

Block-Designs, Row-Column-Designs, Geostatistics: Improved Experimental Designs in Plant Protection Research

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Agricultural Field Trials

- Agricultural Field Trials (often) laid out in small plots combined to larger units in a two-dimensional array (rows and columns).
- Heterogeneity often connected to these Rows and Columns (due to machinery, soil gradient, ...).
- Block Design to control heterogeneity in data analysis

Status Quo at BASF Limburgerhof

- Research Station Limburgerhof is using a set of well-prepared established Designs.
- Mostly ***Randomized Complete Block Design (RCBD)***

Can we do it better?

- what means „*better*“? how much better?
- to which price or increase in complexity?
- is software available?

Trial with 5 treatments in 4 replicates
4 rows * 5 columns



Generated with Microsoft Copilot

Some Typical Experimental Designs (*not only*) for Agricultural Field Trials

Randomized Complete Block Design (RCBD)

4 trt, 3 reps

Block 3	2	3	4	1
Block 2	3	2	4	1
Block 1	2	1	3	4

Row-Column-Design (RCD), 4 trt, 3 reps

(*Latin Rectangle*)

row 3	2	1	3	4
row 2	1	2	4	3
row 1	3	4	1	2
	col 1	col 2	col 3	col 4

Row-Column-Design, 6 trt, 2 reps

(*Latin Rectangle?*)

row 3	4	1	3	5
row 2	3	5	6	2
row 1	1	6	2	4
	col 1	col 2	col 3	col 4

Latin-Square-Design,

4 trt, 4 reps

row 4	4	3	2	1
row 3	2	1	3	4
row 2	1	2	4	3
row 1	3	4	1	2
	col 1	col 2	col 3	col 4

Resolvable Row-Column-Design

Latinized in rows, 9 trt, 3 reps,

(*Latin Rectangle*)

6	2	3
7	1	5
9	4	8

7	4	8
2	9	6
3	5	1

1	5	9
4	8	3
6	2	7

2 possibilities for complete replicates
+ row:replicate + col:replicate

In other context **Row** and **Column**
can also mean

- Days
- Lab Technicians
- Raw Material Batches
- ...

Some Examples from Limburgerhof Agricultural Trial Station

VR A/07/4

1	7	3	8	2	21	4	22
7	6	4	9	1	20	6	23
6	5	5	10	3	19	7	24
5	4	6	11	5	18	2	25
3	3	7	12	4	17	1	26
4	2	2	13	6	16	3	27
2	1	1	14	7	15	5	28

336 m²

VR A/09/4

9	9	4	10	1	27	3	28
5	8	6	11	2	26	8	29
7	8	12	5	5	5	6	30
4	6	3	13	9	24	2	31
1	5	7	1	8	23	5	32
6	4	9	15	4	22	1	33
3	2	2	16	7	21	9	34
8	2	5	7	3	20	4	35
2	1	1	18	6	19	7	36

432 m²

VR A/11/4

9	11	5	12	2	33	7	34
8	10	10	13	11	32	1	35
3	9	6	14	4	31	6	36
11	8	2	15	3	30	8	37
7	7	9	16	10	29	4	38
5	6	7	17	1	28	9	39
2	5	11	18	8	27	3	40
4	4	1	19	6	26	5	41
10	3	8	20	7	25	2	42
6	2	4	21	5	24	10	43
1	1	3	22	9	23	11	44

528 m²

VR A/12/4

10	12	3	13	12	36	6	37
4	11	5	14	7	35	1	38
2	10	8	15	9	34	11	39
12	9	7	16	4	33	10	40
11	8	9	17	8	32	5	41
6	7	2	18	1	31	3	42
5	6	4	19	11	30	7	43
1	5	10	20	6	29	8	44
3	4	12	21	2	28	9	45
8	3	6	22	10	27	12	46
7	2	11	23	3	26	4	47
9	1	1	24	5	25	2	48

576 m²

VR A/13/4

13	13	9	14	8	39	3	40
11	12	5	15	4	38	2	41
10	11	7	16	12	37	6	42
12	10	11	17	2	36	1	43
3	9	4	18	6	35	13	44
8	8	1	19	9	34	7	45
6	7	12	20	5	33	10	46
2	6	3	21	13	32	4	47
5	5	8	22	7	31	11	48
4	4	10	23	1	30	9	49
7	3	13	24	11	29	5	50
1	2	2	25	3	28	8	51
9	1	6	26	10	27	12	52

624 m²

Maybe not optimal

VR A/08/4

3	8	5	9	4	24	1	25
7	7	2	10	6	23	8	26
1	6	4	11	8	22	6	27
5	5	7	12	2	21	3	28
6	4	8	13	5	20	4	29
2	3	3	14	1	19	7	30
4	2	6	15	7	18	2	31
8	1	1	16	3	17	5	32

384 m²

VR A/10/4

8	10	6	11	1	30	4	31
9	9	10	12	3	29	7	32
7	8	5	13	2	28	9	33
2	7	4	14	6	27	5	34
3	6	1	15	8	26	10	35
6	5	7	16	4	25	3	36
5	4	8	17	9	24	2	37
4	3	3	18	10	23	1	38
1	2	2	19	5	22	6	39
10	1	9	20	7	21	8	40

480 m²

VR A/06/4

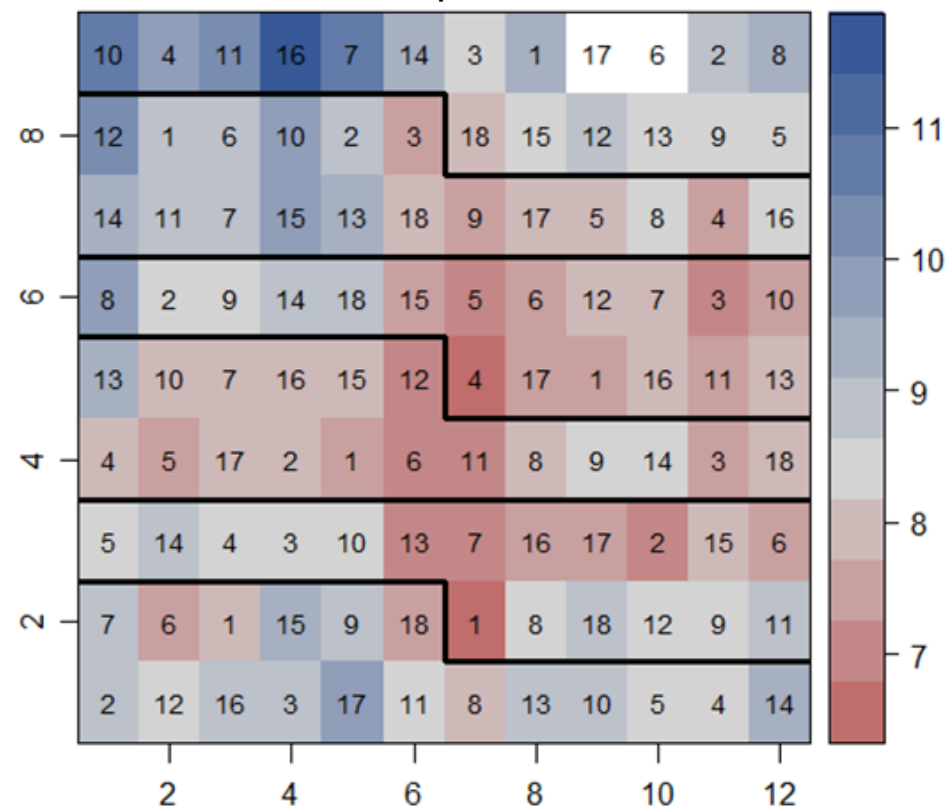
1	6	6	7	4	18	5	19
5	5	3	8	6	17	2	20
4	4	2	9	1	16	4	21
6	3	4	10	5	15	3	22
2	2	5	11	3	14	1	23
3	1	1	12	2	13	6	24

288 m²

These designs are made based on practical considerations and designs like these are used successfully since decades.

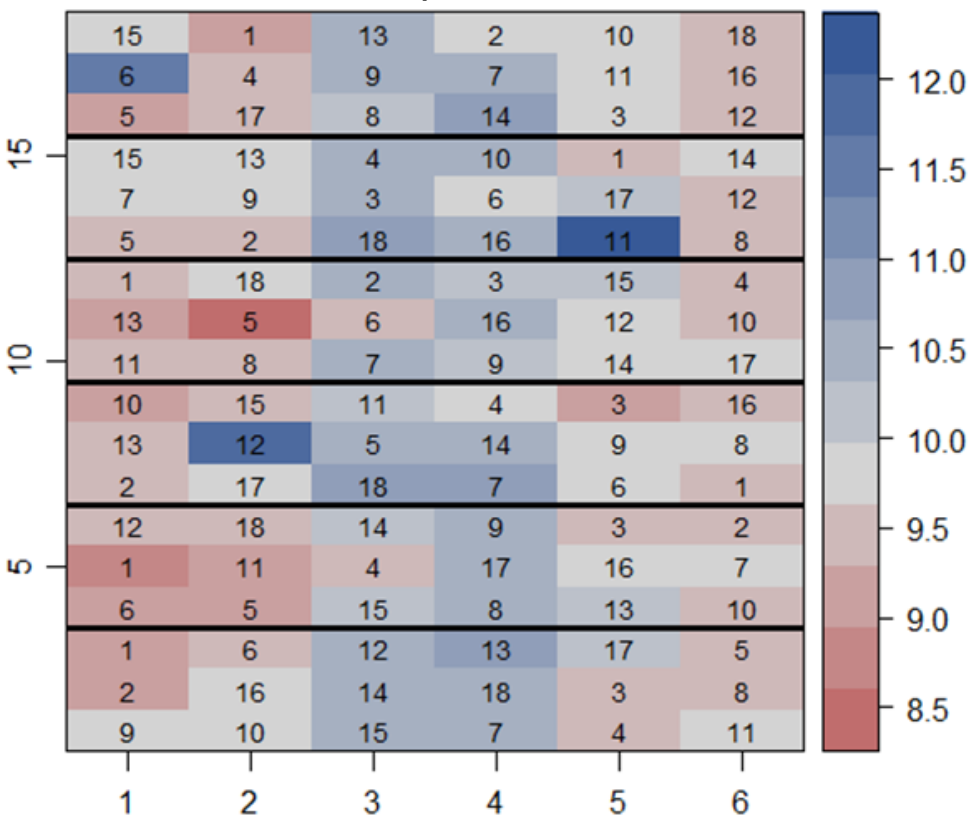
More Examples from Limburgerhof Agricultural Trial Station

Trial #996: 18 trt, 6 reps, 9 rows, 12 columns



Layout of trial [...]996: 18 Treatments in six replicates. Numbers show treatments, colors show fresh matter yield. The solid black lines show the complete replicates (blocks).

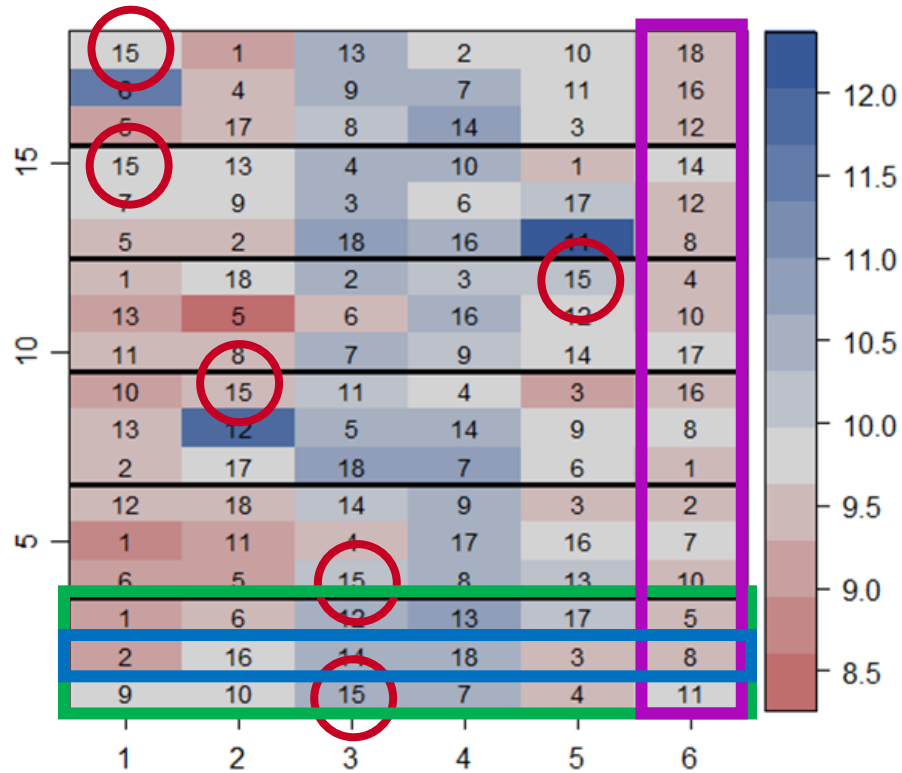
Trial #997: 18 trt, 6 reps, 18 rows, 6 columns



Layout of trial [...]997: 18 Treatments in six replicates. Numbers show treatments, colors show fresh matter yield. The solid black lines show the complete replicates (blocks).

Possible Analysis for data of original trial #997 -> Post Blocking

Trial #997: 18 trt, 18 rows, 6 columns



Layout of trial [...]997: 18 Treatments in six replicates. Numbers show treatments, **colors show fresh matter yield**. The solid black lines show the complete replicates.

Randomized Complete Block Design (RCBD):

$$y_{ij} = \mu + rep_i + trt_j + e_{ij} \quad e \sim N(0, \sigma^2 e)$$

```
lm1 <- lm(ERTFR ~ rep + trt, ...)
```

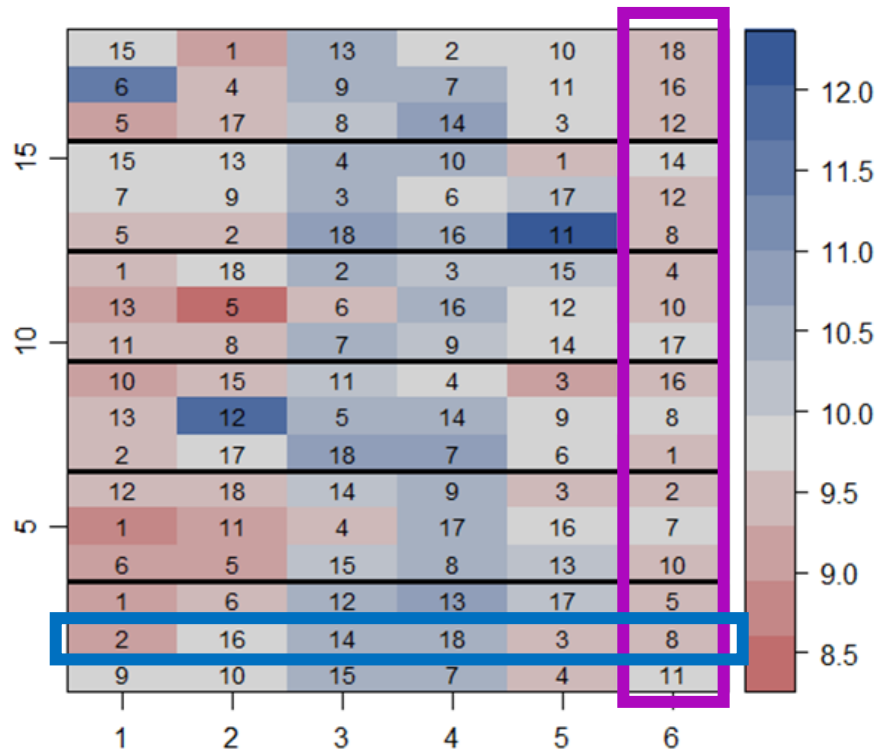
Post-Blocking: $y_{ijk} = \mu + rep_i + trt_j + col_k + e_{ijk}$

```
lm2 <- lm(ERTFR ~ rep + trt + col, ...)
```

*Post-Blocking: $y_{ijkl} = \mu + rep_i + trt_j + col_k + (rep*row)_{il} + e_{ijkl}$*

```
lm3 <- lm(ERTFR ~ rep + trt + col + rep:row, ...)
```

Taking (incomplete) blocks fix or random?



Layout of trial [...]997: 18 Treatments in six replicates.

Numbers show treatments, **colors show fresh matter yield**. The solid black lines show the complete replicates.

Random Blocks yield „interblock-information“ (Patterson & Thompson, 1971)

Block number large enough to allow estimation of variance? ✓

$$y_{ijk} = \mu + rep_i + trt_j + col_k + e_{ijk}$$

```
lm2 <- lm(ERTFR ~ rep + trt + col, ...)
```

```
lm2r <- lmer(ERTFR ~ rep + trt + (1|col), ...)
```

$$y_{ijkl} = \mu + rep_i + trt_j + col_k + (rep*row)_{il} + e_{ijkl}$$

```
lm3 <- lm(ERTFR ~ rep + trt + col + rep:row, ...)
```

```
lm3r <- lmer(ERTFR ~ rep+trt + (1|col) + (1|rep:row), ...)
```

Results

```
Model 1: ETRFR ~ rep + trt
Model 2: ETRFR ~ rep + trt + col
Model 3: ETRFR ~ rep + trt + col + row
```

	Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
1	85	29.322				
2	80	18.604	5	10.7181	10.1040	2.902e-07 ***
3	68	14.427	12	4.1772	1.6408	0.1009

```
> AIC(lm1, lm2, lm3)
      df      AIC
lm1  24 213.6805
lm2  29 174.5439
lm3  41 171.0801
```

StdErr of trt comparisons (s.e.d.) for different models, data of trial #997

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
lm1	0.3391	0.3391	0.3391	0.3391	0.3391	0.3391
lm2	0.2784	0.2815	0.2832	0.2847	0.2862	0.2984
lm2r	0.2784	0.2814	0.2832	0.2846	0.2861	0.2981
lm3	0.2703	0.2890	0.2954	0.2951	0.3001	0.3166
lm3r	0.2691	0.2804	0.2838	0.2839	0.2863	0.3015

Randomized Complete Block Design

Row-column-design with random blocks

16% reduction in stderr_of_diff; ~ like 8.56 replicates instead of 6 in RCBD

$$\sigma_e^2 = RSS / df = 29.3 / 85 = 0.345$$

$$s.e.d._{lm1} = \sqrt{2 \cdot \sigma_e^2 / r} = \sqrt{2 \cdot 0.345 / 6} = \sqrt{0.115} = 0.3391$$

$$s.e.d._{lm1*} = \sqrt{2 \cdot \sigma_e^2 / r} = \sqrt{2 \cdot 0.345 / 8.56} = \sqrt{0.0812} = 0.2839$$

From Post-Blocking to well planned Row-Column-Designs

16% lower stderr!?

- Can we achieve such improvements in other experiments also?
- We used Post-Blocking! What if we had planned and conducted the trial initially as a Row-Column-Design?

Analyze as randomized!? Is Post-Blocking allowed at all?

How to get the design?

- (Resolvable) Row-Column-Designs can be produced with CycDesign (VSNi) and PROC OPTEX (SAS).
 - **See *PIEPHO, H. P. (2015). Generating efficient designs for comparative experiments using the SAS procedure OPTEX. Communications in Biometry and Crop Science, 10, 96–114.***

SAS PROC OPTEX to create efficient row-column-design for #997

```
data TreatmentLabels;  
do trt=1 to 18;  
output; end;  
run;
```

```
data layout;  
do rep=1 to 6;  
do row=1 to 3;  
do col=1 to 6;  
output; end; end; end;  
run;
```

```
proc optex data=TreatmentLabels seed=253385;  
class trt;  
model trt;  
blocks design=layout niter=100 keep=10;  
class rep row col;  
model rep, row(rep) col / prior=0,100;  
output out=RRCD;  
run;
```

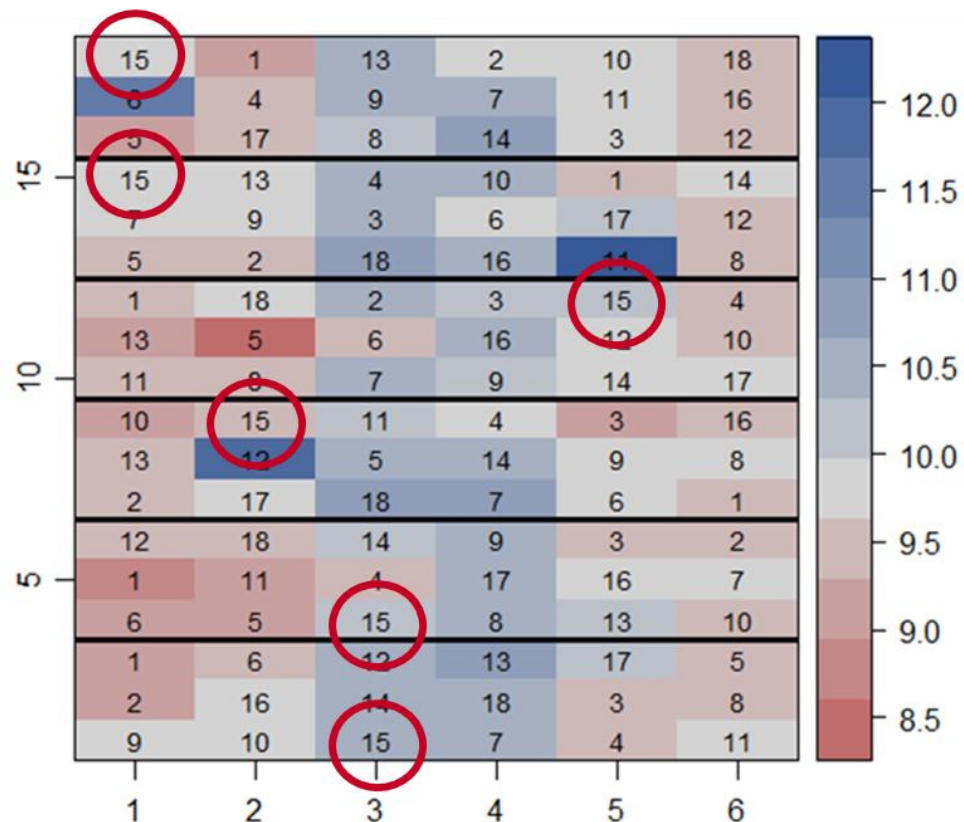
PIEPHO, H. P. (2015). Generating efficient designs for comparative experiments using the SAS procedure OPTEX.

Communications in Biometry and Crop Science, 10, 96–114.

6	16	12	7	1	13
5	3	4	2	8	9
10	11	15	18	14	17
16	14	5	12	15	4
9	8	1	10	13	11
3	17	2	6	18	7
14	4	3	13	17	16
11	6	10	1	2	5
15	12	9	8	7	18
18	10	7	16	9	3
17	2	8	15	4	1
13	5	14	11	6	12
7	1	17	9	5	14
2	18	13	4	12	10
8	15	11	3	16	6
12	9	16	17	11	2
1	13	18	5	3	15
4	7	6	14	10	8

Alternative Experimental Design: Row-Column-Design

Trial #997: 18 trt, 18 rows, 6 columns



Layout of trial [...]997, numbers show treatments, colors show fresh matter yield. The solid black lines show the complete replicates.

Alternative Design: 18 trt, 18 rows, 6 columns

6	16	12	7	1	13
5	3	4	2	8	9
10	11	15	18	14	17
16	14	5	12	15	4
9	8	1	10	13	11
3	17	2	6	18	7
14	4	3	13	17	16
11	6	10	1	2	5
15	12	9	8	7	18
18	10	7	16	9	3
17	2	8	15	4	1
13	5	14	11	6	12
7	1	17	9	5	14
2	18	13	4	12	10
8	15	11	3	16	6
12	9	16	17	11	2
1	13	18	5	3	15
4	7	6	14	10	8

SAS PROC OPTEX

Resolvable Row-Column-Design with 18 treatments in 6 complete columns and 18 incomplete rows. Rows are building 6 complete superblocks.

Compute StdErr of difference (Piepho 2015)

```
data RRCD; set RRCD;
dummy_response = 1;  Set Dummy Response to „1“
run;
ods output diffs=diffs;
proc mixed data=RRCD;
class trt rep row col;
model dummy_response = trt rep row(rep) col;  Define the model
random;
parms (1) / hold=(1);  fix residual error variance to unity
lsmeans trt /pdiff;  Calculate StdErr of Treatment Difference
run;
```



```
data diffs; set diffs;
vd = stderr**2;  Variance of Difference
run;
```



```
proc means data=diffs;
var stderr;
output out=mean_vd mean=stderr_mean;  Average stderr of diff over all trt comparisons
run;
```

Standard error of treatment difference to quantify efficiency

Original Design of Trial #997

Variable	Label	N	Mean	Std Dev	Minimum	Maximum
vd		153	0.4108003	0.0231646	0.3443117	0.4724334
StdErr	Standard Error	153	0.6406832	0.0180948	0.5867808	0.6873379

Optimal Design
produced by PROC OPTEX

Variable	Label	N	Mean	Std Dev	Minimum	Maximum
vd		153	0.3812256	0.0085038	0.3656883	0.4024637
StdErr	Standard Error	153	0.6173966	0.0068816	0.6047217	0.6344003

Planning as Resolvable Row-Column-Design theoretically gives 3.6% lower stderr.

And more homogeneous stderr!

Treatment comparison is main interest. Low stderr_of_diff is goal -> that is A-efficiency
Other efficiency metrics not necessary

Possible improvements for other designs used at Limburgerhof?

VR A/06/4							
1 ₆	6 ₇	4 ₁₈	5 ₁₉				
5 ₅	3 ₈	6 ₁₇	2 ₂₀				
4 ₄	2 ₉	1 ₁₆	4 ₂₁				
6 ₃	4 ₁₀	5 ₁₅	3 ₂₂				
2 ₂	5 ₁₁	3 ₁₄	1 ₂₃				
3 ₁	1 ₁₂	2 ₁₃	6 ₂₄				
				288 m ²			

Avg. stderr = 0.762

PROC OPTEX

6	2	3	4
5	3	1	2
3	5	4	1
1	4	2	6
4	6	5	3
2	1	6	5

Avg. stderr = 0.748

Precision + 1.8%

Design	Treatments	Replicates	Rows	Cols	stderr_diff original	Stderr OPTEX	OPTEX relativ
VR A/06/4	6	4	6	4	0,762	0,748	98,2%
VR B/06/4					0,748	0,748	100,0%
VR A/07/4	7	4	7	4	0,777	0,756	97,3%
VR B/07/4					0,760	0,756	99,5%
VR A/08/4	8	4	8	4	0,813	0,767	94,3%
VR B/08/4					0,778	0,767	98,6%
VR A/09/4	9	4	9	4	0,790	0,774	98,0%
VR B/09/4					0,795	0,774	97,4%
VR A/10/4	10	4	10	4	0,800	0,779	97,4%
VR B/10/4					0,815	0,779	95,6%
VR A/11/4	11	4	11	4	0,822	0,782	95,1%
VR B/11/4					0,807	0,782	96,9%
VR A/12/4	12	4	12	4	0,816	0,784	96,1%
VR B/12/4					0,821	0,784	95,5%
VR A/13/4	13	4	13	4	0,814	0,788	96,8%
VR B/13/4					0,803	0,788	98,1%
VR A/14/4	14	4	14	4	0,813	0,789	97,0%
VR B/14/4					0,834	0,789	94,6%
VR A/16/4	16	4	16	4	0,821	0,797	97,1%
VR B/16/4					0,828	0,797	96,3%

On average 3% smaller stderr, equals 6.3% more replicates.
A fifth replicate at every fourth trial. Zero additional costs!
(Theoretically, at the trials where additional block effect needed)

Average 97,0%

Software to create (resolvable) Row-Column-Designs

(CycDesigN, PROC OPTEX, R, JMP)

Using JMP

DOE (

```
Custom Design,
{Add Response( Maximize, "Y", ., ., . ),
Add Factor( Categorical, {"L1", "L2", "L3", "L4", "L5", "L6"}, "trt", 0 ),
Add Factor( Blocking, 4, "row" ), Add Factor( Blocking, 6, "col" ),
Set Random Seed( 30898004 ), Number of Starts( 37453 ), Add Term( {1, 0} ),
Add Term( {1, 1} ), Add Term( {2, 1} ), Add Term( {3, 1} ),
Set Sample Size( 24 ), Simulate Responses( 0 ), Save X Matrix( 0 ), Make Design}
```

);

Treatment Levels

Block sizes

Number of Plots

VR A/08/4				384m ²			
3	8	5	9	4	24	1	25
7	7	2	10	6	23	8	26
1	6	4	11	8	22	6	27
5	5	7	12	2	21	3	28
6	4	8	13	5	20	4	29
2	3	3	14	1	19	7	30
4	2	6	15	7	18	2	31
8	1	1	16	3	17	5	32

8 trt, 4 col, 6 row

6	7	5	8
4	3	1	5
8	2	3	6
1	6	2	4
7	4	8	3
2	5	7	1

For simple cases like this, JMP Custom Design generates Designs with absolutely the same efficiency as SAS PROC OPTEX does.

More complex resolvable and latinized Row-Column-Designs need manual optimization.
Sudoku 😊

Using R - library(FieldHub)

#https://cran.r-project.org/web/packages/FieldHub/vignettes/row_column.html

```
library(FieldHub)
rcd <- row_column(
  t = 18,
  nrows = 9,
  r = 4,
  l = 1,
  plotNumber = 101,
  locationNames = "Test",
  seed = 1244)
)
```

Latinization over replicates not optimal

1		2	
1	2	1	14
8	4	10	6
16	14	9	18
13	10	15	16
7	18	5	13
11	6	12	17
17	3	8	2
9	15	11	7
12	5	3	4
3		4	
13	2	17	15
3	9	4	13
16	4	5	1
12	18	6	12
6	8	7	10
10	15	9	2
17	1	18	16
5	11	11	3
7	14	8	14

Using R – other packages:

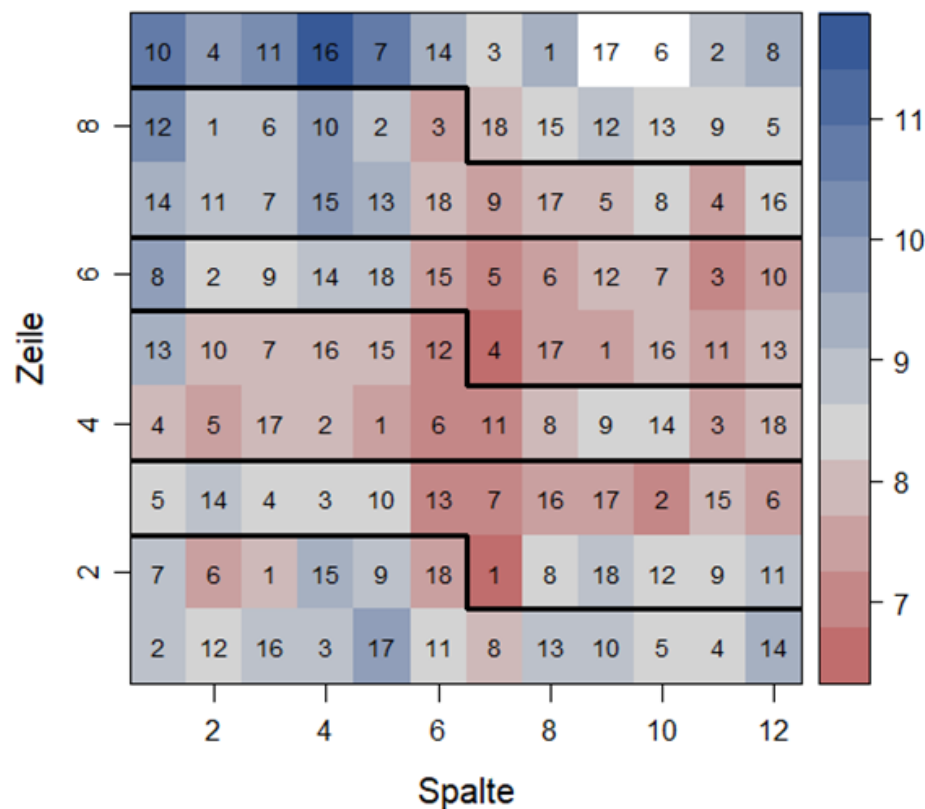
AlgDesign, DiGGer, blocksdesign, agricolae

Summary Software

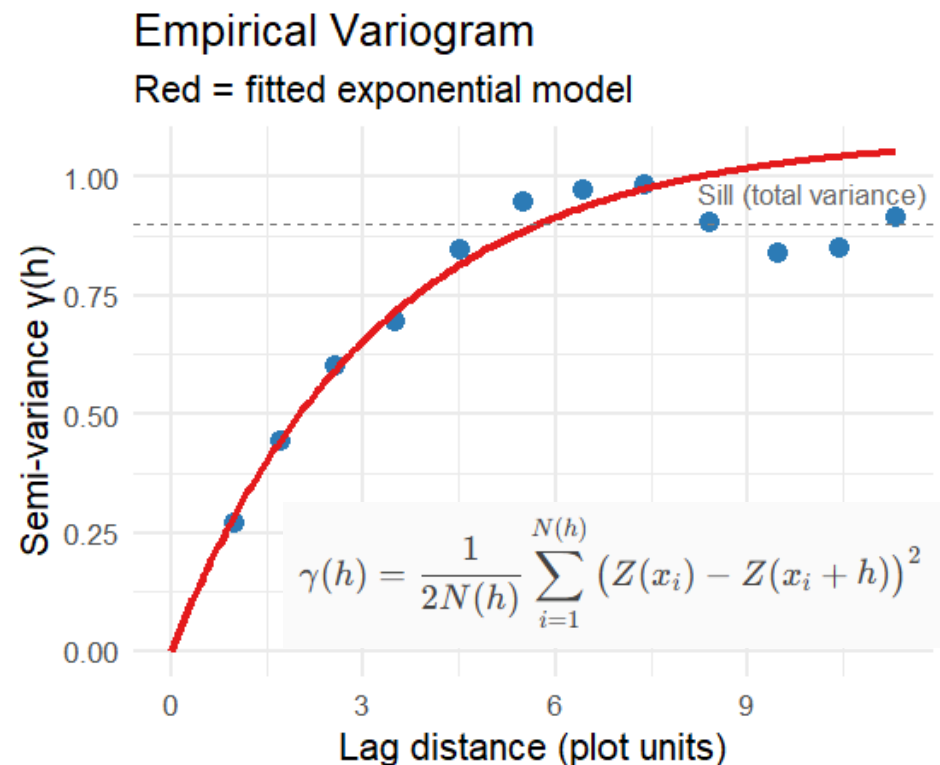
- **CycDesign** is best in class (especially latinization): <https://vsni.co.uk/software/cycdesign/>
- **SAS Proc Optex** allows a lot (See *Piepho 2015*).
- **JMP** and **R::AlgDesign** allow general design optimization but might ignore field trial constraints
- **R::FieldHub**, **R::agricolae**, **R::blocksdesign**: made for field trials but with some limitations

What's about Geostatistics?

Trial #996: Yield



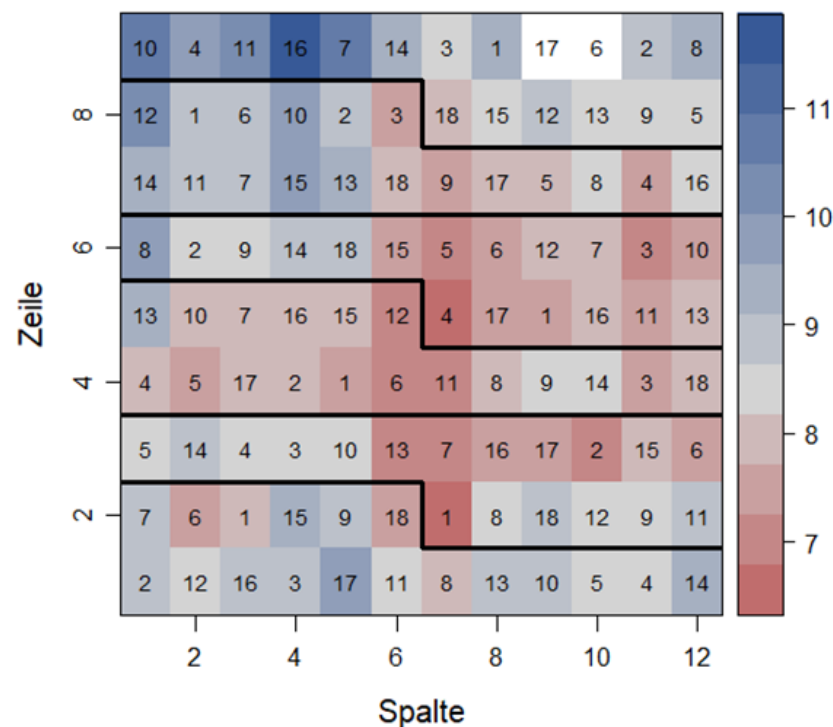
Make use of the correlation between neighboring plots



- Shamshad, M. (2026): <https://www.shamshad.in/posts/2026/05/spatial-ar1-analysis/>, Updated: May 02, 2026)
- Gilmour, A. R., Cullis, B. R., & Verbyla, A. P. (1997). Accounting for natural and extraneous variation in the analysis of field experiments. *JABES*, 2(3), 269–293.

What's about Geostatistics?

Trial #996: Yield



RCBD: average stderr_diff = 0.4447

RCD, Row-Column-Design (fixed blocks): avg. stderr_diff = 0.2270

Spatial Correlation (AR(1) * AR(1)): avg. stderr_diff = 0.2926

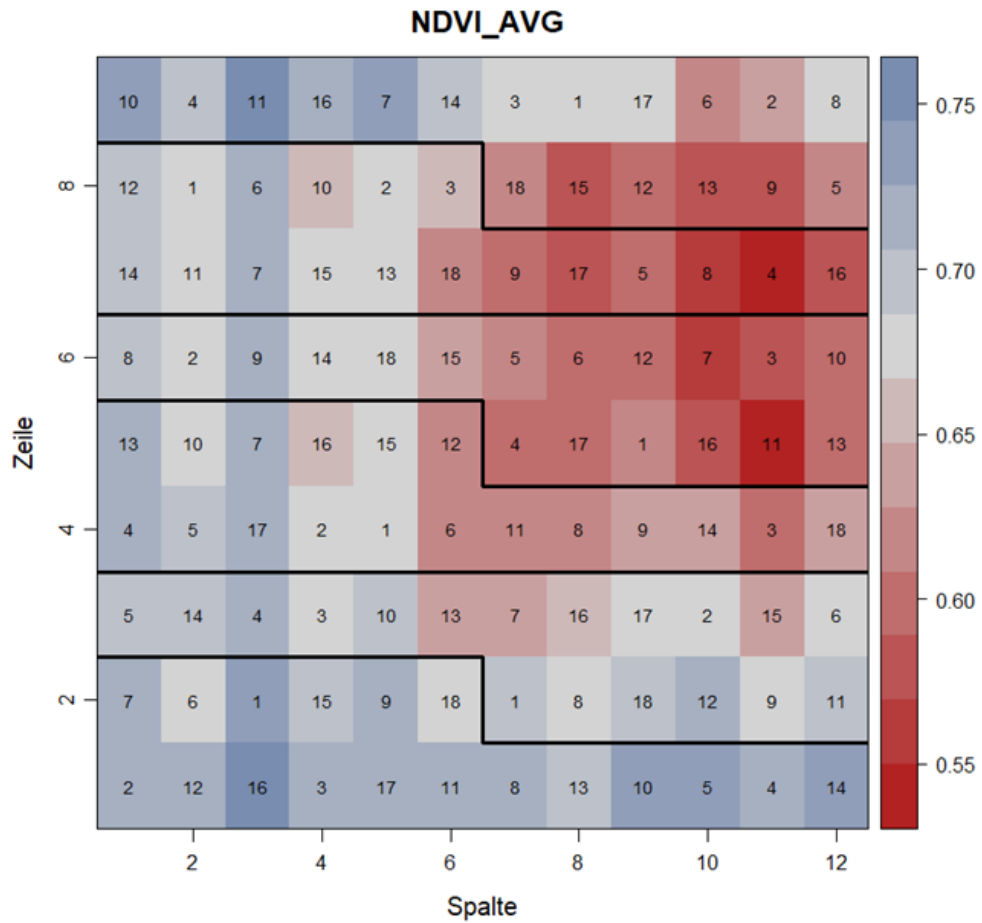
Polynomial Trend + AR(1)*AR(1): avg. stderr_diff = 0.2032

```
library(nlme)
mydata_clean <- na.omit(mydata)
m_spatial <- gls(ERTFR ~ trt + poly(row.n, 2) + poly(col.n, 2),
  data = mydata_clean,
  correlation = corAR1(form = ~ row.n|col.n) * corAR1(form = ~
    col.n|row.n))
```

- Spatial model yields some gain in precision in this example.
- But Row-Column-Postblocking already is big win, although design is unbalanced and not optimal.

What's about using covariates? (here: NDVI before Treatment)

Trial #996: NDVI



See Presentation Robin Kümmerer ☺

Summary

- **Use Row-Column-Design for Agricultural Field Trials if row and/or column effects might occur**
- While Post-Blocking in Data Analysis is beneficial, planning the trials as row-column design can improve precision even further
- **Software to generate the designs is available**
- **Geostatistics is a possible add-on**
- **Analyze as randomized!?**
 - *For research trials we have no problem with model selection after the trial -> post-blocking*
 - *For official registration trials we propose to follow the “analyze-as-randomized”-rule.*
 - *If planned as RCD, then analyze as RCD. If planned as RCBD, then analyze as RCBD. Not?*
 - *Should be discussed at the Barbeque, maybe ...*

Thanks to Daniel A. Houtz (BASF, RGQ/D) for sponsoring this work.



We create chemistry