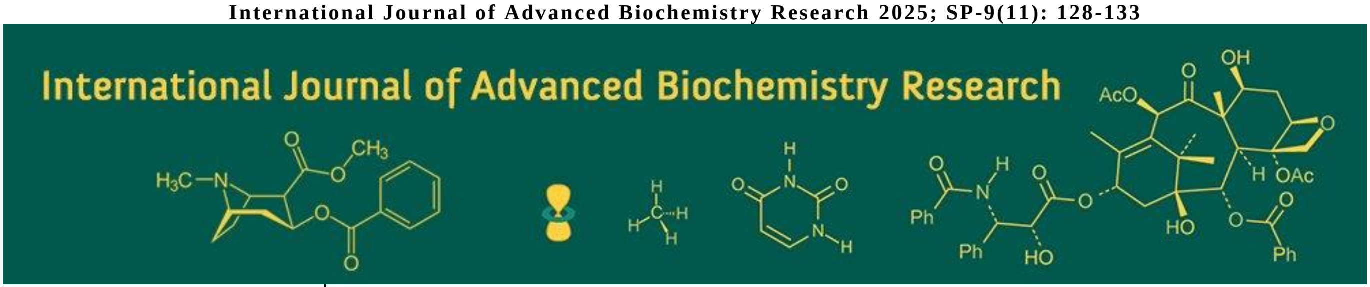

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Weather driven multiple regression model for stage-dependent yield prediction in pigeonpea

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Abstract
A field experiment was conducted at the Instructional Farm of the College of Agriculture, Odisha University of Agriculture and Technology (OUAT), Bhubaneswar, to quantify the relationships between environment as influenced by sowing dates and the growth, phenological development, and grain yield of pigeonpea (*Cajanus cajan* L. Millsp.) varieties. The experiment comprised four sowing dates (21st October, 3rd November, 16th November, and 29th November) and four pigeonpea varieties (TDRG-59, GRG-152, GT-104, and Pant A-7). Results revealed that grain yield was significantly influenced by sowing dates, with the earliest sowing (21st October) producing the highest yield (939 kg ha^{-1}), which was statistically at par with the 3rd November sowing (878 kg ha^{-1}). Delayed sowing on 29th November resulted in the lowest grain yield (681 kg ha^{-1}), representing a 27.5% reduction compared to the earliest sowing date. As the date of sowing delayed, there was decrease in accumulation of GDD, HTU & PTU values so as to reach different phenological stages across the sowing dates at Bhubaneswar agro-climatic conditions, except for PTI. The multiple linear regression models explained 46-66% of yield variability (R^2 values), with the mid to late pod formation stage model showing the highest accuracy ($R^2 = 0.66$). Predicted yields closely matched observed values, with errors as low as 0.1-0.8% for specific variety-sowing combinations, enabling forecasts one to one and a half months of pre-harvest. The weather-index-based regression models provide a reliable, statistical tool for timely yield prediction, aiding farmers in agronomic decision-making and resource optimization amid climate variability.

Keywords: Sowing time, phenophases, pheno-thermal Index (PTI), yield forecasting

1. Introduction

Pigeonpea (*Cajanus cajan* L. Millspaugh) is an important pulse crop in the tropics and subtropics. It is ranked as India's second most important pulse after chickpea. It thrives in temperatures between 26-30 °C during the rainy season (June to October) and 17-22 °C in the post-rainy season (November to March). The crop is sensitive to low light during pod development; cloudy weather can hinder pod formation. Flowering and crop production are significantly influenced by rainfall and temperature, with cooler conditions during the reproductive phase enhancing the yield.

Understanding the phenology of pigeonpea is absolutely essential, as the production of biomass and seed yield is profoundly impacted by environmental conditions during its growth stages. Temperature plays a crucial role in influencing biological processes and it is characterized by three cardinal temperatures: minimum, optimum and maximum. The optimal temperature ranges are 30-35 °C for germination, 20-25 °C for vegetative growth, 15-18 °C for flowering and pod setting and 35-40 °C for maturity. Delving into the response to temperature within these ranges is vital for comprehending crop phenology, adaptation and ultimately maximizing yield (Singh and Singh, 2011) [17].

The variability in weather significantly affects pigeonpea productivity, making the relationship between weather and yield crucial for optimizing farming practices to improve yield. Crop phenology, which is closely linked to temperature variations, plays a key role in determining production potential (Patel *et al.*, 2000) [11]. Weather indices, which assess the use of natural resources such as sunshine, rainfall and temperature, also influence the different growth stages of pigeonpea, ultimately affecting overall yield.

Plants require a certain amount of heat to go through their different life cycle stages. Research indicates that tracking accumulated heat over time provides a more accurate estimate of physiological progress compared to simply counting calendar days. Temperature and GDD are important dynamic climatic factors that directly impact plant functions like evapotranspiration, photosynthesis and nutrient movement (Borque *et al.*, 2000) [2].

Pigeonpea phenology is strongly affected by temperature (Hodges 1991; Jones *et al.* 1991; Ritchie and Ne Smith 1991) [4, 6, 14] and photoperiod (Omanga *et al.* 1996) emphasized that the effect of temperature on the rates of pigeonpea development can be similar in magnitude to those of photoperiod. The optimum range of temperature for proper growth and development of pigeon pea is 18-38 °C (Van der Maesen, 1989) [20].

Crop yield prediction has long been a subject of interest to agronomists, soil scientists, plant physiologists, and meteorologists. Approaches to yield prediction generally fall into two categories: statistical models (Stewart and Dwyer, 1990) [19] and crop simulation models (Singh *et al.*, 1999) [16]. Statistical approaches rely primarily on empirical correlations between yield and climatic factors, whereas simulation models represent the biophysical processes governing crop growth and development to estimate yield outcomes. For instance, Parthasarathy *et al.* developed a predictive equation model for total Indian food grain production based on monsoon rainfall.

Statistical approaches to pre-harvest crop yield estimation have commonly incorporated time-series analyses of yield and climatic variables. Rai and Chandrahas (2000) [13] employed discriminant function analysis on weather data to generate predictive models for rice yield in Chhattisgarh's Raipur district. Agrawal *et al.* (2012) [1] subsequently adapted this discriminant methodology for wheat yield forecasting in Uttar Pradesh's Kanpur district. Sisodia *et al.* (2014) [18] have also use the the approach with weekly weather variables to develop pre-harvest forecast models for wheat yields in Faizabad district of Uttar Pradesh.

Pigeonpea, being particularly sensitive to environmental perturbations and subject to extensive intra-seasonal weather variability, necessitates targeted predictive strategies. Therefore, weather-yield relationship may help to determine the best time to apply specific agronomic practices in order to maximize yield. Production potential for a given crop is often strongly related to crop phenology which is largely sensitive to temperature variations (Patel *et al.* 2000) [11]. Hence, this paper presents discriminant function-based statistical models, derived from weather variables, for the pre-harvest forecasting of pigeon pea yield in the Bhubaneswar region of India.

2. Materials and Methods

2.1 Site description

The experiment was conducted at the Instructional Farm of the College of Agriculture, Odisha University of Agriculture and Technology, Bhubaneswar, during the rabi season of 2023-24. The test site is situated at 20° 15'N Latitude and 85° 52 'E Longitude, at an elevation of 25.9 meters above the active coastline, approximately 64 km from the Bay of Bengal. It falls within the East and South Eastern Coastal Plain Agro-climatic Zone of Odisha.

2.2 Experiment details

In this study, we tested four varieties of pigeonpea (viz. TDRG-59, GRG-152, GT-104 & Pant A-7) using four different sowing dates (i.e. 21st October, 3rd November, 16th November & 29th November), resulting in a total of sixteen treatment combinations. The experiment followed a factorial randomized block design with three replications. Treatments were randomly assigned to each replication, with a plot size of 5.46 m x 1.5 m.

2.3 Data collection

Daily weather data, including maximum and minimum temperatures and relative humidity, was gathered from the meteorological observatory of the Department of Agro-meteorology at O.U.A.T. for the entire crop-growing season.

2.4 Agro-meteorological index

The phenological stages of pigeonpea (such as bud initiation, flowering, early pod formation, mid pod formation, late pod formation and physiological maturity) were observed through field inspections every 10 days across four different sowing dates.

Growing degree-days (GDD) for each stage were then calculated using (Nuttonson, 1995) [8] formula:

$$\mathrm{GDD} = \sum \frac{[\mathrm{T\,max} + \mathrm{T\,min}]}{2} - \mathrm{Tb}$$

Where,

T max is the daily maximum temperature (°C), T min is the daily minimum temperature (°C) and Tb is the base temperature (10 °C).

Photo thermal unit (PTU) were calculated by multiplying the GDD with maximum possible day length. The PTU for each planting date and variety was calculated for each phonological stage by the formula of (Singh *et al.*, 1990) [15]:

$$\mathrm{PTU} = \mathrm{GDD} * \mathrm{L}$$

Where

GDD is growing degree days and L is the maximum possible daylight hour.

The Helio-thermal unit (HTU) was determined by multiplying the growing degree days (GDD) with the actual daily sunshine hours (BSS), as recorded by a sunshine recorder, following the equations outlined by (Nuttonson, 1948) [7]:

$$\mathrm{HTU} = \mathrm{GDD} * \mathrm{BSS}$$

Where

GDD is growing degree days and BSS is the bright sunshine hours of the day

The Pheno-thermal index (PTI) gives an idea about the rate of development of various phenological events with reference to heat units, which will eventually help in evaluating relative performance of different varieties. It expresses per day degree days requirements of plants and expressed as °C days day^{-1}. The PTI was calculated by using the following formula:

$$PTI = \frac{\text{Total accumulation of GDD}}{\text{No. of days taken between two phenophase}}$$

2.5 Multiple regression equation for yield forecasting of pigeonpea
The development of a regression equation based on crop data and weather data is crucial for accurately forecasting crop yield. By considering the various stages of pigeonpea growth and weather parameters, we can utilize the multiple regression equation model to effectively predict yield.
Regression equation was developed for different varieties and sowing dates by using the model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_i X_i$$

Where
Y and Xi are the yield and weather parameters respectively, along with constants and regression coefficients.

3. Results and Discussion
3.1 Date of sowing and variety on yield attributes and yield
Data on yield components showed that the number of pods per plant and seeds per pod were highest for early sown crop on 21st October followed by that sown on 3rd November and the crop sown on 29th November produced the least number of pods per plant and seeds per pod (Table 1). The results are in line with the findings of Dhingra *et al.*, 1980 [21]. However seed index was not influenced by the date of sowing. The cultivar TDRG-59 produced the highest number of pods per plant followed by Pant A-7 and the cultivar GRG-152 produced the least number of pods per plant.
The interaction between the date of sowing and variety was recorded for the number of pods per plant and seeds per pod. TDRG-59 sown on 21st October recorded the highest number of pods per plant and seeds per pod followed Pant A-7 sown on 16th November and the least number of pods per plant and seeds per pod was recorded with the cultivar GRG-152 sown on 29th November.
The weight of 100 seeds were highest for early sown crops on 21st November and 3rd November. The crop that was sown on 29th November produced the least seed index. The results are in line with the findings of Ram *et al.* 2011 [17].
The cultivar TDRG-59 produced the highest seed index followed by GT-104 and the cultivar GRG-152 produced the least seed index.
The interaction between the date of sowing and variety was recorded for the seed index. TDRG-59 sown on 3rd November recorded the highest seed index and the least seed index was recorded with the cultivar GRG-152 sown on 29th November.
Grain yield data in response to date of sowing followed the pattern of yield attributes (Table 1). Yield of pigeonpea crop is a product of its yield components, mainly, number of pods/plant, number of seeds per pod and 100-grain weight. High yield is obtained when all the three are favourable. In the present investigation, early sowing of pigeonpea on 21st October significantly produced the highest grain yield (939 kg/ha) which was at par with sowing on 3rd November (878 kg/ha). The lowest grain yield was produced with the delayed most sowing on 29th November, mainly due to decrease in the growth period. The results are in line with the findings of Dhingra *et al.*, 1980 [21].
The cultivar TDRG-59 produced the highest seed yield (871 kg/ha) which was at par with Pant A-7 (859 kg/ha) and GT-104 (846 kg/ha). The lowest seed yield produced by the variety GRG-152 (735 kg/ha).

Table 1: Effect of date of sowing and variety on yield attributes and yield

Treatment	No. of pods/plant	No. of seeds/pod	100 Seed weight (g)	Seed Yield (kg/ha)
Date of Sowing				
21.10.2023	52.6	3.2	9.2	939
03.11.2023	46.9	3.1	9.2	878
16.11.2023	41.3	3.0	9.1	813
29.11.2023	34.7	2.8	8.7	681
SE (m)	2.0	0.10	0.1	36.4
CD at 5%	5.8	0.2	0.4	105.6
Varieties				
TDRG-59	48.9	3.1	9.4	871
GRG-152	36.1	2.8	8.8	735
GT-104	44.5	3.1	9.1	846
PANT A-7	46.1	3.1	8.9	859
SE (m)	2.0	0.10	0.1	36.4
CD at 5%	5.8	0.2	0.4	105.6
Interaction				
SE (m)	4.0	0.2	0.2	72.8
CD at 5%	11.7	0.5	0.7	211.2
CV%	16.0	9.0	0.9	15.2

3.2 Multiple regression model based on weather indices at different phenophases of pigeonpea
3.2.1 Multiple regression model based on weather indices at flowering to early pod formation stage
A weather indices based multiple regression model was used for forecasting the yield using the phenophase wise data accumulated over four dates of sowing. The phenophase based regression equations was examined and verified using actual seed yield data.

Table 2: Multiple regression analysis at flowering to early pod formation stage

Indices	Regression Coefficients	SE	t value
GDD	23.52	26.71	0.88
HTU	-0.10	0.17	-0.63
PTU	-2.08	2.35	-0.88
PTI	-22.77	33.07	-0.68
$B_0 = 1141.35$	F value = 2.34	$R^2 = 0.46$	

The resultant multiple regression equation was derived and expressed as

$$Y = 1141.35 + 23.52\ X_1 - 0.11\ X_2 - 2.09\ X_3 - 22.77\ X_4\ (R^2 = 0.46)$$

Where,
X_1 = GDD, X_2 = HTU, X_3 = PTU, X_4 = PTI during flowering to early pod formation stage of pigeonpea and R^2 = Coefficient of determination.

Based on Table 2, the equation indicates that weather indices, such as GDD, HTU, PTU and PTI could explain 46% of the change in the expected yield from the flowering to the early pod formation stage. The yield at the blossoming to early pod development stage can be predicted using this equation by utilising the minimal values of weather indices. One and a half to one month ahead of time, the yield prediction model based on weather indices at blooming to early pod developent phenophase can be used to estimate crop production.

3.2.2 Multiple regression model based on weather indices at early pod formation to mid pod formation stage

Table 3: Multiple regression analysis at early pod formation to mid pod formation stage

Indices	Regression Coefficients	SE	t value
GDD	93.91	44.76	2.10
HTU	-0.02	0.18	-0.10
PTU	-8.34	4.01	-2.08
PTI	46.78	37.49	1.25
B_0 = 93.05	F value = 3.74	R^2 = 0.58	

The resultant multiple regression equation was derived and expressed as

$Y = 93.05 + 93.913 X_1 - 0.019 X_2 - 8.342 X_3 + 46.782 X_4$ (R^2 = 0.58)

Where,
X_1 = GDD, X_2 = HTU, X_3 = PTU, X_4 = PTI during early pod formation to mid pod formation stage of pigeonpea and R^2 = Coefficient of determination

The weather indices (i.e., GDD, HTU, PTU and PTI) account for 58% of the change in the expected yield from the early pod formation stage to the late pod formation stage, according to the equation based on Table 3. By applying the minimum values of weather indices, this equation can be used to predict the yield during the early pod formation to mid pod formation stage. For predicting crop yield 30 to 35 days ahead of time, the yield prediction model based on meteorological indices during the early pod formation to mid pod formation phenophase is useful.

3.2.3 Multiple regression model based on weather indices at mid pod formation to late pod formation stage

Table 4: Multiple regression analysis at mid pod formation to late pod formation stage

Indices	Regression Coefficients	SE	t value
GDD	146.27	56.61	2.58
HTU	0.43	0.19	2.24
PTU	-13.12	5.02	-2.62
PTI	97.17	73.02	1.33
B_0 = -703.42	F value = 5.55	R^2 = 0.66	

The resultant multiple regression equation was derived and expressed as

$Y = -703.42 + 146.272 X_1 + 0.429 X_2 - 13.118 X_3 + 97.175 X_4$ (R^2 = 0.66)

Where,
X_1 = GDD, X_2 = HTU, X_3 = PTU, X_4 = PTI during mid-pod formation to late pod formation stage of pigeonpea and R^2 = Coefficient of determination.
The weather indices (i.e., GDD, HTU, PTU and PTI) account for 66% of the change in the expected yield from the mid-pod formation to the late-pod formation stage, according to the equation based on Table 4. The yield at the mid-pod formation to late-pod formation stage can be anticipated using this equation by utilising the weather index minimum values. When predicting crop yield 17-20 days ahead of time, the yield prediction model, which is based on weather indices from the mid-pod formation to the late pod formation phenophase, is useful.
The yield prediction model based on weather indices at flowering to late pod formation phenophase is helpful in assessing the crop yield in advance. The similar model are developed and reported by Patel *et al.* (2000) [11] and on similar line model for groundnut introduced by Jaybhaye *et al.* (2002) [5].

3.3 Comparisons of predicted and observed seed yield of pigeonpea

Table 5: Observed and predicted seed yield (kg ha^{-1}) of pigeonpea by multiple regression at flowering to early pod formation stages

Treatment	Observed	Predicted	Error (O-P)	Error%
D1V1	1,115.3	934.9	180.4	-16.2
D2V1	1,002.6	919.3	83.3	-8.3
D3V1	711.7	765.3	-53.6	7.5
D4V1	653.6	625.5	28.1	-4.3
D1V2	895.4	896.6	-1.2	0.1
D2V2	887.0	920.3	-33.3	3.8
D2V2	602.4	770.9	-168.5	28.0
D2V2	556.7	665.7	-109.1	19.6
D1V3	923.9	920.9	3.0	-0.3
D2V3	850.6	917.3	-66.7	7.8
D3V3	877.1	789.9	87.2	-9.9
D4V3	733.4	703.5	29.9	-4.1
D1V4	822.9	958.2	-135.3	16.4
D2V4	773.6	902.8	-129.2	16.7
D3V4	1,059.5	802.2	257.4	-24.3
D4V4	779.7	752.1	27.6	-3.5

The data presented in Table 5 demonstrated that sowing of the variety GRG-152 on 3rd November and variety GT-104 on 21st October could accurately predict the yield with 0.1% and 0.3% of error from flowering to early pod formation stage of pigeonpea.

Table 6: Observed and predicted seed yield (kg ha^{-1}) of pigeonpea by multiple regression at early pod formation to mid pod formation stages

Treatment	Observed	Predicted	Error (O-P)	Error%
D1V1	1,115.3	995.8	119.5	-10.7
D2V1	1,002.6	907.0	95.7	-9.5
D3V1	711.7	759.6	-47.9	6.7
D4V1	653.6	697.3	-43.7	6.7
D1V2	895.4	1,006.4	-111.0	12.4
D2V2	887.0	925.3	-38.3	4.3
D2V2	602.4	755.0	-152.6	25.3
D2V2	556.7	609.9	-53.3	9.6
D1V3	923.9	934.9	-11.0	1.2
D2V3	850.6	923.9	-73.3	8.6
D3V3	877.1	779.2	97.9	-11.2
D4V3	733.4	661.9	71.4	-9.7
D1V4	822.9	914.1	-91.2	11.1
D2V4	773.6	774.9	-1.3	0.2
D3V4	1,059.5	813.9	245.7	-23.2
D4V4	779.7	786.3	-6.6	0.8

The data in Table 6 shows that sowing the Pant A-7 variety on November 3rd and November 29th can predict pigeonpea yield during the early to mid-pod formation stage with an error margin of 0.1% and 0.8%, respectively.

Table 7: Observed and predicted seed yield (kg ha^{-1}) of pigeonpea by multiple regression at mid pod formation to late pod formation stages

Treatment	Observed	Predicted	Error (O-P)	Error%
D1V1	1,115.3	951.2	164.1	-14.7
D2V1	1,002.6	1,037.5	-34.8	3.5
D3V1	711.7	751.4	-39.7	5.6
D4V1	653.6	708.0	-54.4	8.3
D1V2	895.4	973.2	-77.8	8.7
D2V2	887.0	926.4	-39.4	4.4
D2V2	602.4	735.8	-133.4	22.2
D2V2	556.7	637.5	-80.9	14.5
D1V3	923.9	926.4	-2.5	0.3
D2V3	850.6	829.4	21.2	-2.5
D3V3	877.1	760.3	116.8	-13.3
D4V3	733.4	652.8	80.6	-11.0
D1V4	822.9	806.0	17.0	-2.1
D2V4	773.6	906.6	-133.0	17.2
D3V4	1,059.5	964.1	95.5	-9.0
D4V4	779.7	679.1	100.6	-12.9

The information provided in Table 7 demonstrated that sowing of the variety GT-104 on 21st October could accurately predict the yield with 0.2% error from mid-pod development to late-pod formation stage of pigeonpea.

4. Conclusion

The study demonstrates that early sowing, specifically from the second fortnight of October to the first week of November, is the most suitable period for obtaining superior yield performance of rabi pigeonpea under the studied conditions. Among the four varieties TDRG-59 performed better w.r.t. yield and yield attributes followed by Pant A-7 for Bhubaneswar region. The multiple linear regression analysis of pigeonpea seed yield with meteorological indices showed that the highest coefficient of determination (R^2) was 0.66 for the mid-pod to late-pod formation stage, followed by 0.58 for the early-pod to mid-pod formation stage, and 0.46 for the flowering to early-pod formation stage. The yield prediction model, which utilizes multiple linear regression based on weather indices, provides a practical tool for assessing crop yield approximately one to one and a half months before harvest. This early forecasting helps farmers and agricultural planners make informed decisions well ahead of the harvest period.

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