## Data and Process-Driven Decision-Making To Increase Plant Breeding Efficiency

Michel Ragot, DELTAGee

*XIV International Rice Conference, Panama June 10-14, 2024* 





## **Plant Breeding is a Process**



## How to Improve Plant Breeding Efficiency?



Improve:

- Selection intensity
- Selection accuracy
- Genetic variance
- Cycle time

$$\Delta G = \frac{ir\sigma_A}{y}$$



## **Decision-Making for Process Optimization**



Risk of not getting there? Time it will take? Resources I will need?







# **Decision-Making for Process Optimization**

Decision-making based on descriptive data: insights



End





## **Decision-Making for Process Optimization**

Looks best

Decision-making based on descriptive data: insights





## **Decision-Making for Process Optimization**

Forward-looking decision-making: best path





## **Decision-Making for Process Optimization**



## **Plant Breeding is a Complex Process**

With tens to hundreds of plants at each step (generations), there are millions of potential "itineraries" to go from starting point to end point





Starting Point: Germplasm

End Point: Variety Release

### DECISION-MAKING IN PLANT BREEDING

# **Current: Descriptive Data-Driven**







Generation

## DECISION-MAKING IN PLANT BREEDING

## Future: Forward-Looking Data and Process-Driven



### DECISION-MAKING IN PLANT BREEDING

## Future: Forward-Looking Data and Process-Driven





- Increases breeding efficiency very significantly:
  - o Risk management
  - o Timeline
  - o Resources
- Is permitted by the availability of genotypic data on all selection candidates
- Can be implemented whenever a product objective can be defined by one or a set of genotypes (TI, MAS, GS)

## IMPROVING BREEDING EFFICIENCY

# Can We Improve Decision-Making in Plant Breeding?

1994	* "Since the approximate map positions of the QTLs are known, it is possible to identify those individuals which, upon further crossing are most likely to produce the ideal genotype This approach is a way to breed the most transgressive segregant, applying Mendelian genetics rather than phenotypic selection" (Piet Stam)
2003	"Eventually, knowledge of the map positions of all loci of agronomic interest, the allelic variation at these loci, and their contribution to the phenotype should enable the breeder to design superior genotypes comprising a combination of favorable alleles at all loci Software tools should enable us to determine the optimal route for generating those mosaic genotypes" (Johan Peleman)
2021	*** "Can machine learning be used to mimic the selection decisions made by breeders?… The purpose here would not be to replace breeders with a machine and an algorithm but rather to aid breeders in their work" (Rex Bernardo)

\* P Stam (1994) Marker-assisted breeding. Eucarpia Biometrics

\*\* JD Peleman and JR Van der Voort (2003) Breeding by design. Trends in plant science 8.7: 330-334.

\*\*\* R Bernardo (2021) Predictive breeding in maize during the last 90 years. Crop Science. 61: 2872–2881. https://doi.org/10.1002/csc2.20529

# Forward-Looking Decision-Making



Optimized decision making means:

- Finding the "shortest" path from beginning to end
- Shortest in terms of time, resources, risk
   Requires:
- Whole process approach
- Ability to predict future
- Ability to take operational elements into consideration
- Ability to adjust in real time



# **Line Breeding**



oving crops through better decision

# Cumulated distribution functions of population maximum

CGS: Conventional Genomic Selection – Selection of individuals with the highest GEBV - DESCRIPTIVE

OHV: Optimal Haploid Value – Selection of individuals based on GEBV of best-possible DH progeny – PREDICTIVE 1 GENERATION OPV: Optimal Population Value – Selection of set of individuals based on GEBV of best-possible progeny – PREDICTIVE INFINITE GENERATIONS

LAS: Look-Ahead Selection – Selection of set on individuals based on expected GEBV of best offspring with constraints – PREDICTIVE TERMINAL GENERATION

S Moeinizade et al. (2019) Optimizing selection and mating in genomic selection with a look-ahead approach: An operations research framework. G3 Genes|Genomes|Genetics, 9(7): 2123–2133. https://doi.org/10.1534/g3.118.200842

# **New Line Development**



# Cumulated distribution functions of population maximum

CGS: Conventional Genomic Selection – Selection of individuals with the highest GEBV - DESCRIPTIVE

OHV: Optimal Haploid Value – Selection of individuals based on GEBV of best-possible DH progeny – PREDICTIVE 1 GENERATION OPV: Optimal Population Value – Selection of set of individuals based on GEBV of best-possible progeny – PREDICTIVE INFINITE GENERATIONS

LAS: Look-Ahead Selection – Selection of set on individuals based on expected GEBV of best offspring with constraints – PREDICTIVE TERMINAL GENERATION

S Moeinizade et al. (2019) Optimizing selection and mating in genomic selection with a look-ahead approach: An operations research framework. G3 Genes | Genomes | Genetics, 9(7): 2123–2133. https://doi.org/10.1534/g3.118.200842

Forward-looking decision-making delivers higher performance levels than other approaches

# Trait Introgression



# Cumulated distribution functions of population maximum in BC3

GEBV: Background Selection – Selection of individuals with the highest recurrent parent genome recovery - DESCRIPTIVE

PCV: Predicted Cross Value – Selection of individuals based their probability of production of the "perfect" gamete – PREDICTIVE 1 GENERATION

LMC: Look-Ahead Monte Carlo – Selection of individuals based on their predicted genetic distribution of BC progeny after multiple generations with constraints – PREDICTIVE MULTIPLE GENERATIONS

S Moeinizade et al. (2021) A look-ahead Monte Carlo simulation method for improving parental selection in trait introgression. Sci Rep 11, 3918.



## **Trait Introgression**



# Cumulated distribution functions of population maximum in BC3

GEBV: Background Selection – Selection of individuals with the highest recurrent parent genome recovery -DESCRIPTIVE

PCV: Predicted Cross Value – Selection of individuals based their probability of production of the "perfect" gamete – PREDICTIVE 1 GENERATION

LMC: Look-Ahead Monte Carlo – Selection of individuals based on their predicted genetic distribution of BC progeny after multiple generations with constraints – PREDICTIVE MULTIPLE GENERATIONS

S Moeinizade et al. (2021) A look-ahead Monte Carlo simulation method for improving parental selection in trait introgression. Sci Rep 11, 3918.

# Forward-looking decision-making results in cleaner/faster line conversions



## **General Trait Introgression**





- Difficult and time-consuming compromise between recombination and background
- Selection of plants based on their own, "per se" attributes
- No insights/visibility into how to proceed with selected plants

## General Trait Introgression Software

Edit View Visualization A	nalysis <u>D</u> ata <u>H</u> elp	
New Project 🧻 Open Project	🔚 🐺 Import Data 🛷 🦘 💁 Find 🔢 🗂 🗔 🕼 😴 🕞 📑 Genotypes 🔚 Chromosomes 🔇 🌍 💡	
Data Sets gobil-test 302x61 Trait Data Default View MABC Results	Chromosome: Al Chromosomes  37 lnes, 61 markers, length: 568	
Overview	Line: Marker:	<u>Z</u> oom:
. 말려 한국 석영을	Genotype:	

I Milne et al. (2010) Flapjack – graphical genotype visualization. Bioinformatics 26(24), 3133-3134.

New Project 🛒 Open Pro	oject   🔚   🐳 Imp	oort Data		Find	2.8	- 9-9	Ge Ge	notypes	E Chromos	omes   🌘		<b>6</b>				
Data Sets	Ats Marker Assisted Back Crossing (MABC)															
🦲 gobii-test 202x61	Line	RPP (1)	RPP (2)	RPP (3)	RPP (4)	RPP T F	XPP	LD (Q	Statu Ll	D (O	Statu	OTL	Selec	Rank	Co Do	)
Trait Data	RP	1	1	1	1	1	0.687	0	0	0	0	- 0		0		J
Default View	DP	- 0	- 0	0	- 0	0	0.687	62	2	179	2	4		0		
MABC View 1	RP[1]/DP-176	0.669	0.871	0.963	0.829	0.847	0.687	22	1	4	- 1	2		0		
MABC Results	RP[1]/DP-40	0.5	0.912	1	0.81	0.831	0.687	62	1	34	1	2		0		
	RP[1]/DP-68	0.728	0.776	0.826	0.868	0.812	0.687	16	1	19	1	2	J	0		
	RP[1]/DP-6	0.5	1	0.935	0.626	0.771	0.687	62	1	54	1	2		0		
	RP[1]/DP-105	0.5	1	0.743	0.775	0.767	0.687	62	1	32	1	2	<b>J</b>	0		
	RP[1]/DP-67	0.5	0.841	0.785	0.837	0.765	0.687	62	1	30	1	2	<b>V</b>	0		
2	RP[1]/DP-127	0.5	0.906	1	0.603	0.761	0.687	62	1	149	1	2		0		
	RP[1]/DP-134	0.559	1	1	0.504	0.759	0.687	16	1	177	1	2		0		
H H H H H	RP[1]/DP-174	0.537	1	0.912	0.556	0.748	0.687	42	1	153	1	2		0		
	RP[1]/DP-49	0.5	0.906	0.755	0.727	0.734	0.687	62	1	80	1	2		0		
	RP[1]/DP-17	0.5	0.594	0.824	0.837	0.722	0.687	62	1	30	1	2	<b>V</b>	0		
	RP[1]/DP-66	0.5	0.5	1	0.721	0.712	0.687	62	1	23	1	2	1	0		
.444444	RP[1]/DP-25	0.5	1	0.72	0.62	0.71	0.687	62	1	113	1	2		0		
44444	RP[1]/DP-136	0.5	1	0.72	0.612	0.707	0.687	62	1	34	1	2	<b>V</b>	0		
	RP[1]/DP-42	0.537	0.594	1	0.57	0.688	0.687	42	1	30	1	2	<b>V</b>	0		
444444	RP[1]/DP-172	0.787	0.906	0.528	0.616	0.685	0.687	6	1	66	1	2		0		
	RP[1]/DP-28	0.669	0.871	0.53	0.684	0.679	0.687	22	1	23	1	2	1	0		
	RP[1]/DP-87	0.5	0.559	0.963	0.612	0.678	0.687	62	1	34	1	2	1	0		
	RP[1]/DP-89	0.5	0.906	0.641	0.647	0.676	0.687	62	1	54	1	2		0		
	RP[1]/DP-26	0.526	0.5	1	0.599	0.676	0.687	57	1	140	1	2		0		
	RP[1]/DP-95	0.537	0.965	0.644	0.578	0.673	0.687	42	1	74	1	2		0		
	RP[1]/DP-57	0.754	0.5	0.954	0.5	0.67	0.687	11	1	179	1	2		0		
	RP[1]/DP-197	0.603	0.965	0.676	0.5	0.668	0.687	34	1	179	1	2		0		
	RP[1]/DP-141	0.537	0.594	0.644	0.802	0.667	0.687	42	1	30	1	2	1	0		
	RP[1]/DP-199	0.787	0.776	0.688	0.5	0.662	0.687	6	1	179	1	2		0		
		0.5	0.665	0.678	0.733	0.662	0.687	62	1	24	1	2	1	0		
	RP[1]/DP-126	0.5	0.535	0.963	0.578	0.662	0.687	62	1	76	1	2		0		
Zoom:	RP[1]/DP-152	0.5	0.653	0.766	0.659	0.66	0.687	62	1	100	1	2		0		
	RP[1]/DP-79	0.5	0.659	0.771	0.62	0.649	0.687	62	1	113	1	2		0		
<u> </u>	DD[1]/DD_167	0.5	0.5	0 775	0.688	0.638	0.687	62	1	115	1	2		1 0		

# **Optimized Trait Introgression**





# **Optimized Trait Introgression**



- No compromise between recombination and background
- Selection of plants based on their future potential to deliver the target genotype
- Ability to re/define upcoming steps (population sizes) to secure success

## **Optimized Trait Introgression - On-Demand Services**



# **Optimized Trait Introgression - On-Demand Services**

PLANTID	RISK AT BC1S1 Faster alternative	RISK AT BC2S1 Faster alternative	RISK AT BC3S1 User defined protocol	RPGR	Total LD (%)	Total LD (cM)	Nb recomb (/ max nb rec)	Nb missing DP	Nb het mkr	Nb het segments	Nb homoz REC mkr	Nb homoz DON mkr	
ProjXt3_Plt856	100.00%	98.08%	0.21%	82.42%	6.43%	75.42	2	0	37	16	80	0	See more
ProjXt3_Plt55	100.00%	99.26%	0.42%	78.31%	1.72%	20.12	2	0	55	16	62	0	See more
ProjXt3_Plt222	100.00%	99.27%	1.36%	82.30%	4.05%	47.445	1	0	33	13	84	0	See more
ProjXt3_Plt119	100.00%	99.95%	1.93%	76.88%	3.59%	42.07	2	0	50	21	67	0	See more
ProjXt3_Plt486	100.00%	99.31%	2.13%	81.75%	4.05%	47.445	1	0	43	15	74	0	See more
ProjXt3_Plt425	100.00%	99.35%	2.17%	81.10%	4.05%	47.445	1	0	36	14	81	0	See more
ProjXt3_Plt367	100.00%	99.87%	2.17%	77.37%	3.30%	38.64	2	0	55	21	62	0	See more
ProjXt3_Plt192	100.00%	99.81%	2.94%	82.16%	7.72%	90.47	1	0	43	13	74	0	See more
ProjXt3_Plt227	100.00%	99.64%	3.15%	80.34%	6.89%	80.795	1	0	38	16	79	0	See more
ProjXt3_Plt476	100.00%	99.80%	3.36%	81.19%	10.21%	119.675	1	0	46	15	71	0	See more
ProjXt3_Plt900	100.00%	99.79%	3.39%	80.14%	4.05%	47.445	1	0	40	14	77	0	See more
ProjXt3_Plt97	100.00%	99.97%	5.39%	78.74%	6.89%	80.795	1	0	47	15	70	0	See more
ProjXt3_Plt379	100.00%	99.98%	5.87%	75.22%	1.98%	23.205	2	0	55	22	62	0	See more



# **Optimized Trait Introgression - On-Demand Services**

#### Pre-selected scenarios

User defined pr	otocol	Alternative protocol						
Population sizes: 1	125 in BC2, 800 in BC3, 180 in BC3S1	Population sizes: 600 in BC2, 460 in BC3, 180 in BC3S1						
<b>Risk at BC3S1:</b> 0.8	0%	Risk at BC3S1: 4.91%						
Plants to select ProjXt3_Plt856 ProjXt3_Plt55 ProjXt3_Plt222	BC2 progeny size to develop 300 300 300	Plants to select ProjXt3_Plt856 ProjXt3_Plt55	BC2 progeny size to develop 300 300					
ProjXt3_Plt119	225							

## **Revenue Creation through Operational Savings**



## Decision-Making is Key in Trait/Product Launch

Revenue Creation through Product Launch and Market Capture



- (1) Success rate is defined as the percentage of trait introgression projects that met both quality and time requirements
- (2) Side-by-side comparisons with identical protocols within crop



DATA AND PROCESS-BASED DECISION-MAKING IN PLANT BREEDING

## "It's like having a Breeding Navigator"



From where we are... with high accuracy...

to how to get where we want to go

# Non-Mathematical/Computing Challenges to Forward-Looking/Data and Process-Driven Decision-Making

- Clear description of product objective
   o Product profile and breeding objectives
- Relevant marker-trait models
  - Diagnostic markers for simple traits (Trait Introgression)
  - Predictive models for complex traits (Genomic Selection)
- Access to genome-wide genotyping
  - o Cost of useful data points
  - Data generation turn-around time







## TAKE-HOME POINTS

## Get the Most out of Your Data: Better Decisions

- In order to deliver what our societies need, breeding has to be product/objective-driven – Let's really make it that way; hoping is not enough
- There is more information in your data than you think extract it all
- Making better decisions out of the same data is a very cheap way to improve breeding efficiency – the cost is in generating the data
- Who would want to get on a road trip without a navigation system?





