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PREDICTING FINAL GRAIN YIELD OF BORO RICE USING STEPWISE MULTIPLE REGRESSION AND WEATHER PARAMETERS IN THE NEW ALLUVIAL ZONE OF WEST BENGAL INDIA

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ABSTRACT

A field experiment was conducted during the boro (summer) seasons of 2017–18 and 2018–19 at the D Block Farm, Bidhan Chandra Krishi Vishwavidyalaya, Kalyani, Nadia, West Bengal, to predict final grain yield in boro rice using stepwise multiple regression models. The objective was to identify the most influential weather parameters affecting yield performance across varieties and years. Three rice varieties (Triguna, Shatabdi, and Heera), two seedling ages, and three spacing treatments were evaluated. Separate regression models were developed for each variety and season.

The models revealed significant associations between grain yield and agrometeorological variables such as maximum and minimum temperatures, morning and evening relative humidity, wind speed, rainfall, pan evaporation, and bright sunshine hours. The coefficient of determination (R^2) ranged from 0.92 to 0.99, indicating excellent predictive power. For example, the model for Triguna in 2017–18 yielded an R^2 of 0.99, incorporating key variables like T_{max} , T_{min} , RH-I, RH-II, WS, Rain, and Epan.

The findings confirm that boro rice yield can be reliably forecasted using key weather parameters, enabling proactive crop management under varying climatic conditions. These models hold substantial potential for agrometeorological advisory services and decision support systems aimed at enhancing rice productivity in the New Alluvial Zone of West Bengal.

Keywords : Boro rice, Grain yield prediction, Stepwise regression, Weather parameters, Agrometeorological modelling, New Alluvial Zone, Rice varieties, Climate variability.

Introduction

Rice (*Oryza sativa* L.) is a staple food for more than half of the world's population and a fundamental component of food and livelihood security, particularly in Asia. In India, the eastern states West Bengal, Odisha, Assam, Bihar, and the northeastern region together account for over 45% of the national rice-growing area but contribute only about one-third of the total production (Sarkar & Pal, 2014). Among these, West Bengal plays a pivotal role, especially in the New Alluvial Zone, which is characterized by deep, fertile soils, moderate temperatures, and assured irrigation, making it a prime region for intensive rice cultivation.

Of the three-principal rice-growing seasons in the region aus, aman, and boro the *boro* season (December to May) is particularly significant for augmenting annual rice output due to the availability of irrigation and adoption of improved agronomic practices. However, rice yields during this season are highly sensitive to climatic variability, especially during critical phenological stages such as flowering and grain filling (Kumar *et al.*, 2013). Adverse weather events including temperature extremes, low solar radiation, and erratic rainfall can negatively affect physiological processes like photosynthesis, pollination, and grain development, thereby reducing yield potential.

Adding to these challenges is increasing water scarcity during the dry season, which intensifies competition for irrigation resources (Chapagain & Yamaji, 2010). In this context, there is an urgent need for accurate, site-specific yield prediction models that integrate agrometeorological variables with crop growth stages. Stepwise multiple regression has emerged as a robust statistical approach for selecting the most influential weather parameters from a set of interdependent variables (Agrawal *et al.*, 1986). Previous research has demonstrated the utility of this technique for forecasting yields of rice, wheat, and maize under varying agroclimatic conditions (Rai *et al.*, 2011; Patel *et al.*, 2017). However, model performance and accuracy can be enhanced by tailoring the approach to specific cultivars, seasons, and agroecological zones.

Another underexplored factor in boro rice yield dynamics is surface albedo the fraction of incoming solar radiation reflected by the crop-soil system. Albedo is influenced by factors such as crop canopy structure, soil moisture, crop developmental stage, and solar angle (Ridgwell *et al.*, 2009). Given that solar radiation is a major driver of growth during the boro season, understanding albedo patterns can offer deeper insights into energy balance, canopy temperature regulation, and ultimately, crop productivity. Yet, this remains inadequately studied in Indian boro rice systems.

In light of these considerations, the present study was undertaken with the following objectives:

1. To develop stepwise multiple regression models for predicting final grain yield of three boro rice varieties Triguna, Shatabdi, and Heera;
2. To identify key weather parameters influencing yield during the 2017–18 and 2018–19 boro seasons;
3. To evaluate the predictive accuracy of the models for use in agrometeorological advisories and sustainable crop planning in the New Alluvial Zone of West Bengal.

Materials and Methods

The field experiment was conducted during the boro (summer) seasons of 2017–18 and 2018–19 at the District Seed Farm (D Block Farm), Kalyani, under Bidhan Chandra Krishi Viswavidyalaya (BCKV), located in the Nadia district of West Bengal (22.97°N latitude, 88.43°E longitude), in the New Alluvial Zone. This agroecological zone is characterized by a humid subtropical climate, flat terrain, and homogeneous, well-drained alluvial soils with moderate fertility. The study aimed to assess the influence of

agrometeorological factors and agronomic practices on the yield of boro rice.

The experiment followed a factorial randomized block design (FRBD) with two replications. Treatments comprised three rice varieties Triguna (V_1), Shatabdi (V_2), and Heera (V_3); three spacing levels 20 cm × 15 cm (S_1), 20 cm × 20 cm (S_2), and 15 cm × 15 cm (S_3); and two seedling ages 32-day-old seedlings (A_1) and 25-day-old seedlings (A_2). Standard agronomic practices were followed throughout the crop season, including proper land preparation, timely transplanting, scheduled irrigation, recommended fertilization, weed management, and pest control.

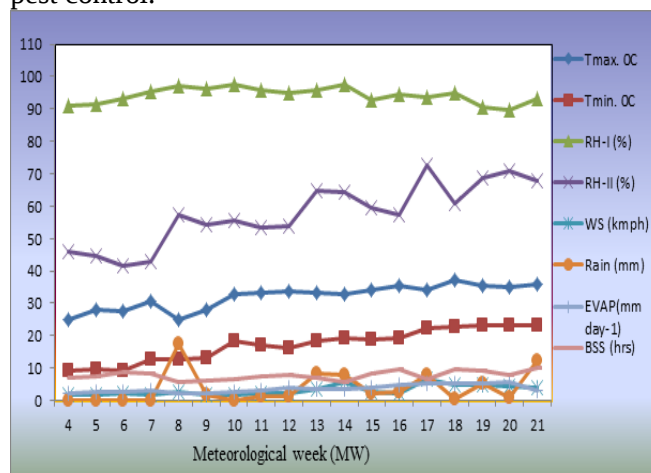


Fig. 1: Weather conditions during the boro rice-growing season 2017-18

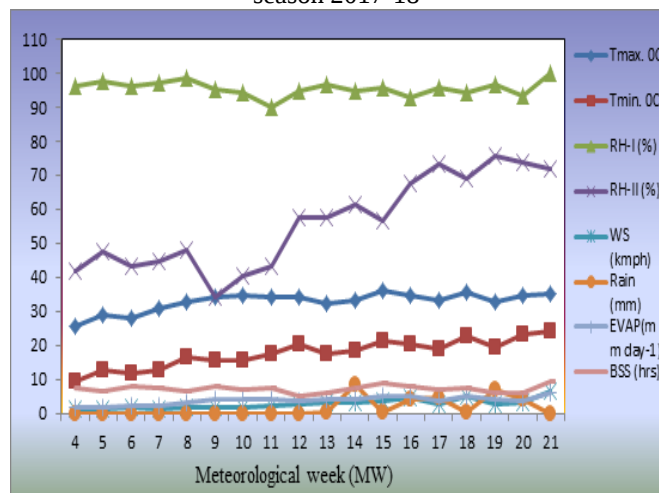


Fig. 2 : Weather condition during the boro rice-growing season 2018-19

Weekly weather data during the crop-growing period, covering the 4th to the 21st standard meteorological weeks (SMW), were collected from the nearby Agrometeorological Observatory of AICRP on Agrometeorology. The recorded parameters included maximum temperature (T_{max}), minimum temperature (T_{min}), morning relative humidity (RH-I), afternoon

relative humidity (RH-II), wind speed (WS), rainfall (RF), evaporation (Epan), and bright sunshine hours (BSS). There also depicted in (Fig. 1&2) the weekly maximum temperature peaked during SMW 18 with values exceeding 35°C, whereas the minimum temperature dropped below 10°C during SMW 4. Morning relative humidity reached as high as 97% during SMWs 4 and 21, while afternoon relative humidity dropped to 35% in SMW 9. Wind speed was lowest in SMW 5 (<1.5 km/hr) and peaked in SMWs 17 and 20 with values above 6 km/hr. Rainfall peaked during SMWs 8 and 13 with values greater than 16 mm, whereas it was negligible (<0.5 mm) in SMWs 10 and 13. Evaporation was highest during SMWs 19 and 20, reaching up to 6 mm/day, and lowest in SMWs 4 and 5 (<2 mm/day). Bright sunshine hours exceeded 8 hours/day in SMW 20 and were lowest (<5 hours/day) in SMWs 8 and 12.

Weather condition during the both growing season values of weather parameters in the vegetative, reproductive and ripening phases of crop growth for Triguna variety in year 2017-18 and 2018-19 in (Fig. 1&2) over different age of seedling and variety showed similar trend.

Phenological observations, including transplanting, tillering, panicle initiation, flowering, and maturity stages, were recorded for each treatment combination. Grain yield was estimated by harvesting five representative hills from each plot, and the weights were adjusted to a 14% moisture content.

The collected data on growth and yield attributes were statistically analyzed using Microsoft Excel and SPSS 7.5 software following the methodology of Gomez and Gomez (1984). The factorial randomized block design was used to analyze variance (ANOVA), and treatment means were compared using the Least Significant Difference (LSD) test at a 5% level of significance.

To examine the relationship between grain yield and weather parameters, stepwise multiple linear regression (SMLR) analysis was carried out using SPSS 7.5. The independent variables considered in the regression analysis included T_{max} , T_{min} , RH-I, RH-II, WS, RF, Epan, BSS, and The general form of the regression model was expressed as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon$$

where Y represents the grain yield ($t\ ha^{-1}$), X_1 to X_n denote the independent weather or agrometeorological variables, β_0 is the intercept, β_1 to β_n are the regression coefficients, and ε is the random error term.

The stepwise selection method was applied to include or exclude predictors based on the F-statistic and a significance level of $p < 0.05$, ensuring both model simplicity and explanatory power. Model

performance was evaluated using the coefficient of determination (R^2), standard error of mean and Willmott's index of agreement (d), as defined below:

- **Willmott's Index (d) =**

$$1 - \left[\sum (Y_i - \hat{Y}_i)^2 / \sum (Y_i - \bar{Y} + |\hat{Y}_i - \bar{Y}|)^2 \right]$$

where Y_i is the observed yield, $\hat{Y}_i$ is the predicted yield, and $\bar{Y}$ is the mean of observed yields.

Results and Discussion

Weather Parameters and Grain Yield Correlation

The relationship between key meteorological variables and the growth and yield of different boro rice varieties was assessed using stepwise multiple regression analysis for the consecutive cropping seasons of 2017–18 and 2018–19. The regression equations derived for each year and variety are presented in Table 1. These equations highlight the specific weather parameters that were most significantly correlated with grain yield. The strength of these relationships was quantified through adjusted R^2 values, with significance assessed at the 1% level. The regression models revealed strong predictive relationships for all varieties, especially for Triguna, which consistently exhibited the highest adjusted R^2 values across both seasons. This suggests that the meteorological parameters considered in the models played a crucial role in influencing the grain yield of boro rice.

(Mondal and Chatterjee 1984) Reported that crop transplanted in January significantly produced more yield to further increase the productivity of boro rice in New alluvial zone of West Bengal.

Year-to-Year Variability in Weather Sensitivity

A comparative analysis of the regression models across seasons revealed significant interannual variability in the weather parameters affecting grain yield. Triguna demonstrated the strongest model performance, are presented in Table 1 with R^2 values of 0.900 in 2017–18 and 0.917 in 2018–19, explaining 90-91% of the yield variability. Shatabdi followed with R^2 values of 0.767 and 0.886, while Heera recorded comparatively lower values of 0.656 and 0.633. These results are consistent with previous studies by Khan *et al.* (2006) and Maity *et al.* (2008), which also noted a significant sensitivity of boro rice productivity to seasonal weather fluctuations. The findings suggest that Triguna may be more resilient and responsive to varying climatic conditions compared to the other varieties, which indicates its potential as a stable cultivar under changing environmental conditions.

Table 1: Stepwise multiple regression equations for grain yield prediction model with meteorological parameters for different Boro rice varieties

Year	Variety	Regression Equation	Adjusted R ²
2017-18	Shatabdi	$Y = 5899.15 + 121.33 (T_{min}) + 310 (RH-I) - 197 (RH-II) - 521 (Epan) + 791 (BSS)$	0.767**
	Heera	$Y = 2724.77 + 174.89 (T_{max}) + 137.32 (T_{min}) - 279.32 (RH-I) - 271.27 (WS) - 235.90 (Rain) + 122.16 (Epan) + 319.51 (BSS)$	0.656*
	Triguna	$Y = -4977.05 - 186 (T_{max}) - 521.23 (T_{min}) + 214.66 (RH-I) + 226.61 (RH-II) + 99.71 (WS) + 245.38 (Rain) + 434 (Epan)$	0.900**
2018-19	Shatabdi	$Y = -1072.48 + 131.13 (T_{max}) - 89.46 (T_{min}) + 161.97 (RH-II) + 508.53 (WS) + 642 (Rain) + 334 (Epan) + 146.96 (BSS)$	0.886**
	Heera	$Y = -3342.55 - 42.83 (T_{max}) - 164.96 (T_{min}) - 27.37 (RH-I) - 45.73 (RH-II) + 14.77 (WS) + 724 (Rain) + 39.45 (BSS)$	0.633*
	Triguna	$Y = 2266 + 131.34 (T_{max}) - 47.69 (T_{min}) + 206.36 (RH-I) - 60.79 (RH-II) - 78.97 (WS) - 694 (Rain) + 180 (Epan) - 84.61 (BSS)$	0.917**

Values are significant at 1% (**) and 5 % (*) levels

Meteorological Parameters Affecting Grain Yield

In the 2017–18 season, the weather parameters that showed strong correlations with yield varied by variety are presented in Table 1 for Shatabdi, the key predictors were minimum temperature (T_{min}), morning relative humidity (RH-I), evening relative humidity (RH-II), evaporation (Epan), and bright sunshine hours (BSS). On the other hand, Heera and Triguna exhibited sensitivity to a broader range of parameters, including maximum temperature (T_{max}), T_{min} , RH-I, RH-II, wind speed (WS), rainfall, Epan, and BSS. In the 2018–19 season, there was a shift in parameter sensitivity. For example, Epan was no longer significant for Heera, whereas Shatabdi became more responsive to T_{max} , WS, and rainfall. Triguna, however, continued to exhibit sensitivity to a wide range of meteorological parameters in both years, reinforcing its adaptability to different environmental conditions.

Implications of Year-to-Year Variations

The findings underscore the pronounced effect of interannual weather variability on grain yield, particularly for varieties like Shatabdi and Heera, where the predictive weather parameters differed between years. The consistent performance of Triguna across both seasons highlights its potential as a stable variety in the face of climate uncertainty. Furthermore, the study underscores the importance of optimizing the planting date, as critical weather variables such as temperature and sunshine hours during early phenological stages significantly influence the final yield outcomes. These conclusions align with the recommendations of Maity *et al.* (2008), who suggested that transplanting during the first fortnight of January in the New Alluvial Zone of West Bengal

could help synchronize crop development with favorable thermal and radiation conditions.

Studies the sensitivity of weather parameters based on regression at different phenological phases:

Plant height (PH), number of tillers (T), dry matter (DM) (g) and Leaf area (LA) of Shatabdi, Heera and Triguna varieties during the 2017-18 and 2018-19 boro season. Which meteorological parameters are sensitive for which phenological phases were evaluated through multiple regression analysis studies and results with adjusted R² and standard error of mean values were summarized in (Table 2,3 & 4).

a) Establishing relationship through regression of plant height (PH) for Shatabdi, Heera & Triguna variety:

It shows that weather parameters which are sensitive to vegetative, reproductive and ripening phases for plant height were not identical, although some meteorological parameters appear as important factors in Shatabdi, Heera & Triguna variety. In case of vegetative phase only four meteorological parameters of RH-II, WS, Epan and BSS are highly sensitive in the year 2017-18, while all the eight considered weather parameters namely T_{max} , T_{min} , RH-I, RH-II, WS, Rain, Epan and BSS highly sensitive in the year 2018-19. Model developed predicting values of total variation (98 % and 99 %) highly significant at 1% level can be used for pre harvest forecast of yield component of plant height (PH).

Similarly, all meteorological parameters are not equally sensitive in the reproductive phase in two different cropping seasons of 2017-18 & 2018-19. In (Table 2, 3&4) indicates that three weather parameters of T_{max} , RH-I and BSS are significantly impacting on boro rice production in the reproductive stage in 2017-18, while seven weather parameters namely i.e. T_{max} ,

RH-I, RH-II, WS, Rain, Epan and BSS are significantly impacting the growth and development of boro rice in reproductive phase in the year 2018-19. The multiple regression model for predicting the plant height for reproductive phase at (97 % to 99 %) of the total variation which was highly significant at 1 % level.

In (Table 2,3&4) also shows in the ripening phase the number of weather parameters impacting on plant height in the year 2017-18 are less compare to year 2018-19. Only three meteorological parameters T_{min} , WS and BSS are significantly impacting on ripening phase of boro rice, while five weather parameters namely i.e., T_{min} , RH-I, WS, Rain and BSS, are sensitive to growth and development of plant height. The coefficient of determination (R^2) of multiple regression model for yield prediction were plant height (83 % to 95 %) of the total variation which was highly significant 1 % level can be adopted to be used for preharvest forecast.

It was indicating that year to year variation of weather parameters in vegetative phase, reproductive & ripening phases plays a significance role to growth and development of plant height of Boro rice.

b) Establishing relationship through regression of number of tillers (T) for Shatabdi, Heera & Triguna variety:

The effect of weather factors sensitive on different stages. If growth was integrated in final biomass production which were found to have strong and significant correlation of number of tillers (T). in (Table 2,3&4) It shows that weather parameters which are sensitive to vegetative, reproductive and ripening phases for number of tillers were not identical, although some meteorological parameters appears as important factors in three major phenological phases of Shatabdi, Heera & Triguna variety. in case of vegetative phase five weather parameters of RH-I, RH-II, WS, Epan and BSS are highly sensitive in the year 2017-18, while the all eight considered weather parameters namely T_{max} , T_{min} , RH-I, RH-II, WS, Rain, Epan and BSS highly sensitive in the year 2018-19. The model for prediction of number of tillers to account for variation in (95% to 97 %) of further coefficient of determination of model is highly significant at 1% levels.

Table 2: Regression equation showing the sensitive meteorological parameters for plant height(PH), number of tillers (T), dry matter (DM) (g) and Leaf area (LA) of Shatabdi variety at three major phenological phases of 2017-18 and 2018-19 boro season.

Year	Growth phases	Regression Equation	Adjusted R^2	S.E of mean
2017-18	Vegetative phase	(PH) $Y = 2814.37 - 30.836 (RH-I) + 26.883 (BSS)$	0.990**	1.655
		(T) $Y = 574.089 - 7.079 (RH-I) + 16.180 (BSS)$	0.971**	1.210
		(DM) $Y = 653.433 - 7.545 (RH-I) + 11.826 (BSS)$	0.971**	1.039
		(LA) $Y = -189.679 + 2.361 (RH-I) + 22.004 (WS) - 9.454 (BSS)$	0.778**	0.628
	Reproductive phase	(PH) $Y = 140.34 + 10.33 (Rain) - 11.345 (BSS)$	0.974**	2.769
		(T) $Y = 67.798 - 11.535 (Ws) + 5.788 (Rain) + 2.677 (Epan) - 5.571 (BSS)$	0.815**	1.561
		(DM) $Y = 448.820 - 19.547 (T_{max}) + 8.398 (T_{min}) + 0.994 (RH-I) + 0.017 (BSS)$	0.984**	2.119
		(LA) $Y = 96.358 + 0.197 (T_{max}) + 0.710 (T_{min}) - 1.413 (RH-I) + 0.062 (RH-II) - 0.245 (WS) + 0.253 (Rain) - 0.140 (Epan) + 3.037 (BSS)$	0.868**	0.346
	Ripening phase	(PH) $Y = 36.33 + 0.515 (RH-II) + 4.313 (BSS)$	0.868**	1.853
		(T) $Y = 40.434 - 0.607 (T_{max}) - 0.014 (T_{min}) - 0.035 (RH-I) - 0.069 (RH-II) + 2.688 (WS) + 0.685 (Rain) + 0.194 (Epan) - 0.146 (BSS)$	0.803**	0.648
		(DM) $Y = -139.90 + 3.248 (T_{max}) - 0.880 (RH-I) + 10.908 (WS) + 6.496 (Rain) - 9.358 (Epan) - 0.988 (BSS)$	0.832**	3.19
		(LA) $Y = 58.686 - 0.946 (T_{max}) - 0.176 (RH-I) - 2.802 (Rain) + 0.910 (Epan) - 0.381 (BSS)$	0.976**	0.228
2018-19	Vegetative phase	(PH) $Y = -105.050 + 0.237 (T_{max}) + 15.856 (T_{min}) + 0.433 (RH-I) - 2.260 (RH-II) - 0.502 (Epan) + 3.776 (BSS)$	0.989**	1.731
		(T) $Y = -149.334 + 0.776 (T_{max}) + 2.045 (T_{min}) + 0.824 (RH-I) + 0.574 (RH-II) + 2.338 (Ws) - 1.819 (Rain) + 1.951 (Epan) + 0.872 (BSS)$	0.950**	1.572
		(DM) $Y = 835.63 + 0.053 (T_{max}) + 0.535 (T_{min}) - 1.332 (RH-I) + 0.511 (RH-II) - 417.611 (WS) + 19.519 (Rain) - 0.671 (Epan) - 0.243 (BSS)$	0.963**	1.094
		(LA) $Y = -83.546 + 0.178 (T_{max}) - 1.994 (RH-I) + 1.443 (RH-II) - 0.362 (Epan) + 4.410 (BSS)$	0.874**	0.473
	Reproductive phase	(PH) $Y = -447.661 + 6.939 (T_{max}) + 2.556 (RH-I) + 1.002 (RH-II) - 3.956 (WS) + 2.958 (Rain) - 0.150 (BSS)$	0.984**	2.156

	Ripening phase	(T) $Y = -78.230 + 10.88 (T_{\max}) - 21.741 (T_{\min}) + 0.367 (RH-I) - 0.222 (RH-II) + 26.684 (WS) + 1.179 (Rain) + 0.685 (BSS)$	0.819**	1.541
		(DM) $Y = -145.476 + -0.278 (T_{\max}) + 4.220 (T_{\min}) + 0.087 (RH-I) + 1.588 (RH-II) - 0.456 (Rain) + 0.579 (BSS)$	0.977**	2.513
		(LA) $Y = 83.221 + 0.153 (T_{\max}) + 0.117 (T_{\min}) - 0.989 (RH-I) - 0.088 (RH-II) - 1.278 (WS) + 1.091 (Rain) - 0.045 (Epan) + 1.807 (BSS)$	0.935**	0.244
		(PH) $Y = 1734.58 - 51.057 (T_{\max}) - 6.706 (T_{\min}) - 1.242 (RH-I) + 0.139 (RH-II) + 0.250 (WS) - 9.100 (Rain) + 93.246 (Epan) + 1.154 (BSS)$	0.834**	2.079
		(T) $Y = -44.824 - 0.230 (T_{\max}) + 0.455 (T_{\min}) + 0.653 (RH-I) + 0.54 (RH-II) + 0.209 (WS) - 0.067 (Epan) + 0.212 (BSS)$	0.836**	0.593
		(DM) $Y = 19.898 - 2.588 (T_{\max}) - 0.101 (T_{\min}) + 0.521 (RH-I) + 0.711 (RH-II) + 2.709 (WS) - 0.994 (Rain) + 4.892 (BSS)$	0.896**	2.508
		(LA) $Y = 13.41 + 0.277 (T_{\max}) - 0.768 (T_{\min}) - 0.079 (RH-I) + 0.007 (RH-II) - 0.119 (WS) + 0.538 (Rain) - 0.038 (BSS)$	0.944**	0.350

Table 3: Regression equation showing the sensitive meteorological parameters for plant height(PH), number of tillers (T), dry matter (DM) (g) and Leaf area (LA) of Heera variety at three major phenological phases of 2017-18 and 2018-19 boro season

Year	Growth phases	Regression Equation	Adjusted R ²	S.E of mean
2017-18	Vegetative phase	(PH) $Y = 2901.798 - 31.807b (RH-I) + 27.865 (BSS)$	0.993**	1.489
		(T) $Y = -9.991 - 0.515 (RH-I) - 0.883 (RH-II) + 14.45 (BSS)$	0.962**	1.327
		(DM) $Y = -352.77 + 3.322 (RH-I) - 0.142 (RH-II) + 6.018 (Epan) + 4.688 (BSS)$	0.603**	4.587
		(LA) $Y = -149.309 - 1.598 (RH-I) + 2.011 (WS) + 0.525 (BSS)$	0.924**	0.312
	Reproductive phase	(PH) $Y = 115.234 + 0.029 (RH-II) + 14.988 (Epan) - 15.848 (BSS)$	0.993**	1.717
		(T) $Y = 140.626 - 1.755 (T_{\max}) - 0.525 (RH-II) + 3.148 (Epan) - 7.743 (BSS)$	0.864**	1.664
		(DM) $Y = 10.000 + 1.154 (T_{\max}) + 6.217 (T_{\min}) + 1.817 (RH-I) + 16.310 (Epan) - 9.238 (BSS)$	0.656**	5.130
		(LA) $Y = 8.569 - 0.01 (RH-II) + 0.994 (Epan) - 1.220 (BSS)$	0.870**	0.563
	Ripening phase	(PH) $Y = 339.172 - 1.737 (T_{\max}) - 1.824 (T_{\min}) + 3.019 (RH-I) + 5.485$	0.921**	2.354
		(T) $Y = -92.695 + 0.517 (T_{\max}) + 0.513 (T_{\min}) + 0.797 (RH-I) + 0.266 (RH-II) + 0.498 (WS) - 0.267 (Rain) + 0.227 (Epan) - 0.910 (BSS)$	0.706**	1.432
		(DM) $Y = -513.285 - 0.542 (T_{\max}) + 5.447 (RH-I) + 10.32 (BSS)$	0.861**	6.685
		(LA) $Y = 265.627 - 0.147 (T_{\max}) - 2.835 (RH-I) + 10.085 (Epan) - 4.992 (BSS)$	0.909**	0.556
2018-19	Vegetative phase	(PH) $Y = -116.935 - 0.324 (T_{\max}) + 17.435 (T_{\min}) + 1.744 (RH-I) - 3.269 (RH-II) - 0.082 (Epan) + 1.778 (BSS)$	0.992**	1.58
		(T) $Y = -583.420 + 1.709 (T_{\max}) + 1.754 (T_{\min}) + 5.723 (RH-I) + 0.313 (RH-II) - 6.055 (WS) - 3.388 (Rain) - 0.101 (Epan) - 0.682 (BSS)$	0.971**	1.170
		(DM) $Y = -145.76 + 0.657 (T_{\max}) + 3.723 (T_{\min}) + 0.978 (RH-I) + 0.580 (RH-II) + 0.787 (WS) - 2.765 (Rain) + 1.245 (Epan) - 2.026 (BSS)$	0.885**	2.475
		(LA) $Y = -45.571 + 0.068 (T_{\max}) + 0.509 (RH-I) - 0.038 (RH-II) - 0.050 (Epan) - 0.033 (BSS)$	0.912**	0.336
	Reproductive phase	(PH) $Y = -329.148 + 2.153 (T_{\max}) + 0.265 (T_{\min}) + 2.018 (RH-I) + 2.572 (RH-II) - 11.700 (WS) - 0.806 (Rain) + 2.283 (Epan) + 1.327 (BSS)$	0.986**	2.408
		(T) $Y = -8.632 + 0.388 (T_{\max}) + 0.798 (T_{\min}) - 0.115 (RH-I) - 0.200 (RH-II) - 0.790 (WS) - 0.148 (Rain) + 0.619 (Epan) + 0.320 (BSS)$	0.929**	1.204
		(DM) $Y = -187.350 + 0.549 (T_{\max}) + 0.317 (T_{\min}) + 1.003 (RH-I) + 0.616 (RH-II) + 1.128 (WS) - 0.057 (Rain) - 9.238 + 6.113 (Epan) + 5.610 (BSS)$	0.576**	5.716
		(LA) $Y = 118.929 - 1.662 (T_{\max}) - 1.450 (RH-I) + 0.079 (RH-II) - 2.033 (WS) - 0.485 (Rain) + 27.720 (Epan) - 0.770 (BSS)$	0.857**	0.590
	Ripening phase	(PH) $Y = 103.801 + 0.973 (T_{\max}) - 1.528 (T_{\min}) + 2.118 (RH-II) - 2.000 (WS) - 1.200 (Rain) + 1.148 (Epan) - 2.639 (BSS)$	0.959**	1.700
		(T) $Y = 10.308 - 0.740 (T_{\max}) + 0.101 (T_{\min}) + 0.260 (RH-I) + 0.030 (RH-II) + 0.056 (WS) + 0.151 (Rain) + 0.251 (Epan) + 0.906 (BSS)$	0.807**	0.653
		(DM) $Y = -157.537 + 6.965 (T_{\max}) + 8.901 (T_{\min}) - 1.753 (RH-I) - 0.033 (RH-II) + 3.020 (WS) + 1.962 (Rain) - 4.796 (BSS)$	0.873**	6.376
		(LA) $Y = 11.909 - 0.262 (T_{\max}) + 0.136 (RH-I) - 0.036 (RH-II) + 0.058 (WS) - 0.164 (Rain) - 1.490 (Epan) - 0.640 (BSS)$	0.926**	0.500

Table 4: Regression equation showing the sensitive meteorological parameters for plant height(PH), number of tillers (T), dry matter (DM) (g) and Leaf area (LA) of Triguna variety at three major phenological phases of 2017-18 and 2018-19 boro season

Year	Growth phases	Regression Equation	Adjusted R ²	S.E of mean
2017-18	Vegetative phase	(PH) Y = -91.447 + 2.002 (RH-II) -4.994 (WS) + 23.783 (Epan) - 2.394 (BSS)	0.984**	2.382
		(T) Y = - 73.112 + 0.250 (RH-I) +0.235 (RH-II) + 33.009(WS) -0.084 (Epan) - 0.157 (BSS)	0.971**	1.507
		(DM) Y = 117.177- 1.462(RH-I) + 0.001 (RH-II) + 18.703 (WS) + 0.965 (Epan) + 0.590 (BSS)	0.958**	1.540
		(LA) Y = 25.459 - 0.284(RH-I) - 0.007(RH-II) +1.433(WS) + 0.440 (Epan) + 0.053(BSS)	0.920**	0.328
	Reproductive phase	(PH) Y= -365.76 + 1.048 (T _{max}) +3.719 (RH-I) +8.971(BSS)	0.994**	1.056
		(T) Y= -14.015 -0.404 (T _{max}) + 2.132(T _{min})+0.337(RH-I)-0.453(RH-II) +7.602 (WS) -1.399(Rain) + 0.855 (Epan) - 2.754(BSS)	0.898**	1.891
		(DM) Y= - 116.459 - 2.693 (T _{max}) + 0.312 (RH-I) + 0.424 (RH-II) + 22.163 (Epan) - 5.561(BSS)	0.985**	2.057
		(LA) Y = 45.255 -1.002 (T _{max}) -0.076 (T _{min}) - 0.108(RH-I) + 0.700 (RH-II) +0.241 (WS) -0.134 (Rain) + 0.097(Epan) -0.044 (BSS)	0.780**	0.510
	Ripening phase	(PH) Y= 55.314 + 1.886 (T _{min}) +15.274 (WS) -6.705 (BSS)	0.880**	1.524
		(T) Y= 129.989 + 1.063 (T _{max}) - 0.046 (T _{min}) - 1.666 (RH-I) + 0.141 (RH-II) + 0.640 (WS) + 0.405(Rain) + 0.993 (Epan) - 0.164 (BSS)	0.835**	2.385
		(DM) Y= 93.914 - 1.926 (T _{max}) + 2.656(T _{min}) - 2.007 (BSS)	0.745**	2.332
		(LA) Y = -6.649 - 110 (T _{min}) +1.464 (BSS)	0.932**	0.326
2018-19	Vegetative phase	(PH) Y = -137.342 + 2.914 (T _{max}) + 2.441(T _{min}) + 1.082 (RH-I) - 0.795 (RH-II) + 8.294 (WS) + 2.364 (Rain) -3.003 (Epan) -1.707 (BSS)	0.977**	2.922
		(T) Y = - 229.813 + 2.012 (T _{max}) - 3.308 (T _{min}) + 0.526 (RH-I) + 2.502 (RH-II) + 27.951 (WS) - 1.442 (Rain) + 3.445 (Epan) + 0.363 (BSS)	0.973**	1.434
		(DM)Y = - 78.468 + 2.468 (T _{max}) + 0.582 (T _{min}) + 0.354 (RH-I) - 0.464 (RH-II) + 2.52 (WS) + 0.973 (Rain) + 0.070 (Epan) -0.441 (BSS)	0.975**	1.327
		(LA) Y = -21.345 + 0.039 (T _{max}) - 0.065 (T _{min}) + 0.166 (RH-I) + 0.054 (RH-II) + 1.150 (WS) - 0.035 (Rain) + 1.035 (Epan) -0.030 (BSS)	0.955**	0.245
	Reproductive phase	(PH) Y= - 43.781 + 0.132 (T _{max}) + 0.397 (RH-I) + 0.442(RH-II) + 4.673 (WS) - 0.136 (Rain) + 9.913 (Epan) + 0.049 (BSS)	0.992**	1.156
		(T) Y= - 7.981 - 0.307 (T _{max}) + 0.900 (T _{min}) + 0.259 (RH-I)-0.275 (RH-II) - 1.173 (WS) - 0.680 (Rain) - 1.459 (BSS)	0.898**	1.891
		(DM) Y= - 26.683 + 1.316 (T _{max}) - 0.855 (RH-I) + 1.084 (RH-II) + 2.910 (WS) + 0.915 (Rain) + 9.235 (Epan) - 0.658 (BSS)	0.981**	2.335
		(LA) Y = 200.907 + 0.189 (T _{max}) - 2.160 (RH-I) + 0.671 (WS) + 0.529 (Rain) + 0.439 (Epan) - 0.130 (BSS)	0.942**	0.333
	Ripening phase	(PH) Y= 18.070 + 1.090 (T _{min}) + 0.458 (RH-I) + 0.843 (WS) + 1.330 (Rain) + 1.095 (BSS)	0.899**	1.404
		(T) Y= - 33.714 - 0.083 (T _{max}) + 0.427 (T _{min}) + 0.446 (RH-I) + 0.114 (RH-II) + 0.092 (WS) + 0.102(Rain) + 0.211 (Epan) + 0.225 (BSS)	0.835**	2.385
		(DM) Y= - 79.337 + 1.907 (T _{max}) + 7.125 (T _{min}) + 0.777 (RH-I) + 2.435 (WS) + 1.255 (Rain) - 33.479 (Epan) + 0.024 (BSS)	0.783**	2.397
		(LA) Y = 31.987 - 0.680 (T _{min}) - 0.193 (RH-I) + 0.311 (Ws) - 0.176 (Rain) + 0.272 (BSS)	0.963**	0.241

Similarly, all meteorological parameters are not equally sensitive in the reproductive phase in two different cropping seasons of 2017-18 & 2018-19. (Table 2,3&4) indicates that all eight considered weather parameters of T_{max}, T_{min}, RH-I,RH-II,WS, Rain, Epan and BSS are significantly impacting on boro rice production in the reproductive stage in 2017-18, while seven weather parameters namely i.e., T_{max}, T_{min}, RH-I, RH-II, WS, Rain and BSS are significantly impacting the growth and development of boro rice in

reproductive phase in the year 2018-19. So it is also noticed that variation of weather in different years has impacting the number of tillers in reproductive phase differently. The model for prediction of number of tillers at reproductive phase at (81% to 92%) of total variation thus coefficient of determination (R²) of multiple regression which was highly significant at 1 % level.

In (Table 2,3&4) also shows in the ripening phase the number of weather parameters impacting on

number of tillers in the year 2017-18 are more compare to year 2018-19. The all eight considered meteorological parameters T_{max} , T_{min} , RH-I, RH-II, WS, Epan and BSS are significantly impacting on ripening phase of boro rice, while the all eight weather parameters namely i.e. T_{max} , T_{min} , RH-I, RH-II, WS, Rain, Epan and BSS, are sensitive to growth and development of number of tiller productions. It was shows that multiple regression model at ripening phase (70 % to 83 %) of total variation in yield prediction values in number of tillers significant at 1 % level.

c) Establishing relationship through regression of dry matter (DM)) for Shatabdi, Heera & Triguna variety:

In case of vegetative phase five weather parameters of RH-I, RH-II, WS, Rain, Epan and BSS are highly sensitive in the year 2017-18, while all eight considered weather parameters namely T_{max} , T_{min} , RH-I, RH-II, WS, Rain, Epan and BSS highly sensitive in the year 2018-19. (Table 2,3&4) In the dry matter accounting for (75 % to 98 %) of total variation of multiple regression model for yield prediction were highly significant at 1% level.

It was shows that (74% to 89 %) of total variation in dry matter at ripening phase. The coefficient of determination of multiple regression model for yield prediction were which was highly significant at 1 % levels. The model can be developed for preharvest forecasted yield.

In the reproductive phase in two different cropping seasons of 2017-18 & 2018-19. In (Table 2,3&4) indicates that five weather parameters of T_{max} , RH-I, RH-II, Epan and BSS are significantly impacting on boro rice production in the reproductive stage in 2017-18, while seven weather parameters namely i.e. T_{max} , RH-I, RH-II, WS, Rain, Epan and BSS are significantly impacting the growth and development of boro rice in reproductive phase in the year 2018-19. In model prediction for dry matter to account the total variation in (67 % to 98 %) at highly significant at 1 % level.

The three meteorological parameters T_{max} , T_{min} and BSS are significantly impacting on ripening phase of boro rice, while seven weather parameters namely i.e., T_{max} , T_{min} , RH-I, RH-II, WS, Rain and BSS, are sensitive to growth and development of dry matter (g) production.

This inter seasonal variation of weathers may alter the net productivity of boro rice in different years under fixed agronomical management practices in the same field.

d) Establishing relationship through regression of leaf area (LA)) for Shatabdi, Heera & Triguna variety:

In case of vegetative phase five meteorological parameters of RH-I, RH-II, WS, Epan and BSS are highly sensitive in the year 2017-18, while all eight considered weather parameters namely T_{max} , T_{min} , RH-I, RH-II, WS, Rain, Epan and BSS highly sensitive in the year 2018-19. It was indicating that year to year variation of weather parameters in vegetative phase plays a significance role on leaf area index of boro rice. In (Table 2,3&4) the model predicting leaf area in vegetative phase at (77 % to 95 %) of the total variation highly significant at 1 % levels.

Reproductive phase in two different cropping seasons of 2017-18 & 2018-19. In (Table 2,3&4) indicates that all eight considered weather parameters of T_{max} , T_{min} , RH-I, RH-II, WS, Rain, Epan and BSS are significantly impacting on boro rice production in the reproductive stage in 2017-18, while six weather parameters T_{max} , RH-I, WS, Rain, Epan and BSS significantly impacting the growth and development of boro rice in reproductive phase in the year 2018-19. In reproductive phase at (78 % to 93 %) of the total variation to account for coefficient of determination by multiple regression model it shows highly significant at 1 % levels.

In (Table 2,3&4) indicates also shows in the ripening phase the number of weather parameters impacting on leaf area index in the year 2017-18 are less compare to year 2018-19. The only two meteorological parameters T_{min} and BSS are significantly impacting on ripening phase of boro rice, while five weather parameters namely i.e., T_{min} , RH-I, WS, Rain and BSS, are sensitive to growth and development of leaf area index. In ripening phase for predicting the preharvest forecast for leaf area in (90 % to 97 %) of total variation at highly significant at 1 % level.

The sensitivity of weather parameters based on regression at different phenological phases wise for two years of field experiments (2017-18 and 2018-19), it is concluded that all weather parameters are not equally importance for the growth and development of boro rice at three major phenological phases. Some weather parameters are highly sensitive in vegetative phase while other parameters are sensitive in reproductive or ripening phases. Therefore, this phenological phase-wise sensitivity analysis of weather parameters will provide valuable information to the farming community to grow their crops in the field level in the efficient manners and they will able to

utilize natural resources and agronomic management practises to achieve optimum production.

Conclusion and Future Directions

This study concludes that meteorological parameters play a significant role in determining the grain yield of boro rice, with noticeable variability across different varieties and cropping seasons. The stepwise multiple regression models developed for Shatabdi, Heera, and Triguna in vegetative, reproductive and ripening phases were effective in capturing the relationship between yield and key weather variables. Triguna, in particular, demonstrated superior predictive performance across both years, indicating its potential resilience to climatic variations. The analysis revealed that parameters such as temperature, relative humidity, wind speed, rainfall, evaporation, and sunshine hours had varying impacts on yield, depending on the variety and seasonal conditions. The boro crop utilizes the early morning and afternoon relative humidity, minimum temperature morning during the tillering to panicle (vegetative phase), Panicle initiation to flowering (reproductive phase), physiological maturity (Ripening) phases for higher grain yield. These results emphasize the complexity of crop-weather interactions and affirm the utility of weather-based yield forecasting models in guiding agronomic decision-making.

Looking ahead, future research should aim to:

1. Integrate long-term climate projections, such as those from CMIP5/CMIP6 scenarios, to assess the potential impacts of climate change on boro rice productivity.
2. Enhance model accuracy and flexibility by employing advanced analytical techniques, including machine learning algorithms like random forests or artificial neural networks, to better capture complex, non-linear relationships between yield and weather.
3. Develop decision support tools that integrate real-time weather data with predictive models to assist farmers, extension personnel, and policymakers in making timely and site-specific management decisions.
4. Focus on the phenological growth stages most sensitive to weather fluctuations, enabling more precise agronomic interventions such as irrigation scheduling and fertilizer application.
5. Validate the models across diverse agro-climatic zones to enhance their applicability and strengthen region-specific recommendations.

In conclusion, this research provides a comprehensive understanding of how weather variability influences boro rice yields, laying the foundation for the development of climate-resilient and data-driven rice cultivation practices in eastern India.

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References

- Agrawal, R., Jain, R. C., & Mehta, S. C. (1986). Yield estimation of rice and wheat using weather parameters. *Mausam*, **37**(1), 67–70.
- Chapagain, T., & Yamaji, E. (2010). The effects of irrigation method, age of seedling and spacing on crop performance, productivity and water-wise rice production in Japan. *Paddy and Water Environment*, **8**, 81–90.
- Kumar, K., Rao, K. K., Rao, A. V. M. S., & Venkateswarlu, B. (2013). Climate change and its effect on agriculture. *Journal of Agrometeorology*, **15**(Special Issue), 1–6.
- Patel, H. R., Mehta, A. N., & Mehta, R. V. (2017). Forecasting of crop yield using weather parameters and simulation models. *Journal of Agrometeorology*, **19**(2), 189–192.
- Rai, P. K., Singh, S. K., & Upadhyay, R. (2011). Yield forecasting of rice using weather-based statistical model for Eastern Uttar Pradesh. *Journal of Agrometeorology*, **13**(2), 125–128.
- Ridgwell, A., Singarayer, J. S., Hetherington, A. M., & Valdes, P. J. (2009). Tackling regional climate change by leaf albedo bio-geoengineering. *Current Biology*, **19**(2), 146–150.
- Sarkar, S., & Pal, S. (2014). Eastern Indian agriculture: Problems and prospects. *Indian Journal of Agricultural Economics*, **69**(3), 384–393.
- Khan, S. A., Maity, G. C., & Das, L. (2006). Phasic development models of Kharif rice based on heat unit. *Journal of Interacademia*, **10**(1), 60–64.
- Maity, G. C., & Khan, S. A. (2008). Agroclimatic models for prediction of yield and yield components of boro rice in West Bengal. *Journal of Agrometeorology*, **10**(2), 403–407.
- Maity, G. C., & Khan, S. A. (2008). Yield and yield components of boro rice as influenced by different agroclimatic environments. *Journal of Interacademia*, **12**(1), 32–38.
- Mondal, B.K and Chatterjee, B.N (1984). Growth and yield performance of rice in cool season in subtropics. *J. Agronomy Crop Sci.*, **153**, 148-154.