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Study of relationship between oil quality traits with agro-morphological traits in peanut genotypes by canonical correlation analysis

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Abstract

Seed quality traits of the plants may directly or indirectly depend on agro-morphological traits. Thus the determination between agronomical and oil quality characters of the plants may be important for plant scientists. The relation between agronomical and oil quality traits were studied by using Canonical Correlation Analysis (CCA) in peanut genotypes. CCA is a multivariate statistical model that facilitates the study of interrelationships among sets of multiple dependent variables and multiple independent variables. As a result, the canonical correlation between the first canonical variate pair was found as 0.897. Five canonical functions obtained from morphological and agronomical traits, had attributed about 70% from variation in the oil quality traits. It can be concluded that CCA can be used to simplify the relationship between agro-morphological and oil quality traits of the peanut.

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Introduction

Peanut (*Arachis hypogaea* L.) is the major oilseed crop in the world, grown on 26 million hectares producing nearly 36 million tons annually (Sadeghi and Niyaki, 2012). Peanut seeds are a good source of protein, lipid and fatty acids for human nutrition (Tai and Young, 1975; Gaydou *et al.*, 1983; Grosso and Guzman, 1995; Grosso *et al.*, 1997; Grosso *et al.*, 1999). Total oil and protein content and fatty acid profile are the important seed quality traits that substantially influence the edible uses of peanut (Yoshida *et al.*, 2005). Peanut is rich in oil, naturally containing from 47 to 50 %. The oil is pale yellow and has the characteristic odor and flavor of peanuts (O'Brien, 1998). Oil quality and its stability are therefore very important for the consumers (Jambunathan *et al.*, 1993). Peanut oil chemistry is made up of 12 free fatty acids with only 3 of these being present in amounts exceeding 5%: palmitic, oleic and linoleic (Anderson, 1998). These free fatty acids comprise about 90% of the free fatty composition of the oil, with oleic and linoleic comprising about 81% (Mercer *et al.*, 1990). Grosso *et al.* (2000) have reported the oil, protein, ash, carbohydrate contents, iodine value and fatty acid composition of some wild peanut species (*Arachis*) seeds. The fatty acid composition of peanut oil is well documented (Treadwell *et al.*, 1983). Seed quality traits of the plants may directly or indirectly depend on agro-morphological traits (Norman *et al.*, 2012). Thus the determination of associations between agro-morphological traits and oil quality traits of peanuts were investigated using Canonical Correlation Analysis.

Canonical Correlation Analysis (CCA), one of the most direct ways of analyzing relationships between sets of variables, has been widely applied in various fields such as the plant sciences, biology, chemistry, social and management sciences (Young, 1981; Keskin and Yasar, 2007; Liu *et al.*, 2009; Norman *et al.*, 2012). This analysis allows investigation of the relationship between two sets of variables which one representing a set of independent variables and another set of dependent variables (Green, 1978).

Routine approaches such as multiple linear regression to analyze data that include two sets of variables are usually challenged as they are plagued by the potential issues including multicollinearity and multiple testing. Since CCA assesses correlation of two canonical variates, it is potentially a useful method to evaluate relationship between agro-morphological and oil quality traits. Although CCA has often been applied to peanut studies, the method has been rarely used in Iranian peanut studies. Therefore, the objective of this research was to use a multivariate statistical technique, canonical correlation analysis, to identify the associations between two independent sets of variables, agro-morphological and oil quality traits. Additionally, the present study results enable the researchers to select the appropriate multi variables as selection criteria for peanut traits in threshold studies.

Materials and methods

Data

The experiment was conducted at the research farm of the Tobacco Research Institute (49° 36' east latitude, 37 ° 16' north longitudes), Rasht, Iran, during 2006. The experimental material consisted of 39 peanut genotypes which were provided by the Genetic Research Department of the National Plant Gene Bank of Iran (NPGBI). The experiment was laid out in a randomized complete block design with three replications. The plot size was 3.2 m × 0.9 m. The distance between adjacent rows and adjacent plants were 0.3 and 0.4 meter, respectively while planting depth was 4 cm. All measurements were performed according to instructions stated in the peanut descriptor (Anonymous. 1981). Determinations of peanut oil content and fatty acids were performed by Soxhlet and Gas Chromatography methods respectively (Soxhlet, 1879; Hisil, 1988). Y and X variables sets are defined as follows: X_1: 100-grain weight; X_2: 100-pod weight; X_3: Grain Length; X_4: Grain Width; X_5: Pod Length; X_6: Pod Width; X_7: Grain: pod volume ratio; X_8: Leaflet length; X_9: Leaflet width; X_{10}: Plant Height and X_{11}: Pods per plant. Y_1: Iodine index; Y_2: Saponification value; Y_3: Oleic acid; Y_4: Linoleic acid and Y_5: Acid value.

Statistical analysis

CCA was used to examine dependencies that exist between important agronomical traits of peanuts and their oil quality measurements. Developed by Hotelling (Hotelling, 1935; Hotelling, 1936), as a generalization of multiple regression analysis, CCA seeks to identify and quantify the associations between two sets of variables where each set consists of at least two variables (Kshirsagar, 1972). It is used to investigate the relationship between a linear combination of the set of X variables with a linear combination of a set of Y variables.

Consider two groups of variables (X and Y) such that one has p variables ($X_1, X_2, \ldots, X_p$), and the other has q variables ($Y_1, Y_2, \ldots, Y_q$). Linear combinations of the original variables can be defined as canonical variates (U_m and V_m) as follows:

$$U_m = a_{m1}X_1 + a_{m2}X_2 + \ldots + a_{mp}X_p$$

$$V_m = b_{m1}Y_1 + b_{m2}Y_2 + \ldots + b_{mq}Y_q$$

The correlation between U_m and V_m can be called canonical correlation (C_m). Squared canonical correlation (canonical roots or eigenvalues) represents the amount of variance in one canonical variate accounted for by the other canonical variate (Hair *et al.*, 1998).

The goal is to determine the coefficients, or canonical weights (a_{ij} and b_{ij}), that maximize the correlation between canonical variates U_i and V_i. The first canonical correlation, Corr (U_1, V_1), is the highest possible correlation between any linear combination of the variables in the exposure set and any linear combination of the variables in the outcome set. Further pairs of maximally correlated linear combinations are chosen in turn, and they are orthogonal to those already identified. The maximum number of canonical correlation is equal to the number of variables in the smaller set, which is five in this study (the number of oil quality traits). Canonical correlation maximizes the correlation between linear combinations of variables in X and Y variable sets. To determine how much of the variance in one set of variables is accounted for by the other set of variables, redundancy measure is calculated (Sharma, 1996). Redundancy determines the amount of variances accounted for in one set of variables by the other set of variables. A more detailed description of CCA is given by Hair *et al.* (1998). The three possible methods for interpretation are (1) canonical weights (standardized coefficients), (2) canonical loadings (structure correlations), and (3) canonical cross-loadings (Hair *et al.*, 1998). All the computational work was performed using a SAS for Windows software package (SAS, 1985).

Results and discussion

Canonical Correlation

The canonical correlation analysis was restricted to deriving five canonical functions because the dependent variable set contained five variables. To determine the number of canonical functions to include in the interpretation, the analysis focused on the level of statistical significance.

Table 1. Canonical correlation analysis.

Canonical Function	Canonical Correlation	Canonical R^2	F Statistic	Probability
1	0.8975	0.8055	1.19	0.0173
2	0.8539	0.7292	0.91	0.6342
3	0.7440	0.5535	0.75	0.7895
4	0.6545	0.4284	0.43	0.9511
5	0.2941	0.0865	0.14	0.9927

The test statistics for the canonical correlation analysis are presented in Table 1. The canonical correlation between the first (0.897) pair was found to be significant (p < 0.05) from the likelihood ratio test. The remaining canonical correlation is not statistically significant.

In addition to tests of each canonical function separately, multivariate tests of both functions simultaneously are also performed. The test statistics employed are Wilks' lambda, Pillai's criterion, Hotelling's trace, and Roy's gcr. Table 2 also details the multivariate test statistics, which all indicate that the canonical functions, taken collectively, are statistically significant at the 0.05 level.

Table 2. Multivariate tests of significance.

Statistic	Value	Approximate F Statistic	Probability
Wilk's Lambda	0.0122	1.37	0.0173
Pillai's Trace	2.6034	1.20	0.0446
Hotelling-Lowley Trace	8.9217	1.67	0.0082
Roy's Greatest Root	4.1436	3.77	0.0228

Table 3. Redundancy analysis of dependent variates for the first canonical function.

Standardized Variance of the Dependent Variables Explained by					
	Their Own Canonical Variate (Shared Variance)			The Opposite Canonical Variate (Redundancy)	
Canonical Function	Proportion	Cumulative proportion	Canonical R^2	Proportion	Cumulative proportion
1	0.5330	0.5330	0.8056	0.4294	0.4294
2	0.2251	0.7581	0.7293	0.1642	0.5935
3	0.1719	0.9300	0.5536	0.0951	0.6887
4	0.0424	0.9724	0.4285	0.0182	0.7069
5	0.0276	1.0000	0.0865	0.0024	0.7092

Redundancy analysis is calculated for the independent and dependent variates in Tables 3 and 4. As can be seen, the redundancy index for the dependent variate is 0.5330. The independent variate, however, has a markedly lower redundancy index (.0126). The low redundancy of the independent variate results from the relatively low shared variance in the independent variate (.0156), not the canonical R^2. From the redundancy analysis and the statistical significance tests, the first function should be accepted.

Canonical Correlation Interpretation

Table 5 contains the standardized canonical weights for each canonical variate for both dependent and independent variables. The magnitude of the weights represents their relative contribution to the variate. Standardized canonical coefficients show variation in canonical variate in parallel with one standard deviation increase in original variables. In other words these coefficients represent relative contributions of original variables to the related variate. Based on the size of the weights, the order of contribution of independent variables to the first variate is X_{11}, X_3, X_2, X_{10}, X_1, X_9, X_7, X_5, X_4, X_8 and X_6, and the dependent variable order on the first variate is Y_3, Y_4, Y_5, Y_1 and then Y_2. Because canonical weights can be unstable due to small sample size or presence of multicolinearity in the data, the canonical loading and cross-loadings are considered more appropriate (Hair *et al.*, 1998). A canonical loading gives the product-moment correlation between the original variable and its corresponding canonical variate.

Canonical loadings, also called canonical structure correlations, measure the simple linear correlation between an original observed variable in the dependent or independent set and the set's canonical variate (Hair *et al.*, 1998). The canonical loading reflects the variance that the observed variable shares with the canonical variate and can be interpreted like a factor loading in assessing the relative contribution of each variable to each canonical function. The methodology considers each independent canonical function separately and computes the within-set variable-to-variate correlation. The larger the coefficient, the more important it is in the canonical variate (Hair *et al.*, 1998). Canonical loadings, like weights, may be subject to considerable variability from one sample to another. This variability suggests that loadings, and hence the relationships ascribed to them, may be sample-specific, resulting from chance or extraneous factors (Lambert and Durand, 1975).

Table 4. Redundancy analysis of independent variates for the first canonical function.

Standardized Variance of the Independent Variables Explained by					
	Their Own Canonical Variate (Shared Variance)		The Opposite CanonicalVariate (Redundancy)		
Canonical Function	Proportion	Cumulative proportion	Canonical R^2	Proportion	Cumulative proportion
1	0.0156	0.0156	0.8056	0.0126	0.0126
2	0.0086	0.0242	0.7293	0.0063	0.0188
3	0.0051	0.0293	0.5536	0.0028	0.0216
4	0.0828	0.1120	0.4285	0.0355	0.0571
5	0.2544	0.3665	0.0865	0.0220	0.0791

Table 5. Canonical weights for the first function.

	Standardized canonical coefficients for the independent variables	U_1
X_1	100-grain weight	-0.3571
X_2	100-pod weight	-0.5200
X_3	Grain Length	0.5674
X_4	Grain Width	0.0736
X_5	Pod Length	0.0799
X_6	Pod Width	-0.0329
X_7	Grain: pod volume ratio	0.0940
X_8	Leaflet length	0.0468
X_9	Leaflet width	0.2966
X_{10}	Plant Height	0.3730
X_{11}	Pods per plant	0.6330
	Standardized canonical coefficients for the dependent variables	V_1
Y_1	Iodine index	-0.2454
Y_2	Saponification Value	0.1664
Y_3	Oleic acid	0.7404
Y_4	Linoleic acid	-0.6561
Y_5	Acid value	-0.5019

Table 6 contains the canonical loadings for the dependent and independent variates for the first canonical function. The first independent variate has loadings ranging from .0092 to .5600, with three independent variables (X_4, X_2 and X_6) even having a negative loading. The two variables with the highest loadings on the independent variate are X_3 (grain length), and X_8 (leaflet length). Three of the variables (Y_3, Y_2 and Y_5) have positive loadings and two of the variables (Y_1 and Y_4) have negative loadings on the dependent set. The two variables with the highest loadings on the dependent variate are Y_3 (oleic acid), and Y_1 (iodine value).

Table 6. Canonical loadings for the first function.

	Correlations between the independent variables and their canonical variates	U_1
X_1	100-grain weight	0.0092
X_2	100-pod weight	-0.4091
X_3	Grain Length	0.5600
X_4	Grain Width	-0.4305
X_5	Pod Length	0.1586
X_6	Pod Width	-0.0010
X_7	Grain: pod volume ratio	0.1029
X_8	Leaflet length	0.5049
X_9	Leaflet width	0.1621
X_{10}	Plant Height	0.3783
X_{11}	Pods per plant	0.4255
	Correlations between the dependent variables and their canonical variates	V_1
Y_1	Iodine index	-0.7364
Y_2	Saponification Value	0.1939
Y_3	Oleic acid	0.8874
Y_4	Linoleic acid	-0.3089
Y_5	Acid value	0.1448

Table 7. Canonical cross-loadings for the first function.

	Correlations between the independent variables and dependent canonical variates	V_1
X_1	100-grain weight	0.0083
X_2	100-pod weight	-0.3672
X_3	Grain Length	0.5026
X_4	Grain Width	-0.3864
X_5	Pod Length	0.1423
X_6	Pod Width	-0.0009
X_7	Grain: pod volume ratio	0.0923
X_8	Leaflet length	0.4531
X_9	Leaflet width	0.1455
X_{10}	Plant Height	0.3395
X_{11}	Pods per plant	0.3819
	Correlations between the dependent variables and independent canonical variates	U_1
Y_1	Iodine index	-0.6609
Y_2	Saponification Value	0.1741
Y_3	Oleic acid	0.7965
Y_4	Linoleic acid	-0.2772
Y_5	Acid value	0.1299

Table 8. Sensitivity analysis of the canonical correlation results to removal of an independent variable.

			Results after deletion of		
		Complete Variate	X_3	X_5	X_9
Canonical correlation (R)		0.8975	0.8892	0.8955	0.8915
R^2		0.8055	0.7906	0.8019	0.7947
Independent Variate					
Canonical loadings					
X_1	100-grain weight	0.0092	0.0090	0.0090	0.0088
X_2	100-pod weight	-0.4091	-0.4085	-0.4087	-0.4090
X_3	Grain Length	0.5600	omitted	0.5605	0.5610
X_4	Grain Width	-0.4305	-0.4311	-0.4307	-0.4308
X_5	Pod Length	0.1586	0.1586	omitted	0.1588
X_6	Pod Width	-0.0010	-0.0009	-0.0010	-0.0012
X_7	Grain: pod volume ratio	0.1029	0.1027	0.1026	0.1026
X_8	Leaflet length	0.5049	0.5048	0.5048	0.5040
X_9	Leaflet width	0.1621	0.1618	0.1617	omitted
X_{10}	Plant Height	0.3783	0.3780	0.3782	0.3789
X_{11}	Pods per plant	0.4255	0.4257	0.4249	0.4245
Shared variance		0.0156	0.0155	0.0155	0.0153
Redundancy		0.0126	0.0122	0.0125	0.0125
Dependent Variate					
Canonical loadings					
Y_1	Iodine index	-0.7364	-0.7355	-0.7366	-0.7361
Y_2	Saponification Value	0.1939	0.1927	0.1936	0.1932
Y_3	Oleic acid	0.8874	0.8865	0.8860	0.8870
Y_4	Linoleic acid	-0.3089	-0.3088	-0.3077	-0.3086
Y_5	Acid value	0.1448	0.1443	0.1436	0.1445
Shared variance		0.5330	0.5325	0.5331	0.5330
Redundancy		0.4294	0.4290	0.4291	0.4288

The computation of canonical cross-loadings has been suggested as an alternative to canonical loadings (Dillon and Goldstein, 1984). This procedure involves correlating each of the original observed dependent variables directly with the independent canonical variate, and vice versa. Thus cross-loadings provide a more direct measure of the dependent–independent variable relationships by eliminating an intermediate step involved in conventional loadings. Table 7 includes the cross-loadings for the first canonical function. The highest cross-loadings that were found were 0.796 and -0.660 between Y_3 and Y_1 from dependent variables with the first canonical variate of independent variables. By squaring these terms, we find the percentage of the variance for each of the variables explained by function 1. The results show that 63 percent of the variance in Y_3 and 43 percent of the variance in Y_1 is explained by function 1. These high cross-loadings express that the U_1 index can be used as a selection criteria for breeding with a statistically high reliability, for Y_3 and Y_1. For example, varieties having higher score on the U_1 index are expected to have higher Y_3 and lower Y_1 percentage because of the canonical and cross-loadings values. In other words, these varieties have high oleic acid content and low unsaturated fatty acids. The higher is the iodine value, the more reactive, less stable, softer, and more susceptible to oxidation and ranicidification is the oil (Raheja *et al.*, 1987). High oleic peanuts exhibit improved characteristics of oil chemistry compared to normal oleic acid cultivars. High oleic peanuts have a lower iodine value which translates to the increased oil stability and a higher ratio of unsaturated / saturated fatty acids (Raheja *et al.*, 1987).

Validation

As with any other multivariate technique, canonical correlation analysis should be subjected to validation methods to ensure that the results are not specific only to the sample data and can be generalized to the population. The most direct procedure is to create two subsamples of the data (if sample size allows) and perform the analysis on each subsample separately (Hair *et al.*, 1998). Then the results can be compared for similarity of canonical functions, variate loadings, and the like (Hair *et al.*, 1998). Another approach is to assess the sensitivity of the results to the removal of a dependent and/or independent variable (Hair *et al.*, 1998). Table 8 contains the result of a sensitivity analysis in which the canonical loadings are examined for stability when individual independent variables are deleted from the analysis. As seen, the canonical loadings in our research are remarkably stable and consistent in each of the three cases where an independent variable (X_3, X_5, or X_9) is deleted. The overall canonical correlations also remain stable.

Conclusion

Multivariate data analysis techniques have been used effectively to study latent relationships among measurements (Hair *et al.*, 1998; Johnson *et al.*, 1980). CCA has the ability to deal with two sets of variables simultaneously and to produce both structural and spatial inference. This procedure addresses the question of whether the same forces influence multiple measurements and their relative contribution in explaining these measurements. Moreover, CCA reduces the probability of Type I error that might occur with the computation and comparison of more than one multiple regression analysis in modeling multiple criterion variables (Thompson, 1991). Thus, the use of CCA is more advisable than the calculation and comparison of result of separate regression equations for different dependent measurements. CCA is particularly appropriate when one seeks not an explanation of each of the criterion variables but rather the set of criterion variables taken together (Levine, 1977). This last feature makes CCA particularly appropriate for understanding underlying relationships between agronomical and oil quality traits. It was concluded that high and statistically significant canonical correlations clearly found from the general framework of relationship between dependent and independent traits in peanut variates. Considering some phenotypic and agronomic measurements and relating these measurements can provide a relatively accurate method to estimate important oil quality traits by explaining their correlation with CCA.

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