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Use of the Arcsine and Square Root Transformations for Subjectively Determined Percentage Data[1]

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Abstract. **The arcsine and square root transformations were tested on 82 weed control data sets and 62 winter wheat winter survival data sets to determine effects on normality of the error terms, homogeneity of variance, and additivity of the model. Transformations appeared to correct deficiencies in these three parameters in the majority of data sets, but had adverse effects in certain other data sets. Performing the recommended transformation in conjunction with omitting treatments having identical replicate observations provided a high percentage of correction of non-normality, heterogeneity of variance, and nonadditivity. The arcsine transformation, not generally recommended for data sets having values from 0 to 20% or 80 to 100%, was as effective in correcting non-normality, heterogeneity of variance, and nonadditivity in these data sets as was the recommended square root transformation. A majority of data sets showed differences between transformed and nontransformed data in mean separations determined using LSD (0.05), although most of these differences were minor and had little effect on interpretation of results.**

Additional index words. **Normality, homogeneity of variance, homoscedasticity, additivity.**

INTRODUCTION

Researchers in weed science have made frequent use of subjectively determined percentage data when evaluating efficacy of herbicide treatments. Typically, weed control is estimated visually along a scale from 0 = no control or injury symptoms to 100 = complete necrosis of observable plant parts. Percentage control data commonly are obtained in field experiments in which the collection of objective measurements such as weed height and weight of weed biomass is judged to be either too time consuming or disruptive of subsequent measurements to be taken on the plot. Subjective evaluations also play a significant role in greenhouse weed control experiments because certain components of control or injury may be difficult to measure objectively but are relatively easy to express using a visual estimate. Similarly, researchers in allied disciplines such as entomology, plant pathology, and plant breeding have employed various subjective rating scales in estimating treatment effects.

Validity of the inferences made from analysis of variance relies upon additivity of treatment and environment (replicate) effects, and error terms that are independent and normally distributed with a common variance (12). Bartlett (1), however, indicated that percentage data have error variances that are a function of the mean and are not normally distributed but instead are described by Poisson or binomial distributions depending on whether the data occur over a large portion of the percentage scale (binomial) or are grouped primarily at either end (Poisson). A truly binomial distribution will be transformed into a normal one by use of the arcsine (angular) transformation, and a Poisson distribution is converted to normality by employing the square root transformation (13). Hence, many authors (1, 9, 11, 13, 14) have recommended transformation of percentage data sets prior to analysis of variance in order to correct deficiencies in normality and homogeneity of variance.

The perception that percentage data sets are in need of transformation, particularly by arcsine, has grown in popularity and practice in recent years. Yet many scientists in disciplines using percentage data often have discovered that transformations do not affect the results of analysis of variance and do not alter data interpretation facilitated by various mean separation procedures. Due to the extra work required and potential difficulty of running statistical tests to determine whether transformation is beneficial for particular data sets, and given the questionable reliability of such tests for most agricultural research data having low sample numbers (8), it is desirable to be able to recommend the routine use of transformation for all data sets meeting certain criteria. Such recommendations, of course, require a confidence that transformation will improve underlying statistical parameters in a high percentage of cases. In this communication, we have tested the square root and arcsine transformations on actual sets of percentage data to determine whether these transformations, when used as recommended, improve homogeneity of variance, normality of the residual errors, and additivity of treatment and environmental effects.

MATERIALS AND METHODS

Data sets involving visual estimates of percentage weed control (0% = no control, 100% = complete control) and percentage survival of winter wheat (0% = complete winterkill, 100% = complete winter survival) were randomly selected from data representing several years of field research and three independent research projects. All experiments were arranged as randomized complete block designs. Weed control experiments had four replications (except one which had three replications) and winter wheat experiments had either four (about 45% of experiments) or three (about 55%)

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replications. Data for the untreated check plots of weed control experiments (routinely zeros) were removed prior to use. Data sets were grouped into four classes with respect to the distribution of raw data: 1) 0 to 20%, 2) 80 to 100%, 3) greater than 40% spread between highest and lowest percentages, and 4) less than 40% spread between highest and lowest percentages. Five percent of datum points within any given data set was allowed outside these limits. Rationale for the classes was derived from Steel and Torrie (12) who stated that percentages from 0 to 20% or from 80 to 100% should be handled with the square root transformation and from Little and Hills (9) who indicated that data should be transformed by arcsine when the range in percentages exceeds 40%. The total number of data sets compiled for each of the four classes was 20 to 22 for weed control data and 20 to 21 for winter wheat winter survival data. Raw and transformed data sets were submitted to Bartlett's test for homogeneity of variance (2, 3), univariate analysis for testing normality of distribution of the error terms (11), and Tukey's test for nonadditivity of the model (13). The square root transformation was carried out by computing $\sqrt{X + 1/2}$ (1) for data ranging from 0 to 20% and $\sqrt{(100-X) + 1/2}$ for data from 80 to 100% (12), where X denotes original percentage datum values. The arcsine transformation was done by computing arcsine $\sqrt{X}$ (1).

Additional analysis was done on data sets containing one or more treatments in which all replicates were the same value. In nearly every case, the occurrence of identical replicates involved either zeros or 100s. These treatments were removed from their respective data sets, and univariate analysis, Bartlett's Test, and Tukey's Test were again conducted. Analysis of variance was performed on all weed control experiments following removal of any nonvarying treatments, and an LSD (0.05 level of significance) was calculated and used for mean separation (5) on both transformed and nontransformed data.

RESULTS AND DISCUSSION

A rigorous use of tests for homogeneity of variance (homoscedasticity) and additivity relies upon a large sample size (perhaps 25 or more replications per treatment) (7). The experiments comprising this investigation had only four (in some cases three) replications. Indeed, such low sample numbers are common in agricultural research and this undoubtedly has been a deterrent to use of such tests as Bartlett's and Tukey's in identifying individual data sets deficient in homoscedasticity and additivity. Although this limitation applies to the study reported here, we believe that a reasonable degree of validity of the conclusions from these tests was achieved through the sampling of a relatively large number of data sets (at least 20 per class).

A high percentage of the 82 weed control experiments comprising this study were deficient in fulfilling the assumptions underlying analysis of variance (Table 1). Heterogeneity of variance appeared to be the most frequently encountered problem in these raw data sets while nonadditivity seemed to occur with lowest frequency. Similar results were observed with data on percentage winter survival of winter wheat (Table 2). This may indicate a need for significant concern as to the validity of inferences made from analysis of variance on such data sets, in which effects are estimated visually as a percentage.

The problem of variances differing among treatments is an intuitive outcome for percentage estimates of weed control and winter wheat winter survival. A herbicide treatment that is highly efficacious on a certain species typically would yield replicate observations varying by only a few percentages around a mean in the mid-90s, while another treatment having low efficacy on that species will vary quite widely around a mean in the 30 to 70% range. High variability on the less effective treatments may be a consequence of a greater sensitivity to small changes in environment or may relate to a greater difficulty in making control estimates in the 30 to 70% range. Similarly, a winter-hardy wheat genotype may show excellent survival and low variability between replicate plots while a less hardy genotype in the same experiment will respond with mediocre survival and a relatively high variability. In any case, when herbicide treatments or genotypes within an experiment differ substantially in response as measured along a percentage scale, heteroscedasticity can be expected.

Of primary concern in the use of data transformations is, of course, the degree to which they are able to correct the problems of non-normality, unequal variance, and nonadditivity. From a theoretical standpoint, a bimodal distribution should be transformed into a normal distribution by the

Table 1. Percentage of weed control data sets showing deleterious test results ($\alpha = 0.05$) for homogeneity of variance, normality, and additivity prior to transformation[a].

Class of date set	Heterogeneity of variance	Non-normality	Non-additivity
	%		
0 to 20%	60 (12)	75 (15)	40 (8)
80 to 100%	80 (16)	75 (15)	70 (14)
>40%	86 (19)	50 (11)	23 (5)
<40%	75 (15)	70 (14)	55 (11)

[a]Values in parentheses are the actual number of data sets.

Table 2. Percentage of winter wheat winter survival data sets showing deleterious test results ($\alpha = 0.05$) for homogeneity of variance, normality, and additivity prior to transformation[a].

Class of data set	Heterogeneity of variance	Non-normality	Non-additivity
	%		
80 to 100%	86 (18)	100 (21)	76 (16)
>40%	90 (19)	29 (6)	52 (11)
<40%	80 (16)	75 (15)	65 (13)

[a]Values in parentheses are the actual number of data sets.

Table 3. Effect of the arcsine and square root transformations on normality of weed control and winter wheat survival data sets testing non-normal ($\alpha = 0.05$) prior to transformation[a].

Class of data set	Arcsine transformation: Non-normal to normal[b]	Arcsine: Remained non-normal[c]: Test statistic improved[d]	Arcsine: Remained non-normal[c]: Test statistic impaired	Square root transformation: Non-normal to normal	Square root: Remained non-normal: Test statistic improved	Square root: Remained non-normal: Test statistic impaired
	%					
Weed control:						
0 to 20%	20 (3)	53 (8)	27 (4)	27 (4)	53 (8)	20 (3)
80 to 100%	40 (6)	53 (8)	7 (1)	40 (6)	53 (8)	7 (1)
>40%	9 (1)	82 (9)	9 (1)	...	...	...
<40%	50 (7)	43 (6)	7 (1)	...	...	...
Winter wheat survival:						
80 to 100%	14 (3)	71 (15)	14 (3)	14 (3)	76 (16)	10 (2)
>40%	50 (3)	50 (3)	0	...	...	...
<40%	47 (7)	53 (8)	0	...	...	...

[a]Values represent the percentage of non-normal data sets that responded to transformation in the manner indicated. Values in parentheses are the actual number of data sets.

[b]Data sets that were non-normal before and normal after transformation.

[c]Data sets that were non-normal both before and after transformation.

[d]Improvement of the test statistic indicates a greater probability of acceptance of the null hypothesis (i.e., greater probability of a normal distribution).

arcsine transformation and, similarly, a Poisson distribution should become normal by use of the square root transformation. To the extent that percentage data sets fit these distributions, the appropriate transformation should correct the problem, resulting in a valid analysis of variance. Tables 3, 4, and 5 show the percentage of non-normal, heteroscedastic, and nonadditive data sets, respectively, that responded to transformation in the three possible outcomes. The percentage of non-normal data sets that become normal after transformation was 50% or less (Table 3). Similar degrees of improvement generally were seen with heterogeneity of variance (Table 4) and nonadditivity (Table 5). The highest percentage of success (75%) by transformation in correcting problem data sets involved the parameter of nonadditivity and was observed when the 0 to 20% data class was transformed by arcsine (Table 5). Interestingly, this occurred with a data class reputed to be Poisson in distribution and thus would not have been expected to respond quite so well to arcsine transformation. In general, the 80 to 100% and 0 to 20% data set classes responded as well to arcsine as they did to square

Table 4. Effect of the arcsine and square root transformations on homogeneity of variance of weed control and winter wheat survival data sets testing heteroscedastic ($\alpha = 0.05$) prior to transformation[a].

Class of data set	Arcsine transformation: Hetero-geneous to homogeneous[b]	Arcsine: Remained heterogeneous[c]: Test statistic improved[d]	Arcsine: Remained heterogeneous[c]: Test statistic impaired	Square root transformation: Hetero-geneous to homogeneous	Square root: Remained heterogeneous: Test statistic improved	Square root: Remained heterogeneous: Test statistic impaired
	%					
Weed control:						
0 to 20%	25 (3)	25 (3)	50 (6)	8 (1)	17 (2)	75 (9)
80 to 100%	13 (2)	62 (10)	25 (4)	44 (7)	12 (2)	44 (7)
>40%	16 (3)	63 (12)	21 (4)	...	...	...
<40%	40 (6)	60 (9)	0	...	...	...
Winter wheat survival:						
80 to 100%	6 (1)	55 (10)	39 (7)	16 (3)	10 (2)	74 (14)
>40%	58 (11)	31 (6)	11 (2)	...	...	...
<40%	38 (6)	50 (8)	12 (2)	...	...	...

[a]Values represent the percentage of heteroscedastic data sets that responded to transformation in the manner indicated. Values in parentheses are the actual number of data sets.

[b]Data sets that were heteroscedastic before and homoscedastic after transformation.

[c]Data sets that were heteroscedastic both before and after transformation.

[d]Improvement of the test statistic indicates a greater probability of acceptance of the null hypothesis (i.e., greater probability of a homogeneous variance).

Table 5. Effect of the arcsine and square root transformations on additivity of weed control and winter wheat survival data sets testing nonadditive ($\alpha = 0.05$) prior to transformation[a].

Class of data set	Arcsine transformation: Nonadditive to additive[b]	Arcsine: Remained nonadditive[c]: Test statistic improved[d]	Arcsine: Remained nonadditive[c]: Test statistic Impaired	Square root transformation: Nonadditive to additive	Square root: Remained nonadditive: Test statistic improved	Square root: Remained nonadditive: Test statistic impaired
	%					
Weed control:						
0 to 20%	75 (6)	25 (2)	0	62 (5)	38 (3)	0
80 to 100%	43 (6)	57 (8)	0	43 (6)	57 (8)	0
>40%	40 (2)	40 (2)	20 (1)	. . .	. . .	. . .
<40%	45 (5)	55 (6)	0	. . .	. . .	. . .
Winter wheat survival:						
80 to 100%	50 (8)	44 (7)	6 (1)	50 (8)	50 (8)	0
>40%	46 (5)	36 (4)	18 (2)	. . .	. . .	. . .
<40%	38 (5)	54 (7)	8 (1)	. . .	. . .	. . .

[a]Values represent the percentage of nonadditive data sets that responded to transformation in the manner indicated. Values in parentheses are the actual number of data sets.

[b]Data sets that were nonadditive before and additive after transformation.

[c]Data sets that were nonadditive both before and after transformation.

[d]Improvement of the test statistic indicates a greater probability of acceptance of the null hypothesis (i.e., greater probability of additivity).

root transformation, suggesting that the underlying distribution of these data sets may not be classical Poisson.

In assessing the value of the arcsine and square root transformations for subjectively derived percentage data, movement in the direction of accepting the null hypotheses of normality, homoscedasticity, and additivity may be viewed as desirable. Among non-normal data sets that failed to become normal after transformation, the vast majority responded to transformation by improvement in the univariate analysis test statistic (Table 3). Thus, the percentage of originally non-normal data sets for which acceptance of the null hypothesis of normality became less probable following transformation was low (about 10% overall). Similar results were seen with additivity (Table 5) where only about 5% of nonadditive data sets showed a lower probability of acceptance of the null hypothesis of additivity after transformation. However, a greater percentage of heteroscedastic data sets responded with a lower probability of homoscedasticity, particularly after performing the square root transformation (Table 4). Variance heterogeneity also emerged as a concern in the relatively high percentages of homoscedastic data sets that became heteroscedastic following transformation (Table 6). Transformation only resulted in about 20% or fewer conversions of normal or additive data sets to non-normal or nonadditive data sets, respectively (Table 6). In fairness to conclusions about variance homogeneity, however, it should be noted that validity with Bartlett's test requires a normally distributed data set. Thus, a strict interpretation of Bartlett's test should involve only data sets testing normal by univariate analysis. When this was done, the square root transformation still seemed to be adversely affecting variance homogeneity in a high percentage of heteroscedastic and homoscedastic data sets (data not shown).

One of the features of weed control and winter wheat winter survival data that could play an important role in the problem of variance heterogeneity is the presence of

Table 6. Percentage of normal, homoscedastic, or additive data sets that responded to transformation by becoming non-normal, heteroscedastic, or nonadditive, respectively ($\alpha = 0.05$)[a].

Class of data set	Type of transformation	Normality	Homoscedasticity	Additivity
		%		
Weed control:				
0 to 20%	Square root	20 (1)	50 (4)	8 (1)
80 to 100%	Square root	0	0	0
0 to 20%	Arcsine	20 (1)	62 (5)	17 (2)
80 to 100%	Arcsine	20 (1)	0	0
>40%	Arcsine	9 (1)	33 (1)	6 (1)
<40%	Arcsine	0	0	22 (2)
Winter wheat survival:				
80 to 100%	Square root	0	100 (2)	0
80 to 100%	Arcsine	0	67 (2)	0
>40%	Arcsine	0	0	10 (1)
<40%	Arcsine	0	0	0

[a]Values in parentheses are the actual numbers of data sets.

Table 7. Effect of transformation and omitting nonvarying treatments on the percentage of weed control data sets showing non-normality ($\alpha = 0.05$)[a].

Class of data set	Non-normality					
	Original data	Arcsine	Square root	Omit data[b]	Omit data plus arcsine	Omit data plus square root
	%					
0 to 20%	75 (15)	65 (13)	60 (12)	50 (10)	45 (9)	40 (8)
80 to 100%	75 (15)	45 (9)	50 (10)	40 (8)	20 (4)	10 (2)
>40%	50 (11)	50 (11)	. . .	45 (10)	27 (6)	. . .
<40%	70 (14)	35 (7)	. . .	60 (12)	25 (5)	. . .

[a]Omitting of data involved nonvarying treatments in which all replicates had the same value (usually zeros or 100s). Values in parentheses are the actual number of data sets.

[b]Data were omitted from the following number of data sets: 14 from 0 to 20% class, 15 from 80 to 100% class, 8 from <40% class, and 9 from >40% class.

nonvarying treatments in which all replicates of a particular treatment have the same value. When using a truncated scale such as 0 to 100%, treatments having all zeros or all 100s commonly are encountered, particularly in experiments involving, for instance, highly effective herbicide treatments or a mild winter causing little winter wheat stand losses. The presence of a few or more such treatments would be expected to cause variance heterogeneity because these treatments represent the extreme of zero variance.

The percentage of non-normal data sets in each of the four data classes generally was decreased either by omitting nonvarying treatments or by transformation (Table 7). Several instances in Tables 7 to 9, however, show that transformation or omitting nonvarying treatments had little or no effect in reducing the percentage of data sets having problems, particularly with heteroscedasticity and nonadditivity. In other cases (Tables 8 and 9), transformation reduced the percentage of heteroscedastic and nonadditive data sets while removal of nonvarying treatments did not. The greatest reduction in percentage of problem data sets was achieved when both operations were performed (Tables 7 to 9). Thus it appears that removal of nonvarying treatments may not always improve problem data sets by itself but may be beneficial in promoting a favorable response to transformation, especially where data sets are heteroscedastic or nonadditive.

Using transformation to correct problems affecting analysis of variance may be of limited interest to most researchers unless it can be demonstrated that such corrections result in effects on mean separations and, therefore, on final conclusions drawn from the data. Geng et al. (7) found that the F-test of analysis of variance was scarcely affected by non-normality and heterogeneity of variance, and concluded that testing for these parameters prior to analysis of variance is unnecessary. Their experiments were conducted on data sets generated by computer, given a selected set of means, variances, sample sizes, and population distributions. In experiments involving insect control treatments, Beall (4) reported that transformation resulted in a substantial difference in interpretation of the data. Similarly, in our study involving data sets from actual weed control experiments conducted in the field, application of a protected LSD following analysis of variance yielded mean separations that were different between transformed and nontransformed data in the majority of cases (Table 10), particularly when considering only data sets having a significant F-test. (See footnote b, Table 10.) In one of the 82 weed control data sets, transformation produced a significant F-test while nontrans-

Table 8. Effect of transformation and omitting nonvarying treatments on the percentage of weed control data sets showing heterogeneity of variance ($\alpha = 0.05$)[a].

Class of data set	Heterogeneity of variance					
	Original data	Arcsine	Square root	Omit data[b]	Omit data plus arcsine	Omit data plus square root
	%					
0 to 20%	60 (12)	70 (14)	75 (15)	30 (6)	20 (4)	15 (3)
80 to 100%	80 (16)	70 (14)	45 (9)	75 (15)	30 (6)	35 (7)
>40%	86 (19)	77 (17)	. . .	82 (18)	55 (12)	. . .
<40%	75 (15)	45 (9)	. . .	75 (15)	20 (4)	. . .

[a]Omitting of data involved nonvarying treatments in which all replicates had the same value (usually zeros or 100s). Values in parentheses are the actual number of data sets.

[b]See footnote b in Table 7.

Table 9. Effect of transformation and omitting nonvarying treatments on the percentage of weed control data sets showing nonadditivity ($\alpha = 0.05$)[a].

Class of data set	Nonadditivity					
	Original data	Arcsine	Square root	Omit data[b]	Omit data plus arcsine	Omit data plus square root
	%					
0 to 20%	40 (8)	20 (4)	20 (4)	35 (7)	20 (4)	10 (2)
80 to 100%	70 (14)	40 (8)	40 (8)	70 (14)	20 (4)	25 (5)
>40%	23 (5)	18 (4)	...	23 (5)	18 (4)	...
<40%	55 (11)	40 (8)	...	50 (10)	25 (5)	...

[a]Omitting of data involved nonvarying treatments in which all replicates had the same value (usually zeros or 100s). Values in parentheses are the actual number of data sets.

[b]See footnote b in Table 7.

formed data had a nonsignificant F-test ($\alpha = 0.05$); the converse was not observed. Although mean separations often were different between transformed and nontransformed data, the majority of these differences would be considered minor and would not appreciably affect interpretation of the results (data not shown).

Transformation produced mean separation differences in several cases where there was no change in the outcome of the test for normality (Table 10). This could be considered an undesirable result since failure to alter the underlying distribution theoretically should give rise to identical mean separations. However, we note that in many of these cases where mean separations were different while the distribution remained unchanged, transformation resulted in an improved normality test statistic or an improved test statistic for Bartlett's and Tukey's tests (data not shown).

Failure of subjectively determined percentage data to satisfy the assumptions underlying analysis of variance appears prevalent in weed control and winter wheat winter survival data. The arcsine and square root transformations corrected problems of non-normality, variance heterogeneity, and nonadditivity in a fairly high percentage of data sets, although in other data sets these parameters were impaired by transformation. Omitting nonvarying treatments appears to offer a potential for substantial improvement in the three statistical parameters, either directly or by facilitating a favorable response to transformation. The ramifications of nonvarying treatments may suggest the use of a continuous percentage scale in evaluating weed control and winter wheat winter survival. Use of a discontinuous scale such as a 5% interval (i.e., 70%, 75%, 80%, etc.) may tend to increase the frequency of nonvarying treatments involving values other than 0 and 100%. Transformation gave rise to different mean separations for a majority of data sets, thus potentially affecting the final conclusions of the experiment. The square root transformation appears useful for data sets in which values fall between 0 and 20% or 80 and 100%, although our results show the arcsine transformation to be about as effective for these data classes. For data distributed outside the 20% extremes of the percentage scale, the arcsine transformation appears to be reasonably effective and may be advisable for the <40% data sets as well as those having values ranging beyond 40 percentage points.

In general, the findings of this study lend support to use of the arcsine and square root transformations for percentage data in weed science and related disciplines, providing that nonvarying treatments are omitted prior to analysis of variance. Use of data transformations however, should not be

Table 10. Percentage of weed control data sets for which transformation yielded mean separations that were different from those obtained prior to transformation[a].

Class of data set[b]	Arcsine transformation[c]			Square root transformation		
	Remained non-normal	Non-normal to normal	Remained normal	Remained non-normal	Non-normal to normal	Remained normal
	%					
0 to 20%	15 (3)	10 (2)	25 (5)	15 (3)	15 (3)	25 (5)
80 to 100%	10 (2)	25 (5)	25 (5)	5 (1)	25 (5)	25 (5)
<40%	25 (5)	35 (7)	30 (6)	...	...	...
>40%	27 (6)	18 (4)	36 (8)	...	...	...

[a]Nonvarying treatments were removed from data sets where applicable. Mean separations were done using protected LSD ($\alpha = 0.05$). Values in parentheses are the actual number of data sets.

[b]The percentage of data sets with a nonsignificant F-test on transformed data was as follows: 0 to 20% class, 30%; 80 to 100% class, 35%; <40% class, 0%; >40% class, 0%.

[c]"Remained non-normal", "non-normal to normal", and "remained normal" refer to possible responses of the data sets to transformation.

considered necessary or remedial for all percentage data sets. Yet, to the extent that these data sets fail to meet the assumptions underlying analysis of variance, nonparametric statistics also should be considered (10).

Authors choosing to use data transformations inevitably must decide whether or not to display transformed data in publications. Presentation of transformed or "back-transformed" data seems generally acceptable (9, 12). Back transformations are computed by performing the inverse transformation on transformed means (9). Presentation of transformed data likely will not be preferred by authors in weed science and related disciplines since transformation drastically changes the absolute value of the data, causing difficulty for most readers in understanding experimental results. Back-transformed means are relatively similar to actual (i.e., nontransformed) means in absolute value, yet authors still may find these back-transformed means undesirable given the biological significance of original data values. We propose that means of original data be allowable for presentation in publications in cases where these actual observed means contain essential information not fully conveyed by back-transformed means. Authors must identify the type of means being presented.

Mean differences must be determined on transformed means using LSD, Duncan's New Multiple Range Test (6), or other suitable procedures. Mean differences can then be indicated by placing letters after displayed means such that any two means followed by the same letter are not significantly different.

Transformation can cause difficulty in data interpretation when two identical means in the nontransformed data become different in the transformed data. Worse yet, mean "A" may be higher than mean "B" in the nontransformed data but be lower than mean "B" in the transformed data. When transformation of data reverses the relative ranking of two means, presenting original data creates a dilemma in assigning the letters indicating mean difference separations. Presentation of back-transformed means alleviates this dilemma but does not affect reversals in relative ranking. A reasoned approach to use of the arcsine and square root transformations for percentage data must acknowledge the limitations of their use as well as the potential benefit.

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