

ORIGIN := 0

Split-plot Designs

Split-plot designs are *not* distinguished from factorial (i.e. fully crossed multi-factor) designs by the structure of the data as observed in a data table. Both appear identical, but the difference resides in how the data are collected. In many situations, it is difficult to apply full randomization to all crossed factors because some experimental or observational conditions are harder to apply than others. Thus, in classic agricultural studies, fields are divided into plots related to a hard-to-apply factor (such as irrigation) and within plots, subplots are defined by levels of more easily applied treatments (such as levels of fertilizer). Similar data structures occur in observational studies because observations occur naturally in a hierarchical arrangement such as teachers within schools within districts, etc. All of these kinds of studies have a complex covariance structure between sets of observations that violate the assumptions of crossed-factorial design (constant variance and no covariance between observations). Instead, in advance of analyzing the data, observations can be considered to have different variances for observations at different levels of the hierarchy, and observations within levels of factors are correlated. In such situations, the individual cases (lines within a dataset) are said to be "pseudoreplicated".

"Split-plot design" terminology is usually applied to experimental data involving hierarchical spatial arrangements. However, the overall approach may encompass many other experimental and observational situations variously termed "hierarchical modeling", "repeated measures designs", "nested designs" and others. In addition to terminology, differences also reside in whether the researcher views some or all individual factors to be fixed versus random, and whether some factors comprise numerical data (as in regression). Differences also arise in what the researcher wishes to extract from the analysis including treatment differences for multiple fixed factors with or without interaction, regression coefficients for numerical relationships, and estimates of variance components for random factors.

Analyzed here are classic examples of split-plot designs of differing complexity depending on the number of hierarchical factors involved, and whether the studies are "balanced" or not. Balanced data, consisting of equal numbers of smallest scale replicates per set of treatment factors, can be handled by standard ANOVA methods because sums of squares for treatments or treatments within other factors sum directly to total SS (i.e., SS's are "orthogonal"). For unbalanced data, correction factors may be sometimes be applied to standard least-squares (LS) regressions. However, newer methods and software such as R's `lme()` {nlme} and `lmer()` {lme4} functions involving maximum likelihood (ML) and restricted maximum likelihood (REML) iterative maximizations have largely supplanted LS.

Example - Balanced Case:

Example from W. N. Venables & B. D. Ripley 2002. *Modern Applied Statistics with S*, p. 282. Terminology from M.H. Kutner, C. J. Nachtsheim, J. Neter & W. Li 2005 *Applied Linear Statistical Models 5th Ed.* (KNNL).

KNNL p. 1162 asks us to note that this "split-plot" design is identical to a "two-factor experiment with repeated measures on one factor" design p. 1140, with changes in terminology.

Model:

$$Y_{ijk} = \mu + \rho_{i(j)} + \alpha_j + \beta_k + (\alpha\beta)_{jk} + \varepsilon_{ijk}$$

where:

μ = a constant level (intercept)

$\rho_{i(j)}$ = random variable $\sim N(0, \sigma_\rho^2)$

α_j = fixed constant

β_k = fixed constant

$(\alpha\beta)_{jk}$ = fixed constant

ε_{ijk} = random variable $\sim N(0, \sigma^2)$

Restrictions:

$$\Sigma \alpha_j = 0$$

$$\Sigma \beta_k = 0$$

$$\Sigma (\alpha\beta)_{jk} = 0 \text{ for all } j \text{ and for all } k$$

Model Dimensions:

s := 6 < number of random blocks observed in $\rho_{i(j)}$ i := 1 .. s
 a := 3 < number of treatments for fixed factor α_j j := 1 .. a
 b := 4 < number of treatments for fixed factor β_k k := 1 .. b

> oats

	B	V	N	Y
1	I	Victory	0.0cwt	111
2	I	Victory	0.2cwt	130
3	I	Victory	0.4cwt	157
4	I	Victory	0.6cwt	174
5	I	Golden.rain	0.0cwt	117
6	I	Golden.rain	0.2cwt	114
7	I	Golden.rain	0.4cwt	161
8	I	Golden.rain	0.6cwt	141
9	I	Marvellous	0.0cwt	105
10	I	Marvellous	0.2cwt	140
11	I	Marvellous	0.4cwt	118
12	I	Marvellous	0.6cwt	156
13	II	Victory	0.0cwt	61
14	II	Victory	0.2cwt	91
15	II	Victory	0.4cwt	97
16	II	Victory	0.6cwt	100
17	II	Golden.rain	0.0cwt	70
18	II	Golden.rain	0.2cwt	108
19	II	Golden.rain	0.4cwt	126
20	II	Golden.rain	0.6cwt	149
21	II	Marvellous	0.0cwt	96
22	II	Marvellous	0.2cwt	124
23	II	Marvellous	0.4cwt	121
24	II	Marvellous	0.6cwt	144
25	III	Victory	0.0cwt	68
26	III	Victory	0.2cwt	64
27	III	Victory	0.4cwt	112
28	III	Victory	0.6cwt	86
29	III	Golden.rain	0.0cwt	60
30	III	Golden.rain	0.2cwt	102
31	III	Golden.rain	0.4cwt	89
32	III	Golden.rain	0.6cwt	96
33	III	Marvellous	0.0cwt	89
34	III	Marvellous	0.2cwt	129
35	III	Marvellous	0.4cwt	132
36	III	Marvellous	0.6cwt	124
37	IV	Victory	0.0cwt	74
38	IV	Victory	0.2cwt	89
39	IV	Victory	0.4cwt	81
40	IV	Victory	0.6cwt	122
41	IV	Golden.rain	0.0cwt	64
42	IV	Golden.rain	0.2cwt	103
43	IV	Golden.rain	0.4cwt	132
44	IV	Golden.rain	0.6cwt	133
45	IV	Marvellous	0.0cwt	70
46	IV	Marvellous	0.2cwt	89
47	IV	Marvellous	0.4cwt	104
48	IV	Marvellous	0.6cwt	117
49	V	Victory	0.0cwt	62
50	V	Victory	0.2cwt	90
51	V	Victory	0.4cwt	100
52	V	Victory	0.6cwt	116
53	V	Golden.rain	0.0cwt	80
54	V	Golden.rain	0.2cwt	82
55	V	Golden.rain	0.4cwt	94
56	V	Golden.rain	0.6cwt	126
57	V	Marvellous	0.0cwt	63
58	V	Marvellous	0.2cwt	70
59	V	Marvellous	0.4cwt	109
60	V	Marvellous	0.6cwt	99
61	VI	Victory	0.0cwt	53
62	VI	Victory	0.2cwt	74
63	VI	Victory	0.4cwt	118
64	VI	Victory	0.6cwt	113
65	VI	Golden.rain	0.0cwt	89
66	VI	Golden.rain	0.2cwt	82
67	VI	Golden.rain	0.4cwt	86
68	VI	Golden.rain	0.6cwt	104
69	VI	Marvellous	0.0cwt	97
70	VI	Marvellous	0.2cwt	99
71	VI	Marvellous	0.4cwt	119
72	VI	Marvellous	0.6cwt	121

ANOVA Sums of Squares:

Source of Variation: from KNNL p. 1142, not evaluated here:

Factor A: $SSA = bs\sum_j(Y^{bar}_{.j} - Y^{bar}_{...})^2$
 ^ mean for each class of outside factor A minus grand mean.

Factor B: $SSB = as\sum_k(Y^{bar}_{..k} - Y^{bar}_{...})^2$
 ^ mean for each class of inside factor B minus grand mean.

AB Interactions: $SSAB = s\sum_j\sum_k(Y^{bar}_{.jk} - Y^{bar}_{.j} - Y^{bar}_{..k} + Y^{bar}_{...})^2$
 ^ jk factor block means

Subjects/Blocks within A: $SSS(A) = b\sum_i\sum_j(X^{bar}_{ij} - Y^{bar}_{.j})^2$
 ^ ij block means - factor A class means

Error: $SSB.S(A) = \sum_i\sum_j\sum_k(Y_{ijk} - Y^{bar}_{.jk} - Y^{bar}_{ij.} + Y^{bar}_{.j.})^2$
 ^ observation minus factor AB block means minus ij block means + class A means

Total: $SSTO = \sum_i\sum_j\sum_k(Y_{ijk} - Y^{bar}_{...})^2$
 ^ observation minus grand mean

Degrees of Freedom:

Factor A: a - 1 = 2
Factor B: b - 1 = 3
AB Interactions: (a - 1) · (b - 1) = 6
Subjects/Blocks within A: a · (s - 1) = 15
Error: a · (s - 1) · (b - 1) = 45
Total: a · b · s - 1 = 71

F-Tests for Fixed Factors:

Hypotheses:

H_0 :

all $(\alpha\beta)_{jk} = 0$ for A with B interactions
 all $\alpha_j = 0$ for fixed factor A
 all $\beta_k = 0$ for fixed factor B within A

H_1 :

all $(\alpha\beta)_{jk} \neq 0$ for A with B interactions
 all $\alpha_j \neq 0$ for fixed factor A
 all $\beta_k \neq 0$ for fixed factor B within A

Test Statistics:

$$F_{\alpha\beta} = MSAB/MSB.S(A)$$

$$F_{\alpha} = MSA/MSS(A)$$

$$F_{\beta} = MSB/MSB.S(A)$$

Critical Values for the Tests:

$\alpha := 0.05$ < Type I error rate must be explicitly set.

$$C_{\alpha\beta} = qF(1-\alpha, (a-1)(b-1), a(s-1)(b-1))$$

$$C_{\alpha} = qF(1-\alpha, (a-1), a(s-1))$$

$$C_{\beta} = qF(1-\alpha, (b-1), a(s-1)(b-1))$$

Decision Rules:

If: $F_{\alpha\beta} > C_{\alpha\beta}$ Then Reject H_0
 $F_{\alpha} > C_{\alpha}$
 $F_{\beta} > C_{\beta}$

Note: In R, these tests are obtained by the functions:

`anova()` for serial SS and tests, and
`Anova() {car}` for marginal SS and tests.

Probabilities:

$$P_{\alpha\beta} = 1 - pF(F_{\alpha\beta}, (a-1)(b-1), a(s-1)(b-1))$$

$$P_{\alpha} = 1 - pF(F_{\alpha}, (a-1), a(s-1))$$

$$P_{\beta} = 1 - pF(F_{\beta}, (b-1), a(s-1)(b-1))$$

See *Biostatistics* Worksheet 400 for details.

t-Tests for Fixed Regression Terms:

These tests are directed toward individual regression slope parameters underlying ANOVA. They are marginal tests to determine whether particular slopes are zero. See *2010 Biostatistics 38* for details.

Hypotheses:

H_0 : - a single regression coefficient β is 0 meaning that this regressor is unimportant.

H_1 : - non-zero effect for this regressor.

Test Statistics:

$t_j = b_j/sb_j$ < estimate regression coefficient divided by standard error for that coefficient

Sampling Distributions:

If Assumptions hold and H_0 is true, then $t \sim t(n-k)$

where: n = number of cases in dataset
 k = number of independent variables in model

Prototype in R:

```
#SPLIT-PLOT ANOVA
setwd("c:/DATA/Models/")
#Oats in Venables & Ripley 2002 p. 282
library(MASS)
oats
attach(oats)
S=B #subjects/blocks
A=V #outside factor
B=N #inside factor
LM1=aoV(Y~A*B+Error(S/A))
summary(LM1)

#USING LINEAR MIXED MODELS:
library(nlme)
library(lme4)
LME1a=lme(Y~A*B,random=~1|S/A)
LME1b=lmer(Y~A*B+(1|S/A))
anova(LME1a)
anova(LME1b)
summary(LME1a)
summary(LME1b)
```

< Note: Variables S,A,B are treated as factors by R because values in the dataset are alphanumeric. The authors use an *ordered factor* variable for N, but results here are the same.

```
> summary(LM1)
```

```
Error: S
      Df Sum Sq Mean Sq F value Pr(>F)
Residuals  5 15875.3   3175.1

Error: S:A
      Df Sum Sq Mean Sq F value Pr(>F)
A       2  1786.4    893.2  1.4853 0.2724
Residuals 10  6013.3    601.3

Error: Within
      Df Sum Sq Mean Sq F value Pr(>F)
B       3 20020.5  6673.5  37.6856 2.458e-12 ***
A:B     6   321.7    53.6  0.3028  0.9322
Residuals 45  7968.7   177.1
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

^ The ANOVA reports strata with error partitioned according to stratum. Sums of Squares and degrees of freedom for errors at each level presumably sum to total SSE and df_E .

```
> anova(LME1a)
```

	numDF	denDF	F-value	p-value
(Intercept)	1	45	245.14299	<.0001
A	2	10	1.48534	0.2724
B	3	45	37.68561	<.0001
A:B	6	45	0.30282	0.9322

```
> anova(LME1b)
```

Analysis of Variance Table				
	Df	Sum Sq	Mean Sq	F value
A	2	526.1	263.0	1.4853
B	3	20020.5	6673.5	37.6856
A:B	6	321.8	53.6	0.3028

^ Similar and complementary reports by lme() and lmer() functions in R:

```
> summary(LME1a)
```

Linear mixed-effects model fit by REML

Data: NULL

	AIC	BIC	logLik
	559.0285	590.4437	-264.5143

Random effects:

Formula: ~1 | S

(Intercept)

StdDev: 14.64496

Formula: ~1 | A %in% S

(Intercept) Residual

StdDev: 10.29862 13.30727

Fixed effects: Y ~ A * B

	Value	Std.Error	DF	t-value	p-value
(Intercept)	80.00000	9.106958	45	8.784492	0.0000
AMarvellous	6.66667	9.715026	10	0.686222	0.5082
AVictory	-8.50000	9.715026	10	-0.874933	0.4021
B0.2cwt	18.50000	7.682958	45	2.407927	0.0202
B0.4cwt	34.66667	7.682958	45	4.512151	0.0000
B0.6cwt	44.83333	7.682958	45	5.835426	0.0000
AMarvellous:B0.2cwt	3.33333	10.865343	45	0.306786	0.7604
AVictory:B0.2cwt	-0.33333	10.865343	45	-0.030679	0.9757
AMarvellous:B0.4cwt	-4.16667	10.865343	45	-0.383482	0.7032
AVictory:B0.4cwt	4.66667	10.865343	45	0.429500	0.6696
AMarvellous:B0.6cwt	-4.66667	10.865343	45	-0.429500	0.6696
AVictory:B0.6cwt	2.16667	10.865343	45	0.199411	0.8428

```
> summary(LME1b)
```

Linear mixed model fit by REML

Formula: Y ~ A * B + (1 | S/A)

	AIC	BIC	logLik	deviance	REMLdev
	559	593.2	-264.5	595.9	529

Random effects:

Groups	Name	Variance	Std.Dev.
A:S	(Intercept)	106.06	10.299
S	(Intercept)	214.48	14.645
	Residual	177.08	13.307

Number of obs: 72, groups: A:S, 18; S, 6

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	80.0000	9.1064	8.785
AMarvellous	6.6667	9.7150	0.686
AVictory	-8.5000	9.7150	-0.875
B0.2cwt	18.5000	7.6830	2.408
B0.4cwt	34.6667	7.6830	4.512
B0.6cwt	44.8333	7.6830	5.835
AMarvellous:B0.2cwt	3.3333	10.8653	0.307
AVictory:B0.2cwt	-0.3333	10.8653	-0.031
AMarvellous:B0.4cwt	-4.1667	10.8653	-0.383
AVictory:B0.4cwt	4.6667	10.8653	0.430
AMarvellous:B0.6cwt	-4.6667	10.8653	-0.430
AVictory:B0.6cwt	2.1667	10.8653	0.19

Example - Balanced Case:

Example from Crawley 2007 *The R Book*.

Split-plot example "splyield.txt" in his set of datafiles.

Prototype in R:

```
#SPLIT-PLOT ANOVA
```

```
Y=read.table("splyield.txt",header=T)
```

```
Y
```

```
attach(Y)
```

```
Y=yield
```

```
A=factor(block)
```

```
B=factor(irrigation)
```

```
C=factor(density)
```

```
D=factor(fertilizer)
```

```
#CROSSED DESIGN:
```

```
LM1=lm(Y~B*C*D) #A (blocks) ignored
anova(LM1)
```

```
> anova(LM1)
```

```
Analysis of Variance Table
```

```
Response: Y
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
B	1	8277.6	8277.6	59.5746	2.813e-10 ***
C	2	1758.4	879.2	6.3276	0.0033972 **
D	2	1977.4	988.7	7.1160	0.0018070 **
B:C	2	2747.0	1373.5	9.8853	0.0002197 ***
B:D	2	953.4	476.7	3.4310	0.0395615 *
C:D	4	304.9	76.2	0.5486	0.7008151
B:C:D	4	234.7	58.7	0.4223	0.7918283
Residuals	54	7503.0	138.9		

```
---
```

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

```
LM2=aov(Y~B*C*D) #same result as above using aov()
summary(LM2)
```

```
> summary(LM2)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
B	1	8277.6	8277.6	59.5746	2.813e-10 ***
C	2	1758.4	879.2	6.3276	0.0033972 **
D	2	1977.4	988.7	7.1160	0.0018070 **
B:C	2	2747.0	1373.5	9.8853	0.0002197 ***
B:D	2	953.4	476.7	3.4310	0.0395615 *
C:D	4	304.9	76.2	0.5486	0.7008151
B:C:D	4	234.7	58.7	0.4223	0.7918283
Residuals	54	7503.0	138.9		

```
---
```

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

```
> Y
```

	yield	block	irrigation	density	fertilizer
1	90	A	control	low	N
2	95	A	control	low	P
3	107	A	control	low	NP
4	92	A	control	medium	N
5	89	A	control	medium	P
6	92	A	control	medium	NP
7	81	A	control	high	N
8	92	A	control	high	P
9	93	A	control	high	NP
10	80	A	irrigated	low	N
11	87	A	irrigated	low	P
12	100	A	irrigated	low	NP
13	121	A	irrigated	medium	N
14	110	A	irrigated	medium	P
15	119	A	irrigated	medium	NP
16	78	A	irrigated	high	N
17	98	A	irrigated	high	P
18	122	A	irrigated	high	NP
19	83	B	control	low	N
20	80	B	control	low	P
21	95	B	control	low	NP
22	98	B	control	medium	N
23	98	B	control	medium	P
24	106	B	control	medium	NP
25	74	B	control	high	N
26	81	B	control	high	P
27	74	B	control	high	NP
28	102	B	irrigated	low	N
29	109	B	irrigated	low	P
30	105	B	irrigated	low	NP
31	99	B	irrigated	medium	N
32	94	B	irrigated	medium	P
33	123	B	irrigated	medium	NP
34	136	B	irrigated	high	N
35	133	B	irrigated	high	P
36	132	B	irrigated	high	NP
37	85	C	control	low	N
38	88	C	control	low	P
39	88	C	control	low	NP
40	112	C	control	medium	N
41	104	C	control	medium	P
42	91	C	control	medium	NP
43	82	C	control	high	N
44	78	C	control	high	P
45	94	C	control	high	NP
46	60	C	irrigated	low	N
47	104	C	irrigated	low	P
48	114	C	irrigated	low	NP
49	90	C	irrigated	medium	N
50	118	C	irrigated	medium	P
51	113	C	irrigated	medium	NP
52	119	C	irrigated	high	N
53	122	C	irrigated	high	P
54	136	C	irrigated	high	NP
55	86	D	control	low	N
56	78	D	control	low	P
57	89	D	control	low	NP
58	79	D	control	medium	N
59	86	D	control	medium	P
60	87	D	control	medium	NP
61	85	D	control	high	N
62	89	D	control	high	P
63	83	D	control	high	NP
64	73	D	irrigated	low	N
65	114	D	irrigated	low	P
66	114	D	irrigated	low	NP
67	109	D	irrigated	medium	N
68	131	D	irrigated	medium	P
69	126	D	irrigated	medium	NP
70	116	D	irrigated	high	N
71	136	D	irrigated	high	P
72	133	D	irrigated	high	NP

#WITH ERROR STRATUM A SPECIFIED:

LM3=aov(Y~B*C*D+Error(A))

summary(LM3)

> summary(LM3)

```
Error: A
      Df Sum Sq Mean Sq F value Pr(>F)
Residuals  3 194.444   64.815

Error: Within
      Df Sum Sq Mean Sq F value    Pr(>F)
B         1  8277.6   8277.6  57.7618 6.157e-10 ***
C         2  1758.4    879.2   6.1350 0.0040972 **
D         2  1977.4    988.7   6.8994 0.0022288 **
B:C       2  2747.0  1373.5   9.5845 0.0002926 ***
B:D       2   953.4   476.7   3.3266 0.0438563 *
C:D       4   304.9    76.2   0.5319 0.7128342
B:C:D     4   234.7    58.7   0.4095 0.8009729
Residuals 51  7308.6   143.3
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

#FULL FACTORIAL MODEL

#WITH ENTIRE HIERARCHICAL STRUCTURE CORRECTLY SPECIFIED:

LM4=aov(Y~B*C*D+Error(A/B/C))

summary(LM4)

> summary(LM4)

```
Error: A
      Df Sum Sq Mean Sq F value Pr(>F)
Residuals  3 194.444   64.815

Error: A:B
      Df Sum Sq Mean Sq F value Pr(>F)
B         1  8277.6   8277.6  17.590 0.02473 *
Residuals  3 1411.8   470.6
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Error: A:B:C
      Df Sum Sq Mean Sq F value Pr(>F)
C         2  1758.36   879.18   3.7842 0.05318 .
B:C       2  2747.03  1373.51   5.9119 0.01633 *
Residuals 12  2787.94   232.33
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Error: Within
      Df Sum Sq Mean Sq F value    Pr(>F)
D         2  1977.44   988.72  11.4493 0.0001418 ***
B:D       2   953.44   476.72   5.5204 0.0081078 **
C:D       4   304.89    76.22   0.8826 0.4840526
B:C:D     4   234.72    58.68   0.6795 0.6106672
Residuals 36  3108.83    86.36
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

< Variance including sum of squares and degrees of freedom associated with variable A (block) is now partitioned out of Residual SS.

< Residual sums of squares for all levels add to total SS in LM1 above.

Significance in tests changes as pseudoreplication is removed from the study. This is the appropriate split-plot analysis for balanced data verified in Crawley 2007 p. 470. For unbalanced data, functions `lme()` `{nlme}` or `lmer()` `{lme4}` are instead recommended.

From this starting point, he shows additional model simplification in `lme()` by removing elements from the full factorial model $B*C*D$.

Note: it is unnecessary (but not harmful) to specify smallest level of the hierarchical structure in the `Error(A/B/C/D)` term since the smallest level is already assumed by R.

#USING LINEAR MIXED MODELS:

```
library(nlme)
library(lme4)
LM6=lme(Y~B*C*D, random=~1|A/B/C)
anova(LM6)
```

```
LM7=lmer(Y~B*C*D+(1|A/B/C))
anova(LM7)
```

Corresponding ANOVA Results:**lme() result:****> anova(LM6)**

	numDF	denDF	F-value	p-value
(Intercept)	1	36	2674.6301	<.0001
B	1	3	30.9207	0.0115
C	2	12	3.7842	0.0532
D	2	36	11.4493	0.0001
B:C	2	12	5.9119	0.0163
B:D	2	36	5.5204	0.0081
C:D	4	36	0.8826	0.4841
B:C:D	4	36	0.6795	0.6107

lmer() result:**> anova(LM7)**

Analysis of Variance Table					
	Df	Sum Sq	Mean Sq	F value	
B	1	2670.19	2670.19	30.9206	
C	2	653.58	326.79	3.7842	
D	2	1977.44	988.72	11.4493	
B:C	2	1021.07	510.53	5.9119	
B:D	2	953.44	476.72	5.5204	
C:D	4	304.89	76.22	0.8826	
B:C:D	4	234.72	58.68	0.6795	

^ For this balanced case, the two procedures produce mostly identical results to each other and to the split-plot aov() analysis above (only the F-value for B differs much). What the anova() wrapper reports for the mixed-model functions is different but complementary.

$$1 - pF(30.9207, 1, 3) = 0.011474$$

^ for B

< probabilities may be calculated using the corresponding pf() function in R, specifying F value and associated numerator and denominator degrees of freedom.

Comparing Linear Models as Regression:**#COMPARING FIXED EFFECTS****#MARGINAL t-TESTS:**

summary(LM1)

summary(LM6)

summary(LM7)

> summary(LM1)

Call:

lm(formula = Y ~ B * C * D)

Residuals:

Min	1Q	Median	3Q	Max
-34.25	-5.75	0.50	5.75	23.75

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	80.500	5.894	13.659	< 2e-16 ***
Birrigated	31.750	8.335	3.809	0.000359 ***
Clow	5.500	8.335	0.660	0.512143
Cmedium	14.750	8.335	1.770	0.082432 .
DNP	5.500	8.335	0.660	0.512143
DP	4.500	8.335	0.540	0.591491
Birrigated:Clow	-39.000	11.787	-3.309	0.001673 **
Birrigated:Cmedium	-22.250	11.787	-1.888	0.064459 .
Birrigated:DNP	13.000	11.787	1.103	0.274976
Birrigated:DP	5.500	11.787	0.467	0.642665
Clow:DNP	3.250	11.787	0.276	0.783818
Cmedium:DNP	-6.750	11.787	-0.573	0.569264
Clow:DP	-5.250	11.787	-0.445	0.657820
Cmedium:DP	-5.500	11.787	-0.467	0.642665
Birrigated:Clow:DNP	7.750	16.670	0.465	0.643867
Birrigated:Cmedium:DNP	3.750	16.670	0.225	0.822863
Birrigated:Clow:DP	20.000	16.670	1.200	0.235470
Birrigated:Cmedium:DP	4.000	16.670	0.240	0.811276

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

Residual standard error: 11.79 on 54 degrees of freedom
 Multiple R-squared: 0.6842, Adjusted R-squared: 0.5847
 F-statistic: 6.881 on 17 and 54 DF, p-value: 2.298e-08

Note: hierarchical specification of variance is not possible with lm().

> summary(LM6)

Linear mixed-effects model fit by REML

Data: NULL

AIC	BIC	logLik
481.6212	525.3789	-218.8106

Random effects:

Formula: ~1 | A
(Intercept)

StdDev: 0.0006600339

Formula: ~1 | B %in% A
(Intercept)

StdDev: 1.982461

Formula: ~1 | C %in% B %in% A
(Intercept) Residual

StdDev: 6.975554 9.292805

Fixed effects: Y ~ B * C * D

	Value	Std. Error	DF	t-value	p-value
(Intercept)	80.50	5.893741	36	13.658558	0.0000
Birrigated	31.75	8.335008	3	3.809234	0.0318
Clow	5.50	8.216282	12	0.669403	0.5159
Cmedium	14.75	8.216282	12	1.795216	0.0978
DNP	5.50	6.571005	36	0.837010	0.4081
DP	4.50	6.571005	36	0.684827	0.4978
Birrigated:Clow	-39.00	11.619577	12	-3.356404	0.0057
Birrigated:Cmedium	-22.25	11.619577	12	-1.914872	0.0796
Birrigated:DNP	13.00	9.292805	36	1.398932	0.1704
Birrigated:DP	5.50	9.292805	36	0.591856	0.5576
Clow:DNP	3.25	9.292805	36	0.349733	0.7286
Cmedium:DNP	-6.75	9.292805	36	-0.726368	0.4723
Clow:DP	-5.25	9.292805	36	-0.564953	0.5756
Cmedium:DP	-5.50	9.292805	36	-0.591856	0.5576
Birrigated:Clow:DNP	7.75	13.142011	36	0.589712	0.5591
Birrigated:Cmedium:DNP	3.75	13.142011	36	0.285344	0.7770
Birrigated:Clow:DP	20.00	13.142011	36	1.521837	0.1368
Birrigated:Cmedium:DP	4.00	13.142011	36	0.304367	0.7626

Number of Observations: 72

Number of Groups:

A	B %in% A	C %in% B %in% A
4	8	24

^ In this balanced case, results are equivalent, although small differences are noted in very small variance components for the mixed-models.

Example - Unbalanced Case:

#UNBALANCED EXAMPLE

#Crawley 2007 p. 472

Y=read.table("splityieldunbalanced.txt")

Y

attach(Y)

Y=yield

A=factor(block)

B=factor(irrigation)

C=factor(density)

D=factor(fertilizer)

> summary(LM7)

Linear mixed model fit by REML

Formula: Y ~ B * C * D + (1 | A/B/C)

AIC	BIC	logLik	deviance	REMLdev
481.6	531.7	-218.8	529.5	437.6

Random effects:

Groups	Name	Variance	Std.Dev.
C: (B:A)	(Intercept)	4.8657e+01	6.9755e+00
B:A	(Intercept)	3.9306e+00	1.9826e+00
A	(Intercept)	7.0693e-13	8.4079e-07
	Residual	8.6356e+01	9.2928e+00

Number of obs: 72, groups: C: (B:A), 24; B:A, 8; A, 4

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	80.500	5.894	13.659
Birrigated	31.750	8.335	3.809
Clow	5.500	8.216	0.669
Cmedium	14.750	8.216	1.795
DNP	5.500	6.571	0.837
DP	4.500	6.571	0.685
Birrigated:Clow	-39.000	11.620	-3.356
Birrigated:Cmedium	-22.250	11.620	-1.915
Birrigated:DNP	13.000	9.293	1.399
Birrigated:DP	5.500	9.293	0.592
Clow:DNP	3.250	9.293	0.350
Cmedium:DNP	-6.750	9.293	-0.726
Clow:DP	-5.250	9.293	-0.565
Cmedium:DP	-5.500	9.293	-0.592
Birrigated:Clow:DNP	7.750	13.142	0.590
Birrigated:Cmedium:DNP	3.750	13.142	0.285
Birrigated:Clow:DP	20.000	13.142	1.522
Birrigated:Cmedium:DP	4.000	13.142	0.304

LMu1=lm(Y~B*C*D)

LMu4=aov(Y~B*C*D+Error(A/B/C))

LMu6=lme(Y~B*C*D, random=~1|A/B/C)

lme() doesn't like NA in dataset

LMu7=lmer(Y~B*C*D+(1|A/B/C))

anova(LMu1)

anova(LMu6)

anova(LMu7)

summary(LMu4)

summary(LMu1)

summary(LMu6)

summary(LMu7)

> anova(LMu1)

Analysis of Variance Table

Response: Y

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
B	1	7826.2	7826.2	55.6097	8.292e-10 ***
C	2	1653.2	826.6	5.8736	0.0049652 **
D	2	1869.2	934.6	6.6409	0.0026690 **
B:C	2	2771.5	1385.8	9.8467	0.0002311 ***
B:D	2	911.5	455.7	3.2383	0.0471141 *
C:D	4	337.5	84.4	0.5995	0.6646007
B:C:D	4	228.1	57.0	0.4053	0.8040196
Residuals	53	7458.9	140.7		

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

> summary(LMu4)

Error: A

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
B	1	0.075	0.075	9e-04	0.9788
Residuals	2	167.704	83.852		

Error: A:B

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
B	1	7829.9	7829.9	21.9075	0.04274 *
C	1	564.4	564.4	1.5792	0.33576
Residuals	2	714.8	357.4		

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

Error: A:B:C

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
C	2	1696.47	848.24	3.4044	0.07066 .
D	1	0.01	0.01	2.774e-05	0.99589
B:C	2	2786.75	1393.37	5.5924	0.02110 *
Residuals	11	2740.72	249.16		

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

Error: Within

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
D	2	1959.36	979.68	11.1171	0.0001829 ***
B:D	2	993.59	496.79	5.6375	0.0075447 **
C:D	4	273.56	68.39	0.7761	0.5482571
B:C:D	4	244.49	61.12	0.6936	0.6014280
Residuals	35	3084.33	88.12		

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

> anova(LMu6)

	numDF	denDF	F-value	p-value
(Intercept)	1	35	2615.6915	<.0001
B	1	3	29.5564	0.0122
C	2	12	3.5946	0.0598
D	2	35	10.8796	0.0002
B:C	2	12	5.8611	0.0168
B:D	2	35	5.4231	0.0089
C:D	4	35	0.8447	0.5065
B:C:D	4	35	0.6645	0.6208

> anova(LMu7)

Analysis of Variance Table				
	Df	Sum Sq	Mean Sq	F value
B	1	2610.67	2610.67	29.5567
C	2	635.00	317.50	3.5945
D	2	1921.93	960.96	10.8796
B:C	2	1035.40	517.70	5.8611
B:D	2	958.02	479.01	5.4231
C:D	4	298.43	74.61	0.8447
B:C:D	4	234.79	58.70	0.6645

^ F-values correspond closely between the mixed-models, and correspond more-or-less to estimates made with aov() using correctly specified hierarchical variance. F-values do not correspond to F-values in the crossed-design (LMu1) with pseudoreplication.

> summary(LMu1)

```
Call:
lm(formula = Y ~ B * C * D)
Residuals:
    Min       1Q   Median       3Q      Max
-34.250  -5.750   0.500   5.625  23.750
Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)      80.500     5.932  13.571 < 2e-16 ***
Birrigated       31.750     8.389   3.785 0.000393 ***
Clow              5.500     8.389   0.656 0.514880
Cmedium          14.750     8.389   1.758 0.084460 .
DNP              5.500     8.389   0.656 0.514880
DP               4.500     8.389   0.536 0.593894
Birrigated:Clow  -39.000    11.863  -3.287 0.001798 **
Birrigated:Cmedium -22.250    11.863  -1.876 0.066229 .
Birrigated:DNP   13.000    11.863   1.096 0.278108
Birrigated:DP    5.500    11.863   0.464 0.644818
Clow:DNP         3.250    11.863   0.274 0.785182
Cmedium:DNP     -6.750    11.863  -0.569 0.571767
Clow:DP         -5.250    11.863  -0.443 0.659894
Cmedium:DP      -5.500    11.863  -0.464 0.644818
Birrigated:Clow:DNP 7.750    16.777   0.462 0.646014
Birrigated:Cmedium:DNP 1.833    17.123   0.107 0.915139
Birrigated:Clow:DP 20.000    16.777   1.192 0.238530
Birrigated:Cmedium:DP 4.000    16.777   0.238 0.812474
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 11.86 on 53 degrees of freedom
(1 observation deleted due to missingness)
Multiple R-squared: 0.6765, Adjusted R-squared: 0.5727
F-statistic: 6.519 on 17 and 53 DF, p-value: 6.337e-08
```

> summary(LMu6)

```
Linear mixed-effects model fit by REML
Data: NULL
      AIC      BIC    logLik
474.7823 518.1288 -215.3912

Random effects:
Formula: ~1 | A
(Intercept)
StdDev: 0.0006541865
Formula: ~1 | B %in% A
(Intercept)
StdDev: 2.009935
Formula: ~1 | C %in% B %in% A
(Intercept) Residual
StdDev: 6.9847 9.398264

Fixed effects: Y ~ B * C * D
```

	Value	Std.Error	DF	t-value	p-value
(Intercept)	80.50000	5.940396	35	13.551285	0.0000
Birrigated	31.75000	8.400989	3	3.779317	0.0325
Clow	5.50000	8.279897	12	0.664259	0.5191
Cmedium	14.75000	8.279897	12	1.781423	0.1001
DNP	5.50000	6.645576	35	0.827618	0.4135
DP	4.50000	6.645576	35	0.677142	0.5028
Birrigated:Clow	-39.00000	11.709543	12	-3.330617	0.0060
Birrigated:Cmedium	-22.25000	11.709543	12	-1.900160	0.0817
Birrigated:DNP	13.00000	9.398264	35	1.383234	0.1754
Birrigated:DP	5.50000	9.398264	35	0.585214	0.5622
Clow:DNP	3.25000	9.398264	35	0.345809	0.7316
Cmedium:DNP	-6.75000	9.398264	35	-0.718218	0.4774
Clow:DP	-5.25000	9.398264	35	-0.558614	0.5800
Cmedium:DP	-5.50000	9.398264	35	-0.585214	0.5622
Birrigated:Clow:DNP	7.75000	13.291152	35	0.583095	0.5636
Birrigated:Cmedium:DNP	3.89578	13.638668	35	0.285643	0.7768
Birrigated:Clow:DP	20.00000	13.291152	35	1.504760	0.1414
Birrigated:Cmedium:DP	4.00000	13.291152	35	0.300952	0.7652

< Comparison of crossed design (left) with mixed-model designs (below).

Estimates of parameter match in all cases. Standard errors and t-test with match closely between mixed-model designs, but do not match the crossed design (although roughly similar in reported values).

> summary(LMu7)

```
Linear mixed model fit by REML
Formula: Y ~ B * C * D + (1 | A/B/C)
      AIC      BIC    logLik deviance REMLdev
474.8 524.6 -215.4 523.2 430.8

Random effects:
Groups Name Variance Std.Dev.
C: (B:A) (Intercept) 48.7861 6.9847
B:A (Intercept) 4.0395 2.0098
A (Intercept) 0.0000 0.0000
Residual 88.3275 9.3983
Number of obs: 71, groups: C: (B:A), 24; B:A, 8; A, 4
```

	Estimate	Std. Error	t value
(Intercept)	80.500	5.940	13.551
Birrigated	31.750	8.401	3.779
Clow	5.500	8.280	0.664
Cmedium	14.750	8.280	1.781
DNP	5.500	6.646	0.828
DP	4.500	6.646	0.677
Birrigated:Clow	-39.000	11.710	-3.331
Birrigated:Cmedium	-22.250	11.710	-1.900
Birrigated:DNP	13.000	9.398	1.383
Birrigated:DP	5.500	9.398	0.585
Clow:DNP	3.250	9.398	0.346
Cmedium:DNP	-6.750	9.398	-0.718
Clow:DP	-5.250	9.398	-0.559
Cmedium:DP	-5.500	9.398	-0.585
Birrigated:Clow:DNP	7.750	13.291	0.583
Birrigated:Cmedium:DNP	3.896	13.639	0.286
Birrigated:Clow:DP	20.000	13.291	1.505
Birrigated:Cmedium:DP	4.000	13.291	0.301