On Deficient Experimental Designs and Their Analysis

COBORU

Centralny Ośrodek Badanfa Odmian Roślin Uprawnych

XII WORKING SEMINAR ON STATISTICAL METHODS IN VARIETY TESTING

08 - 09 Sep 2025, Słupia Wielka, Poland

A Reconsideration of Classical Principles in Plant Breeding Practice

Karen Wolf[12*], Pierre Fernique[1], Hans-Peter Piepho[2]

[1] Limagrain Europe, [2] University of Hohenheim

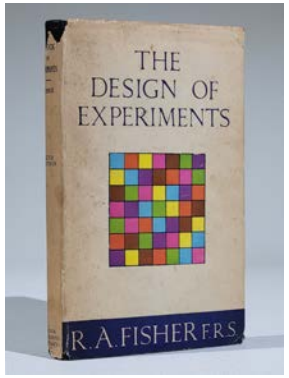
**karen.wolf@limagrain.com*

INTRODUCTION

Field Trials – Classical Principles

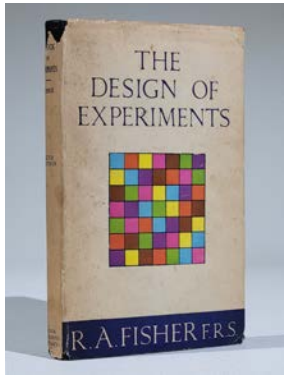
John, J.A., and Williams, E.R., *Cyclic and Computer Generated Designs*, (Monographs on Statistics and Applied Probability 38), London: Chapman & Hall (1995)

A priori		*A posteriori*
1) Experimental Design	**2) Field Trial**	**3) Trial Analysis**



Fisher, R.A., *The design of experiments*, 8th ed, New York: Hafner (1971)

Field Trials – Classical Principles

A priori **1) Experimental Design**	**2) Field Trial**	*A posteriori* **3) Trial Analysis**
	 	
'Block what you can, randomise what you cannot'		$\boldsymbol{Y} \sim N(\mathbf{1}\boldsymbol{\mu} + \boldsymbol{X}\boldsymbol{\tau} + \boldsymbol{Z}\boldsymbol{\beta}, \boldsymbol{\Sigma})$ *'Analyse as randomised'*

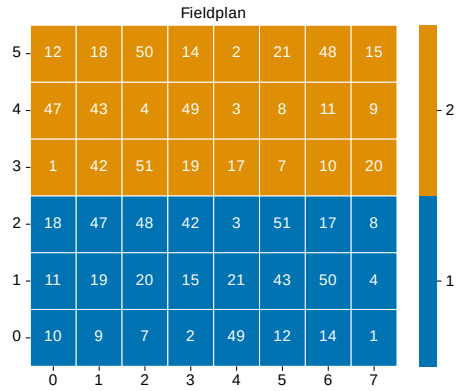
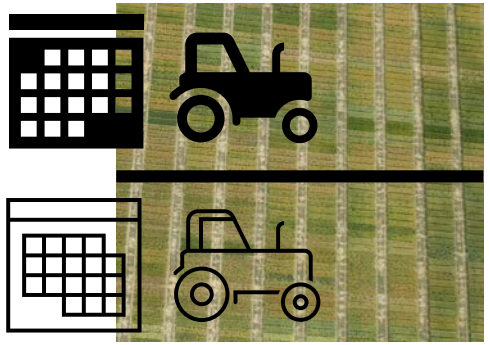
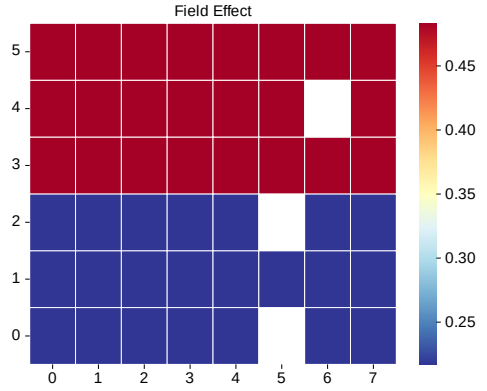
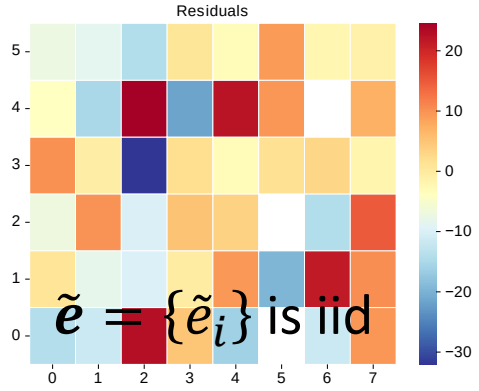
Field Trials – Classical Principles in Theory

Cond. residuals $\tilde{e} = \{\tilde{e}_i\}$ with $\tilde{e}_i = y_i - \hat{y}[y_i|y_{\{-i\}}]$ for $\{i = 1, \dots, n\}$

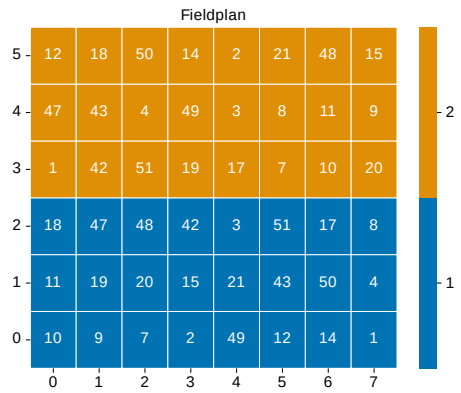
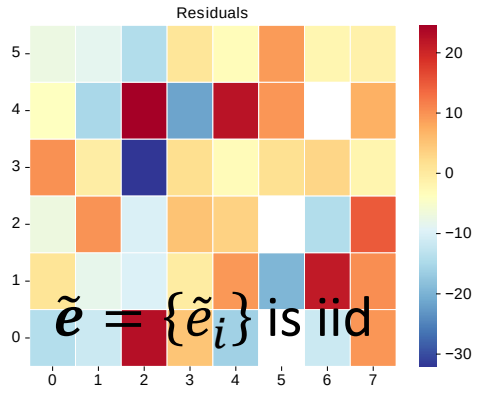
Haslett, J., and Haslett, S. J., *The three basic types of residuals for a linear model,* International Statistical Review (2007)

A priori **1) Experimental Design**	**2) Field Trial**	*A posteriori* **3) Trial Analysis**
'Block what you can, randomise what you cannot'		$\boldsymbol{Y} \sim N(\mathbf{1}\boldsymbol{\mu} + \boldsymbol{X}\boldsymbol{\tau} + \boldsymbol{Z}\boldsymbol{\beta}, \boldsymbol{\Sigma})$ *'Analyse as randomised'*

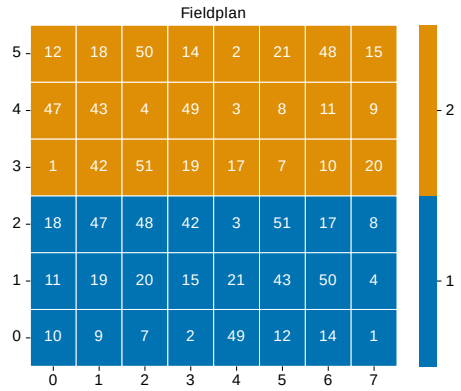
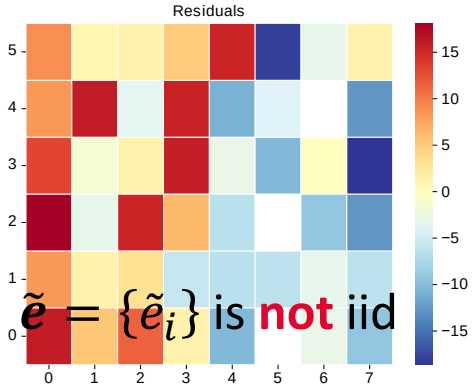
Field Trials – Classical Principles in Practice

A priori **1) Experimental Design**	**2) Field Trial**	*A posteriori* **3) Trial Analysis**
	 	 $\tilde{\boldsymbol{e}} = \{\tilde{e}_i\}$ is iid
'Block what you can, randomise what you cannot' $\rightarrow \boldsymbol{Z}_{design}$ define blocks based on a priori information (RCBD)	Split harvest in two days (e.g., due to large size of the field) $\rightarrow \boldsymbol{Z}_{design} = \boldsymbol{Z}_{field}$ field effects	$\boldsymbol{Y} \sim N(\mathbf{1}\boldsymbol{\mu} + \boldsymbol{X}\boldsymbol{\tau} + \boldsymbol{Z}\boldsymbol{\beta}, \boldsymbol{\Sigma})$ *'Analyse as randomised'* $\rightarrow \boldsymbol{Z} = \boldsymbol{Z}_{design}$ encodes for block effects (RCBD)

Field Trials – Classical Principles in Practice

A priori **1) Experimental Design**	**2) Field Trial**	*A posteriori* **3) Trial Analysis**
		
'Block what you can, randomise what you cannot' $\rightarrow \boldsymbol{Z}_{design}$ define blocks based on a priori information (RCBD)	Split harvest in two days (e.g., due to large size of the field) Transient features, etc. $\rightarrow \boldsymbol{Z}_{design} \neq \boldsymbol{Z}_{field}$ field effects	$\boldsymbol{Y} \sim N(\mathbf{1}\boldsymbol{\mu} + \boldsymbol{X}\boldsymbol{\tau} + \boldsymbol{Z}\boldsymbol{\beta}, \boldsymbol{\Sigma})$ *'Analyse as randomised'* $\rightarrow \boldsymbol{Z} = \boldsymbol{Z}_{design}$ encodes for block effects (RCBD)

Field Trials – Classical Principles in Practice

A priori **1) Experimental Design**	**2) Field Trial**	*A posteriori* **3) Trial Analysis**
		 $\tilde{\boldsymbol{e}} = \{\tilde{e}_i\}$ is **not** iid
'Block what you can, randomise what you cannot' $\rightarrow \boldsymbol{Z}_{design}$ define blocks based on a priori information (RCBD)	Split harvest in two days (e.g., due to large size of the field) Transient features, etc. $\rightarrow \boldsymbol{Z}_{design} \neq \boldsymbol{Z}_{field}$ field effects	$\boldsymbol{Y} \sim N(\mathbf{1}\boldsymbol{\mu} + \boldsymbol{X}\boldsymbol{\tau} + \boldsymbol{Z}\boldsymbol{\beta}, \boldsymbol{\Sigma})$ *'Analyse as randomised'* ?? $\rightarrow \boldsymbol{Z} = \boldsymbol{Z}_{design}$ encodes for block effects (RCBD)

RELATED WORK

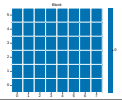
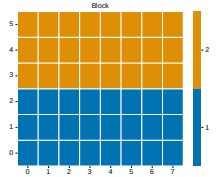
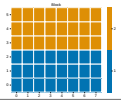
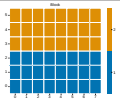
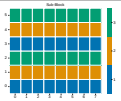
Related Work

A priori **1) Experimental Design**	**2) Field Trial**	*A posteriori* **3) Trial Analysis**
Bailey, R.A., *Design of comparative experiments*. Vol. 25. Cambridge University Press (2008) **Calinski, T., and Sanpei K.**. *Block Designs: A Randomization Approach: Volume I: Analysis*. Vol. 150. Springer Science & Business Media (2000) → **Blocking may be inefficient but we ensure that estimates are accurate due to ' […] *randomise what you cannot [block]*'.**	**Pearce, S.C.**, *Some design problems in crop experimentation. I. The use of blocks*, Experimental Agriculture (1995) → **Cases, where $Z_{design} \neq Z_{field}$ (e.g., transient features) exist and lead to harmful blocks.**	**Frey, J., Hartung, J., Ogutu, J., and Piepho, H.-P.**, *Analyze as randomized—why dropping block effects in designed experiments is a bad idea*, Agronomy Journal (2024) → **In the case of $Z_{design} = Z_{field}$: *Analyse as randomised*.**
3) We quantify the impact of randomisation (,[…]*randomise what you cannot* ') on the accuracy of estimations and the implications in practice.	**1) We simulate cases such as $Z_{design} \prec Z_{field}$, $Z_{design} \equiv Z_{field}$ and $Z_{design} \succ Z_{field}$.**	**2) We answer the question if, in such cases, we should '*Analyse as randomised*'.**

SIMULATION STUDY

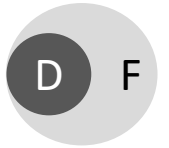
Simulation Study – Different Scenarios

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$

Block	Sub-Block	Z_{design}		Z_{field}	Block	+ Sub-Block
		CR-design	$\prec$	RCB-field		
		RCB-design	$\equiv$			
		α-design	$\succ$			

$Z_{design} \prec Z_{field}$

‚forgot‘

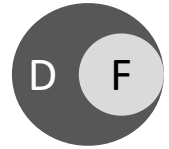


$Z_{design} \equiv Z_{field}$

‚perfect‘

$Z_{design} \succ Z_{field}$

‚too far‘



Completely Randomised (CR)
Randomised Complete Block (RCB)
α

Patterson, H.D., Williams, E.R., and Hunter, E.A., *Block designs for variety trials*, The Journal of Agricultural Science (1978)

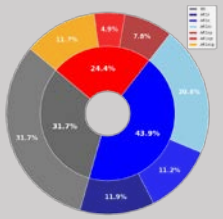
Gilmour A.R., *Post blocking gone too far! Recovery of information and spatial analysis in field experiments.*, *Biometrics* 56.3 (2000)

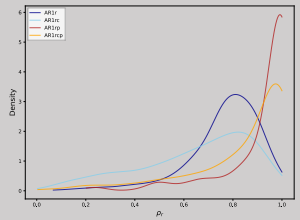
Simulation Study – Different Scenarios (Example)

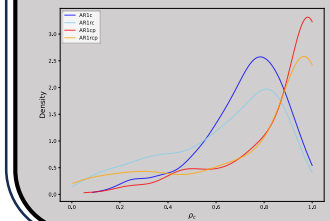
Randomly draw effect estimates of one trial

DATABASE

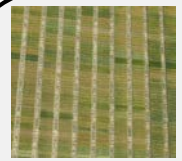
Effect estimates of thousands of historical trials



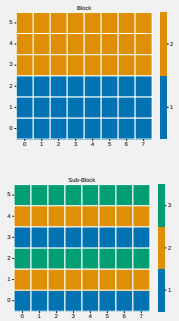




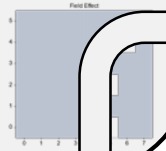
Data of one historical trial



→ $\boldsymbol{Z}_{trial}$
- →#Rows, #Columns
- →Blocks, Sub-Blocks



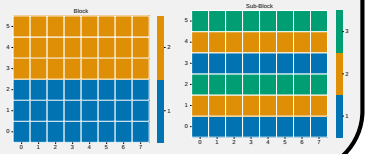
→Estimated Genot-typic values $\hat{\boldsymbol{\tau}}_{trial}$



→NAs

$\boldsymbol{Z}_{trial}$

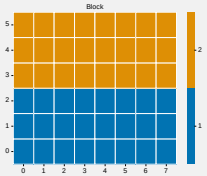
Randomise geno-types according to $\boldsymbol{Z}_{design} \preceq \boldsymbol{Z}_{trial}$



$\boldsymbol{Z}_{design}$ $\boldsymbol{X}$

$\boldsymbol{Z}_{trial}$

Define $\boldsymbol{Z}_{field} \preceq \boldsymbol{Z}_{trial}$



$\boldsymbol{\tau} = \hat{\boldsymbol{\tau}}_{trial}$ $\boldsymbol{Z}_{field}$

σ^2_{blocks}

Simulate field effects:

$\boldsymbol{\beta}$ ↻ $N(0, \sigma^2_{blocks})$

e.g.,

$\boldsymbol{\beta\_block}$ ↻ $N(0, \sigma^2_{block})$

$\boldsymbol{\beta}$

σ^2

Simulate residuals:

$\boldsymbol{\epsilon}$ ↻ $N(0, \sigma^2)$

$\boldsymbol{\epsilon}$

NAs

1. Simulate trial: $\boldsymbol{y = 1\mu + X\tau + Z_{field}\beta + \epsilon}$

2. Analyse trial: $\boldsymbol{Y \sim N(1\mu + X\tau + Z\beta, \Sigma)}$

Design-based analysis (*'Analyse as randomised'*), i.e., $\boldsymbol{Z = Z_{design}}$

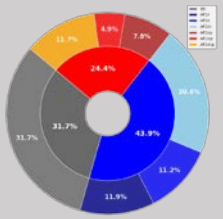
Data-driven analysis, i.e., $\boldsymbol{Z = Z_{model\_selection}}$ (SSE), where $\boldsymbol{Z_{model\_selection} \preceq Z_{design}}$

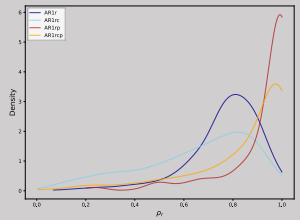
Simulation Study – Different Scenarios (Example)

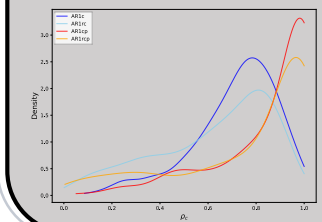
Randomly draw effect estimates of one trial

DATABASE

Effect estimates of thousands of historical trials







Data of one historical trial

→ Z_{trial}
- → #Rows, #Columns
- → Blocks, Sub-Blocks

→ Estimated Genot-typic values $\hat{\tau}$

→ NAs

Repetition at a new location

Z_{trial}

Randomise geno-types according to $Z_{design} \preceq Z_{trial}$

Z_{design} X

Z_{trial}

Define $Z_{field} \preceq Z_{trial}$

$\hat{\tau}$ Z_{field}

σ^2_{blocks}

Simulate field effects: β ↻ $N(0, \sigma^2_{blocks})$

σ^2

Simulate residuals: ϵ ↻ $N(0, \sigma^2)$

β ϵ

NAs

1. Simulate trial: $y = 1\mu + X\tau + Z_{field}\beta + \epsilon$

2. Analyse trial: $Y \sim N(1\mu + X\tau + Z\beta, \Sigma)$

Design-based analysis (‘*Analyse as randomised*‘), i.e., $Z = Z_{design}$

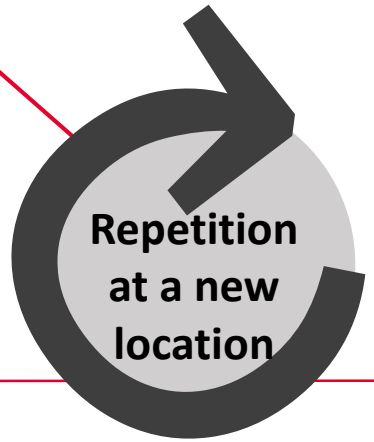
Data-driven analysis, i.e., $Z = Z_{model\_selection}$ (SSE), where $Z_{model\_selection} \preceq Z_{design}$

Simulation Study – Different Scenarios

3) We quantify the impact of randomisation (‚[…]*randomise what you cannot*‘) on the accuracy of estimations and the implications in practice.

2) We answer the question if, in such cases, we should *’Analyse as randomised‘*.

1) We simulate cases such as
$Z_{design} \prec Z_{field}$,
$Z_{design} \equiv Z_{field}$, and
$Z_{design} \succ Z_{field}$.



1. Simulate trial: $y = 1\mu + X\tau + Z_{field}\beta + \epsilon$

2. Analyse trial: $Y \sim N(1\mu + X\tau + Z\beta, \Sigma)$

Design-based analysis (‘*Analyse as randomised*‘), i.e., $Z = Z_{design}$

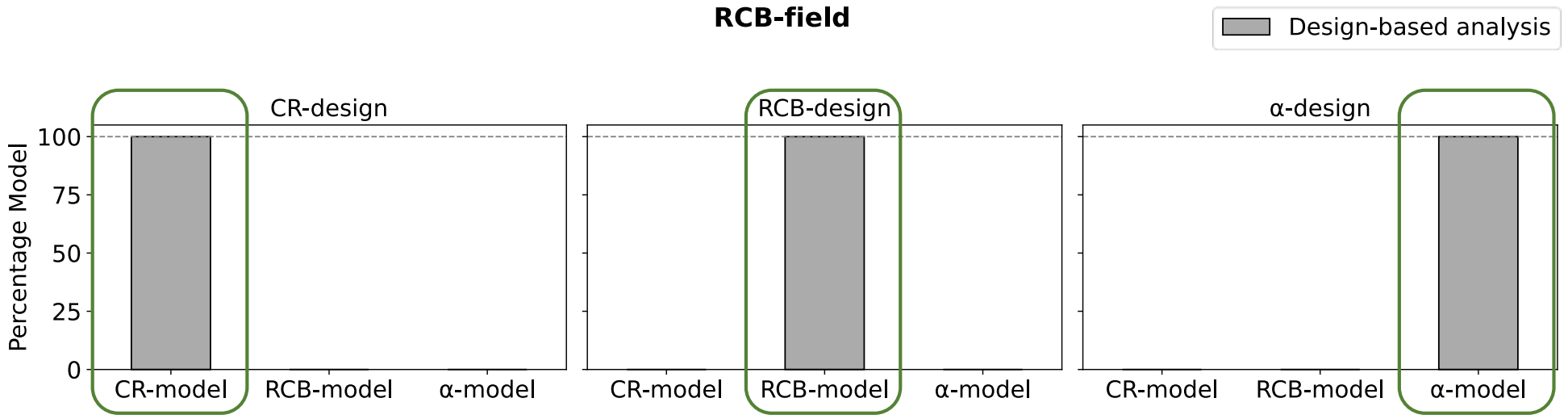
Data-driven analysis, i.e., $Z = Z_{model\_selection}$ (SSE), where $Z_{model\_selection} \preceq Z_{design}$

RESULTS

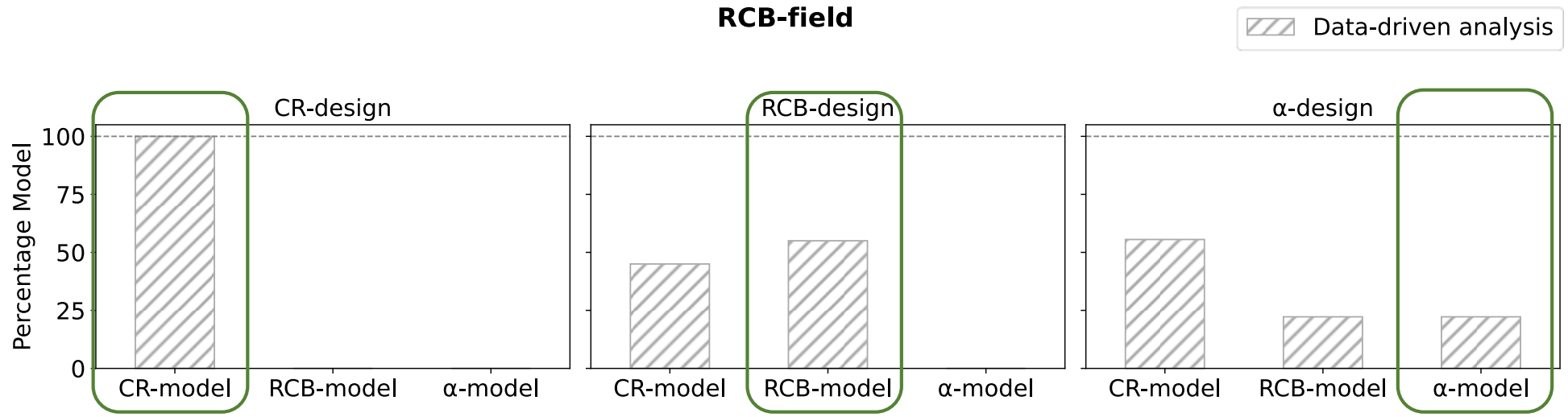
Results - Models

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$

Design-based analysis (‘*Analyse as randomised*‘), i.e., $Z = Z_{design}$



Data-driven analysis, i.e., $Z = Z_{model\_selection}$



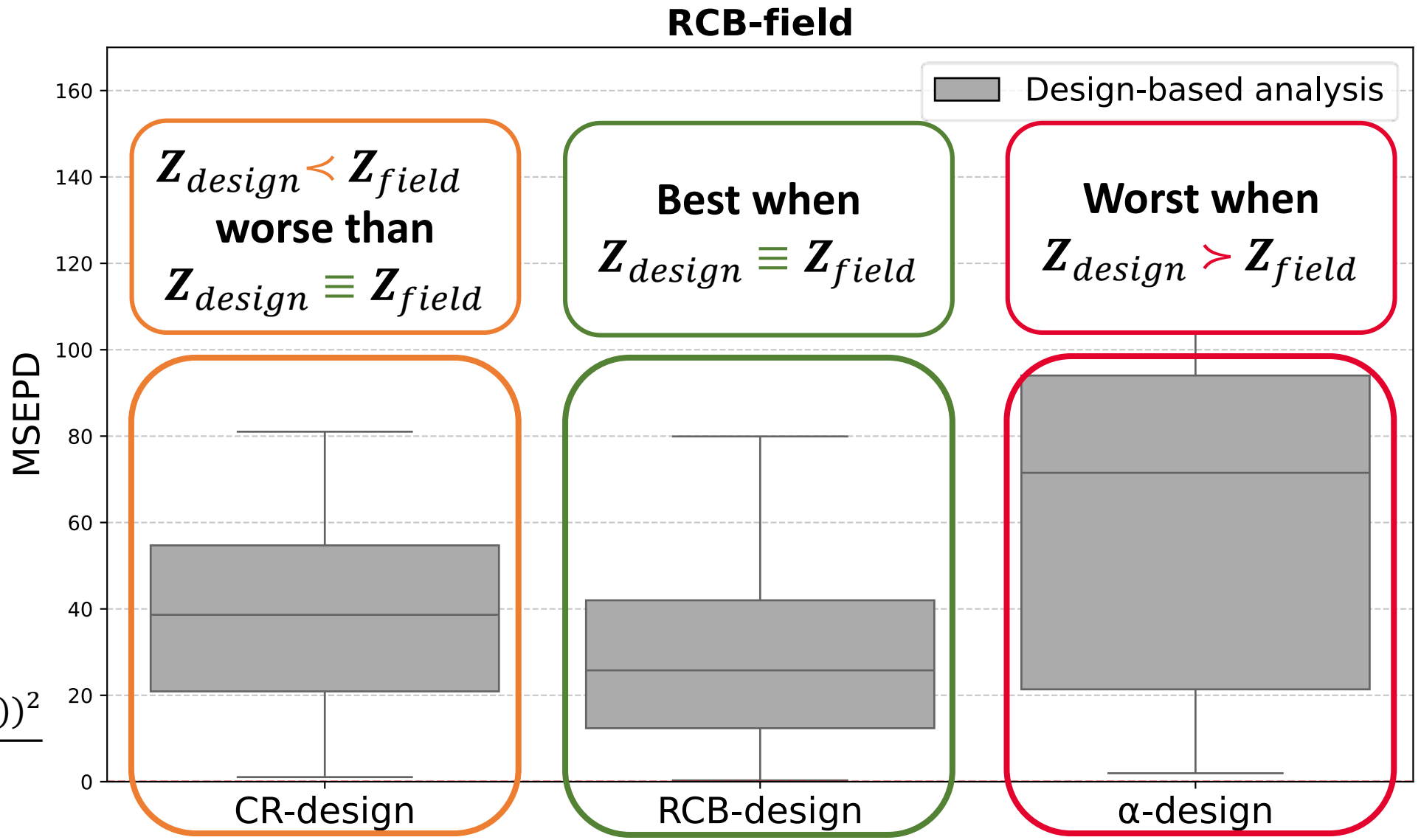
Results – MSEPD of $\hat{\tau}$ to τ

Mean squared error of prediction differences (MSEPD)

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$

Design-based analysis (‘*Analyse as randomised*‘), i.e., $Z = Z_{design}$

$$MSEPD = \frac{\sum_{i<j}^{n}((\hat{\tau}_i - \hat{\tau}_j) - (\tau_i - \tau_j))^2}{n(n-1)}$$



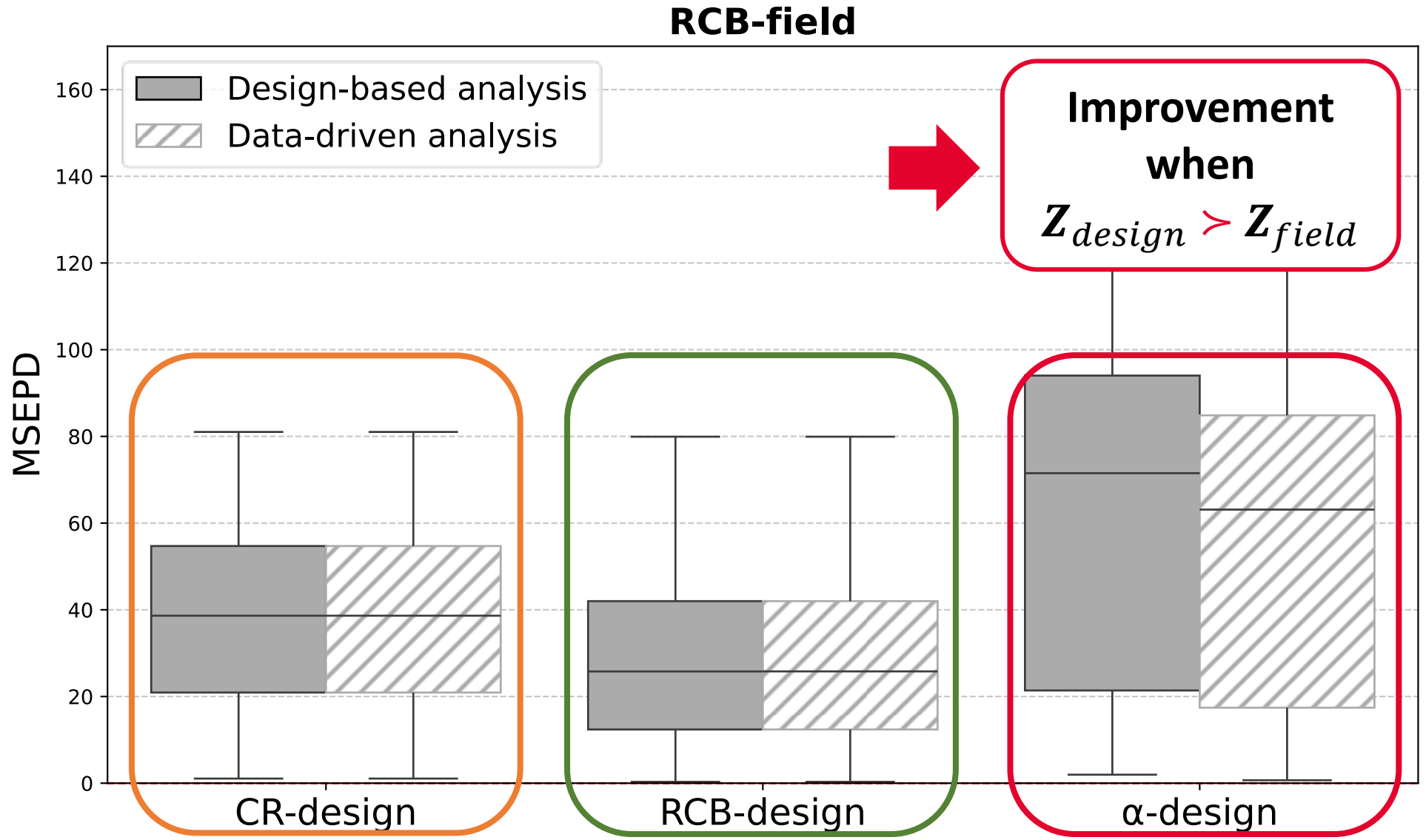
Results – MSEPD of $\hat{\tau}$ to τ

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$

Design-based analysis (‘*Analyse as randomised*‘), i.e., $Z = Z_{design}$

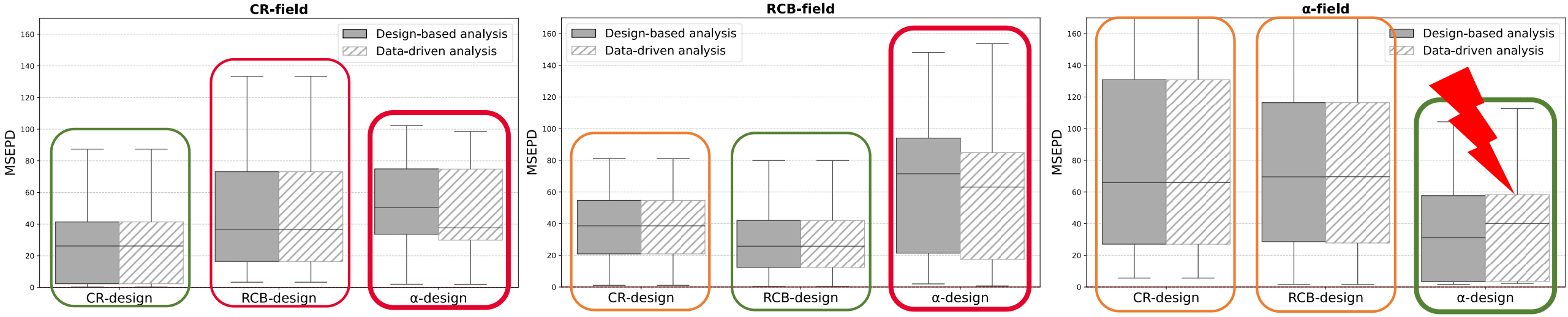
versus

Data-driven analysis, i.e., $Z = Z_{model\_selection}$



Results – MSEPD of $\hat{\tau}$ to τ

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$



2) We answer the question if, in such cases, we should *‚Analyse as randomised‘*.

Generally, we should not *‚Analyse as randomised‘*, but use data-driven analysis. This improves the estimations when we went ‘too far‘ in the design.

<u>We must verify model selection, especially for α-design $\equiv$ α-field!</u>

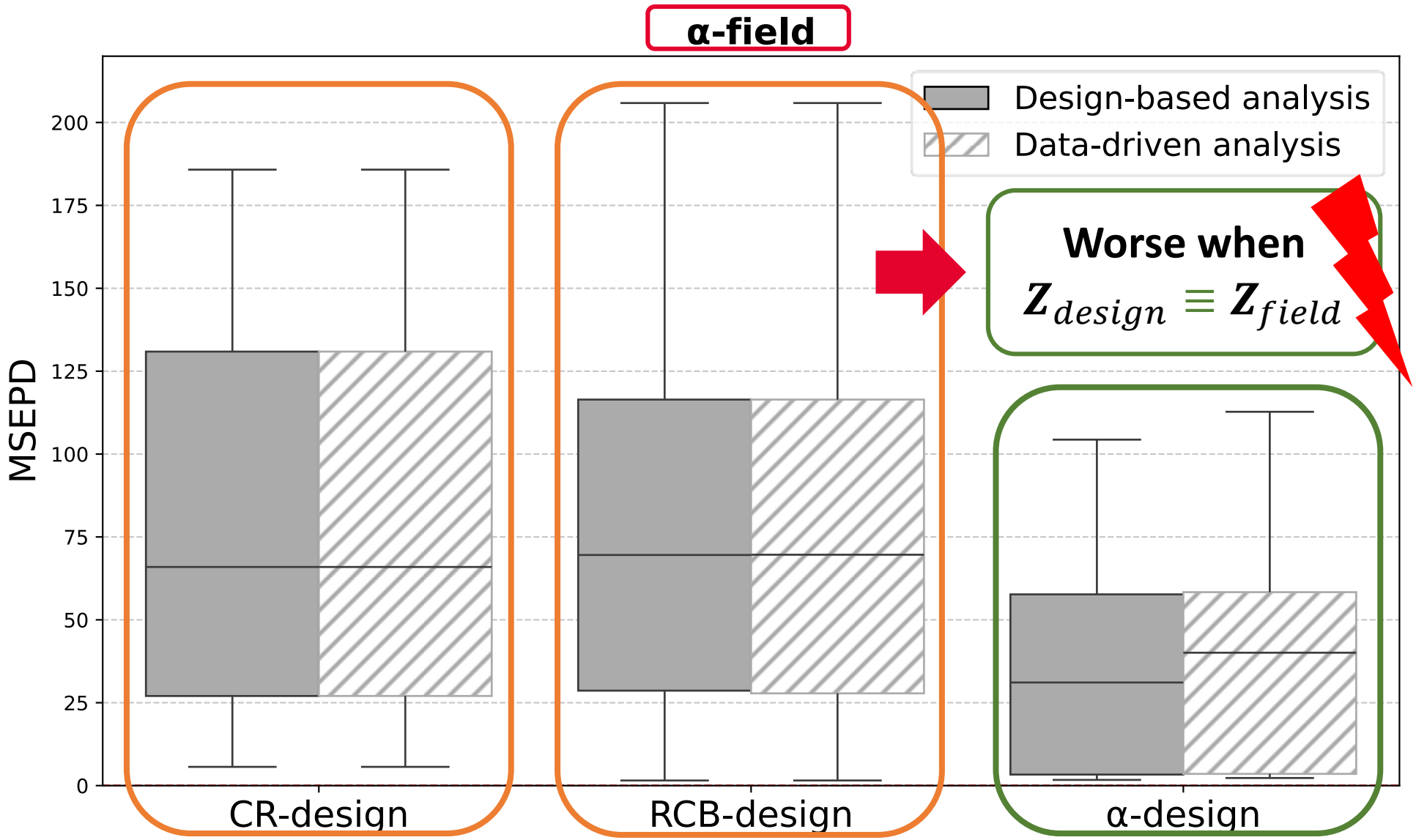
Results – MSEPD of $\hat{\tau}$ to τ

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$

Design-based analysis (‘*Analyse as randomised*‘), i.e., $Z = Z_{design}$

versus

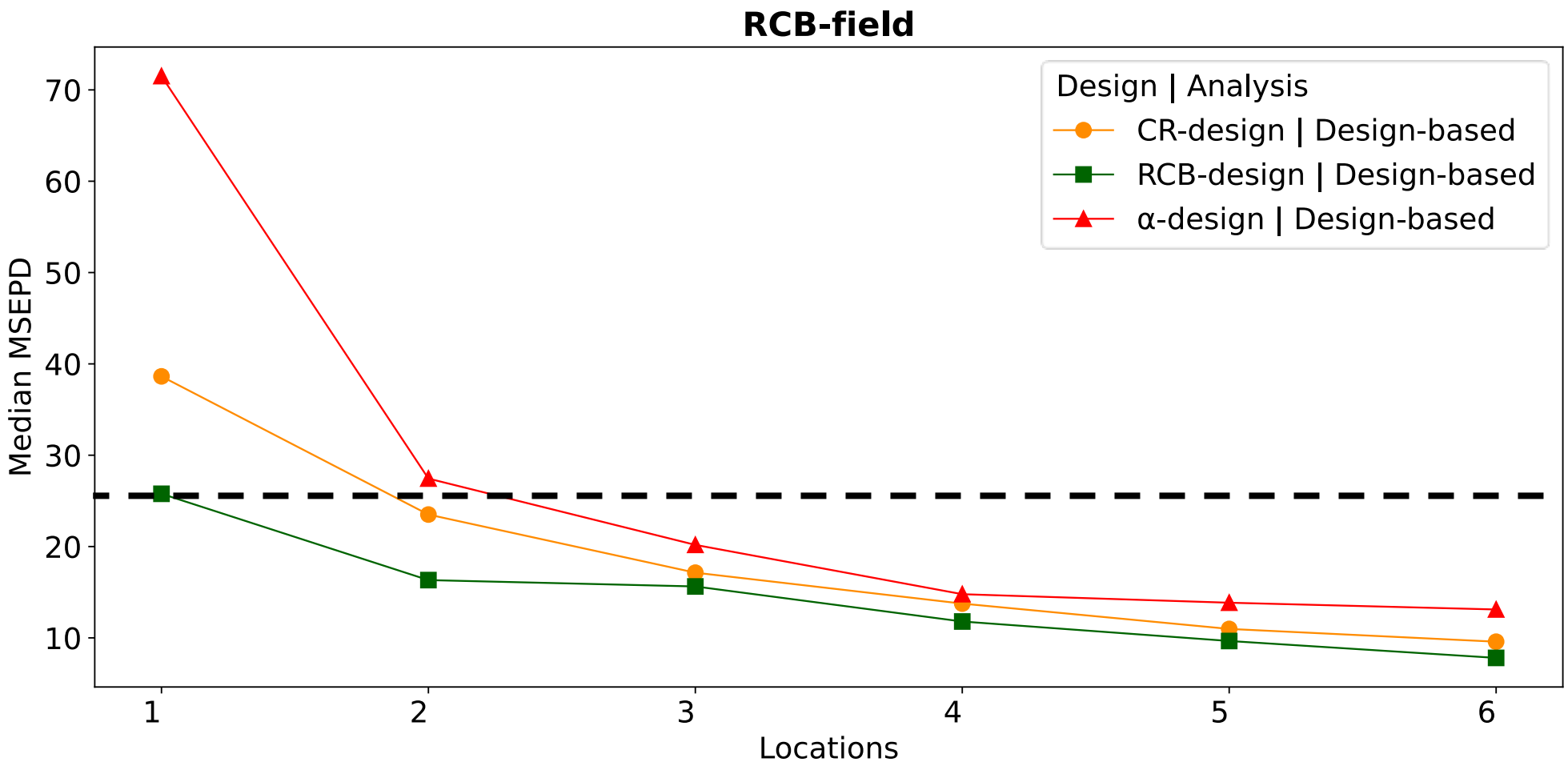
Data-driven analysis, i.e., $Z = Z_{model\_selection}$



Results – Convergence of $\hat{\tau}$ to τ (MSEPD)

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$

Design-based analysis (‘*Analyse as randomised*‘), i.e., $Z = Z_{design}$



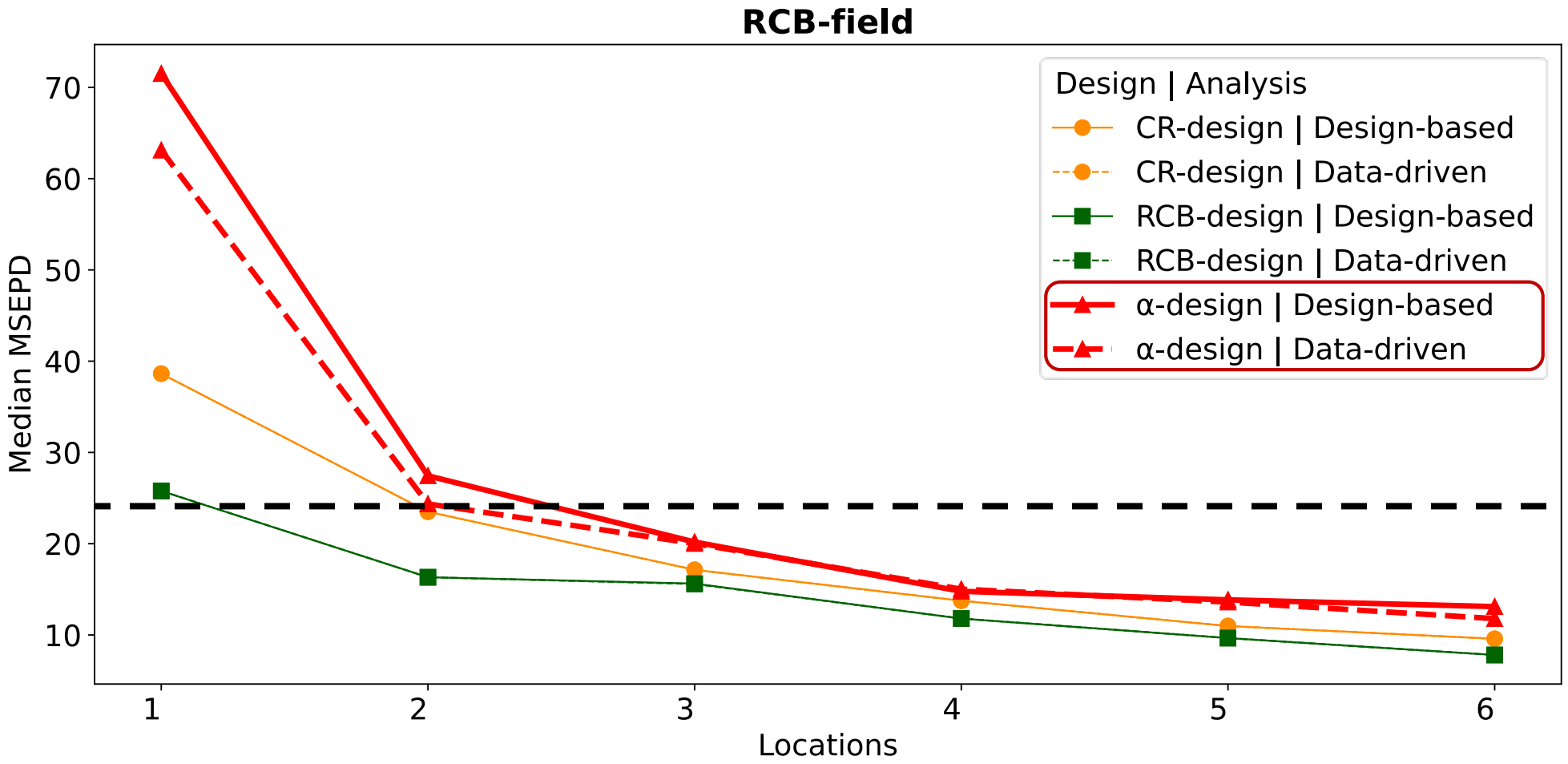
Results – Convergence of $\hat{\tau}$ to τ (MSEPD)

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$

Design-based analysis (‘*Analyse as randomised*‘), i.e., $Z = Z_{design}$

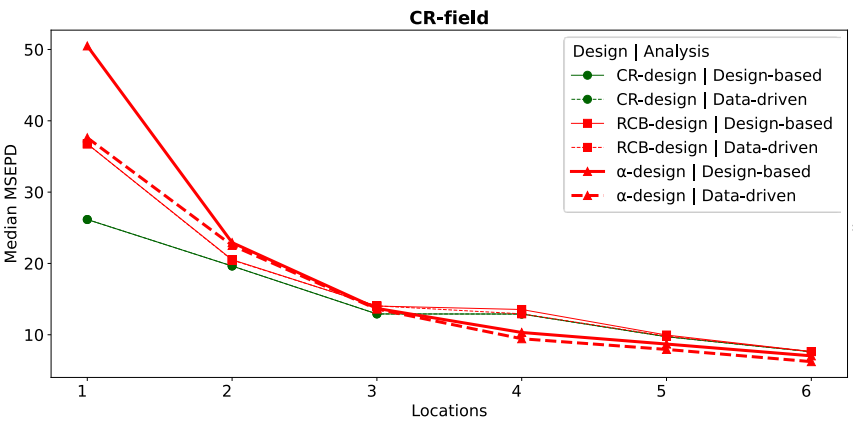
versus

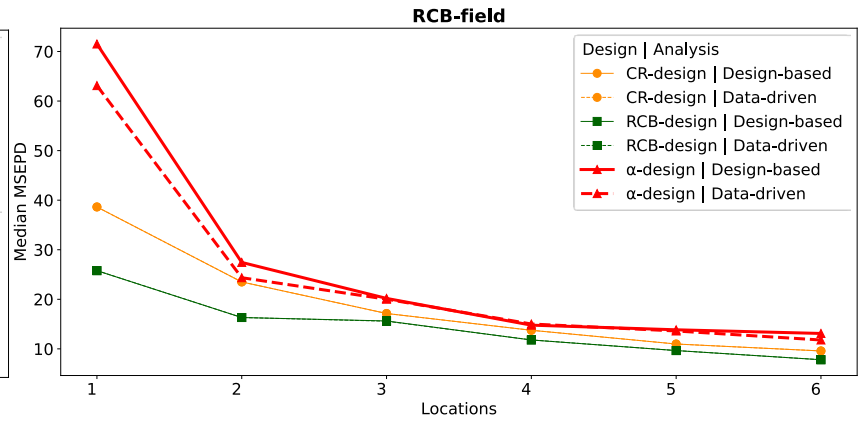
Data-driven analysis, i.e., $Z = Z_{model\_selection}$

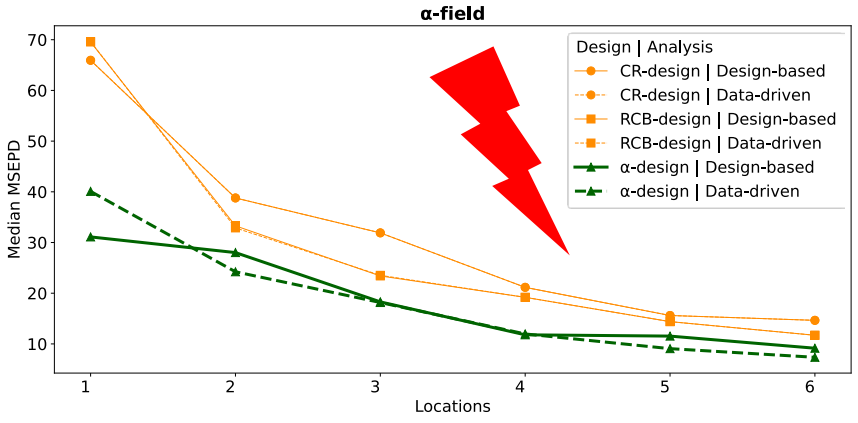


Results – Convergence of $\hat{\tau}$ to τ (MSEPD)

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$





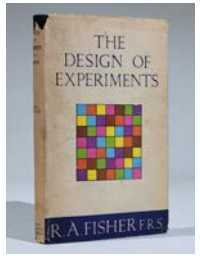


3) We quantify the impact of randomisation (‚[…]*randomise what you cannot*‘) on the accuracy of estimations and the implications in practice.

Theoretically, randomisation ensures accurate estimations. However, to the cost of more replications.

SUMMARY

Field Trials – Classical Principles in Practice

A priori **1) Experimental Design**	**2) Field Trial**	*A posteriori* **3) Trial Analysis**
'Block what you can, randomise what you cannot'	 	$\boldsymbol{Y} \sim N(\mathbf{1}\boldsymbol{\mu} + \boldsymbol{X}\boldsymbol{\tau} + \boldsymbol{Z}\boldsymbol{\beta}, \boldsymbol{\Sigma})$ *'Analyse as randomised'*

If $\boldsymbol{Z}_{design} \neq \boldsymbol{Z}_{field}$

→ **Generally, we should not ,*Analyse as randomised*', but use data-driven analysis.**

→ **This improves the estimations when we went 'too far' in the design.**

→ **Theoretically, randomisation (,[…] *randomise what you cannot*') ensures accurate estimations.**

→ **However, to the cost of more replications.**

*** We must verify model selection, especially for α-design ≡ α-field!**

OUTLOOK

OUTLOOK - Simulation

Simulation Study – Different Scenarios

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$

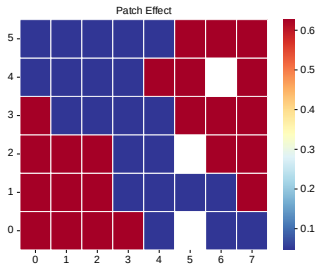
Block	Sub-Block	Z_{design}		Z_{field}	Block	+ Sub-Block
		CR-design	$\not\equiv$	CR-field		
		RCB-design	$\not\equiv$			
		α-design	$\not\equiv$			
		CR-design	$\not\equiv$	RCB-field		
		RCB-design	$\not\equiv$			
		α-design	$\not\equiv$			
		CR-design	$\not\equiv$	α-field		
		RCB-design	$\not\equiv$			
		α-design	$\not\equiv$			

$Z_{design} \prec Z_{field}$ ‚forgot‘ D F

$Z_{design} \equiv Z_{field}$ ‚perfect‘ D = F

$Z_{design} \succ Z_{field}$ ‚too far‘ D F

4) We want to additionally add patch effects



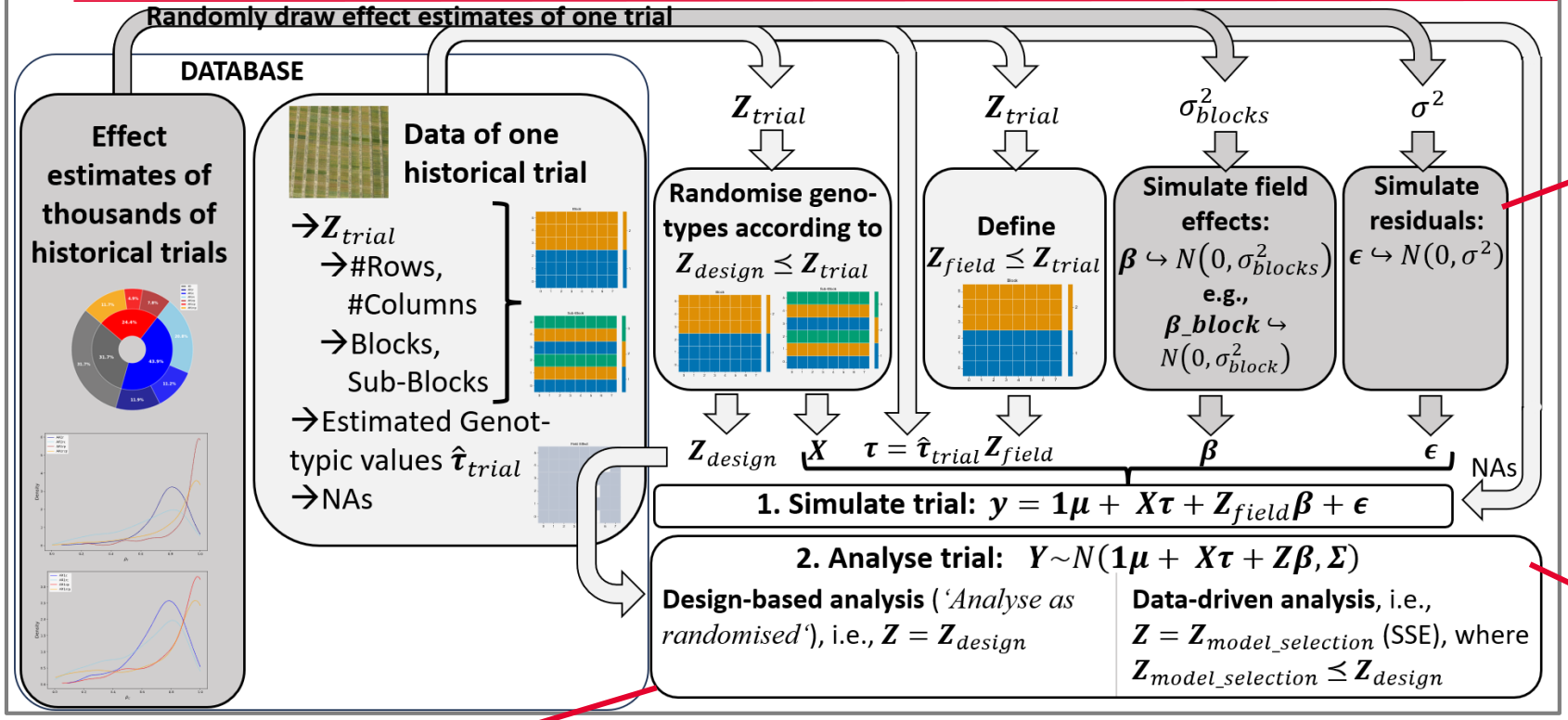
to simulate the case

$Z_{design} \not\equiv Z_{field}$

‚wrong‘ D F

OUTLOOK - Simulation

Simulation Study – Different Scenarios (Example)



5) We want to additionally simulate AR1 processes

→ Correlation within rows (ρ_r), columns (ρ_c), and nugget effect (ϕ)

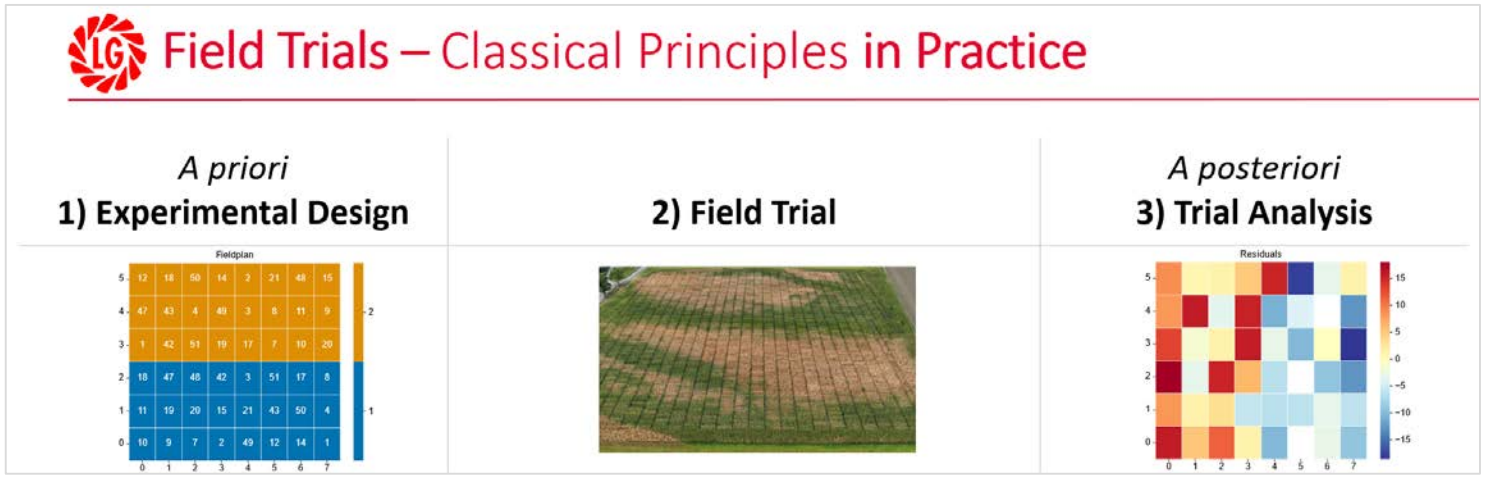
6) And study the effect of the analysis with and without estimation of AR1 processes.

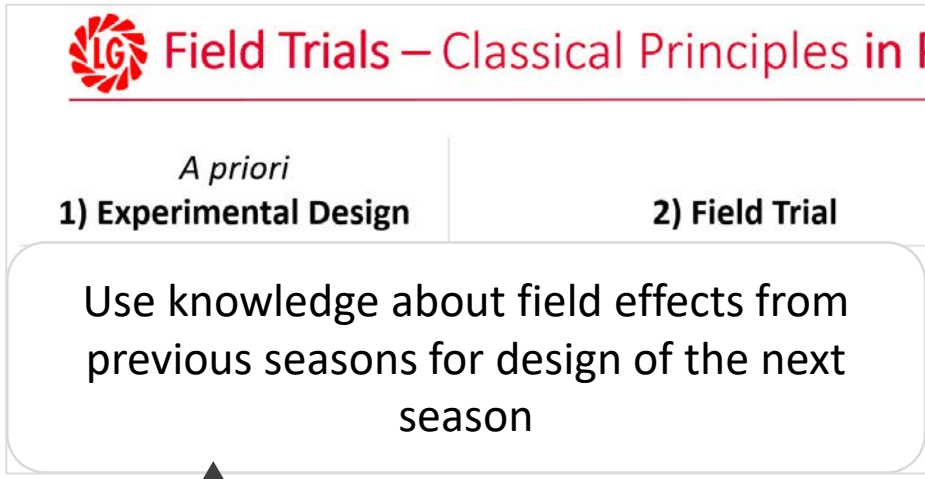
7) Generally, use also other criteria than SSE for model selection.

OUTLOOK – Use a priori Information for Design

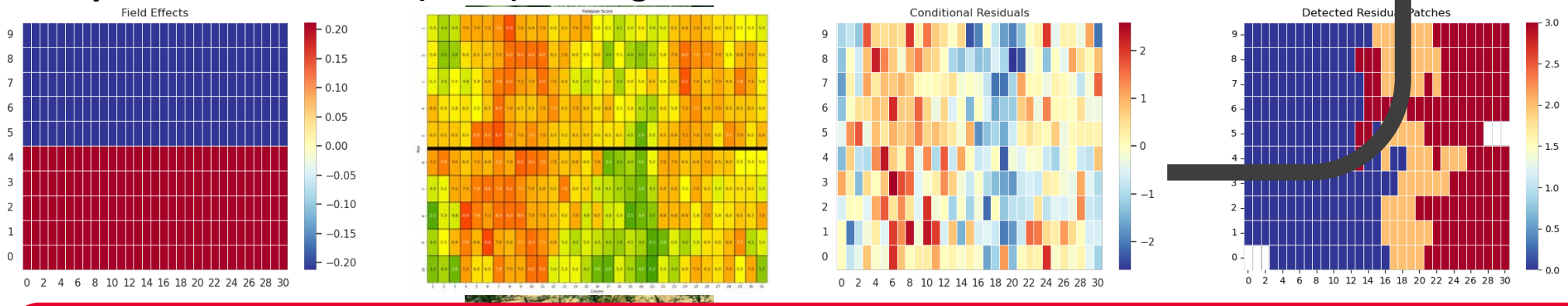
Current season:

Next season:





Barley Yellow Dwarf Virus (BYDV) – Limagrain trial 2025:



Data from Fabien LE COUVIOUR (Limagrain)

8) We want to study how we can 'Block [as good as] we can' with and without prior knowledge.

Thank you very much for your attention!

COBORU
Centralny Ośrodek Badanfa Odmian Roślin Uprawnych

XII WORKING SEMINAR ON STATISTICAL METHODS IN VARIETY TESTING
08 - 09 Sep 2025, Słupia Wielka, Poland

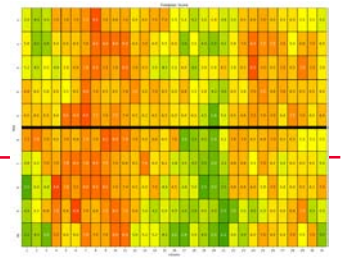
Karen Wolf[12*], Pierre Fernique[1], Hans-Peter Piepho[2]

[1] Limagrain Europe, [2] University of Hohenheim

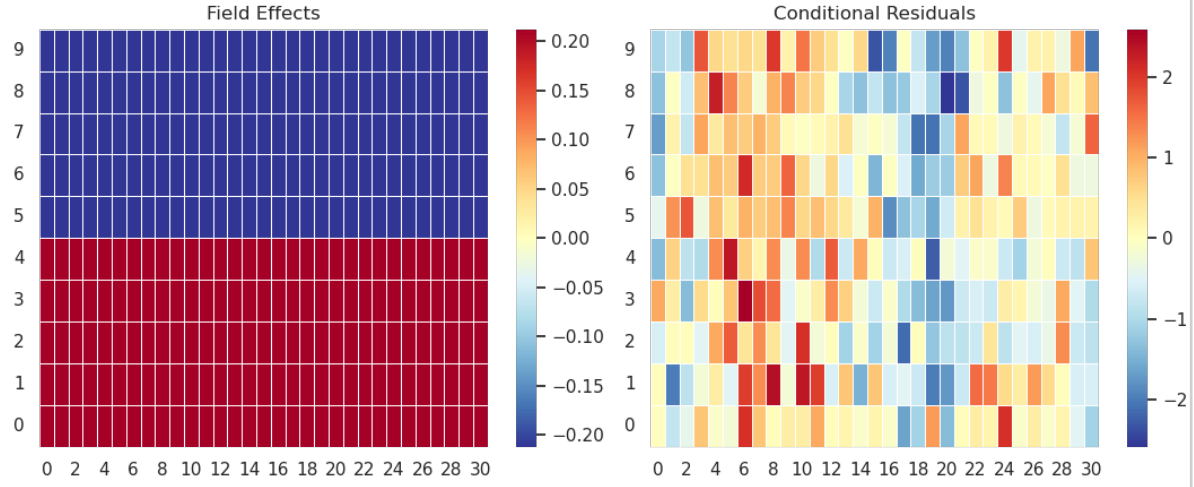
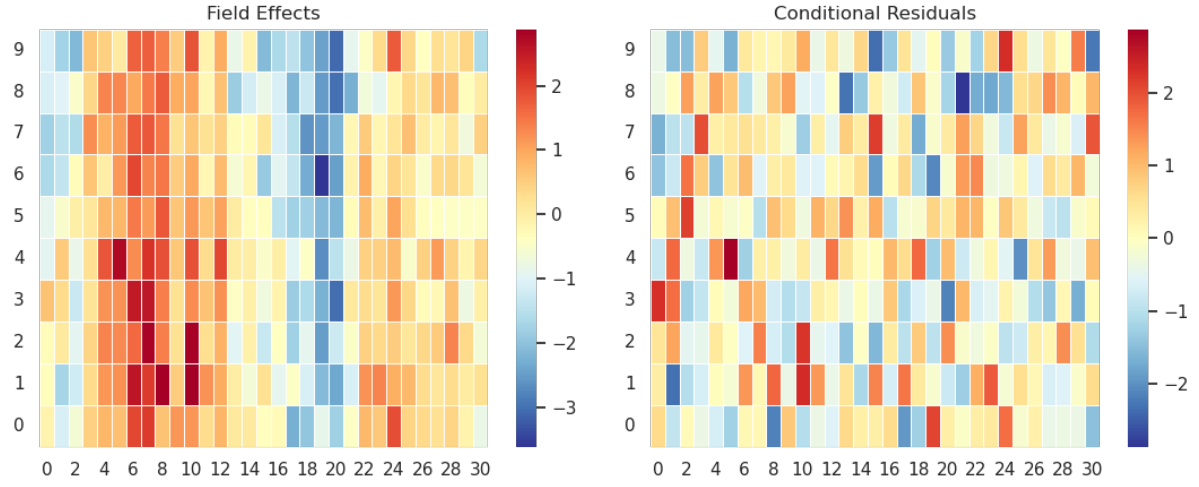
**karen.wolf@limagrain.com*

ADDITIONAL SLIDES

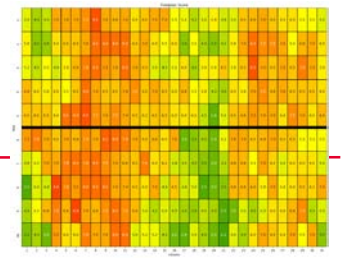
OUTLOOK - Optimal Design



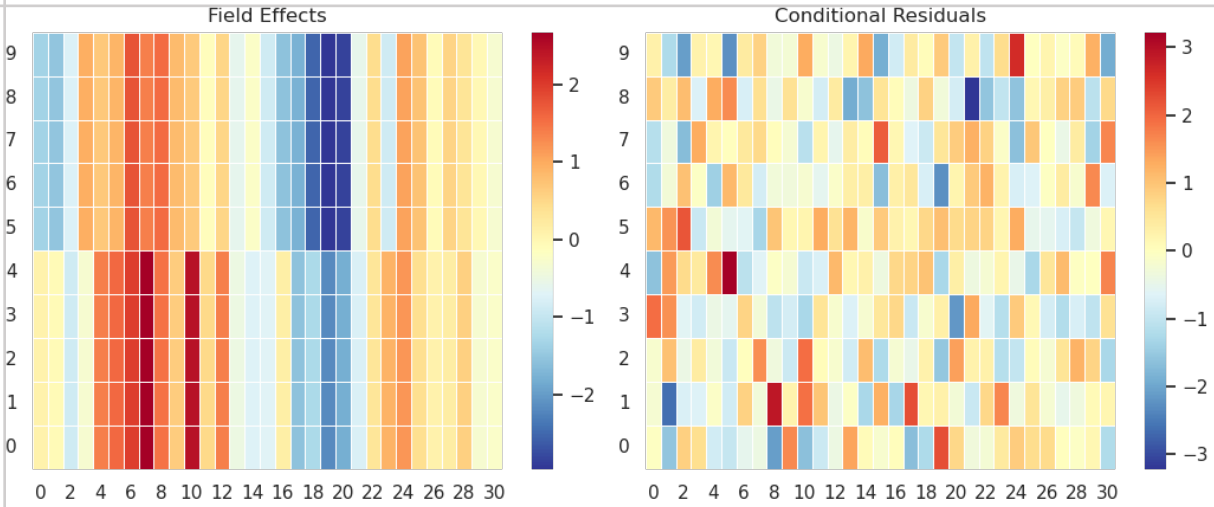
‚Analyse as randomised‘

	‚Analyse as randomised‘, here as RCBD NO check for autocorrelation	‚Analyse as randomised‘, here as RCBD check for autocorrelation
Model Params	Block	Block Correlation within rows (1.0) Additional variance (nugget 0.71)
Field effects & Residuals		
Summary	No model selection, but simply fit of block effect. The residuals do not look good (clear patterns visually detectable).	No model selection, but simply fit of block effect and fit of correlation within rows and nugget effect. High row correlation estimation (1.0). The residuals look OK (no clear patterns visually detectable).

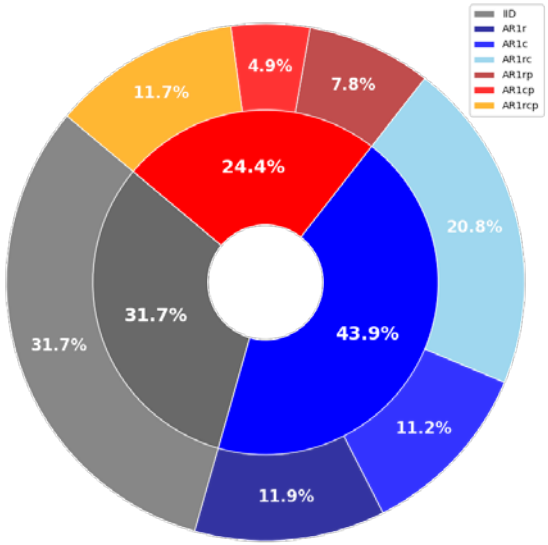
OUTLOOK - Optimal Design

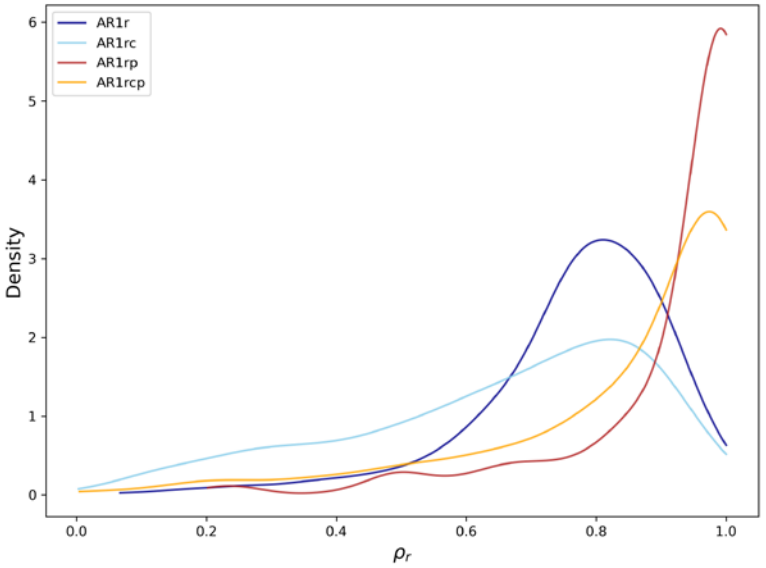


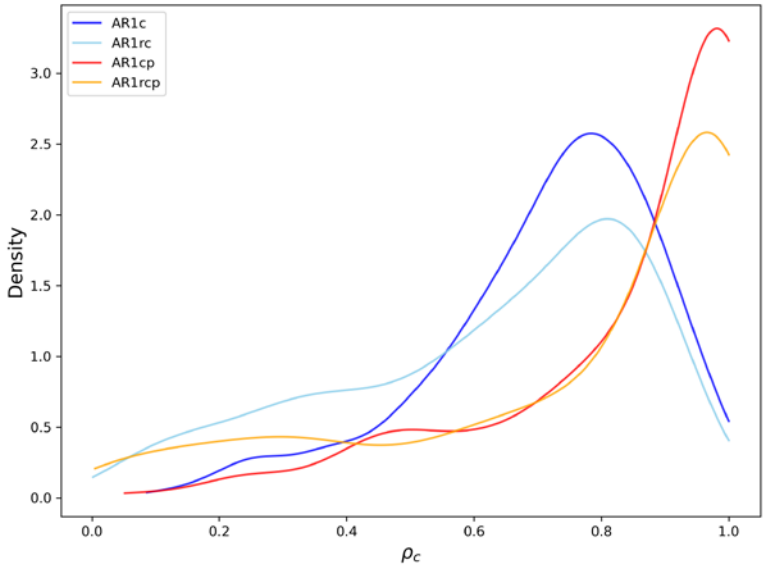
Model Selection

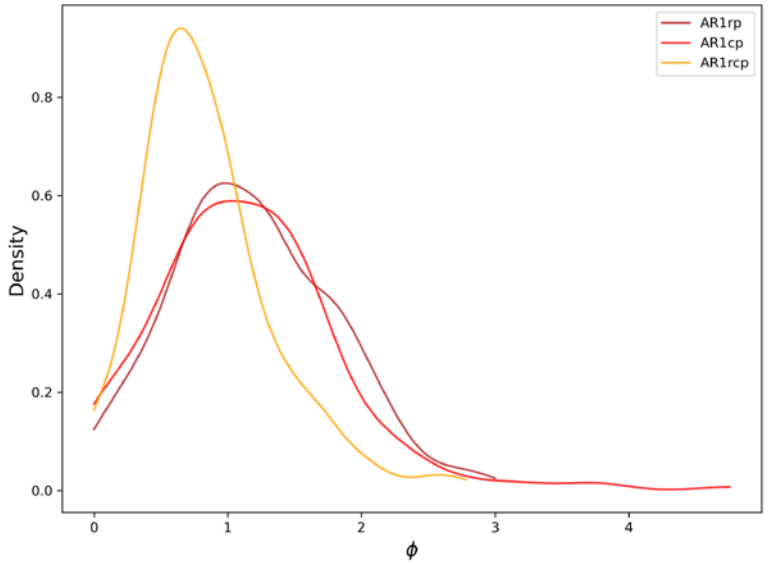
	Model selection NO check for autocorrelation	Model selection check for autocorrelation
Model Params	Block Block|Column	
Field effects & Residuals		
Summary	In both cases, the same model is selected and fitted (with block and column effect, no autocorrelation). The residuals look OK (no clear patterns visually detectable).	

OUTLOOK - Simulation







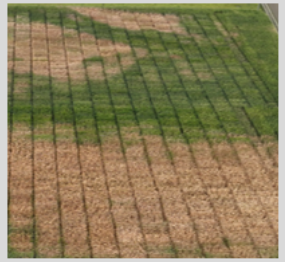


OUTLOOK - Optimal Design

Quality Control in Agricultural Field Trials

Detection of Nonstationarity in Grid-indexed Data

FIELD TRIAL ANALYSIS - Assumption of stationarity:



If assumption of stationarity does not hold, breeders cannot reliably select plant varieties

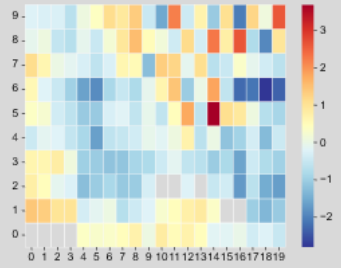
PROBLEM - Manual quality control:

Visual inspection

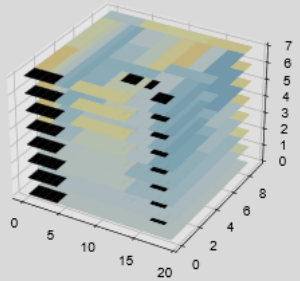
Time consuming

SOLUTION - Automatic quality control (Verification of the assumption of stationarity):

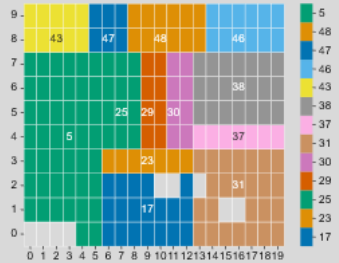
Grid data



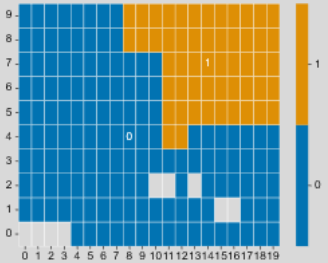
Tree indexation



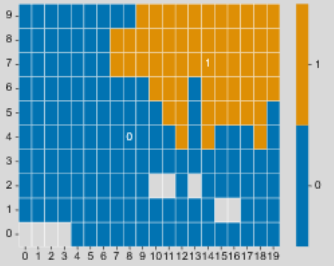
Identification



Authentication



Verification



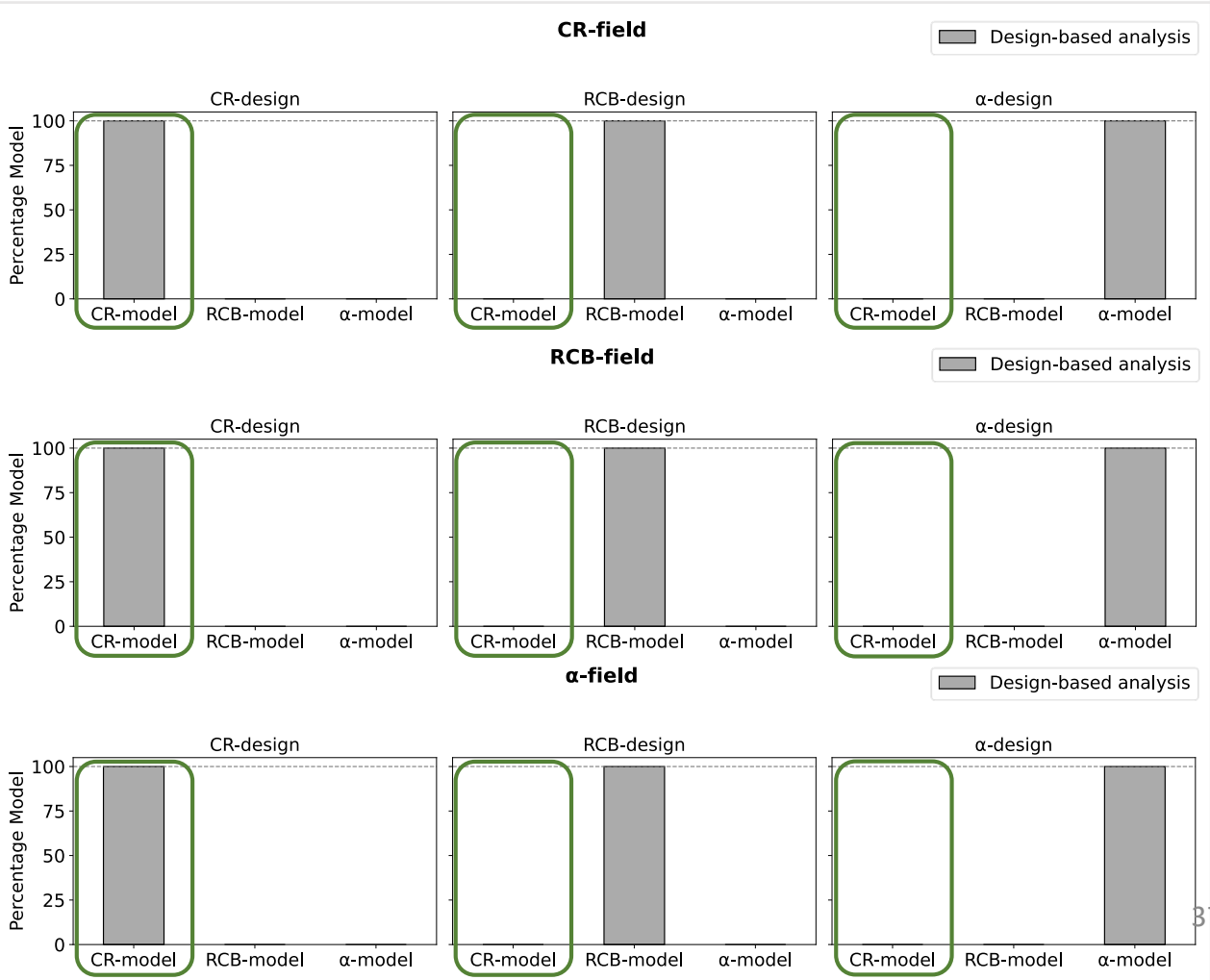
Field Trials – Model Selection

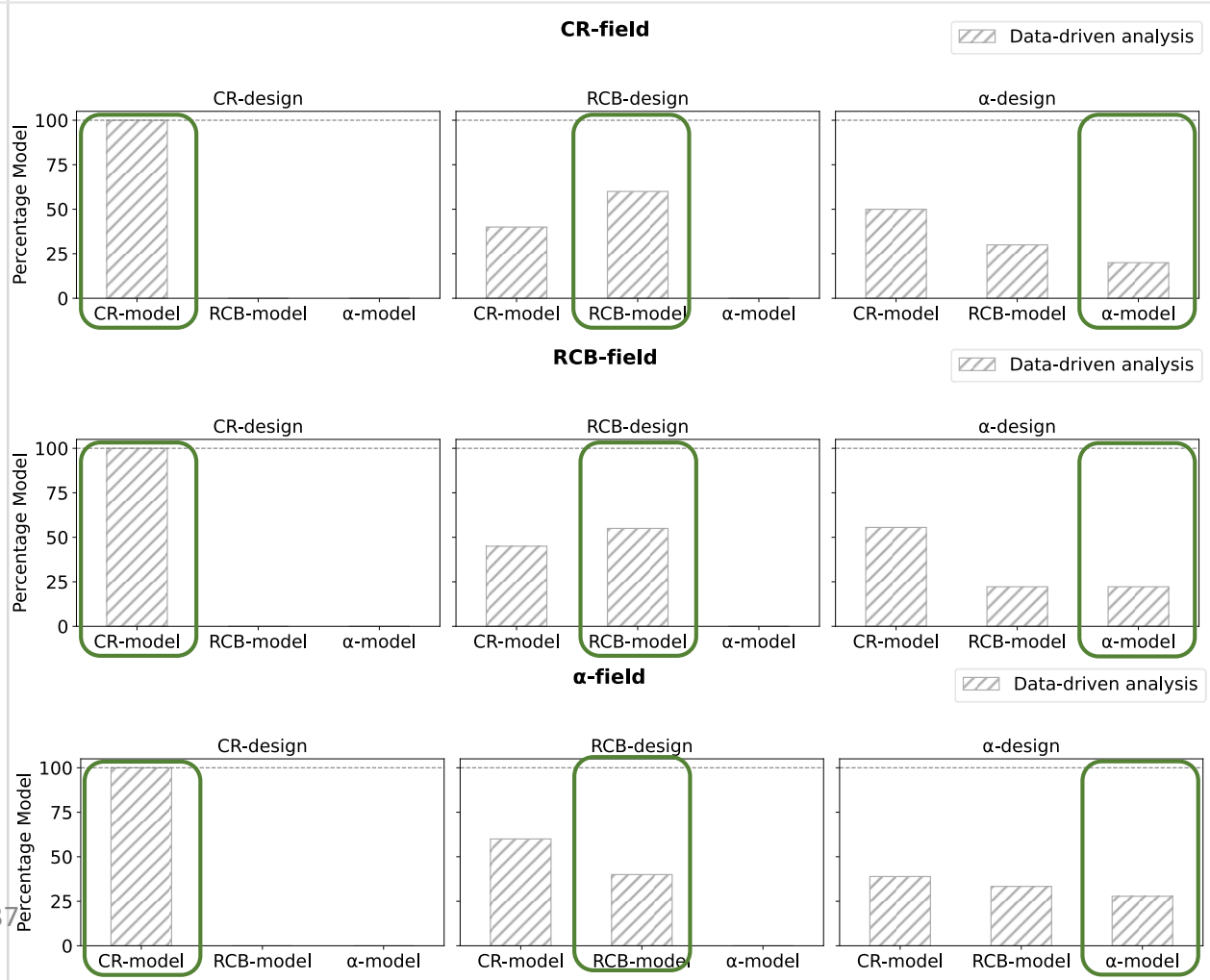
$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$

Question 1: *'Analyse as randomised' ?*

Design-based analysis (*'Analyse as randomised'*), i.e.,
$Z = Z_{design}$

Data-driven analysis, i.e.,
$Z = Z_{model\_selection}$





MSE

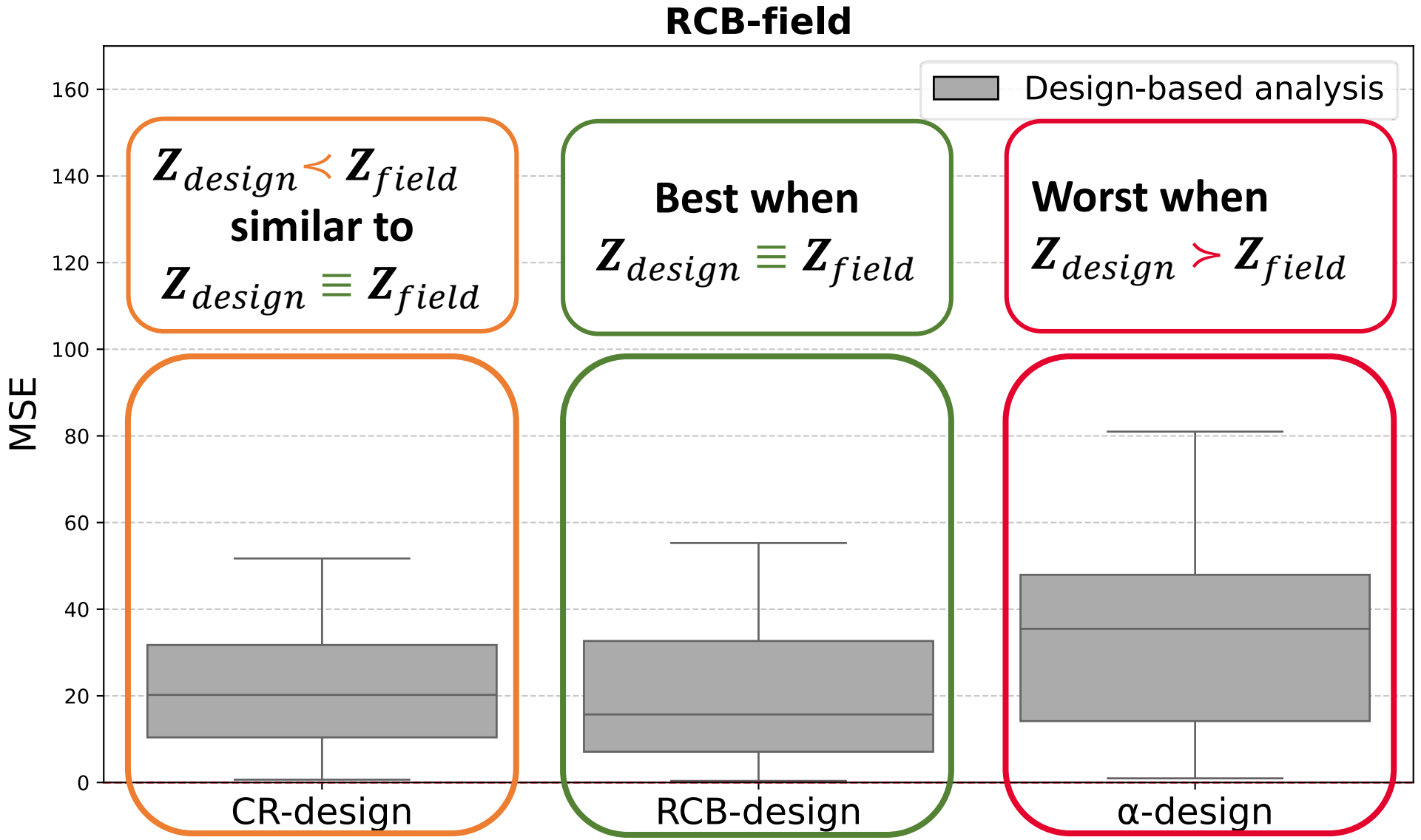
Results – MSE of $\hat{\tau}$ to τ

Mean squared error (MSE)

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$

Design-based analysis (‘*Analyse as randomised*‘), i.e., $Z = Z_{design}$

$$MSE = \frac{\sum_i^n (\hat{\tau}_i - \tau_i)}{n}$$



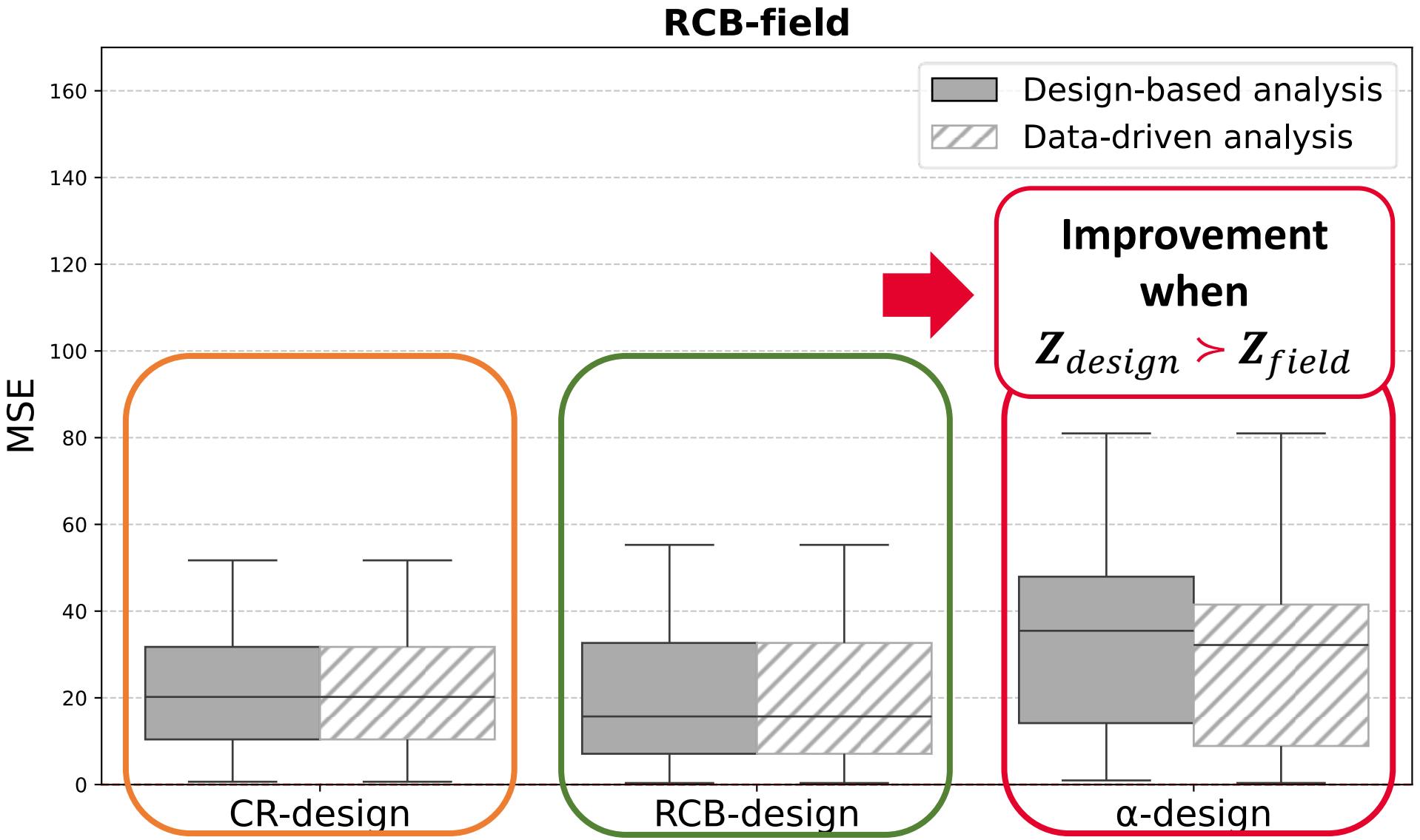
Results – MSE of $\hat{\tau}$ to τ

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$

Design-based analysis (‘*Analyse as randomised*‘), i.e., $Z = Z_{design}$

versus

Data-driven analysis, i.e., $Z = Z_{model\_selection}$



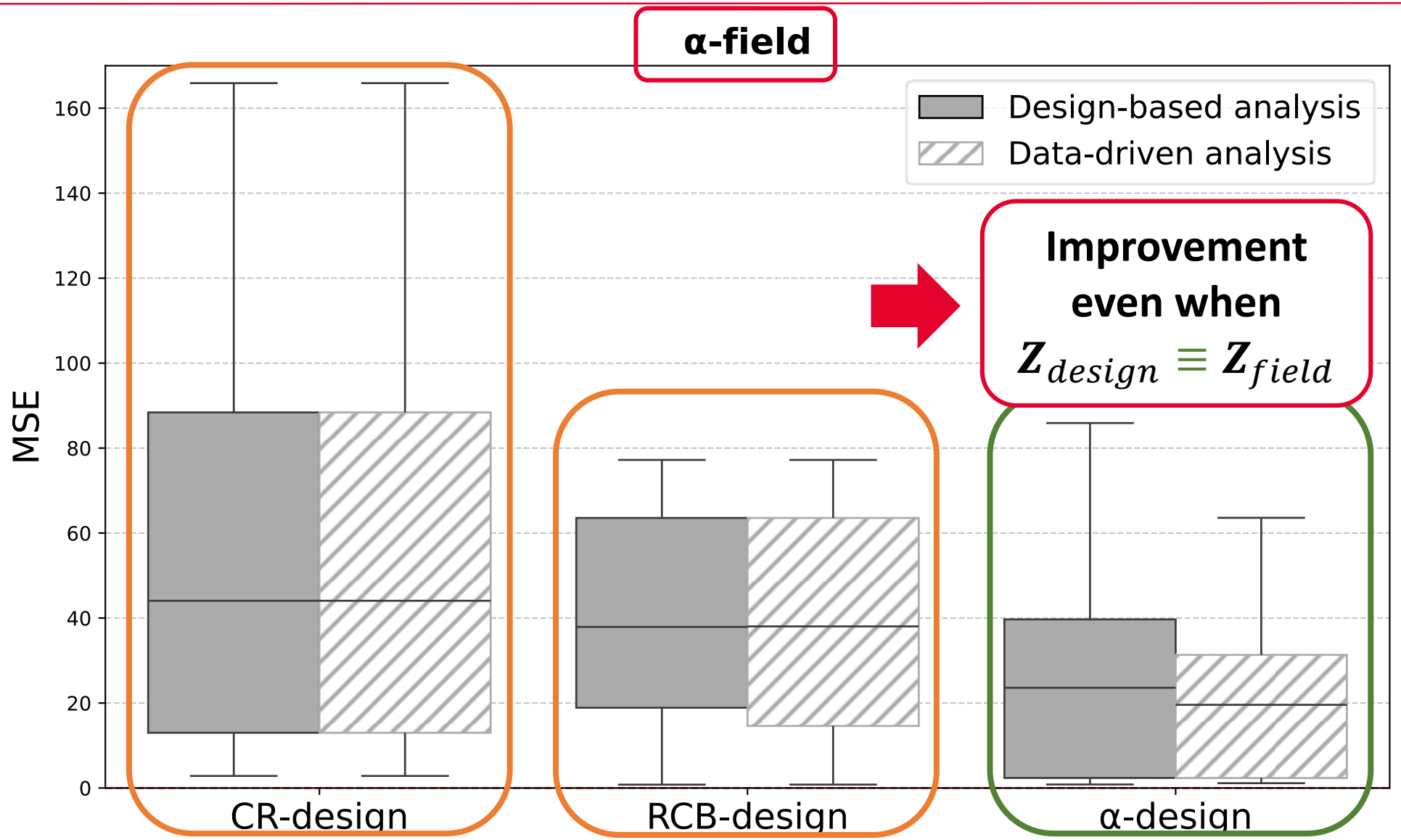
Results – MSE of $\hat{\tau}$ to τ

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$

Design-based analysis (‘*Analyse as randomised*‘), i.e., $Z = Z_{design}$

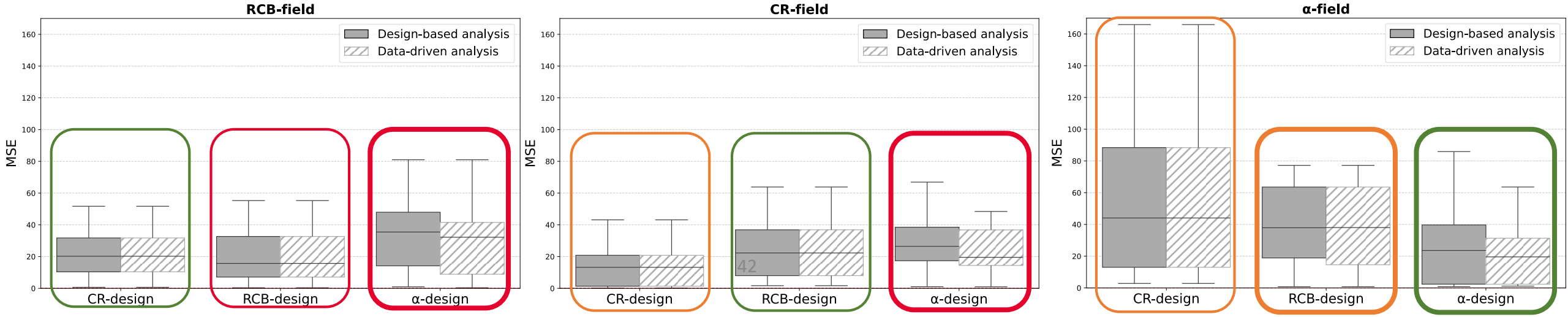
versus

Data-driven analysis, i.e., $Z = Z_{model\_selection}$



Results – MSE of $\hat{\tau}$ to τ

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$



2) We answer the question if, in such cases, we should *‚Analyse as randomised‘*.

We should not *‚Analyse as randomised‘*, but use data-driven analysis.
This improves the estimations when we went ‘too far‘ in the design.

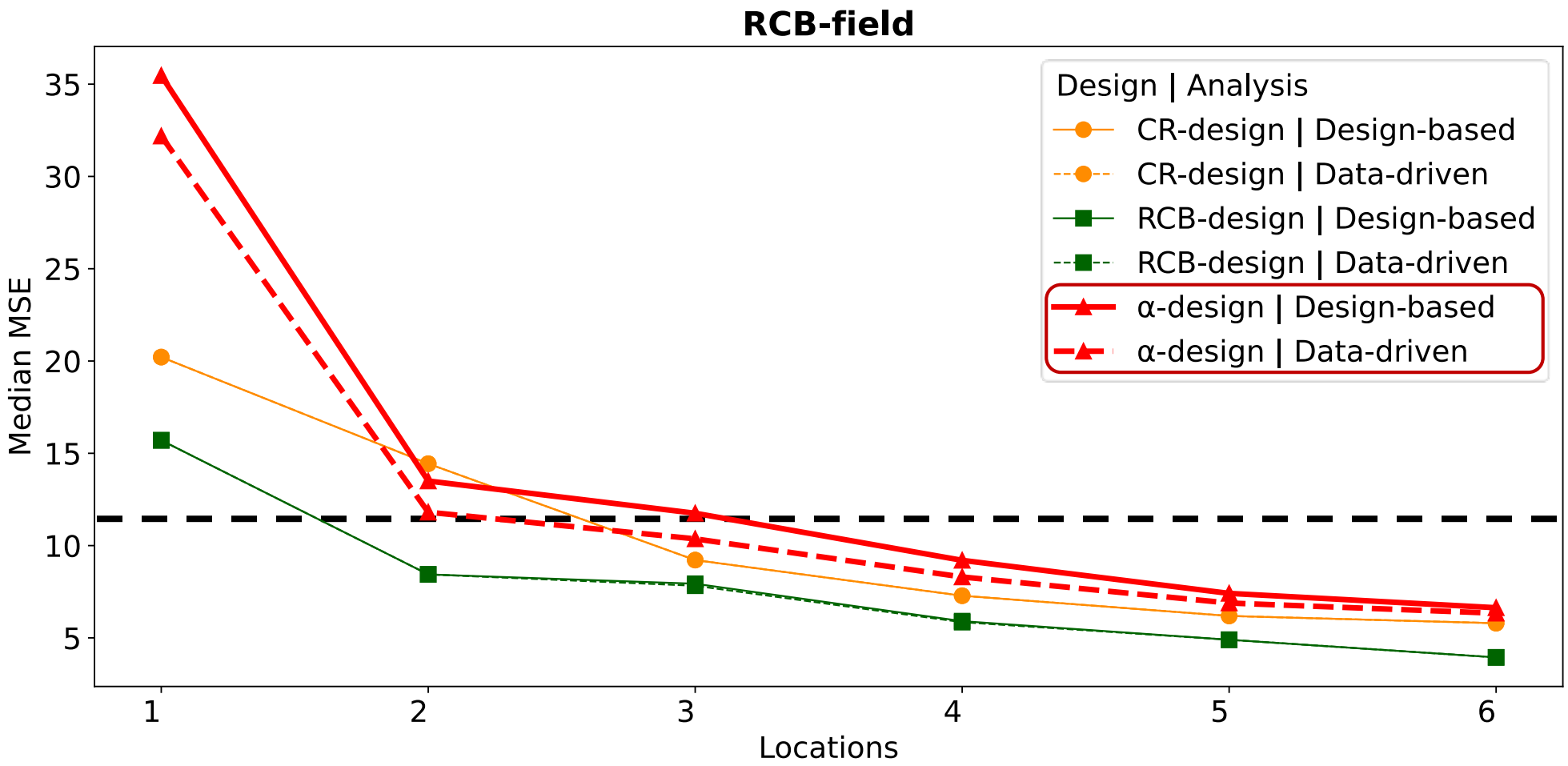
Results – Convergence of $\hat{\tau}$ to τ (MSE)

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$

Design-based analysis (‘*Analyse as randomised*‘), i.e., $Z = Z_{design}$

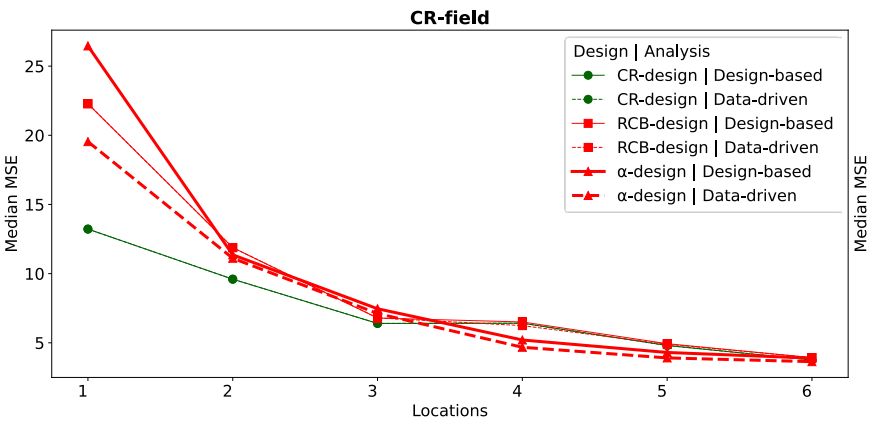
versus

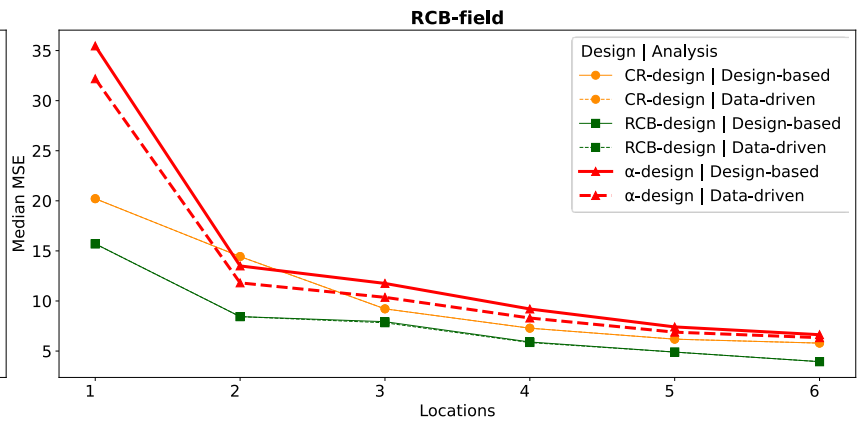
Data-driven analysis, i.e., $Z = Z_{model\_selection}$

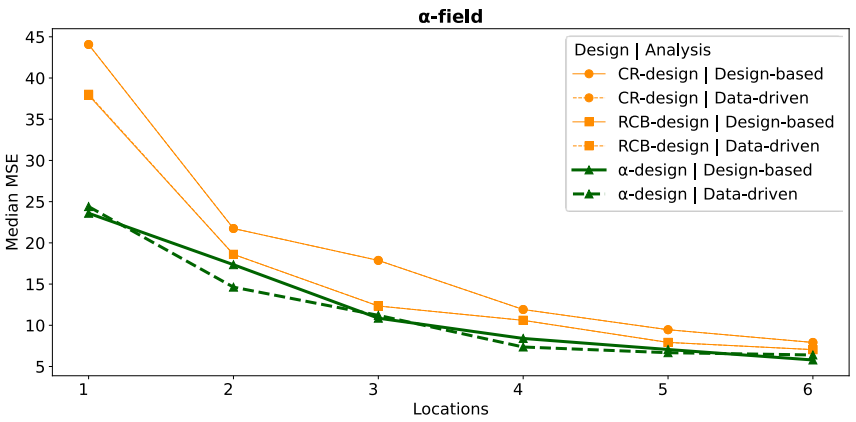


Results – Convergence of $\hat{\tau}$ to τ (MSE)

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$







3) We quantify the impact of randomisation on the accuracy of estimations and the implications in practice.

Theoretically, randomisation ensures accurate estimations. However, to the cost of more replications.

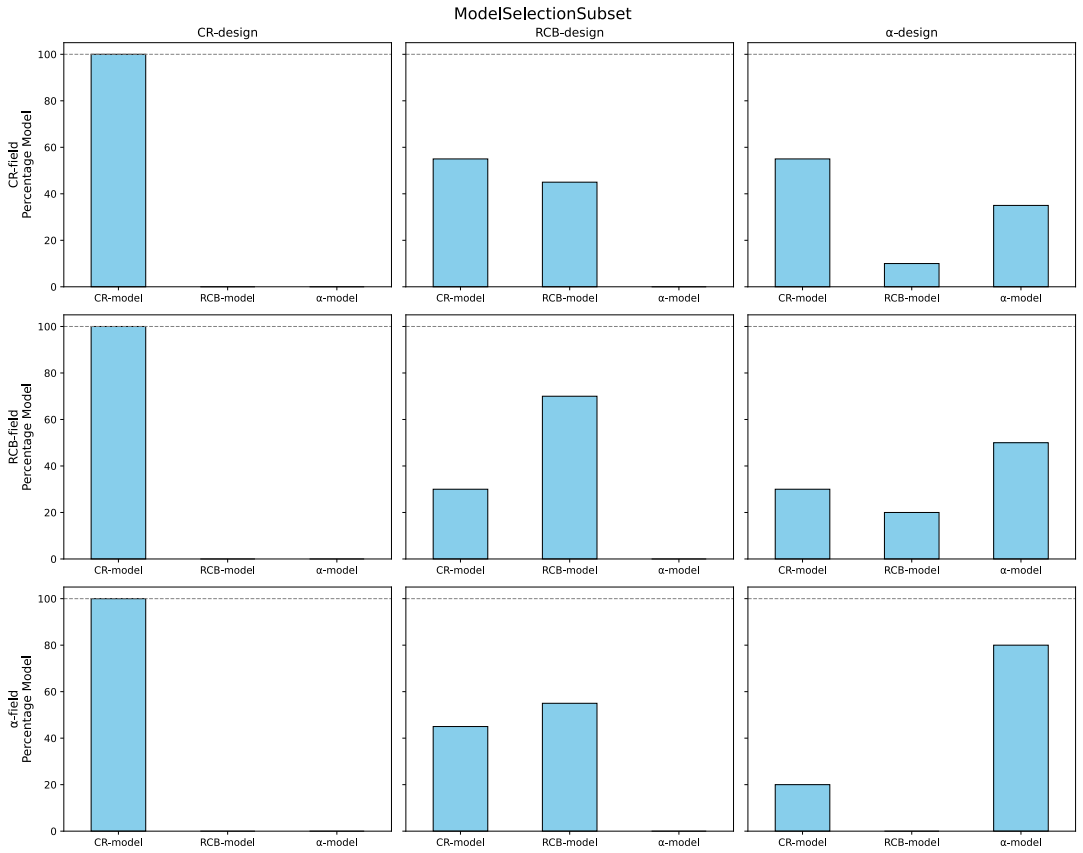
More Slides

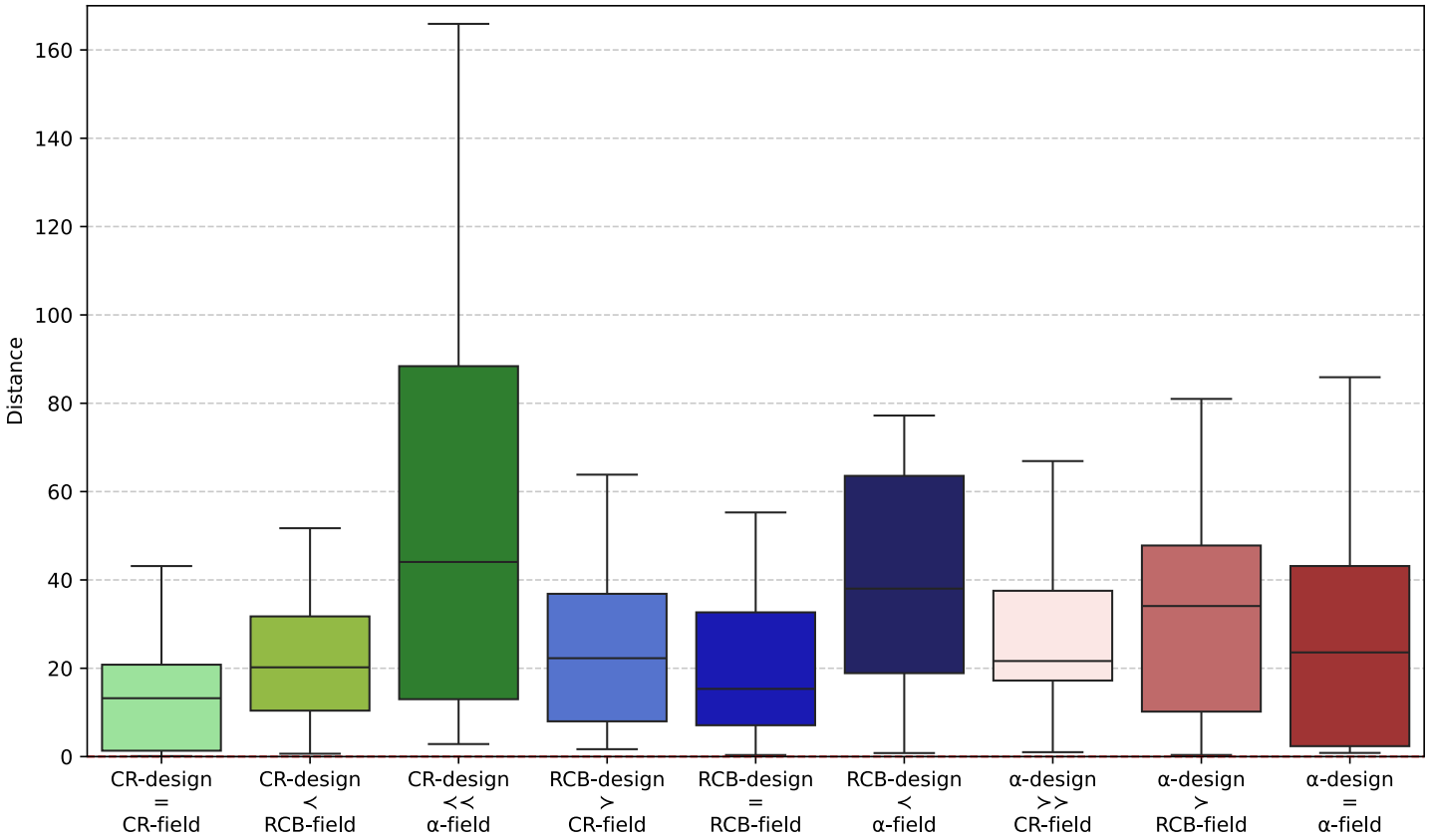
Simulation Study – Different Scenarios

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$

Z_{design}			Z_{field}		Genotypic values τ randomised according to Z_{design}		Field effects β simulated according to Z_{field}	Residual error ϵ
Block	**Sub-Block**		**Block**	**+ Sub-Block**				
		$\equiv$			CR-design	$\equiv$	CR-field	
		$\succ$			RCB-design	$\succ$		
		$\succ\succ$			α-design	$\succ\succ$		
		$\prec$			CR-design	$\prec$	RCB-field	
		$\equiv$			RCB-design	$\equiv$		
		$\succ$			α-design	$\succ$		
		$\prec\prec$			CR-design	$\prec\prec$	α-field	
		$\prec$			RCB-design	$\prec$		
		$\equiv$			α-design	$\equiv$		

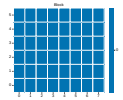
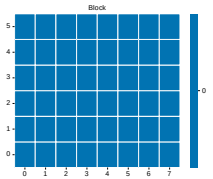
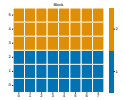
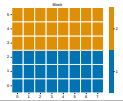
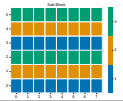
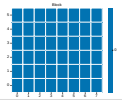
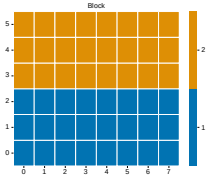
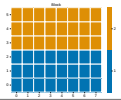
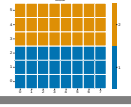
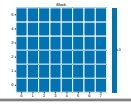
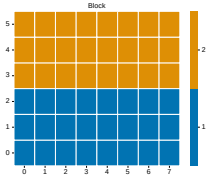
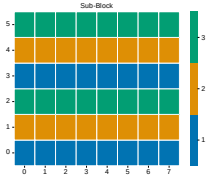
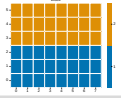
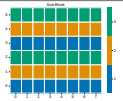
OUTLOOK - Model Selection, NLL





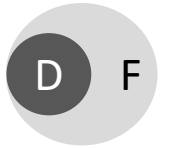
Simulation Study – Different Scenarios

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$

Block	Sub-Block	Z_{design}		Z_{field}	Block	+ Sub-Block
		CR-design	$\not\equiv$	CR-field		
		RCB-design	$\not\equiv$			
		α-design	$\not\equiv$			
		CR-design	$\not\equiv$	RCB-field		
		RCB-design	$\not\equiv$			
		α-design	$\not\equiv$			
		CR-design	$\not\equiv$	α-field		
		RCB-design	$\not\equiv$			
		α-design	$\not\equiv$			

$Z_{design} \prec Z_{field}$

‚forgot‘

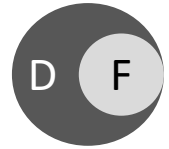


$Z_{design} \equiv Z_{field}$

‚perfect‘

$Z_{design} \succ Z_{field}$

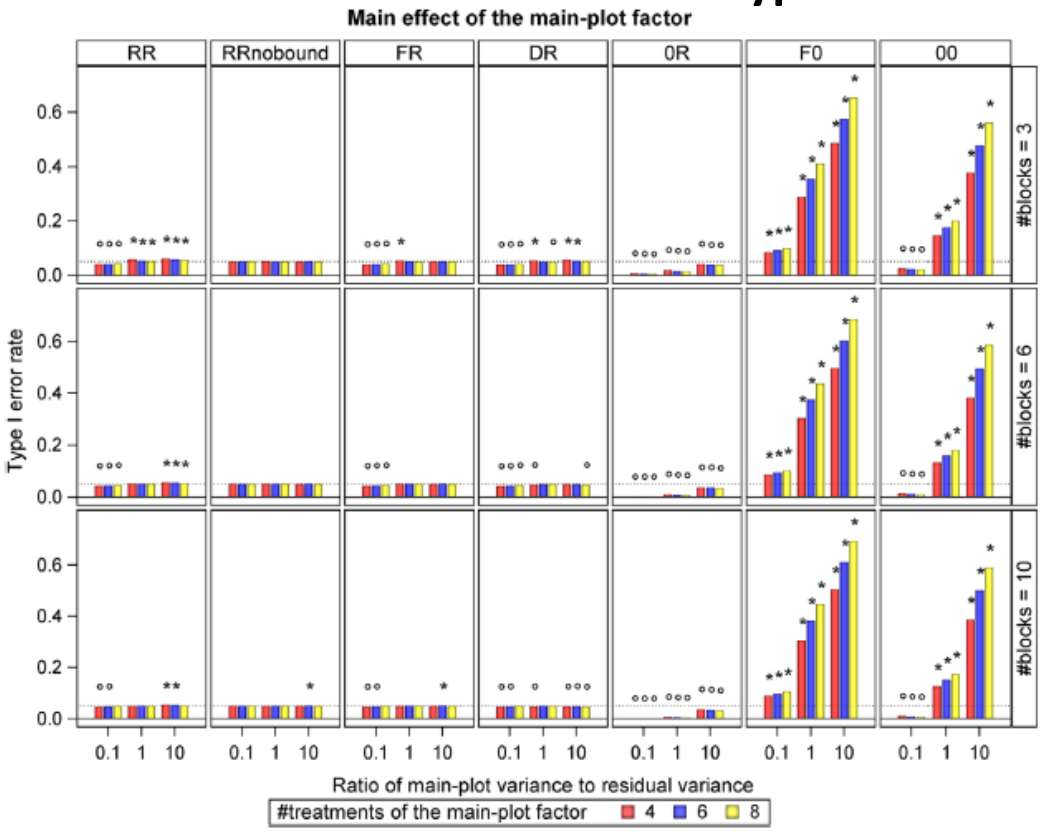
‚too far‘



Related Work

Frey, J., Hartung, J., Ogutu, J., and Piepho, H.-P., *Analyze as randomized—why dropping block effects in designed experiments is a bad idea*, Agronomy Journal (2024) → **In the case of $Z_{design} \equiv Z_{field}$: *Analyse as randomized.***

Type I Error Rate



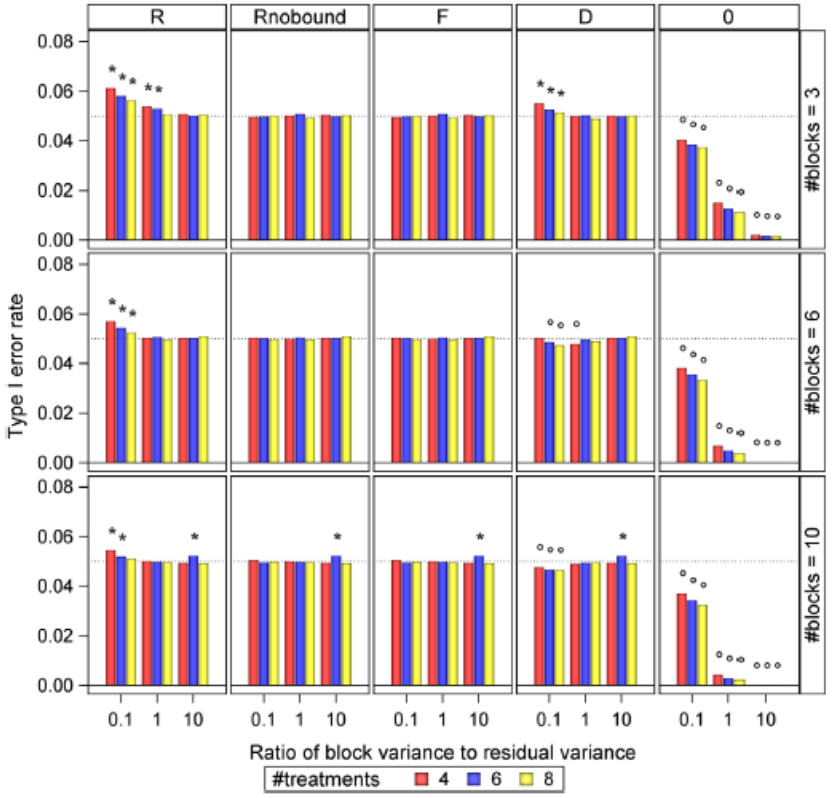
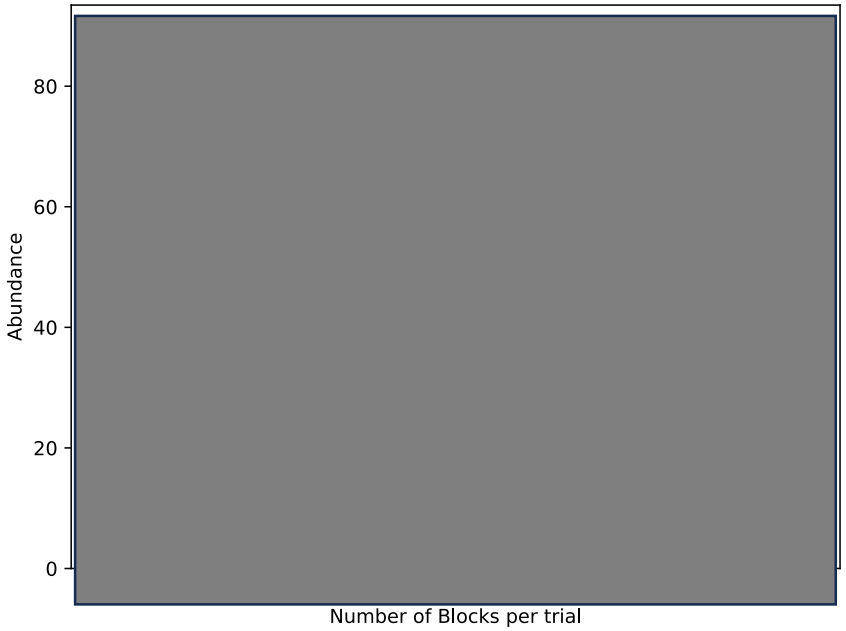


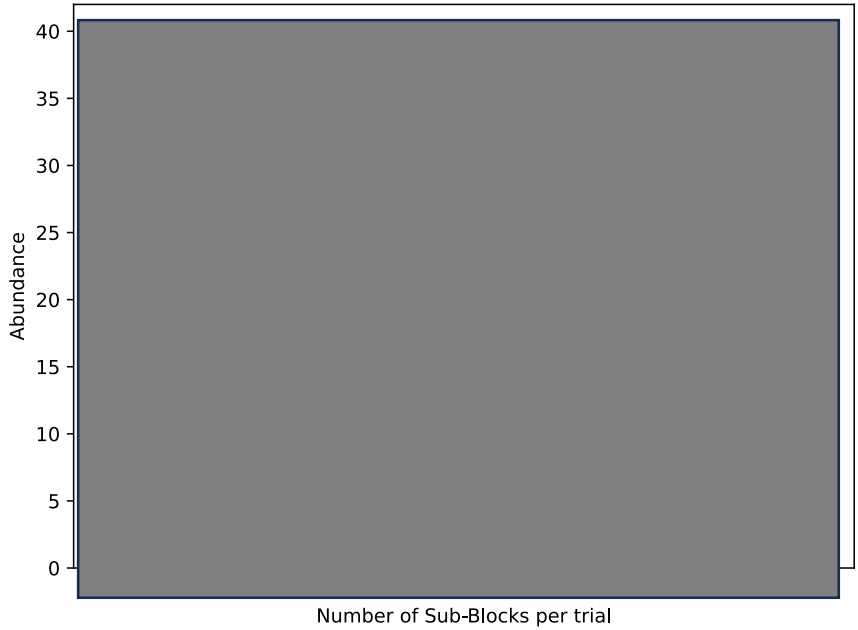
FIGURE 2 Type I error rate for the main-plot factor for 27 scenarios for the split-plot designs (SPDs) varying in the number of blocks and treatments and block-to-residual error variance ratio and analyzed using seven different approaches. The dashed lines represent the nominal error rate of $\alpha = 0.05$. Significantly inflated error rates were marked with an asterisk (*), and significantly deflated error rates were marked with circles (°). The analysis approaches given in columns represent an analysis with random block and main-plot error effects (RR), random block and main-plot error effects using the nobound option in restricted maximum likelihood (REML) method (RRnobound), fixed block and random main-plot error effects (FR), dropping non-significant block effects and random main-plot error effects (DR), no block effects and random main-plot error effects (0R), fixed block effects and no main-plot error effects (FO), and no block and main-plot error effects (00).

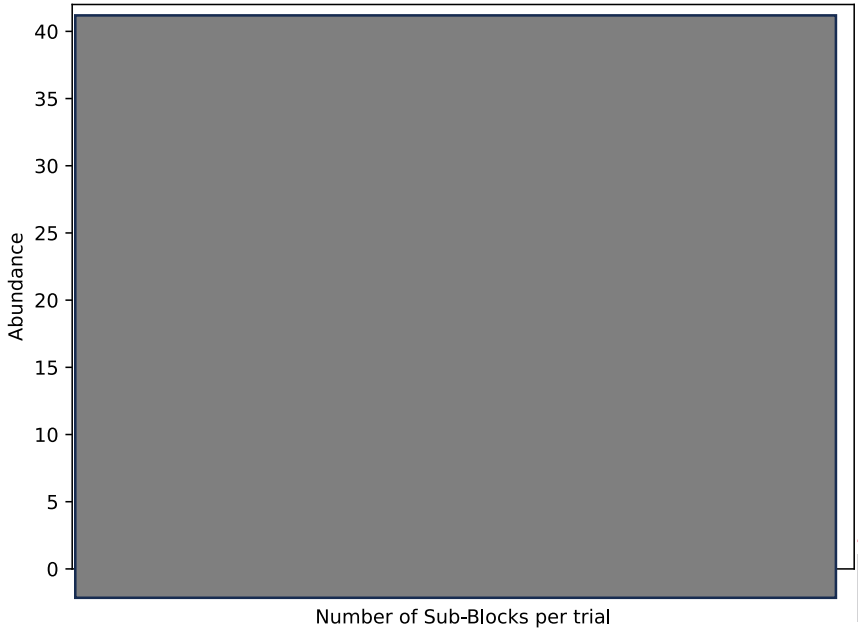
FIGURE 1 Type I error rate for 27 scenarios of randomized complete block designs (RCBDs) varying in the number of blocks and treatments and block-to-error variance ratio and analyzed using five different approaches. The dashed lines represent the nominal error rate of $\alpha = 0.05$. Significantly inflated error rates were marked with an asterisk (*), and significantly deflated error rates were marked with circles (°). The analysis approaches given in columns represent an analysis with random block effects (*R*), random block effects using nobound option in restricted maximum likelihood (REML) method (Rnobound), fixed block effects (F), dropping non-significant block effects (D), and no block effects (0).

Related Work

Moehring, J., Williams, E., and Piepho, H.-P., *Inter-block information: to recover or not to recover it?*. Theoretical and Applied Genetics 128.8 (2015)

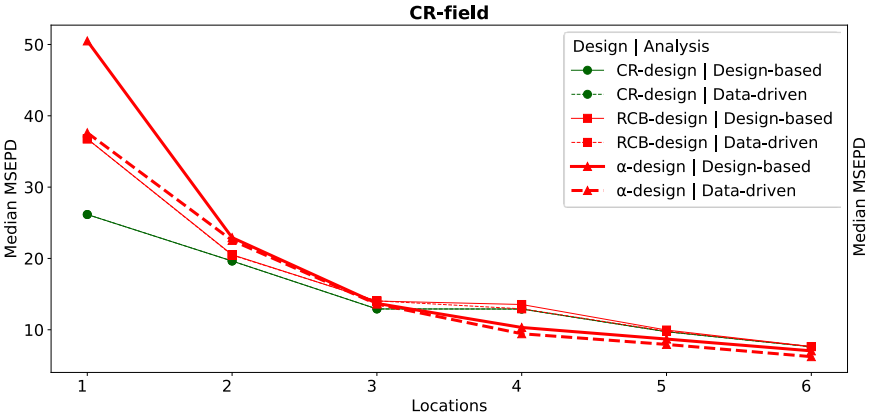


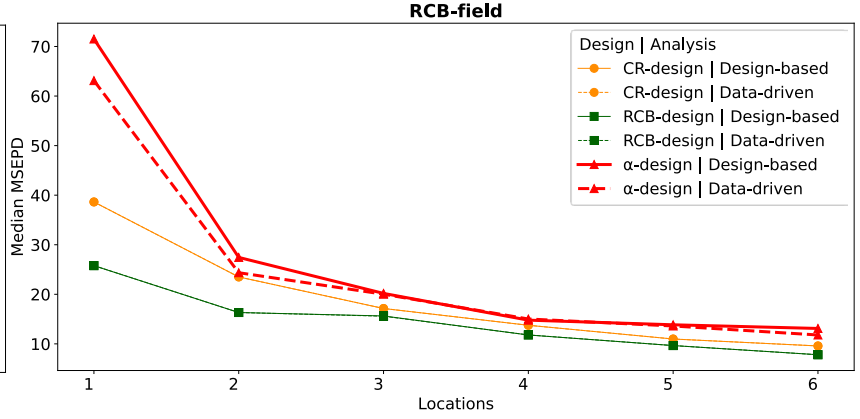


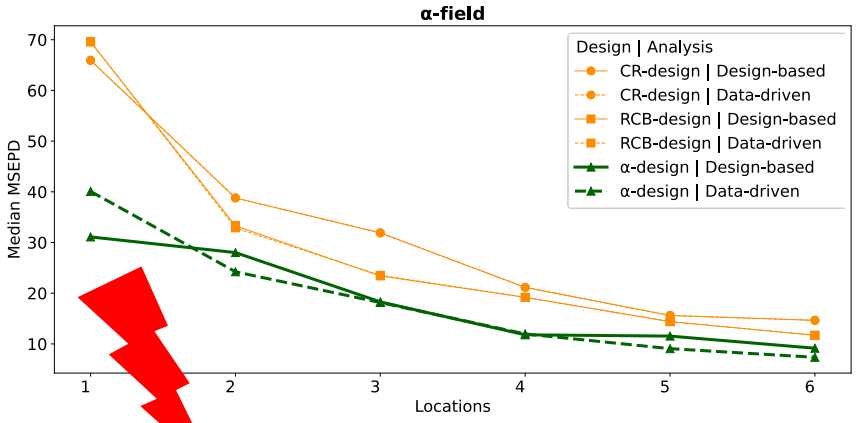


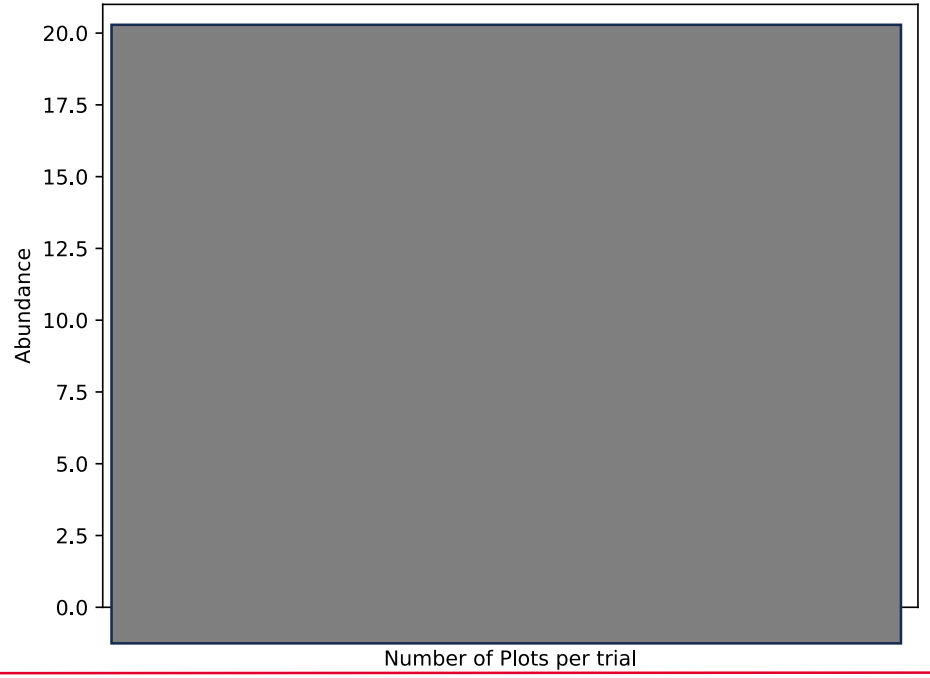
Results – Convergence of $\hat{\tau}$ to τ (MSEPD)

$Z_{design} \prec Z_{field}$	$Z_{design} \equiv Z_{field}$	$Z_{design} \succ Z_{field}$









Median Plots per trial

€/Plot

€/Plot

On Deficient Experimental Designs and Their Analysis

A Reconsideration of Classical Principles in Plant Breeding Practice

Karen Wolf[12*], Pierre Fernique[1], Hans-Peter Piepho[2]

[1] Limagrain Europe, [2] University of Hohenheim

**karen.wolf@limagrain.com*