Outline for today

- Random vs fixed effects

- Two-factor example

- Why the calculations are different with random effects

- Unbalanced designs with random effects

- Examples of experiments with random effects

- Linear mixed-effects models

- Example: Estimating repeatability of a measurement

- Assumptions of linear mixed-effects models

- An example violating assumptions, with solutions

What are fixed effects

Fixed effects are <u>predetermined</u> categories of a variable, of <u>direct interest</u>, and are <u>repeatable</u>. An experiment with the same treatment levels could be repeated.

For example:

- medical treatments in a clinical trial

- predetermined doses of a toxin

- diet or fertilization treatments

- age groups in a population

- habitat, season

Any conclusions reached in the study about differences among groups can be applied <u>only</u> to the groups included in the study. The results cannot be generalized to other treatments, habitats, etc. not included in the study.

Example of factorial experiment with fixed effects

Field transplant experiment to investigate how herbivores affect the abundance of the red alga, *Mazzaella parksii* in the intertidal habitat of coastal Washington State using (Harley 2004). I analyzed a subset of treatments:

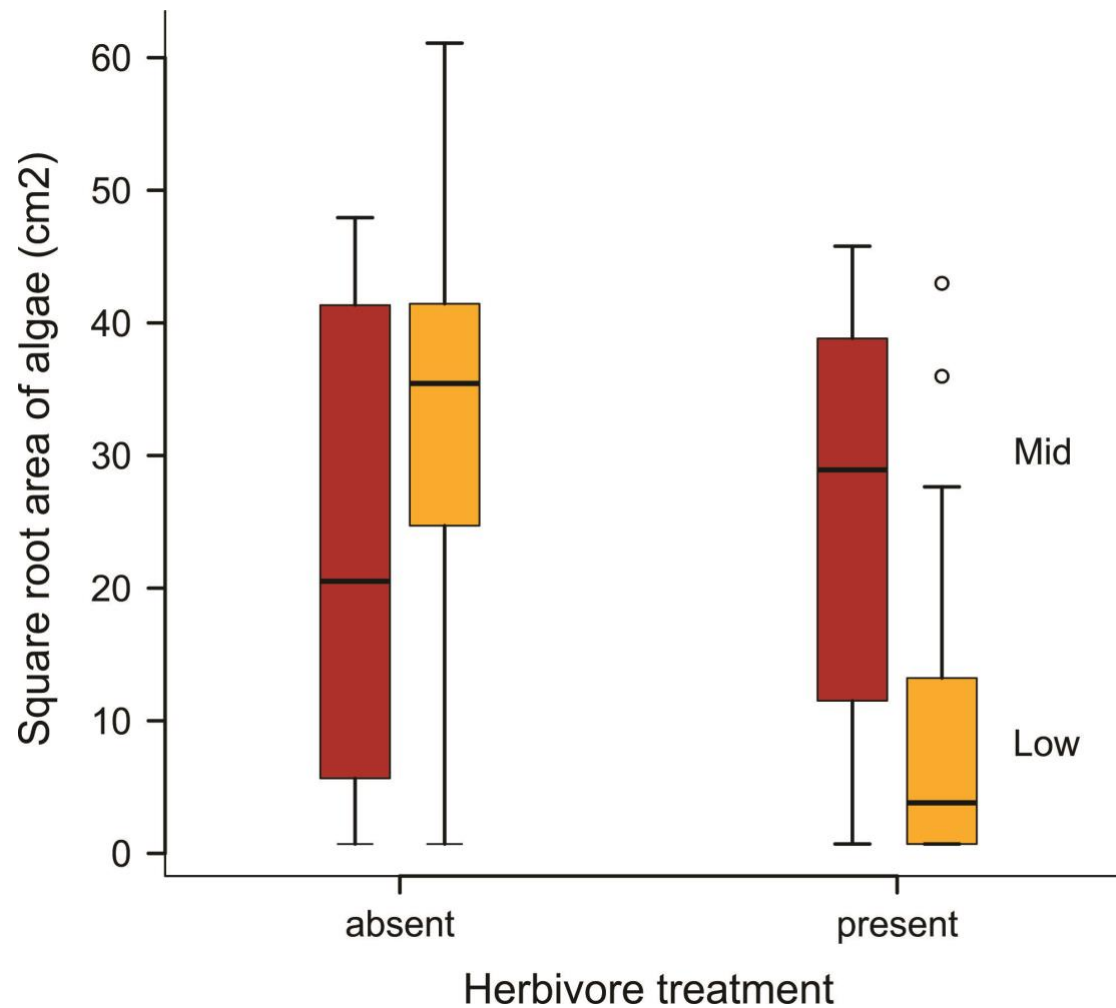|	herbivory treatment	
intertidal zone	**present**	**absent**
low	$n = 16$ plots	$n = 16$ plots
mid	$n = 16$ plots	$n = 16$ plots

$N = 64$ plots in a completely randomized design

Factorial experiment with fixed effects

Response variable: surface area of red alga, *Mazzaella parksii* in plots.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2$$

Linear model for factorial experiment with fixed effects

```
z <- lm(sqrtarea ~ herbivores * zone)
```

The denominator of the F statistic for the treatment effect is $MS_{residual}$

Source	SS	df	MS	F	P
zone	89	1	89	89/238= 0.37	0.54
herbivory	1512	1	1512	1512/238= 6.36	0.01
zone*herbivory	2617	1	2617	2617/238= 11.0	<0.01
residual (error)	14271	60	238		

Because each of the 64 plots is independent, the residual mean square ($MS_{residual}$) is the appropriate quantity to use as a reference when asking whether treatment mean squares are larger than expected by chance (i.e., whether F $\gg$ 1).

What are random effects

Randomly sampled categories of a variable, representing groups or clusters of measurements or units. An experiment with the same treatment levels could *not* be repeated. For example:

- randomly sampled families made up of siblings

- randomly sampled subjects measured repeatedly

- randomly placed transects each of multiple quadrats in a sampling survey

- arbitrary field plots each growing multiple plants

- arbitrary environment chambers each containing many aquariums

Groups are assumed to be randomly sampled from a *population of groups*. Therefore, conclusions reached about groups *can* be generalized to this population.

What are random effects

In some cases, the random effects are of no interest themselves – a nuisance.

- field plots each with many plants

- environment chambers containing aquariums

In other cases, measuring the variance associated with each level of random groupings is a major point of the study.

- families of siblings (to estimate heritability, etc)

- subjects measured repeatedly (to estimate repeatability)

- transects each of multiple quadrats (to estimate α- and β-diversity)

Repeated measurements of groups are not independent.

Failing to model random effects leads to pseudoreplication. Modeling random effects properly (using mixed effects models) avoids pseudoreplication.

Factorial experiment when one of the factors is random

Futuyma and Philippi (1987)

Fall cankerworm, *Alsophila pometaria*

*http://cfs.nrcan.gc.ca/subsite/glfc-sugarbush/alsophila-pometaria-images*

Caterpillars of the fall cankerworm feed on the leaves of hardwood trees. Adult female moths are wingless. Many reproduce clonally, producing only daughters genetically identical to themselves.

Research question: What is the effect of tree species on growth; and how much do clones vary in growth? This is a not a question about specific clones but about the population of clones.

Factorial experiment when one of the factors is random

Design: Sample 9 female moths from a population in NY. Raise larvae from 9 clones on leaves of 4 tree species. Measure growth after 15 days.
Two factors: **Tree species** (fixed), **Clone** (random)
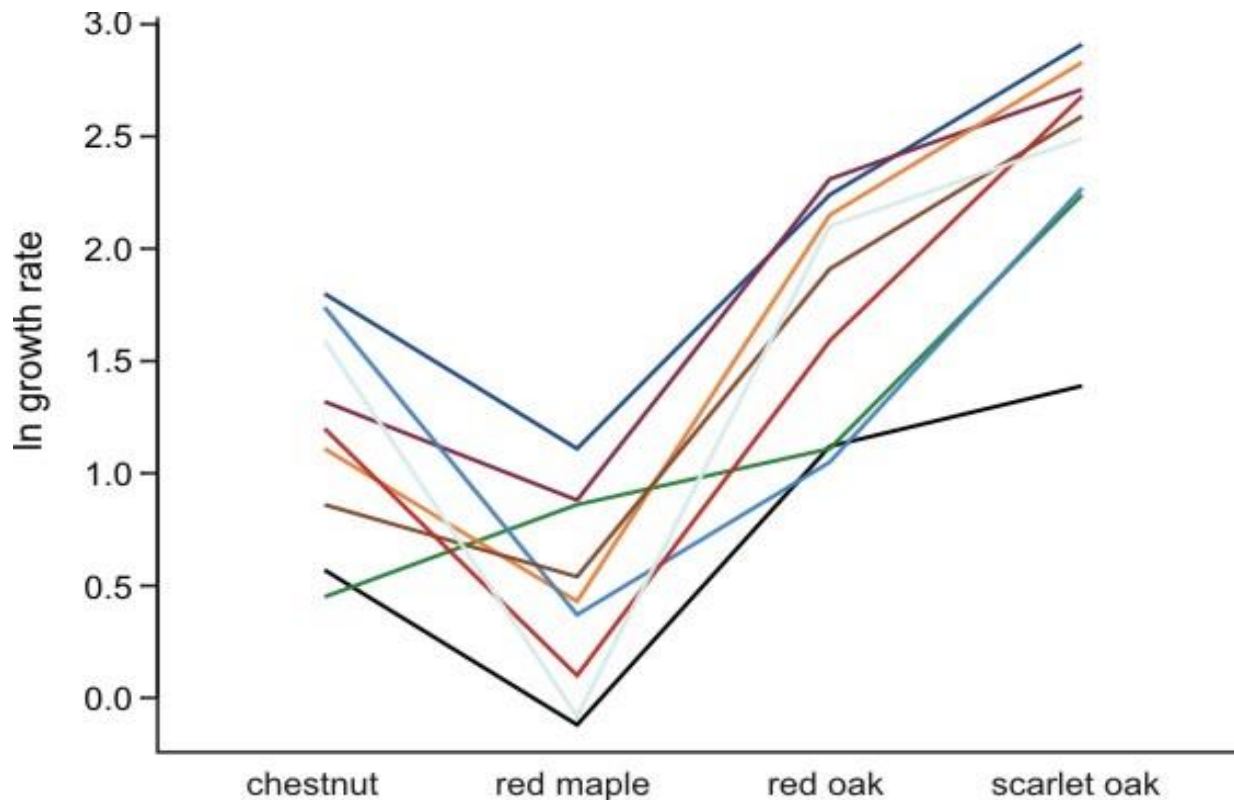
Interaction plot:

Mean growth of caterpillars from 9 families (clones) raised on four tree species.
$N = 326$ caterpillars total.

Factorial experiment when one of the factors is random

Caterpillars from the same clone are <u>not independent</u>. There are 326 caterpillars but only 9 clones. In this case the residual mean square ($MS_{residual}$) of a linear model fit is no longer the appropriate quantity to use as a reference when asking whether treatment mean squares are larger than expected by chance. To do so would commit pseudoreplication.

Instead, the variance among clones is the key to testing treatment effects.

Always report df with *F*-statistic in your papers to prove you analyzed such data correctly.
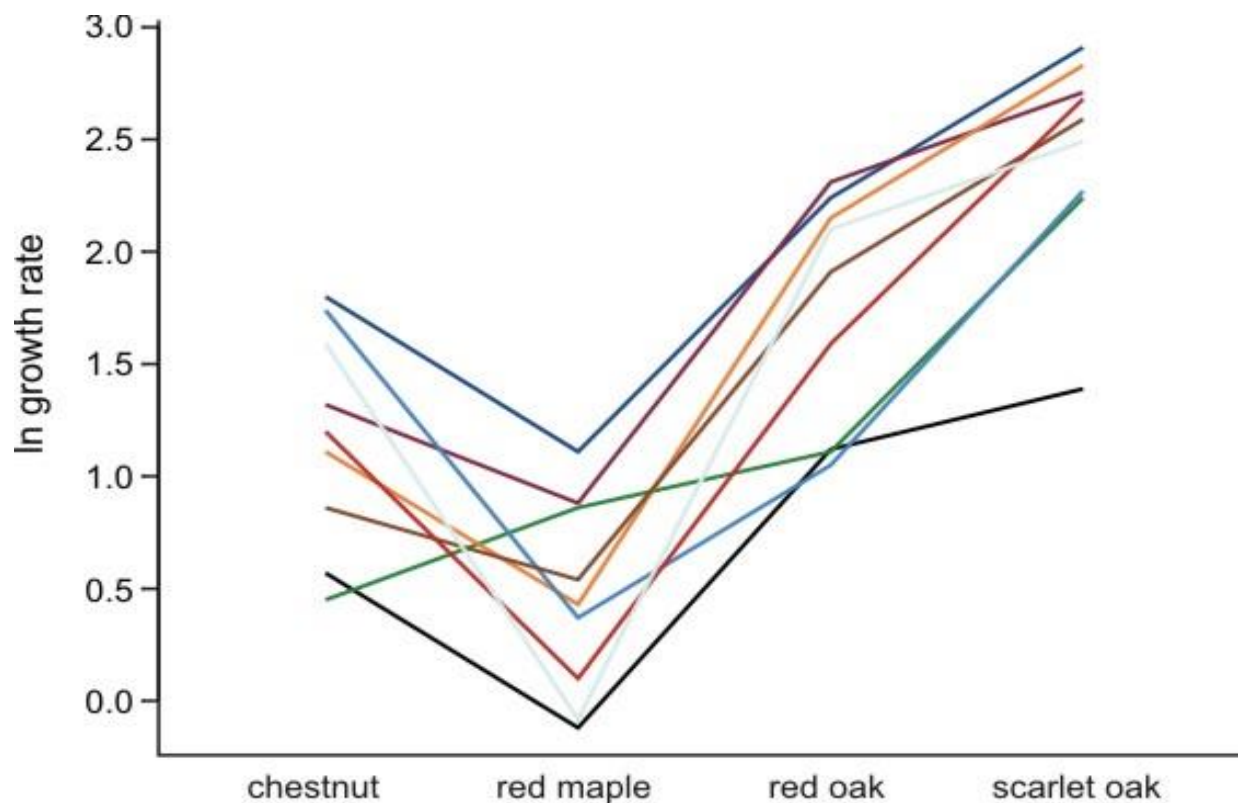
Factorial experiment when one of the factors is random

The presence of a random factor adds another layer of random variation. A 2-factor experiment with a random effect then has two components:

1) Within clone i, tree species affects caterpillar growth ± individual variation.

2) Mean effect of tree species on caterpillar growth is modeled is the mean of clone means ± clone variation.
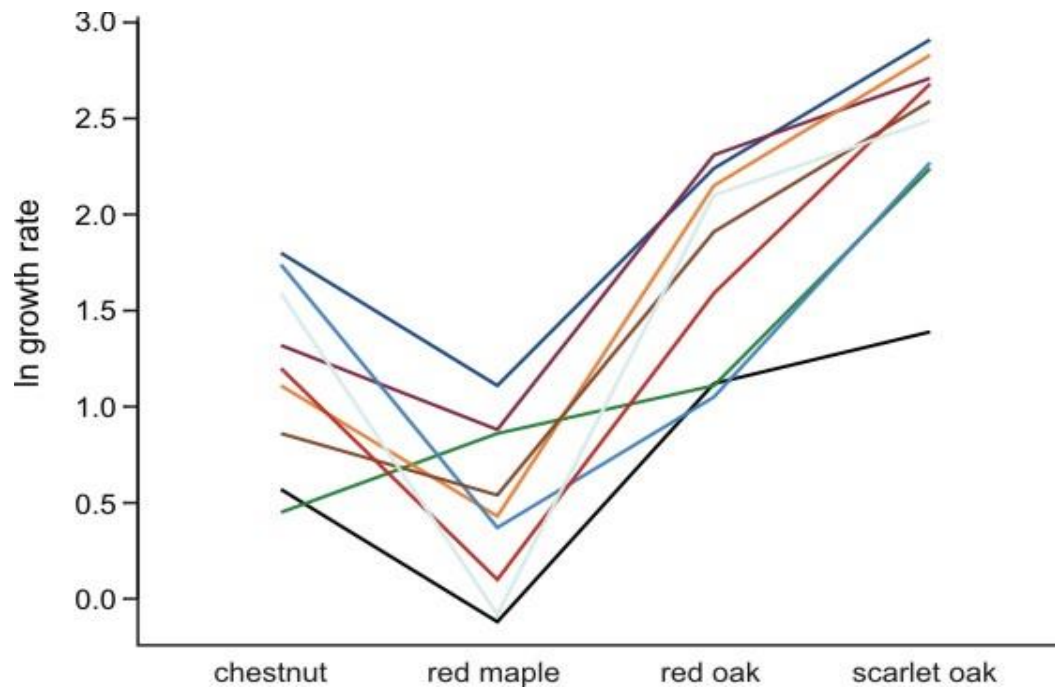
More reasons why analysis is different with random effects

1. Unlike fixed groups, the means of the specific random groups (e.g., clones) are not of direct interest. Instead, interest is focused on the <u>variance among the random groups</u> (*variance components*). A goal of the Futuyma and Philippi experiment was to *estimate* these variances.

2. When a design including random effects is <u>unbalanced</u>, the standard formulas for *F* statistics (as calculated above in the case of fixed effects) are not *F*-distributed. Standard ANOVA table calculations don't work with unequal sample sizes. Sorry!

3. With unbalanced designs, mixed models calculate approximate *F*-statistics and degrees of freedom for tests of fixed effects. Results are approximate.

How to know when you have random effects in your study

You have random effects:

- whenever your sampling design is nested: quadrats within transects; transects within woodlots; woodlots within districts.

- whenever your measurements are clustered spatially or temporally within randomly sampled units i.e., in *blocks*, which are typically analyzed as random effects.

- whenever you divide up plots, or families, clones, ponds, etc, and apply separate fixed treatments to subplots, or siblings, pond-halves, etc.

- whenever you take measurements on related individuals.

- whenever you measure subjects or other sampling units *repeatedly*.

Caution when analyzing random effects

Many statistical packages assume that all factors are fixed unless you instruct otherwise (e.g., JMP).

Designating factors as random takes extra work and probably a read of the manual.

In R, `lm` assumes that all effects are fixed. Do not use if you have random effects.

Instead, use linear mixed effects models to analyze random effects.

In R, use `lmer` (in the `lme4` / `lmerTest` package) or `lme` (in the `nlme` package) to analyze models containing random effects. These packages model the variance structure of random effects explicitly.

Tests of treatment effects using the Kenward-Roger or Satterthwaite approximations for degrees of freedom are most accurate (only available in `lme4` / `lmerTest` package).

Attributes of linear mixed-effects models

- Linear models that include both fixed and random effects.

- There is a different error variance for each level of random variation.

- Estimation and testing are based on restricted maximum likelihood (REML), which can handle unequal sample size.

- *P*-values for tests of fixed effects are conservative when designs are unbalanced.

- Implemented in the `lme4/lmerTest` and `nlme` packages in R.

Example 1: Study of measurement repeatability (simple nested design)

The walking stick, *Timema cristinae*, is a wingless herbivorous insect on plants in chaparral habitats of California. Nosil and Crespi (2006) measured individuals using digital photographs. To evaluate measurement repeatability they took two separate photographs of each specimen. After measuring traits on one set of photographs, they repeated the measurements on the second set.
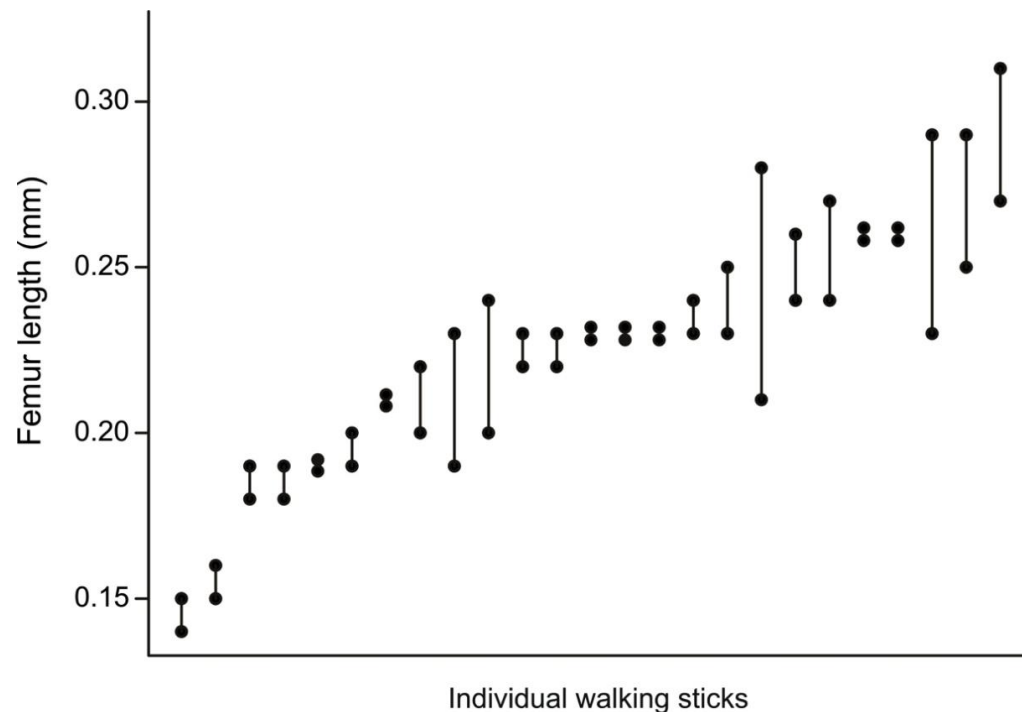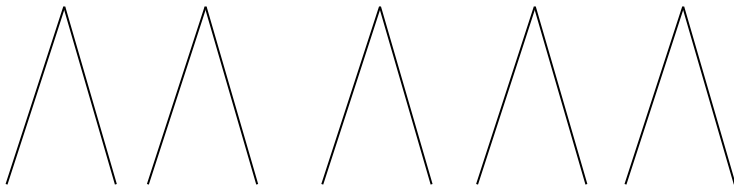
Example 1: Study of measurement repeatability (simple nested design)

Fit the data with a linear mixed model: $Y_i = \beta_0 + b_i + \text{error}$
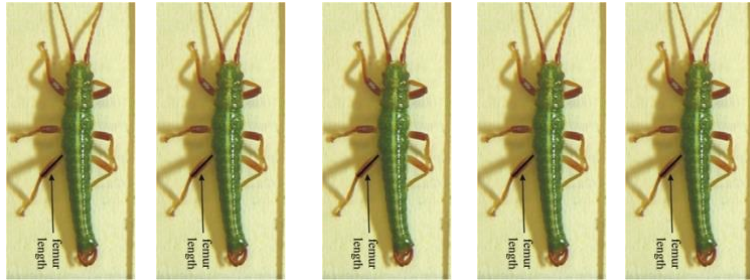
individual bugs i

.....

1   2 3   4 5   6 7   8 9   10   (measurements)

The individual bugs are the random groups in this study, with two repeated measurements per group.

Model has two parts, each with its own source of error variance:

1) Random part: the measurement of individual bug i: $b_i \pm$ measurement error.

2) Fixed part: the mean of bug means: $\beta_0 \pm$ bug error (i.e., variation among bugs)

Example 1: Study of measurement repeatability (simple nested design)

```
library(lmerTest)

z <- lmer(femurlength ~ 1 + (1|individual))
```

Fixed part of the formula:

```
femurlength ~ 1
```

Random part of the formula

```
+ (1|individual)
```

Example 1: Study of measurement repeatability (simple nested design)

The **fixed** part of the formula instructs R to fit a constant (intercept) based on the fitted values of the random groups (individual bugs)

```
femurlength ~ 1
```

The ***random*** part of the formula instructs R to fit a constant (an intercept) to the two measurements within each individual. This yields a fitted value for each individual walking stick.

```
+ (1|individual)
```
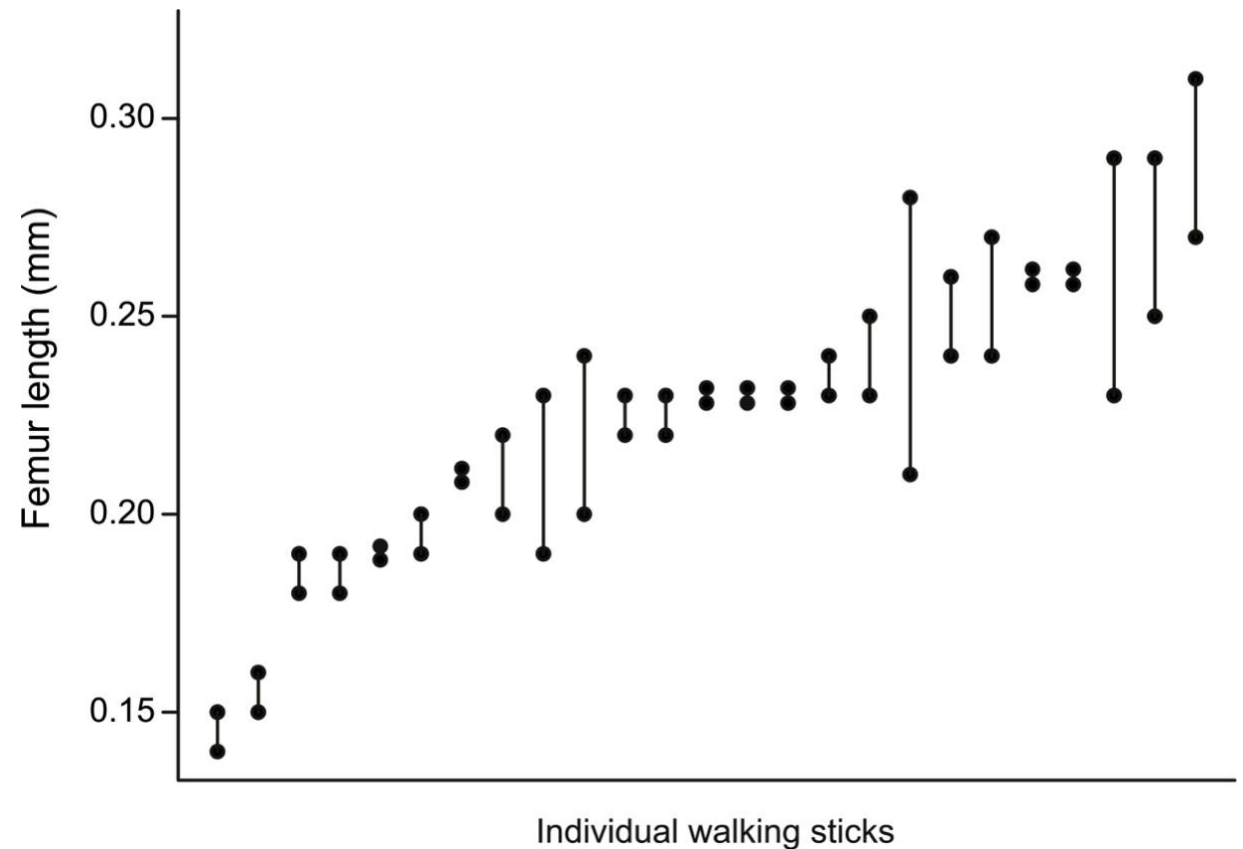
Example 1: Study of measurement repeatability (simple nested design)

```
z <- lmer(femurlength ~ 1 + (1|individual))
```

`fitted(z)` # yields best linear unbiased predictors (BLUPs):

R fits them all together, rather than in two stages, yielding variance components and BLUPs.

The BLUPs are not the means for each insect. They are "shrunk" towards the centre compared with the group means.
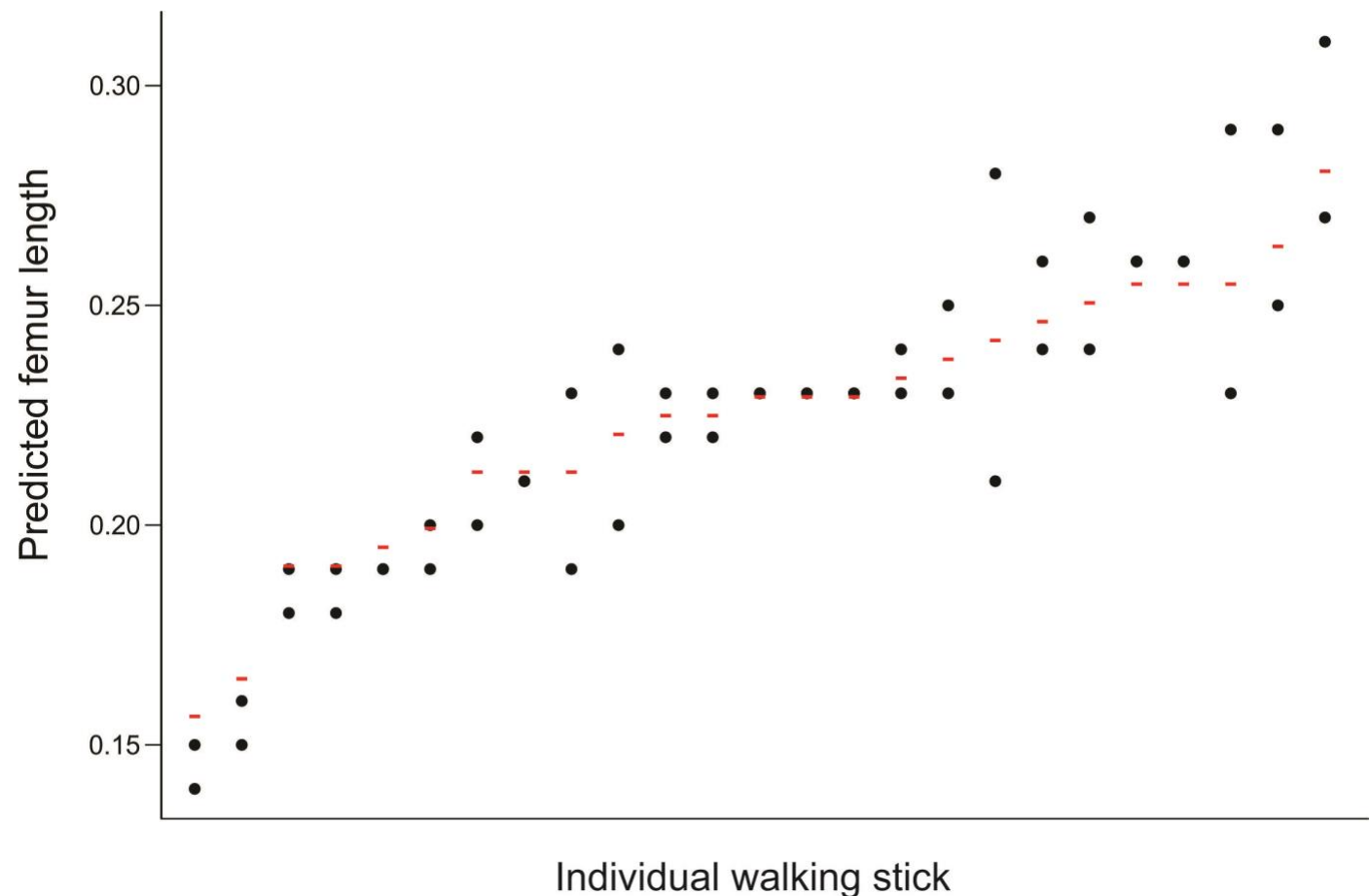
Example 1: Study of measurement repeatability (simple nested design)

`VarCorr(z)` extracts the variance components (square the standard deviations to obtain the variances)

| Groups	Name	Std.Dev.	
individual	(Intercept)	0.032464	= variance among random groups (individuals)
Residual		0.018868	= variance within random groups

We can use these quantities to calculate the fraction of variation that is among individuals (repeatability):

repeatability = σ^2_{among} / (σ^2_{among} + σ^2_{within})

estimate of repeatability = 0.032464^2 / (0.032464^2 + 0.018868^2)

$$= 0.75$$

Example 2: "Subjects by treatment" repeated measures design

Cronly-Dillon and Muntz (1965) used the optomotor response to measure color vision in the goldfish. Each fish was tested at different wavelength in <u>random order</u>.
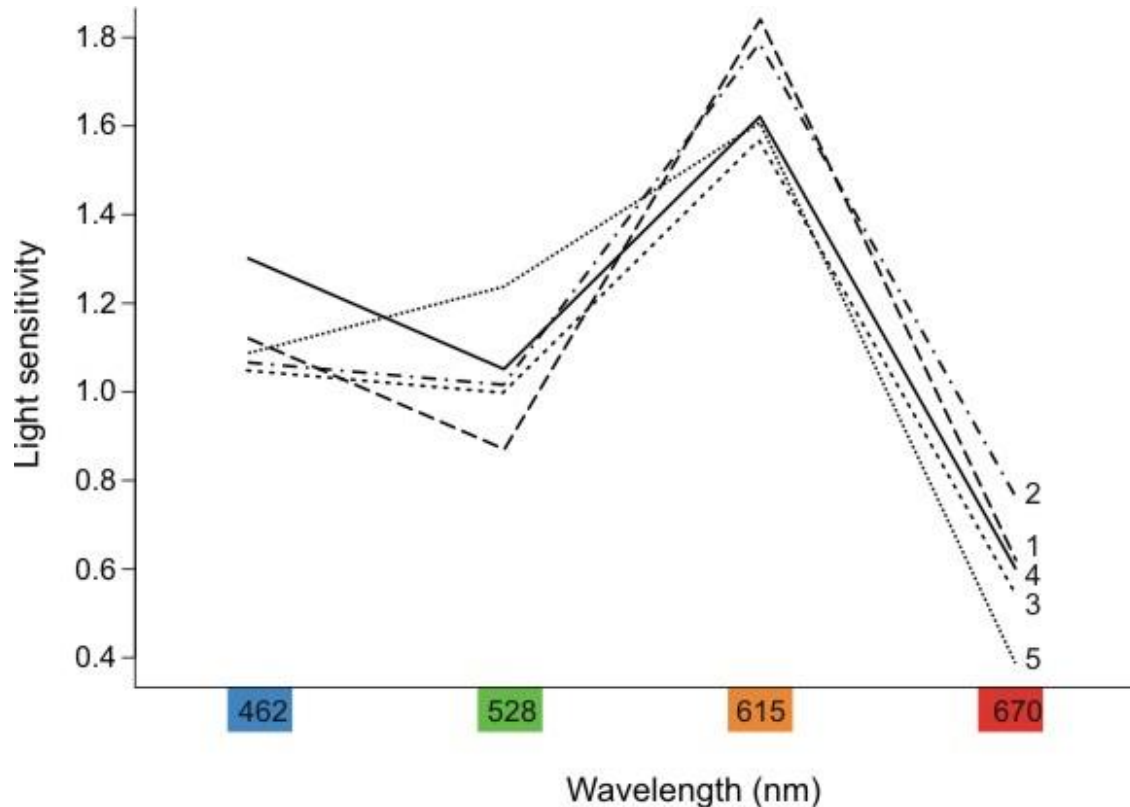
A large value indicates that the fish has high sensitivity --- it can detect a low light intensity.

Factors:

Wavelength (fixed, repeated measure)

Fish (random)

Light sensitivity of 5 goldfish to specific wavelengths of light.
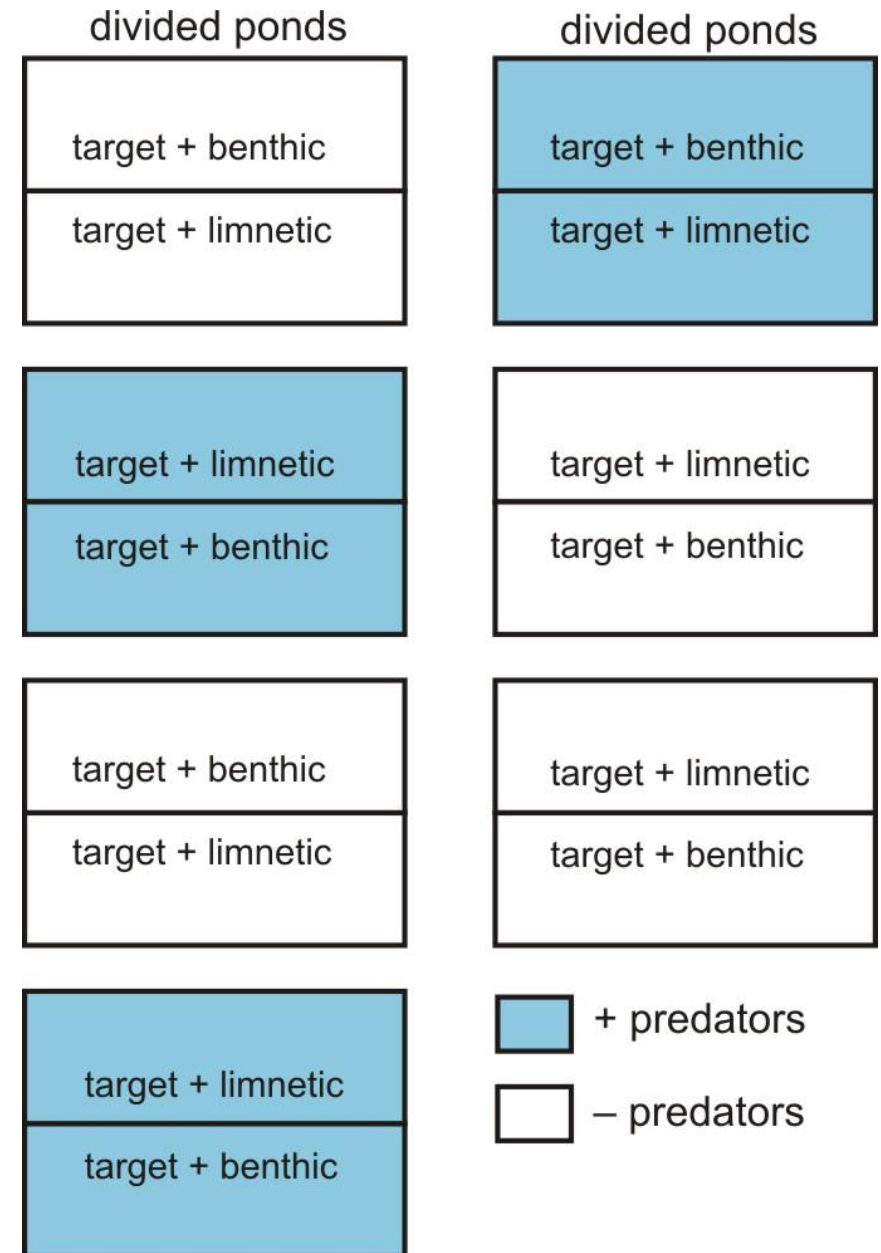
Example 3: Split plot design

Factors:

Predation treatment (fixed), whole ponds

Competition treatment (fixed), split ponds

Pond (random)

Assumptions of linear mixed-effects models

- Variation within groups follows a normal distribution with equal variance among groups.

- Groups are randomly sampled from a "population" of groups (i.e., are independent and sampled without bias).

- Group effects have a normal distribution.

- Replicates within groups are also randomly sampled (i.e. independent and sampled without bias).

- No carry-over between repeated measurements on the same subject.

- Sphericity: the variances of the differences between all pairs of factor levels are equal. (Problems can arise when one of the factors is time.)

Example 4: "Subjects by trials" repeated measures design

GRANIVORY IN A DESERT ECOSYSTEM: EXPERIMENTAL EVIDENCE FOR INDIRECT FACILITATION OF ANTS BY RODENTS[1]

D. W. DAVIDSON
Department of Biology, University of Utah, Salt Lake City, Utah 84112 USA

AND

R. S. INOUYE[2] AND J. H. BROWN
Department of Ecology and Evolutionary Biology, University of Arizona, Tucson, Arizona 85721 USA

Factors:
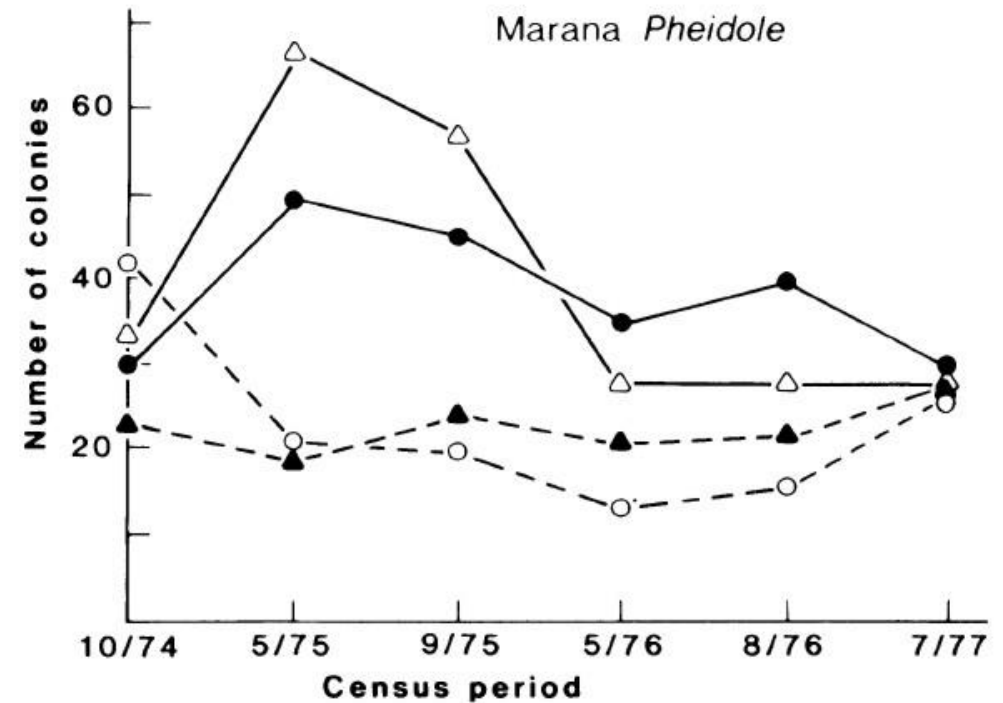
Rodent treatment (fixed)

Date (fixed)

Plot (random)

FIG. 3. Changes in density of *Pheidole* spp. (including *P. xerophila tucsonica, P. sitarches,* and *P. gilvescens*) on two rodent removal plots (——) and two control plots (— —) at Marana, Arizona over a 2¾-yr period.

Example 4: Warning about "subjects by trials" repeated measures design

Factors:

Rodent treatment (fixed)

Census date (fixed)

Plot (random)

Tempting to analyze these data using a linear mixed-effects model:

Fixed part of formula:

```
ncolonies ~ treatment + date
```
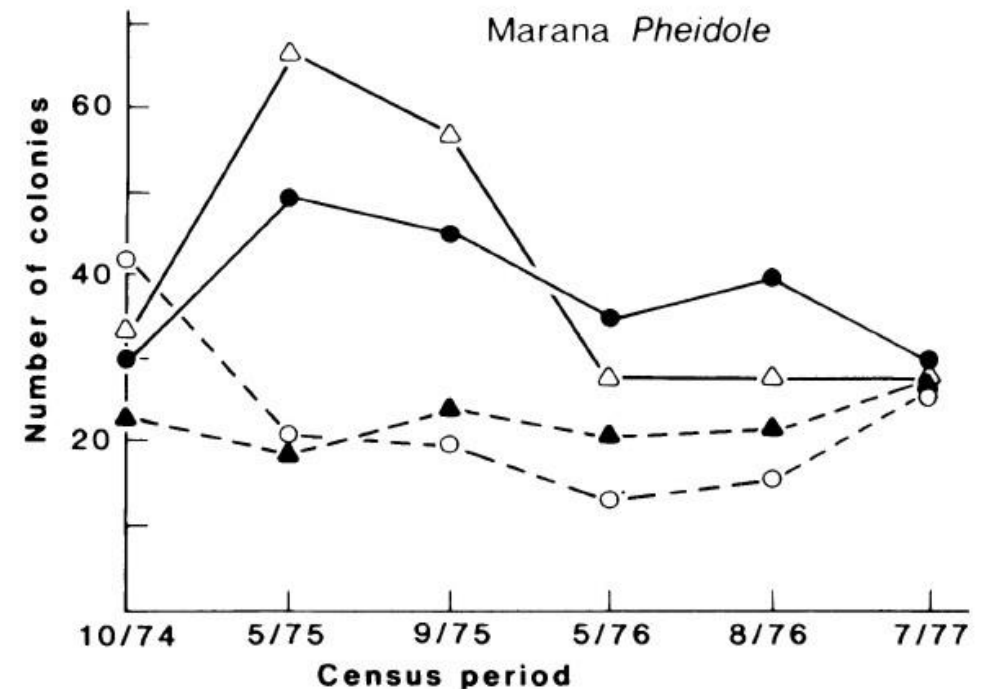
Random part of formula:

```
+ (1|plot)
```


FIG. 3. Changes in density of *Pheidole* spp. (including *P. xerophila tucsonica, P. sitarches,* and *P. gilvescens*) on two rodent removal plots (——) and two control plots (− −) at Marana, Arizona over a 2¾-yr period.

Example 4: Warning about "subjects by trials" repeated measures design

Problem: Including Census date as a factor would likely lead to a violation of the spericity assumption: among plots, the variance of the pairwise difference between values of the response variable will be lower between nearby dates than dates that are farther apart.

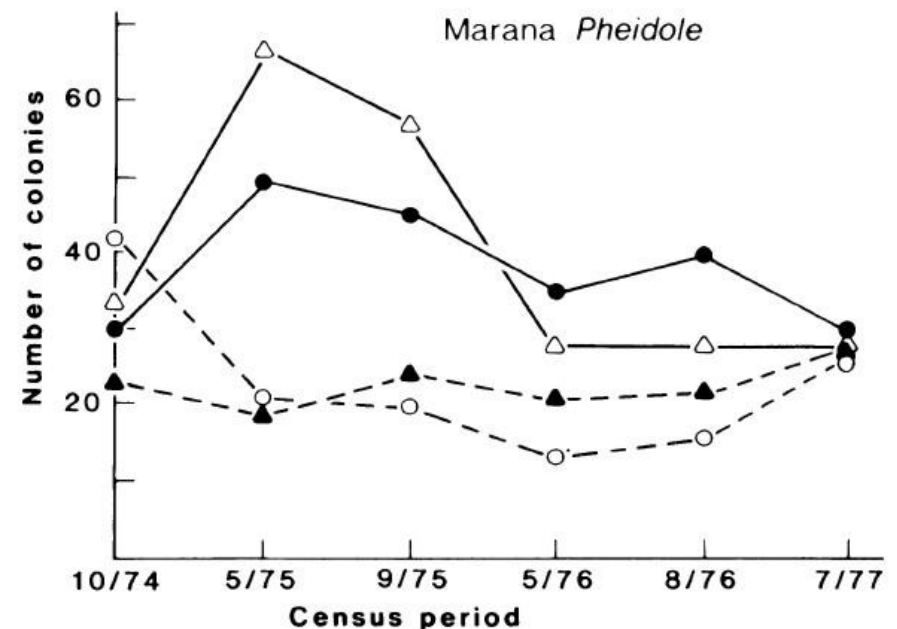Increases Type 1 errors
(*P*-values inaccurate)

FIG. 3. Changes in density of *Pheidole* spp. (including *P. xerophila tucsonica, P. sitarches,* and *P. gilvescens*) on two rodent removal plots (———) and two control plots (— —) at Marana, Arizona over a 2¾-yr period.

Example 4: Warning about "subjects by trials" repeated measures design

Analyses of growth curves in time might have the same problem.

Any repeated measures experiment in which the treatment levels are given in the same sequence (i.e., not in random order) might have the same problem.

Sphericity correction is possible.

`Anova()` in `car` package:

Mauchly test for Sphericity

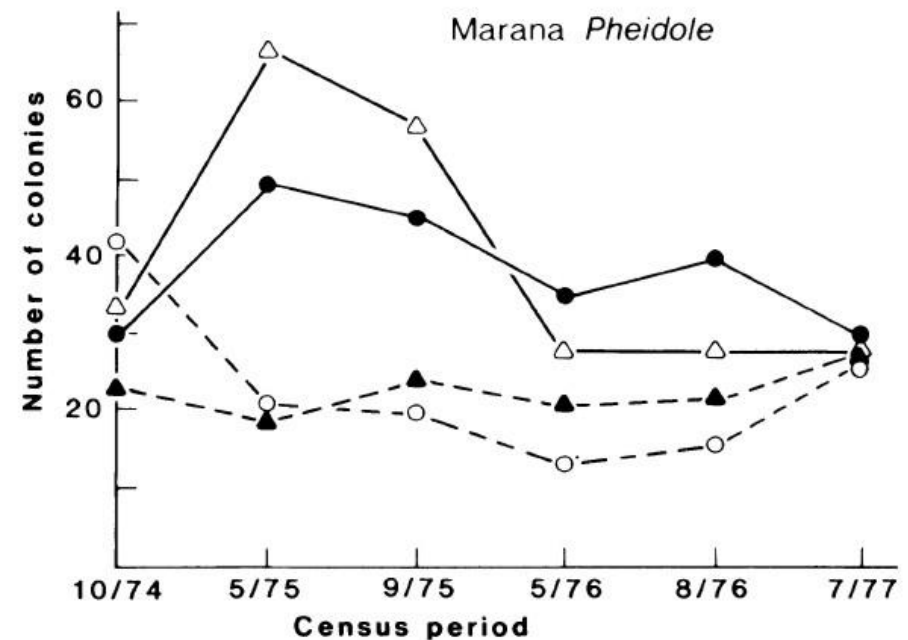Greenhouse-Geisser and Huynh-Feldt corrections to *P*-values.

FIG. 3. Changes in density of *Pheidole* spp. (including *P. xerophila tucsonica, P. sitarches,* and *P. gilvescens*) on two rodent removal plots (———) and two control plots (— —) at Marana, Arizona over a 2¾-yr period.

Where to get further advice

I have found Quinn & Keough to be very useful in understanding design and assumptions of mixed-effects models (though it won't help you with modeling using maximum likelihood in R).

Quinn & Keough 2002. Experimental design and data analysis for biologists

Online books on mixed-effects models in R (see Books tab at course web site):

Pinheiro and Bates (2000). Mixed-effects models in S and S-PLUS.

Zuur et al (2009). Mixed effects models and extensions in ecology with R.

Article:

Bates, Douglas, et al. 2015. Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software* 67: 1-48.

Discussion paper for next week:

Murtaugh (2007) Simplicity and complexity in data analysis.
Ecology 88: 56–62.

Presenters: _____ & _____

Moderators: _____ & _____

Homework assignment 2

Obtain data set from supervisor/lab and fit a linear model in R.

Details on "Homework" page on course web site

Due Friday, November 2.