

# Optimization of breeding schemes with GS in R

## Friedrich Longin

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### Aims to learn





- What are the key parameter to decide about breeding schemes?
- Golden rules from selection theory
- How is the R package selection gain constructed and how to use it for our questions
- First steps into the R package

## **University of Hohenheim, Stuttgart**



#### 3 faculties

- 1 <u>life sciences</u> (biology, physics, biotechnology, food production and ingredients); ~ 14 institutes
- 2 <u>agriculture</u> (breeding, quantitative genetics, molecular genetics, agronomy, plant health, agroeconomics, animal sciences,...); ~ 15 institutes
- 3 <u>Economy</u> (management, economics, law, social sciences...); ~ 8 institutes
- ~ 4000 students per year, all B.Sc. and M.Sc.
   Master of crop science (english)
- 4 state institutes incorporated into the University
- Experimental station for agriculture

## **Excellence Unit in Plant Breeding**



#### Institute of Plant Breeding, Seed Science and Population Genetics

Subject Areas:

Applied Genetics and Plant Breeding

Prof. Dr. Tobias Würschum

**Crop Biodiversity and Breeding Informatics** 

Prof Dr. Karl Schmid

**Seed Science and Technology** 

Prof. Dr. Michael Kruse

# State Plant Breeding Institute

Head: Dr. Willmar Leiser

Research groups:

**Genomics & Biotechnology** 

N.N.

**Rye and Biotic Stress Resistance** 

Prof. Dr. Thomas Miedaner

Triticale and Breeding Methodology

Dr. Hans P. Maurer

**Wheat Breeding and Selection Theory** 

Prof. Dr. Friedrich Longin

**Sunflower and Soybean Breeding** 

Dr. Volker Hahn

**Experimental Station** 

### **Experimental stations**





Ihinger Hof
Heidfeldhof/Hohenheim
Kleinhohenheim/organic
Lindenhöfe

**Eckartsweier** 

Five experimental stations ensure high-quality phenotyping which is the basis for breeding and science

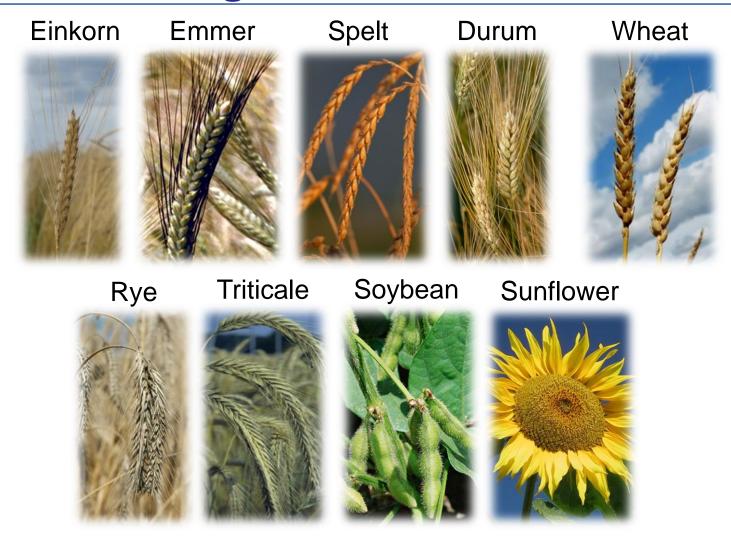
## **State Plant Breeding Institute (LSA)**



- Six scientists with broad range of expertise,
- PhD and PostDocs (from agronomy, bioinformatics, mathematics)
- Experienced technical staff (>20) with phenotyping facilities, green houses, climate chambers, biotechlab,...
- ~ 20 peer-reviewed publications per year in leading international journals
- ~ 1.800.000€ extramural grants per year
- Cooperations with leading international agricultural research centers (e.g. CAAS, CIMMYT, INRA, ACPFG, NIAB)

## **Breeding activities at the LSA**





LSA has competitive breeding programs

## Wheat group - aims



- Elite breeding in rare wheat species
- Breeding programs in T. aestivum
  - Pre-Breeding for grain yield: aim to deliver material to community for elite breeding starts



- Research accompanying these efforts
  - Genetic architecture of regarded traits
  - Special quality (wheat sensitivity, asparagine, aroma...)
  - Optimized breeding schemes



## Wheat group



- 1 scientist Dr. F. Longin
- 6 technicians
- 1 PostDoc, 2 PhD, students.
- ~ 8 ha of nurseries
- > 30 different field locations
- Special nurseries for stress FHB, virus, frost
- Quality lab for b- value, sds, falling, GI, protein content, vitreousness and dark points
- Machinery for threshing and dehulling

https://weizen.uni-hohenheim.de/



### You are a breeder



- Congratulations → fantastic job!
- A breeder is the <u>head of product</u> <u>development</u>
  - You must be innovative
  - You must be able to rapidly take decisions
  - You must define the strategies
  - You must have success
  - You are responsible for whole product chain





# Wheat breeding – my framework













**Breeder** 

**Farmer** 

Miller

**Baker** 

Consumer



Requests

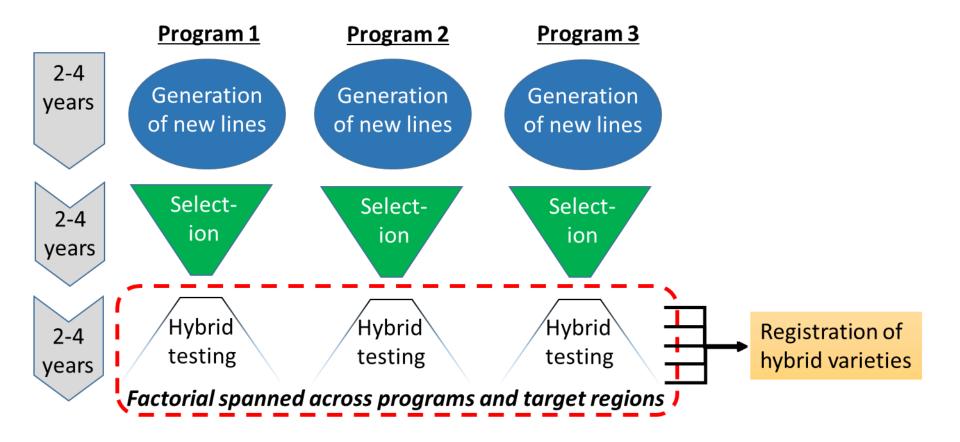
Which of the supply chain requests have to be worked by me (the breeder)?

→ My market traits

Foto: BeckaBeck

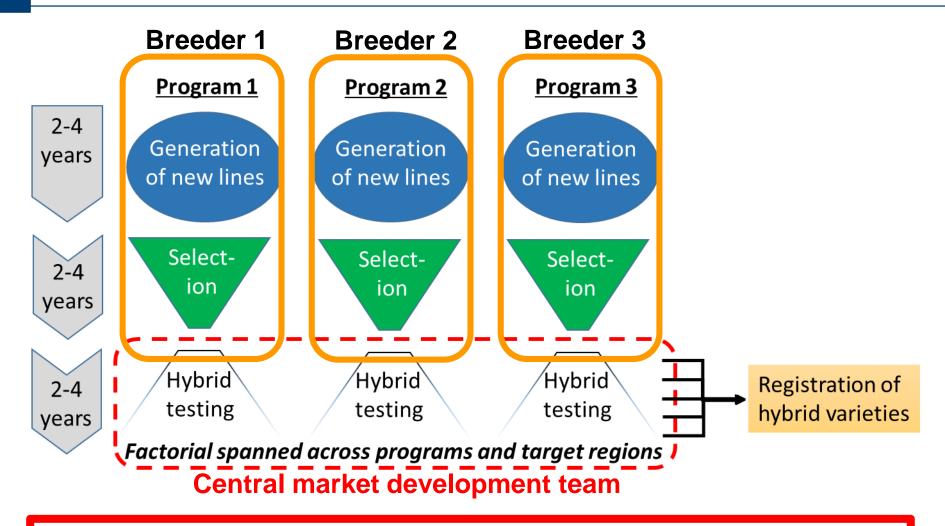
## "Breeding get's a product chain"





## "Breeding get's a product chain"

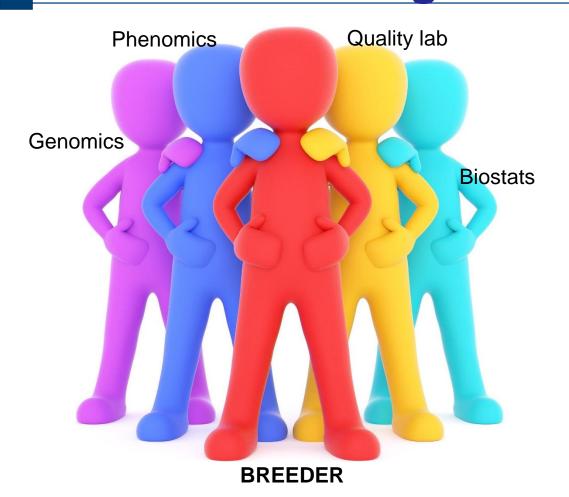




Breeder delivers lines to market development team with high combining ability

## **Breeding is teamwork**





R & D Teams:
Breeder is
responsible for
final outcome =
decider











**Breeder** 

**Farmer** 

Miller

Baker

Consumer

# You have to decide = you're responsible

- Marketing tells you your <u>specific framework</u>
  - ? Strategies ?

# You have to decide = you're responsible

Marketing tells you your <u>specific framework</u>

# ? Strategies?

Which breeding scheme?

Which quality lab analyses?

Molecular markers?

Trial management?

Priorisation of traits?

Orga of phenotyping?

Disease management?



# This lecture: decision support package

Marketing tells you your <u>specific framework</u>

# ? Strategies ?

Which breeding scheme?

Which quality lab analyses?

Molecular markers?

Trial management?

Orga of phenotyping?

Disease management?

Other lectures

### Let's start – what we will do



- Introduction: Breeding categories → focus line breeding
- Theorectical background of selection gain package: formula of selection gain
- Variables influencing the selection gain
  - Important existing results
  - Realization in R package
- GS breeding schemes
  - Important results
  - Realization in R package
- Run your own first simulations

## **Beeing lost today**



Second chance ©



Search "Friedrich Longin"

https://www.youtube.com/channel/UCa5OSM9I-e2qBKBq7wQb4-w

# **Breeding categories**



Line breeding

Wheat

Hybrid breeding

Clone breeding

Population breeding



**Potato** 



Maize

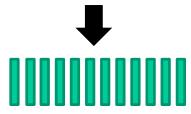


Rye

# Line breeding based on per se performance

#### Line breeding

New breeding lines from DH, ssd,...



Field trials – per se performance





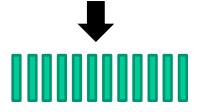
New line varieties

## Hybrid breeding based on GCA



#### Line breeding

New breeding lines from DH, ssd,...



Field trials – per se performance



New line varieties

Hybrid breeding

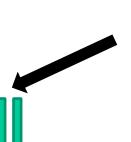
New breeding lines in heterotic group 1

New breeding lines in heterotic group 2



GCA-Tester

**GCA- Tester** 



Field trials –

combining ability

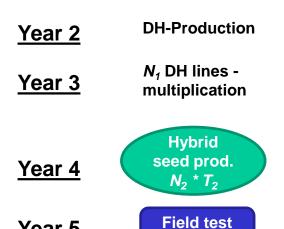
New lines for hybrid production in heterotic group 1

New lines for hybrid production in heterotic group 2

## 3 Phases in a breeding scheme



#### **Example: phenotypic selection in hybrid breeding**

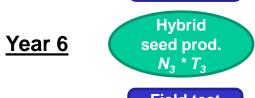


Year 1

Year 5

P1 x P2, ...

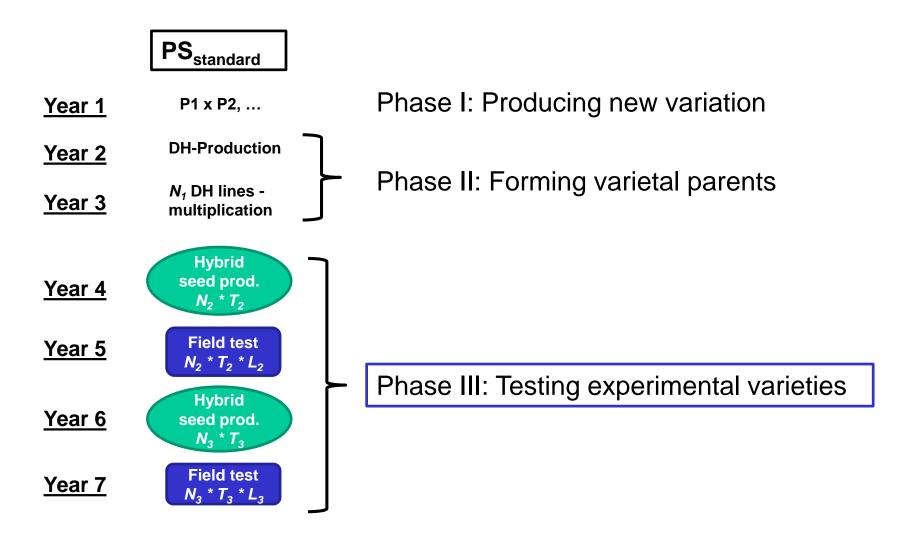
 $N_2 * T_2 * L_2$ 



Field test Year 7  $N_3 * T_3 * L_3$ 

## 3 Phases in a breeding scheme

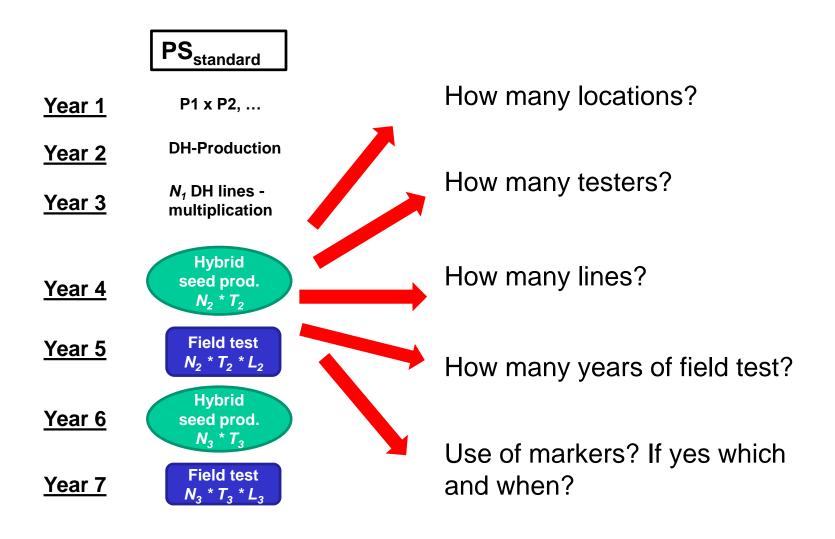




Source: Longin et al. 2015

## Many questions...







**Year 1** P1 x P2, ...

Year 2 DH-Production

Year 3  $N_1$  DH lines - multiplication

Year 4 Hybrid seed prod.  $N_2 * T_2$ 

Year 5 Field test  $N_2 * T_2 * L_2$ 

Year 6

Hybrid seed prod.

N<sub>3</sub> \* T<sub>3</sub>

Year 7 Field test  $N_3 * T_3 * L_3$ 

e.g. 1: maximum N
→ minimum L



<u>Year 1</u> P1 x P2, ...

Year 2

**DH-Production** 

Year 3  $N_1$  DH lines - multiplication

Year 4 Hybrid seed prod.  $N_2 * T_2$ 

Year 5 Field test  $N_2 * T_2 * L_2$ 

Year 6

Hybrid seed prod.

N<sub>3</sub> \* T<sub>3</sub>

Year 7 Field test  $N_3 * T_3 * L_3$ 

e.g. 1: maximum N
→ minimum L

P1 x P2, ...

**DH-Production** 

N<sub>1</sub> DH lines - multiplication

Hybrid seed prod.  $N_2 * T_2$ 

Field test  $N_2 * T_2 * L_2$ 

Hybrid seed prod.

N<sub>3</sub> \* T<sub>3</sub>

Field test  $N_3 * T_3 * L_3$ 

e.g. 2: minimum N
→ maximum L

P1 x P2, ...

**DH-Production** 

N₁ DH lines -

multiplication

Hybrid

seed prod.

 $N_2 * T_2$ 

Field test

 $N_2 * T_2 * L_2$ 

Hybrid

seed prod.

 $N_3 * T_3$ 

Field test

 $N_3 * T_3 * L_3$ 



P1 x P2, ... Year 1

Year 2

**DH-Production** 

N₁ DH lines -Year 3 multiplication

**Hybrid** seed prod. Year 4  $N_2 * T_2$ 

Field test Year 5  $N_2 * T_2 * L_2$ 

**Hybrid** Year 6 seed prod.  $N_3 * T_3$ 

Field test Year 7  $N_3 * T_3 * L_3$ 

> e.g. 2: minimum N → maximum L

P1 x P2, ...

**DH-Production** 

N₁ DH lines multiplication

**Hybrid** seed prod.  $N_2 * T_2$ 

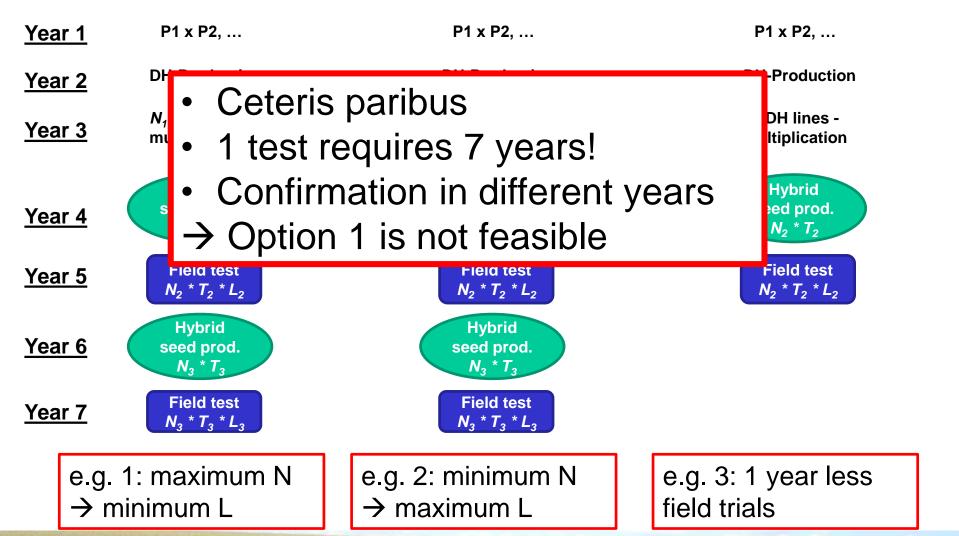
Field test  $N_2 * T_2 * L_2$ 

e.g. 3: 1 year less field trials

e.g. 1: maximum N → minimum L

Source: Longin et al. 2015





Source: Longin et al. 2015

## Option 2: Simulation of breeding methods



P1 x P2, ... Year 1

**DH-Production** Year 2

N₁ DH lines -Year 3 multiplication

**Hybrid** seed prod. Year 4  $N_2 * T_2$ 

Field test Year 5  $N_2 * T_2 * L_2$ 

**Hybrid** Year 6 seed prod.  $N_3 * T_3$ 

Field test Year 7  $N_3 * T_3 * L_3$ 

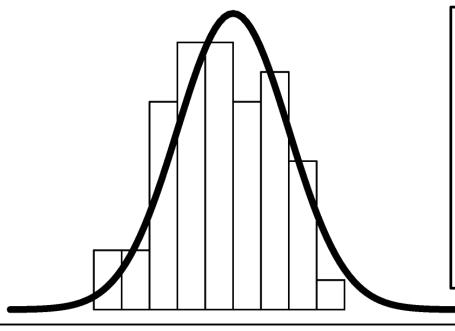
> e.g. 1: maximum N → minimum L

- Prediction the gain from selection in breeding schemes → Breeder's equation
- Simulation of different breeding schemes
- R Package "selection gain"

# Choice of breeding method



## Concept of selection gain



Distribution of phenotypes in the field for quantitative traits:

$$P = G + E;$$

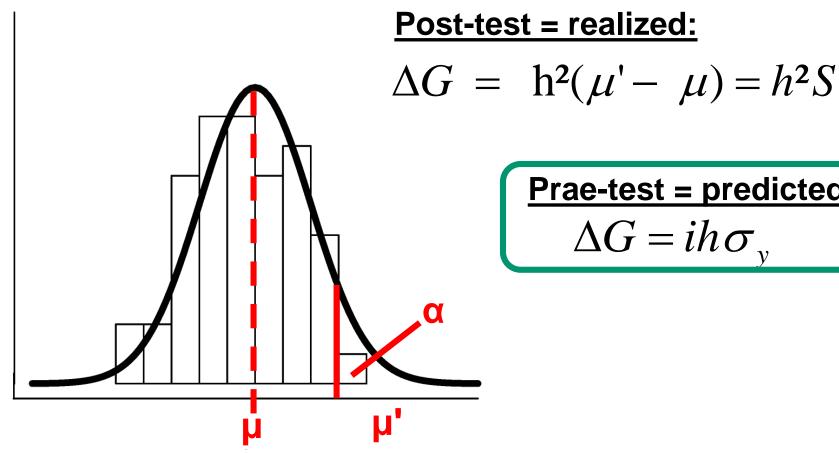
In R:

rnorm (N, 0,  $\sigma^2_G + \sigma^2_E$ )

Phenotypic value

# Selection gain





#### **Post-test = realized:**

**Prae-test = predicted:** 

 $\Delta G = ih\sigma$ 

Phenotypic value

## Prediction of selection gain



### Selection gain

$$\Delta G = ih\sigma_y$$

- *i* = selection intensity,
- *h* = square root of the heritability,
- $\sigma_y$  = square root of the genetic variance of the target variable

#### **Annual selection gain**

$$\Delta G_a = ih\sigma_v / Y$$

 Y = no. of years required to finish one breeding cycle

# Variables influencing selection gain



#### **Annual selection gain**

$$\Delta G_a = ih\sigma_y / Y$$

- *i* = selection intensity,
- *h* = square root of the heritability,
- $\sigma_v$  = square root of the genetic variance of the target variable
- Y = no. of years required to finish one breeding cycle

### Selection gain is maximized by an

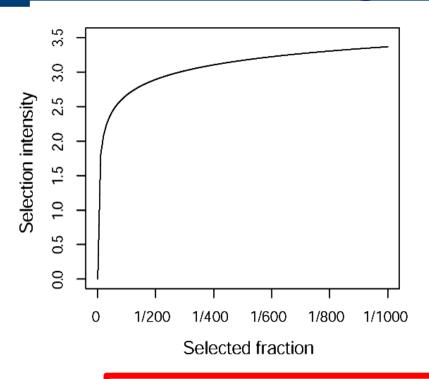
Increase of i

→ reduction of Y

- Increase of h
- Increase of  $\sigma_{_{\hspace{-0.05cm}V}}$

## **Increasing selection intensity**





#### Selected fraction

$$\alpha = \frac{no.selected\ lines}{no.tested\ lines}$$

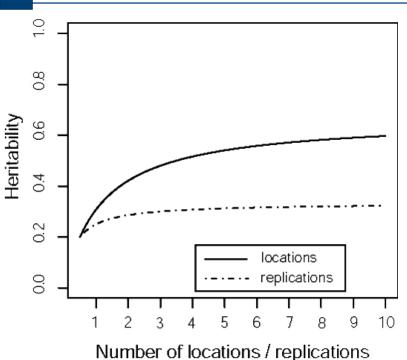
#### Selection intensity is increased by

- Increasing the number of tested lines
- Decreasing the number of selected lines

**BUT: Increase is not linear** 

## **Increasing heritability**





$$h^{2} = \sigma_{G}^{2} / \sigma_{P}^{2}$$

$$\sigma_{P}^{2} = \sigma_{G}^{2} + \sigma_{GxE}^{2} / L + \sigma_{e}^{2} / (L*R)$$

L = Locs, R = Reps,  $\sigma_G^2$  = genet. variance;  $\sigma_P^2$  = phenotyp. variance,  $\sigma_{GXE}^2$  = variance due to Genotyp-environment - interaction;  $\sigma_e^2$  = error variance

→ estimated via ANOVA

#### Heritability is increased by

- Increasing the number of locations
- Increasing the number of replications, but less than for locations!

**BUT: Increase is not linear** 

### **Allocation of resources**



$$\Delta G = ih\sigma_y/Y$$
 Allocation of resources i: function of  $\alpha = N_{sel}/N_1$  
$$h^2 = \sigma_G^2/\sigma_P^2 \rightarrow \sigma_P^2 = \sigma_G^2 + \sigma_{GxE}^2/L + \sigma_e^2/(L*R)$$

L = Locs, R = Reps,  $\sigma^2_G$  = genet. variance;  $\sigma^2_P$  = phenotyp. variance,  $\sigma^2_{GxE}$  = variance due to Genotypenvironment - interaction;  $\sigma^2_e$  = error variance

→ estimated via ANOVA

## Optimize allocation of resources



#### Framework

Target criteria: maximize selection gain

#### – Variables to optimze:

- No. of locations
- No. of replications
- No. of lines
- No. of testers, type of tester
- Splitting of lines on crosses and lines within crosses

→ Fixed annual budget

## Budget of a breeding program = annual budget

budget of a breeding program – annual budget															
Seed production		Seed stock		Bree	ding sche	eme							Spec	ial nurs	eries
Resp.	Min trials	Ex of	Season	Prod	l. Tes	sts	Tr	aits		Resp.	Allocation	Frost	WiSo	FHB	Virus
			Winter									НВ	ВҮ	BY	VL
BY			<b>Summer</b>	P1 x F	2					BY	1 Loc				
			Winter <b>Winter</b>												
BY			<b>Summer</b>	F1 se	elf					BY	1 Loc				
			Winter <b>Winter</b>												
BY			<b>Summer</b>	F2 se	elf Single	plant ear	quality, kernel o	quality		BY	1 Loc				
		rest F1	Winter												
BY			Summer	F3 se	elf Ear to	row row	obs, kernelqual	ity, colou	, sds	BY	1 Loc				
		rest F2	Winter												
BY			Summer	F4 se	elf Ear to		obs, kernelqual	-		BY	1 Loc	25 K			
		rest F3	Winter				ading, lodging,	height,	diseases,						
BY	1200g		Summer <b>Summer</b>	F5 se	elf LP	7.0	ld, colour, sds		vitreousity	ВН	4 Loc, 2 reps	25 K	1 row	3 rows	2 Loc, 2 rows
		rest F4	Winter <b>Winter</b>			hea	ading, lodging,	height,	diseases,						
BY	2500g		Summer	F6 se	e <mark>lf LP</mark>	2 yie	ld, colour, sds,	Protein,	vitreousity	ВН	10 Loc, 2 reps		1 row	3 rows	2 Loc, 2 rows
			Off	icial	offer										_
Breeding scheme									D.,		-4- b-	<b></b>			
Seasor	n Prod.	Tests							Bu	age	et: hoi ertical		ont	al	
2013/1	<b>4</b> P1 x P2	-	Breeding so						and	ما س	ortion	11			
	- PIXPZ	-	Prod. T	ests	Prooding	scheme			and	JV	erucai				
2014/1	5 F1 self		P1 x P2		Prod.	Tests									
			1 1 1 1 2	-	1100.	10313	Breeding so	cheme							
2015/1	6 F2 self	Single plant	F1 self		P1 x P2		_	Tests							
		on gio piant						. 50.0	Breeding	schem	ne				
2016/1	7 F3 self	Ear to row	F2 self 3ing	le plar	F1 self		P1 x P2	•	Prod.	Test					
201511											Breedin	g sche	me		
2017/1	F4 self	Ear to row	F3 self Ear	to row	F2 self	Single pla	nt F1 self		P1 x P2		Prod.		ests		

2018/19

2019/20

F5 self

F6 self

LP1

LP2

F4 self Ear to row F3 self

LP1

F5 self

F4 self

Ear to row

Ear to row

F2 self

F3 self

Single plant

Ear to row

F1 self

F2 self

Single plant

P1 x P2

F1 self

**Breeding scheme** 

**Tests** 

Prod.

P1 x P2

## **Examples for budgets per program**



#### Maize

Large: >1.000.000€

- Small: ~ 500.000€

#### Wheat

Large: 600.000€

- Small: 200.000€

#### Barley

Large: 400.000€

- Small: 100.000€



## **Budget of a breeding program**



- Staff: 125.000€
  - Breeder = 75.000 €
  - 1 Technician = 40.000€
  - Seasonal workers = 5.000€
  - Travelling, car, mobile, computer,... = 5.000€
- <u>DH Lab:</u> 150.000€
- Marker Lab: 40.000€
- Quality Lab: 20.000€
- <u>Field:</u> 250.000€
  - Rows: 50.000 €
  - Yield plots: 200.000€
- Further costs: ??
  - Machinery
  - Seed maintenance
  - Consumables: 10.000€

Annual budget: 600.000€



Source: Sieber

#### Costs - wheat



#### Molecular markers

- For major QTL: 0.5€ per data point
- Genome wide: 40€ per line

#### Quality

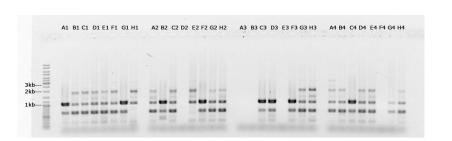
- Protein: NIRS: 2€ / sample
- SDS : 15€ / sample
- Dough tests: 100€/sample
- Baking test: 100€/sample

#### Field costs

- DH line: 20 €
- F3 row: 2€
- Special nursery: row: 5€
- Yield plot: 25 €; 35 € (external)

#### Just an example





## Dimension of a wheat program



#### Just an example

#### Lines

- 200 crosses/year
- 50 crosses \* 150 lines  $\rightarrow$  DH = 7500 lines
- 150 crosses \* 1000 F2 plants → 20.000 F3 rows
- Yield test 1: 2000 lines at 4 Locs
- Yield test 2: 250 lines at 8 Locs

#### Marker Lab

- 10.000 F2 plants on 5 major QTL = 25.000€
- 250 lines genome wide \* 40 = 10.000€

#### Quality Lab

- Best 30 lines from yield test 2 from 8 locs = 240 samples
- Baking + dough = 240 \* 80 = 19.200€

## Simple budget formula

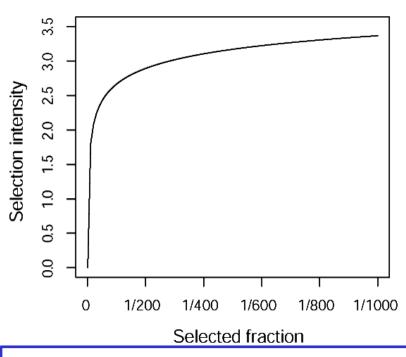


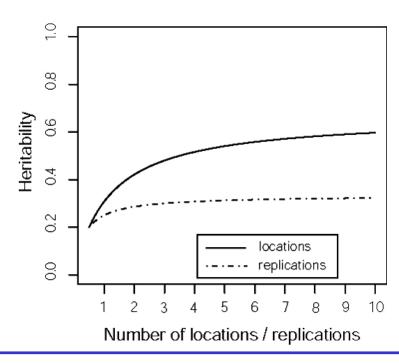
#### Budget = N\*L\*R (\*T) + Production of N

- N = no. of test candidates
- L = no. of test locations
- R = no. of replications
- T = no. of testers

## Selection intensity vs. heritability





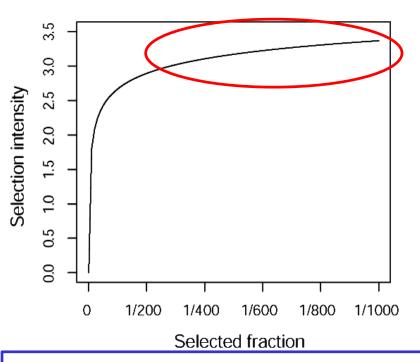


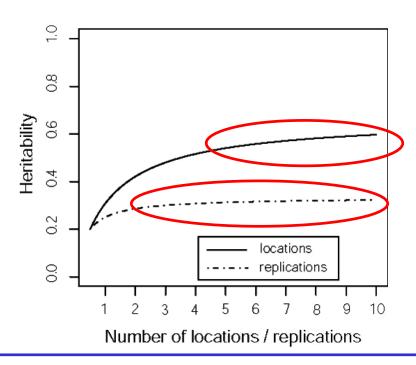
For a fixed budget, maximization of  $\Delta G$  represents a compromise between a high number of test candidates and a high intensity of testing.

Quelle: Becker 1993

#### Golden rule







For a fixed budget, maximization of  $\Delta G$  represents a compromise between a high number of test candidates and a high intensity of testing.

Golden rule: Curves of i and h<sup>2</sup> level off and increase by L > than in R

Quelle: Becker 1993

## Variables influencing selection gain



#### **Annual selection gain**

$$\Delta G_a = ih\sigma_y / Y$$

- *i* = selection intensity,
- *h* = square root of the heritability,
- $\sigma_v$  = square root of the genetic variance of the target variable
- Y = no. of years required to finish one breeding cycle

### Selection gain is maximized by an

Increase of i

> reduction of Y

- Increase of h
- Increase of  $\sigma_v$

## Reduce cycle length



	PS <sub>standard</sub>	<b>GS</b> <sub>rapid</sub>
Year 1	P1 x P2,	P1 x P2,
Year 2	DH-Production	DH-Production
Year 3	<i>N</i> ₁ DH lines - multiplication	<i>N₁</i> DH lines - multiplication
		Genomic selection $N_1$
Year 4	Hybrid seed prod.  N <sub>2</sub> * T <sub>2</sub>	Hybrid seed prod.  N <sub>2</sub> * T <sub>2</sub>
Year 5	Field test N <sub>2</sub> * T <sub>2</sub> * L <sub>2</sub>	Field test $N_2 * T_2 * L_2$
Year 6	Hybrid seed prod.  N <sub>3</sub> * T <sub>3</sub>	
Year 7	Field test  N <sub>3</sub> * T <sub>3</sub> * L <sub>3</sub>	2 years faster breeding scheme

## Annual selection gain



$$\Delta G_a = ih\sigma_y/Y$$
 Assumptions:

- h = 0.7
- $\sigma_v = 5 \text{ dt/ha}$

#### **Example:**

$$\Delta G = 2*0.7*5/7 = 1$$

$$\Delta G = 2*0.7*5/5 = 1.4$$

> 40 % higher annual selection gain

Cycle length has very strong effect on annual selection gain

→You must be faster than your competitor

## Variance components



	Variance components due to							
Crop	G	GxL	GxY	GxLxY	E			
Winter wheat	14.2	2.4	2.4	9.2	14.4			
Winter barley	6.1	1.6	1.6	6.7	13			
Grain maize early	19.6	6.1	5.1	11.7	27.1			
Forage maize early	38.7	15.6	8.6	17.8	80.8			
Winter oil seed rape	3.3	1.7	2	3.8	9.7			
Sugarbeet	33.6	9.1	1.7	4.8	35.2			

Source: Laidig et al. 2008

## **Variance components**



	Variance components due to						
Crop	G	GxL	GxY	GxLxY	E		
Winter wheat	14.2	2.4	2.4	9.2	14.4		
Winter barley	6.1	1.6	1.6	6.7	13		
Grain maize early	19.6	6.1	5.1	11.7	27.1		
Forage maize early	38.7	15.6	8.6	17.8	80.8		
Winter oil seed rape	3.3	1.7	2	3.8	9.7		
Sugarbeet	33.6	9.1	1.7	4.8	35.2		

#### High variance due to

- genotype x year and
- genotype x year x location interaction

Source: Laidig et al. 2008

## Year -> large effect on genotype ranking

Genotyp	Rank 2015	Rank 2016	Yield 2016	Yield 2015
	21	1	58,71	77,10
Miradoux		2	58,66	
W-10066-217-316/14/3-512-2/1	8	3	58,57	82,33
W-10037-210-309/17/1-487-1/3	2	4	58,03	86,39
W-10021-204-307/4/3-468-2/1	1	5	57,89	90,33
W-10029-207-305/11/1-439-4/1	17	6	57,22	79,24
W-10066-217-316/9/2-511-3/1	6	7	57,02	83,49
W-10013-202-302/9/1-408-2/1	16	8	56,44	79,45
Lupidur	10	9	55,87	81,85
W-10058-214-313/21/2-501-1/3	9	10	55,68	82,07
W-10033-209-308/3/1-474-1/3	19	11	55,00	78,42
W-10064-216-315/10/3-506-2/1	13	12	54,97	80,86
W-10021-204-307/2/2-466-6/3	18	13	54,97	79,24
W-10058-214-313/11/1-499-1/3	15	14	54,89	80,46
W-10031-208-306/22/1-460-3/1	5	15	54,87	84,43
W-10066-217-316/23/3-514-6/3	4	16	54,65	84,81
W-10064-216-315/17/3-507-1/1	3	17	54,54	86,30
W-10043-211-310/19/2-494-3/3	12	18	54,34	81,28
W-10033-209-308/10/3-476-6/3	23	19	54,32	76,02

# Further advantages of multiple year testing

- Disease resistance (natural occurring)
- Frost
- Drought, heat
- → Speed of the program is also a compromise between a maximum annual selection gain and a security of the results

## **Compromise necessary**



#### **Annual selection gain**

$$\Delta G_a = ih\sigma_v/Y$$

#### Annual selection gain is maximized by an

increase of i

→ reduction of Y

- increase of h
- increase of  $\sigma_y$

Compromise necessary between theory and practice!

## R package "selection gain"



- Open source software package R (<u>www.r-project.org</u>)
- Package selectiongain
- https://cran.rproject.org/web/packages/selectiongain/index.html



selectiongain: A Tool for Calculation and Optimization of the Expected Gain from Multi-Stage Selection

Multi-stage selection is practiced in numerous fields of life and social sciences and particularly in breeding. A special characteristic of multi-stage selection is fraction of the superior candidates is selected and promoted to the next stage. For the optimum design of such selection programs, the selection gain plays a cr While mathematical formulas for calculating the selection gain and the variance among selected candidates were developed long time ago, solutions for nume selection programs for a given total budget and different costs of evaluating the candidates in each stage.

Version: 2.0.50.1

Depends:  $R (\geq 3.0.0)$ , mvtnorm, parallel

Published: 2016-03-14

Author: Xuefei Mi, Jose Marulanda, H. Friedrich Utz, Albrecht E. Melchinger (Project contact person: Melchinger@uni-hohenheim.de)

Maintainer: Xuefei Mi <mi xue fei at hotmail.com>

License: <u>GPL-2</u> NeedsCompilation: no

CRAN checks: selectiongain results

Downloads:

Reference manual: selectiongain.pdf

Package source: selectiongain 2.0.50.1.tar.gz

Windows binaries: r-devel: selectiongain 2.0.50.1.zip, r-release: selectiongain 2.0.50.1.zip, r-oldrel: selectiongain 2.0.50.1.zip

OS X Mavericks binaries: r-release: selectiongain 2.0.50.1.tgz, r-oldrel: selectiongain 2.0.50.1.tgz

Old sources: selectiongain archive

Linking:

Please use the canonical form https://CRAN.R-project.org/package=selectiongain to link to this page.

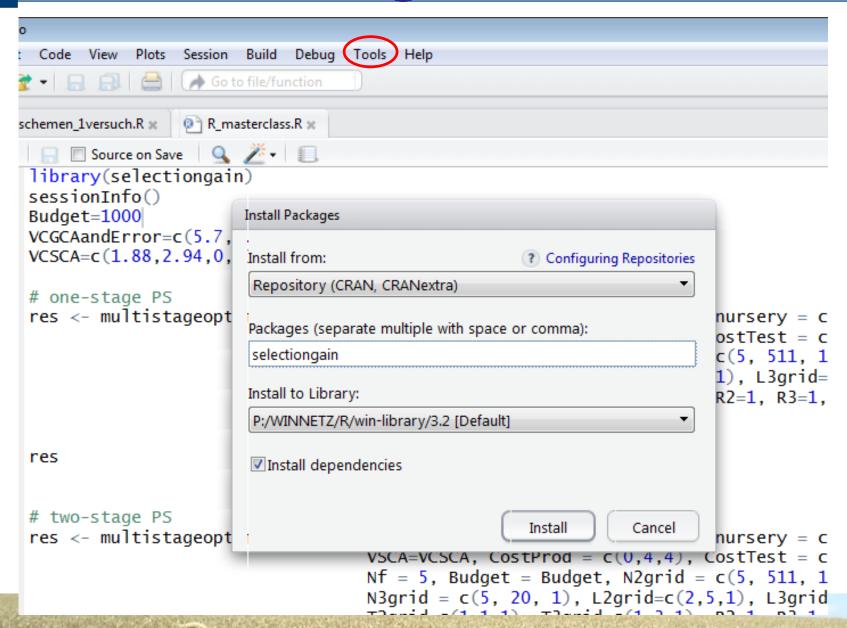
## Selectiongain - Manual



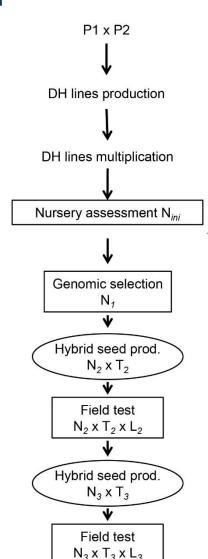
Q wetter :tiongain.pdf Package 'selectiongain' March 14, 2016 Type Package Title A Tool for Calculation and Optimization of the Expected Gain from Multi-Stage Selection Version 2.0.50.1 Date 2016-02-28 Author Xuefei Mi, Jose Marulanda, H. Friedrich Utz, Albrecht E. Melchinger (Project contact person: Melchinger@uni-hohenheim.de ) Maintainer Xucfci Mi <mi\_xue\_fei@hotmail.com> Depends R (>= 3.0.0), mvtnorm,parallel Description Multi-stage selection is practiced in numerous fields of life and social sciences and particularly in breeding. A special characteristic of multi-stage selection is that candidates are evaluated in successive stages with increasing intensity and effort, and only a fraction of the superior candidates is selected and promoted to the next stage. For the optimum design of such selection programs, the selection gain plays a crucial role. It can be calculated by integration of a truncated multivariate normal (MVN) distribution. While mathematical formulas for calculating the selection gain and the variance among selected candidates were developed long time ago, solutions for numerical calculation were not available. This package can also be used for optimizing multi-stage selection programs for a given total budget and different costs of evaluating the candidates in each stage. License GPL-2 NeedsCompilation no Repository CRAN Date/Publication 2016-03-14 12:58:02 R topics documented: 

## Selectiongain - download





## What is possible? – Breeding scheme



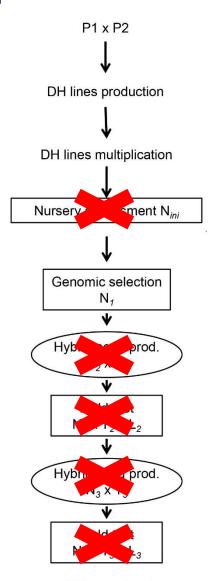
**GSstandard** 

#### **Breeding scheme:**

- DH production
- Nursery selection on traits not correlated to yield
- GS on yield
- 2 stage phenotypic selection on yield

 $N_i$ ,  $L_i$ ,  $R_i$ ,  $T_i$ = number of lines, locations, replications and testers used in stage  $i \rightarrow optimized$ 

## What is possible? – Breeding scheme



GSstandard

#### **Breeding scheme**:

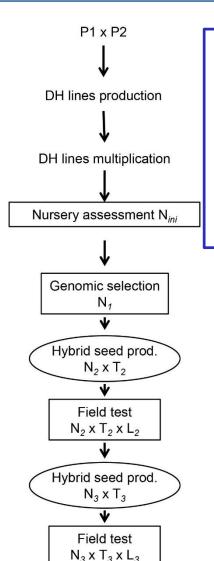
- DH production
- Nursery selection on traits not correlated to yield
- GS on yield
- 2 stage phenotypic selection on yield

#### **Breeding scheme - modifications**

- Each test stage can be switched off
- You can enter minimum/maximum numbers in each test stages of N, L, R, T
- GS → yes/no

## **Budget & Costs**





**GSstandard** 

$$Budget =$$

 $N_{ini}(Cost_{DH}+Cost_{nursery\ test})$ 

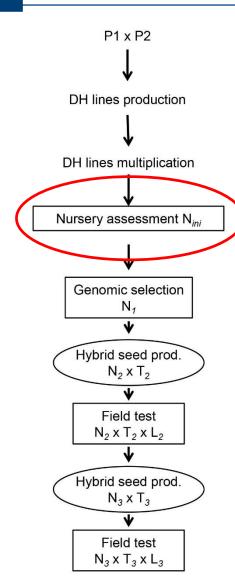
- $+ N_1(Cost_{Genotyping}) + N_2T_2Cost_{Hybridseed}$
- $+ N_2 T_2 L_2 R_2 (Cost_{Test}) + N_3 (T_3 T_2) Cost_{Hybridseed}$
- $+N_3T_3L_3R_3$  (CostTest)

#### **Costs for:**

- DH production
- Nursery selection
- GS
- Hybrid seed production
- Field plot,....
- → All "redefined" in field plot equivalents

## **Nursery selection**





**GSstandard** 

#### We assume:

Nursery selection on traits not correlated to yield (e.g. lodging, leaf rust resistance, SDS,...)

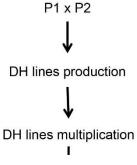
- → Nursery selection will not impact the selection gain formula
- → Nursery selection: costs money (budget impact)
- → Affects number of test lines
- → Nursery selection intensity is predefined (not optimized!) as  $\alpha = \frac{N_{ini}}{N_2}$





## First step of simulations

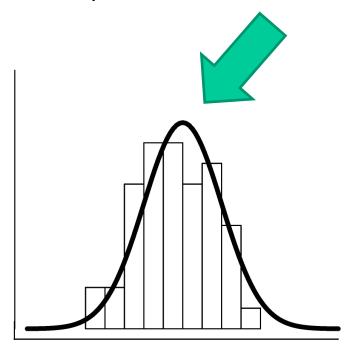




-requencies

#### We define basics:

- Budget (for crossing, line development, GS, field tests) in field plot equivalents
- Crop & Trait to select for → variance components



$$\sigma_{P}^{2} = \sigma_{GCA}^{2} + \sigma_{GCAxy}^{2} + \sigma_{GCAxl}^{2} / L + \sigma_{GCAxlxy}^{2} / L +$$

$$\sigma_{SCA}^{2} / TM + \sigma_{SCAxy}^{2} / TM + \sigma_{SCAxl}^{2} / TML + \sigma_{SCAxlxy}^{2} / TML$$

$$\sigma_{e}^{2} / (TLR)$$

 $\sigma^2_{GCA}$  = GCA variance;  $\sigma^2_{SCA}$  = SCA variance;  $\sigma^2_{P}$  = phenotyp. variance,  $\sigma^2_{GCAx...}$  = variance due to Genotypenvironment - interaction;  $\sigma^2_{e}$  = error variance

→ estimated via ANOVA

## Getting started with the code



**library**(selectiongain) → load the package

sessionInfo() → Info on the version you use

#### **Important input parameters**

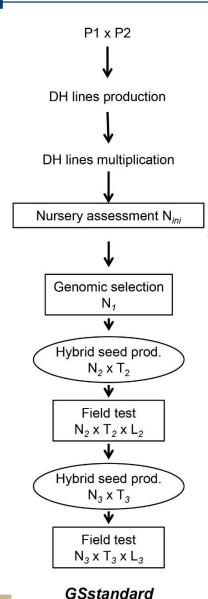
- Budget = in field plot eqivalents
- VCGCAandError = c(GCA,GCA\*loc, GCA\*year, GCA\*loc\*year, error)
- VCSCA = c(SCA, SCA\*loc, SCA\*year, SCA\*loc\*year)

#### **Example for hybrid wheat:**

- Budget =10 000
- VCGCAandError=c(5.7, 5.19, 0, 0, 24.37)
- VCSCA=c(1.88, 2.94, 0,0)

## Second step of simulations





#### We define breeding operations:

- Intensity of nursery selection
- GS: yes/no; predictive ability
- Number of test stages in field
- Maximum numbers of testers, locations,...
- Costs for each operation

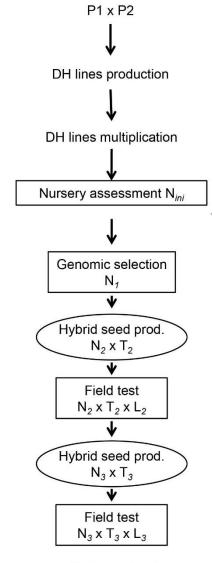
## Most important code



```
Budget = 10000
VCGCAandError = c(5.7,5.19,0,0,24.37)
VCSCA = c(1.88, 2.94, 0, 0)
multistageoptimum.search (
       maseff=NA, alpha.nursery = 1,
      VGCAandE=VCGCAandError, VSCA=VCSCA,
       cost.nursery = c(1,0.3), CostProd = c(0,4,4),
       CostTest = c(2,1,1), t2free = T,
       Nf = 5, Budget = Budget,
      N2grid = c(Nf, 511, 10), N3grid = c(Nf, 20, 1),
      L2grid=c(2,5,1), L3grid=c(1,5,1),
      T2grid=c(1,1,1), T3grid=c(1,5,1),
      R2=1, R3=1, alg = Miwa(),
      detail=FALSE, fig=FALSE)
```

Nf Nini N1 N2 N3 L2 L3 T2 T3 R2 5.000 204.000 0.000 51.000 9.800 5.000 10.000 1.000 2.000 1.000

R3 Bini B1 B2 B3 Budget Gain 1.000 265.200 0.000 459.000 274.900 1000.000 3.278



**GSstandard** 

## Most important code - explained

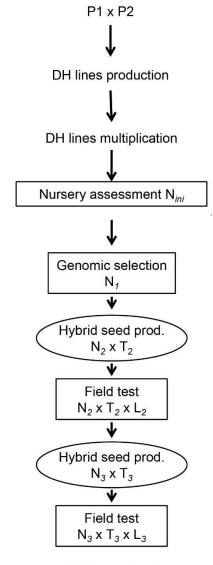


```
multistageoptimum.search (
      maseff = GS pred. abbility,
      alpha.nursery = selected fraction in disease nursery,
      VGCAandE=VCGCAandError, VSCA=VCSCA,
      cost.nursery = c(line prod., test in nursery),
      CostProd = c(0, hybrid seed prod., hybrid seed prod.),
      CostTest = c(GS, yield plot, yield plot), t2free = T,
      Nf = no. finally selected lines, Budget = Budget,
      N2grid = c(Nf, 511, 10), N3grid = c(Nf, 5, 1),
      L2grid=c(1,5,1), L3grid=c(1,5,1),
      T2grid=c(1,1,1), T3grid=c(1,3,1),
      R2=1, R3=1, alg = Miwa(),
      detail=FALSE, fig=FALSE)
```

## Step by step: nursery



```
multistageoptimum.search (
        maseff=0.2, alpha.nursery \neq 0.3,
        VGCAandE=VCGCAandError,
        VSCA=VCSCA,
        cost.nursery = c(1, 0.3)
        CostProd = c(0,4,4),
        CostTest = c(2,1,1),
        Nf = 5, Budget = Budget,
        N2grid = c(Nf, 511, 10), N3grid = c(Nf, 20, 1),
       L2grid=c(2,5,1), L3grid=c(1,5,1),
        T2grid=c(1,1,1), T3grid=c(1,5,1),
        R2=1, R3=1,
       alg = Miwa(), detail=FALSE, fig=FALSE)
```

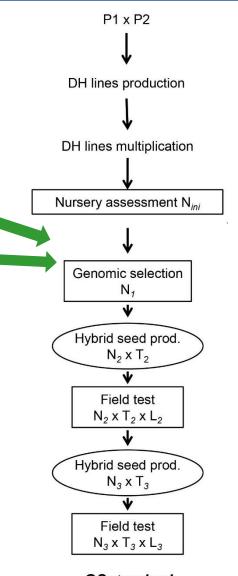


**GSstandard** 

## Step by step: Genomic selection

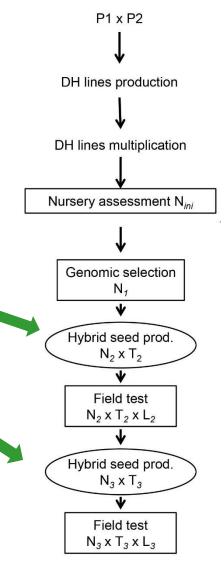


```
multistageoptimum.search (
       maseff=(0.2) alpha.nursery = 0.3,
        VGCAandE=VCCCAandError,
       VSCA=VCSCA,
       cost.nursery = c(1, 0.3),
       CostProd = c(0,4,4),
       CostTest = c(2)1,1)
       Nf = 5, Budget = Budget,
       N2grid = c(Nf, 511, 10), N3grid = c(Nf, 20, 1),
       L2grid=c(2,5,1), L3grid=c(1,5,1),
       T2grid=c(1,1,1), T3grid=c(1,5,1),
       R2=1, R3=1,
       alg = Miwa(), detail=FALSE, fig=FALSE)
```



## Step by step: Hybrid seed production

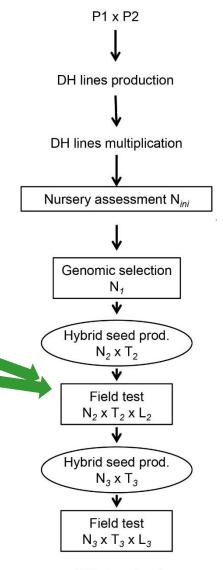
```
multistageoptimum.search (
       maseff=0.2, alpha.nursery = 0.3,
        VGCAandE=VCGCAandError,
       VSCA=VCSCA,
       cost.nursery = c(1, 0.3),
       CostProd = c(0,4)4
       CostTest = c(2,1,1),
       Nf = 5, Budget = Budget,
       N2grid = c(Nf, 511, 10), N3grid = c(Nf, 20, 1),
       L2grid=c(2,5,1), L3grid=c(1,5,1),
       T2grid=c(1,1,1), T3grid=c(1,5,1),
       R2=1, R3=1,
       alg = Miwa(), detail=FALSE, fig=FALSE)
```



## Step by step: Field test 1



```
multistageoptimum.search (
       maseff=0.2, alpha.nursery = 0.3,
       VGCAandE=VCGCAandError,
       VSCA=VCSCA,
       cost.nursery = c(1, 0.3),
       CostProd = c(0.4,4),
       CostTest = c(2,1,1)
       Nf = 5, Budget = Budget,
        N2grid = c(Nf, 511, 10), N3grid - c(Nf, 20, 1),
       L2grid=c(2,5,1), =2grid=c(1,5,1),
        T2grid=c(1,1,1), T3grid=c(1,5,1),
        R2=1, R3=1,
       alg = Miwa(), detail=FALSE, fig=FALSE)
```



## Step by step: Field test 2

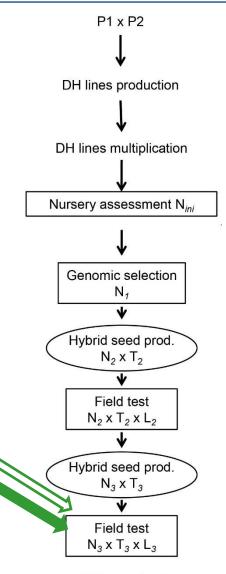


```
multistageoptimum.search (
    maseff=0.2, alpha.nursery = 0.3,
    VGCAandE=VCGCAandError,
    VSCA=VCSCA,
    cost.nursery = c(1, 0.3),
    CostProd = c(0,4.4),
    CostTest = c(2,1,1),
    Nf = 5, Budget = Budget,
    N2grid = c(Nf, 511, 10), N3grid = c(Nf, 20, 1),
    L2grid=c(2,5,1), L3grid=c(1,5,1),
    T2grid=c(1,1,1), T3grid=c(1,5,1),
```

R3=1.

alg = Miwa(), detail=FALSE, fig=FALSE,

R2=1.



**GSstandard** 

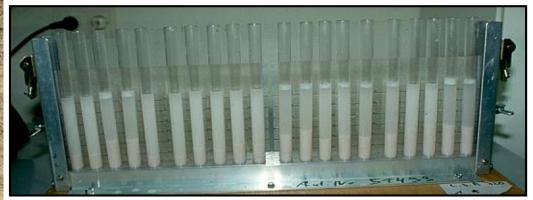
## Let's go into breeding world











## Modeling the optimum allocation



#### 1. Basic level

- Target criterion
- Trait

#### 2. Breeding level

- Scheme
- Scenario

#### 3. Optimization level

Test resources

# Modeling the optimum allocation



#### 1. Basic level

Target criterion = selection gain

Trait = grain yield in wheat

#### 2. Breeding level

Scheme = PS standard

Scenario = variance components, budget, selected fraction, technical requirements,...

#### 3. Optimization level

Test resources = number of test locations, testers,
 replications, DH lines

# Determining the opt. allocation within a given model framework



#### 1. Basic level

- Selection gain
- Maize grain yield

#### 2. Breeding level

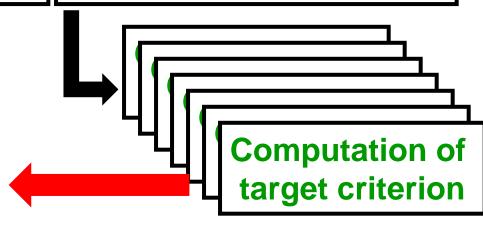
- PSstandard
- Given scenario

#### 3. Optimization level

specific allocation of the number of testers, test locations, DH lines, replications

AIM: Find the allocation maximizing selection gain for that specific def. of level 1 and 2

= optimum allocation



#### Use of molecular markers



#### Nothing else than indirect selection

$$\Delta G = i\rho \, \sigma_y / Y$$

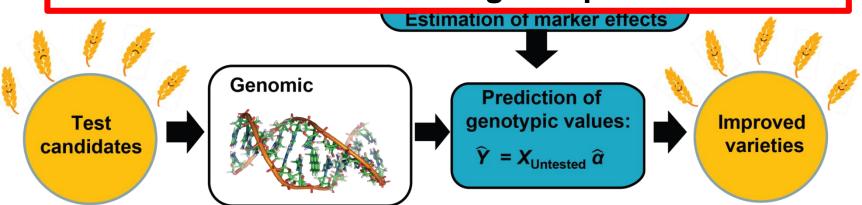
- 0 < ρ < 1: selection gain is only increased if the use of the test criteria enables
  - Increase of i → high throughput: N₁
  - Increase of h
  - Increase of  $\sigma_v$
  - Decrease of Y → fast recycling

### **Genomic selection**



#### We assume, that

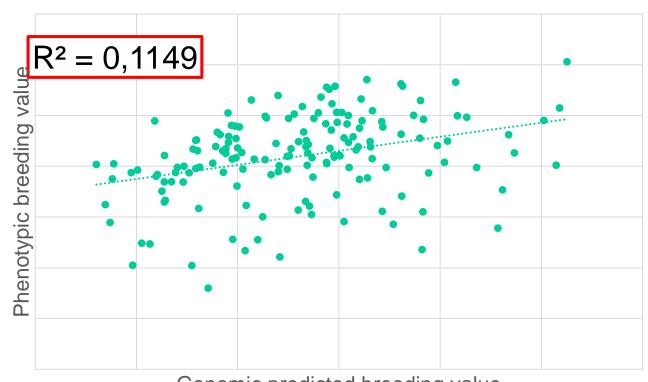
- prediction models have been developed in previous projects 
   no budget required for it now!
- Retraining of the model is done with routine field trials → no additional budget required for it!



Source: Zhao et al. 2015

# We need prediction ability





Correlation between observed and predicted breeding value = prediction ability

→ that's what we need for our simulations

$$Prediction \ accuracy = \frac{prediction \ ability}{h}$$

### **Modifications of the framework**



# Besides budget, variance components, costs for line production and phenotyping we need further data:

- Correlation GS with GCA: ρ(GS, GCA)= 0.3 (for T0 scenario; Zhao et al. 2014)
- Costs GS = high density genotyping of 1 line costs as much as 2 field plots
- (data is shown for wheat with framwork based on papers below)

### **Breeding schemes**



# PS<sub>standard</sub>

Year 1 P1 x P2, ...

Year 2 DH-Production

Year 3  $N_1$  DH lines - multiplication

Year 4 Hybrid seed prod. N<sub>2</sub> \* T<sub>2</sub>

Year 5 Field test  $N_2 * T_2 * L_2$ 

Year 6

Hybrid seed prod.

N<sub>3</sub> \* T<sub>3</sub>

Year 7 Field test  $N_3 * T_3 * L_3$ 

Year 8, 9,... Pre-registration trials

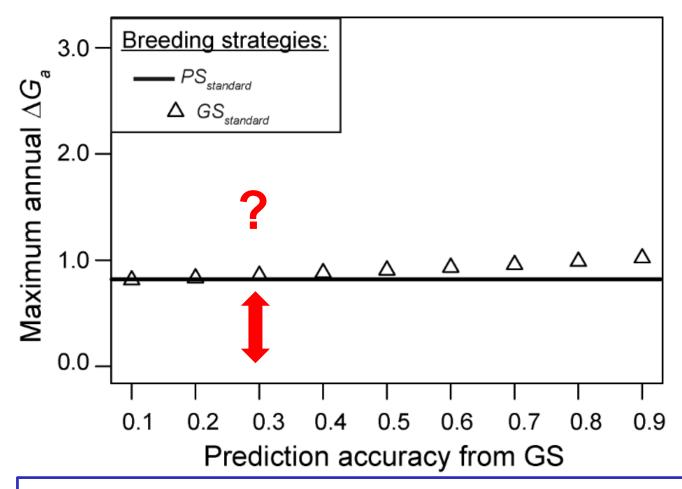
# **Breeding schemes**



	<b>PS</b> <sub>standard</sub>	<b>GS</b> <sub>standard</sub>
Year 1	P1 x P2,	P1 x P2,
Year 2	DH-Production	DH-Production
Year 3	<i>N</i> ₁ DH lines - multiplication	<i>N</i> ₁ DH lines - multiplication
		Genomic selection $N_1$
Year 4	Hybrid seed prod.  N <sub>2</sub> * T <sub>2</sub>	Hybrid seed prod.  N <sub>2</sub> * T <sub>2</sub>
Year 5	Field test N <sub>2</sub> * T <sub>2</sub> * L <sub>2</sub>	Field test $N_2 * T_2 * L_2$
Year 6	Hybrid seed prod.  N <sub>3</sub> * T <sub>3</sub>	Hybrid seed prod.  N <sub>3</sub> * T <sub>3</sub>
Year 7	Field test $N_3 * T_3 * L_3$	Field test N <sub>3</sub> * T <sub>3</sub> * L <sub>3</sub>

### Increase in selection gain with GS





The higher the prediction accuracy the larger is the advantage of GS schemes

### Reduce cycle length with GS



	PS <sub>standard</sub>	<b>GS</b> <sub>standard</sub>	<b>GS</b> <sub>rapid</sub>	<b>GS</b> <sub>only</sub>		
Year 1	P1 x P2,	P1 x P2,	P1 x P2,	P1 x P2,		
Year 2	DH-Production	DH-Production	DH-Production	DH-Production		
Year 3	<i>N₁</i> DH lines - multiplication	<i>N</i> ₁ DH lines - multiplication	<i>N</i> ₁ DH lines - multiplication	<i>N</i> ₁ DH lines - multiplication		
		Genomic selection $N_1$	Genomic selection $N_1$	Genomic selection $N_1$		
Year 4	Hybrid seed prod.  N <sub>2</sub> * T <sub>2</sub>	Hybrid seed prod.  N <sub>2</sub> * T <sub>2</sub>	Hybrid seed prod.  N <sub>2</sub> * T <sub>2</sub>			
Year 5	Field test N <sub>2</sub> * T <sub>2</sub> * L <sub>2</sub>	Field test N <sub>2</sub> * T <sub>2</sub> * L <sub>2</sub>	Field test N <sub>2</sub> * T <sub>2</sub> * L <sub>2</sub>			
Year 6	Hybrid seed prod.  N <sub>3</sub> * T <sub>3</sub>	Hybrid seed prod.  N <sub>3</sub> * T <sub>3</sub>				
Year 7	Field test  N <sub>3</sub> * T <sub>3</sub> * L <sub>3</sub>	Field test $N_3 * T_3 * L_3$				

Source: Longin et al. 2015

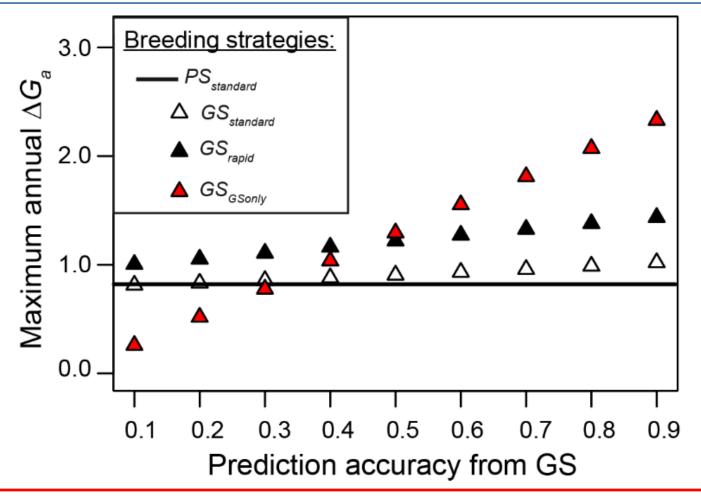
# Reduce cycle length with GS



	PS <sub>standard</sub>	<b>GS</b> <sub>standard</sub>	<b>GS</b> <sub>rapid</sub>	<b>GS</b> <sub>only</sub>
Year 1	P1 x P2,	P1 x P2,	P1 x P2,	P1 x P2,
Year 2	DH-Production	DH-Production	DH-Production	DH-Production
Year 3	<i>N₁</i> DH lines - multiplication	<i>N</i> ₁ DH lines - multiplication	<i>N₁</i> DH lines - multiplication	<i>N</i> ₁ DH lines - multiplication
		Genomic selection $N_1$	Genomic selection $N_1$	Genomic selection $N_1$
Year 4	Hybrid seed prod.  N <sub>2</sub> * T <sub>2</sub>	Hybrid seed prod.  N <sub>2</sub> * T <sub>2</sub>	Hybrid seed prod.  N <sub>2</sub> * T <sub>2</sub>	
Year 5	Field test N <sub>2</sub> * T <sub>2</sub> * L <sub>2</sub>	Field test	Field test N <sub>2</sub> * T <sub>2</sub> * L <sub>2</sub>	
Year 6	Hybrid seed prod.  N <sub>3</sub> * T <sub>3</sub>	Hybrid seed prod.  N <sub>3</sub> * T <sub>3</sub>		Up to 4 years faster breeding schemes
Year 7	Field test <i>N</i> <sub>3</sub> * <i>T</i> <sub>3</sub> * <i>L</i> <sub>3</sub>	Field test $N_3 * T_3 * L_3$		feasible with GS

### **GS** for yield is interesting

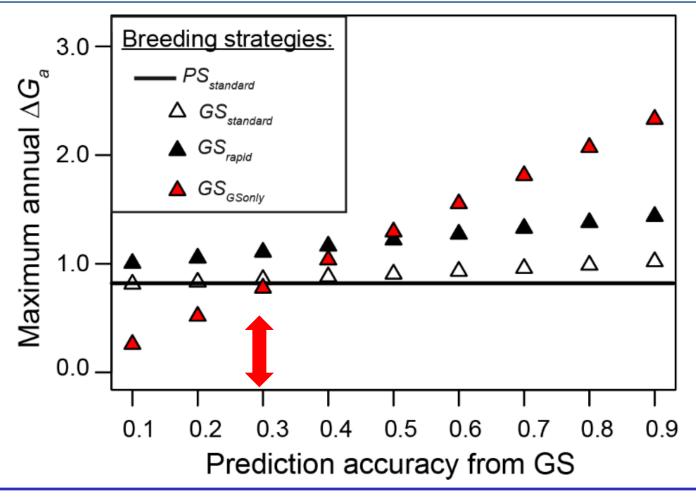




Genomic selection is promising for grain yield especially when used to shorten breeding cycle length

### **GS** for yield is interesting





With recent GS accuracy breeding scheme  $GS_{rapid}$  seems most promising: + 35% in annual selection gain

#### **Generalisation of results**

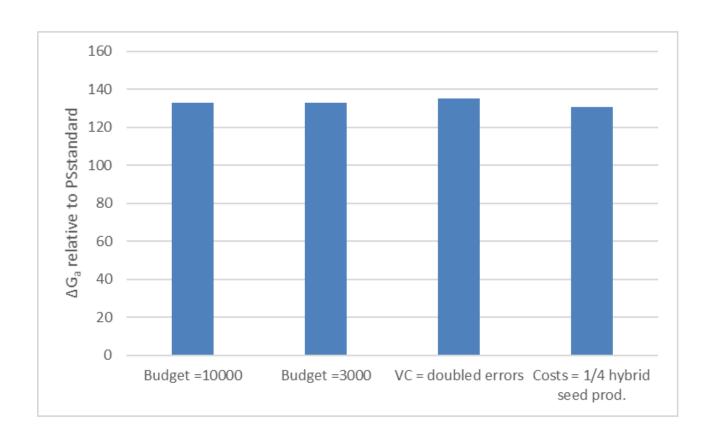


We state that a breeding scheme using GS, namely GSrapid, is top and should be used; but is it also the truth for

- small budgets?
- different variance components?
- reduced hybrid seed production costs?

### Broad advantage of GSrapid

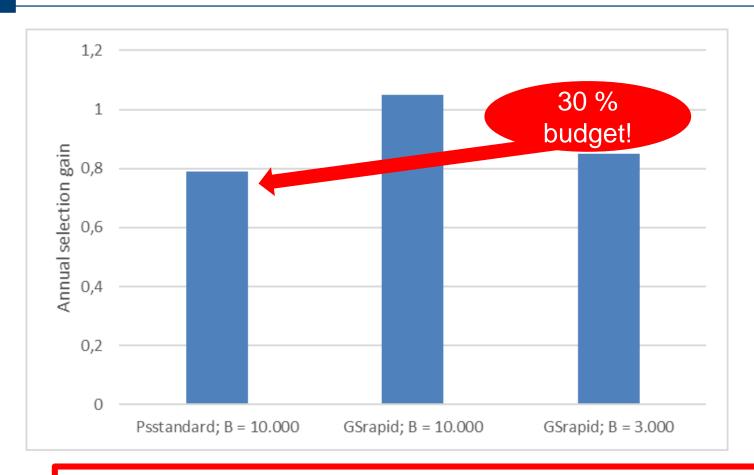




The use of GS in elite breeding is recommended for a broad range of scenarios; also for small breeding programs!

#### Think about....





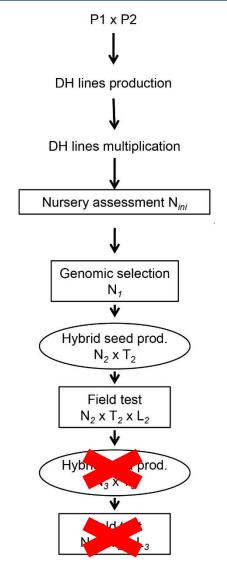
Using **GSrapid** with a budget of 3.000 field plots has a 7.6 % higher annual selection gain than PSstandard with a budget of 10.000 field plots!

Source: Marulanda et al. 2016

# Realization of GSrapid



```
Budget = 10000
VCGCAandError = c(5.7, 5.19, 0, 0, 24.37)
VCSCA = c(1.88, 2.94, 0, 0)
multistageoptimum.search (
       maseff = 0.3, alpha.nursery = 0.25,
      VGCAandE=VCGCAandError, VSCA=VCSCA,
        cost.nursery = c(1,0.3), CostProd = c(0,4,0),
       CostTest = c(2,1,0), t2free = T,
       Nf = 5, Budget = Budget,
      N2grid = c(Nf, 511, 10), N3grid = c(Nf, 5, 1),
      L2grid=c(1,5,1), L3grid=c(0,0,1),
      T2grid=c(1,3,1), T3grid=c(0,0,1),
      R2=1, R3=1, alg = Miwa(),
      detail=FALSE, fig=FALSE)
```



### **Student simulations**





### Line breeding



PS<sub>standard</sub>

GS<sub>rapid</sub>

Year 1

P1 x P2, ...

P1 x P2, ...

Year 2

**DH-Production** 

**DH-Production** 

Year 3

Nursery with N<sub>nurs</sub> DH lines Nursery with N<sub>nurs</sub> DH lines

selection  $N_{GS}$ 

Year 4

Field test  $N_1 * L_1$ 

Year 5

Field test  $N_2 * L_2$ 

Field test  $N_1 * L_1$ 

Genomic



1 year faster

# **Questions – durum breeding**



- Is GSrapid better than PSstandard also for line breeding?
- Speed up in DH method worthwile also if very expensive?
- What about breeding schemes for durum breeding in developing countries?
- → Look on annual and absolute selection gain and elaborate potential differences in the allocation of resources

# **Questions – durum breeding**



- Is GSrapid better than PSstandard also for line breeding?
- Speed up in DH method worthwile also if very expensive?
- What about breeding schemes for durum breeding in developing countries?
- → Look on annual and absolute selection gain and elaborate potential differences in the allocation of resources
- Three student groups
  - 1. Optimize both classical breeding schemes for different budgets, variance components, GS pred. abilities
  - 2. Optimize both breeding schemes with fast DH for different budgets, variance components, ...
  - Optimize both breeding schemes in a context of very low budgets and high GS costs

# **Questions – durum breeding**



- Is GSrapid better than PSstandard also for line breeding?
- Speed up in DH method worthwile also if very expensive?
- What about breeding schemes for durum breeding in developing countries?
- → Each student group works on parts of these questions, thus you should compare the 2 breeding schemes in your given situation and look on the influence of budget, GS prediction ability, variance components on that comparison and on the optimum allocation of test resources
- → Finally, the achieved selection gains should be compared across the groups to answer the above mentioned questions; especially group 1+2, because they have same budgets
- → For group 3: do you have the same findings then group 1+2 regarding which breeding scheme is better?

### How to realize



#### **Excel files**

- Breeding schemes defined
- All necessary input parameters (variance components, costs,...)
- Just let the package work for you:
  - ➤ For each defined scenario, you will get the maximum possible absolute selection gain and the allocation of resources → put it all to an Excel table
  - Run next scenario
  - Finally compare the results and find the best scheme with its best allocation of ressources

# **Example table**



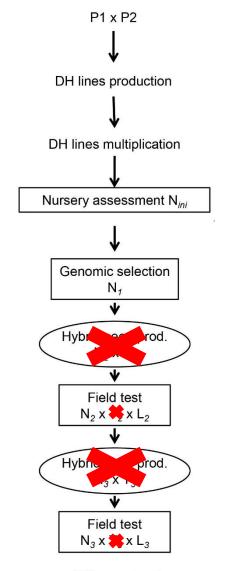
Breeding	A lobe in -	Optimum allocation of test resources								
strategy	Alpha in – Nursery	Nini	N1	N2	N3	L2	L3	<i>T</i> 2	<i>T3</i>	$\Delta G_a$
PSstandard	0.1	3170	-	317	30	7	10	1	6	0.75
PSstandard	0.2	2190	-	438	35	6	10	1	6	0.79
PSstandard	0.3	1680	-	504	35	6	10	1	6	0.80
PSstandard	0.4	1395	-	558	40	5	10	1	6	0.81
PSstandard	0.5	1178	-	589	40	5	10	1	6	0.81
<b>GS</b> rapid	0.1	3440	344	115	-	10	-	3	-	0.99
<b>GS</b> rapid	0.2	2790	558	125	-	10	-	3	-	1.04
<b>GS</b> rapid	0.3	2500	750	125	-	10	-	3	-	1.06
<b>GS</b> rapid	0.4	2060	824	135	-	10	-	3	-	1.07
<b>GS</b> rapid	0.5	1882	941	135	-	10	_	3	-	1.08

Source: Marulanda et al. 2016

# Changes in code



```
Budget = 10000
VCGCAandError = c(14.06,22.27,0,0,24.37)
VCSCA = c(0,0,0,0)
multistageoptimum.search (
       maseff=NA, alpha.nursery = 0.25,
       VGCAandE=VCGCAandError,
       VSCA=VCSCA, cost.nursery = c(1,0.3),
       CostProd = c(0, 0, 0),
       CostTest = c(2,1,1), t2free = T,
       Nf = 5, Budget = Budget,
       N2grid = c(Nf, 6011, 40), N3grid = c(Nf, 1511,
       5), L2grid=c(1,5,1), L3grid=c(2,10,1),
       T2grid=c(1,1,1), T3grid=c(1,1,1),
       R2=1, R3=1, alg = Miwa(),
       detail=FALSE, fig=FALSE)
```



### **Contact**



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