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Quantitative evaluation of apple (*Malus* × *domestica* Borkh) yield based on morphological characterizations

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ABSTRACT

The fruit, that's consumed the most worldwide, is apple. In this study, morphological features have been used to try and predict the apple production. The choice of the significant factors was made using principal components analysis. An optimum sample size of 200 apple trees was selected randomly in farmers' fields and observations were recorded on various characters viz yield per tree (Y), plant girth (X_2), plant spread (X_3), number of leaves per branch (X_4), annual shoot extension growth (X_5), number of flowers per branch (X_6), number of fruits per branch (X_7), fruit weight (X_8), fruit set (X_9) and LD ratio (X_{10}). The discriminate function was used for categorizing the trees as high and low yielders. It was found that plant spread (X_3), number of leaves per branch (X_4) and number of flowers per branch (X_6) were the most important characters that discriminate the groups. The explanatory advances knowledge of the intricate connections between crop output and morphological features.

Keywords: Apple; discriminate analysis; principle component analysis; Gutmann's lower bound

INTRODUCTION

Apple is the main fruit crop in Himachal Pradesh. In the high mountain regions of the state, apple cultivation has dramatically altered the socio-economic status of the rural population. In general, it is not sufficient to examine a series of univariate statistical studies performed on each variable, as this ignores the inter-relationships among variables that affect apple yield. On the other hand, multivariate approaches allow imultaneous analysis of datasets to examine their overall structure, measure redundancy in measurements, examine the inter-dependence and relative importance of the different features involved, summarize key aspects of the study and form groups. Common features provide more meaningful information. In the current study, principal component analysis (PCA) was used to reduce redundancy by decomposing the observed variable into a set of principal components that account for most of the variance of the observed variable. The most important principal components are then extracted to explain the results. According to Gutmann's lower bound principle (Kaiser 1958), factors with Eigen values less than 1 are often ignored. By reducing the amount of data, an attempt was made to determine the relative contribution of morphological traits to the increase in apple yield in Himachal Pradesh. Basically, PCA creates the same number of new variables from old ones, where the direction of maximum data spread is considered as the first principal components (PCs). Using discriminant and principal component analysis, Verma et al (2018) investigated the relative contribution of morphological characteristics responsible for enhancing the yield of kinnow in Kangra district of Himachal Pradesh.

MATERIAL and METHODS

Field experiment was conducted during 2021 in Mandi district, Himachal Pradesh as this area also represented the apple growing belt of the state. An optimum sample size of 200 apple trees was selected randomly in farmers' fields by following a two-step approach as suggested by Stein (1945) and Cox (1958). Four branches from each tree in four directions, as per the practice in vogue, were selected and the observations were recorded on yield per tree (Y), plant girth (X_2), plant spread (X_3), number of leaves per branch (X_4), annual shoot extension growth (X_5), number of flowers per branch (X_6), number of fruits per branch (X_7), fruit weight (X_8), fruit set (X_9) and LD ratio (X_{10}). The data collected were subjected to discriminant analysis to define a systematic and statistically valid procedure for categorizing the trees as high and low yielders. For these two populations, PCA was carried out to bring out the basic components associated with the above referred morphological characters of apple. Under the present study, in order to reduce the redundancy, PCA was employed to reduce the observed variables into a number of principal components that accounted for most of the variance in the observed variables and most important components were extracted for interpreting the results. Generally, the factors corresponding to Eigen values less than one are not considered as per Gutman's lower bound principal (Kaiser 1958). However, another methodology includes the amount of total variance explained (ie >80%) by the principal components (Johnson and Wichern 2007).

RESULTS and DISCUSSION

Discriminant analysis: Two hundred apple trees were discriminated into two groups namely high yielder and low yielder groups. The discriminate analysis resulted into the following equation:

A – d

$$D = -6.434 + 0.356\, X_3 + 0.0.10\, X_4 + 0.045\, X_6$$

The equation revealed that the characters, plant spread (X_3), number of leaves per branch (X_4) and number of flowers per branch (X_6) were the most important characters that discriminated the two groups. To test the statistical hypothesis of no difference in mean vectors (μ_1 and μ_2) of ten characters for these two groups; the value of Wilk's lambda (λ) statistic was used. It was concluded that smaller the lambda for an independent variable, the more that variable contributed to the discriminant function.

Lambda varies from 0 to 1, with 0 means that group means differ and 1 means all group means are the same. The value of λ was obtained to be 0.548 which, in turn, gave the computed value of chi-square (χ^2) as 118.139 is much more than the table value of χ^2 at 5 per cent level; the hypothesis of equity of group mean vectors was rejected; it means principle component analysis would be appropriate for data reduction. Having found that the groups differed statistically, the trees were assigned to group I (high yielder) if $D \geq -0.12$ otherwise to group II (low yielder), where $m = -0.12$ was the average of groups centroids. The groups formed on the basis of allocation rule were subjected to PCA. The interpretation of classification rule can thus be stated as allocate the tree to group I (high yielder) if $D_1 > m_1$, otherwise to group II (low yielder).

High yielder group: Data in Table 1 exhibit that three of the ten principal components (PCs) had Eigen values greater than unity (Gutman's lower bound) which played the main role in the analysis, pertaining to high yielder. These components explained 31.34, 20.49 and 12.04 per cent of total variation for PC_1, PC_2 and PC_3 respectively accounting 63.87 per cent of the total variation of the original variables. First principal component (PC_1) had Eigen value of 3.13 and it explained 31.34 per cent of total variation in the data that showed relative maximum value for plant height (X_1), number of flowers per branch (X_6), number of fruits per branch (X_7) and fruit set (X_9).

The second component was correlated with some of the observed variables that did not display strong correlations with first component. Thus the second principal component (PC_2) with Eigen value 2.05 explained 20.49 per cent of the total variation and these variations were accounted by fruit weight (X_8) and fruit set (X_9), whereas, plant girth (X_2) gave negative weights. The third principal component (PC_3) had Eigen value 1.20 explaining 12.04 per cent of total variation. In this component, plant spread (X_3) was found to be highly positive while number of leaves per branch (X_4) showed negative weights.

The variable weighted for first principal component was highest for plant height (X_1), number of flowers per branch (X_6), number of fruits per branch (X_7) and fruit set (X_9) which may be interpreted as growth and fruiting characteristics. The second principal component (PC_2) was dominated by fruit weight (X_8), fruit set (X_9) and plant girth (X_2) and was termed as fruiting and volume characteristics. The third principal component (PC_3) was combination of plant spread (X_3) and number of leaves per branch (X_4) and was termed as volume and growth characteristics. The results are in close agreement with the work of Iezzoni and Pritts (1991).

Table 1. Eigen vectors of the principal component analysis of high yielder group

Variable	Principal component		
	PC_1	PC_2	PC_3
Plant height (X_1)	0.37	–0.26	0.34
plant girth (X_2)	0.34	–0.35	–0.06
Plant spread (X_3)	0.20	0.08	0.71
Number of leaves/branch (X_4)	0.20	0.11	–0.56
Annual shoot extension growth (X_5)	0.15	–0.21	–0.14
Number of flowers/branch (X_6)	0.43	–0.17	–0.11
Number of fruits/branch (X_7)	0.51	0.23	–0.05
Fruit weight (X_8)	0.15	0.58	–0.03
Per cent fruit set (X_9)	0.34	0.47	0.01
LD ratio (X_{10})	0.26	–0.31	–0.16
Eigen value	3.13	2.05	1.20
Per cent of variance	31.34	20.49	12.04
Cumulative per cent of variance	31.34	51.83	63.87

Table 2. Eigen vectors of the principal component analysis of low yielder group

Variable	Principal component		
	PC_1	PC_2	PC_3
plant girth (X_2)	0.41	–0.21	0.03
Plant spread (X_3)	0.13	0.33	0.39
Number of leaves/branch (X_4)	0.10	0.05	0.81
Annual shoot extension growth (X_5)	0.28	–0.45	0.24
Number of flowers/branch (X_6)	0.42	–0.05	–0.30
Number of fruits/branch (X_7)	0.43	0.35	–0.21
Fruit weight (X_8)	–0.30	0.45	0.04
Per cent fruit set (X_9)	0.28	0.55	–0.04
LD ratio (X_{10})	0.28	–0.03	0.01
Eigen value	3.64	1.77	1.01
Per cent of variance	36.39	17.71	10.07
Cumulative per cent of variance	36.39	54.11	64.18

Low yielder group: Three principal components having Eigen values greater than one contributed 64.18 per cent of the total variation among the ten characters of apple. It was found that PC_1 contributed 36.39 per cent, whereas, PC_2 and PC_3 contributed 17.71 and 10.07 per cent of the total variation (Table 2).

The traits which contributed more to PC_1 were plant height (X_1), plant girth (X_2), number of flowers per branch (X_6) and number of fruits per branch (X_7).

None of the characters was found to be negative in PC_1. The second principal component (PC_2) had Eigen value 1.77 and explained 17.71 per cent of the total variation and these variations were accounted by per cent fruit set (X_9) followed by fruit weight (X_8) and number of fruits per branch (X_7).

Therefore, the second component extracted was account for a maximum amount of variance in the data set that was not accounted by the first component, while in the PC_3, plant girth (X_2) and number of leaves per branch (X_4) explained 10.07 per cent of the total variation with Eigen value 1.01.

The variable loading for first principal component was highest for plant height (X_1), plant girth (X_2), number of flowers per branch (X_6) and number of fruits per branch (X_7), termed as growth and fruiting or fruitfulness. The second principal component (PC_2) was dominated by per cent fruit set (X_9), fruit weight (X_8) and number of fruits per branch (X_7), termed as fruiting characteristics. The third principal component (PC_3) included plant girth (X_2) and number of leaves per branch (X_4), termed as plant vigour component.

CONCLUSION

The multivariate analysis, being an important tool in explanatory work, has brought out some basic factors associated with morphological characters of apple and can help to determine the nature and sequence of traits to be selected to speed up the breeding programmes. The discriminant function revealed that plant spread (X_3), number of leaves per branch (X_4) and number of flowers per branch (X_6) were the most important characters that discriminate the trees into high yielder and low yielder groups.

Three of the ten principal components (PCs) had Eigen values greater than unity (Gutman's lower bound) pertaining to high yielder group and explained 31.34 per cent of total variation in the data that showed relative maximum value for plant height (X_1), number of flowers per branch (X_6), number of fruits per branch (X_7) and fruit set (X_9).

The groups were subjected to principal component analysis. In both populations, three principal components were extracted, which played the main role in the analysis. Thus the principal component analysis has brought out some of the basic components associated with morphological characters of apple and could be considered as important tool in explanatory work for optimizing apple productivity.

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