in this study. Landsat-8/OLI were obtained from the United States Geological Survey (USGS) Earth Explorer website (http://earthexplorer.usgs.gov/) which capture images of the Earth's surface in 9 spectral bands at 30 m spatial resolution (15 m for panchromatic band) (Roy *et al*., 2014) while Sentinel-2A/MSI were obtained from the European Space Agency (ESA) Copernicus portal (https://scihub.copernicus.eu) which capture images of the Earth's surface in 13 spectral bands at 10 m, 20 m and 60 m spatial resolution (Drusch *et al*., 2012). The main bands that were used in the study are bands 4 (Red) and 5 (NIR) from Landsat-8, and bands 4 (Red) and 8 (NIR) from Sentinel-2A. Spectral response function for band 8A (Narrow NIR, ~20 m) from Sentinel-2A was not like Landsat-8's band 5 was presented in Fig. 3.

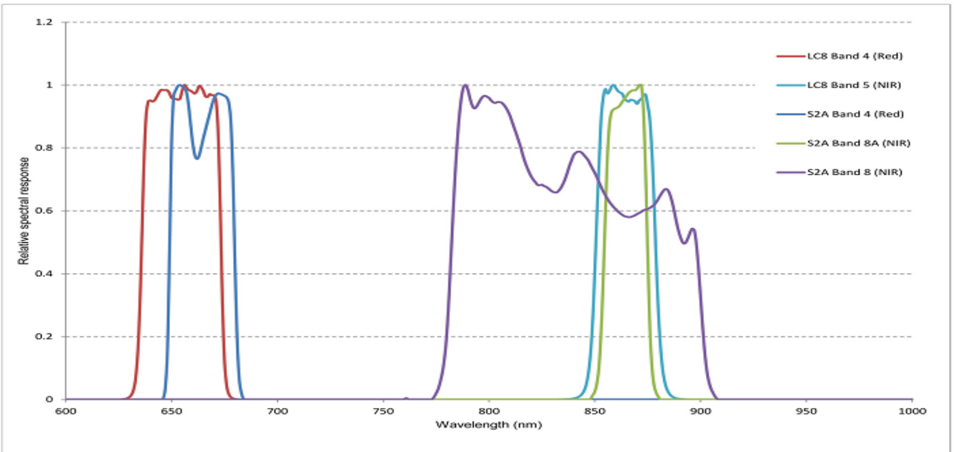


Fig. 3: Relative spectral response functions of Landsat-8/OLI and Sentinel-2A/MSI for red and near-infrared spectral bands.

However, only the Red and NIR spectral bands for Landsat 8/OLI and Sentinel 2A/MSI were used for the study purposes. So, Landsat 8 (OLI) and Sentinel 2A (MSI) with 16-day (~ 30 m) and 10-day (~ 10 m) high spatial resolution data respectively were used in this study. A total of 06 cloud free satellite images of both satellites (single image for each satellite for each growing season) were downloaded and analyzed. Among them, two images were selected from the 2018 to 2019 growing seasons and the remaining four images were selected from other growing seasons i.e., 2019-2020 and 2020-2021, respectively. The single date of image acquisition based on maximum NDVI for each growing season was used for this study. The maize plantation date was considered as the last week of November and first week of December for these locations viz. Sundarganj Upazila for each growing season for the entire study area based on the information collected from the field visits. Every single image was calculated from the starting day of the plantation. The data of image acquisition of Landsat 8/OLI and Sentinel 2A/MSI for the three maize growing seasons 2018-19, 2019-20 and 2020-21, respectively, for the study area used for this study are presented in Table 1.

Table 1. Model development using Landsat 8 and Sentinel 2A satellite image at Sundargonj Upazila, Gaibandha district

Satellite images	Landsat 8			Sentinel 2A		
Growing season	2018-19	2019-20	2020-21	2018-19	2019-20	2020-21
IAD	19/03/2019	21/03/2020	24/03/2021	16/03/2019	20/03/2020	15/03/2021
DAP	111	106	109	108	105	100

IAD=Image acquisition date; DAP= Days after plantation

Satellite Image Pre-processing

For Landsat data, raw digital numbers (DN) were modified to top-of-atmosphere (TOA) reflectance values (Simonetti et al., 2015). For Sentinel-2, we kept the inventive Level-1C TOA reflectance values. The corresponding spectral bands accessible for both sensors were considered in this process: Green blue, near infrared (NIR) and red, short-wave infrared 1 (SWIR-1), and short-wave infrared 2 (SWIR-2). The SWIR-2 band in the Sentinel-2 image has a resolution of 20 m; as a result, it was resampled using the nearest neighbor resampling method to a resolution of 10 m. For Sentinel-2 satellite imagery, considering land use and land cover maps, downscaling has been found to have superior performance compared to upscaling, even when it was based on the most straightforward technique, the nearest neighbor resampling (Zheng *et al*., 2017). Downscaling was recommended over upscaling for the reasons mentioned above as well as the fact that we planned for small-scale disturbances. All images were cropped to represent the research locations. The European Commission's image processing (IMPACT) package was used to fulfill these tasks (Simonetti *et al*., 2015). Although low cloud coverage was preferred, clouds could not be completely avoided. To mask off the clouds and cloud shadows, we employed semi-automatic object-oriented criteria. First, a multiresolution segmentation (Baatz *et al*., 2000), applying the three visible bands of the electromagnetic spectrum, was executed in eCognition®software.

Vegetation Index (VI)

The vegetation index, especially the Normalized Difference Vegetation Index (NDVI), was applied for the images acquired from Landsat-8 and Sentinel-2 for maize yield assessment. The related band combinations were illustrated in Table 2.

Table 2. Vegetation index using Sentinel-2 and Landsat-8 satellite images

Index	Sentinel 2A	Landsat 8
NDVI	$\frac{B_8 - B_4}{B_8 + B_4}$	$\frac{B_5 - B_4}{B_5 + B_4}$
	B_8=NIR Band, B_4=RED Band	B_5=NIR Band, B_4=RED Band

Where, NIR is the reflectance of near infrared light (Band 8 or Band 5), Red is the reflectance of red light (Band 4).

Maize yield prediction model by satellite-based RS technique

The red band of the calibrated images and NIR were selected from each dataset and exported into QGIS 3.28.2. A simple raster calculation was done by QGIS 3.28.2 using Table-2 to find the NDVI images. Finally, the NDVI images were masked using the shape file from different locations like Sundarganj Upazil, Gaibandha district. The field points of the location were imported, and the mean NDVI values for each point were extracted from the satellite image considering a 3 × 3 matrix surrounding each point on the image.

The relationship between NDVI and maize growing period was established by plotting the respective values in terms of single days from the start date of maize plantation to the harvesting period. The day of the maximum NDVI was selected from their relationship with crop yield. To establish this relationship, NDVI data from growing season 2018-2020 were used. Then, a total of four satellite images viz., two images each were collected from Landsat 8 as well as Sentinel 2A, depending on the date of the maximum NDVI, and were selected from two growing seasons, namely 2018-2019 and 2019-2020 to build a relationship between the NDVI values and field level maize yield. This relationship based on each farmer's field point NDVI values, was validated using the satellite image of the 2020-2021 growing season. NDVI values less than 0.25 and more than 0.95 were removed from the listed fields to reduce the influence of reflectance of other objects like bare soil, settlements, water bodies, non-agricultural crops, and infrastructure. The maize yield prediction workflow is presented in Fig. 4.

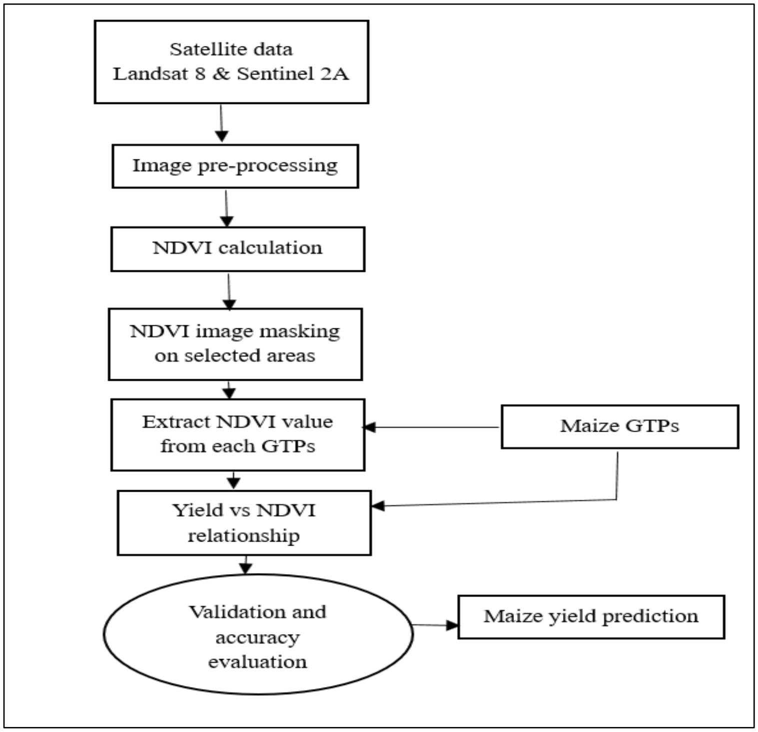


Fig. 4. Maize yield prediction workflow.

Yield forecasting model

The final step is to determine the relationship between NDVI and maize yield from farmers' fields with the equation below:

$$Y = f(X) \qquad (1)$$

Where Yand X are maize yield data collected from farmers' fields and NDVI, respectively. The relationship between NDVI and maize yield has been observed through the linear regression model, where the response variable is denoted by maize yields and the predictor by NDVIs. Several studies (Ren *et al.*, 2008) applied a linear regression model to describe the relationship between NDVI and crop (wheat) yield in distinct locations. To develop the maize yield estimation model for both fields, the data of maize yield and Landsat 8 (OLI) and Sentinel 2A (MSI) images were used for 2018-2021.

Accuracy evaluation

Three metrics were employed to evaluate model performance. The coefficient of multiple determinations (R^2), the root means square error (RMSE) and the normalized RMSE (NRMSE) were selected as performance evaluation metrics

$$R^2 = \frac{\sum_{i=1}^{n}[(P_i - \bar{P})(O_i - \bar{O})]}{[\sum_{i=1}^{n}(P_i - \bar{P})^2][\sum_{i=1}^{n}(O_i - \bar{O})^2]} \ldots\ldots\ldots\ldots(2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(3)$$

$$NRMSE = \frac{\text{RMSE}}{\bar{O}} \times 100\% \ldots\ldots\ldots\ldots\ldots..\ldots\ldots\ldots\ldots(4)$$

Where P_i is the predicted yield, $\bar{P}$ is the predicted yield mean, O_i is the observed yield, $\bar{O}$ is the observed yield mean, and n is the sample size.

Results and Discussion

Maize yield from farmers' fields and corresponding NDVI values for different locations

Maize yield data and NDVI values from different dates satellite images of Landsat 8 and Sentinel 2A for corresponding farmers' fields have been collected from Sundarganj Upazila during the maize growing season 2018-19 and 2019-20 respectively. Twenty farmers' field yield data collected from study area and their corresponding NDVI values for two satellite images have been presented in Figure 5 and 6 for consecutive maize growing seasons 2018-19 and 2019-20 respectively.

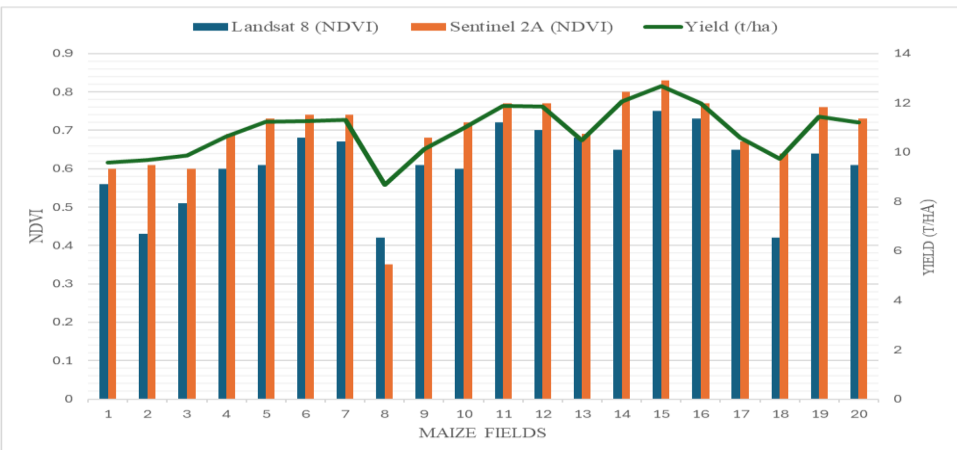


Fig. 5: NDVI values of satellite images and yields of corresponding farmers' fields at Sundarganj, Gaibandha during the season of 2018-19.

Fig. 5 shows that NDVI values are 0.75 and 0.83 which were the highest for Landsat 8 and Sentinel 2A, and the yield was a maximum of 12.68 t/ha for farmer's field 15, but the yield is a minimum of 8.67 t/ha for field 8. NDVI values are 0.42 for Landsat 8 and 0.35 for Sentinel 2, which were the lowest for farmers' fields 8 and 18 respectively during 2018-19.

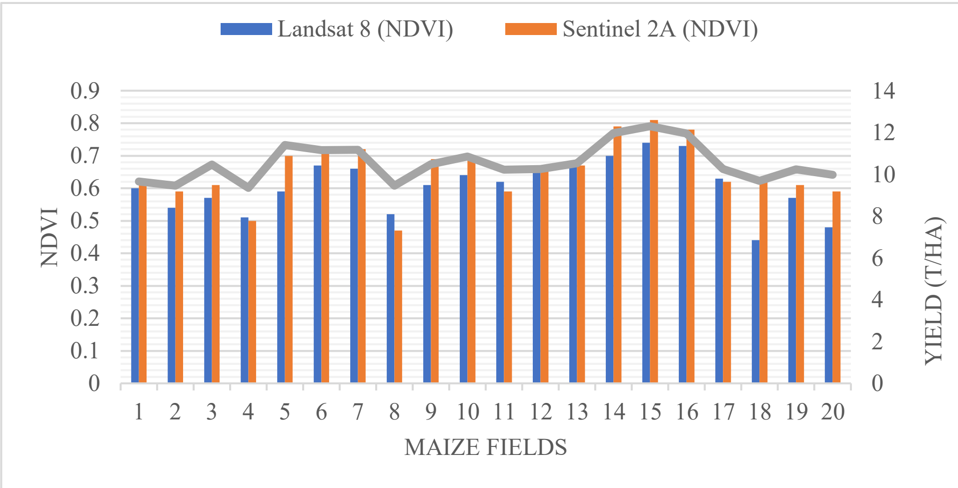


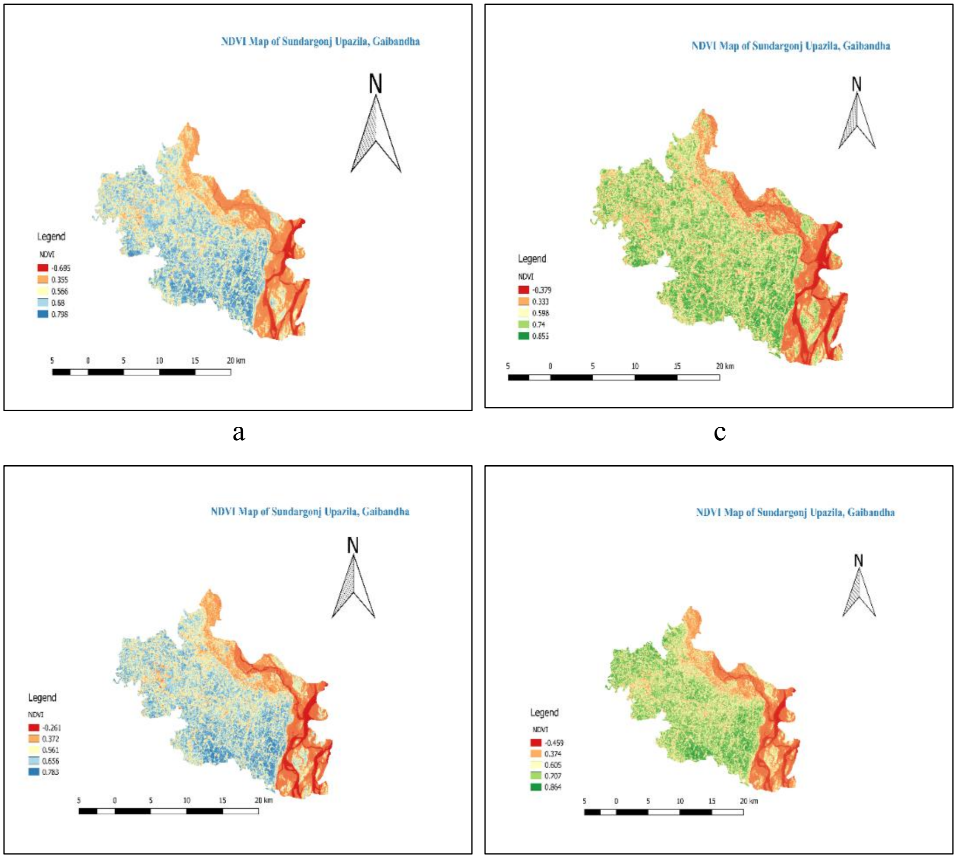
Figure 6: NDVI values of satellite images and yields of corresponding farmers' fields at Sundarganj, Gaibandha during the season of 2019-20.

Maximum NDVI for Sundargonj were 0.74 and 0.81 for farmer's field 15 and minimum NDVI were 0.44 and 0.47 for Landsat 8 and Sentinel 2A for farmer's field 18 and 8, but the highest and lowest yield were 12.30 t/ha and 9.35 t/ha for farmer's field 15 and 4, respectively during 2019-20 in Figure 6.

NDVI values over the field locations

A total of four satellite images (2 images each for Landsat 8 and Sentinel 2A) from two growing seasons during 2018-2019 and 2019-2020 were selected. Based on available images, those sowing the maximum NDVI in each growing season were found 111th, and 106th days after plantation for Sundarganj Upazila from Landsat 8 images as well as 108th, and 105th days after plantation for Sundarganj Upazila from Sentinel 2A images for 2018-2019 and 2019-2020 growing seasons, respectively. The spatial distribution of the NDVI varies from year to year. Spatial distribution of the NDVI over the selected location for selected distinct satellite images against different growing seasons is presented in Figure 7.

For Landsat 8 data, the NDVI distribution was maximum during 2018-2019 and the distribution was minimum during the season 2019-20 at Sundarganj upazila in Fig. 7. On the other hand, for Sentinel 2A data, NDVI distribution was maximum during the season 2019-2020 and minimum during the season 2018-2019 at Sundarganj upazila in Figure 7. The NDVI distribution from different locations of Sentinel 2A data outperforms Landsat 8 data during the maize growing season 2018-2019 and 2019-2020, respectively, in Fig. 7.



a c

b d

Fig. 7. Spatial distribution of the NDVI for different satellite images during the growing season 2018-19 and 2019-20. a. 111th days after plantation during 2018-19; b. 106th days after plantation during 2019-20 for Landsat 8; c. 108th days after plantation during 2018-19; d. 105th days after plantation during 2019-20 for Sentinel 2A at Sundarganj Upazila.

For two satellites viz., Landsat 8 and Sentinel 2A, the NDVI values and their corresponding yields for twenty farmers' maize fields from the study area during individual maize growing seasons 2018-2019 and 2019-2020, respectively are shown in Figures 5 and 6. From Figure 5 and 6, the mean NDVI and mean yield for two satellite data, Landsat 8 and Sentinel 2A for this location during the combined season 2018-2019 and 2019-2020 respectively were calculated which are represented below in Figure 8. Mean NDVI and mean yield are calculated for two satellite images for the combined two seasons because maize yield in each season i.e., 2018-19 and 2019-20 is mostly the same for this location. Mean NDVI and mean yield of the combined maize season performed better than NDVI and its corresponding yield of the individual maize season for each satellite image in this location because according to best model criteria viz. Multiple determination of coefficient (R^2), Mean Absolute Percentage Error **(**MAPE), Normalized Root Mean Square Error **(N**RMSE) and Root Mean Square Error **(**RMSE) fitted the best for the mean NDVI and the mean yield of the combined maize season rather than single maize growing seasons like 2018-19 and 2019-20 (Fig. 8). Mean NDVI is the largest, which is 0.75 for farmers' field 15 as well as the smallest, which is 0.43 for farmers' field 18 for Landsat 8. Similarly, the largest and lowest are 0.82 and 0.41 for farmers' field 15 and 8 for Sentinel 2A for the combined year respectively. The highest and lowest mean yields of the two-satellite data are 12.49 (t/ha) and 9.06 (t/ha) respectively, for this location in Fig. 8.

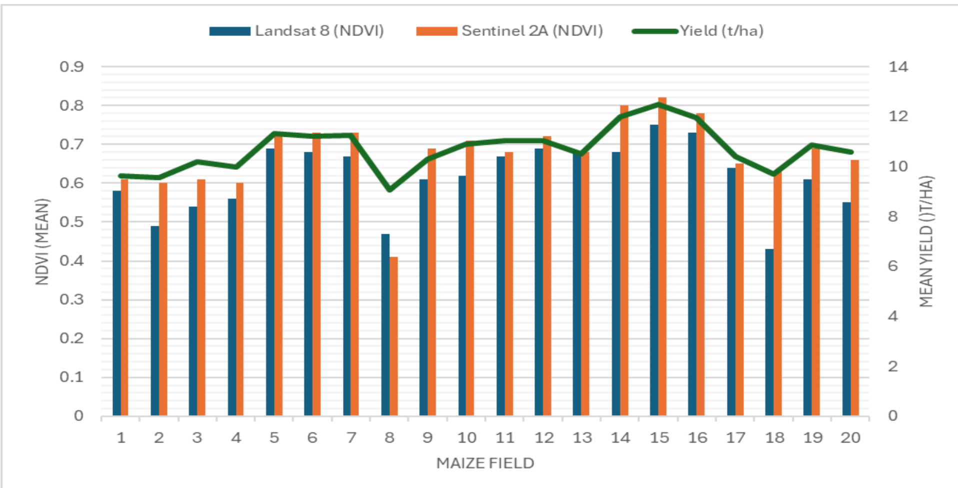


Fig. 8: Mean NDVI values for two satellite images and corresponding mean yields of farmers' maize fields at Sundarganj, Gaibandha during the combined season of 2018-19 and 2019-20.

Maize yield and NDVI relationship using a regression model

Regression analysis of maize yield against the single season basis NDVI and combined season basis mean NDVI for Sundarganj was performed for two satellite images, Landsat 8 and Sentinel 2A, and are graphically presented in Fig. 9.

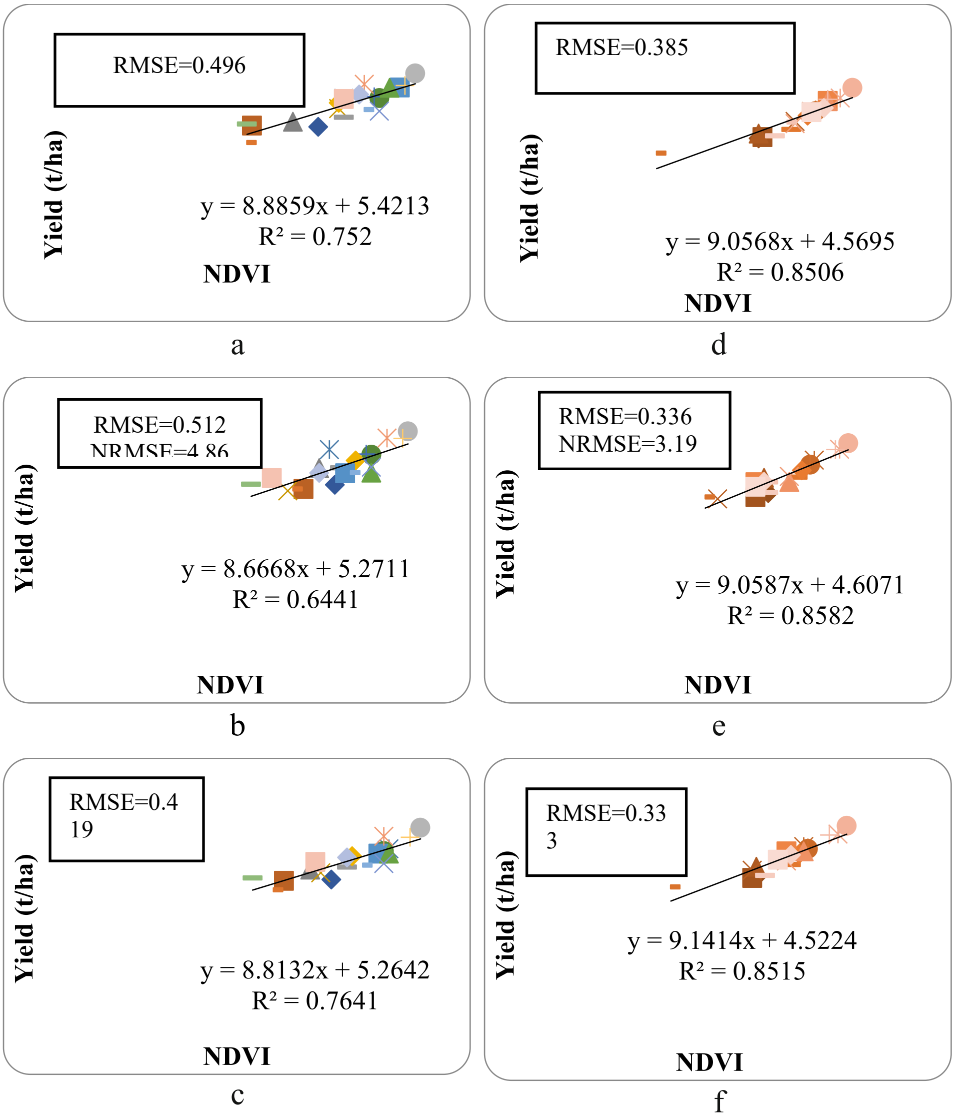


Fig. 9. Yield prediction model established from regression analysis between yield data collected from 20 farmers' maize fields for different images; [a. yield vs NDVI, 2018-19 b. yield vs NDVI, 2019-20 c. yield vs NDVI (mean), combined 2018-19 and 2019-20 for Landsat 8.] ; [d. yield vs NDVI, 2018-19 e. yield vs NDVI, 2019-20 f. yield vs NDVI (mean), combined 2018-19 and 2019-20 for Sentinel 2A] at Sundarganj Upazila.

The yield vs. NDVI relationship for Landsat 8 and Sentinel 2A satellite images is shown in Fig. 9, revealing that R^2 is the highest and other accuracy criteria like MAPE, RMSE and NRMSE of mean NDVI for the combined maize growing season i.e., 2018-2019 and 2019-2020, respectively for the selected location. The parameters of the regression analysis estimated from the yield vs. NDVI relationship for the combined season, together with the value of R^2, MAPE, RMSE and NRMSE are presented in Table 3. The relationship between mean NDVI for the combined two maize growing seasons and yield is compared well to the single-season basis NDVI vs. yield relationship for two satellite images.

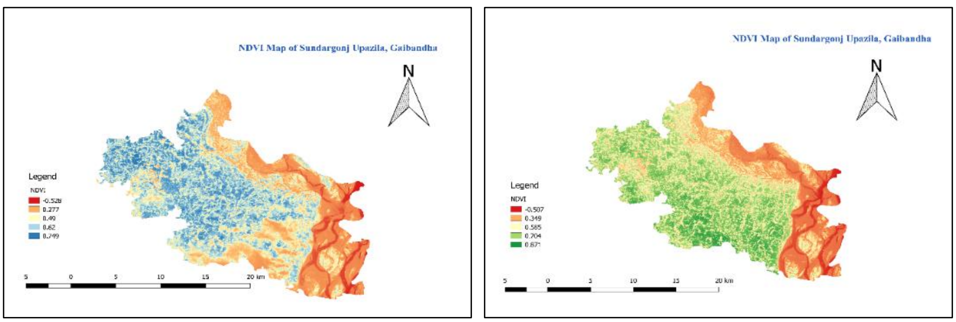
Table 3: Regression parameter and model criterion for the combined season at Farmers' maize field

Location	Satellite data	Regression parameter for mean value				Best model criteria			
		β_0	β_1	SE(β_1)	P-Value	MAPE	RMSE	NRMSE	R^2
Sundargonj	Landsat 8	5.26	8.81	1.15	0.0000	0.032	0.419	3.92	0.76
	Sentinel 2A	4.52	9.14	0.89	0.0000	0.023	0.333	3.11	0.85

Here, the regression coefficients of all the fitted models of two satellite images show a highly significant effect for Sundarganj Upazila in Table 7. Multiple determination of coefficient (R^2=0.898) along with MAPE (0.023), RMSE (0.333) and NRMSE (3.11) perform better for Sentinel 2A satellite image than Landsat 8 satellite image for Sundarganj Upazila, Gaibandha that are shown in Table 3.

Development and validation of the yield prediction model

The yield prediction model based on the regression analysis was developed based on the yield data collected from the 2018–2019 and 2019–2020 maize growing season. Evaluating the performance of the model validation is essential. Based on the deviation from the estimated and model prediction, model performance can be determined. Hence, the model has been further validated using yield data for the 2020-2021 maize growing seasons. After 109th and 100th days after plantation, an NDVI image was selected for two satellite images *viz.*, Landsat 8 and Sentinel 2A from 2020 to 2021 growing seasons at the respected location shown in Fig. 10.



a b

Fig. 10: Spatial distribution of the NDVI over the selected location for Landsat 8 and Sentinel 2A satellite images during the growing season of 2020-2021. 109th and 100th days after plantation for Sundarganj Upazila, Gaibandha for different satellite images.

The NDVI value was extracted from each of the 20 farmers' fields for two satellite images from a selected location during the maize growing season 2020-2021, which were presented in Table 3. As the coefficient of determination (R^2) was found to be high from the relationship of the mean value of NDVI and the yield of the combined season, the validation was done using the general mean value equation (NDVI and the yield relationship of the combined maize growing season) for two satellite images. The general mean value equation that was elaborately defined in Table 3 has been used separately in two developed regression models for validation along with two satellite images for the study area. The general regression equation from the mean NDVI (combined maize growing season) is presented in equation 5.

$$\text{Yield} = \beta_0 + \beta_1 * \text{NDVI}_{\text{mean (Combined maize growing season)}} \quad (5)$$

For Landsat 8: $\text{Yield} = 5.26 + 8.81 * \text{NDVI}_{\text{mean (Combined maize growing season)}}$ (6)

For Sentinel 2A: $\text{Yield} = 4.52 + 9.14 * \text{NDVI}_{\text{mean (Combined maize growing season)}}$ (7)

The actual yield (t/ha) of maize and predicted yield (t/ha) using equations 3 and 4 for two different satellite images for the study area during the 2020-2021 maize growing season were also presented in Table 4.

Table 4: Estimated yield and predicted yield from selected farmers' Maize Fields at Sundarganj Gaibandha during the season of 2020-2021

Farmer's field	Actual yield(t/ha)	NDVI values		Predicted yield (t/ha)		Error of yield (%)	
		Landsat 8	Sentinel 2A	Landsat 8	Sentinel 2A	Landsat 8	Sentinel 2A
1	11.12	0.58	0.66	10.38	10.56	6.65	5.04
2	10.57	0.45	0.57	9.23	9.73	12.68	7.94
3	10.25	0.41	0.49	8.88	9	13.37	12.19
4	9.96	0.33	0.47	8.17	8.82	17.97	11.44
5	9.65	0.31	0.43	7.99	8.45	17.2	12.43
6	11.5	0.65	0.74	10.99	11.29	4.43	1.83
7	12.65	0.68	0.75	11.26	11.38	10.98	10.03
8	9.11	0.31	0.43	7.96	8.45	12.62	7.24
9	10.81	0.52	0.62	9.85	10.19	8.88	5.73
10	11.23	0.6	0.68	10.55	10.74	6.05	4.36
11	11.65	0.62	0.72	10.73	11.1	7.89	4.72
12	11.62	0.6	0.76	10.55	11.47	9.2	1.29
13	10.1	0.39	0.57	8.7	9.73	13.8	3.66
14	12.57	0.64	0.75	10.9	11.38	13.28	9.46
15	11.59	0.61	0.68	10.64	10.74	8.19	7.33
16	11.54	0.61	0.71	10.64	11.01	7.79	4.59
17	10.45	0.51	0.64	9.76	10.37	6.60	0.76
18	10.55	0.4	0.52	8.79	9.28	16.68	12.03
19	10.32	0.52	0.53	9.85	9.37	4.55	9.20
20	10.77	0.5	0.64	9.67	10.37	10.21	3.71

The highest and lowest observed yield of maize were 12.65 (t/ha) and 9.65 (t/ha) as well as maximum and minimum NDVI values were 0.68 and 0.31 for Landsat 8; 0.76 and 0.43 for Sentinel 2A for farmers' fields 4 7 and 12 respectively during the maize growing season 2020-2021 (Table 4). The largest and smallest predicted yield of maize for Landsat 8 were 11.26 (t/ha) and 7.99 (t/ha) as well as for Sentinel 2A these were 11.47 (t/ha) and 8.45 (t/ha) for farmers' field 5, 7 and 14 respectively during the maize growing season 2020-2021 (Table 3). Maximum and minimum yield gaps (%) for Landsat 8 were 17.97 and 4.43 for farmers' fields 4 and 6 respectively and for Sentinel 2A were 12.43 and 0.76 for farmers' fields 5 and 18 respectively in selected areas during the maize growing season 2020-2021 (Table 4). The predicted yield of maize for two satellites was less than the actual yield of maize (underestimated) in each farmer's field for the study areas shown in Table 8. Depending on the value of Table 5, the validation of maize yield for two satellite images viz., Landsat 8 and Sentinel 2A was presented in Table 5 during the maize season 2020-2021.

Table 5: Validation of maize yield during the season 2020-2021

Location	Actual yield (Mean)	Predicted yield (Mean)		Mean error of yield (%)	
		Landsat 8	Sentinel 2A	Landsat 8	Sentinel 2A
Sundarganj, Gaibandha	10.90	9.77	10.17	10.30	6.70

The estimated farmers' field yield (mean) was 10.90 (t/ha) and the predicted yield (mean) for Landsat 8 and Sentinel 2A were 9.77 (t/ha) and 10.17 (t/ha) respectively in this study areas during the maize growing season 2020-2021. The percentage of mean yield error was 10.30 for Landsat 8 and 6.70 for Sentinel 2A. The error of mean yield (%) of Sentinel 2A performed better than Landsat 8 during the maize growing season 2020-2021 (Table 5). In Bangladesh, a few researchers used satellite data to forecast the yield of some crops like potatoes, rice, wheat and maize. Mohammad *et al*. (2024) developed a maize yield model using NDVI and found the percentage of the yield gap was at 8.82 Sentinel 2A and 10.15 at Kaharole in Dinajpur district. Here, we found that Sentinel 2A was performed better at Sundarganj Upazila (6.70 %) than Kaharole upazila (8.82%) for maize yield prediction. However, some researchers used the yield-NDVI relationship for maize yield prediction globally. Strong relationships (R^2 from 0.77 to 0.84) were observed between NDVI and the grain yield of maize using RapidEye imagery satellite and promising results for yield prediction were found with a 5% error of estimation in Hungary (Bu *et al*., 2017). Feng *et al.* (2025) showed that combining these GSIs derived from the complete NDVI dataset with the third-period NDVI achieved the highest model accuracy (R^2 = 0.7, rRMSE = 12.3 %) for maize yield estimation. GSIs improved estimation accuracy (R^2 = 0.661, rRMSE = 13.2 %), increasing R^2 by 0.023 and reducing rRMSE by 0.4 %, approximately one month before harvest. Li et al. (2025) observe that the model demonstrated high accuracy ($R^2 = 0.896$, RMSE = 908.33 kg/ha) and exhibited strong robustness in both earlier years and during extreme climatic events which enables maize yield prediction 1–2 months in advance by leveraging historical patterns of environmental and agricultural variables.

Conclusion

The aim of this study was to provide an operational technique with adequate technological components for monitoring and estimating maize yield in Bangladesh. The developed system investigates the combined use of satellite based remote sensing (RS) and Geographic Information System (GIS) technology in the farmers' fields of Sundarganj Upazila, Gaibandha. The study aimed to generate a remotely sensed yield forecasting model that used the high spatial resolution of Sentinel 2A and Landsat 8 data to predict maize yield 40 to 50 days before harvest. The study has investigated the prediction capacity of remote sensing NDVI data for maize yield in the study area. It has also investigated the relationship between NDVI and yield for the study region. Here the two satellite images Landsat 8 (OLI) and Sentinel 2A (MSI) which were high spatial resolution data were used in this study in the consecutive years 2018-19, 2019-20 and 2020-21 respectively. Mean NDVI and mean yield of the combined maize season performed better than NDVI and its corresponding yield of the single maize season for each satellite image. The yield prediction equations were found based on mean values of NDVI for the combined growing season against the yield of maize. The yield against NDVI relationship for both satellite images showed that R^2 along with MAPE, RMSE and NRMSE of mean NDVI for the combined maize growing season performed better than the single maize growing season for the study area. The absolute mean error of prediction was found to be about 9.77% for Landsat 8 and 10.17% for Sentinel 2A compared to the actual yield during the maize growing season 2020-2021. The predicted yield (mean) of Sentinel 2A which is 1.33% closer to the actual yield than Landsat 8 was observed in this research. The yield prediction model for Sentinel 2A images performed better than Landsat 8 because of the high spatial resolution (~10m) that was revealed in this study. So, it can be concluded that the maize yield prediction based on Sentinel 2A images may be used to predict the yield before harvesting.

Limitations

- We could use more advanced indices like EVI (Enhanced Vegetation Index), SAVI (Soil Adjusted Vegetation Index) then the results could be more precise. But for technical issues it could not be used. So, yield prediction oriented advanced indices along with NDVI and other factors will be used in future research.

- On the other hand, we used single image selection for each season for both satellites manually, but we will be used sensitivity analysis for image selection for crop growing stage in future.

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