Interrelationships between Seed Yield and 16 Related Traits of 81 Garden Cress Landraces

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Abstract. This research uses path analysis to determine the interrelationships among seed yield and 16 related Morphological traits. Eighty-one garden cress accessions from IPK (Department of Leibniz Institute of Plant Genetics and Crop Plant Research) were grown in two growing seasons (2012–13) to determine the important components of seed yield. Observations were recorded on 20 other canola traits. Correlation coefficient analysis revealed that seed yield was positively correlated with all traits except plant height (PH) in the first year and except main axis length (MAL) and PH in the second year. Sequential path analysis (SPA) identified the thousand-seed weight (TSW), number of siliques per plant (NSP) and height of first silique (HFS) as important first order traits influenced seed yield in first year. Plant height, NSP, and the TSW were important first-order traits that influenced seed yield in the second year. This indicates that breeding programs should be based on these traits for further improvement of the garden cress. All direct effects were significant, as indicated by bootstrap analysis. The results suggest that TSW and NSP could be used as a selection criterion in selecting for increased seed yield in garden cress.

Garden cress has gained more interest from different food consumers and vegetable producers worldwide, and can be a good choice for health promoting substances such as glucotropaeolin. It is native to Southwest Asia and probably Iran and is cultivated in North America, parts of Europe, and as culinary vegetable all over Asia (Doke and Guha, 2014). Since ancient times, garden cress has been used in local traditional medicine and so it also highlights the good potential of garden cress seeds and its extracts for various medicinal uses and industrial uses for edible oil (Rehman et al., 2012).

The common path analysis approach might result in multicollinearity for variables, particularly when associations among some of the traits are high. Samonte et al. (1998) adopted a new method as SPA for determining interrelationships among seed yield and related traits. The abovementioned model has several benefits over the commonly used path analysis model in discerning actual effects of different predictor variables and can provide a better fit for various datasets. However, collinearity of predictor variables was not tested before organization of the variables into different path orders. Therefore, this investigation has been initiated in view of

filling such an information gap in garden cress genotype and to investigate direct and indirect effects of yield components on seed yield via path coefficient analysis in 81 international germplasm collections of garden cress for 16 traits.

Materials and Methods

Trials. A total of 77 accessions were chosen from the garden cress germplasm in the IPK in Gatersleben, Germany. Also, four Iranian accessions named as Birjand, Tabriz, Kerman, and Shiraz genotypes were used in this research. The sources of the accessions are shown in Sabaghnia et al. (2015). Each accession was grown in a plot of 3.6 m² (six 2-m long rows), planted 10 cm apart in and a row spacing of 30 cm. Standard agricultural practice was followed. For each trial, a replicated 9 × 9 simple lattice design with four replications was used and sowing was performed in the first week of May which is the optimal sowing time.

Morphological measurements. The 10 individuals were chosen randomly and marked for each accession to measure the height of the first branch (HFB), HFS, MAL, number of lateral branches (NLB), number of silique per lateral branches (NSL), number of siliques per main axis (NSM), NSP, number of seeds per silique of lateral branches (SLB), number of seeds per silique of main axis (SMA), number of seeds of silique per plant (NSSP), and PH. Also, days to emergence

(DE), days to flowering (DF), and flowering period (FP) were recorded as was as possible. Days to flowering were recorded when 50% of the plants in the plot had at least one open flower. The TSW was measured on a subsample of seed harvested from each plot. The middle four rows (1.8 m²) were harvested to determine biological and seed yield.

Data analysis. Stepwise multiple regression models were performed to determine the predictor variables into first, second, and third order paths. The level of multicollinearity in each component was measured from the tolerance value and the variance inflation factor (VIF). Thus, very small tolerance values (much lower than 0.1) or high VIF values (>10) indicate high collinearity. Partial coefficients of determination were computed from the path coefficients for all predictor variables. To estimate the standard error of path coefficients, bootstrap analysis was performed.

Results

The adjusted coefficient of determination (Adjusted $R^2 = 0.93$) represents the influence of the TSW, NSP, and HFS traits as first-order variables involved in the research of total variability of seed yield in the first year (Table 1), whereas the TSW, NSP, and PH traits, as first-order variables, accounted for nearly 86% of the variation in seed yield in the second year (Table 1). In the year 2012 among the TSW, NSP, and HFS traits, the TSW had the greater direct effect (2.32) than other two traits on seed yield. The indirect effect of the TSW was high and negative (−1.135) via NSP but the indirect effect of the TSW was low and negative (−0.506) via HFS in the first year. Also, the indirect effect of the NSP was high and positive (2.007) via TSW but the indirect effect of the TSW was low and negative (−0.373) via HFS. The indirect effect of the HFS was high and positive (1.694) via TSW but the indirect effect of the NSP was moderate and negative (−0.692) via NSP in the first year. The results of SPA, when the second-order variables were used as predictors and the first-order variables as response variables, indicated that NSSP and NLB positively impressed the TSW and accounted for more than 77% of the observed variation in the year 2012 (Table 1). The NSSP, NLB, and NSL positively influenced NSP and accounted for more than 98% of the total variation, whereas DE and HFB positively influenced the HFS and accounted for more than 60% of the observed variation in the first year.

In the year 2013 among the TSW, NSP, and PH traits, TSW had the greater direct effect (1.31) than the other two traits on seed yield (Table 2). The indirect effect of TSW was moderate and negative (−0.783) via NSP but low and positive (0.134) via PH in the second year, and the indirect effect of NSP was low and positive (0.074) via PH but high and positive (1.125) via TSW in the second year. The indirect effect of the PH was low and negative (−0.176) via NSP but moderate

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Table 1. Measures of collinearity values [tolerance and variance inflation factor (VIF)] for predictor variables in conventional path analysis (CPA; all predictor variables as first-order variables) and sequential path analysis (SPA; predictors grouped into first-, second-, and third-order variables).

2012						2013					
Pred.	Res.	Tolerance		VIF		Pred.	Res.	Tolerance		VIF	
		CPA	SPA	CPA	SPA			CPA	SPA	CPA	SPA
TSW	SY	0.086	0.151	11.6	6.6	PH	SY	0.367	0.837	2.7	1.2
NSP		0.008	0.230	117.9	4.3	TSW		0.071	0.228	14.0	4.4
HFS		0.211	0.429	4.7	2.3	NSP		0.013	0.250	76.4	4.0
NSSP	TSW	0.122	0.683	8.2	1.5	FP	PH	0.164	0.868	6.1	1.2
NLB		0.030	0.683	32.9	1.5	HFS		0.256	0.805	3.9	1.2
						NSSP		0.280	0.863	3.6	1.2
NSSP	NSP	0.122	0.367	8.2	2.7	SMA	TSW	0.205	0.688	4.9	1.5
NSL		0.020	0.511	49.3	2.0	NLB		0.037	0.796	27.3	1.3
NLB		0.030	0.637	32.9	1.6	NSL		0.031	0.715	32.6	1.4
DE	HFS	0.014	0.578	69.9	1.7	NSL	NSP	0.031	0.864	32.6	1.2
HFB		0.296	0.578	3.4	1.7	NLB		0.037	0.864	27.3	1.2
SLB	NSSP	0.086	0.487	11.6	2.1	MAL	FP	0.462	0.881	2.2	1.1
SMA		0.274	0.487	3.6	2.1	DE		0.025	0.098	40.2	10.2
SLB	NLB	0.086	0.795	11.6	1.3	DF		0.023	0.101	42.7	9.9
MAL		0.356	0.795	2.8	1.3	DE	HFS	0.025	0.807	40.2	1.2
NSM	NSL	0.208	0.717	4.8	1.4	HFB		0.488	0.807	2.0	1.2
SMA		0.274	0.476	3.6	2.1	DE	NSSP	0.025	0.917	40.2	1.1
DF		0.017	0.515	59.6	1.9	SLB		0.396	0.917	2.5	1.1
DF	DE	0.017	0.977	59.6	1.0	DE	SMA	0.025	1.000	40.2	1.0
FP		0.103	0.977	9.7	1.0	DE	NLB	0.025	0.917	40.2	1.1
DF	HFB	0.017	1.000	59.6	1.0	SLB		0.396	0.917	2.5	1.1
						NSM	NSL	0.406	1.000	2.5	1.0

PH = plant height; MAL = main axis length; TSW = thousand-seed weight; NSP = number of siliques per plant; HFS = height of first silique; NSSP = number of seeds of silique per plant; NSL = number of silique per lateral branches; NLB = number of lateral branches; SMA = number of seeds per silique of main axis; DE = days to emergence; DF = days to flowering; FP = flowering period; HFB = height of first branch; NSM = number of siliques per main axis; SLB = number of seeds per silique of lateral branches; SY = seed yield; Res. = response; Pred. = prediction.

and positive (0.385) via TSW in the year 2013. The results of SPA, when the second-order variables were used as predictors and the first-order variables as response variables, indicated that SMA, NLB, and NSL positively affected the TSW (Table 2) and accounted for more than 83% of the total variation in the second year (Table 3). The NLB and NSL traits positively influenced NSP and accounted for more than 97% of the observed variation whereas FP, HFS, and NSSP traits positively impressed the PH and accounted for more than 33% of the observed variation in the year 2013 (Table 3).

Results of SPA when the third-order variables were used as predictors, and second-order variables as response variables in the year 2012, indicated that SMA and SLB positively influenced NSSP and accounted for more than 80% of observed variation in the first year (Table 2). Also, SLB positively and MAL negatively impressed NLB and accounted for more than 56% of total variation and; NSM, SMA, and DF positively influenced NSL and accounted for more than 56% of observed variation in the first year (Table 2). FP positively and DF negatively affected DE and accounted for more than 98% of the observed variation whereas HFB positively influenced the DF and accounted for more than 40% of the total variation in the year 2012 (Table 2). Results of SPA when the

third-order variables were used as predictors, and second-order variables as response variables in the second year, indicated that MAL and DE positively and DF negatively affected FP and accounted for more than 78% of observed variation in the first year (Table 2). Also, DE and HFB positively impressed HFS and accounted for more than 36% of observed variation and; DE and SLB positively influenced NSSP and accounted for more than 44% of total variation in the first year (Table 2). The DE and SLB traits positively influenced NLB and accounted for more than 47% of the observed variation whereas SMA positively influenced the DE and accounted for more than 47% of the observed variation, and NSL positively influenced the NSM and accounted for more than 28% of the total variation in the year 2013 (Table 3).

Discussion

The investigation presented in this article shows the results of high association between seed yield with two important yield component characteristics (TSW and NSP) in both years, but HFS and PH characters had an important role only in 1 year. For future breeding attempts and making selection programs, it is essential to ascertain the variation available for plant structure and yield components in garden cress regarding TSW

Table 2. Direct and indirect effects for the predictor variables in sequential path analysis (grouped into first-, second- and third-order variables) in the first year (2012).

SY			
	TSW	NSP	HFS
TSW	2.316	-1.135	-0.506
NSP	2.007	-1.310	-0.373
HFS	1.694	-0.706	-0.692
NLB			
	NSSP	NSL	NSP
NSSP	0.123	0.406	0.303
NSL	0.083	0.603	0.119
NSP	0.069	0.133	0.537
NSL			
	NSM	SMA	DF
NSM	0.632	0.182	-0.109
SMA	0.325	0.354	-0.165
DF	0.286	0.243	-0.240
DE			
	DF	FP	
DF	0.905	0.044	
FP	0.137	0.289	
TSW			
	NSSP	NLB	
NSSP	0.641	0.190	
NLB	0.361	0.337	
HFS			
	DE	HFB	
DE	0.469	0.248	
HFB	0.305	0.382	
NSSP			
	SLB	SMA	
SLB	0.651	0.219	
SMA	0.466	0.306	
NLB			
	SLB	MAL	
SLB	0.840	-0.147	
MAL	0.380	-0.326	

MAL = main axis length; TSW = thousand-seed weight; NSP = number of siliques per plant; HFS = height of first silique; NSSP = number of seeds of silique per plant; NSL = number of silique per lateral branches; NLB = number of lateral branches; SMA = number of seeds per silique of main axis; DE = days to emergence; DF = days to flowering; FP = flowering period; HFB = height of first branch; NSM = number of siliques per main axis; SLB = number of seeds per silique of lateral branches.

and NSP. A better understanding of how yield components affect seed yield formation in different crops can be obtained by using path analysis to determine the direct and indirect effects of primary, secondary, and tertiary traits on seed yield formation. We found some morphological and yield component traits such as NSSP, NSL, NLB, DE, HFB, FP, and SMA characteristics as secondary traits through path analysis. The advantage of path analysis is not only the identification of the most important traits directly influencing important characteristics such as seed yield, but also indicating how

Table 3. Direct and indirect effects for the predictor variables in sequential path analysis (grouped into first-, second- and third-order variables) in the second year (2013).

SY			
	PH	TSW	NSP
PH	0.385	0.455	-0.176
TSW	0.134	1.310	-0.783
NSP	0.074	1.125	-0.912

PH			
	FP	HFS	NSSP
FP	0.461	-0.138	0.073
HFS	0.158	-0.404	0.110
NSSP	0.107	-0.141	0.315

TSW			
	SMA	NLB	NSL
SMA	0.436	0.178	0.145
NLB	0.179	0.432	0.106
NSL	0.220	0.159	0.287

FP			
	MAL	DE	DF
MAL	0.183	0.454	-0.183
DE	0.034	2.413	-2.123
DF	0.015	2.275	-2.251

NSP		
	NSL	NLB
NSL	0.612	0.214
NLB	0.226	0.580

HFS		
	DE	HFB
DE	0.410	0.131
HFB	0.180	0.299

NSSP		
	DE	SLB
DE	0.480	0.099
SLB	0.138	0.344

PH = plant height; MAL = main axis length; TSW = thousand-seed weight; NSP = number of siliques per plant; HFS = height of first silique; NSSP = number of seeds of silique per plant; NSL = number of silique per lateral branches; NLB = number of lateral branches; SMA = number of seeds per silique of main axis; DE = days to emergence; DF = days to flowering; FP = flowering period; HFB = height of first branch; NSM = number of siliques per main axis; SLB = number of seeds per silique of lateral branches.

traits affect the characteristics indirectly through other traits (Kozak and Kang, 2006). Previous investigations showed that path coefficient analysis provides more information on the interrelationships between target yield and its components and other morphological traits than correlation coefficients in vegetable crops (Asghari-Zakaria et al., 2007). This analysis helps to determine yield component compensation which occurs when two, or more, yield components affecting yield or any other yield component act inversely in their effects.

Bedassa et al. (2013) reported the highest strong direct effect of number of seeds per plant, DF initiation, biomass yield, harvest index, and TSW on garden cress seed yield regarding common path coefficient analysis. Similarly, we found highest strong direct effect of TSW, NSP, HFS, and PH on seed yield and there are relatively similar reports for path analysis of rapeseed and indian mustard (Tuncturk and Ciftci, 2007; Ul-Hasan et al., 2014). Other yield components or important traits such as NSSP, NLB, NLS, and NSM influenced indirectly as the second-order or the third-order variables. In a study of Uddin et al. (1995), on indian mustard, TSW and primary branches were found to have high positive direct effects on seed yield, which supports the result of the this research. However, our study demonstrated the utility of SPA over common path analysis in discerning the direct and indirect effects of various yield-related traits and it could be concluded that the traits SMA, NLB, NSL, FP, NSSP, SLB, NSM, MAL, DF, and HFB were identified as the first-, second-, and third-order variables in both years.

Conclusions

The study revealed that TSW, NSP, PH, and HFS traits had direct effects on seed yield based on path analysis. These three traits were the key contributors to seed yield suggesting the need of more emphasis on these traits for genetic improvement of the seed grain yield in garden cress. Therefore,

improvement of seed yield in garden cress could be brought through selection of component traits directly concerned with final seed yield like TSW and NSP which showed positive direct effects and could serve as selection criteria in garden cress breeding programs.

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