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### **Research Article**



# Multivariate analysis of morpho-physiological traits in bread wheat genotypes under terminal heat stress

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#### Abstract

Terminal heat stress has great impact on the quantity and quality of bread wheat that ultimately pose a serious concern about the food security. The presence of the genetic variability and suitable selection criteria is imperative for screening of genotypes for heat tolerance. Therefore, 60 advanced breeding lines and four standard checks were evaluated for morpho-physiological traits under late sown condition to understand the importance of the principal component analysis in reduction of the large correlated data into few major principal components that account for maximum genetic variability. Out of twenty principal components, only three were retained having 67.10% contribution towards total variability on the basis of eigen values and scree plot. Grain yield (0.995), days to heading (0.912) and plant height (0.752) were having maximum positive loading in the first, second and third principal component respectively. Therefore, principal component analysis holds great promise in the crop improvement programme.

Keywords: terminal heat stress, wheat, genetic variability, principal component and scree plot

#### INTRODUCTION

Wheat is a staple food which is consumed worldwide. Only three species of wheat namely, Triticum aestivum (Common bread wheat), Triticum durum (Macroni or Durum wheat) and Triticum dicoccum (Emmer wheat) are grown commercially in India. The largest area comes under common bread wheat followed by Durum and Emmer wheat. The same pattern is followed in case of production wherein 87% is under bread wheat, 12% under Durum Wheat and 1% under Emmer wheat. Wheat being nutri-rich cereal provides not only 21% of the total food calories but also 20% of the protein for more than 4.5 billion people in 94 developing countries (Braun et al., 2010). Wheat crop has nutritive components like 70% carbohydrate, 2.7 % minerals, 1.7 % fats, 2 % fibre and vitamins such as thiamine and vitamin B, as well as minerals such as zinc and iron, selenium and magnesium (Sharma and Jain, 2004). Wheat is used as food, feed, seed, and as a processed commodity for uses such as fuel. Wheat contains a protein called gluten which is

necessary for the basic structure in forming the dough system for bread, rolls and other baked goods. Due to its wide spread use, it is demanded all across the globe.

The major achievement of the green revolution was introduction of input responsive semi dwarf wheat varieties and development of new high yielding cultivars in the subsequent years. Though wheat yield has been doubled, there are certain constraints that affect the grain quality and quantity.

The most important biometric parameter in any crop is grain yield which is affected by genotype, environment and genotype and environment interaction (Dia *et al.*, 2016). Various biotic and abiotic factors constraints crop yield, among which major concern nowadays is about the abiotic stresses in which heat stress is becoming prominent due to climate change as a result of global warming. A report published by UNEP 2019, warns that if the increase in the greenhouse gas emissions continues then the projected rise in temperature by the end of century will be on the higher end of the scale at 3.5°C. Wheat is a cold loving crop and requires a temperature 21±3°C during most of the crop stages. Heat stress has great impact on yield and quality affecting nearly 7.0 million hectares area in developing countries and near about 36.0 million hectare area of temperate countries (Reynolds *et al.*, 2001).

Heat stress causes physiological changes by reducing chlorophyll content that leads to leaf senescence in cool-season cereal species. High temperature directly affects the grain filling duration and rate (Kumar *et al.*, 2012; Lobell and Gourdji 2012; Gourdji *et al.*, 2013) which results in lesser grain number and reduced kernel size (Ferris *et al.*, 1998).Canopy temperature depression (Reynolds *et al.*, 1998; Bilge *et al.*, 2011) and chlorophyll fluorescence (Moffatt *et al.*, 1990) have been used as physiological screening techniques for heat tolerance. If stress is given at seedling stage there is reduction in soluble sugar content and biomass (Wang *et al.*, 2014).

Heat tolerance is the ability of the plants to grow and produce economic yield under high temperature (Hall, 2001). Grain yield has been major focus for plant breeders which is a complex quantitative trait governed by many genes and low heritability due to its dependency on the environmental factors (Khairnar et al., 2018). So, direct selection for yield will be less effective and therefore indirect selection for grain yield by screening of its associated traits will further help the breeders to improve heat tolerance in wheat. Multivariate analysis tools like cluster and principal component analysis measure the quantity of genetic diversity and assesse the relative contribution of each morphological-physiological trait to the total variation in grain yield (Phougat and Verma, 2022). The presence of genetic variability and its subsequent utilization is key factor for the development of new varieties by analysing the major principal components and the major traits having highest positive or negative loadings in each component that govern the clustering pattern of different genotypes. Therefore, the present study was carried out to identify the principal components as well as the traits which were deciphering the major amount of variability and responsible for diversity among the breeding lines.

### MATERIALS AND METHODS

To examine the impact of heat stress on grain yield and its major contributing traits, an experiment was conducted during *Rabi* 2019- 20 at Research Area of Wheat and Barley Section, Department of Genetics and Plant Breeding, Chaudhary Charan Singh Haryana Agricultural University (CCS HAU), Hisar. A total of 60 advanced breeding lines of bread wheat (**Table 1**) along with four standard heat tolerant check varieties namely WH 1124, WH 1021, HD 3059 and DBW 90 were sown on 16-12-2019 to give comparatively high temperature conditions at the reproductive stage especially, at grain filling. The lines were planted according to Randomized Block Design (RBD) with three replications and recommended package of practice was followed to raise a good crop. The average maximum and minimum temperature at reproductive stage was 30.70°C and 15.12°C, respectively.

Observations were recorded for 20 morpho-physiological traits like: days to heading, plant height (cm), number of productive tillers per meter, peduncle length (cm), flag leaf length (cm), main spike length (cm), number of spikelets per spike, number of grains per spike, days to maturity, grain filling duration, 1000 grain weight (g), biological yield per plot (kg), grain yield per plot (kg), harvest index (%), physiological traits like normalized difference vegetation index at seven days of anthesis (NDVI-1), normalized difference vegetation index at 14 days of anthesis (NDVI-2), canopy temperature depression (°C) at seven days of anthesis (CTD-1), canopy temperature depression (°C) at 14 days of anthesis (CTD-2), chlorophyll content at seven days of anthesis (CHF-1) and chlorophyll content at 14 days of anthesis (CHF-2) by randomly selecting five plants per line for each replication and their mean was taken for evaluation of different statistical parameters.

Principal Component Analysis (PCA) was carried out on the basis of correlation matrix to reduce the data from a large number of correlated variables into a substantially smaller set of new variables. The components having eigenvalue more than one were retained and the major components having largest contribution towards total variability were found using scree plot. All the data was analysed using SPSS software version 26.0.

### **RESULTS AND DISCUSSION**

Principal Component Analysis is a multivariate analysis used to compress or transform the original data set containing many possibly correlated variables into smaller number of variables called as principal component. The analysis is based on the correlation matrix and component which were having eigen values greater than one were retained. Assessment of diversity by multivariate biplot analysis has been established as prerequisite in any breeding programme (Phougat and Verma, 2022).

PCA indicated that the first five components with eigen value more than one as significant and expressed nearly 79.32% of total phenotypic variability (**Table 2**). The results indicated that these components were playing major role in classification of genotypes based on the variability present among them. The remaining 15 components explained non-significant source of variation. Goyal *et al.* (2020) also reported five principal components expressing maximum variability. First principal component (PC I) had highest benefaction of 46.93%, followed by second (PC II) 12.14%, third (PC III) 8.02%, fourth (PC IV) 7.14% and fifth (PC V) 5.08% towards the total variation. Similar results were reported by Jaydev *et al.* (2016). Munjal (2017) and

S. No.	Advanced breeding line	Pedigree	S. No.	Advanced breeding line	Pedigree
1	P-13348	FRANCOL 1 N # 1/WBLL 1	31	P-14053	ICARDA-46
2	P-13350	MILAN/S8732//BAU92/3/AKUR	32	P-14054	ICARDA-60
3	P-13355	MILAN/S8732//BAU92*2/3/AKUR	33	P-14055	ICARDA-67
4	P-13377	TUKURU//BAU92/RAYON/3/FRNLLN	34	P-14056	ICARDA-68
5	P-13514	HPYT 423 (2014-15)	35	P-14057	ICARDA-70
6	P-13543	SAWYT 332 (2014-15)	36	P-14058	ICARDA-72
7	P-13582	STEMRJN 6025 (2014-15)	37	P-14059	ICARDA-74
8	P-13620	ESWYT 116 (2015-16)	38	P-14060	ICARDA-75
9	P-13633	ESWYT 137 (2015-16)	39	P-14061	ICARDA-77
10	P-13638	ESWYT 149 (2015-16)	40	P-14062	ICARDA-81
11	P-13640	HTWYT 4 (2015-16)	41	P-14103	BGRI-93
12	P-13673	SOKOL/WBLL1/4/D 67.2/PARANA 66.270// AE.SQVARR0SA (320)/3/CUNN/NGHAM	42	P-14104	BGRI-96
13	P-13676	IBWSN 1108 (2015-16)	43	P-14105	BGRI-104
14	P-13686	IBWSN 1232 (2015-16)	44	P-14106	BGRI-107
15	P-13694	IBWSN 1259 (2015-16)	45	P-14107	BGRI-109
16	P-13709	EIGN 91 (2015-16)	46	P-14108	BGRI-112
17	P-13808	SAWYT 305 (2016-17)	47	P-14109	BGRI-114
18	P-13811	SAWYT 335 (2016-17)	48	P-14110	HTWYT 9 (2018-19)
19	P-13816	MONAL # 1*2//SOKOLL/ WBLL 1	49	P-14111	HTWYT 10 (2018-19)
20	P-13820	ESWYT 114 (2016-17)	50	P-14112	HTWYT 20 (2018-19)
21	P-14043	ICARDA-1	51	P-14113	HTWYT 41 (2018-19)
22	P-14044	ICARDA-4	52	P-14114	HTWYT 121 (2018-19)
23	P-14045	ICARDA-10	53	P-14115	ESWYT 145 (2018-19)
24	P-14046	ICARDA-14	54	P-14116	ESWYT 150 (2018-19)
25	P-14047	ICARDA-16	55	P-14117	SAWYT 304 (2018-19)
26	P-14048	ICARDA-17	56	P-14118	SAWYT 314 (2018-19)
27	P-14049	ICARDA-32	57	P-14119	SAWYT 321 (2018-19)
28	P-14050	ICARDA-35	58	P-14120	SAWYT 323 (2018-19)
29	P-14051	ICARDA-37	59	P-14121	SAWYT 343 (2018-19)
30	P-14052	ICARDA-45	60	P-14122	SAWYT 347 (2018-19)

Table 1. List of 60 advanced breeding lines of bread wheat

Khare (2022) reported that first principal component had 47.25% contribution towards total phenotypic variation. To retain the major components having largest contribution towards the total variability and clustering pattern, scree plot (**Fig. 1**) was used. On the basis of scree plot only first three components that contributed for 67.10% variability were used for further analysis.

Generally, the number of variables is equal to the sum of all eigen values. The traits which possess higher absolute value closer to unity in the domain of first principal component have more impact on the clustering behaviour of genotypes than those which have lower absolute value closer to zero (Chahal and Gosal, 2002). So, in the current study instead of all variables just few traits that were having greater component loading score were responsible for major differentiation among genotypes. Accordingly, in the first principal component highest positive component loading came from GY (0.955), followed by NDVI-1 (0.916), NDVI-2 (0.898), TGW (0.883), NSPS (0.846), CTD- 1 (0.844), PL (0.835), CTD-2 (0.818) and lowest from MSL (0.199). Only one variable was having negative loading i.e. DH (-0.059). The results are reflected in table 3. In general, traits with higher PC 1 values and lower values of other components are preferred in determining their potential to be used as selection criteria. Direct selection for the grain yield will be ineffective because of its polygenic nature and sensitivity to the environmental conditions. So, more reliance should be on its associated traits. The findings indicate that the first principal component showed highest positive association with yield and its major contributing

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Principal Components	Total	% of Variance	Cumulative %
1	9.386	46.932	46.932
2	2.428	12.142	59.074
3	1.606	8.028	67.102
4	1.428	7.139	74.241
5	1.017	5.083	79.324
6	0.980	4.898	84.222
7	0.696	3.478	87.700
8	0.561	2.807	90.507
9	0.412	2.059	92.565
10	0.371	1.853	94.418
11	0.329	1.645	96.063
12	0.257	1.287	97.350
13	0.162	0.810	98.160
14	0.112	0.559	98.719
15	0.100	0.498	99.216
16	0.063	0.317	99.533
17	0.055	0.276	99.809
18	0.031	0.153	99.963
19	0.006	0.029	99.991
20	0.002	0.009	100
Sum of Eigen values	20.002		

Table 2. Eigen values of different morpho-physiological components in wheat





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Characters	PC-I	PC-II	PC-III
GY	0.955	0.055	0.060
NDVI-1	0.916	0.000	0.183
NDVI-2	0.898	-0.016	0.193
TGW	0.883	-0.123	0.122
NSPS	0.846	0.051	0.017
CTD-1	0.844	0.004	0.022
PL	0.835	-0.034	0.193
CTD-2	0.818	-0.114	0.093
FLL	0.720	-0.318	0.082
BY	0.711	0.524	-0.005
CHF-1	0.670	0.023	-0.496
CHF-2	0.663	0.057	-0.453
NPTM	0.655	0.181	-0.164
NGPS	0.601	0.215	-0.216
DH	-0.059	0.912	0.183
DM	0.223	0.761	-0.189
HI	0.471	-0.609	0.047
PH	0.233	0.164	0.752
GFD	0.431	-0.302	-0.411
MSL	0.199	-0.189	0.363

#### Table 3. Factor loading of different characters with respect to principal factor in wheat

(GY: Grain Yield per plot, NDVI-1: Normalized difference vegetation index at 7 days of anthesis, NDVI-2: Normalized difference vegetation index at 14 days of anthesis, TGW: Thousand grain weight, NSPS: Number of spikelets per spike, CTD-1: Canopy temperature depression at 7 days of anthesis, PL: Peduncle length, CTD-2: Canopy temperature depression at 14 days of anthesis, FLL: Flag leaf length, BY: Biological yield per plot, CHF-1:Chlorophyll content at 7 days of anthesis, CHF-2:Chlorophyll content at 14 days of anthesis, NPTM: Number of productive tillers per meter, NGPS: Number of grains per spike, DH: Days to heading, DM: Days to maturity, HI: Harvest Index, PH: Plant height, GFD: Grain filling duration, MSL: Main spike length)

traits like NDVI-1, NDVI-2, THW, NSPS, CTD-1 and PL that designated it as a productive potential component. Several researchers have reported significant contribution of morpho-physiological traits like peduncle length (main component of stem reserve mobilization), thousand grain weight, flag leaf length, chlorophyll content and NDVI for high yield under heat stress conditions. It is therefore, possible to develop heat tolerant lines by selection of only those traits which show positive association and are responsible for highest difference among genotypes. The results were in agreement with the findings of Poudel et al. (2021) for grain yield that was exhibiting maximum positive loading in the first principal component. Singh et al. (2022) also reported grain yield as one of the major trait in the first component. In the second principal component (Table 3) highest positive contribution was explained by DH (0.912), followed by DM (0.761) and lowest from NDVI-1 (0.000). Heat stress at reproductive stage shortens the gap between days to heading and maturity ultimately affecting the duration and rate of grain filling. Thus, variability for these traits between the breeding lines holds importance in development of lines tolerant to heat stress. Characters like HI (-0.609) and FLL

(-0.318) demonstrated highest negative association with this component. In this component, both days to heading and harvest index were found to contribute for maximum variability. The results are in line with the finding of Jaydev et al. (2016) for the days to maturity. In the third principal component (Table 3) maximum positive component loading was observed for PH (0.752), followed by MSL (0.363) and PL (0.193). Maximum negative component loading was shown by CHF-1 (-0.496), followed by CHF-2 (-0.453). In both second and third component, traits which were contributing less to yield showed high positive values and greater negative association with major yield contributing traits suggesting that the variation among genotypes for these traits may does not have any worth towards heat tolerance. Hence, selection for these traits may not yield any progress towards development of heat tolerant lines. So, principal component analysis explains the importance of the largest contributor to the gross variation at each axis of differentiation.

Principal component analysis (PCA) revealed that first five principal components accounted for 79.32% of the total variation that were further compressed into three

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major components that explained 67.10% of gross variability. Highest positive and negative values within a principal component are responsible for maximum differentiation in clustering. The first component was designated as productive potential component based on positive association of this component with yield and its contributing traits. Likewise, second and third components were designated as susceptible and variations explained by these components were not found to contribute much to yield and its associated traits. Therefore, results of principal component analysis might be used for identification of plant characters which contribute maximum towards economic yield and in determining selection criteria that can be used for the selection of superior lines for the heat stress tolerance.

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