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Cathryn S. Miller

Dawn M. VanLeeuwen

Jill Schroeder

Mike Kenney

See next page for additional authors

Author Information
Cathryn S. Miller, Dawn M. VanLeeuwen, Jill Schroeder, and Mike Kenney

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Cathryn S. Miller, Dawn M. VanLeeuwen, Jill Schroeder,
and
Mike Kenney
College of Agriculture and Home Economics
New Mexico State University

Abstract

Studies of interrelationships among factors typically focus on factor effects related to the mean response. In some instances, response variances, as well as, or even rather than, response means, may be affected by the factors under consideration. In this paper, generalizations of Levene's test and the Jackknife test to two-factor experimental designs are studied via simulation studies to assess their ability to identify differences in the variance as an interaction effect or as a factor main effect. These tests are then applied to a particular example where relationships between chile plants and two prominent pests of chile plants -- nematodes and yellow nutsedge -- are under study. This example illustrates the utility of these tests in studying relationships among factors in agricultural systems.

1. INTRODUCTION

Chile peppers are an economically important agricultural commodity in New Mexico, where yellow nutsedge and root-knot nematodes are prominent pests. As noted in Schroeder et al. (1994), tightened restrictions on nematicide use increasingly complicate nematode management. Little is known about the joint interactions of chile, nematodes, and nutsedge and the effect of these interactions on plant development and other system variables. Data from studies of this agricultural system suggest analysis of means may not provide adequate understanding of the interrelationships in this system. Response variances also appear to be affected by system factors.

Such interdisciplinary studies in agriculture may involve many factors. In these studies, interest lies in factor effects on a response variable. In some instances, response variances as well as response means may be affected by the factors under consideration. Thus information obtained from analysis of factor effects on the variance can lead to better understanding of the entire agricultural system under consideration. In addition, if variances are found to be dependent on factor levels, analysis of factor effects on the means should be modified, because the most commonly employed statistical methodology for analyzing means requires that errors be independently, normally distributed with common variance.

This paper considers the variance as a factor effect in a two-way factorial design. Most existing methodology for detecting unequal or heterogeneous variances focuses on the one-way analysis of variance or completely randomized design. Several tests have been proposed for this case. Conover et al. (1981) conducted a comprehensive simulation study of tests for heterogeneity of variance in the completely randomized design. They considered fifty-six tests and recommended three tests based on simulations investigating power and robustness. A modification of a test suggested by Levene was among those recommended. Levene's tests (1960) are based on the idea of conducting analysis of variance on a function of the residuals, such as the absolute value or the square of the residuals. Modifications of Levene's test using absolute deviations from the median rather than the mean were later suggested by Miller (1968) and Brown and Forsythe (1974) for data from asymmetric parent distributions. A jackknife test for detecting heterogeneity of variance in the two-sample case was first proposed by Miller (1968). Layard (1973) studied four tests via simulations and recommended Miller's jackknife as a procedure that was both reasonably robust and powerful. He then generalized the jackknife test to the case of several samples.

Limited methodology exists to test for heterogeneity of variance in the two-way analysis of variance with one observation per treatment combination. Han (1969) proposed two tests for detecting heterogeneity of column variances under the assumption that row variances are equal. His tests require that the number of rows be greater than the number of columns. Shukla (1972, 1982) presented two tests for detecting heterogeneity of variance in the two-way design where the equality of column variances while assuming constant row variances or vice versa is tested. This test produced satisfactory results for even a small number of rows and columns. Goad and Johnson (1994) modified Levene's test for detecting heterogeneity of variances in a randomized complete block design. They investigated several functions of the residuals, such as the absolute value, the square, the square root, and the logarithm of the residuals. The absolute value of the residuals and the square of the residuals were found to have higher power.

This paper explores three procedures for detecting heterogeneity of variance as a factor effect in a two-way design. Two of the procedures considered are variations of Levene's test: one using the square of the residuals and the other using the absolute value of the deviations from the sample median. The third procedure is a generalization of Layard's jackknife. Behavior of the procedures is examined through simulation studies. An example from the crop-pest interdisciplinary study of chile, yellow nutsedge, and nematodes illustrates the application of the results to data analysis.

2. DISCUSSION OF MODEL, HYPOTHESES, AND TESTS

The Model. The cell-means model for the two-way design with equal replication is

$$y_{ijk} = \mu_{ij} + \epsilon_{ijk} \,,$$

where $i=1,\ldots,a>1$, $j=1,\ldots,b>1$, $k=1,\ldots,n>1$. We look at the special case where $a=2$ and $b=2$. Y_{ijk} represents the kth response from the ith level of factor A and the jth level of factor B. The average response due to the ith level of factor A and the jth level of factor B is μ_{ij}. The ϵ_{ijk} represent random error associated with the observation y_{ijk}, and are assumed to be independent with expectation 0 and variance σ_{ij}^2.

Hypotheses. Utilizing the above model, the null hypothesis to be investigated is:

H_0: $\sigma_{11}^2 = \sigma_{12}^2 = \sigma_{21}^2 = \sigma_{22}^2$, all variances are equal.

The alternative hypothesis is that at least one equality in H_0 does not hold. Testing this hypothesis directly is equivalent to the test for a completely random design. Instead, we conduct an analysis that is analogous to the usual analysis for a two-factor design. That is, the question of whether there are differences in the variance is examined through the following series of hypotheses:

1. H_0: $\sigma_{11}^2 - \sigma_{12}^2 = \sigma_{21}^2 - \sigma_{22}^2$, interaction of factors A and B exists.
2. H_0: $\sigma_{11}^2 + \sigma_{21}^2 = \sigma_{12}^2 + \sigma_{22}^2$, there is an effect contributed by a level of factor B.
3. H_0: $\sigma_{11}^2 + \sigma_{12}^2 = \sigma_{21}^2 + \sigma_{22}^2$, there is an effect contributed by a level of factor A.

If interaction is significant, hypotheses 2 and 3 are not considered for the same reasons main effects are not considered in the presence of interaction in the analysis of means. The purpose of investigating these hypotheses is to discover when differences in the variance exist and how those differences relate to factor structure.

Tests. We propose three methods of testing the above hypotheses. All three methods first calculate pseudo-observations from the original data, then perform a two-way analysis of variance on them. The methods differ only in the way pseudo-observations are calculated. In all cases the pseudo-observations in some way reflect the magnitudes of the variance for each combination of factor levels. Procedures based on the following pseudo-observations are to be investigated.

1. Levene's Test (Lev1). Pseudo-observations are computed by taking the square of the residuals:

$$z_{ijk} = (y_{ijk} - \bar{y}_{ij.})^2 .$$

2. Levene's test modified by substituting the median for the mean (Lev2). Pseudo-observations are computed by taking the absolute value of the deviations from the median:

$$z_{ijk} = |y_{ijk} - \tilde{y}_{ij.}| .$$

3. The Jackknife Test (Jack). Pseudo-observations are computed by jackknifing one observation in each group at a time. The pseudo-observations are calculated as

$$U_{ijk} = n\ln(s_{ij}^2) - (n-1)\ln(s_{ij(k)}^2)$$

where

$$s_{ij(k)}^2 = \sum_{l \neq k} \frac{(y_{ijl} - \bar{y}_{ij(k)})^2}{n-2} ,$$

$$\bar{y}_{ij(k)} = \sum_{l \neq k} \frac{y_{ijl}}{n-1} .$$

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The first two tests are modifications of Levene's test, which proposed computing an analysis of variance on functions of the residuals from various designs. Levene observed that to draw inference to the variance, an analysis of variance can be applied to any function of the residuals that is monotonically increasing on $(0,\infty)$. Analysis of the resulting pseudo-observations relies on robustness of ANOVA because virtually all assumptions of ANOVA procedures are likely to be violated by the pseudo-observations. Pseudo-observations are not likely to be normally distributed. If the distributions of the y_{ijk} vary by a scale factor for different treatments, the pseudo-observations will not only have different means but will also have different variances. Additionally, due to estimation of the mean or the median, there will be a slight dependence among the residuals that will decrease as sample size increases. Difficulties due to violations of the assumptions diminish as $n \rightarrow \infty$. For symmetric parent distributions, when variances are equal, F-statistics follow F-distributions asymptotically.

Miller (1968) noted that Levene's test will not be asymptotically distribution-free if the distribution's median and mean are not equivalent. For asymmetric distributions, he suggested replacing the mean by the median to obtain better asymptotic properties. This suggestion leads to a variation of Levene's test that replaces the sample mean with the sample median in obtaining residuals. Lev2 uses these modified residuals with the absolute value function.

The third test is a generalization of Layard's modification of the jackknife test presented by Miller. Tukey suggested that these pseudo-observations are approximately independent.

Each method results in pseudo-observations that reflect changes in the magnitude of the variance. They do so, however, on different scales. For example, the expected value of $(y_{ijk} - \bar{y}_{ij.})^2$ is $(n-1)\sigma_{ij}^2/n$. Thus, expected values of pseudo-observations for Lev1 are on the scale of the variance while the pseudo-observations for Lev2 are more nearly on the scale of the standard deviation. Pseudo-observations for Jack are on the scale of the log transformed variance. These differences can affect interpretation of the ANOVA. If a procedure suggests that there is no interaction but that both main effects are significant, interpretation in terms of the variance depends on the scale. It suggests approximate additivity of effects on one scale but not necessarily on other scales. This ambiguity does not exist when only one main effect is significant.

3. SIMULATIONS AND RESULTS

Simulations. Simulations were conducted to compare the observed significance levels and power of the three procedures. A reasonably wide range of distributions, variance configurations, and sample sizes were included in the simulations.

Simulations included the following distributions: uniform (short-tailed distribution), normal, double exponential (long-tailed distribution), and chi-squared (skewed distribution); and the following groups of variance combinations (as indicated by $(\sigma_{11}^2, \sigma_{12}^2, \sigma_{21}^2, \sigma_{22}^2)$):

1. (1, 1, 1, 1),
2. (1,1,2,2), (1,1,4,4), (1,1,8,8),

3.a.) (1,2,2,1), (1,4,4,1), (1,8,8,1),

3.b.) (1,1,1,2), (1,1,1,4), (1,1,1,8),
4. (1,2,2,3), (1,4,4,7), (1,8,8,15);

with samples of size 5, 10, and 20 observations.

The first variance combination is used to assess the observed significance level of the tests and to determine whether or not the procedure is robust. The second group of three variance combinations is used to assess power of the procedures when a factor A main effect exists. The two groups of variance combinations 3a) and 3b) are used to assess the behavior of the procedures in the presence of interaction. The interactions are slightly different with the interaction in combination 3a) being more extreme. Finally, the variance combinations in 4 are used to assess the power of the procedures when both factor A and factor B main effects are present.

Each distribution-variance configuration-sample size combination was simulated 1,000 times, except in the case where all variances were equal. This case was simulated 3,000 times. Simulations were run using SAS/STAT® software and procedures in version 6.08 in VM/ESA® (SAS® 1990).

Results. Tables 1 and 2 summarize the results of all simulation runs, reporting the percentage of runs that were significant at $\alpha=.05$ for each category. For the simulations the categories INT, A & B, A, and B are all mutually exclusive. Category INT contains the number of simulations in which the interaction was found to be significant; category A&B contains the number in which both factors A and B were found to be significant, not including those runs in which interaction was also significant; category A (B) contains the number in which factor A (B) was found to be significant, not including those runs in which interaction or both factors A and B were significant; MODEL contains the number in which the model was significant. This F-test is equivalent to the corresponding test for the completely random model. Although not traditionally done in analysis of variance, some practitioners use this overall test for differences among the treatments before proceeding to the usual ANOVA. For completeness, information on this test is reported.

There are several ways of interpreting the results of these tables. Similar to Conover et al. (1981), the numbers in tables 1 and 2 represent the averages over the three variance combinations for groups 2, 3a, 3b and 4. In the case where all variances are equal the figures in the tables represent averages over 3,000 simulations. Our definition of robustness will follow Conover et al. (1981) in that if the observed level of significance is less than 0.10 for a stated level of significance of 0.05 the test will be considered robust. When the null hypothesis is true, the proportion of times the null is rejected gives an estimate of the actual level of significance when the stated level is 0.05. When the null hypothesis is not true, this proportion gives an estimate of the power of the test for the given underlying distribution, variance combination, and sample size.

In general, all tests were observed to have higher power as sample size increased and as the difference in variances increased. As sample size increased, observed significance levels become closer to the stated significance level of 0.05.

When the sample size is small, i.e. n=5, under the normal distribution, all three tests are robust. Lev1 has higher power than Jack, and Jack has higher power than Lev2. When the observations are from the double exponential distribution, all three tests are robust. The

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power of Lev1 and Jack are similar; both have higher power than Lev2. When the observations are from the uniform distribution, all three tests are again robust. Lev1 has higher power than Jack, and Jack has higher power than Lev2. When the observations are from the chi-squared distribution, Lev2 is robust, while Lev1 and Jack are not robust.

When the sample size is moderate, i.e. n=10, and the observations are from a normal distribution or a double exponential distribution, Lev1, Lev2 and Jack are robust and have similar power. When the observations are from the uniform distribution, all three tests are robust. The power of Lev1 and Jack is similar, whereas Lev2 has lower power than Lev1 and Jack. When the observations are from the chi-square distribution, Lev1 and Lev2 are robust procedures and Jack is not robust. Lev2 has higher power than Lev1.

When the sample size is large, i.e. n=20, and the distribution is normal, all three tests are robust and have high power. When the observations are from the double exponential distribution, all three tests are robust and powerful, although Lev2 is slightly more powerful than Lev1 and Jack. When the observations are from the uniform distribution, all three tests are robust. Lev1 and Jack have higher power than Lev2. When the observations are from the chi-squared distribution, Lev1 and Lev2 are robust procedures; however Jack is not robust. Lev2 has higher power than Lev1.

For variance configurations 2 and 3a, there is a tendency to have more power by isolating specific hypotheses, rather than by treating the experiment as a completely randomized design. For variance configurations 3b and 4 this does not hold. Jack correctly identified the underlying form of variance combination 4 (both row and column significant) more often than Lev1 or Lev2 However, Jack did not detect significant results for variance combination 3b (interaction) as often as did Lev1 and Lev2.

Overall, Lev1 can be recommended for short-tailed or normal distributions. For long-tailed or skewed distributions, Lev2 can be recommended as having the best balance of robustness and power for most sample sizes. For long-tailed distributions, Jack may be slightly better than Lev2 for small sample sizes.

4. REAL-DATA EXAMPLE

Experiments were conducted in an attempt to better understand interrelationships among chile peppers, yellow nutsedge, and root-knot nematodes. Chile seeds, and later nutsedge tubers, were planted in pots. Nematodes were then added to the pots when the chile plants reached the two-leaf stage. The treatment structure for nutsedge variables was a 2 (chile present and absent) by 4 (nematode from chile, from tomato, from nutsedge, and absent) factorial (Kenney 1992). Several response variables were recorded. While the procedures examined here can be extended and applied to data from any factorial experiment, we consider a subset of the resulting data here. By employing the three tests to detect heterogeneity of variance we see new relationships between factors of interest.

In this example, tuber germination of the yellow nutsedge is the response variable of interest. Data of the tuber germination as affected by chile and nematodes from chile and from tomato are considered (Tables 3 and 4). The three tests, Lev1, Lev2, and Jack were computed and the analysis of variance conducted (Table 5). All three procedures suggest that the absence or presence of chile affects the variance of nutsedge tuber germination. When chile is present, the variance of the tuber germination is significantly higher than when chile is absent.

Because variability of nutsedge tuber germination is affected by the presence or absence of chile, there are at least two distinct groups among the four treatment groups. Of interest is whether nematode source influences tuber germination within each level of chile. If nematode source does affect tuber germination, the four treatments are distinct; if they do not then there are only two distinct groups defined by chile. Variances appear to be equal within chile level so that, if the parent distributions are roughly normal, the usual two-sample t-test may be employed to compare the two means within each chile level. For chile absent, the two-sample t-test comparing the two means yields a p-value of 0.4622, while for chile present, the test comparing the two means is again not significant, $p=0.7857$. Thus it is useful to describe the response of nutsedge tuber germination by pooling the means and variances across nematode source (Table 6). Variances were recalculated using the pooled estimates of the means.

In conclusion, the data suggest that nutsedge tuber germination may be affected by the presence or absence of chile but not by nematode source. In particular, the variance is significantly affected. Means were not compared across chile level; however, the estimated standard error of the mean for chile absent is 3.84 and for chile present is 9.13, so that the magnitude of the difference between the two means is not large in terms of the standard error of the difference. From the researchers' point of view, the difference in variability raises some interesting questions. Nutsedge and nematodes are pests which probably coexisted before the introduction of chile. In the absence of chile, nutsedge tuber germination appears to be relatively stable. Nutsedge tuber germination was more variable when chile was present. One possible explanation may be that, in some instances, chile competition with nutsedge slows tuber development and this leads to greater variability in tuber germination. Future research may attempt to further examine these competitive interactions between chile and yellow nutsedge in order to identify possible management strategies for yellow nutsedge.

REFERENCES

Brown, M.B. & Forsythe, A.B. (1974). Robust tests for the equality of variances. Journal of the American Statistical Association, 69, 364-367.

Conover, W.J., Johnson, M.E. & Johnson, M.M. (1981). A comparative study of tests for homogeneity of variances, with application to the outer continental shelf bidding data. Technometrics, 23, 351-361.

Goad, C. & Johnson, D.E. Tests for homogeneity of variances applied to a randomized complete block design. (In Preparation).

Han, C.P. (1969). Testing the homogeneity of variances in a two-way classification. Biometrics, 25, 153-158.

Kenney, M.J. (1992). Population development of root-knot nematode on yellow nutsedge and chile peppers as effected by inoculum source and metolachlor. Unpublished master's thesis, New Mexico State University, Las Cruces, NM.

Kansas State University

Layard, M.W. (1973). Robust large-sample tests for homogeneity of variance. Journal of the American Statistical Association, 68, 195-198.

Levene, H. (1960). Robust tests for equality of variances. Contributions to Probability and Statistics. In Olkin (ED), (pp 278-292). California: Stanford Univ. Press.

Miller, R.G., Jr. (1968). Jackknifing variances. Annals of Mathematical Statistics, 39, 567-582.

SAS Institute Inc., (1990) SAS® Language: Reference, Version 6, First Edition Cary, NC: SAS Institute Inc.

Schroeder, J., M.J. Kenney, S.H. Thomas, & L. Murray. (1994) Yellow nutsedge response to southern root-knot nematodes, chile peppers, and metolachlor. Weed Science, 42, 534-540

Shukla, G.K. (1972). An invariant test for the homogeneity of variances in a two-way classification. Biometrika, 28, 1063-1072.

Shukla, G.K. (1982). Testing the homogeneity of variances in a two-way classification. Biometrika, 69, 411-416.

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Table 1. Percents based on 3,000 simulations. Categories INT, A&B, A and B are mutually exclusive. MODEL corresponds to the completely randomized design. COMB refers to the variance combination on pg. 3. COMB 1 all variances are equal. COMB 2 investigates an A main effect. COMB 3a and b investigate interaction and COMB 4 investigates both A and B main effect.

NORMAL N=5

		MODEL	A	B	A&B	INT
LEV 1	1	6.267	5.333	5.067	0.333	6.467
	2	18.433	29.667	2.600	0.900	7.100
	3a	20.100	1.900	2.667	0.333	34.933
	3b	22.733	5.800	6.067	1.600	16.633
	4	15.900	12.333	11.300	2.567	7.933
LEV 2	1	0.267	0.967	0.833	0.000	0.833
	2	4.667	17.300	0.600	0.233	1.100
	3a	4.400	0.533	0.667	0.000	17.233
	3b	8.033	3.700	3.267	0.533	4.967
	4	2.567	5.533	4.200	0.267	1.600
JACK	1	3.733	2.500	2.800	0.267	3.267
	2	16.267	24.900	1.533	1.700	3.100
	3a	16.267	1.267	1.367	0.333	27.500
	3b	13.033	5.667	5.233	1.500	8.967
	4	16.167	9.467	9.600	3.333	6.633

UNIFORM N=5

		MODEL	A	B	A&B	INT
LEV 1	1	7.667	5.467	4.967	0.533	7.033
	2	29.033	40.867	1.567	1.567	7.933
	3a	28.267	1.800	1.833	0.533	48.067
	3b	32.967	5.967	5.500	2.600	23.833
	4	20.767	14.467	13.267	4.467	8.233
LEV 2	1	0.200	0.567	0.400	0.000	0.433
	2	3.833	18.500	0.267	0.100	0.500
	3a	3.233	0.533	0.433	0.033	16.633
	3b	6.500	2.700	2.767	0.433	4.500
	4	1.533	4.167	4.333	0.100	1.067
JACK	1	1.833	1.333	1.233	0.067	1.967
	2	16.267	28.733	0.867	1.000	2.133
	3a	16.067	0.900	0.567	0.233	30.933
	3b	12.900	4.400	5.067	1.767	8.733
	4	14.067	8.567	7.867	4.000	4.867

DBL EXP N=5

		MODEL	A	B	A&B	INT
LEV 1	1	6.600	4.133	4.733	0.367	6.300
	2	14.900	20.133	2.433	0.833	6.867
	3a	15.067	3.533	3.000	0.300	22.467
	3b	15.367	5.367	6.267	0.833	11.300
	4	11.833	8.600	8.000	1.033	6.467
LEV 2	1	0.667	1.233	1.900	0.033	1.633
	2	4.633	14.700	0.867	0.200	1.367
	3a	4.700	1.367	1.100	0.033	14.467
	3b	5.933	2.967	3.233	0.367	4.733
	4	2.667	5.300	4.200	0.133	2.067
JACK	1	5.633	3.667	4.067	0.633	5.433
	2	16.200	20.000	3.133	1.500	4.667
	3a	16.867	3.400	3.333	0.300	24.233
	3b	14.600	6.700	5.633	1.300	11.567
	4	16.000	9.633	9.467	2.700	7.633

CHISQ N=5

		MODEL	A	B	A&B	INT
LEV 1	1	13.700	5.300	5.133	0.767	10.533
	2	22.500	24.133	3.333	0.933	10.100
	3a	21.367	3.367	3.367	0.367	30.800
	3b	24.967	6.567	7.400	1.100	18.700
	4	18.700	11.133	10.433	1.967	10.567
LEV 2	1	3.367	2.400	2.733	0.333	2.700
	2	9.800	23.233	0.967	0.400	2.133
	3a	9.400	1.000	1.367	0.067	26.400
	3b	11.833	5.100	5.567	0.733	9.267
	4	6.133	7.933	7.533	0.733	2.633
JACK	1	15.067	5.500	5.667	1.533	11.600
	2	22.167	13.800	4.333	2.933	10.767
	3a	23.000	3.800	3.433	1.000	25.733
	3b	19.800	7.533	6.633	2.067	13.967
	4	25.333	7.167	8.767	4.867	14.000

NORMAL N=10

		MODEL	A	B	A&B	INT
LEV 1	1	4.667	4.067	5.667	0.200	5.367
	2	45.633	60.400	1.033	2.267	5.367
	3a	42.733	1.367	1.100	0.300	65.067
	3b	49.100	7.700	7.400	3.667	33.800
	4	32.767	21.533	20.100	7.667	6.833
LEV 2	1	2.500	2.600	3.400	0.200	3.600
	2	43.300	56.200	1.033	1.267	3.333
	3a	42.367	1.000	1.433	0.100	60.167
	3b	41.900	8.100	8.400	4.233	29.100
	4	33.567	19.800	19.200	8.500	5.667
JACK	1	4.867	2.467	4.300	0.200	4.233
	2	49.700	57.067	0.967	3.333	4.367
	3a	48.467	1.033	1.167	0.167	62.167
	3b	41.967	9.967	9.167	6.400	25.767
	4	50.133	16.867	14.833	17.233	13.233

UNIFORM N=10

		MODEL	A	B	A&B	INT
LEV 1	1	6.367	4.533	4.900	0.233	5.967
	2	66.367	72.667	0.767	2.100	7.433
	3a	64.467	0.700	0.800	0.167	78.600
	3b	66.867	5.967	6.433	4.467	52.167
	4	53.967	20.567	21.867	22.600	6.300
LEV 2	1	2.600	2.567	2.333	0.100	3.267
	2	50.233	62.833	0.800	1.600	3.400
	3a	48.800	0.733	0.500	0.133	65.200
	3b	48.233	6.967	7.133	4.333	35.367
	4	39.667	18.400	19.467	14.767	4.867
JACK	1	2.567	1.467	2.000	0.233	2.300
	2	62.167	72.167	0.367	1.733	2.700
	3a	60.900	0.367	0.533	0.100	74.500
	3b	53.367	6.467	6.833	7.633	37.500
	4	62.667	11.667	12.533	30.867	17.467

Table 2. Percents based on 3,000 simulations. Categories INT, A&B, A and B are mutually exclusive. MODEL corresponds to the completely randomized design. COMB refers to the variance combination on pg. 3. COMB 1 all variances are equal. COMB 2 investigates an A main effect. COMB 3a and b investigate interaction and COMB 4 investigates both A and B main effect.

			DBL EXP	N=10		
		MODEL	A	B	A&B	INT
LEV 1	1	5.267	4.167	4.567	0.167	5.467
	2	23.667	37.700	1.533	1.300	4.467
	3a	25.300	2.133	1.667	0.300	42.600
	3b	28.967	7.900	8.067	1.533	17.900
	4	17.533	13.900	14.067	2.133	5.800
LEV 2	1	3.933	3.700	3.933	0.167	4.233
	2	28.133	43.367	1.667	1.567	3.967
	3a	29.400	2.000	1.300	0.167	47.233
	3b	29.367	8.967	9.133	2.500	19.100
	4	21.033	15.333	15.600	3.800	5.833
JACK	1	8.200	5.567	5.700	0.367	6.567
	2	36.400	39.933	2.433	3.233	6.933
	3a	36.967	2.433	2.000	0.233	47.400
	3b	31.000	9.500	10.567	3.800	19.400
	4	37.933	14.967	14.800	8.667	12.467

			CHISQ	N=10		
		MODEL	A	B	A&B	INT
LEV 1	1	7.667	4.433	4.100	0.533	5.700
	2	30.067	35.900	2.600	1.900	7.567
	3a	29.567	2.333	2.600	0.100	42.267
	3b	32.833	9.467	7.433	1.567	22.467
	4	25.567	14.900	14.767	4.667	7.533
LEV 2	1	4.167	3.300	3.133	0.167	4.467
	2	40.733	50.700	1.567	1.700	4.767
	3a	40.500	1.633	1.233	0.100	56.067
	3b	38.667	10.867	9.667	3.300	26.167
	4	34.867	17.833	18.167	9.267	6.967
JACK	1	15.067	7.067	7.900	1.100	11.433
	2	31.667	23.633	3.567	3.600	11.633
	3a	30.733	3.833	3.033	1.000	33.000
	3b	25.033	9.700	8.833	2.467	16.233
	4	33.233	9.033	9.133	7.167	18.333

			NORMAL	N=20		
		MODEL	A	B	A&B	INT
LEV 1	1	5.033	4.700	4.633	0.367	5.167
	2	72.667	77.033	0.667	1.000	5.500
	3A	71.933	0.700	0.933	0.100	83.367
	3B	69.800	7.467	7.300	4.133	58.767
	4	67.833	23.100	22.867	28.600	5.567
LEV 2	1	3.633	3.933	3.500	0.133	3.633
	2	70.933	73.967	0.700	2.133	4.833
	3a	70.567	0.467	0.867	0.100	80.133
	3b	68.000	7.633	7.600	5.600	52.700
	4	71.033	19.300	17.833	35.833	7.400
JACK	1	4.533	3.967	4.167	0.367	4.500
	2	74.500	74.200	0.733	3.367	5.333
	3a	73.900	0.767	0.967	0.067	81.967
	3b	68.167	7.733	8.600	8.300	49.433
	4	74.833	11.533	10.800	34.567	27.733

			UNIFORM	N=20		
		MODEL	A	B	A&B	INT
LEV 1	1	5.000	4.467	4.400	0.433	5.700
	2	87.900	87.900	0.033	2.500	5.100
	3a	89.167	0.100	0.167	.033	95.567
	3b	86.600	3.733	3.400	3.500	78.133
	4	90.033	11.833	11.767	65.600	5.500
LEV 2	1	2.433	2.600	2.867	0.200	3.400
	2	77.700	80.767	0.300	2.633	3.067
	3a	77.700	0.267	0.233	.033	87.467
	3b	74.133	4.700	5.467	4.867	63.433
	4	78.933	13.833	14.867	51.467	7.533
JACK	1	2.567	2.667	1.933	0.300	3.300
	2	87.033	88.867	1.033	1.967	3.167
	3a	88.600	0.133	0.067	0.000	95.333
	3b	79.900	4.433	4.600	5.900	70.667
	4	93.167	7.267	7.333	36.867	44.200

			DBL EXP	N=20		
		MODEL	A	B	A&B	INT
LEV 1	1	4.000	3.867	3.833	0.200	5.167
	2	47.200	60.867	1.333	1.800	4.833
	3a	45.000	1.467	1.500	0.067	65.533
	3b	51.967	8.967	7.400	3.733	36.167
	4	34.067	20.833	21.167	8.300	6.167
LEV 2	1	3.733	3.533	4.100	0.167	4.500
	2	58.333	65.367	1.200	1.333	5.233
	3a	58.033	1.300	1.367	.067	70.600
	3b	55.733	8.600	8.200	5.033	40.833
	4	53.667	21.533	21.100	18.100	7.667
JACK	1	7.867	5.233	5.167	0.400	5.900
	2	58.467	60.033	1.300	3.967	6.567
	3a	57.967	1.967	1.967	0.167	67.433
	3b	51.167	10.600	10.500	6.167	33.033
	4	62.167	15.800	16.267	20.733	18.700

			CHISQ	N=20		
		MODEL	A	B	A&B	INT
LEV 1	1	5.533	4.333	3.600	0.167	4.433
	2	40.300	48.367	1.500	2.167	5.533
	3a	40.800	1.400	1.600	.067	53.767
	3b	44.233	8.567	8.867	2.633	32.733
	4	39.100	18.733	18.800	12.267	6.167
LEV 2	1	3.800	4.333	3.933	0.400	4.767
	2	63.833	66.100	1.067	2.833	5.033
	3a	63.300	0.833	3.167	.033	73.567
	3b	60.400	9.133	9.200	5.233	45.767
	4	66.000	18.100	18.167	30.433	9.133
JACK	1	14.633	6.600	7.000	1.133	10.433
	2	40.767	32.667	3.267	4.867	11.000
	3a	39.700	2.733	2.564	0.600	45.033
	3b	31.900	10.500	10.333	4.267	20.467
	4	45.133	10.300	10.900	12.933	20.500

Table 3. Nutsedge tuber germination data as affected by chile and nematode source.

		Nematode Source	
		Chile	Tomato
Chile	Absent	86 100 70 80 88 70	100 60 67 71 70 90
	Present	30 100 100 63 100 30	40 100 44 100 29 78

Table 4. Means and variances of Nutsedge tuber germination as affected by chile and nematode source.

Treatment		Mean	Variance
Chile	Nematode Source		
Absent	Chile	82.3333333	133.4666667
	Tomato	76.3333333	233.8666667
Present	Chile	70.5000000	1189.50
	Tomato	65.1666667	996.1666667

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Table 5. Analysis of variance procedure for Nutsedge tuber germination as affected by chile and nematode source.

Lev1					
Source	DF	SS	MS	F	Pr > F
Model	3	3542970.82	1180990.27	7.42	0.0016
Chile	1	3444100.11	3444100.11	21.64	0.0002
Nemacult	1	8996.46	8996.46	0.06	0.8145
C*N	1	89874.24	89874.24	0.56	0.4611
Error	20	3182798.22	159139.91		
Corr Tot	23	6725769.04			

Lev2					
Source	DF	SS	MS	F	Pr >F
Model	3	2111.00	703.67	4.90	0.0103
Chile	1	2090.67	2090.67	14.55	0.0011
Nemacult	1	0.17	0.17	0.00	0.9732
C*N	1	20.17	20.17	0.14	0.7119
Error	20	2874.33	143.72		
Corr Tot	23	4985.33			

Jack					
Source	DF	SS	MS	F	Pr > F
Model	3	18.02	6.01	4.06	0.0210
Chile	1	16.99	16.99	11.47	0.0029
Nemacult	1	0.21	0.21	0.14	0.7082
C*N	1	0.82	0.82	0.55	0.4658
Error	20	29.62	1.48		
Corr Tot	23	47.64			

Table 6. Means and variances of Nutsedge tuber germination as affected by chile.

Treatment	Mean	Variance
Chile		
Absent	79.3333333	176.7878788
Present	67.8333333	1001.24