CLOUD SEEDING EXPERIMENT

6. Displaying a Multiplicative Treatment Effect

We will use the data to examine the nature of the relationship between seeded and unseeded rainfalls. The bolded hyperlinks displayed below lead directly to the corresponding topics.

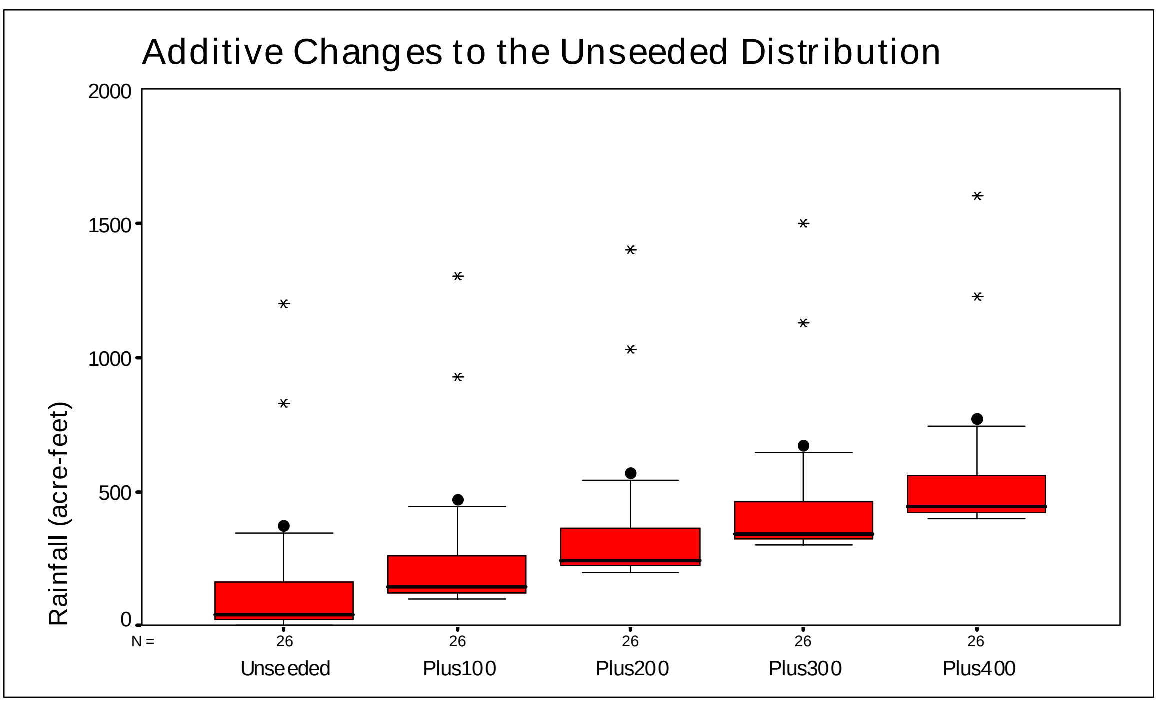
6.1 **Is the effect of seeding multiplicative or additive? Simple Simulations.**

6.2 **Determining the nature of the treatment effect by comparing the boxplots for the seeded and unseeded groups on the log scale.**

6.3 **What do the normal Q-Q plots of seeded and unseeded rainfalls say about the nature of the effect of seeding?**

6.1 Is the treatment effect additive or multiplicative? We will demonstrate how the boxplot for the seeded days would look like if the treatment effect were additive or multiplicative. You will be able to determine the nature of the effect in the real data by comparing the boxplots with the boxplot for the seeded days.

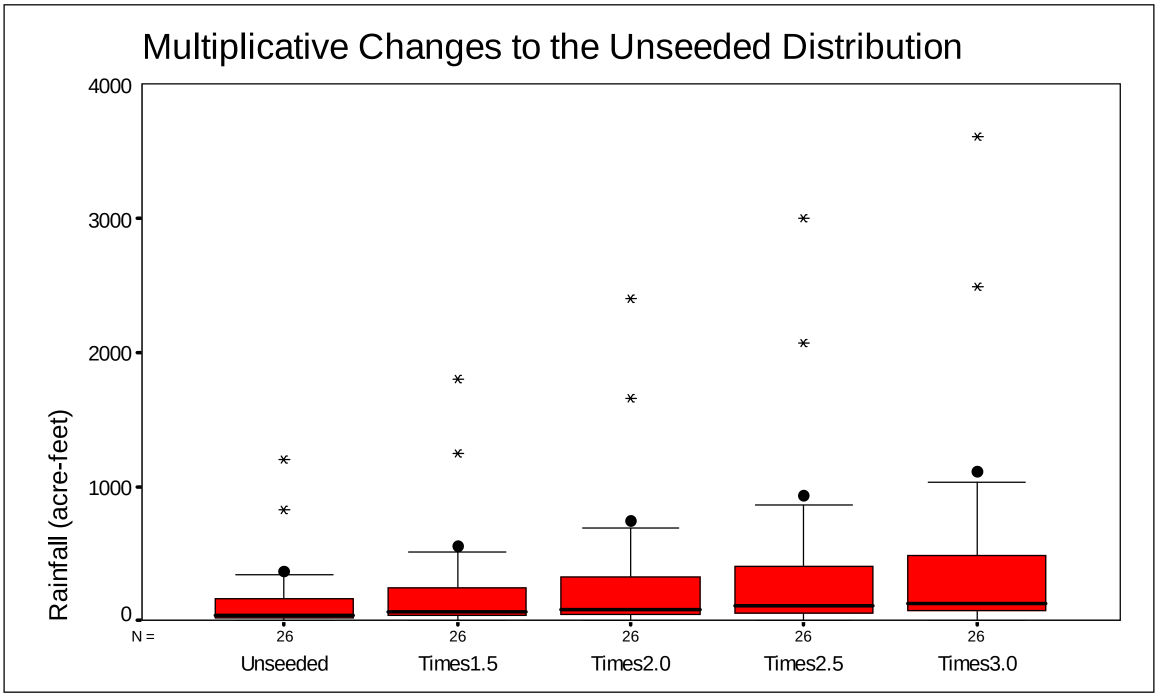
We will create first a variable containing the rainfall amounts for only the unseeded days. Then we create four new variables by adding 100, 200, 300, and 400 to each of unseeded day rainfall amounts. We will use SPSS to display a set of five boxplots to illustrate what one might expect if the effect of seeding were additive.



Adding the same amount to each of the unseeded day rainfall amounts does not affect the shape of the distribution. This is why the boxplots obtained by adding 100, 200, 300, and 400 can be obtained by shifting the boxplot for unseeded days by 100, 200, 300, and 400 units up, respectively. Adding a constant to all of the observations changes the location of the distribution but leaves the spread unaltered.

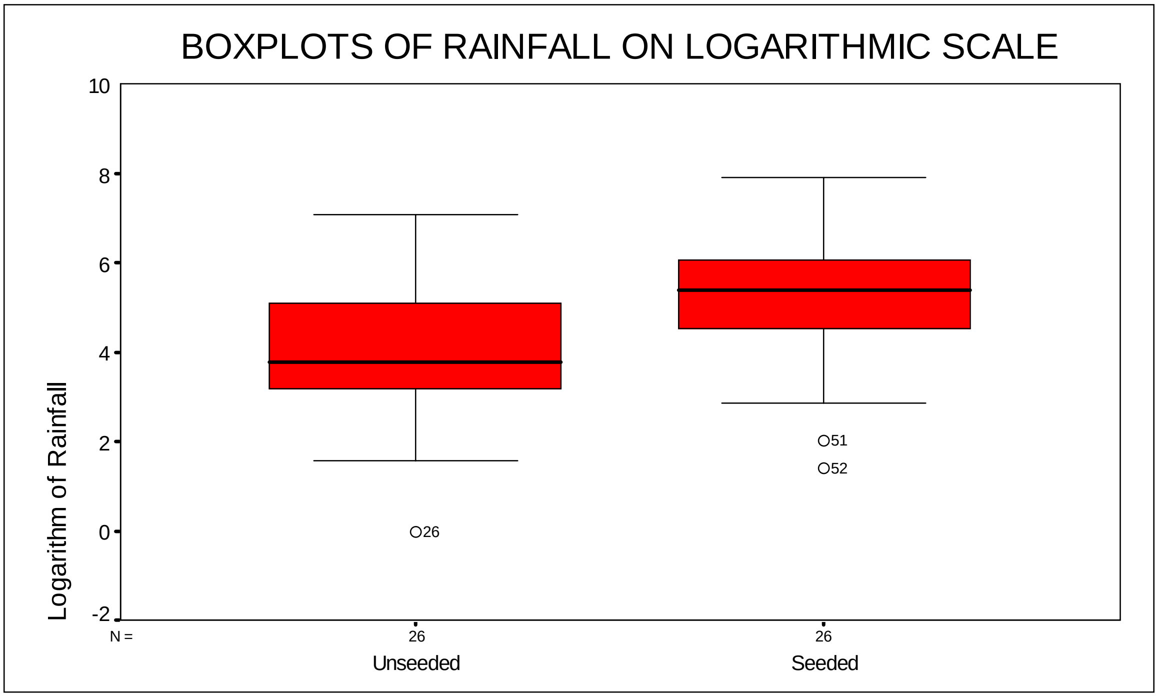
None of the four boxplots (Plus100, Plus200, Plus300, and Plus400) is similar to the boxplot for seeded days (see 4.1). The boxplot for the seeded days indicates that the distribution for seeded days is almost symmetrical and it has a larger spread than the distribution for unseeded days. This is indicated by the position of the line within the box (median) and by the length of the box (interquartile range). The above boxplots do not support the additive effect.

Now we will repeat the procedure assuming multiplicative effect. Let us create four additional variables by multiplying each of the unseeded day rainfall amounts by 1.5, by 2.0, by 2.5, and by 3. We will use SPSS to display a set of five boxplots to illustrate what one might expect if the effect of seeding were multiplicative.



Observe that the distributions obtained by multiplying each of the unseeded day rainfall amounts by 1.5, by 2.0, by 2.5, and by 3 have larger spread and are less skewed than the distribution of rainfalls for the unseeded days. The boxplot Times3.0 resembles the boxplot for the seeded days. We can conclude that the experiment supports the multiplicative effect.

6.2 The comparison of the boxplots for seeded and unseeded clouds can also give some insight in the nature of the seeding effect in the experiment. In Section 4.2 we obtained the following side-by-side boxplots of log-transformed observations for the two treatment groups.



As you can see, the distributions have approximately the same shape and spread. The appearance of the boxplot for seeded rainfalls suggests that it might be obtained by shifting the boxplot for unseeded rainfalls by a specific number of units up. It looks as if the seeding added the same rainfall amount to any cloud rainfall. Therefore, the additive treatment effect holds for the log-transformed data, and that translates into the multiplicative treatment effect on the original scale of measurement.

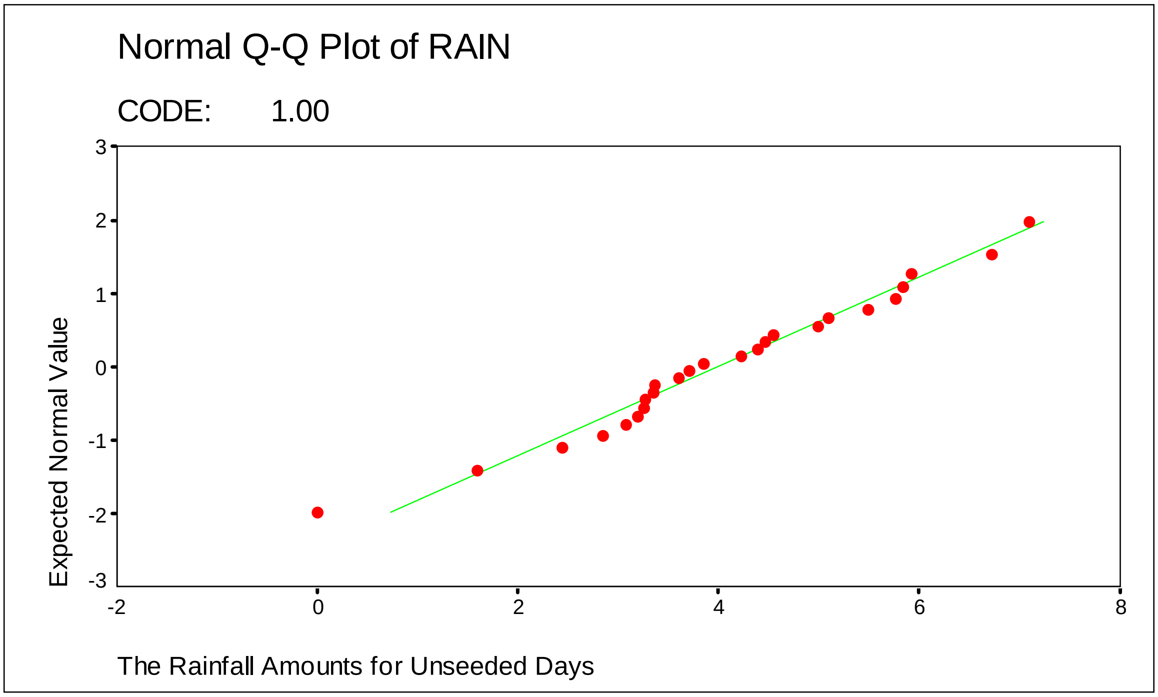
6.3 The *Normal Q-Q* plot plots the quantiles of a variable's distribution against the quantiles of the normal distribution. If the data come from a normal distribution, the plot should resemble a straight line. Normal Q-Q plots are generally used to determine whether or not a variable is normally distributed.

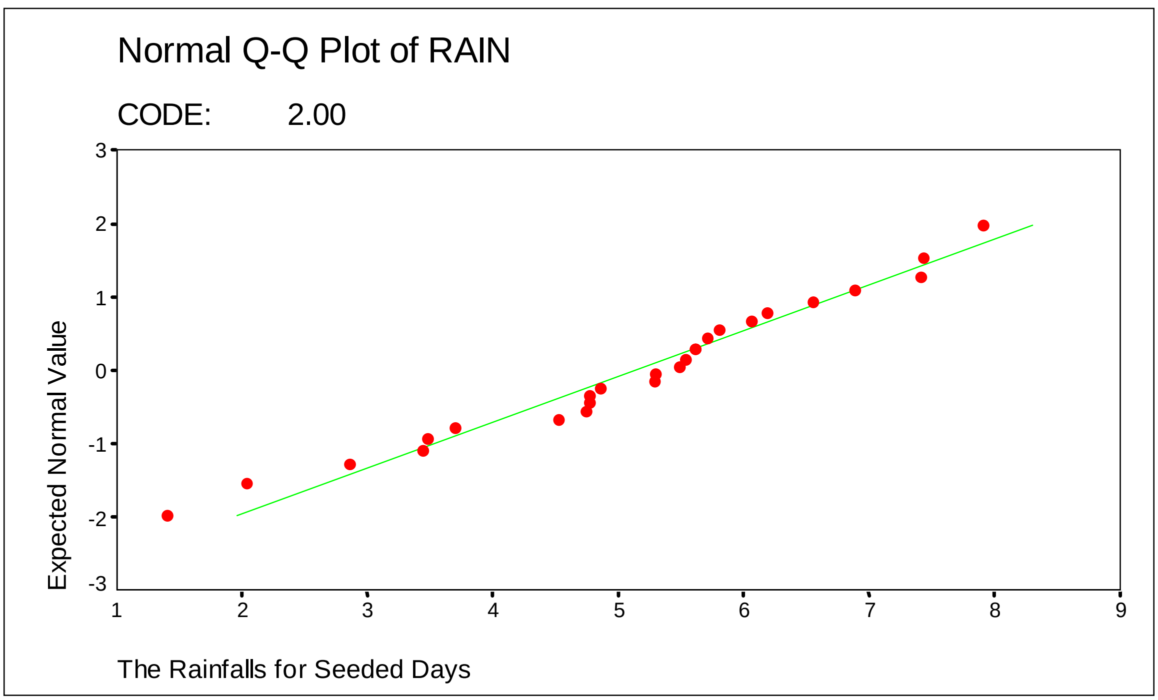
In our case study we will use the plot not only to check the normality assumption for each distribution but also to examine the nature of the relationship between the two distributions. We will carry out our analysis on the log scale for both distributions.

What could be expected if the effect of seeding were multiplicative? In order to answer the question, notice that if the values of one variable are the multiples of the values of the other variable, then their logarithms differ by a constant. Thus if you consider the quantiles of both distributions, they differ by a constant. Graphically, that means that the normal Q-Q plots for both distributions are approximately parallel. Thus we can use SPSS to obtain both plots and compare them to verify the hypothesized multiplicative treatment effect.

Another possible method to verify the multiplicative effect would be to obtain the quantile-quantile plot of seeded cloud rainfall versus control cloud rainfall. If the shift of the points in the plot from the line y=x could be described by a parallel line, the plot lends support to the multiplicative assumptions.

We will use the first approach and SPSS to support the hypothesis of the multiplicative effect. In order to achieve this, we will obtain the normal Q-Q plots for the unseeded and seeded days. Remember that the unseeded days are coded as 1 and seeded days are coded as 2.





In each case the natural logarithms of data values were used instead of the original values themselves. Each of the above normal plots resembles a straight line and hence it supports the assumption of normality of the transformed observations.

The fact that the slopes of both lines are approximately equal supports the hypothesis that the effect of seeding is multiplicative.