



# Predicting Wheat Yield by Principal Component and Regression Techniques based on Morpho-Physiological and Quality Traits

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**Abstract:** The study reviewed morpho-physiological and quality traits of 194 wheat genotypes to identify the traits determinant to wheat yield exploring principal component and regression techniques. The experiment was performed at Chaudhary Charan Singh Haryana Agricultural University, Hisar (Haryana) during 2023-24 crop season. Principal component analysis identified eight components that cumulatively explained 66.30 % of the total variation of 25 morpho-physiological and quality traits. The first principal component was associated with grain yield, grain filling duration, harvest index and 1000-grain weight and also showed strong association with quality traits viz., crude protein, gluten content and sedimentation value. The coefficient of multiple regression ( $R^2$ ) explained 86.74% of the variability and showed positive correlation between the dependent and independent variables. The stepwise regression analysis identified four traits - harvest index, biological yield per plot, chlorophyll content, and days to 50% heading - as significant contributors to grain yield in wheat. These variables were sequentially retained in the model based on their statistical significance indicating substantial proportion of the variation in yield. Hence, these traits emerged as the most reliable predictors of grain yield and may serve as important selection criteria in wheat improvement programmes.

**Keywords:** Wheat, Principal component, Regression, Yield traits.

## 1. INTRODUCTION

In India, wheat is the second most important staple food crop after rice, occupied over 32.76 million hectares and produced 117.51 million tonnes with national average productivity of 35.87 quintals per hectare (ICAR-IIWBR, 2025). While sustaining and further enhancing wheat crop productivity is central to national food security under population pressure and erratic climatic conditions. Grain yield, being complex quantitative trait, is governed by the interaction of several morpho-physiological and phenological attributes, making direct selection for yield less effective.

Understanding the complex interaction between grain yield and its component traits is therefore essential for identifying reliable selection criteria in breeding programmes. Multivariate statistical approaches provide an effective framework for disentangling such complex interrelationships among traits and for identifying those variables that contribute most significantly to yield variation. Among these, principal component analysis (PCA) has been widely used to reduce data dimensionality and to identify major sources of variation by grouping

correlated traits into a smaller number of independent components (Das et al., 2017). PCA thus helps in minimizing redundancy and highlighting key traits influencing yield performance.

Regression analysis, particularly stepwise regression, is another powerful multivariate tool used to quantify the contribution of individual plant traits to grain yield and to identify an optimal subset of predictors. In cereal crops, yield is influenced by several interrelated attributes, and regression-based approaches assist breeders in prioritizing traits with higher predictive ability and selection value (Budka et al., 2015). Previous studies in wheat have demonstrated the usefulness of regression techniques for identifying yield-determining traits; however, many such studies were limited either in the number of genotypes evaluated or in the range of traits considered, and often relied primarily on weather-based predictors (Przulj and Momcilovic, 2011; Kumar et al., 2014).

Although climatic variables play a major role in determining crop yield, reliance solely on weather-based models neglects the contribution of intrinsic plant characteristics that directly reflect genetic potential and

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physiological efficiency. Integrating morpho-physiological and quality traits into yield prediction models can therefore provide a more biologically meaningful and breeder-relevant understanding of yield formation. However, comprehensive studies combining large genotype sets with multiple statistical techniques remain limited, particularly for major wheat-growing regions of India.

In view of these considerations, the present study was undertaken using 194 diverse wheat genotypes to (i) assess the interrelationships among key morpho-physiological and quality traits, (ii) identify the major sources of variation using Principal Component Analysis, and (iii) develop an efficient yield prediction model through stepwise regression analysis. The results are expected to aid in identifying reliable trait-based predictors of grain yield and to support more effective selection strategies in wheat improvement programmes.

## 2. MATERIALS AND METHODS

### 2.1. Experimental Area

The experiment was performed during crop season 2023-24 at Department of Genetics and Plant Breeding, CCS Haryana Agricultural University, Hisar (Latitude 29°10'N, Longitude 75°46'E and Altitude 215.2 m).

### 2.2. Experimental Material and Design

The study included a set of 194 wheat genotypes (Table 1), planted and evaluated in Augmented Design. Each genotype was planted in two rows spaced at 20 cm apart, occupied a plot size of 2.5 m × 0.4 m. The experiment was conducted under timely sown and irrigated conditions, and the recommended agronomic package of practices (Anonymous, 2023). The observations were recorded for 25 morpho-physiological and quality traits (Table 2).

### 2.3. Methodology

Canopy temperature (°C) was recorded using a portable infrared thermometer (IRT) 'Model AG-42, Teletemp crop Fullerton'. The difference between canopy temperature and ambient temperature was calculated to determine canopy temperature depression. Observations were taken at anthesis and subsequently at 15 days after anthesis. Relative Water Content (%) was calculated using the method outlined by Barrs and Weatherley (1962). Chlorophyll content (SPAD value) was recorded using a portable optical chlorophyll meter (Model No. Minolta SPAD 502 Plus) at anthesis. The quality traits *viz.*, crude protein (%), gluten content (%) and sedimentation value (ml) were estimated by Infratec 1241 grain analyzer. Hectolitre weight (Kg/hl) was measured with the help of test weight instrument developed at IIWBR, Karnal. It represents the weight of 100 litres of wheat and

provides a general estimate of grain soundness, density and flour yield.

### 2.4. Statistical Analysis

The principal component analysis (PCA) was employed to reduce the number of variables into a few correlated components and to identify traits that load the most in explaining the observed variability of original set in order to know the variables (traits) associated with grain yield. Further, to quantify the contribution of particular variable toward grain yield, regression analysis was performed. The recorded data was analyzed for principal component and regression using R Studio software (2025.05.01+513) (R Core Team, 2025).

## 3. RESULTS AND DISCUSSION

### 3.1 Identification of Major Sources of Variation

In the present investigation, PCA was performed on 25 morpho-physiological and quality traits of 194 wheat genotypes (Table 2). The first eight principal components, each with an eigenvalue greater than one, collectively explained 66.30% of the total variation embedded in the wheat genotypes. The remaining components contributed only marginally to the variation and were therefore of limited practical value for wheat improvement.

Among these, the first principal component (PC1) accounted for 15.61% of the total variation, followed by PC2, PC3, PC4, PC5, PC6, PC7 and PC8. Earlier studies also indicated similar findings (Bhatti et al., 2022; Abdelghany et al., 2023; Atsbeha et al., 2023; Khan et al., 2023). Kumar et al. (2021) analyzed 440 bread wheat genotypes for 12 agromorphological and physiological traits and reported first five components with eigenvalues exceeding one that explained 63.84% of the total variation. Comparable contributions of principal components have also been described in wheat by Prakash et al. (2023); Arshad et al. (2025) and Yadav et al. (2025).

### 3.2. Assessment of the Interrelationships among Key Morpho-physiological and Quality Traits

The factor loadings of individual traits on the eight principal components indicated the strength of association of each trait with the corresponding principal component. PC1 was primarily associated with yield-related traits such as grain yield, grain filling duration, harvest index, and 1000-grain weight, along with quality attributes such as crude protein, gluten content, and sedimentation value (Table 2). PC2 was defined by number of grains per spike, spikelets per spike, and flag leaf breadth, and also showed strong loadings for phenological traits such as days to heading, anthesis, and maturity. PC3 was dominated by flag

**Table 1.** List of wheat genotypes used in the present study

Genotypes	Genotypes	Genotypes	Genotypes
DDW 48	GW 1339(d)	HS 679	PBW 821
BFKW 7	GW 1346(d)	HS 681	PHSL 10
BNSR 6	GW-2014-596	HS 661	QLD 118
CG 1029	GW 499	HUW 338	QLD 120
CG 1036	GW 509	IC 212176	QLD 121
CG 1040	HD 2967	IC 376265	RWP-2019-38
CG 1023	HD 3369	IC 78841	HI 1617
GW 477	HD 3386	IC 252459	WSM 138
DBW 166	HD 3407	IC 252454	RAJ 4541
DBW 187	HD 3411	IWBR DN 502	RAJ 3448
DBW 243	HD 3437	IWBR PHY 2	RAJ 3765
DBW 278	HD 3438	HPW 360	RAJ 4238
DBW 302	HD 3440	JKW 261	RW 5
DBW 308	HD 2864	K 1616	RWP-2017-21
DBW 316	HD 2932	K 1317	RWP-2018-31
DBW 318	HD 3086	RWP-2019-41	RWP-2018-32
DBW 325	HD 3406	KARAN POSHAN 1	RWP-2018-3
DBW 342	HD 3293	KARAN POSHAN 2	Sonalika
DBW 357	HI 1544	KRL 283	UAS 3022
DBW 370	HI 1650	KRL 35	UAS 478 (d)
DBW 371	HI 1653	KRL 99	UAS 481 (d)
DBW 372	HI 1654	LBP-2017-2	UASQ 332 (d)
DBW 377	HI 1655	LBP-2023-24	Unnat PBW 550
DBW 400	HI 1665	LBP-2023-25	UP 2909
DBW 107	HI 8818 (d)	KHTW 1	UP 2938
DBW 110	HI 8826 (d)	MACS 4100 (d)	UP 2944
DBW 168	HI 8827 (d)	MACS 6768	VL 3024
DBW 173	HI 8830 (d)	MACS 6795	VL 3028
DBW 252	HI 8839 (d)	MACS 4058(d)	VL 3035
DBW 303	HI 8840 (d)	MP 1323	VL 2028
DBW 221	HI 8846 (d)	MP 1378	VL 2041
DBW 327	HI 8847	GW-2010-288	VL 3010
DBW 222	HI 1633	MP 3535	VL 2015
DBW 322	HI 1636	MPO 1357 (d)	VL 3022
DBW 332	HI 1634	NIAW 4028	VL 3020
DBW 296	HI 8627	QLD 122	VL 3021
DBW 328	HI 8802(d)	PBS-NGSN-23-01	WAP 2320
UP 2903	HI 8805(d)	PBS-NGSN-23-02	WAP 2321
HUW 838	HI 8823(d)	PBW 766	WAP 2210
GW 513	HI 8808	PBW 803	WAP 2211
DBW 88	GW 1348 (d)	PBW 824	WAP 2212
DBWH 221	HPW 484	PBW 835	WCF-12-19
DDW 47 (d)	HPW 487	PBW 869	WCF-12-208
DTW 119	HPW 489	PBW 870	WCF-12-61
DWAP 1608	HPW 493	PBW 875	WH 1402
GW-2019-957	HPW 368	PBW 902	WH 1403
GW 528	HPW 373	PBW 723	WHD 965 (d)
GW 532	HS 545	PBW 752	
GW 547	HS 628	PBW 771	

leaf length and spike length, while PC4 was associated with plant height and awn length. PC5 was characterized by chlorophyll content, relative water content, and peduncle length, whereas PC6 was strongly associated with canopy temperature depression and biological yield. PC7 showed a strong relationship with hectolitre weight, and PC8 with number of tillers per meter.

The clear grouping of traits within components illustrates the successful reduction of 25 correlated variables into eight independent dimensions, which together explained more than two-thirds of the total variability. Similar clustering of traits on principal components in wheat has been reported by Shiramakrishnan et al. (2016); Dagnaw et al. (2023) and Vijeth et al. (2025).

**Table 2.** Variance attributable to principal components with loading of different variables

Variance	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Eigen value	3.90	3.11	2.47	1.77	1.54	1.42	1.22	1.15
Percentage of variance	15.61	12.43	9.88	7.07	6.16	5.69	4.88	4.58
Cumulative percentage of variance	15.61	28.04	37.92	44.99	51.15	56.84	61.72	66.30
Factor loadings								
Variables	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
DH	0.474	0.694	-0.460	-0.026	0.004	0.116	0.003	-0.049
DA	0.497	0.683	-0.477	-0.041	0.005	0.112	-0.054	-0.039
DM	-0.059	0.473	-0.381	0.110	0.320	-0.183	0.438	0.174
PH	0.086	-0.114	0.265	-0.514	0.450	0.078	-0.222	0.172
AL	-0.146	0.297	-0.243	0.428	-0.087	-0.042	-0.110	0.372
FLL	0.160	0.352	0.473	0.185	0.247	-0.237	-0.173	0.102
FLB	0.064	0.518	0.240	-0.015	0.154	-0.207	-0.075	-0.136
NT/M	-0.133	0.130	0.041	0.342	0.313	-0.253	0.201	-0.509
SL	0.009	0.270	0.555	-0.487	-0.288	-0.090	0.026	-0.139
PL	-0.013	0.263	0.284	0.174	0.469	0.011	0.214	0.233
NS/S	0.101	0.499	0.420	-0.473	-0.038	0.034	0.136	0.108
NG/S	-0.122	0.439	0.134	-0.409	0.145	-0.107	0.119	0.105
BY	-0.404	0.387	0.341	0.264	0.072	0.446	-0.026	-0.360
GY	-0.580	0.424	0.350	0.277	-0.087	0.385	0.091	-0.120
GFD	-0.581	-0.427	0.265	0.121	0.209	-0.250	0.355	0.157
HI	-0.492	0.075	0.122	0.023	-0.267	0.003	0.299	0.314
TGW	-0.523	0.120	-0.041	0.056	0.077	0.213	-0.291	0.329
CTD 1	-0.183	-0.231	0.018	-0.128	0.109	0.551	0.068	-0.157
CTD 2	-0.158	0.046	-0.174	-0.055	0.159	0.470	-0.019	0.248
CC	0.235	0.205	0.283	0.178	-0.539	0.082	0.164	0.254
RWC	0.081	0.230	0.343	0.300	-0.396	-0.258	-0.221	0.008
CP	0.819	-0.269	0.290	0.180	0.091	0.152	0.149	0.057
GC	0.723	-0.074	0.389	0.266	0.072	0.273	0.128	0.082
SV	0.799	-0.275	0.237	0.177	0.140	0.097	0.055	0.108
HW	-0.148	0.066	0.211	0.236	0.260	-0.106	-0.613	0.105

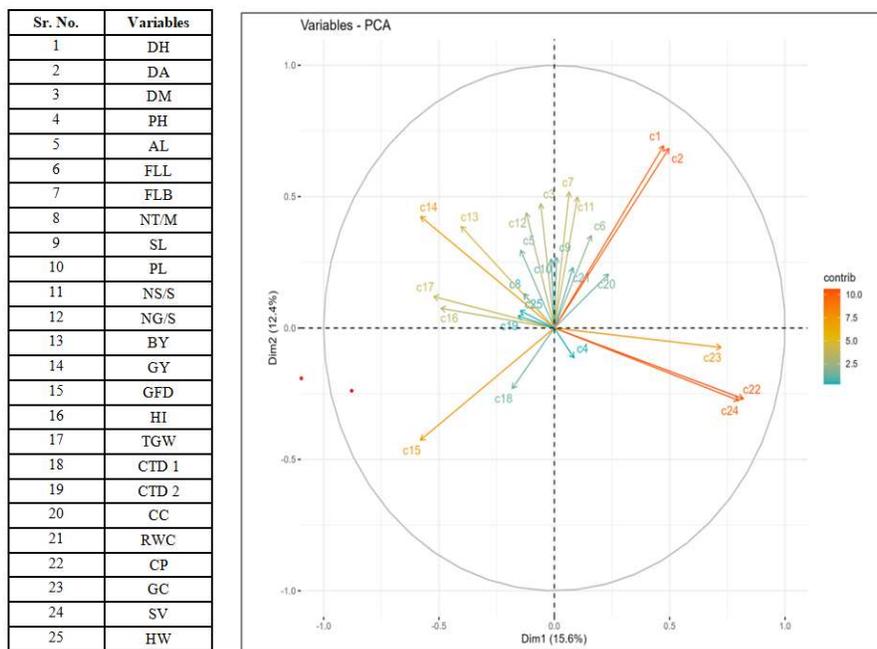
DH-Days to 50% heading, DA-Days to anthesis, DM-Days to physiological maturity, PH-Plant height (cm), NT/M-Number of effective tillers per meter, SL-Spike length (cm), PL-Peduncle length (cm), FLL-Flag leaf length (cm), FLB-Flag leaf breadth (cm), AL-Awn length (cm), NS/S-Number of spikelets per spike, NG/S-Number of grains per spike, BY-Biological yield per plot (g), GY-Grain yield per plot (g), GFD-Grain filling duration, HI-Harvest index (%), TGW-1000 grain weight (g), CTD 1-Canopy temperature depression at anthesis(°C), CTD 2-Canopy temperature depression at 15 days after anthesis (°C), RWC-Relative water content (%), CC-Chlorophyll content (SPAD value), CP-Crude protein (%), GC-Gluten content (%), SV-Sedimentation value (ml) and HW-Hectolitre weight (kg/hl)

In the biplot analysis, the variables contained in different quadrants depicts the correlation among them, facilitate in determining the variables contributing to yield. The angle between vectors defines the relationship of variables, when the angle between vectors is  $< 90$  (acute) degrees indicated the positive association and when the angle is  $> 90$  (obtuse) degrees that explained negative correlation. First two principal components explained 28.04 % variability, were exploited to construct biplot for comparing relationship between variables (Figure 1). The variables occupied their position in a particular quadrant signifies positive association among them. The biplot displayed positive association of grain yield with variables placed in 3<sup>rd</sup> quadrant. In addition, grain filling duration, flag leaf length and breadth, days to heading and anthesis, spike length, number of spikelets per spike and relative water content also

exhibited positive association with grain yield, as indicated by acute angles between their vectors. The remaining variables were negatively correlated with grain yield, deciphered by obtuse angles between their vectors. Similar approach has also been followed in wheat by Vijeth et al. (2025) for clear visualization of variable representation based on PCA.

### 3.3. Development of Yield Prediction Model

To further dissect the contribution of individual traits to grain yield, stepwise regression analysis was performed (Table 3). Seven traits were retained in the final model: days to 50% heading, biological yield per plot, harvest index, 1000-grain weight, canopy temperature depression at 15 days after anthesis, chlorophyll content, and sedimentation value. Among these, harvest index, biological yield, chlorophyll content, and days to 50% heading showed



**Figure 1.** Biplot of morpho-physiological and quality traits studied (DH-Days to 50% heading, DA-Days to anthesis, DM-Days to physiological maturity, PH-Plant height (cm), NT/M-Number of effective tillers per meter, SL-Spike length (cm), PL-Peduncle length (cm), FLL-Flag leaf length (cm), FLB-Flag leaf breadth (cm), AL-Awn length (cm), NS/S-Number of spikelets per spike, NG/S-Number of grains per spike, BY-Biological yield per plot (g), GY-Grain yield per plot (g), GFD-Grain filling duration, HI-Harvest index (%), TGW-1000 grain weight (g), CTD 1-Canopy temperature depression at anthesis(°C), CTD 2-Canopy temperature depression at 15 days after anthesis (°C), RWC-Relative water content (%), CC-Chlorophyll content (SPAD value), CP-Crude protein (%), GC-Gluten content (%), SV-Sedimentation value (ml) and HW-Hectolitre weight (kg/hl)

significant regression coefficients, suggesting that improvement in these traits would substantially enhance grain yield. The model explained 86.74% of the variation in grain yield; adjusted R<sup>2</sup>, indicating robustness and absence of overfitting. These findings emphasize the priority of selection for harvest index, biological yield, chlorophyll content, and favorable heading time in wheat breeding programs. Comparable yield predictors have been highlighted in previous studies (Abderrahmane et al., 2013; Nasri et al., 2014; Kumar et al., 2016; Fouad, 2018; Eid, 2020; Pirzado et al, 2021; Karuna et al., 2024).

Based on stepwise regression, the following predictive model for grain yield (y) was obtained (eq. 1):

$$y = - 620.8+1.49DH + 0.27 BY+11.61 HI+2.2 CC.....(1)$$

where DH = days to 50% heading, BY = biological yield per plot, HI = harvest index, and CC = chlorophyll content.

Scatter plots of these predictors against grain yield (Figure 2) confirmed their strong associations, consistent with patterns observed by Marzougui and Chargui (2018). Similar regression-based yield prediction approaches in wheat have also been reported by Bhutto et al. (2016), Shastry et al. (2017), Hu et al. (2018) and Shar et al. (2024).

AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) values indicated model fit and complexity, with sharp decreases signifying major

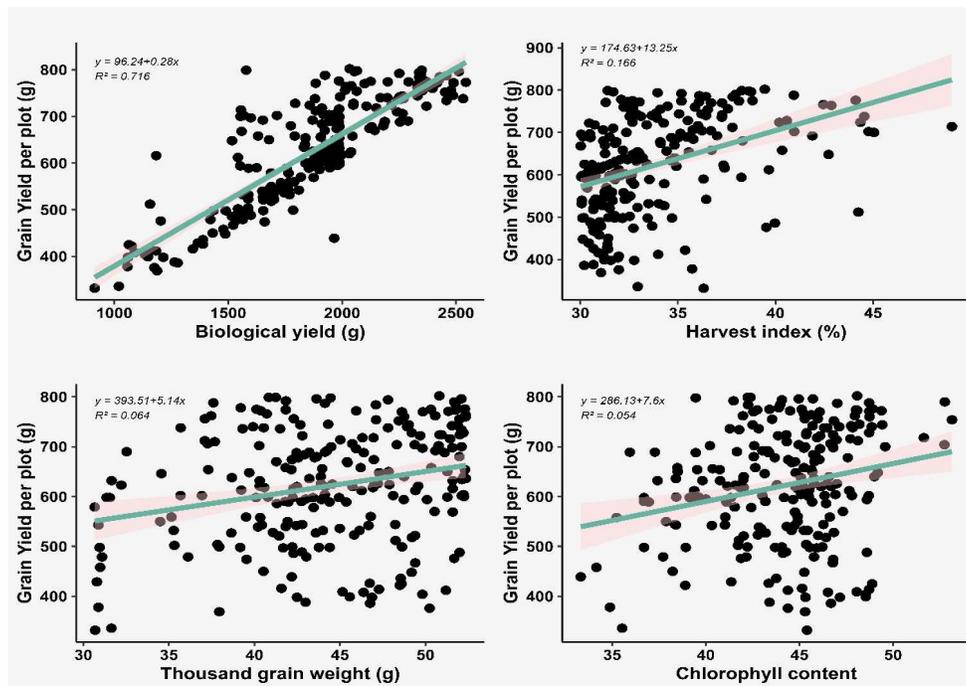


Figure 2. Scatter diagram based on simple regression of grain yield with important variables

Table 3. Stepwise regression analysis

Variables	Regression coefficients	Estimate Std. Error	t value	Pr (> t )	Significance
(Intercept)	-620.8	79.01	-7.86	0	***
DH	1.49	0.63	2.37	0.02	*
BY	0.27	0	32.67	<0	***
HI	11.61	0.82	14.22	<0	***
TGW	0.94	0.55	1.73	0.08	.
CTD2	5.15	3.12	1.65	0.09	.
CC	2.2	0.86	2.56	0.01	*
SV	0.57	0.31	1.86	0.06	.

Significance: \*\*\*> 0.001 \*\*> 0.01 \*> 0.05 .> 0.1; Multiple R<sup>2</sup>: 0.8674; Adjusted R<sup>2</sup>: 0.8632

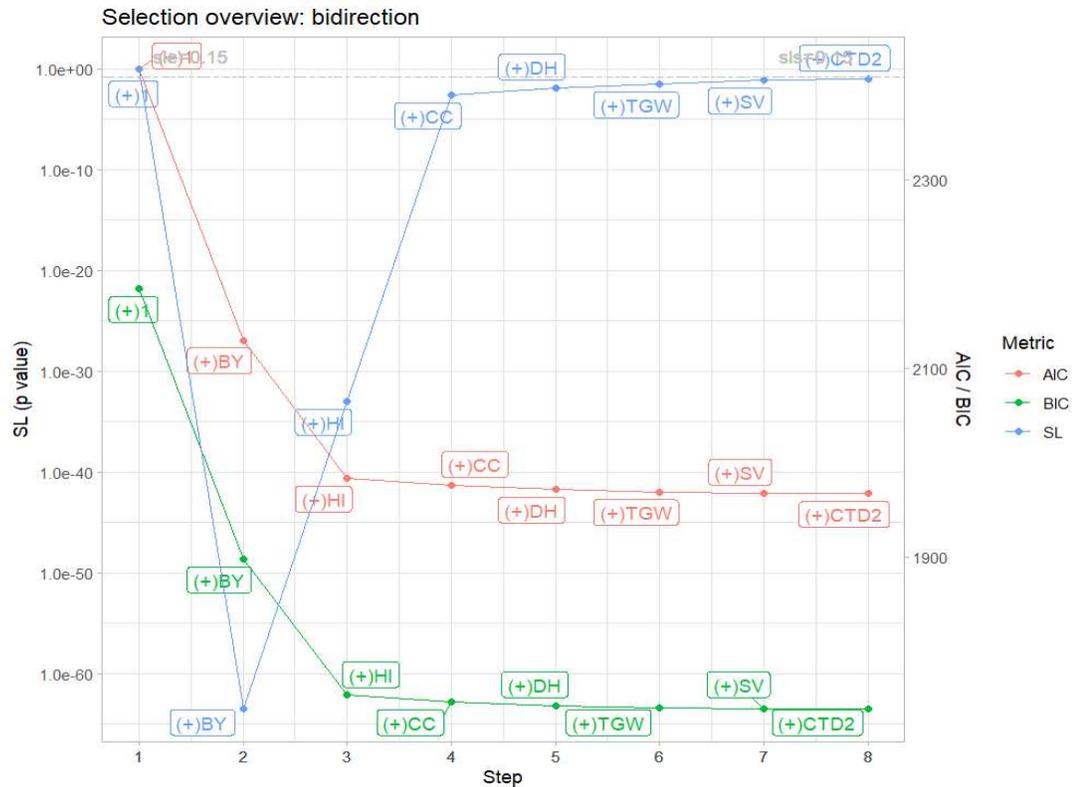


Figure 3. Stepwise regression illustrating trait selection in both forward and backward direction

contributors (Figure 3). Biological yield was the strongest predictor, entering first with the largest reduction in AIC/BIC, followed by harvest index. Days to 50% heading and chlorophyll content improved the model moderately, whereas the remaining traits contributed less substantially. Previous studies have also explored the use of principal components as predictors for yield forecasting in wheat (Goyal and Verma, 2018; Chetna et al., 2022).

**4. CONCLUSION**

Principal component identified eight components with eigen value exceeding one that altogether explained 66.30 % of the total variation of 25 morpho-physiological and quality traits of 194 genotypes. The first principal component was associated with grain yield, grain filling duration, harvest index and 1000-grain weight and also showed strong association with quality traits viz., crude protein, gluten content and sedimentation value. The coefficient of multiple regression showed a positive correlation between the dependent and independent variables, explaining 86.74% of the variability. Similarly, the modified (Adj.) indicated that, even with the modification, the regression model closely reflects the variance in the data set without changing the parameter. Stepwise regression revealed that biological

yield, harvest index, chlorophyll content and days to 50% heading proved to be the main predictors of wheat yield.

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**Authors' Contributions**

P: Execution of field experiment, data recording and compilation, YK: Conceptualization, manuscript writing & finalization, DK: Statistical analysis. All the listed authors read and approved the manuscript.

**Conflict of Interest**

The authors declare that there is no conflict of interest.

**Declaration of Generative Ai and Ai-Assisted Technologies in the Writing Process**

The authors declare that none of AI tools have been used in the writing process.

**REFERENCES**

Abdelghany, M., Makhmer, K., Zayed, E., Salama, Y., & Amer, K. (2023). Genetic variability, principal components and cluster analysis of twenty-eight Egyptian wheat genotypes. *Scientific Journal of Agricultural Sciences*, 5(1), 107-118.  
 Abderrahmane, H., Abidine, F.Z.E., Hamenna, B., & Ammar,

- B.(2013). Correlation, path analysis and stepwise regression in durum wheat (*Triticum Durum* Desf.) under rainfed conditions. *Journal of Agriculture and Sustainability*,3(2), 122-131.
- Ali, Y., Raza, A., Iqbal, S., Khan, A.A., Aatif, H.M., Hassan, Z., Hanif, M.S., Ali, H.M., Mosa, W.F.A., Mubeen, I., & Sas-Paszt, L.(2022). Stepwise regression models-based prediction for leaf rust severity and yield loss in wheat. *Sustainability*,14(21), 13893.
- Anonymous (2023). *Package of practices - Rabi crops*. CCS Haryana Agricultural University, Hisar, Haryana, India.
- Arshad, S., Jamil, M., Ali, A., Saleem, Y., Khan, U.A., Maqsood, M.F., Zulfiqar, U., Ali, M.F., Binobead, M.A.,& AlMunqedhi, B.M.(2025). Exploring multivariate relationships among seed morphometric and yield-related traits in bread wheat (*Triticum aestivum* L.). *Polish Journal of Environmental Studies*,34(3), 2003-2010.
- Atsbeha, G., Mekonnen, T., Kebede, M., Haileselassie, T., & Tesfaye, K.(2023). Multivariate analyses, heritability and genotype environment interaction of bread wheat genotypes in Ethiopia. *Ecological Genetics and Genomics*,29, 100209.
- Barrs, H.D.,& Weatherley, P.E.(1962). A re-examination of the relative turgidity technique for estimating water deficits in leaves. *Australian Journal of Biological Sciences*,15(3), 413-428.
- Bhatti, N., Dalal, M.S., Phougat, D.,& Devi, S. (2022). Multivariate analysis of morpho-physiological traits in bread wheat genotypes under terminal heat stress. *Electronic Journal of Plant Breeding*,13(4), 1180-1186.
- Bhutto, A.H., Rajpar, A.A., Kalhor, S.A., Ali, A., Kalhor, F.A., Ahmed, M., Raza, S.,& Kalhor, N.A.(2016). Correlation and regression analysis for yield traits in wheat (*Triticum aestivum* L.) genotypes. *Natural Science*,8, 96-104.
- Budka, A., Lacka, A., Gaj, R., Jajor, E.,& Korbas, M.(2015). Predicting winter wheat yields by comparing regression equations. *Crop Protection*,8, 84-91.
- Chetna, Devi, M., Mohammed, J., Raghav, Y.S.,& Mishra, P.(2022). Modelling and forecasting of electricity consumption used in agriculture purpose in India. *Journal of Crop and Weed*,18(3), 245-250.
- Dagnaw, T., Mulugeta, B., Haileselassie, T., Geleta, M., Ortiz, R.,& Tesfaye, K. (2023). Genetic diversity of durum wheat (*Triticum turgidum* L. ssp. durum, Desf.) germplasm as revealed by morphological and SSR markers. *Genes*,14, 1155.
- Das, S., Das, S.S., Chakraborty, I., Roy, N., Nath, M.K.,& Sarma, D. (2017). Principal component analysis in plant breeding. *Biomolecules*,3, 1-3.
- Eid, M.A.S.M.(2020). Genetic divergence in advanced bread wheat genotypes for yield and its attributes. *Journal of Plant Production Sciences*, 9(1), 39-46.
- Fouad, H.M.(2020). Principal component and cluster analyses to estimate genetic diversity in bread wheat (*Triticum aestivum* L.) genotypes. *Journal of Plant Production*,11(4), 325-331.
- Fouad, H.M.(2018). Correlation, path and regression analysis in some bread wheat (*Triticum aestivum* L) genotypes under normal irrigation and drought conditions. *Egyptian Journal of Agronomy*,40(2), 133-144.
- Goyal, M., & Verma, U.(2018). Wheat yield prediction using weather based statistical model in northern zone of Haryana. *International Journal of Humanities and Social Sciences*,7(4), 47-50.
- Hu, Y., Wei, X., Hao, M., Fu, W., Zhao, J.,& Wang, Z.(2018). Partial Least Squares Regression for determining factors controlling winter wheat yield. *Agronomy Journal*,110, 281-292.
- ICAR-IIWBR,(2025). *Directors report of AICRP on Wheat and Barley 2024-25*. Ratan Tiwari, Sindhu Sareen, Dinesh Kumar, Anuj Kumar & CN Mishra(Eds.). ICAR-Indian Institute of Wheat and Barley Research, Karnal, Haryana, India. P. 84.
- Karuna, Solanki, Y.P.S., Singh, V., Rai, N.K.,& Gangadhar, N.(2024). Development of yield forecast model in bread wheat using regression analysis. *International Journal of Plant and Soil Science*,36(7), 875-881.
- Khan, M.A., Waseem Akram, M., Iqbal, M., Ghulam Muhi-Din Ahmed, H., Rehman, A., Arslan Iqbal, H.S.M.,& Alam, B.(2023). Multivariate and association analyses of quantitative attributes reveal drought tolerance potential of wheat (*Triticum aestivum* L.) genotypes. *Communications in Soil Science and Plant Analysis*,54(2), 178-195.
- Kumar, D., Kerkhi, S.A., Singh, Y.P.,& Harinarayan, B.(2016). Regression analysis for yield components and quality traits in wheat. *Journal of Wheat Research*,8(1), 25-29.
- Kumar, N., Pisal, R.R., Shukla, S.P.,& Pandey, K.K.(2014). Crop yield forecasting of paddy, sugarcane and wheat through linear regression technique for south Gujarat. *Mausam*,65 (3), 361-364.
- Kumar, S., Gupta, V., Yadav, S.S., Mamrutha, H.M., Singh, S.K., Chatrath, R.,& Singh, G. P.(2021). Multivariate analysis in wheat germplasm captures variability for agro-morphological and physiological traits. *The Indian Journal of Agricultural Sciences*,91(9), 1322-1327.
- Mansouri, A., Oudjehih, B., Benbelkacem, A., Fellahi, Z.E.,& Bouzerzour, H.(2018). Variation and relationships among agronomic traits in durum wheat [*Triticum turgidum* (L.)] under south Mediterranean growth conditions: Stepwise and path analyses. *International Journal of Agronomy*,3(1), 1-11.
- Nasri, R., Kashani, A., Paknejad, F., Vazan, S.,& Barary, M.(2014). Correlation, path analysis and stepwise regression in yield and yield component in wheat (*Triticum aestivum* L.) under the temperate climate of Ilam province, Iran. *Indian Journal of Fundamental and Applied Life Sciences*,4(4), 188-198.
- Pirzado, A.A., Sutahar, S.K., Sutahar, V., Qurashi, N.A., Jatoi, I.K., Khaskeli, S.A., Chandio, R.A., Aarain, K.,& Peerzad, M.B.(2021). Checking the significance of correlation coefficient from the regression analysis using wheat yield. *Journal of Applied Research in Plant Sciences*,2(2), 132-141.
- Prakash, S., Kumar, A.,& Mehandi, S.(2023). Genetic profiling and characters association in wheat (*Triticum aestivum* L.) genotypes: Implications for breeding programs. *Journal of Food Chemistry & Nanotechnology*,9(S1), S524-S533.
- Przulj, N.,& Momcilovic, V.(2011). Characterization of vegetative and grain filling periods of winter wheat by stepwise regression procedure. I. Vegetative period. *Genetika*,43(2), 349-359.
- R Core Team (2025). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.
- Shar, P.A., Kumar, J., Otho, S.A., Soomro, A.A., Gadahi, A.A., Fareed, G., Shar, W.A., Shar, M.B.,& Buriro, K.A.(2024). Correlation and regression analysis for yield and related attributes in F<sub>2</sub> population of bread wheat (*Triticum aestivum* L.) genotypes. *Pakistan Journal of Biotechnology*,21(2), 323-331.
- Shastri, A., Sanjay, H.A.,& Bhanusree, E.(2017). Prediction of crop yield using regression techniques. *International Journal of Soft Computing*,12(2), 96-102.
- Shivramakrishnan, R., Vinoth, R., Arora, A., Singh, G.P., Kumar, B.,& Singh, V.P.(2016). Characterization of wheat genotypes for stay green and physiological traits by principal component

- analysis under drought condition. *International Journal of Agricultural Sciences*, 12(2), 245-251.
- Vijeth, G.M., Govindareddy, U., Gopalareddy, K., & Shashidhar, N. (2025). Genetic variability and principal component analysis in durum wheat germplasm for terminal drought stress. *The Indian Journal of Agricultural Sciences*, 95(5), 522-528.
- Yadav, S., Singh, V., Hari Kesh, Kumar, M., Mor, V.S., & Yashveer, S. (2025). Genetic diversity analysis for morpho-physiological traits in bread wheat (*Triticum aestivum* L.). *Vegetos*, doi.org/10.1007/s42535-025-01182-5.