



EVROPSKÁ UNIE



MINISTERSTVO ŠKOLSTVÍ,
MLÁDEŽE A TĚLOVÝCHOVY



OP Vzdělávání
pro konkurenceschopnost

INVESTICE DO ROZVOJE VZDĚLÁVÁNÍ

Tento projekt je spolufinancován Evropským sociálním fondem a Státním rozpočtem ČR
InoBio – CZ.1.07/2.2.00/28.0018

Statistical Analysis in Ecology using R

ANOVA, Linear Regression, ANCOVA

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INVESTMENTS IN EDUCATION DEVELOPMENT

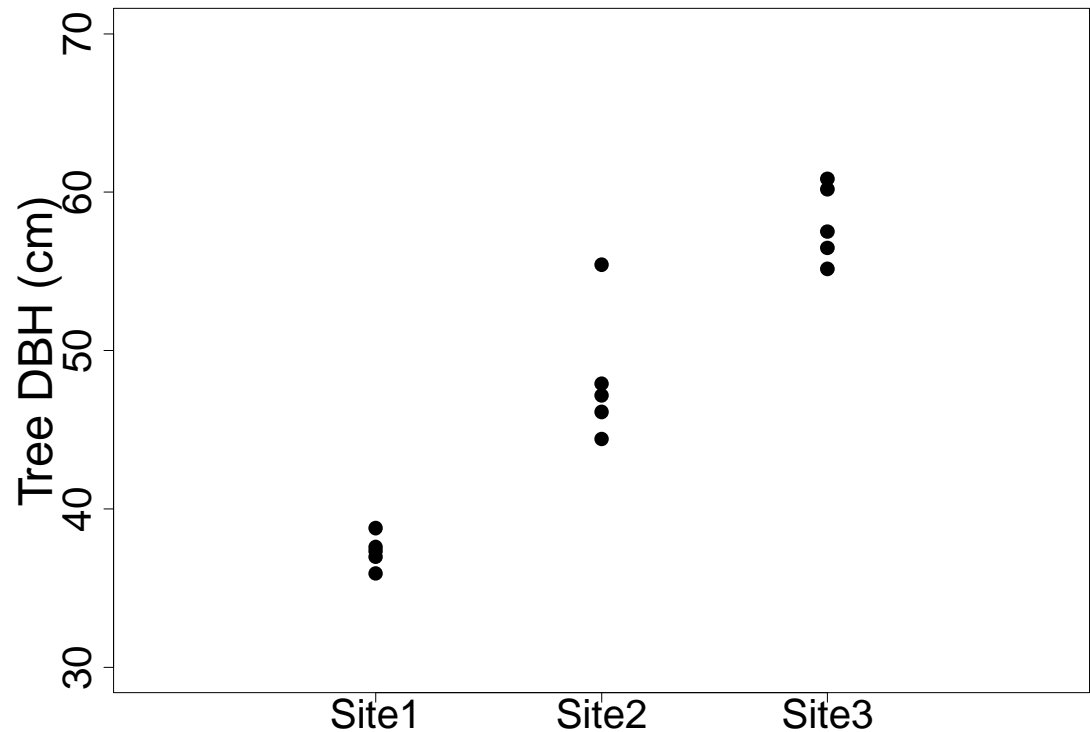
Recap

- Type of data
- We want to **explain Y**
 - Central tendency
 - Dispersion around the central tendency
- Correlations
- Visuals (graphs)

ANalysis Of VAriance (ANOVA)

- Used to analyze how **mean values** of continuous variable (Y) **differ among groups** of elements.
- Y (size)
- Groups (sites)
- Elements (trees)

- $k = 3$ sites
- $n = 15$ trees



ANOVA: Assumptions

- **Independence:** The elements have been sampled randomly and independently from each group.
- **Normality:** For each group the values of Y follow a normal distribution.
- **Homoscedasticity:** the variance should be the same for each group.

ANOVA: Hypotheses

- H_0 : The **null hypothesis**. The mean value of Y is the same for all groups. The observed variability is only within groups and is due to random sampling. **Nothing interesting is happening.**
- H_A : The **alternative hypothesis**. The mean value of Y differs among populations. There is variability within groups AND among groups. **Something might be of interest.**
- **We test H_0**

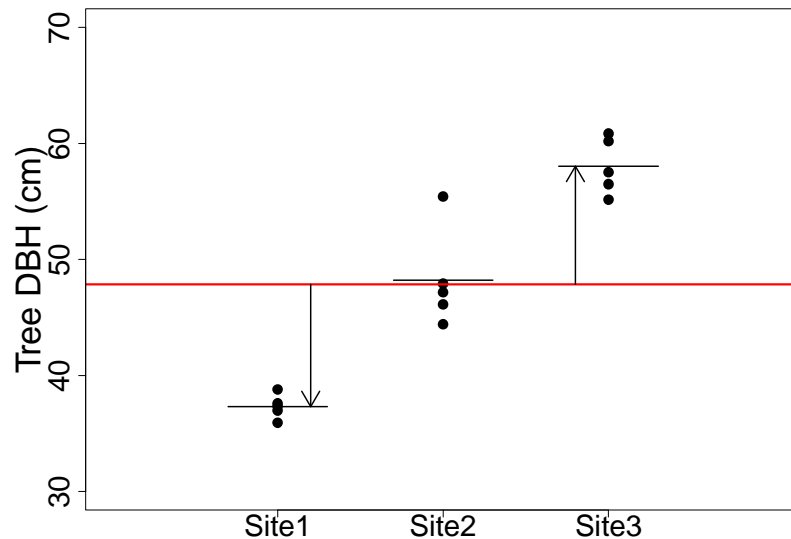
ANOVA: F ratio:

Variation among groups/Variation within groups

$$SS_{among} = \sum_{ij} (\bar{y}_j - \bar{y})^2 = \sum_j n_j (\bar{y}_j - \bar{y})^2$$

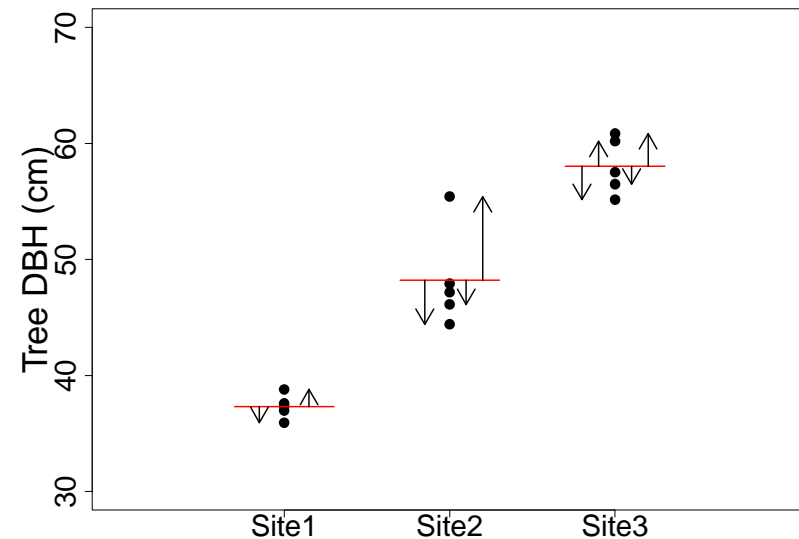
$$SS_{within} = \sum_{ij} (y_{ij} - \bar{y}_j)^2$$

- “Group effects”



SS = Sum of Squares
 n_j = number of elements in group j

- “Residuals”



y_{ij} = value of element i in group j
 \bar{y}_j = mean of y_{ij} for group j
 \bar{y} = overall mean

ANOVA: F ratio:

Variation among groups/Variation within groups

- **F-ratio = MS among groups/MS within groups**

- $MS = SS/df$

- MS = Mean Square

- df = degree of freedom

- df total = n-1

- df among = k-1

- df within = n-k

- **Total = residual + group**

k = number of groups (j = 1 to k)

n = total sample size (sum of n_j)

$$MS_{\text{total}} = MS_{\text{residual}} + MS_{\text{group}}$$

$$SS_{\text{total}} = SS_{\text{residual}} + SS_{\text{group}}$$

$$df_{\text{total}} = df_{\text{residual}} + df_{\text{group}}$$

ANOVA: F ratio:

Variation among groups/Variation within groups

- If F-ratio = 1: $MS_{\text{residual}} = MS_{\text{group}}$
- H_0 is true: no difference between groups
- The bigger the F-ratio is, the more likely H_0 to be rejected

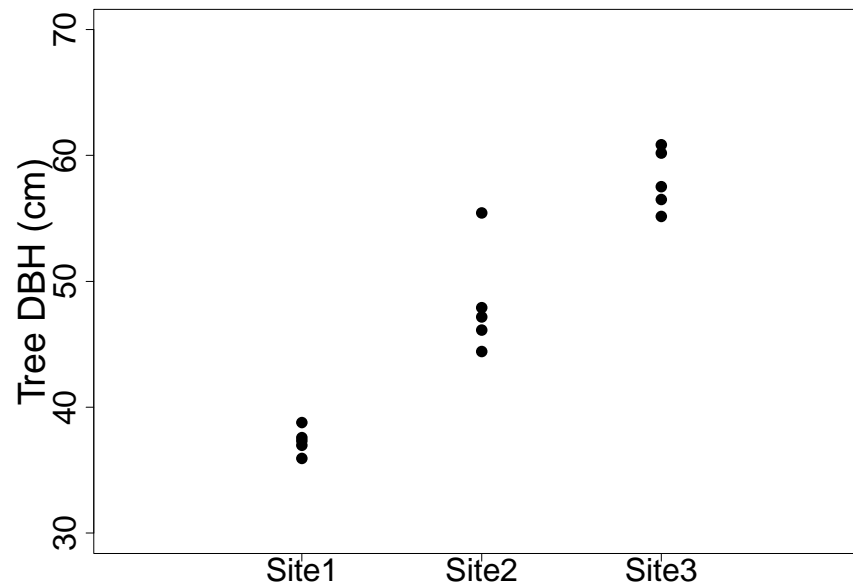
- R squared indicates the fraction of the total variation that is due to differences among groups.
- **R squared = SS of group effects / SS total**
- $0 < R \text{ squared} < 1$

ANOVA in R: aov()

```
> model.aov <- aov(size ~ site, data = data)
```

```
> summary(model.aov)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
site	2	1073.4	536.7	64.54	3.79e-07 ***
Residuals	12	99.8	8.3		



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n = 15 trees -> $df_{\text{total}} = n - 1 = 14$

k = 3 sites -> $df_{\text{groups}} = k - 1 = 2$

-> $df_{\text{residuals}} = 14 - 2 = 12$

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$$\begin{aligned} MS_{\text{among}} &= MS_{\text{groups}} = SS_{\text{groups}} / df_{\text{groups}} = 1073.4/2 \\ MS_{\text{within}} &= MS_{\text{residuals}} = SS_{\text{residuals}} / df_{\text{residuals}} = 99.8/12 \end{aligned}$$

ANOVA in R: aov()

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Residuals	12	99.8	8.3		

$$F \text{ value} = MS_{\text{groups}} / MS_{\text{residuals}} = 536.7 / 8.3$$

Much bigger than 1

ANOVA in R: aov()

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```

```
> summary(model.aov)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
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P value = Probability of observing data as extreme as this if the null hypothesis were true.

Here, the P value is almost 0, so it is very unlikely that H_0 is true.

Therefore, we accept H_A : "There is a difference among groups".

ANOVA

H_A:

Tree size = Mean size + site effect + effects of age, genes, species...

Y = Fitted value + residual (error)

H₀:

Tree size = Mean size + effects of age, genes, species...

Data = Fitted value + residual (error)

SS site effect = SS residual (model without site effect)

- SS residual (model with site effect)

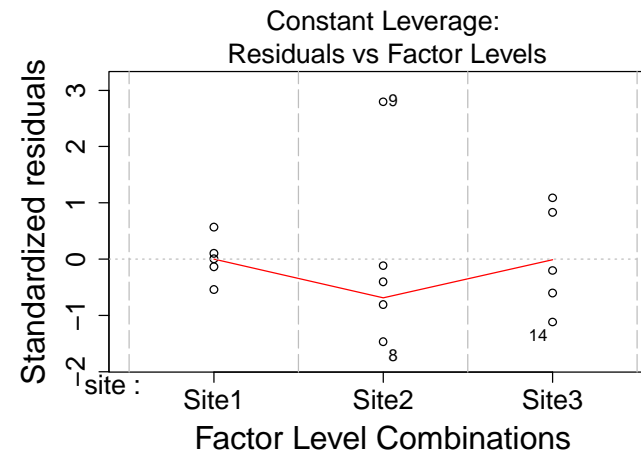
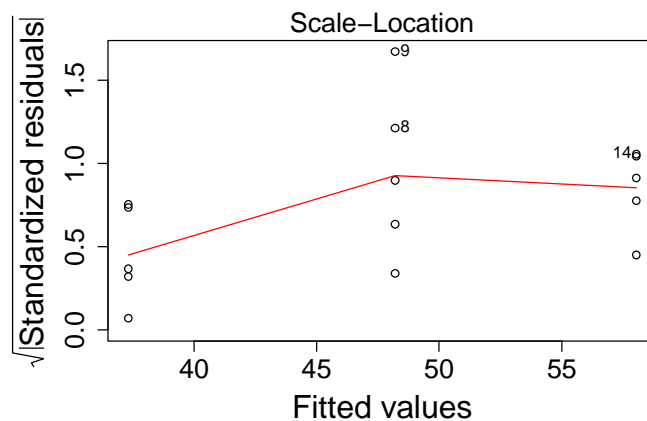
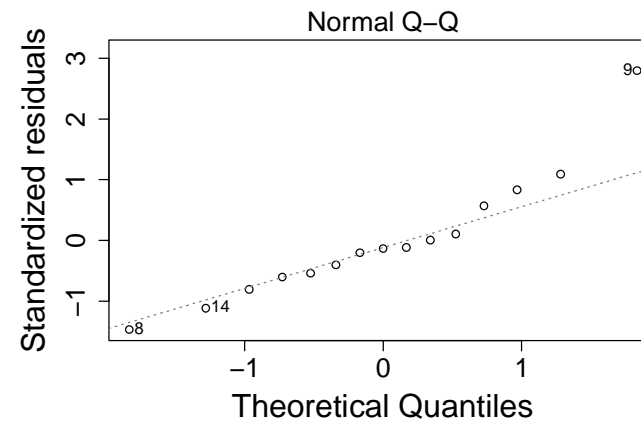
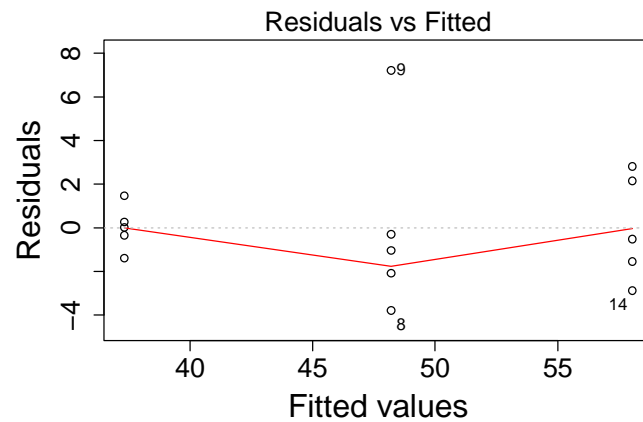
ANOVA

- Answers 3 questions:
 - Do mean values of Y differ among the sites from which samples were taken?
 - Is the variability of group means larger than expected from the variability within groups?
 - Does a model with site effects describe the data better than a model without site effects?

ANOVA in R: checking assumptions

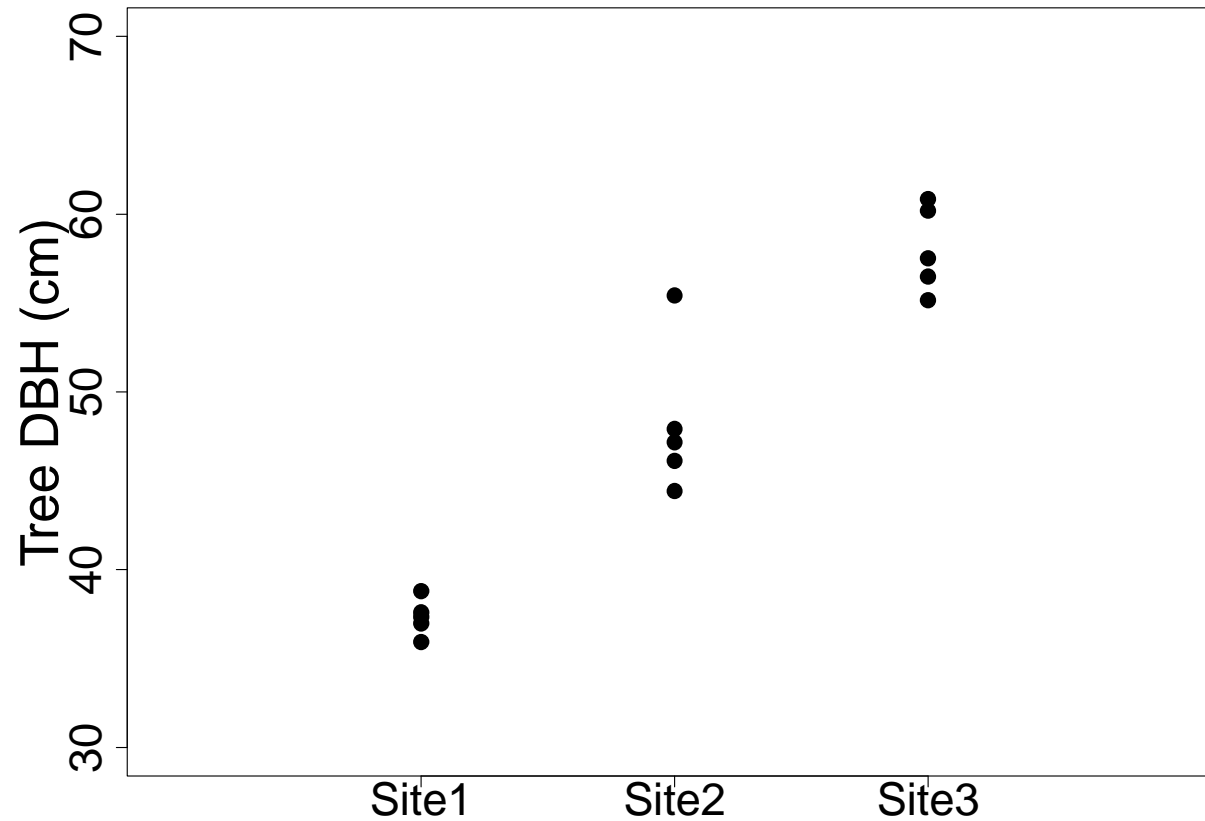
```
> par(mfrow=c(2,2))
```

```
> plot(model)
```



One Way-ANOVA: one factor

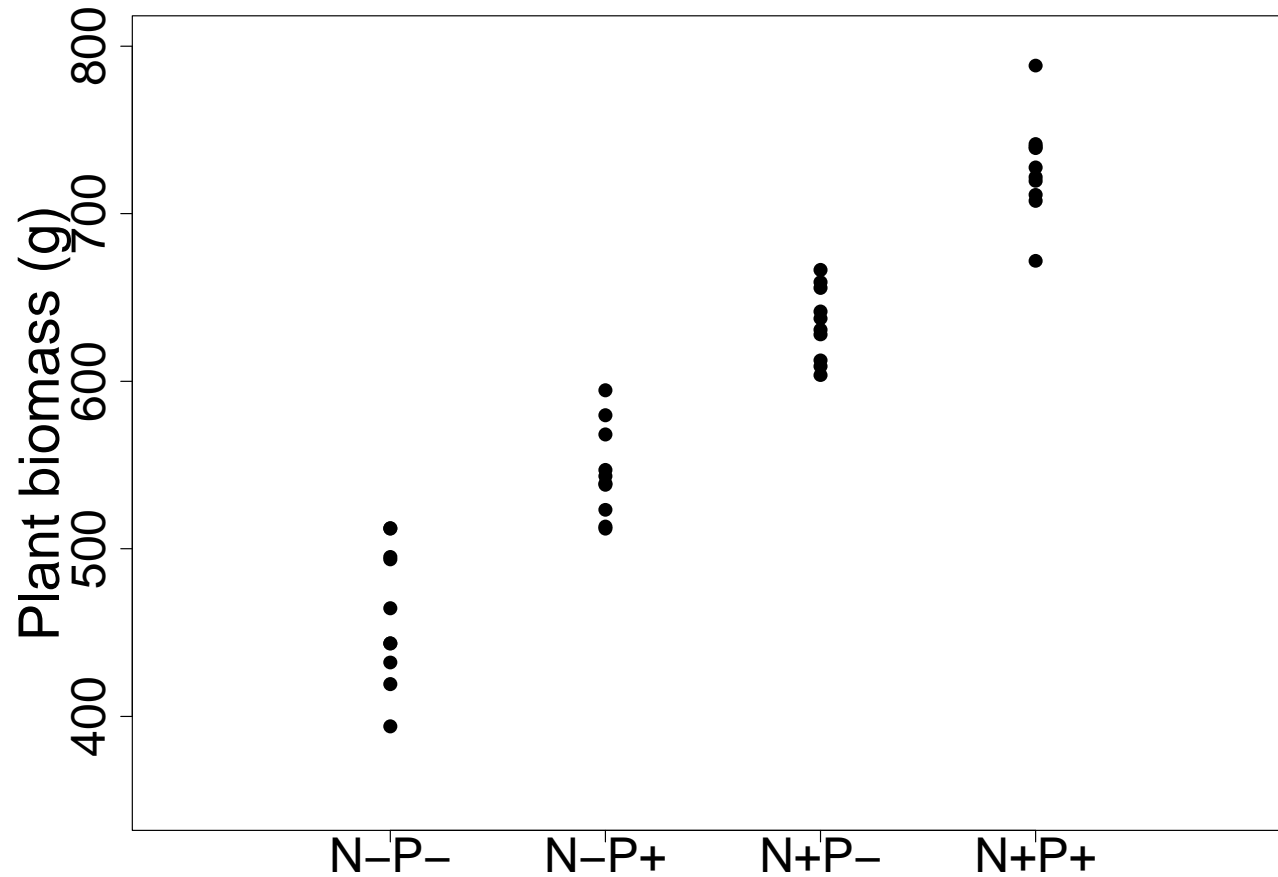
```
model <- aov(Y~X, data=data)
```



Two Way-ANOVA: two factors

- $Y \sim X1 * X2$
- $Y =$ Plant biomass (g)
- N+/N- : Nitrogen addition / control
- P+/P- : Phosphate addition / control

Two Way-ANOVA: two factors



Two Way-ANOVA: two factors

```
> model.aov <- aov(biomass ~ nitrogen * phosphate, data =  
fert)
```

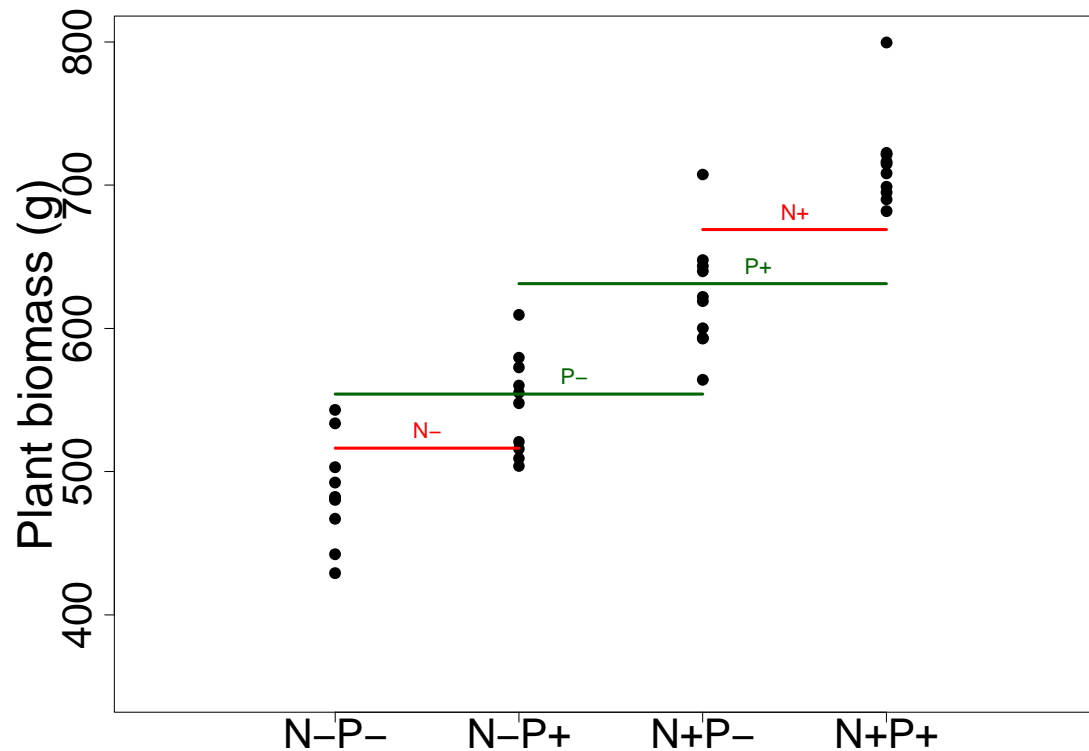
```
> summary(model.aov)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
nitrogen	1	191576	191576	232.983	< 2e-16	***
phosphate	1	78295	78295	95.217	1.19e-11	***
nitrogen:phosphate	1	1	1	0.001	0.976	
Residuals	36	29602	822			

Two Way-ANOVA: two factors

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> summary(model.aov)
```

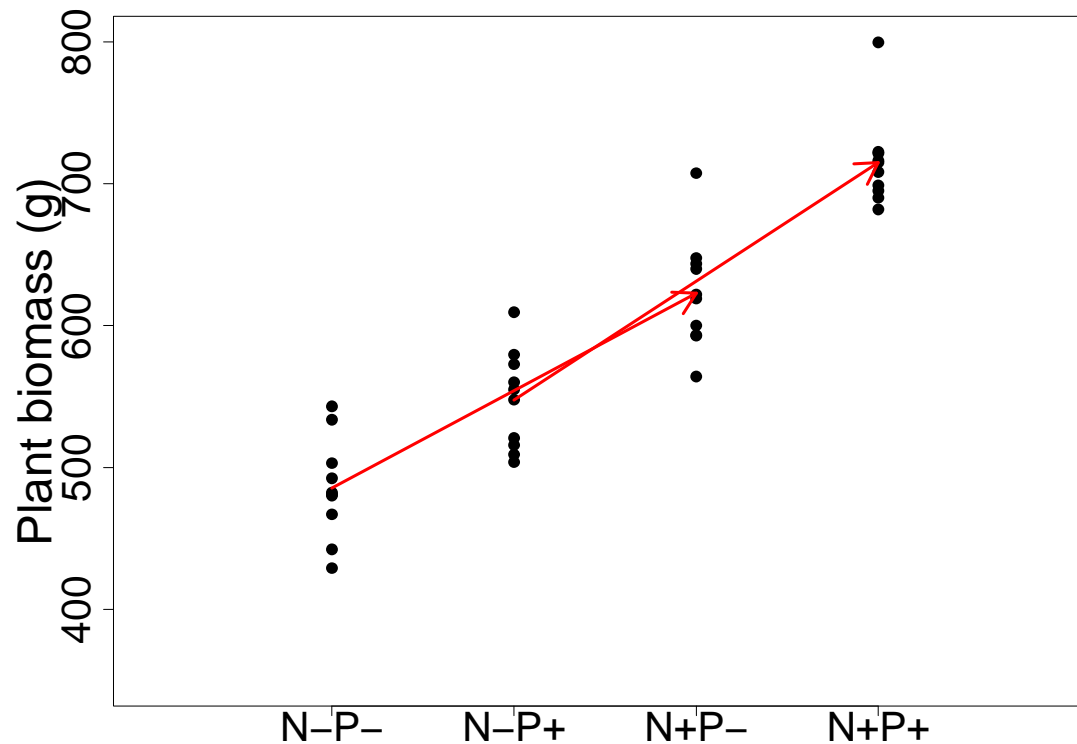
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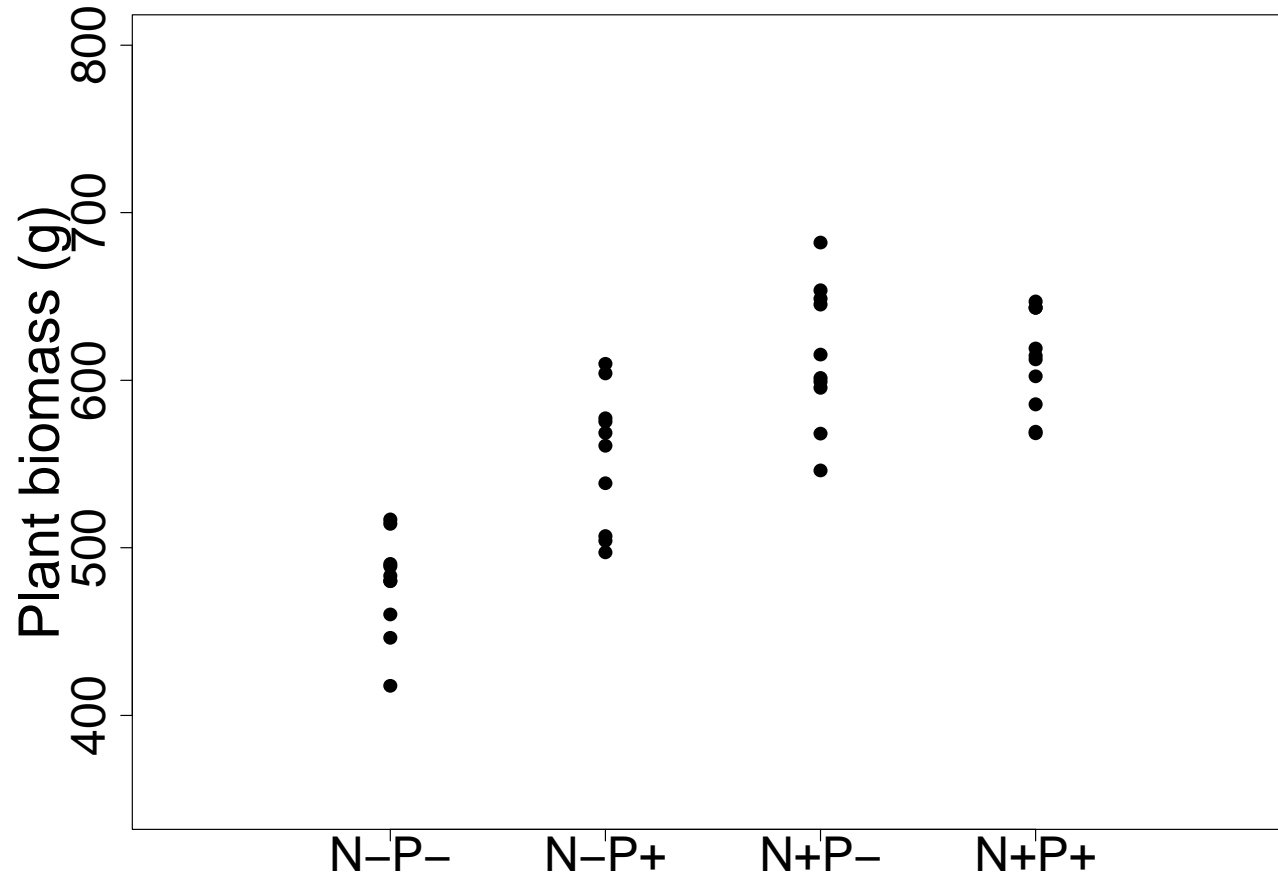
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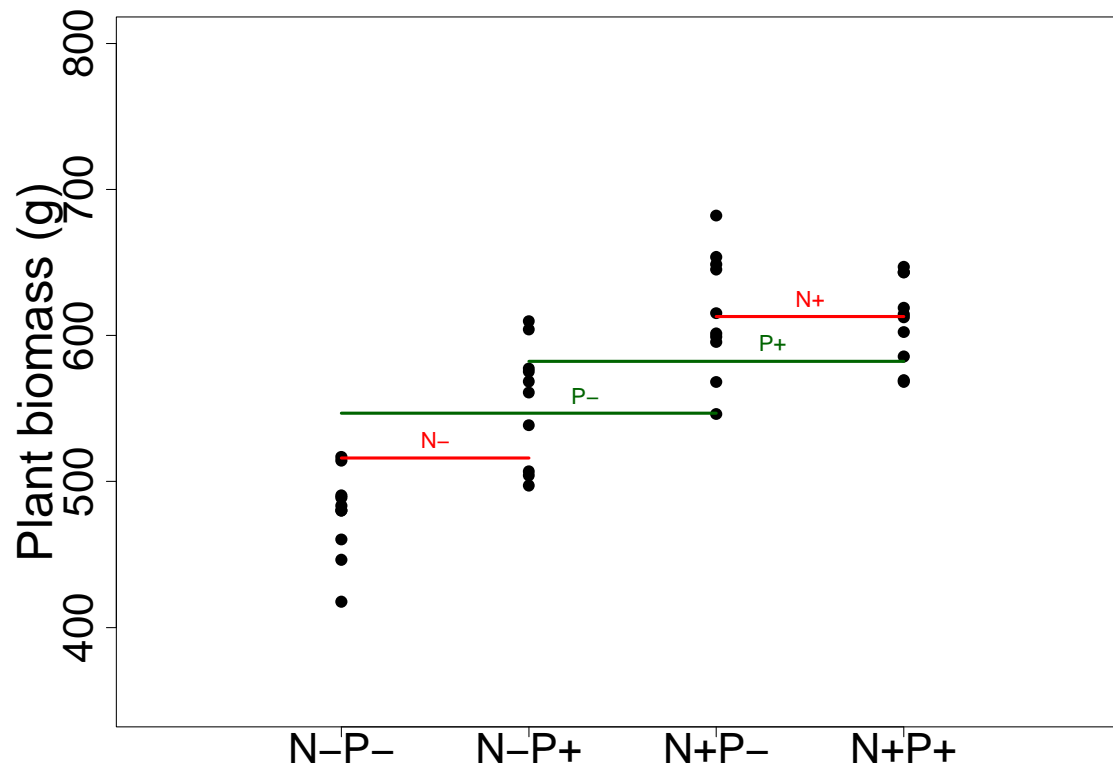
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```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
nitrogen	1	93956	93956	72.499	3.79e-10	***
phosphate	1	12747	12747	9.836	0.00340	**
nitrogen:phosphate	1	16586	16586	12.798	0.00101	**
Residuals	36	46655	1296			

Two Way-ANOVA: two factors

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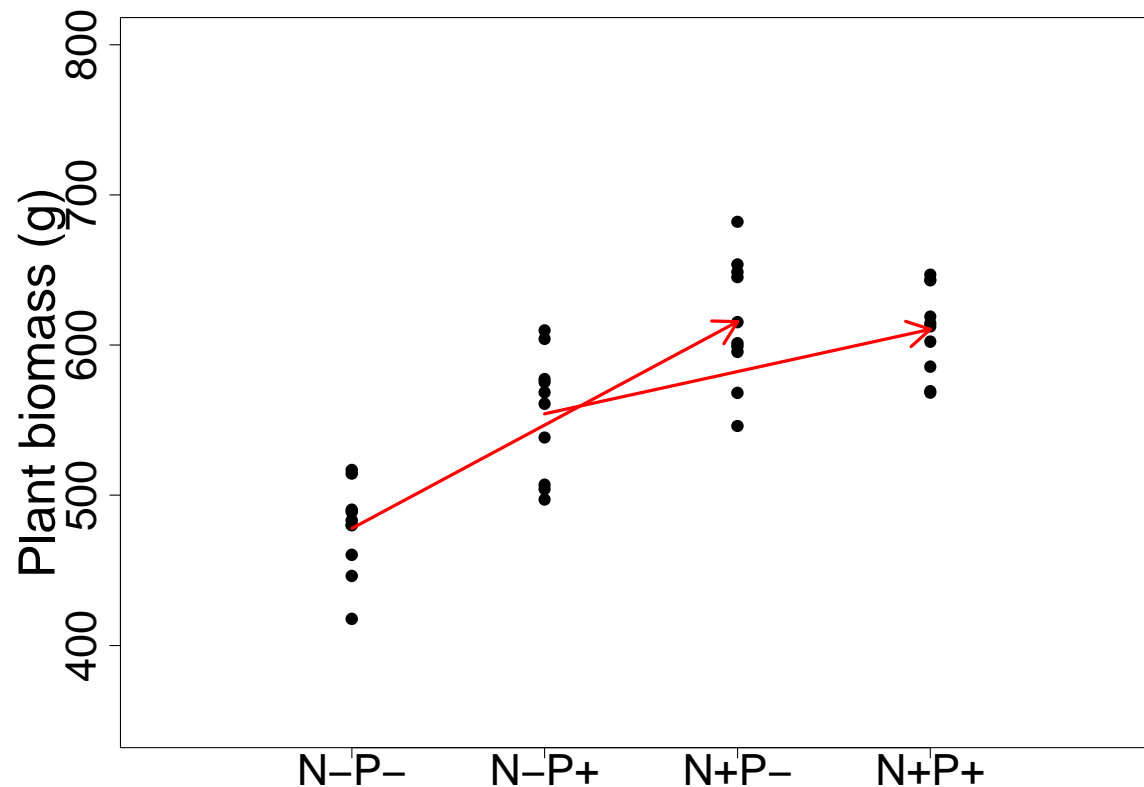
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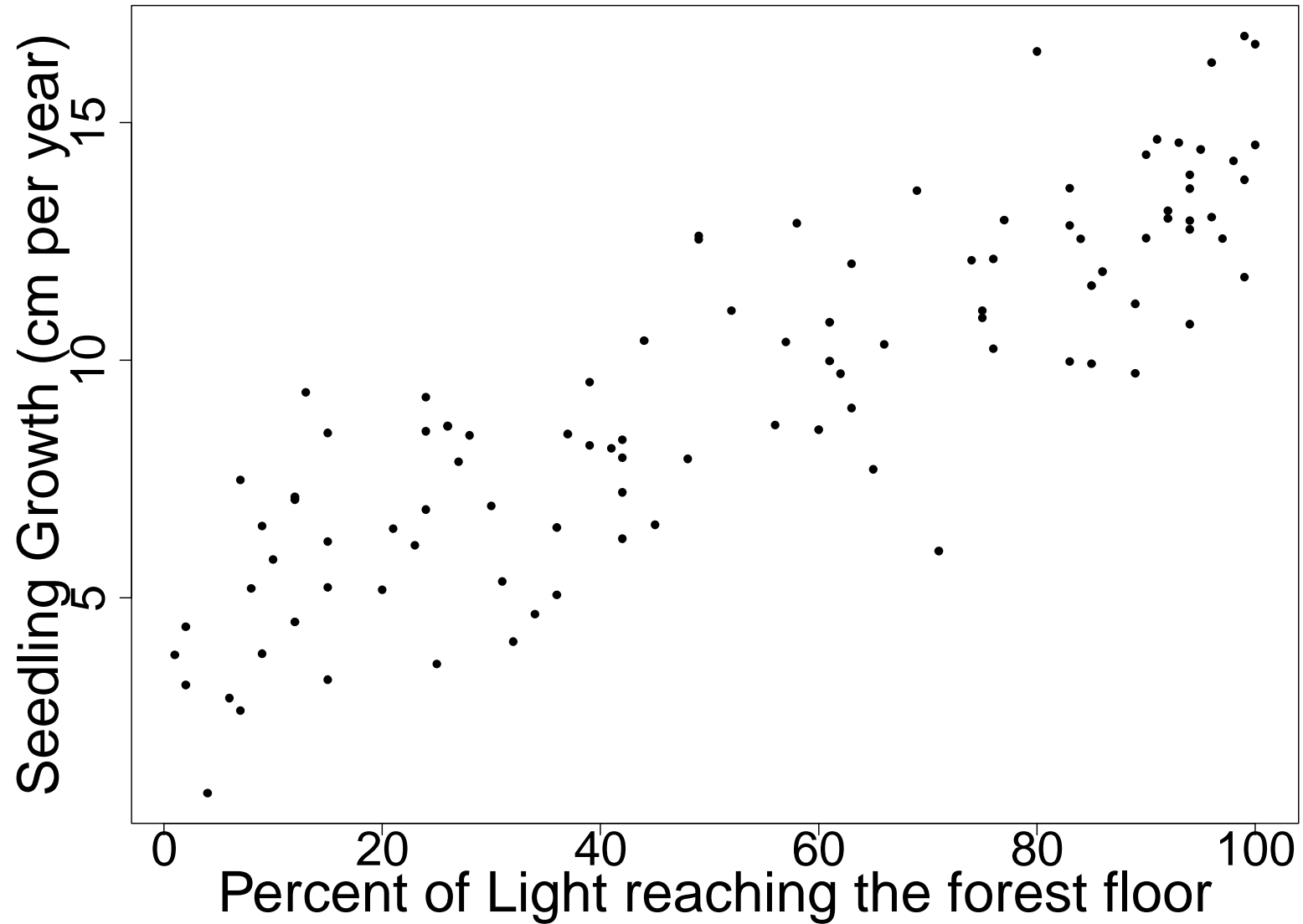
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Linear regression

- Same assumptions as ANOVA:
 - Independence
 - Normality
 - Homoscedasticity
- Here the explanatory variable **X is continuous**
- Instead of difference among groups, we want to model the **intercept** (a= value of Y when X=0) and the **slope** (b) of the regression.
- $Y \sim a + b * X$

Linear regression



Linear regression in R: lm()

```
> model.lm <- lm(growth ~ light, data = data)
> summary(model.lm)
```

Call:

```
lm(formula = growth ~ light, data = data)
```

Residuals:

Min	1Q	Median	3Q	Max
-5.1620	-1.1587	-0.0605	1.2966	4.4653

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	4.168827	0.362514	11.50	<2e-16	***
light	0.098287	0.005811	16.91	<2e-16	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.854 on 98 degrees of freedom

Multiple R-squared: 0.7449, Adjusted R-squared: 0.7423

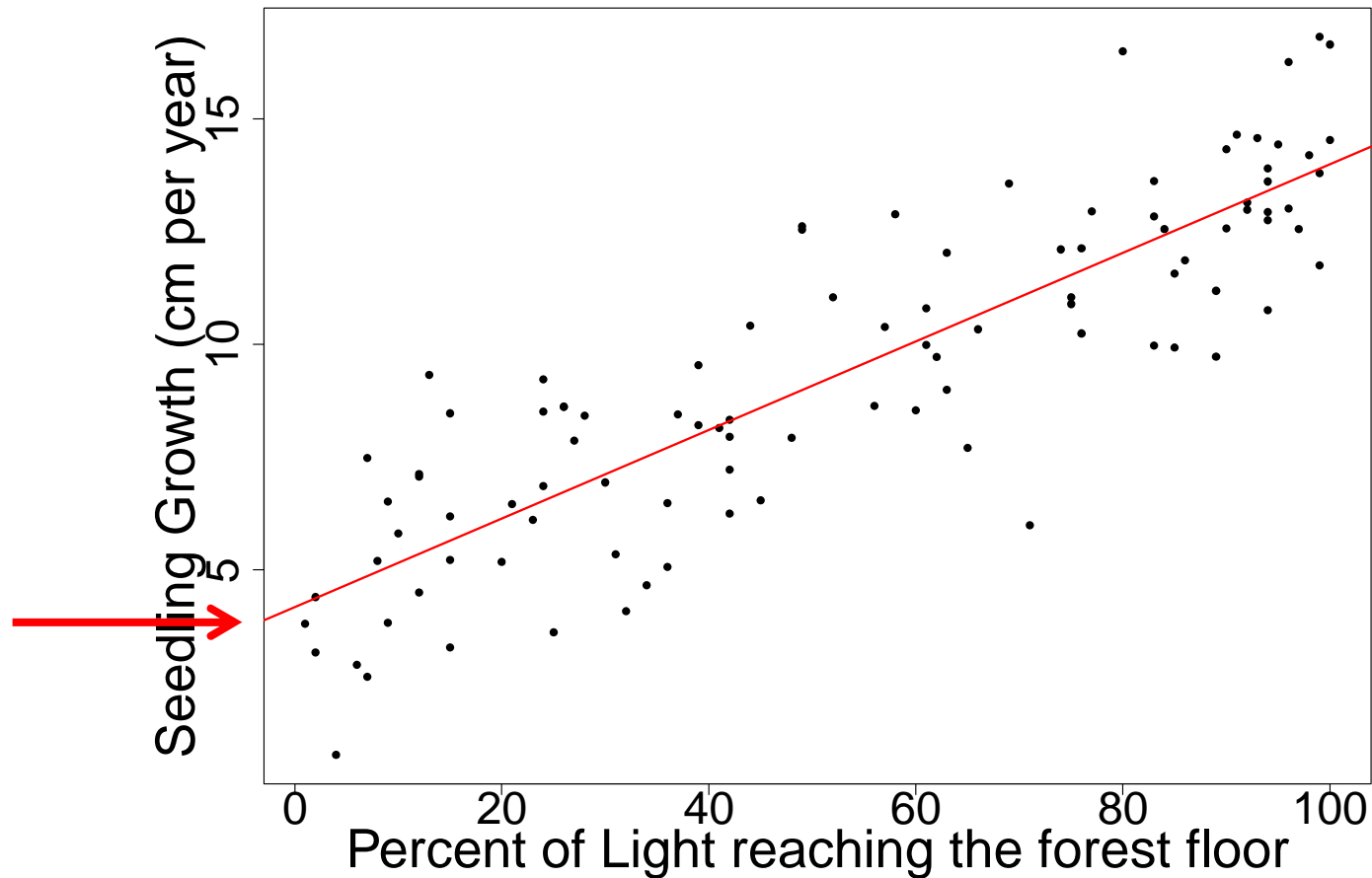
F-statistic: 286.1 on 1 and 98 DF, p-value: < 2.2e-16

Linear regression in R: lm()

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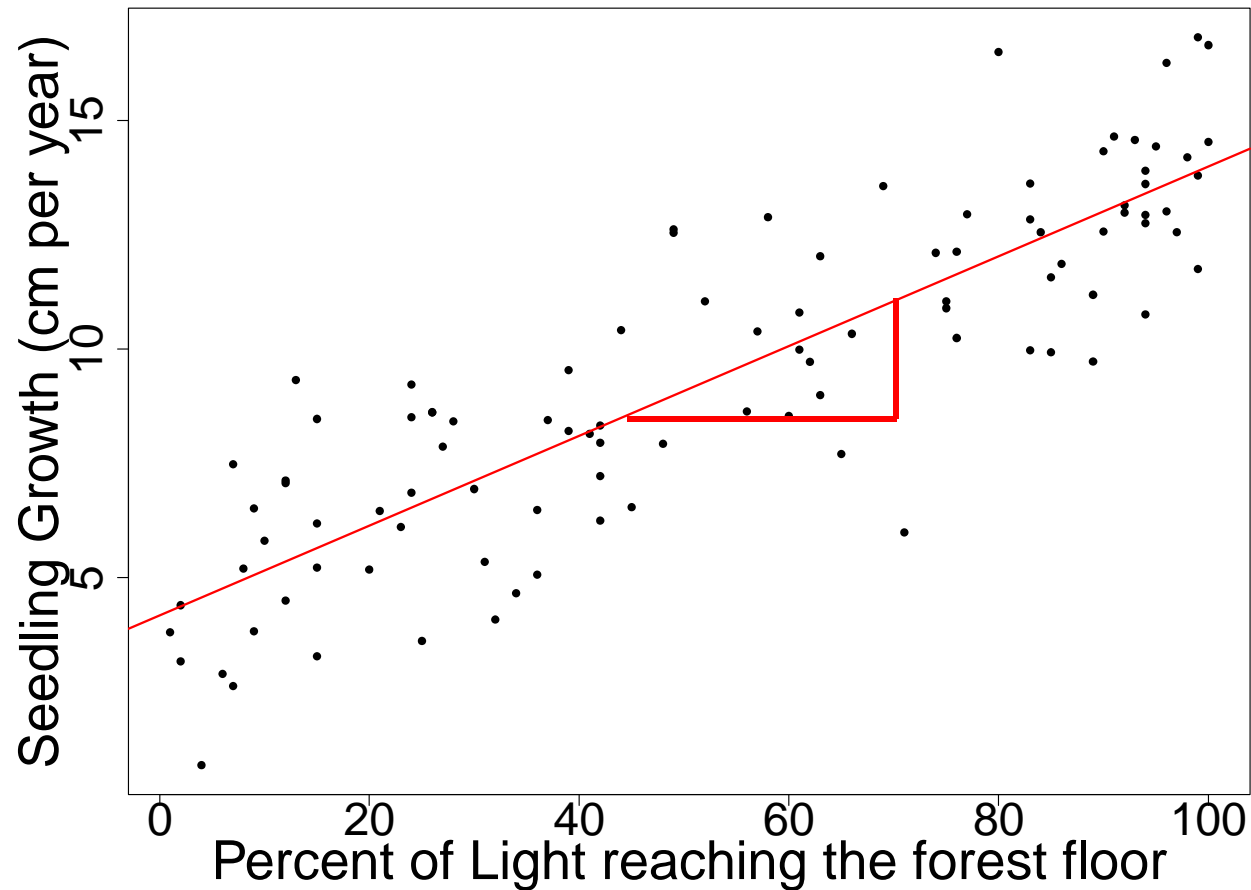


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SE of the mean:

SD/ \sqrt{n}

SE: Standard Error

SD: Standard Deviation

n: population size

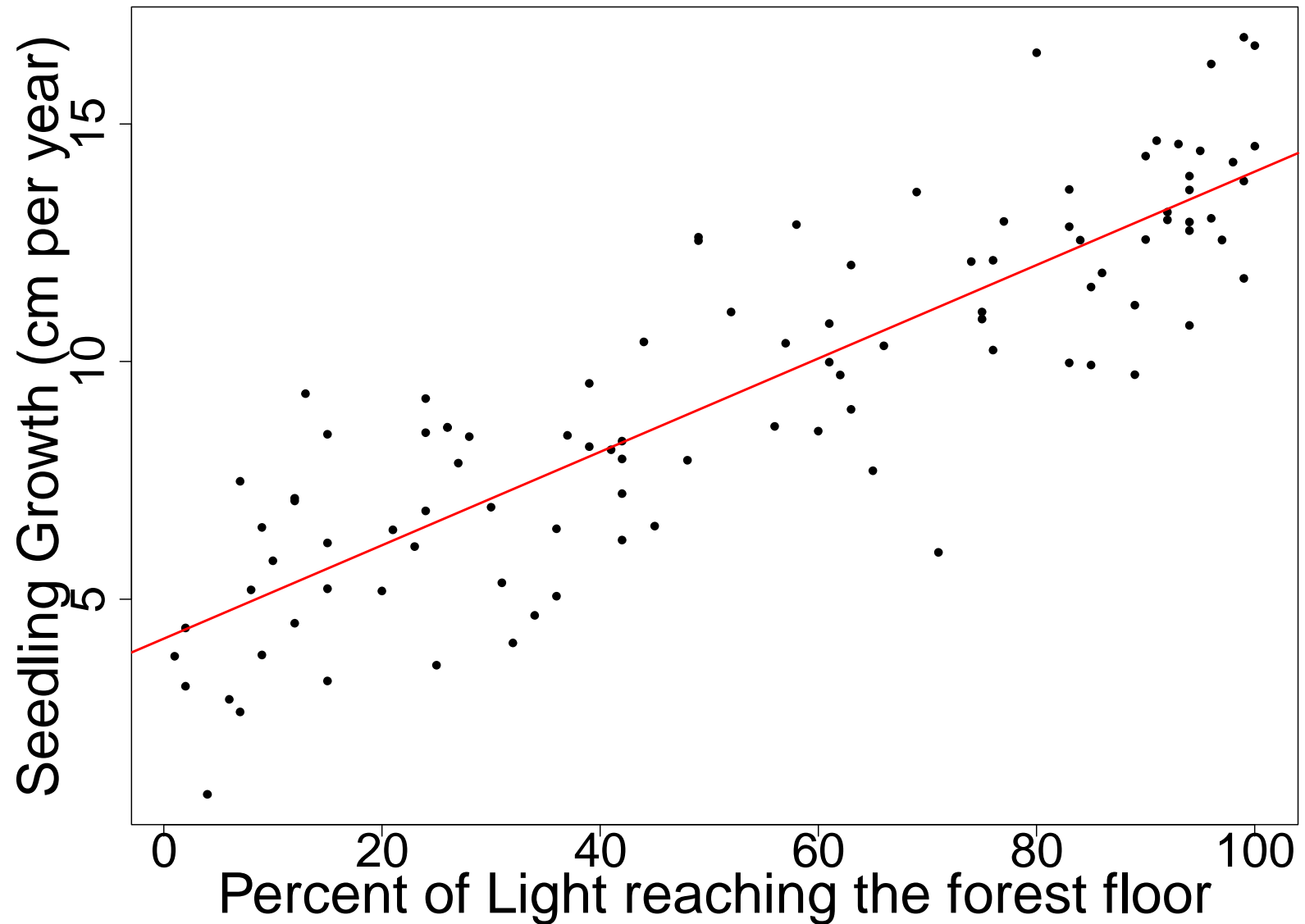
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Linear regression in R: lm()

```
> anova(model.lm)
```

```
Analysis of Variance Table
```

```
Response: growth
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
light	1	983.50	983.50	286.11	< 2.2e-16 ***
Residuals	98	336.88	3.44		

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

- Gives the same output as `summary(aov(model.aov))`

ANOVA is a special case of LM

- Confusing because we can use the function `anova()` to get a table of analysis of variance whatever the model was made with (`aov()` or `lm()`)
- ANOVA = special case of LM when X:factors
- `lm()` in R works for anova, but the way it's shown is a bit different.
- Same assumptions

ANOVA is a special case of LM

- In the end, you can always use `lm()` :
 - As long as your Y is continuous, and all the assumptions are met;
 - You can use the function `anova(model)` to get the degrees of freedom, SS, MS, F-test and p-value of every X variable in your model
 - You can use the function `summary(model)` to get the estimated means and SE of each levels, and the differences between levels

Exercise: Forest: ANCOVA (ANalysis of COVAriance)

- Productivity: continuous Y variable that we want to explain
- Forest type: factorial X variable
- Species Diversity: continuous X variable

- ANCOVA: $Y \sim \text{fact.X} * \text{cont.X}$