

Statistics for the Sciences

Split-plot Designs

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Outline

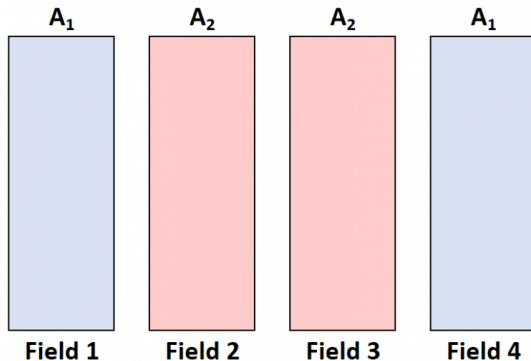
- Split-plot design
- Lab

Split-plot design

- A **split-plot design** is an experimental design in which researchers are interested in studying two factors in which:
 - ▶ One of the factors is 'easy' to change or vary.
 - ▶ One of the factors is 'hard' to change or vary.
- This type of design was developed in 1925 by mathematician Ronald Fisher for use in agricultural experiments.
- To illustrate the idea of the split-plot design, consider an example in which researchers want to study the effects of two irrigation methods (Factor A) and two fertilizers (Factor B) on crop yield.
 - ▶ There are four treatments: $A_1B_1, A_1B_2, A_2B_1, A_2B_2$
 - ▶ Suppose there are only 4 fields (**experimental units**)
 - ★ A completely randomized design does not work

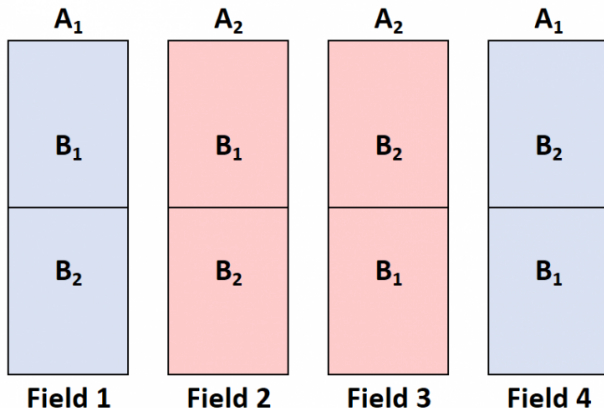
Split-plot design

- In this particular example, it's not possible to apply different irrigation methods to areas smaller than one field, but it is possible to apply different fertilizers to small areas.
 - ▶ We can randomly assign one of the irrigation methods (A_1 and A_2) to each field:



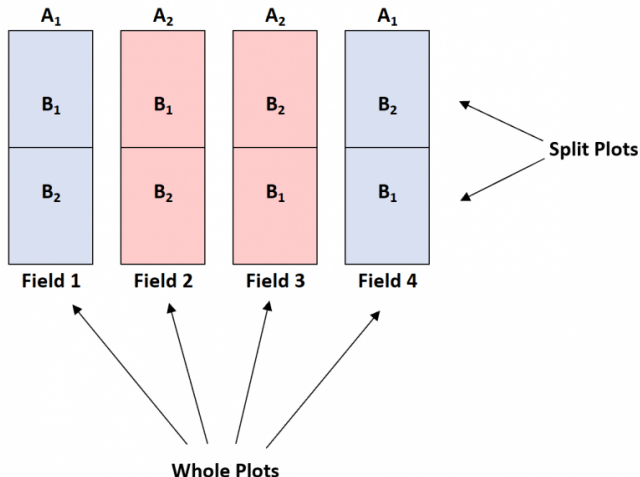
Split-plot design

- Then we can split each field in half and randomly assign one fertilizer (B_1 and B_2) to each half:



Split-plot design

- In this example, we have 4 “whole” plots and within each whole plot we have 2 “split” plots.



Split-plot design

Split-plot designs have two **advantages** over completely randomized designs:

- **Cost:** Since one of the factors in a split-plot design doesn't have to be changed for each split-plot, this means this type of design tends to be cheaper to carry out in practice.
- **Efficiency:** A split-plot design leads to an increase in precision in the estimates for all factor effects except for the whole-plot main effects.

Split-plot design

- Statistical model:

$$Y_{ijk} = \mu + \tau_i + \eta_{k(i)} + \beta_j + (\tau\beta)_{ij} + \varepsilon_{ijk},$$
$$i = 1, \dots, a; j = 1, \dots, b; k = 1, \dots, c$$

- Whole plot effects:
 - ▶ τ_i : whole plot treatment effects (factor A)
 - ▶ $\eta_{k(i)}$: whole plot errors
- Split-plot effects
 - ▶ β_j : the split-plot treatment (factor B)
 - ▶ $(\tau\beta)_{ij}$: interaction effects
 - ▶ ε_{ijk} : subplot random error

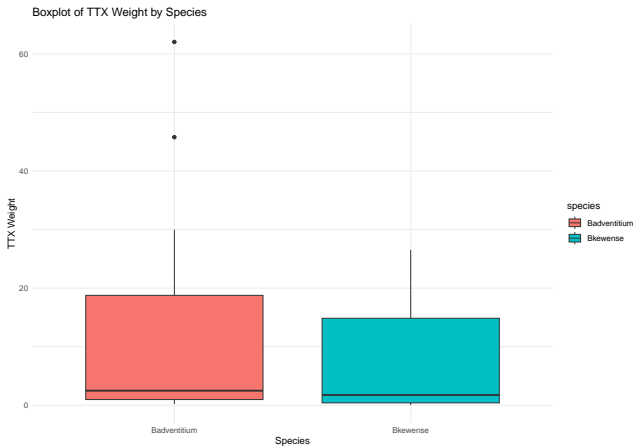
Split-plot design

- Example (`stokes.csv`): Stokes et al. (2014) studied the neurotoxin tetrodotoxin (TTX) in flatworms. The between-plots factor was flatworm species (fixed with two groups: *Bipalium adventitium* and *Bipalium kewense*) with individual flatworms (plots) nested within species. The within-plots factor was body segment (fixed with three groups: head, anterior body, posterior body) and each segment represented a “sub-plot”. The response variable was the TTX concentration of tissue adjusted for weight.
 - ▶ The main research questions were about the fixed effects of **species**, **body segment** and their **interaction** on TTX concentration, but the analyses also provide information about the variances associated with the random effects of individual within species and the random interaction between individuals within species and body segment.
 - ▶ Response Variable: TTX concentration `ttxweight`
 - ▶ Main factor: flatworm species with two levels: *Badventitium* and *Bkewense*
 - ▶ Whole plots: Individual flatworms nested within each species, `indiv`.
 - ▶ Split Plot Factor: Body segment with three groups: `h`, `b`, and `p`

Split-plot design

##	indiv	species	segment	finalttx	ttxweight	conc
## 1	1	Badventitium	h	59.942130	29.97106516	78.86305
## 2	1	Badventitium	p	18.330584	0.22354371	26.84862
## 3	1	Badventitium	b	36.837527	0.63512977	49.98230
## 4	2	Badventitium	h	62.033825	62.03382496	81.47767
## 5	2	Badventitium	p	46.976133	0.62634844	62.65555
## 6	2	Badventitium	b	61.316483	0.94333051	80.58099
## 7	3	Badventitium	h	29.104440	14.55221979	41.90968
## 8	3	Badventitium	p	50.882196	1.88452579	69.13188
## 9	3	Badventitium	b	66.454131	4.74672366	88.59680
## 10	4	Badventitium	h	46.064966	23.03248288	63.11034
## 11	4	Badventitium	p	55.289019	1.08409841	74.64041
## 12	4	Badventitium	b	64.832549	1.75223104	86.56982
## 13	5	Badventitium	h	40.353001	20.17650074	55.97038
## 14	5	Badventitium	p	42.508300	0.67473492	58.66451
## 15	5	Badventitium	b	83.629044	2.69771109	110.06544
## 16	6	Badventitium	h	45.773678	45.77367827	62.74623
## 17	6	Badventitium	p	75.437948	2.28599842	99.82657
## 18	6	Badventitium	b	66.198278	3.67768214	88.27698
## 19	7	Bkewense	h	108.396182	21.67923649	182.72076
## 20	7	Bkewense	p	58.131332	2.07611899	76.59955
## 21	7	Bkewense	b	6.653189	0.05544324	12.25188
## 22	8	Bkewense	h	100.120317	12.51503962	166.86719
## 23	8	Bkewense	p	26.944873	0.31699851	37.61648
## 24	8	Bkewense	b	50.761514	0.31925480	67.38728
## 25	9	Bkewense	h	78.199376	15.63987512	103.27835
## 26	9	Bkewense	p	9.360317	0.07091150	17.22953
## 27	9	Bkewense	b	49.695106	1.71362435	67.64801
## 28	10	Bkewense	h	51.972824	17.32427480	70.49516
## 29	10	Bkewense	p	49.734262	0.68129127	67.69696
## 30	10	Bkewense	b	50.483634	1.80298694	68.63367
## 31	11	Bkewense	h	75.669326	25.22310859	100.11579
## 32	11	Bkewense	p	19.082570	0.20518892	29.38234
## 33	11	Bkewense	b	76.367489	2.31416634	100.98849
## 34	12	Bkewense	h	53.084960	26.54247987	71.88533
## 35	12	Bkewense	p	49.266253	0.74645838	67.11195
## 36	12	Bkewense	b	44.945554	1.66465016	61.71107

Split-plot design

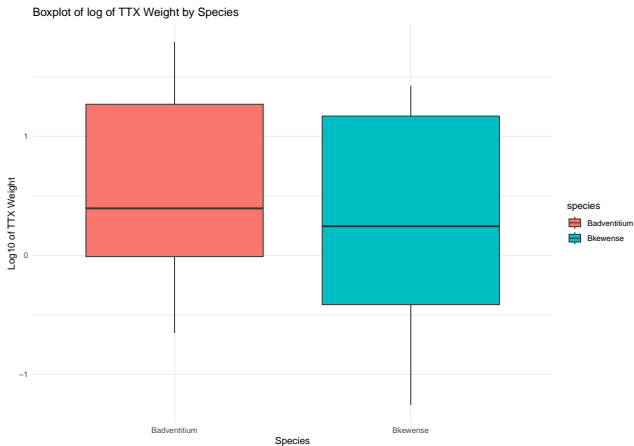


Split-plot design

- Consider log10 transformation of ttxweight

##	indiv	species	segment	finalttx	ttxweight	conc
## 1	1	Badventitium	h	59.942130	29.97106516	78.86305
## 2	1	Badventitium	p	18.330584	0.22354371	26.84862
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## 36	12	Bkewense	b	44.945554	1.66465016	61.71107

Split-plot design



Split-plot design

- LMER estimation with hypothesis testing

```
## Linear mixed model fit by REML. t-tests use Satterthwaite's method [
## lmerModLmerTest]
## Formula: logttweight ~ species + segment + species * segment + (1 | indiv)
## Data: stokes
##
## REML criterion at convergence: 41.9
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.81144 -0.39960  0.08694  0.72676  1.72771
##
## Random effects:
## Groups Name Variance Std.Dev.
## indiv (Intercept) 0.0000 0.0000
## Residual 0.1654 0.4067
## Number of obs: 36, groups: indiv, 12
##
## Fixed effects:
##              Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)    1.4600    0.1660 30.0000   8.793 8.36e-10 ***
## speciesBkewense -0.1780    0.2348 30.0000  -0.758  0.454
## segmentb      -1.1777    0.2348 30.0000 -5.015 2.23e-05 ***
## segmentp      -1.5192    0.2348 30.0000 -6.470 3.78e-07 ***
## speciesBkewense:segmentb -0.2171    0.3321 30.0000  -0.654  0.518
## speciesBkewense:segmentp -0.1482    0.3321 30.0000  -0.446  0.659
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) spcsBk sgmntb sgmntp spcsBkwns:sgmntb
## specisBkwns    -0.707
## segmentb      -0.707  0.500
## segmentp      -0.707  0.500  0.500
## spcsBkwns:sgmntb  0.500 -0.707 -0.707 -0.354
## spcsBkwns:sgmntp  0.500 -0.707 -0.354 -0.707  0.500
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see help('isSingular')
```

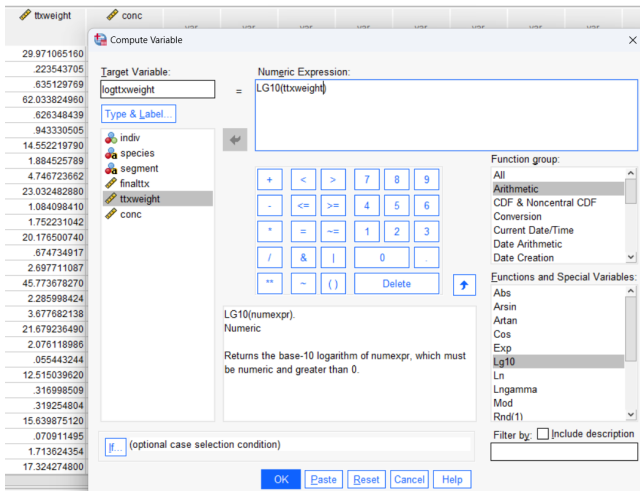
Lab

- ANOVA table

```
## Type III Analysis of Variance Table with Satterthwaite's method
##              Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## species           0.8087   0.8087     1     30  4.8890   0.03479 *
## segment          17.1494   8.5747     2     30 51.8402 1.844e-10 ***
## species:segment   0.0738   0.0369     2     30  0.2232   0.80128
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Lab

- After importing the data `stokes.csv`, add a variable of `log10` transformation of `ttweight`



Lab

- Click on Analyze → Mixed Models → Linear... and
▶ then click Continue

Linear Mixed Models: Specify Subjects and Repeated

Click Continue for models with uncorrelated terms.
Specify Subject variable for models with correlated random effects.
Specify both Repeated and Subject variables for models with correlated residuals within the random effects.

Subjects:

Repeated:

Repeated Covariance Type:

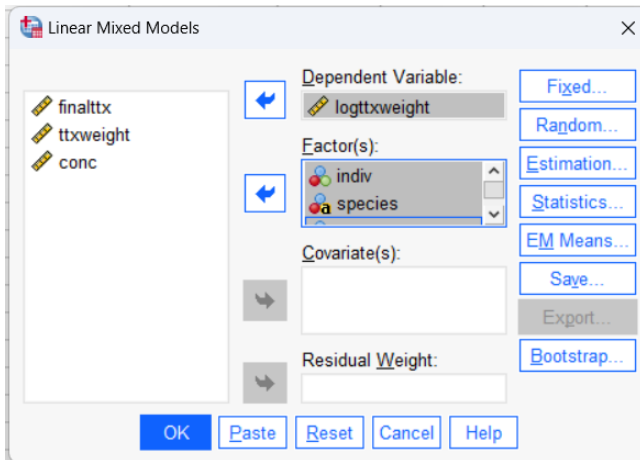
Kronecker Measures:

Spatial Covariance Coordinates:

indiv
species
segment
finaltx
ttweight
conc
logttweight

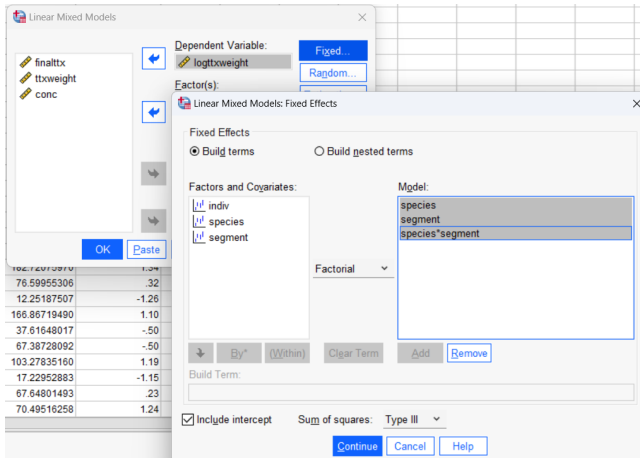
Lab

- Move the response variable to the Dependent Variable box and move the three factors indiv, species and segment to Factor(s) box.



Lab

- Click on Fixed Effects to specify the interaction between species and segment



Lab

- Click on the Random... tab. We build the nested term `indiv(species)`: individuals nested in species

Linear Mixed Models: Random Effects

Random Effect 1 of 1

Previous Next

Covariance Type: Variance Components

Random Effects

☐ Build terms ☒ Build nested terms ☒ Include intercept

Factors and Covariates: Model:

indiv
species
segment

Factorial

↓ By* (Within) Clear Term Add Remove

Build Term:

Subject Groupings

Subjects: Combinations:

Display parameter predictions for this set of random effects

Continue Cancel Help

Lab

- Click on the Random... tab. We build the nested term `indiv(species)`: individuals nested in species

Linear Mixed Models: Random Effects

Random Effect 1 of 1

Previous Next

Covariance Type: Variance Components

Random Effects

☐ Build terms ☒ Build nested terms ☒ Include intercept

Factors and Covariates: Model:

indiv
species
segment

Factorial

By* (Within) Clear Term Add Remove

Build Term:
indiv

Subject Groupings

Subjects: Combinations:

☐ Display parameter predictions for this set of random effects

Continue Cancel Help

Lab

- Click on the Random... tab. We build the nested term `indiv(species)`: individuals nested in species

Linear Mixed Models: Random Effects

Random Effect 1 of 1

Previous Next

Covariance Type: Variance Components

Random Effects

☐ Build terms ☒ Build nested terms ☒ Include intercept

Factors and Covariates: Model:

indiv
species
segment

Factorial

↓ By* Within Clear Term Add Remove

Build Term:
indiv()

Subject Groupings

Subjects: Combinations:

→

☐ Display parameter predictions for this set of random effects

Continue Cancel Help

Lab

- Click on the Random... tab. We build the nested term `indiv(species)`: individuals nested in species

Linear Mixed Models: Random Effects

Random Effect 1 of 1

Previous Next

Covariance Type: Variance Components

Random Effects

☐ Build terms ☒ Build nested terms ☒ Include intercept

Factors and Covariates: Model:

indiv
species
segment

Factorial

↓ By* Within Clear Term Add Remove

Build Term:
indiv(species)

Subject Groupings

Subjects: Combinations:

☐ Display parameter predictions for this set of random effects

Continue Cancel Help

Lab

- Click on the Random... tab. We build the nested term `indiv(species)`: individuals nested in species

Linear Mixed Models: Random Effects

Random Effect 1 of 1

Previous Next

Covariance Type: Variance Components

Random Effects

☐ Build terms ☒ Build nested terms ☒ Include intercept

Factors and Covariates:

- indiv
- species
- segment

Model:

- indiv(species)

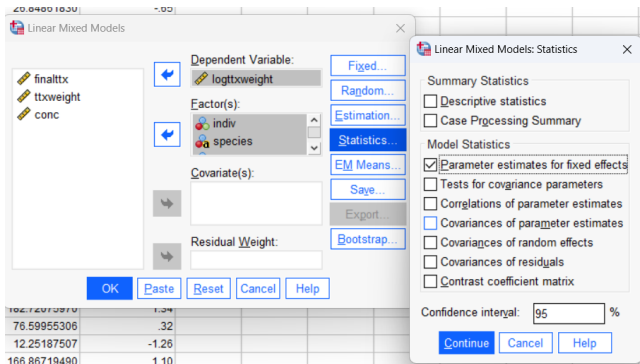
Build Term:

Subject Groupings

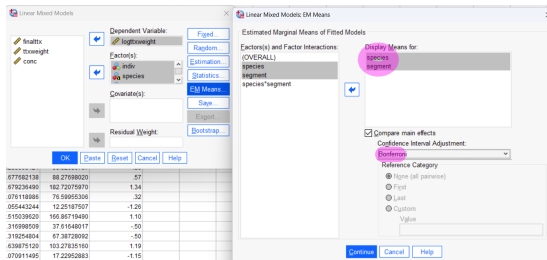
Subjects: Combinations:

☐ Display parameter predictions for this set of random effects

Continue Cancel Help



- We may want to compare the means of the fixed effects



Type III Tests of Fixed Effects^a

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	30	2.198	.149
species	1	30	4.889	.035
segment	2	30	51.840	<.001
species * segment	2	30	.223	.801

a. Dependent Variable: logttweight.

Estimates of Fixed Effects^a

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	-.385	.316	30	-1.219	.232	-1.031	.260
[species=Bacventitium]	.326	.235	30	1.389	.175	-.153	.806
[species=Bkewense]	0 ^b	0
[segment=b]	.273	.235	30	1.161	.255	-.207	.752
[segment=h]	1.667	.235	30	7.101	<.001	1.188	2.147
[segment=p]	0 ^b	0
[species=Bacventitium] *	.069	.332	30	.207	.837	-.609	.747
[segment=b]							
[species=Bacventitium] *	-.148	.332	30	-.446	.659	-.826	.530
[segment=h]							
[species=Bacventitium] *	0 ^b	0
[segment=p]							
[species=Bkewense] *	0 ^b	0
[segment=b]							
[species=Bkewense] *	0 ^b	0
[segment=h]							
[species=Bkewense] *	0 ^b	0
[segment=p]							

a. Dependent Variable: logttweight.

b. This parameter is set to zero because it is redundant.

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