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Original Article

Statistical modeling for analyzing grain yield of durum wheat under rainfed conditions in Azad Jammu Kashmir, Pakistan

Modelagem estatística para analisar o rendimento de grãos de trigo durum sob condições de chuva em Azad Jammu Kashmir, Paquistão

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Abstract

One of the most important traits that plant breeders aim to improve is grain yield which is a highly quantitative trait controlled by various agro-morphological traits. Twelve morphological traits such as Germination Percentage, Days to Spike Emergence, Plant Height, Spike Length, Awn Length, Tillers/Plant, Leaf Angle, Seeds/Spike, Plant Thickness, 1000-Grain Weight, Harvest Index and Days to Maturity have been considered as independent factors. Correlation, regression, and principal component analysis (PCA) are used to identify the different durum wheat traits, which significantly contribute to the yield. The necessary assumptions required for applying regression modeling have been tested and all the assumptions are satisfied by the observed data. The outliers are detected in the observations of fixed traits and Grain Yield. Some observations are detected as outliers but the outlying observations did not show any influence on the regression fit. For selecting a parsimonious regression model for durum wheat, best subset regression, and stepwise regression techniques have been applied. The best subset regression analysis revealed that Germination Percentage, Tillers/Plant, and Seeds/Spike have a marked increasing effect whereas Plant thickness has a negative effect on durum wheat yield. While stepwise regression analysis identified that the traits, Germination Percentage, Tillers/Plant, and Seeds/Spike significantly contribute to increasing the durum wheat yield. The simple correlation coefficient specified the significant positive correlation of Grain Yield with Germination Percentage, Number of Tillers/Plant, Seeds/Spike, and Harvest Index. These results of correlation analysis directed the importance of morphological characters and their significant positive impact on Grain Yield. The results of PCA showed that most variation (70%) among data set can be explained by the first five components. It also identified that Seeds/Spike; 1000-Grain Weight and Harvest Index have a higher influence in contributing to the durum wheat yield. Based on the results it is recommended that these important parameters might be considered and focused in future durum wheat breeding programs to develop high yield varieties.

Keywords: parsimonious model, triticum durum, step-wise regression, PCA, rain-fed.

Resumo

Uma das características mais importantes que os produtores de plantas visam melhorar é o rendimento de grãos, que é uma particularidade altamente quantitativa e controlada por várias características agromorfológicas. Foram considerados 12 traços morfológicos como fatores independentes, como Porcentagem de Germinação, Dias para Emergência da Espiga, Altura da Planta, Comprimento da Espiga, Comprimento da Aresta, Perfilhos /Planta, Ângulo da Folha, Sementes /Espiga, Espessura da Planta, Peso de 1000 Grãos, Índice de Colheita e Dias até a Maturidade,. A correlação, regressão e análise de componentes principais (em inglês *Principal Component Analysis* (PCA)) são usadas para identificar as diferentes características do trigo duro, que contribuem significativamente para o rendimento. As suposições necessárias exigidas para a aplicação da modelagem de regressão foram testadas e todas as suposições são adequadas de acordo com os dados observados. Os *outliers* são detectados nas observações de características fixas e rendimento de grãos. Algumas observações são detectadas como *outliers*, mas as observações *outliers* não mostraram qualquer influência no ajuste da regressão. Para selecionar um modelo de regressão parcimonioso para

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o trigo duro, foram aplicadas tanto a melhor regressão de subconjunto quanto as técnicas de regressão *stepwise*. A melhor análise de regressão de subconjunto revelou que a porcentagem de germinação, perfilhos /planta e sementes /espiga tem um efeito de aumento acentuado, enquanto a espessura da planta tem um efeito negativo sobre o rendimento do trigo duro. Enquanto a análise de regressão passo a passo identificou que as características, porcentagem de germinação, perfilhos/planta e sementes /espiga contribuem significativamente para aumentar a produtividade do trigo duro. O coeficiente de correlação simples especificou a correlação positiva significativa do rendimento de grãos com a porcentagem de germinação, número de perfilhos/planta, sementes / espiga e índice de colheita. Esses resultados da análise de correlação direcionaram a importância dos caracteres morfológicos e seu impacto positivo e significativo no rendimento de grãos. Os resultados da PCA mostraram que a maior parte da variação (70%) entre o conjunto de dados pôde ser explicada pelos cinco primeiros componentes. Também identificou que Sementes / Espiga, Peso de 1000 Grãos e Índice de Colheita têm uma maior influência na contribuição para o rendimento do trigo duro. Com base nos resultados, recomenda-se que esses importantes parâmetros possam ser considerados e focados em futuros programas de melhoramento de trigo duro para desenvolver variedades de alto rendimento.

Palavras-chave: modelo parcimonioso, *Triticum durum*, regressão passo a passo, PCA, agricultura de sequeiro.

1. Introduction

Durum wheat (*Triticum durum*) is an important crop with an estimated global cultivation area over 13 million hectares that constitute only 5-8% of the world wheat production (Kadkol and Sissons, 2016). Turkey and Canada are the world's largest durum wheat producers with the cultivated area of 2 million hectares each (STAT CA, 2017; USDA FAS, 2015), while Pakistan is cultivating durum wheat on only a little above than half-million hectares (USDA FAS, 2015). Whereas, urbanization in Pakistan is increasing @ 3% annually which is helping the pasta market to grow further, therefore, the demand of durum wheat products is also increasing (Joshi et al., 2015; Kotkin and Cox, 2013).

Durum wheat, which is also named as pasta wheat (macaroni wheat), is a type of wheat that has relatively hard, bold, yellow grain with high protein contents, hence, suitable for making pasta products (Noodles, spaghetti, macaroni, Lasagna, shells, fettuccine, and vermicelli), Bulgur, Couscous, bread, etc. and in 2018 worldwide annual production of pasta was 14.5 million tons (IPO, 2020). Keeping in view the changing food priorities and increasing demand for pasta synthesized products in Pakistan, CIMMYT is making efforts to alter the local market dynamics to promote disease resistance and high yielding durum wheat varieties with improved grain quality (Joshi et al., 2015).

Grain yield is a very complex attribute, which is determined by many different yield components. Thus, it is essential to detect the yield components having the greatest effect on the yield and their relative contribution to the total variability of the yield. Correlation and path coefficient analysis is the important statistical techniques used to assist crop breeding programs to study the direct and indirect impact of yield components on grain yield. Similarly, the identification of the minimum, but the most important, parameters by building a parsimonious model to predict yield have significant importance to suggest specific parameters that might be used as selection criteria for future breeding programs to improve crop yield. Mohammadi et al. (2011) applied correlation and regression analysis and identified the existence of high heritability for growth vigor, days to maturity, plant height, peduncle length, number of kernel per spike, flag leaf senescence, spike length, thousand kernel weight and test weight as most effective selection parameters for yield. Good wheat yield could be gained through the selection of breeding materials such as 100-grain weight, high spikes per m^2, biological yield, and grain's weight per spike (Lodhi et al., 2017; Leilah and Al-Khateeb, 2005). The significant positive correlations of grain yield were observed with number of pods/plant, pod length, and number of seeds/pod. Factor analysis indicated a significant correlation of seed yield of common bean with number of pods/plant and number of seeds/pod in factor 1 (Salehi et al., 2008). Through the regression modeling process, the factors Erucic Acid and Pods Length were identified that significantly contribute to increasing the production of the mustard crop in Pakistan (Saleem et al., 2013). Mohsen (2013) used best subset and stepwise regression and identified all the independent variables as significant traits excluding number of seed/spike and seed weight.

The selection of appropriate statistical techniques is the most essential phase in analyzing the statistical data; otherwise, the obtained results may provide a flawed impression for the observed information. It is often observed that the researchers use statistical methodology to analyze their research data without taking into account the feasibility of that statistical technique. To overcome this shortcoming, before the regression model fitting process, assumptions related to residuals have been tested by using different statistical techniques. Multivariate is a statistical procedure about simultaneous perceptions and dissecting at least two factual factors. (Moucheshi et al., 2013). In the present study, we are making an effort to explain how multivariate statistical techniques like multiple regression analysis and principal component analysis can be applied as techniques to describe the relationships among various statistical variables and making recommendations for future studies with examples concerning the science of agriculture and plants. The main objective of the study is to identify the most significant traits that have a major influence in improvement of the production of durum wheat.

2. Material and Methods

The secondary data of Agro-Morphological characterization of durum (Triticum turgidum/Triticum durum/Macaroni wheat) wheat accessions has been obtained from Agronomy Research Farm Gahridopatta (34°13'28.8"N, 73°36'55.4"E; atl. 772m) Department of Agriculture Muzaffarabad, Azad Kashmir. The data set is the average of the values recorded during Rabi 2017-18-; Nov 2017 to May 2018. The climate of Gahridopatta is arid with an average annual rainfall of 110 mm (AJ&K, 2018). Agro-Morphological characteristics of durum wheat plant such as Germination Percentage (X_1), Days to Spike Emergence (X_2), Plant Height (X_3), Spike Length (X_4), Awn Length (X_5), Tillers/Plant (X_6), Leaf Angle (X_7), Seeds/Spike (X_8), Plant Thickness (X_9), 1000-Grain Weight (X_{10}), Harvest Index (X_{11}) and Days to Maturity (X_{12}) are considered as explanatory variables whereas Grain Yield (Y) is considered as a response variable. Morphological parameters were recorded before and after harvesting of crop by using the standard descriptors formulated by International Board for Plant Genetic Resources (IBPGR, 1980). A number of assumptions: normality of residuals, the linearity of a regression model, homoscedasticity, autocorrelation and multicollinearity among the variables are tested. Various statistical techniques such as residual plots (Jarque and Bera, 1987), scatter plot, Variance Inflation Factor (Montgomery et al., 2004) and Durbin Watson test (Durbin and Watson, 1951) are used to see whether the particular regression modeling is suitable for such kind of data or not.

Methods of leverage values (Chatterjee and Hadi, 1986) and Mahalanobis distance (Mahalanobis, 1936) have been used to detect the outlying observations in fixed traits (X observations) while outlying observations in grain yield (Y observations) have been detected using studentized deleted residuals (Margolin, 1977).

Cook's distance (Cook, 1977) and DFFITS (Belsley et al., 1980) statistical tests have been used to identify the influence of the detected outliers if any. Different statistical techniques such as best subset regression (Furnival and Wilson, 1974) and stepwise regression (Efroymson, 1960) procedures have been applied to select a parsimonious statistical model.

Pearson's product moment coefficient of correlation has been worked out to pick up the most correlated yield traits of durum wheat. To identify the traits that explain most of the variation among the fixed traits, multivariate statistical technique principal component analysis has been employed as described by Curry et al. (1983).

3. Results and Discussion

Before selecting a parsimonious statistical model, basic assumptions of regression were tested.

3.1. Normality of the residuals

Normal probability plot of residuals is presented in Figure 1 and most of the points fall reasonably closer to the straight line, suggesting that the errors are approximately normally distributed.

3.2. Linearity and homoscedasticity

To check the appropriateness of a linear regression model, the scattered plot of residuals versus fitted values ($\hat{y}_i$) is presented in Figure 2. Random scatters of the points with a horizontal axis suggesting that the linear regression model can be used safely and it indicates the linear relationship between Grain Yield and independent variables. Moreover, Figure 2. indicates that there is no systematic pattern in the plotted points, and points are randomly scattered. This suggests that the error variance is constant or homoscedastic.

3.3. Autocorrelation between the errors

To detect the autocorrelation, Durbin Watson Test is used and the value of Durbin Watson test statistic for the durum wheat data is 1.9594 that is very close to "d = 2" showing that there is no first-order autocorrelation present in the model explaining the durum wheat yield

3.4. The problem of multicollinearity

Variance Inflation Factor (VIF) criterion has been used as a device to detect the problem of multicollinearity in durum wheat data. The VIF against each predictor is computed and presented in Table 1. The values of VIF for all the variables are less than 10 indicating that the multicollinearity problem is not present in durum wheat data.

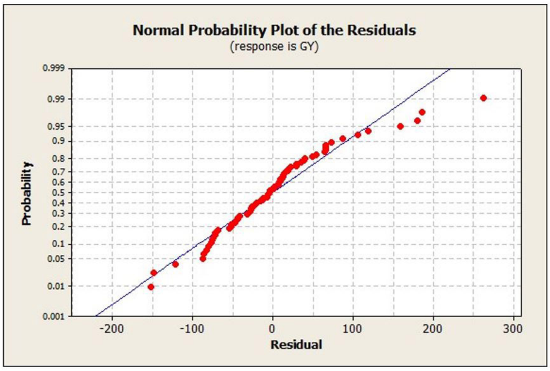

Figure 1. Normal probability plot of residuals.

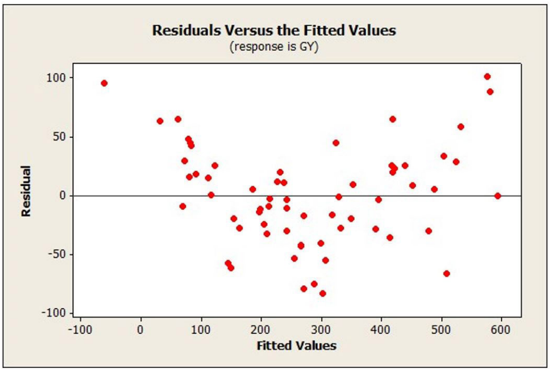

Figure 2. The plot of residuals versus fitted values.

Table 1. Values of VIF for the predictors of durum wheat data.

Predictor	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}
VIF	1.2	1.5	1.3	1.6	1.8	1.3	1.1	8.8	1.2	1.5	8.9	1.2

3.5. Detection of outliers

To detect the outliers in durum wheat data, different criteria such as Leverage value, Mahalanobis distance, and Studentized deleted residuals were applied and their values are presented in Table 2.

3.6. Leverage Value

leverage values $h_{1,1} = 0.44010$, $h_{39,39} = 0.40271$ and $h_{55,55} = 0.67554$ indicated by (*) in Table 2, corresponding to observation 1, 39 and 55 respectively exceed the criterion value that is twice the leverage mean value, $2\bar{h} = 2(0.16216) = 0.32432$. So, it is concluded that the above-mentioned observations are outlying concerning the fixed traits (X values).

3.7. Mahalanobis Distance

According to this criterion, an observation is reflected as an outlier if any squared Mahalanobis distance corresponding to that observation lies outside the ellipse, $\chi^2_{12,0.05} = 21.026$. Mahalanobis distance values 32.12714, 29.39796, and 49.31471 indicated by (*) in Table 2 corresponding to the observations 1, 39, and 55 respectively lie outside the above criterion. So, it is concluded that these observations are outlying to the fixed traits. Here we observed that both the outlying detection techniques detect the same observations as outlying in fixed traits.

3.8. Studentized Deleted Residuals

To identify outliers in Grain Yield (Y observations), studentized deleted residuals (d_i^*) for large absolute values are considered. An observation is considered as outlying observations if it satisfies the condition that $d_i^* > t_{22,0.95} = 1.671$. It is observed from Table 2, that the observations 8, 12, 17, 24, 31, 41, 65, and 74 have values of studentized deleted residuals larger than the above-mentioned criterion. So, these observations of grain yield are detected as outliers.

3.9. Identification of influential observations

To identify whether the outlying observations have any influence on model fitting or not, Cook's distance and DFFITS statistics were used. It was observed that all the values of Cook's distance are below $F_{(13,61;0.05)} = 1.89$ and all the values of DFFITS are less than $2/\sqrt{p/n} = 4.77$, which indicates that the influence of these outlying observations is not enough strong to carry out the remedial measures.

3.10. Correlation analysis

The association of various parameters is generally determined by the presence of linkage and pleiotropic effect of different genes. In the present study, a simple correlation is calculated for each pair of the response variable and an explanatory variable to identify the correlation of grain yield with other yield traits of durum wheat. The results of the correlation coefficients with p-values, within parenthesis, are presented in Table 3. A significant positive correlation of grain yield was observed with germination percentage, tiller/plant, seeds/spike, harvest index, and 1000-grain weight. Similar results were reported in different investigations where a significant and positive correlation of grain yield was observed with germination percentage (Al-Musa et al., 2012), tiller/plant (Ahmad et al., 2016; Yousif et al., 2015; Masood et al., 2014; Anwar et al., 2009;), seeds/spike (Khan and Hassan, 2017; Uddin et al., 2015; Yousif et al., 2015; Gelalcha and Hanchinal, 2013; Iftikhar et al., 2013; Sokoto et al., 2012; Akram et al., 2008), harvest index (Sokoto et al., 2012) and 1000-grain weight (Khan and Hassan, 2017; Ahmad et al., 2016; Uddin et al., 2015; Yousif et al., 2015; Iftikhar et al., 2013; Sokoto et al., 2012; Akram et al., 2008). These results also approve the conclusions of Doğan (2009), Aycicek and Yildirim (2006), and Abderrahmane et al. (2013). The other parameters such as Plant Height, Awn Length, Leaf Angle, Plant Thickness, and Days to Maturity showed positive and non-significant association with grain yield. Similarly, Days to Spike Emergence and Spike Length recorded negative and non-significant correlation with grain yield. Akram et al. (2008) also reported a negative and non-significant relationship of Plant Height and Spike Length with grain yield at the phenotypic level. Similarly, a negative non-significant association of Spike Length and Days to Maturity with Grain Yield was reported by Akram et al. (2008). The positive relationship of Awn Length with grain yield was reported by Motzo and Giunta (2002). They also concluded that the association of Awn Length with grain yield depends upon different factors e.g. genetic background and environmental conditions. Furthermore, Tungland et al. (1987) concluded that the leaf angle has less or no effect on grain yield. The results of the present study for few parameters are also contrary to the findings of previous investigations which could be the result of different environmental conditions, genetic background and sample size and varieties used, as the environment and genetic background play a significant role in the development of phenotypic correlation (Ali et al., 2009; Motzo and Giunta, 2002). The positive significant relationship between grain yield and the important agronomic parameters describes the true relationship between grain yield and these parameters, which is evident that these parameters have pronounced influence upon grain yield. Therefore, based on present findings it is suggested that these parameters should be given prime importance in future wheat breeding programs regarding their significant contribution to enhancing yield.

Table 2. Results of residual analysis for durum wheat data.

Obs. No.	Leverage Value (h_{ii})	Mahalanobis Distance	d_i^*	Cook's Distance	DFFITS
1	0.44010*	32.12714*	0.84881	0.046223	0.77340
2	0.14480	10.57043	0.01322	0.000003	0.00573
3	0.27553	20.11363	0.28275	0.002538	0.18029
4	0.20820	15.19842	0.09962	0.000221	0.05317
5	0.04974	3.63071	0.11164	0.000066	0.02901
6	0.15070	11.00084	-1.04006	0.016327	-0.46101
7	0.15184	11.08425	0.13195	0.000270	0.05873
8	0.22481	16.41108	4.36504*	0.353863	2.44166
9	0.07917	5.77944	0.17801	0.000253	0.05689
10	0.14645	10.69056	-0.10250	0.000156	-0.04473
11	0.13433	9.80604	-0.28111	0.001071	-0.11709
12	0.16294	11.89485	2.64760*	0.105173	1.22554
13	0.14717	10.74326	0.48238	0.003470	0.21106
14	0.21036	15.35632	-0.45119	0.004577	-0.24232
15	0.09131	6.66530	-0.69351	0.004369	-0.23731
16	0.19263	14.06205	0.92249	0.017040	0.47008
17	0.24788	18.09529	-2.33775*	0.138629	-1.39072
18	0.11696	8.53802	-0.29111	0.000993	-0.11277
19	0.16038	11.70758	-0.75560	0.009310	-0.34667
20	0.19250	14.05222	-0.09317	0.000176	-0.04746
21	0.20274	14.80020	1.54435	0.049498	0.81123
22	0.10288	7.51024	-0.34409	0.001217	-0.12489
23	0.11276	8.23182	0.26423	0.000788	0.10045
24	0.24689	18.02281	2.44306*	0.149474	1.44963
25	0.25219	18.41017	-0.39561	0.004417	-0.23797
26	0.11550	8.43164	-0.05614	0.000037	-0.02161
27	0.15942	11.63732	-1.12035	0.020104	-0.51229
28	0.10393	7.58701	-0.20296	0.000428	-0.07404
29	0.07370	5.38026	-0.16597	0.000206	-0.05130
30	0.18874	13.77776	0.09474	0.000178	0.04770
31	0.20699	15.11045	-2.20840*	0.099783	-1.17458
32	0.19866	14.50238	-0.62346	0.008134	-0.32355
33	0.14818	10.81714	-0.95623	0.013586	-0.41996
34	0.17334	12.65408	-1.07897	0.020524	-0.51723
35	0.12077	8.81642	-0.62350	0.004686	-0.24557
36	0.15513	11.32440	-0.65978	0.006856	-0.29716
37	0.13301	9.70967	0.22383	0.000672	0.09274
38	0.06267	4.57488	-0.31278	0.000630	-0.08982
39	0.40271*	29.39796*	0.66952	0.024809	0.56534
40	0.13963	10.19307	-0.72026	0.007274	-0.30629
41	0.20673	15.09112	1.74405*	0.063946	0.92689
42	0.12208	8.91185	0.90802	0.009977	0.35963
43	0.14875	10.85907	-1.05142	0.016443	-0.46274
44	0.06999	5.10953	0.18903	0.000254	0.05706
45	0.07129	5.20427	-0.41340	0.001235	-0.12584
46	0.12851	9.38148	-0.07757	0.000078	-0.03156
47	0.12186	8.89593	0.89303	0.009637	0.35336
48	0.10303	7.52152	0.39052	0.001569	0.14184
49	0.21496	15.69202	-1.04915	0.025032	-0.57093
50	0.11274	8.22968	0.52881	0.003145	0.20101

Table 2. Continued...

Obs. No.	Leverage Value (h_{ii})	Mahalanobis Distance	d_i^*	Cook's Distance	DFFITS
51	0.11572	8.44786	-0.04408	0.000023	-0.01698
52	0.13949	10.18279	1.20581	0.020055	0.51250
53	0.08158	5.95540	-0.58847	0.002830	-0.19077
54	0.07807	5.69910	0.15109	0.000180	0.04797
55	0.67554*	49.31471*	-0.62504	0.067269	-0.93046
56	0.19013	13.87925	-0.58265	0.006751	-0.29463
57	0.12370	9.03042	0.17566	0.000384	0.07005
58	0.07609	5.55463	0.03400	0.000009	0.01067
59	0.13635	9.95358	-1.13844	0.017490	-0.47799
60	0.14617	10.67071	-0.06050	0.000054	-0.02638
61	0.09003	6.57218	-0.37736	0.001283	-0.12825
62	0.17656	12.88863	0.13127	0.000316	0.06359
63	0.07721	5.63604	0.72322	0.004046	0.22844
64	0.12695	9.26712	-1.19715	0.017888	-0.48394
65	0.28428	20.75272	-1.88842*	0.111639	-1.22978
66	0.14646	10.69139	0.91248	0.012231	0.39820
67	0.08779	6.40852	0.38661	0.001314	0.12980
68	0.09773	7.13394	-0.15596	0.000238	-0.05518
69	0.13587	9.91846	-0.99417	0.013355	-0.41662
70	0.26926	19.65603	0.01980	0.000012	0.01243
71	0.19273	14.06914	-1.24118	0.030520	-0.63267
72	0.08154	5.95233	0.96818	0.007582	0.31378
73	0.20995	15.32611	0.32765	0.002412	0.17576
74	0.13322	9.72535	2.68474*	0.086543	1.11335

Table 3. Correlation coefficient and P-values of grain yield and yield components.

	Y	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
X1	0.555 (0.000)											
X2	-0.125 (0.287)	-0.210 (0.073)										
X_3	0.148 (0.209)	-0.079 (0.505)	-0.218 (0.062)									
X_4	-0.119 (0.313)	-0.096 (0.415)	-0.135 (0.250)	0.004 (0.976)								
X_5	0.025 (0.834)	-0.012 (0.921)	-0.361 (0.002)	0.188 (0.109)	0.122 (0.155)							
X_6	0.563 (0.000)	0.101 (0.392)	-0.039 (0.740)	0.303 (0.009)	-0.051 (0.668)	0.106 (0.370)						
X_7	0.060 (0.613)	-0.128 (0.278)	0.041 (0.727)	-0.001 (0.994)	0.013 (0.916)	0.071 (0.548)	0.185 (0.114)					
X_8	0.451 (0.000)	-0.133 (0.258)	-0.037 (0.751)	0.014 (0.904)	-0.057 (0.627)	-0.026 (0.824)	-0.061 (0.607)	0.045 (0.704)				
X_9	0.067 (0.572)	0.013 (0.911)	-0.161 (0.170)	-0.068 (0.565)	0.131 (0.265)	0.096 (0.417)	0.194 (0.098)	0.048 (0.686)	0.019 (0.876)			
X_{10}	0.247 (0.034)	-0.107 (0.364)	-0.024 (0.839)	0.074 (0.532)	0.100 (0.396)	0.159 (0.176)	-0.010 (0.934)	0.074 (0.529)	0.016 (0.675)	-0.005 (0.966)		
X_{11}	0.441 (0.000)	-0.146 (0.214)	-0.050 (0.670)	0.077 (0.516)	-0.030 (0.802)	-0.018 (0.877)	-0.028 (0.813)	0.012 (0.919)	0.019 (0.890)	0.027 (0.818)	0.056 (0.076)	
X_{12}	0.091 (0.439)	0.034 (0.772)	0.285 (0.097)	-0.130 (0.271)	0.022 (0.850)	-0.171 (0.145)	-0.046 (0.696)	-0.013 (0.915)	0.102 (0.386)	0.200 (0.088)	0.053 (0.657)	0.123 (0.295)

3.11. Selection of parsimonious model

In the present investigation thirteen yield parameters from durum wheat crop were used to build a model, for the current study, which was parsimonious, which, had the minimum number of parameters and maximum predictive power. To select such a suitable model for predicting grain yield of durum wheat, best subset regression, and stepwise regression techniques were applied. A best subset regression model was obtained through different statistics such as R_p^2, R_{Adj}^2, and Mallow's C_p. The results of these statistics are summarized in Table 4 and also plots of R_p^2, R_{Adj}^2, MSE, and C_p are presented in Figure 3a-d. The results from Table 4 and Figures indicated that a model with 4 predictors Germination Percentage (X_1), Tillers/Plant (X_6), Seeds/Spike (X_8), and Plant Thickness (X_9) with $R_p^2 = 87.8\%$, $R_{Adj}^2 = 87.1$ and $C_p = 3.5$ seems to be a good model. These results indicate that above-selected durum wheat traits are the foremost traits for predicting grain yield of durum wheat. By using the stepwise regression technique, it was observed that a model with 3 predictors such as Germination Percentage (X_1), Tillers/Plant (X_6), and Seeds/Spike (X_8) was a good one. The results of the stepwise regression procedure reveal that the above durum wheat traits involved in the selected regression model, significantly contribute to predicting the durum wheat yield. The best subset regression indicates that Germination Percentage (X_1), Tillers/Plant (X_6), Seeds/Spike (X_8), and Plant Thickness (X_9) are the foremost traits for predicting grain yield of durum wheat (Table 5). Stepwise regression identifies Germination Percentage (X_1), Tillers/Plant (X_6) and Seeds/Spike (X_8) significantly contributes to predicting the durum wheat yield which is consistent with the findings of Ashmawy et al. (2010), who reported the importance of spikes/m^2 and number of grains/spike to predict variability of wheat grain yield. Similarly, other studies which used stepwise regression techniques also reported the importance of biological yield (Abderrahmane et al., 2013; Nasri et al., 2014; Leilah and Al-Khateeb, 2005; Ahmadizadeh et al., 2011 and Zarei et al., 2011) in wheat, seeds per pod, pods per plant (Rameeh, 2016) in rapeseed and beans (Rahnamaeetak et al., 2007). However, the results of the present study were not in a complete agreement

Table 4. Values of statistics for a selection of best subset regression model.

Vars	P	R^2	Adj R^2	C_p	MSE	Variables in the equation
1	2	31.7	30.8	289.0	30758.14	X_6
1	2	30.8	29.8	293.8	31169.90	X_1
2	3	58.8	57.7	148.5	18807.38	X_1 X_8
2	3	58.6	57.4	149.5	18900.75	X_1 X_{11}
3	4	87.5	87.0	8.8	5784.36	X_1 X_6 X_8
3	4	85.3	84.7	19.5	6803.61	X_1 X_6 X_{11}
4	5	87.8	87.1	3.5	5716.72	X_1 X_6 X_8 X_9
4	5	87.8	87.0	3.8	5781.47	X_1 X_6 X_8 X_{11}
5	6	88.1	87.2	4.2	5662.26	X_1 X_6 X_8 X_9 X_{12}
5	6	88.0	87.1	4.3	5709.92	X_1 X_6 X_8 X_9 X_{11}
6	7	88.3	87.2	4.5	5677.62	X_1 X_6 X_8 X_9 X_{11} X_{12}
6	7	88.2	87.1	5.3	5716.87	X_1 X_6 X_8 X_9 X_{10} X_{12}
7	8	88.3	87.1	5.5	5736.85	X_1 X_6 X_8 X_9 X_{10} X_{11} X_{12}
7	8	88.3	87.1	6.3	5752.16	X_1 X_2 X_6 X_8 X_9 X_{11} X_{12}
8	9	88.3	86.9	6.8	5812.84	X_1 X_2 X_6 X_8 X_9 X_{10} X_{11} X_{12}
8	9	88.3	86.9	7.1	5817.27	X_1 X_3 X_6 X_8 X_9 X_{10} X_{11} X_{12}
9	10	88.4	86.7	7.2	5889.18	X_1 X_2 X_3 X_6 X_8 X_9 X_{10} X_{11} X_{12}
9	10	88.4	86.7	8.8	5896.24	X_1 X_2 X_6 X_7 X_8 X_9 X_{10} X_{11} X_{12}
10	11	88.4	86.6	9.0	5973.59	X_1 X_2 X_3 X_6 X_7 X_8 X_9 X_{10} X_{11} X_{12}
10	11	88.4	86.5	9.1	5982.40	X_1 X_2 X_3 X_5 X_6 X_8 X_9 X_{10} X_{11} X_{12}
11	12	88.4	86.3	11.0	6069.97	X_1 X_2 X_3 X_4 X_6 X_7 X_8 X_9 X_{10} X_{11} X_{12}
11	12	88.4	86.3	11.0	6069.97	X_1 X_2 X_3 X_5 X_6 X_7 X_8 X_9 X_{10} X_{11} X_{12}
12	13	88.4	86.1	13.0	6169.47	X_1 X_2 X_3 X_4 X_5 X_6 X_7 X_8 X_9 X_{10} X_{11} X_{12}

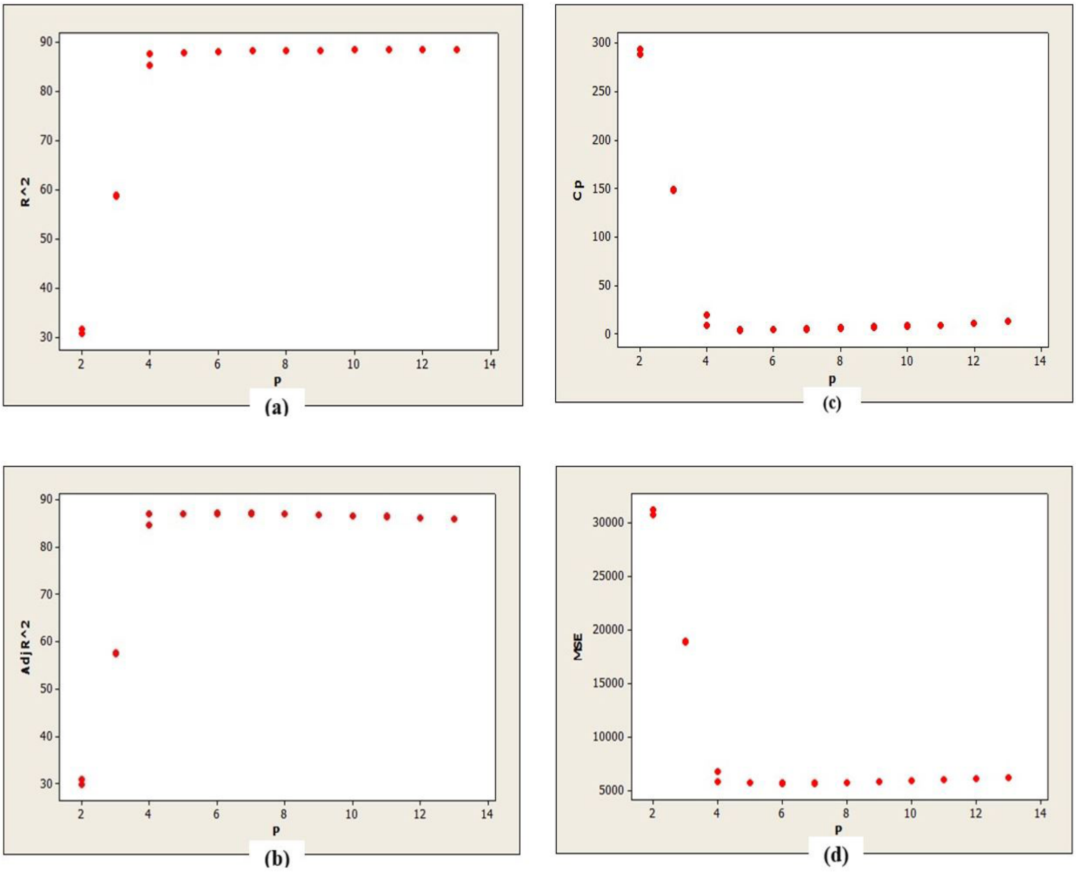

Figure 3. Plots of R^2(a), adjusted R^2(b), C_p (c) and MSE (d) against P.

Table 5. Summary of the parsimonious model selected by different model selection techniques.

Best subset regression	**GY = -564.56 + 6.35X_1(Germination percentage) + 46.48X_6(Tillers/plant) + 5.57X_8(Seeds/spike) – 86.01X_9(Plant thickness)**				
Coefficients (p-value)	β_0 -564.56 (0.000)	β_1 6.35 (0.000)	β_2 46.48 (0.000)	β_3 5.57 (0.000)	β_4 -86.01 (0.181)
	R_p^2 = 87.8%	R_{Adj}^2 = 87.1%	C_p = 3.5		
Stepwise regression	GY = -600.12 + 6.35X_1(Germination percentage) + 45.52X_6(Tillers/plant) + 5.55X_8(Seeds/spike)				
Coefficients (p-value)	β_0 -600.12 (0.000)	β_1 6.35 (0.000)	β_2 45.52 (0.000)	β_3 5.55 (0.000)	
	R_p^2 = 87.51%	R_{Adj}^2 = 86.98%			

with the findings of other researchers, who found that spikes/m^2, 1000 grain weight and plant height (Soleymanifard et al. 2012-75%), biological yield and harvest index (Abderrahmane et al., 2013), biological yield, harvest index and weight spike/unit (Nasri et al., 2014) contributes to predicting 75%, 98.3% and 98.3% yield in wheat, respectively. This difference may be due to the environmental factors, plant growth conditions, and time of sowing which could modify the yield predictive model of stepwise regression techniques

Table 6. Eigenvalues of correlation matrix and related statistics.

Component No.	Eigenvalues	Proportion	Cumulative
1	2.6991	0.208	0.208
2	2.0001	0.154	0.361
3	1.7781	0.137	0.498
4	1.3245	0.102	0.600
5	1.2561	0.097	0.697
6	0.9387	0.072	0.769
7	0.9091	0.070	0.839
8	0.6603	0.051	0.890
9	0.5690	0.044	0.933
10	0.3937	0.030	0.964
11	0.3479	0.027	0.991
12	0.0724	0.006	0.996
13	0.0510	0.004	1.000

(Golabadi et al., 2005; Rameeh, 2016). Golabadi et al. (2005) executed a stepwise regression technique to predict the yield and reported a model with biological yield under full irrigation and harvest index under stress conditions. Similarly, Rameeh (2016) also revealed that under different sowing dates different yield components had entered the seed yield prediction model while using stepwise regression techniques.

3.12. Principal component analysis

To identify the factors that explain most of the variation in grain yield, we used a multivariate technique such as principal component analysis. The factors with eigenvalues are presented in Table 6. The first five components have eigenvalues higher than 1 and can explain almost 70% of the total variation among data. Variation explained by different components is also indicated in Figure 4. Principal component analysis suggests that the first five principal components out of thirteen components account for almost 70% of the total variation. Moreover, the first component includes the traits, Seeds/Spike (X_8), 1000-Grain Weight (X_{10}), and Harvest Index (X_{11}). The second principal component includes Days to Spike Emergence (X_2) having a positive loading sign whereas Awn Length (X_5) having a negative loading sign that explains that these traits have a higher effect on grain yield. A similar kind of investigation has also been carried out in wheat by Kumar et al., (2016) and reported that six principal components including yield parameters accounted for 81.75% of the total variation for grain yield. Beheshtizadeh et al., (2013) also concluded that four principal components out of eleven agronomic parameters were responsible for about 76% of the total variation among traits in bread wheat cultivars. Similar results were also

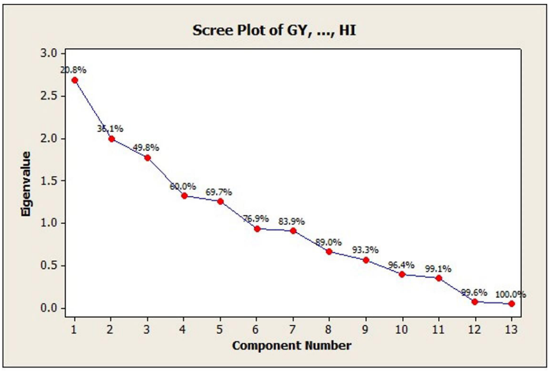

Figure 4. Scree plot of principal components against eigenvalues.

reported by Ahmad et al. (2017), Krzysko et al. (2013), and Rymuza et al. (2012) during variability studies in wheat crop. They reported 1000 grain yield and grain yield as the first principal component and the major contributor followed by spike related parameters.

4. Conclusion

In the present study, Germination Percentage, Tiller/Plant, Seeds/Spike, Harvest Index, and 1000-Grain Weight showed significant and positive association to grain yield and performed as the major contributors towards grain yield. Similarly, the best subset regression indicated that Germination Percentage, Tillers/Plant, Seeds/Spike, and Plant Thickness are the main parameters with maximum predictive power to access grain yield and this parsimonious regression model with 4 predictors appeared to be good and suitable. Furthermore, the principal component analysis suggested that Seeds/Spike, 1000-Grain Weight, Harvest Index, Days to Spike Emergence, and Awn Length accounted for almost 70% of the total variation. Therefore, it is suggested that these parameters might be used as selection criteria by plant breeders and could be focused while breeding high yielding durum wheat varieties.

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