

Article



Optimum Sowing Window and Yield Forecasting for Maize in Northern and Western Bangladesh Using CERES Maize Model

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Abstract: Determination of the optimum sowing window not only can improve maize yield significantly but also can fit maize in the existing cropping pattern. To get the advantages of sowing maize at the optimum time, a study was designed and carried out at the research field of Bangladesh Agricultural Research Institute, Rangpur, Bangladesh during 2015–2017. Another aim of the study was to forecast the yield of maize for the northern and western regions of Bangladesh using the CERES-Maize model. The study considered 5 November, 20 November, 5 December, 20 December, and 5 January as sowing dates for maize to identify the optimum sowing window. Three hybrid maize varieties, viz., BARI Hybrid Maize-9 (BHM-9), NK-40, and Pioneer30V92 were used. The study was laid out in a split-plot design, assigning the sowing dates in the main plot and the varieties in the sub-plot. To forecast the yield, the daily weather data of 2017 were subjected to run the model along with thirty years (1986–2015) of weather data. The genetic coefficients of the tested maize varieties were obtained through calibration of the model by using the observed field data of 2015–2016 and through validation by using the data of 2016–2017. The seasonal analysis was done using the DSSAT CERES-Maize model to confirm the experimental findings for optimizing the sowing window for maize at the northern region (Rangpur) of the country and subsequently adjusted the model for the western region (Jashore). The model performances were satisfactory for crop phenology, biomass, and grain yield. The NRMSE for anthesis was 0.66% to 1.39%, 0.67% to 0.89% for maturity date, 1.78% to 3.89% for grain yield, and 1.73% to 3.17% for biomass yield. The optimum sowing window for maize at the Rangpur region was 5 November to 5 December and 5 to 20 November for the Jashore region. The CERES-Maize model was promising for yield forecasting of the tested maize varieties. It gave a realistic yield forecast at approximately 45 days prior to the harvest of all the tested varieties. The study results are expected to be useful for both the farmers and the policy planners to meet up the future maize demands.

Keywords: climate change; crop model; grain yield; maize; sowing window; yield forecast



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1. Introduction

The area of maize (*Zea mays* L.) is remarkably increasing in Bangladesh [1] as it has a great demand in the poultry industry [2]. Over the last 10 years (2010–2020), the production of maize has substantially increased from 1954 to 4400 thousand tons [3]. The northern and western parts of Bangladesh are the important regions for maize production [2–4]. The major hindrance of growing maize in these regions is to fit the crop within the existing rice-based cropping pattern. In those areas, the transplanted rainy season rice (*aman* rice) is commonly grown in all the existing patterns, which is rice occupied in field upto the end of October; and therefore, no lands can get free for growing maize early than November. Moreover, after the harvest of rainy season rice, the lands remain moist due to the late monsoon. Therefore, it is very crucial to optimize sowing time for maize to fit in a pattern.

Maize has the benefit to grow both in winter and pre-monsoon seasons because of its facultative nature to day-length [5]. Tropical maize varieties are photo-period sensitive, and thus, long days in high latitudes allow maize plants to grow tall but with less grain yield. Moreover, air temperature sometimes can directly influence the grain growth of maize [6]. Several studies have confirmed that maize yield significantly decreases with falling temperature [7]. Usually, plants require a definite growing degree day (GDD) to get maturity, depending on daily temperature and date of sowing.

The sowing date has a great influence on both growth and yield of crops because of environmental variations over time and space. For example, late sowing of sunflower experiences lower temperature, with a decrease in GDD from 1731 to 1621 during the grain filling period [8] resulting in low yield. However, the response of maize varieties to sowing dates can be dissimilar depending on adopted management practices. Soler et al. [9] reported a 55% yield loss in four hybrid maize varieties because of delay in sowing under rainfed condition, whereas the loss was only 21% in irrigated condition. Therefore, the knowledge on the sowing window of a variety at any particular location is important to attain maximum yield [10].

To ensure the attainable yield under the changing climatic scenario and also to avoid the costly time-consuming long-term experiments to address the long-term climatic variability issues, a reliable well-accepted strategic validated crop model can be helpful [11–13]. Among the crop models, APSIM (Agricultural Production Systems Simulator) and DSSAT (Decision Support System for Agro-technology Transfer) are the most widely and frequently used models [14]. Tovihoudji [14] and several other researchers notified that the DSSAT CERES-Maize module implemented in DSSAT [15] for simulating maize growth and yield is suitable for a broad range of soil, management, and climatic conditions in comparison to APSIM [16–19]. Many researchers have already used the DSSAT model to get good crop management practices to minimize production risks [20–25]. Soler et al. [26] used this model to forecast maize yield. Therefore, the present study was designed and executed with an aim to identify the best sowing date for hybrid maize varieties in the northern region of Bangladesh and to forecast the yield before harvest. Another aim of the study was to adjust the sowing window for maize in the western region of the country based on the results of the northern region.

2. Materials and Methods

2.1. Field Experiments

An experiment was conducted with three hybrid maize varieties, viz., BARI Hybrid Maize-9 (BHM-9), NK-40, and Pioneer30V92 at the research field of On-Farm Research Division, Bangladesh Agricultural Research Institute (BARI), Rangpur ($25^{\circ}43'28.9''$ N and $89^{\circ}15'80.7''$ E, elevation 8 m) during 2015 to 2017. Five dates were considered for maize varieties, viz., 5 November, 20 November, 5 December, 20 December, and 5 January, to get the optimum sowing window. The experimental design was split-plot, arranging the sowing date in main plots and the varieties in the sub-plots. The number of replication was three and the unit plot size was 6 m × 4m. Maize seeds were sown at 20 kg ha⁻¹maintaining 60 cm × 20 cm plant spacing. The experimental field was fertilized with N, P, K, and S

@ 250, 55, 100, and 30 kg ha⁻¹, respectively. The sources of N, P, K, and S were urea, triple superphosphate, muriate of potash and gypsum, respectively. One-third of N and the entire amounts of other plant nutrients were applied one day prior to sowing. The remaining two-thirds N was applied at 35 and 65 days after sowing as a top dressing. Supplementary irrigation was added at knee height and cob initiation stage. Manual weeding was done as and when necessary to keep the crop–weed competition at a minimum level. No control measure was required for pest or disease.

2.2. Weather and Soil Information

Daily air temperatures (maximum and minimum), rainfall, and sunshine hours were collected from the nearby weather station of the experimental field under the Bangladesh Meteorological Department, Rangpur. Solar radiation was derived from sunshine hour using Weather Man software in the CERES-Maize model (Figure 1). The averages of the two years' cumulative total rainfall were around 413, 601, 650, 667, and 773 mm for the 1st, 2nd, 3rd, 4th, and 5th sowing dates, respectively. Similarly, maize plants received 1828, 1901, 1809, 1847, and 1822 MJ m⁻²d⁻¹solar radiations for five different sowing dates, respectively. Maximum temperatures (°C) were 27.2, 27.4, 27.4, 28.1, and 28.6, respectively, for first to 5th seeding. Similarly, minimum temperatures (°C) were 15.5, 15.2, 15.4, 16.1, and 16.9, respectively. Total rainfall during the crop growing period of 2015–2016 was much higher than that of 2016–2017, therefore, irrigation frequency and quantity were more in the second year (Table 1).

2.3. Model Description

DSSAT CERES-Maize model is used to simulate crop growth and development on a daily basis under a wide range of environments [27]. This model effectively considers all the parameters in the simulation that directly or indirectly influence the grain yield of maize. The model also assesses the commencement of phenological events.

Cultivar specific parameters (CSPs) are developed by the generalized likelihood uncertainty estimation (GLUE) program of DSSAT v4.6. To perform such task scientifically, the model requires date of emergence, anthesis, physiological maturity duration, grain yield, biomass yield, grains in cob, and individual grain weight, thermal time interval from seedling emergence to end of the juvenile stage (P1), coefficient of photoperiod sensitivity (P2), degree days requirement for physiological maturity considering the base temperature of 8 °C (P5), maximum possible kernel number in a plant (G2), grain filling rate in mg day⁻¹ (G3), and phyllocron interval (PHINT) in days. Initially, a large number (6000) of parameter values are generated by GLUE and then likelihood values are calculated for each set of coefficients using differences between observed and simulated data [28].

2.4. Model Calibration and Validation

The CERES-Maize model was calibrated according to Hunt and Boote [29] by utilizing the data of grain yield, aboveground biomass yield, anthesis period, physiological maturity, number and weight of kernel that were collected from the first-year trial (2015–2016). These data were copied in an existing DSSAT maize file and run in the model with the observed weather and soil file. The process was repeated and error was adjusted until the best match was found for the observed and simulated growth duration and grain yield. The derived genotypic coefficients were used for validation of the model based on the observed data of 2016–2017 and then the model performance was evaluated for application.



Figure 1. Monthly average of temperature, rainfall, and solar radiation for the two consecutive growing seasons of maize (2015–2016 and 2016–2017) at Rangpur, Bangladesh.

Table 1	. Historical	weather da	ta of Rangpur	and Jashore	during the g	rowing season	of maize (ave	erage of 30 y	ears).
				2			`		

	Average Temperature (°C)						A		
Month	Maximum		Minimum		- Iotal Kair	lotal Kainfall (mm)		Average Sunsnine (n)	
-	Rangpur	Jashore	Rangpur	Jashore	Rangpur	Jashore	Rangpur	Jashore	
October	30.7	32.5	22.5	22.9	169.1	124.0	7.2	6.2	
November	28.5	30.3	17.3	17.4	7.8	28.2	7.8	6.8	
December	24.8	26.7	13.0	12.5	7.9	11.1	6.7	6.1	
January	23.0	25.4	10.9	11.1	9.1	13.4	6.1	6.3	
February	26.4	29.0	13.4	14.7	11.7	25.4	7.5	7.2	
March	30.5	33.6	17.5	19.7	27.6	42.3	7.8	7.4	
April	31.7	35.9	21.3	23.6	117.9	72.6	7.1	7.6	
Ŵay	31.9	35.5	23.4	25.2	284.7	180.3	6.5	6.9	

For soil properties, initially, soil samples were collected from four depths (0–15, 15–30, 30–60, and 60–90 cm). Collected samples were subjected to analysis to determine the physical properties such as texture, bulk density, moisture content, and field capacity; and the chemical properties such as pH, organic matter, and total N (Tables 2 and 3).

Soil Depth (cm)	Sand (%)	Silt (%)	Clay (%)
0–15	11	63	26
15–30	11	60	29
30-60	14	33	53
60–90	27	38	35

Table 2. The soil texture of the initial soil in the experimental field.

Table 3. Physicochemical properties of the initial experimental soil.

Soil Depth (cm)	рН	Bulk Density (g cm ⁻³)	Organic Carbon (%)	TotalN (%)	Field Capacity (%)
0–15	5.4	1.37	1.60	0.10	39.54
15-30	6.5	1.42	0.61	0.08	39.37
30-60	6.4	1.37	0.45	0.05	40.79
60–90	6.5	1.44	0.21	0.03	38.29

2.5. Evaluation of CERES-Maize Model

The model was evaluated using the index of agreement (d) [30], root mean square error (RMSE) and normalized RMSE [31], mean absolute percentage error (MAPE) [32], and percentage of predicted deviation (PD), as shown in Equations (1)–(5). Variables such as the emergence of maize, anthesis and maturity, aboveground biomass, and grain yields were evaluated in the study.

$$PD = \frac{O_i - S_i}{O_i} \tag{1}$$

Here, O_i and S_i refers to observed and simulated variables.

$$d = 1 - \left\lfloor \frac{\sum (P_i - O_i)^2}{\sum (|P_i| + |O_i|)^2} \right\rfloor$$
(2)

Here, P_i and O_i refers to predicted and observed data.

RMSE =
$$\sqrt{\frac{1}{n} \sum_{1}^{n} (X_s - X_o)^2}$$
 (3)

MAPE was determined as follows:

$$MAPE = \frac{1}{n} \sum_{1}^{n} \frac{X_s - X_o}{X_s} \times 100\%$$
(4)

Here, *n* indicates the number of comparisons, X_s is the simulated yield, and X_o is the observed yield. NRMSE was determined as follows:

$$NRMSE = \frac{RMSE}{X} \times 100\%$$
(5)

Here, "x" is the average observed yield.

PD value tending to zero indicates perfect prediction. Negative divergence indicates under prediction, but positive deviation means over prediction. A closer d-stat value to unity indicates good simulation. The RMSE is widely used to find out statistical differences between predicted and observed data [33]. If NRMSE is <10 and >10 but <20, then the prediction is considered as excellent and good, respectively.

2.6. Seasonal Analysis and Model Application

The validated CERES-Maize model was utilized to predict grain yields through seasonal analysis considering the same weather and soil data, and coefficients of tested genotypes under multiple runs for one season and five sowing times. Thirty years of weather data obtained from the Bangladesh Meteorological Weather Station at Rangpur and Jashore were used for running the model.

2.7. Yield Forecasting

Yield forecasting for three hybrid maize was accomplished through the use of the CERES-Maize model. Daily weather data for 30 years from Bangladesh Meteorological Weather Station, Rangpur were normalized and combined with daily recorded weather data for 2017. Bi-weekly yield forecasting were made, starting from mid-January until the end of May 2017. For these forecast results, the antecedent daily weather data of 2017 were used until the forecast date, complemented with 30 years of normalized weather data for the remaining growing season. For each forecast, the mean and standard deviations for the forecasted yield were determined.

3. Results and Discussion

3.1. Genetic Coefficient Determination

The adjustment of CSPs is needed for model calibration so that observed data match well with simulated values [34]. The "P" values (P1, P2, and P5) of CSPs were computed by observed dates of anthesis and physiological maturity. These values were used to find out the dates of the phenological events such as anthesis and physiological maturity for field application. The values of G2 and G3 control the yield contributing characters such as grain dry matter yield, straw yield (aboveground biomass), grain size, etc. Detailed descriptions of the genetic coefficient values are shown in Table 4. The computed CSPs values for BHM-9, NK-40, and Pioneer30V92 were put into the cultivar (CUL) file (MZCER046.CUL) to calibrate and validate the model.

Table 4. CERES-Maize	e genetic coefficient for	BHM-9, NK-40, a	and Pioneer30V92 varieties
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Variates	Cultivar Specific Parameters (CSPs)								
variety	P1	P2	P5	G2	G3	PHINT			
BHM-9	308.1	0.300	950.6	785.1	8.40	47.00			
NK-40	310.0	0.300	948.0	782.0	8.50	47.00			
Pioneer30V92	306.0	0.300	940.0	776.0	8.50	47.00			

3.2. Model Calibration Results

The simulated grain and biomass yields, anthesis, and physiological maturity of all the tested maize varieties during 2015–2016 were similar with observed data. However, observed data were slightly lower than the simulated values (Figure 2). The calibration results under five dates of sowings at Rangpur location for grain yields were $R^2 = 0.96$, RMSE = 128, NRMSE = 1.26, and d = 0.94, for biomass $R^2 = 0.93$, RMSE = 298, NRMSE = 1.40, and d = 0.91, for anthesis date $R^2 = 0.98$, RMSE = 0.42, NRMSE = 0.43, and d = 0.96, and for physiological maturity were $R^2 = 0.99$, RMSE = 58, NRMSE = 0.42, and d = 0.96 (Figure 2). Therefore, model calibrations for grain and biomass yields, anthesis date, and physiological maturity were analogous to the observed values with R^2 approaching one. These differences were rather small and also supported the good statistical indices.



Figure 2. Calibration results of grain yield with their goodness of fit during the year 2015–2016.

3.3. Model Validation

The simulated grain and biomass yields, anthesis, and physiological maturity dates of all the tested maize varieties under five sowing dates were similar to the observed data. The test statistics for validation results were $0.93 < R^2 < 0.97;175 < RMSE < 401; 1.78 < NRMSE < 3.89; and 0.98 < d < 0.99 for grain yields; 0.91 < R^2 < 0.97; 373 < RMSE < 658; 1.73 < NRMSE < 3.17; and 0.86 < d < 0.96 for biomass yields; 0.82 < R^2 < 0.95; 0.63 < RMSE < 1.34; 0.66 < NRMSE < 1.39; and 0.91 < d < 0.94 for anthesis date, and 0.99 < R^2 < 1.00; 0.94 < RMSE < 1.13; 0.67 < NRMSE < 0.82; and 0.96 < d < 0.97 for physiological maturity (Table 5). Therefore, model validation for grain and biomass yields, anthesis day, and physiological maturity were well fitted to the observed values with R² approaching to one. However, the CERES-Maize model was well parameterized, showing a good performance in simulating phenology, growth, and yield of maize varieties. In previous studies, this model was also provided with comparable results [35,36].$

3.4. Phenological Development Phases and Yields

The observed and simulated outputs were compared after the calibration of the model. The percent deviation (%PD) of the simulated data from the observed values were calculated. The model predicted anthesis and physiological maturity periods for five sowing dates, which have been presented in Table 6. Irrespective of varieties, the differences between observed and simulated anthesis and physiological maturity were +1 to +3 and +1 to +3 days, respectively. Close prediction of anthesis and maturity days with 0- to 2-days difference between observed and simulated values were also noticed by Soler et al. [26]. Chisanga et al. [27] found the CERES-Maize model predicted days to anthesis (-2 to ± 1) and maturity (-4 to ± 1) within the range of observed data. Deviations of phenological stages from the observed values were 0 to -3.13% at anthesis and from -0.8% to -2.2% at physiological maturity.

Parameters	R ²	RMSE	MAPE	NRMSE	D	
			BH	BHM-9		
Yield, kg ha ^{-1}	0.93	192	13.93	1.92	0.98	
Tops weight, kg ha ^{-1}	0.97	373	7.81	1.73	0.96	
* ADAP, days	0.82	1.34	2.54	1.39	0.93	
* MDAP, days	1	0.94	3.59	0.67	0.96	
			NI	K-40		
Yield, kg ha ^{-1}	0.97	401	13.21	3.89	0.98	
Tops weight, kg ha ^{-1}	0.91	476	7.21	2.21	0.92	
ADAP, days	0.95	0.63	2.76	0.66	0.94	
MDAP, days	1	0.94	3.73	0.67	0.96	
			Pione	er30V92		
Yield, kg ha ^{-1}	0.91	175	14.01	1.78	0.99	
Tops weight, kg ha ^{-1}	0.97	658	7.95	3.17	0.86	
ADAP, days	0.93	0.85	3.00	0.89	0.91	
MDAP, days	0.99	1.13	3.77	0.82	0.97	

Table 5. Indicators of the goodness of fit for grain and biomass yields, and growth duration using CERES-Maize model validation irrespective of sowings dates at Rangpur, Bangladesh during 2016–2017.

* ADAP = anthesis days after planting, and MDAP = maturity days after planting.

Table 6. Comparison between observed and simulated, and percent differences for phenological development stages, grain, and biomass yields as affected by different sowing dates and maize hybrids with the CERES-Maize model at Rangpur, Bangladesh during 2016–2017.

Phenological	Obs.	Sim.	% PD	Obs.	Sim.	% PD	Obs.	Sim.	% PD	
Stages		BHM-9 NK-40					Pi	Pioneer30V92		
				5	November					
Anthesis day	99	98	1.01	98	98	0.00	98	98	0.00	
Maturity day	145	148	-2.1	145	148	-2.1	145	148	-2.1	
Grain (kg ha ^{-1})	10,062	10,047	0.1	10,020	10,150	-1.3	10,285	10,065	2.1	
Biomass ($kg ha^{-1}$)	22,319	23,231	-4.1	23,457	23,464	0.0	22,633	23,310	-3.0	
				20	November					
Anthesis day	99	99	0.0	98	99	-1.02	96	99	-3.13	
Maturity day	144	146	-1.4	144	146	-1.4	143	145	-1.4	
Grain (kg ha $^{-1}$)	11,650	10,833	7.0	11,474	10,925	4.8	11,042	10,626	3.8	
Biomass (kg ha ^{-1})	22,306	23,207	-4.0	17,440	18,617	-6.7	22,075	23,328	-5.7	
		5 December								
Anthesis day	96	98	-2.1	96	98	-2.1	96	98	-2.1	
Maturity day	140	142	-1.4	140	142	-1.4	139	142	-2.2	
Grain (kg ha ^{-1})	11,150	11,220	-0.6	11,481	11,315	1.4	10,998	11,240	-2.2	
Biomass (kg ha ^{-1})	22,763	23,557	-3.5	21,701	23,405	-7.9	23,115	23,287	-0.7	
				20) December					
Anthesis day	95	97	-2.1	95	97	-2.1	95	97	-2.1	
Maturity day	136	138	-1.5	136	138	-1.5	135	138	-2.2	
Grain (kg ha $^{-1}$)	10,051	10,542	-4.9	10,847	10,631	2.0	9904	10,561	-6.6	
Biomass (kg ha ^{-1})	17,942	18,677	-4.1	21,935	23,246	-6.0	21,745	23,257	-7.0	
				ļ	5 January					
Anthesis day	93	93	0.0	92	93	-1.1	91	92	-1.10	
Maturity day	131	132	-0.8	130	131	-0.8	129	130	-0.8	
Grain (kg ha ^{-1})	7005	6937	1.0	7005	6937	1.0	6971	6730	3.5	
Biomass ($kg ha^{-1}$)	21,420	23,330	-8.9	21,619	23,215	-7.4	17,100	17,888	-4.6	

However, up to November seeding, observed anthesis and maturity days were 99 and 145, respectively. Anthesis and maturity days reduced under late sowing dates. On 5 January sowing, anthesis and maturity days were 91 to 92 and 129 to 131, respectively. Due to late planting from November to January, days to anthesis of maize decreased. The possible reason could be prevailing high temperatures during the pre-flowering stage in late-planted maize, decreased GDD, and thus leading to early maturity of the crop. Ahmed et al. [31] also reported a similar incidence in late-planted maize. The increment of both maximum and minimum temperature shortens the duration of flowering and maturity of maize [33]. In the present study, the deviation in simulated grain and biomass yields from the observed values ranged from -2.2% to +1% and -8.9% to 0%, respectively. The second and third sowing dates (20 November and 5 December) produced higher grain yields satisfactorily which was close to the yield of 5 November sowing. Grain yield reduced beyond 5 December sowing, and the lowest was obtained from 5 January planting. Liaqat et al. [37] also marked a reduction in grain yield for delayed planting. Biswas [38] reported similar findings and identified 20 to 30 November as the optimum sowing time for hybrid maize at Jamalpur district of Bangladesh.

3.5. Seasonal Outputs

Long-term simulated grain yield of maize varied from 10,039 to 11,839 kg ha⁻¹in Rangpur. Varietal performances were almost similar for five sowing dates. The highest grain yield of maize was attained when sown on 5 November, and the lowest on 5 January seeding, which was similar to the 4th and 5th sowing dates (Figure 3a). Gradual decrement of grain yield was from November to early January sowing. Biomass yield also followed a similar trend. Prolonged life duration and favorable temperature, especially at the grain filling stage, might be the main reason for the higher grain yield of maize in early sowing dates. Ahmed et al. [31] also reported similar findings in maize. The relationship between grain yield and different sowing dates of maize are linear. Simulated grain yield was higher in November sowing and decreased thereafter. The lowest grain yield was obtained in January sowing. Considering varietal performances, NK-40 and Pioneer30V92 gave higher grain yields in all the sowing dates compared to BHM-9, though the differences were not remarkable. On average, about 300 kg ha⁻¹ grain yields reduced for every 15 days' delay in sowing date. On the other hand, the long-term simulated grain yield of maize in the Jashore region ranged from 6512 to 10,034 kg ha $^{-1}$. Varietal performances were almost similar in five sowing dates (Figure 3b). Sowing dates follow a sharp linear relationship; the simulated yield on 5 November was higher and close to 20 November sowing, and then declined gradually with late sowing dates. With a delay in the sowing date from 5 November to 20 November, yield reductions were 872–891 kg ha⁻¹. This indicates that a farmer may delay sowing because of the unsuitability of land or other socioeconomic conditions, but he/she has to lose about one-ton grain yield than the optimum seeding time. Our findings are concurrent with that of Porter and Semenov [39] and Adnan et al. [16] that early planting offered benefit to achieve targeted maize yield while the risk of yield reduction increased with the delay in planting.

3.6. Yield Forecasting

High variability with yield forecasting was observed during February and March sowing, as seen from the large standard deviations (Figure 4). The standard deviation of simulated grain yield decreased for all three hybrids with the progress of a growing season when the simulations were run, considering an extensive period with real weather data of 2017 (Figure 4). For all the tested varieties, the standard deviation of the estimated yields for 1st April was close to zero (Figure 4a–c), but at the end of the growing season, the simulated and observed yields in 2016–2017 were similar (triangle points in Figure 4). These similarities were expected because the CERES-Maize model was evaluated using observed grain yields. Using observed weather data of 2017, we found perfect yield prediction at least 45 days prior to harvest for all three maize varieties. Similar findings have been

reported by others for millets [40], groundnut [41], and maize [6]. The tested CERES-Maize model showed many potentialities for yield predictions. The present study confirms the findings of Boggione et al. [42] and Amaral et al. [43], who forecasted maize yield through CERES-Maize and got satisfactory results. However, the study suggests calibrating and validating the model before application for new hybrids in the new location under different agro-climatic conditions.





Figure 3. (a) Grain yield of maize as affected by sowing dates at Rangpur region considering 30 years of historical data. (b) Grain yield of maize as affected by sowing dates at Jashore region considering 30 years of historical data.



Figure 4. Average forecasted yield and standard deviation from the observed yield of the year 2017 considering the forecast date and yield (kg ha⁻¹) for maize (**a**) BHM-9, (**b**) NK-40, and (**c**) Pioneer30V92.

4. Conclusions

The CERES-Maize model was capable of simulating phenology and yield of three hybrid maize varieties for five sowing dates in the northern and western regions of Bangladesh. The simulated results were in close agreement with the observed values. The validated CERES-Maize model was able to estimate the attainable grain yield satisfactorily for various sowing dates. The seasonal analysis option of the model identified the optimum sowing windows for maize for both the northern and western region of Bangladesh. The optimum sowing window for Rangpur (northern region) was between 5 November to 5 December, and 5 to 20 November for Jashore (western region). Therefore, the study claimed that now maize can easily be fitted into rice-based cropping patterns at the northern and western regions of the country. Moreover, the model successfully forecasted the grain yield of the tested maize varieties at approximately 45 days prior to harvest. The study results will definitely be beneficial for the farmers to boost up the maize production under the adverse climatic conditions and also for the policy planners to estimate the future requirement for import maize to meet the national demand or for export if production is surplus. Further research would be needed for new varieties to determine the optimum sowing window(s) at different locations and to forecast the yield at the early stage of maize by using a multi-criteria model following an artificial neural network as well as using the DSSAT model.

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