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ANOVA and MANOVA : A Comparative Study for Correlated Characters of Wheat

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ABSTRACT

To study the joint relationships of intercorrelated characters multivariate analysis technique is appropriate whenever several responses are measured on each object or experimental unit. This paper describes a general procedure of performing Bivariate Analysis of Variance technique for the secondary data collected, on grain yield and straw yield for wheat crop from Department of Agronomy at Crop Physiology Area, Chaudhary Charan Singh Haryana Agricultural University, Hisar in plot size of 5.0 x 3.6 m using randomized block design with three replications in the **rabi** season (2018) using 10 treatments. Analysis of variance (ANOVA) and Multivariate analysis of variance technique (MANOVA) were performed on secondary data for wheat to test the significance for the inter-correlated i. e. grain yield and straw yield characters, respectively. It was observed that in case of MANOVA technique there was a significant effect for treatment effects and replication effects for both characters, whereas ANOVA showed significant effect for treatments of grain yield only and replication effects for straw yield only. So, this study interpreted MANOVA technique should be applied when more than one inter-correlated characters are being used for testing the significance in spite of a series of ANOVA's. Further, the use of several univariate analyses leads to a greatly inflated overall Type I error rate.

Key words : Randomized block design, inter-correlated variables, analysis of variance, multivariate analysis of variance

INTRODUCTION

Multivariate analysis of variance (MANOVA) is used in two major situations (i) when there are several correlated dependent variables, and the researcher desires a single, overall statistical test on this set of variables instead of performing multiple individual Analysis of Variance (ANOVA) tests. Secondly, in some cases, the more important purpose is to explore how independent variable influences some patterning of response on the dependent variable. For example, an agronomist may be interested in studying the effect of tillage and nutrient interactions on the growth and yield of rice crop. Besides yield, he/she records the data on dry weight, root weight, leaf area, nitrogen uptake, etc. to study the plant growth. Plant height, number of primary branches per plant, 1000-seed weight and disease resist characteristics, etc. are other examples on which data are collected in varietal trials. In case of two univariate tests for two dependent variables to test for group differences on each of the dependent variable at an α – level of 0.05, one has to conduct two univariate tests by assuming a 95% chance of no type I error. Because of the assumptions of independence, one can multiply the probabilities. The effect of these errors rate is compounded over all of the tests such that the overall probability of not making a Type I error becomes :

$$(0.95)(0.95) = 0.9025$$

In other words, the probability of at least one false rejection (i.e. Type I error) becomes

$$1 - 0.9025 = 0.0975 = 0.10 \text{ approximation}$$

This is an unacceptably high rate of possible statistical decision error. Analysis and designing for multiresponse experiments is conducted by Warne (2014), Konietschke *et al.* (2015), Patel *et al.* (2015), Porter and O'Reilly (2017), Friendly and Sigal (2018), Friedrich *et al.* (2018), Saleh *et al.* (2019), Frost (2020), Smith *et al.* (2020) and Din and Hayat (2021).

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Therefore, this article was undertaken to confirm preference of MANOVA where observations on more than one correlated response variable were recorded.

MATERIALS AND METHODS

The basic logic behind a Multivariate Analysis of Variance is essentially the same as in a univariate analysis of variance. The purpose of an ANOVA is to test whether the means for two or more groups for a single variable are taken from the same sampling distribution. The purpose of MANOVA is to test whether the vectors of means for the two or more groups are sampled from the same sampling distribution.

Data layout and multivariate modelling notations for a two way classified multivariate model Ω was given by Tabachnick and Fidell (2019). Like analysis of variance in the use of multivariate analysis of variance, there were several important assumptions that need to be met such as randomness, multivariate normality, the assumption of homoscedasticity and linearity.

Unlike the univariate situation in which there was only one statistical test available (F- test), the multivariate situation provided several alternatives statistical test statistic for hypothesis testing such as (a) Wilk's lambda statistics: Λ; (b) Hotelling's- Lawley Trace; (c) Pillai's trace statistic and (d) Roy's largest root or Roy's largest Eigen Value.

RESULTS AND DISCUSSION

This section presents the results obtained from bivariate analysis of variance using R-software. The data from the field experiment for grain yield and straw yield were observed. Firstly, several important assumptions that need to be met are described. Secondly, separate analysis for each of the two characters (Grain and straw yield) was performed and then multivariate analysis of variance considering both the characters simultaneously was presented.

Normality : Shapiro-Wilks test was used to test this assumption for both the variables. It was observed that the value for grain and straw yield was found to be 0.96774 and 0.97932 with p-value (0.4793 and 0.8071, respectively). Hence, null hypothesis was accepted for both the variables i. e. data followed the assumption of normality.

Homogeneity of variances : Bartlett test was used for testing this assumption for both the variables. The value of the test statistic was found to be 4.4883 and 12.013 with p-value 0.8764 and 0.2126, respectively. Hence, null hypothesis was accepted. Like ANOVA, several important assumptions that need to be met in MANOVA also. Here normality assumption was assumed by the property of bivariate normal distribution i. e. If $X_1 \sim (\mu_1, \sigma_{21})$ and $X_2 \sim (\mu_2, \sigma_{22})$ as previously discussed : then the distribution of joint variable also followed normal distribution. Secondly, if the design was

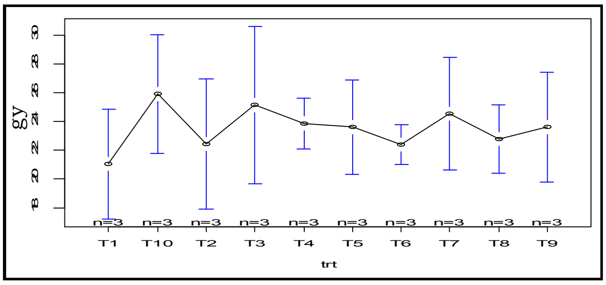

Fig. 1. Grain yield with standard error.

Table 1. Analysis of variance (Grain yield : Y1)

	d. f.	Sum of squares	Mean squares	F-value	Pr (>F)
Factor (replications)	2	0.845	0.42	0.18	0.84
Factor (treatments)	9	55.84	6.20	2.64	0.04*
Residuals	18	42.26	2.35		

Significant Codes : *P=0.05 .

Multiple comparisons of treatments using t-tests : least significant difference (LSD) for grain yield

Alpha	0.05
Degrees of freedom for error	18.00
Mean square error	2.35
Critical value of t	2.10
Least significant difference	2.63

Table 2. Pair-wise significant difference for means of grain yield

Treatments	T_{10}	T_7	T_3	T_4	T_5	T_9	T_8	T_2	T_6	T_1
Mean	25.90a	24.53ab	25.13abc	23.86abc	23.60abcd	23.60abcd	22.76abcd	22.43cd	22.40cd	21.03d

Means superscripted by a common letter are not significantly different at 5% level.

Table 3. Analysis of variance (straw yield : Y2)

	d. f.	Sum of squares	Mean squares	F-value	Pr (>F)
Factor (replications)	2	155.41	77.71	15.102	<0.01**
Factor (treatments	9	40.97	4.55	0.89	.56
Residuals	18	92.58	5.14		

Significant codes : **P=0.01.

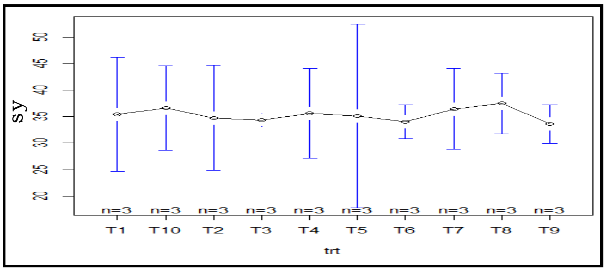

Fig. 2. Straw yield with standard error.

balanced i.e. when an equal number of observations in each cell the robustness of the MANOVA tests was guaranteed for equality of covariance matrices. If the design was unbalanced, the equality of covariance matrices using Box's M test was tested.
The straw yield was found to be non-significant so multiple comparison test was used only for the grain yield not for the straw yield. Fig. 2 shows the mean straw yield with standard error below.

This study demonstrated measuring several dependent variables instead of only one, the chances of discovering what actually changed as a result of the differing treatments or characteristics (and any interactions). It was observed from analysis of variance (Table 1) that the treatment effects for the grain yield were found to be significant but Table 3 shows that treatment effects for the straw yield were found to be non-significant. So, multiple comparison tests were used only for the grain yield and not for the straw yield and hence Table 2 presents the multiple comparison test for means of the grain yield only. Figs. 1 and 2 graphically show the mean yield with standard error for grain yield, and straw yield, respectively. Treatment with highest yield was best performing treatment, whereas best treatments for both the response variables were observed different i. e. T_{10} for grain yield and T_8 for straw yield. Similarly, variations

Table 4. Multivariate test statistic value for treatment effects

Statistic	d. f.	Approximate value	F-value	Numerator d. f.	Denominator d. f.	Prob>F
Wilks' lambda	9	0.20	2.30	18	34	0.02*
Pillai's trace	9	0.98	1.91	18	36	0.04*
Hotelling-Lawley trace	9	3.04	2.70	18	32	<0.01**
Roy's greatest root	9	2.71	5.42	9	18	<0.01**

Significant Codes : *P=0.05 and **P=0.01

Table 5. Multivariate test statistic value for replications

Statistic	d. f.	Approximate value	F-value	Numerator d. f.	Denominator d. f.	Prob>F
Wilks' lambda	2	0.25	8.53	4	34	<0.01**
Pillai's trace	2	0.75	5.42	4	36	<0.01**
Hotelling–Lawley trace	2	3.01	12.05	4	32	<0.01**
Roy's Greatest Root	2	3.01	27.11	2	18	<0.01**

Significant codes : **P=0.01.

were seen for other pairs of treatments also. Therefore, to rank the treatments collectively for both the characters, the bivariate analysis of variance was to be carried out. Considering both the characters simultaneously, it was observed from Tables 4 and 5 that both the treatment and replication effects were found to be statistically significant. So, it was better to use the MANOVA instead of a series of ANOVA's when more than one inter-correlated characters were used for testing of significance.

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