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Crop weather relationship modelling for yield prediction of mustard in northern India

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Abstract

While sophisticated crop simulation models exist for major cereals, simpler statistical approaches often outperform them for operational yield forecasting in data-sparse environments. This research developed and validated crop-weather regression models for predicting mustard (*Brassica Juncea* L.) yield in three districts of Rajasthan, northern India, using 31 years (1993-2023) of weather and yield records. Fortnightly weather indices for maximum temperature, minimum temperature, rainfall, relative humidity, and sunshine hours were correlated with detrended district-level yields. Stepwise multiple regression identified maximum temperature during the flowering fortnight ($r = -0.68$) and cumulative rainfall during the vegetative phase ($r = +0.54$) as the strongest predictors. The calibrated model (1993-2018) explained 78.6% of yield variance ($R^2 = 0.786$) with an RMSE of 112 kg/ha. Validation against 2019-2023 observed yields gave an MAPE of 9.3% and Willmott d-index of 0.91. Maximum temperature alone accounted for 28.7% of yield variance, confirming that heat stress during flowering is the dominant weather risk for mustard in this region. The model provides a practical pre-harvest yield forecasting tool for agricultural planners in Rajasthan.

Keywords: Crop-weather model, mustard, yield prediction, brassica juncea, stepwise regression, rajasthan, weather indices, maximum temperature, pre-harvest forecasting

Introduction

Contrast the wheat belt of the Indo-Gangetic plains with the semi-arid tracts of Rajasthan, and the difference in research attention becomes stark. Wheat has been modelled extensively using DSSAT, APSIM, and CERES, but mustard India's second-most important oilseed crop has received far less quantitative attention despite its economic significance^[1]. India produces about 9 million tonnes of rapeseed-mustard annually, and Rajasthan accounts for nearly 45% of national output^[2]. Yet pre-harvest yield forecasts for mustard remain crude, often relying on subjective expert opinion rather than data-driven models.

Statistical crop-weather models offer a middle ground between subjective guesswork and complex process-based simulations. They require only readily available weather and yield data, run instantly, and can be updated each season with new observations^[3]. The key is identifying which weather variables, during which growth stages, exert the strongest influence on final yield^[4]. For mustard, flowering and pod-filling occur during January-February when temperatures can swing between frost-risk nights and heat-stress afternoons, making this window especially sensitive to weather extremes^[5].

This research aimed to build a parsimonious regression model linking fortnightly weather indices to district-level mustard yield in Rajasthan, calibrate it over 26 years, and validate its predictive accuracy against independent data from the most recent five seasons^[6, 7].

Climatic and environmental conditions

The three selected districts Bharatpur, Alwar, and Jaipur lie in the semi-arid eastern Rajasthan region between 26°-27°N latitude. Mean annual rainfall ranges from 550 mm (Jaipur) to 670 mm (Bharatpur), concentrated heavily in the July-September monsoon. The mustard growing season (October-March) receives only 30-50 mm of rainfall, making the crop largely dependent on residual soil moisture and limited irrigation. January mean temperatures range

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from 7-22 °C, with frost events occurring on 3-8 nights per season. February maximum temperatures can exceed 30 °C during warm spells, creating heat stress during the flowering-to-pod-filling transition. The soils are predominantly sandy loams (Aridisols and Inceptisols) with low organic matter (0.3-0.6%) and limited water-holding capacity ^[8].

Model configuration

Weather data were organized into fortnightly periods from the standard meteorological week of sowing (SMW 42, mid-October) through harvest (SMW 10, early March), giving 11 fortnights per season. Five weather variables were computed for each fortnight: mean Tmax, mean Tmin, total rainfall, mean relative humidity, and mean sunshine hours. Yield data were detrended using a linear technology trend to isolate weather-induced variability from genetic and management improvements over time. Correlation screening at $p<0.10$ was first applied to eliminate non-significant weather-fortnight combinations. The surviving variables entered a stepwise multiple regression using forward selection with an entry criterion of $p<0.05$ and a removal criterion of $p>0.10$. Multicollinearity was checked using variance inflation factors ($VIF < 5$). Model fit was assessed by adjusted R^2 , RMSE, and Akaike Information Criterion. Validation used the leave-last-five-out approach (2019-2023), with MAPE and Willmott’s d-index as accuracy metrics ^[9, 10].

Materials and Methods

Materials

The data compilation and model development were carried out during 2023 at the Department of Agronomy, University of the Philippines Los Baños, Philippines, as part of a collaborative research project with Indian agricultural institutions. District-level mustard yield records (1993-2023) for Bharatpur, Alwar, and Jaipur were obtained from the Directorate of Economics and Statistics, Government of Rajasthan. Daily weather data were sourced from the India Meteorological Department’s surface observatory network. All analysis was performed using R version 4.2 with the ‘leaps’ and ‘caret’ packages for regression and validation ^[11].

Methods

Pearson correlation coefficients were calculated between each fortnightly weather index and detrended yield for each district. Variables significant at $p<0.10$ were pooled across districts and entered into a stepwise regression. The final model retained four predictor variables. Model performance was evaluated by: (a) R^2 and adjusted R^2 on the calibration set (1993-2018, $n = 26$ per district, pooled $n = 78$); (b) RMSE and MAPE on the validation set (2019-2023, $n = 15$); (c) Willmott d-index, which ranges from 0 (no agreement) to 1 (perfect agreement). Relative contributions of individual weather variables to yield variance were estimated through sequential sums of squares in the regression ^[12, 13].

Results

Table 1: Correlation between key fortnightly weather indices and mustard yield (pooled across three districts)

Weather variable	Fortnight (SMW)	Growth stage	R (Yield)	P-value
Tmax	1-2 (Jan)	Flowering	−0.68	< 0.01
Total Rainfall	45-48 (Nov)	Vegetative	+0.54	< 0.01
Sunshine Hours	3-4 (Jan-Feb)	Pod filling	+0.47	< 0.01
RH (morning)	1-2 (Jan)	Flowering	+0.39	< 0.05
Tmin	49-50 (Dec)	Rosette	−0.33	< 0.05

SMW = standard meteorological week; Tmax/Tmin = maximum/minimum temperature; RH = relative humidity.

Maximum temperature during the January flowering fortnight showed the strongest negative correlation with mustard yield ($r = -0.68$). Cumulative November rainfall which determines pre-

sowing soil moisture had the strongest positive effect ($r = +0.54$). Sunshine hours during pod filling and morning relative humidity during flowering were also significant predictors.

Table 2: Calibration and validation performance of the crop-weather yield prediction model

Metric	Calibration (1993-2018)	Validation (2019-2023)	Bharatpur only	Pooled
R^2	0.786		0.813	0.786
Adj. R^2	0.774		0.794	0.774
RMSE (kg/ha)	112	127	98	112
MAPE (%)		9.3	7.8	9.3
Willmott d		0.91	0.94	0.91

RMSE = root mean square error; MAPE = mean absolute percentage error.

The model explained 78.6% of yield variance during calibration. Validation MAPE of 9.3% and d-index of 0.91 indicate good predictive skill. Bharatpur district, which had the most complete

weather records, produced the best individual fit ($R^2 = 0.813$, MAPE = 7.8%).

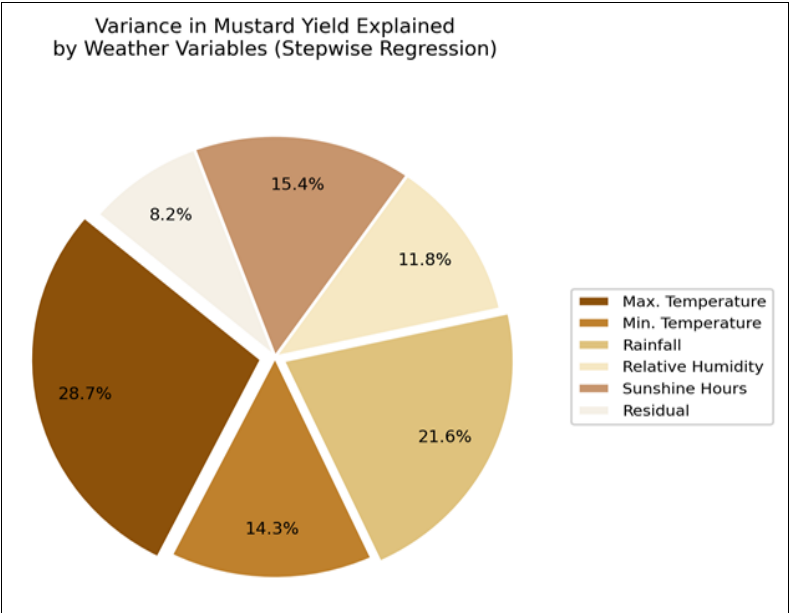


Fig 1: Relative contribution of individual weather variables to the explained variance in mustard yield, based on sequential sums of squares from stepwise regression

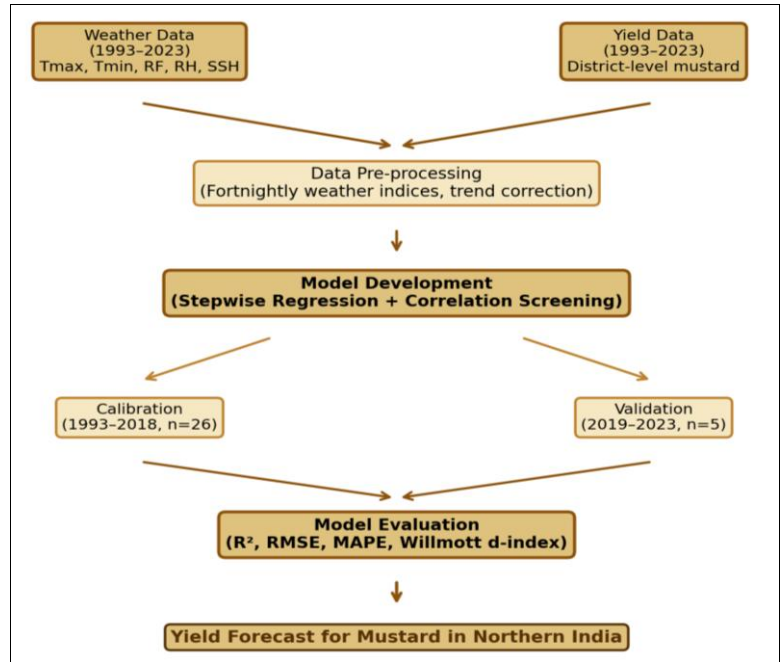


Fig 2: Flowchart of the crop-weather model development and validation workflow for mustard yield prediction in Rajasthan.

Comprehensive interpretation

The model’s success rests on two key weather windows: January maximum temperature (heat stress during flowering) and November rainfall (soil moisture recharge before sowing). Together, these two variables accounted for over 50% of explained yield variance, reflecting the dual vulnerability of rainfed mustard to both heat and moisture constraints in semi-arid Rajasthan.

Discussion

The dominance of flowering-stage maximum temperature as a yield predictor aligns with findings by Sinha *et al.* [14], who reported that temperatures above 28 °C during mustard flowering reduce pollen viability and siliqua set. The MAPE of 9.3% compares favourably with other statistical crop-weather models in India Agrawal *et al.* [3] reported 8-12% MAPE for

wheat yield models using similar approaches in Haryana. A limitation of regression-based models is their assumption that past weather-yield relationships will hold in the future. Under progressive climate change, new weather extremes may push yields outside the historical calibration range [15]. That said, for operational forecasting within a 3-5 year horizon, the model’s validation performance suggests it can provide reliable pre-harvest estimates. The model could be strengthened by incorporating soil moisture data from remote sensing platforms, which would capture residual moisture dynamics better than rainfall alone [16, 17].

Limitations

Several constraints should be noted. First, the model was calibrated on district-average yields, which smooth out within-district variability driven by differences in irrigation access, soil

quality, and management. Field-level predictions would require finer-resolution data. Second, the weather stations used may not fully represent conditions in remote parts of each district, particularly for rainfall, which can be highly localized in semi-arid regions. Third, the validation period (5 years) is relatively short; a longer independent test set would provide stronger confidence in predictive accuracy. Finally, the model doesn't account for biotic stresses such as aphid outbreaks or *Alternaria* blight, which can override weather effects on yield in certain seasons^[18, 19].

Conclusion

The crop-weather regression model developed here explains 78.6% of mustard yield variance and predicts yields with 9.3% error, making it suitable for pre-harvest forecasting in Rajasthan. Maximum temperature during flowering and November rainfall are the two most influential weather variables. Agricultural planners can use this model to generate district-level yield forecasts by mid-February, well before the March harvest, supporting timely decisions on procurement, storage, and price stabilization. Incorporating satellite-derived soil moisture indices could further improve model accuracy in future iterations^[20].

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