

## Opportunities and challenges on the use of genomic information in plant breeding

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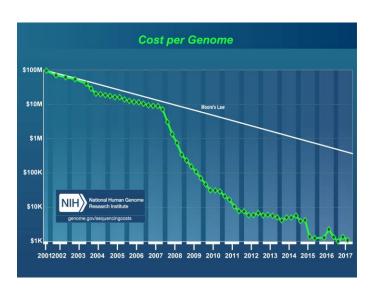
#### **Growth of DNA Sequencing** Recorded growth Double every 7 months (Historical growth rate) □ Double every 12 months (Illumina Estimate) ■ Double every 18 months (Moore's Law) ExAC 1st PacBio TCGA Chaisson et al 1000 Genomes 1st 454 Wheeler et al. 1st Sanger 1st Personal Genome IHGSC et al Bentley et al. Levy et al. Venter et al.

Stephens, Z. D.et al. (2015). Big data: astronomical or genomical? *PLoS biology*, *13*(7), e1002195.

2015

2020

2010



The Cost of Sequencing a Human Genome. NIH. https://www.genome.gov/27565109/the-cost-of-sequencing-a-human-genome/

2000

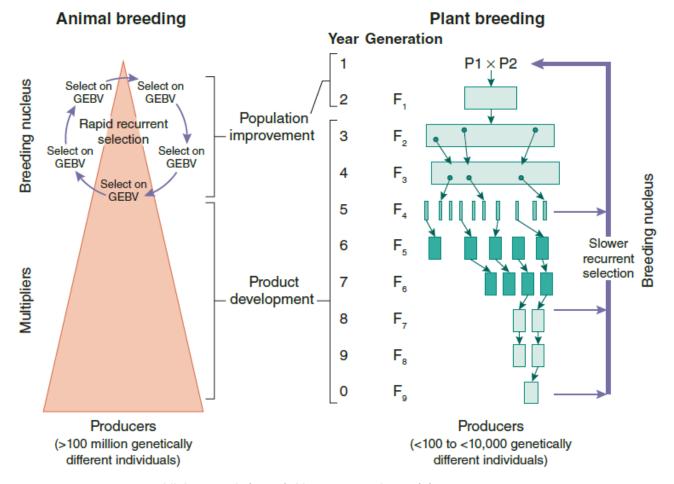
2025

2005



# BREEDING PIPELINE





Hickey et al. (2017) Nature genetics 49(9):1297



#### Varietal Wheat

Example from one program in one geography

~120 crosses



Product development				
Year	Generation		Number of plants	Action
1	F <sub>1</sub>		124 half-sib families	Increase in greenhouse
2	F <sub>2</sub>		1,000 plants per family	Bulk 50 plants per family
3	F <sub>3</sub> ×124 —		1,000 plants per family	Bulk 50 plants per family
4	F <sub>4</sub>		1,000 plants per family	Derive new lines from 50 plants per family
5	F <sub>4:5</sub>		6,200 headrows	Advance 1,000 lines
6	PYT, F <sub>4:6</sub>		1,000 lines	Yield trial, genotype
7	AYT, F <sub>4:7</sub>		100 lines	Yield trial
8	EYT, F <sub>4:8</sub>	ı İ	10 lines	Yield trial
9	EYT, F <sub>4:9</sub>	ĎĎ	10 lines	Yield trial
10	F <sub>4:10</sub>		1 line	Release variety

>120.000 F2s (100% genotyped)

~10 parents 1-2 products

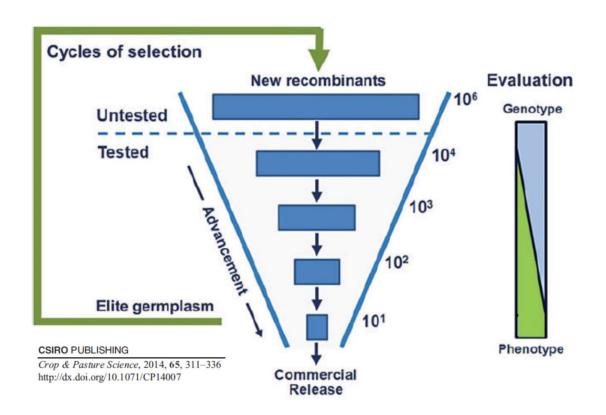


Hickey et al. (2017) Nature genetics 49(9):1297



#### Types of plant breeding

- Varietal
- 2. Hybrid
- 3. Population
- 4. Clonal



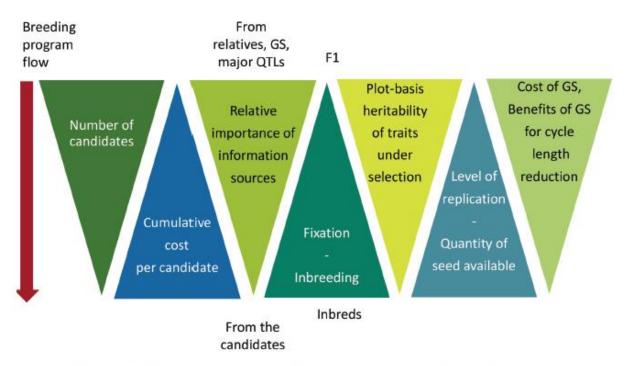
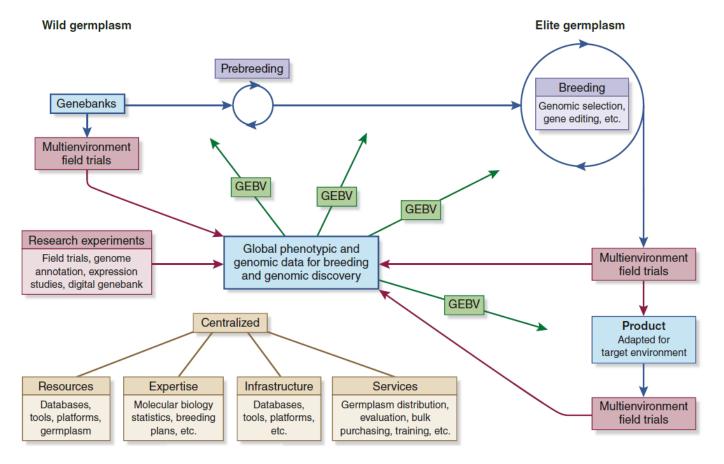


Figure 1. Key parameters and changes during a breeding cycle, to consider in implementing genomic selection (GS). The triangles indicate increase or decrease of the quantity considered. QTL, quantitative trait loci.

Heslot, N., Jannink, J. L., & Sorrells, M. E. (2015). Perspectives for genomic selection applications and research in plants. Crop Science, 55(1), 1-12.



Hickey et al. (2017) Nature genetics 49(9):1297







## Modeling genetic merit Single-stage? Single-step?



#### Single-step (Animal Breeding)

Phe = Env + Gen  

$$y = Xb + Zu + e$$
  
 $u \sim N(0, H\sigma_a^2)$   
 $e \sim N(0, I\sigma_e^2)$ 

$$H = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & G \end{bmatrix}$$

Single-step is an alternative to two-step analysis where pedigree EBV are degressed then fed to the genomic model

### Single-stage (Plant Breeding)

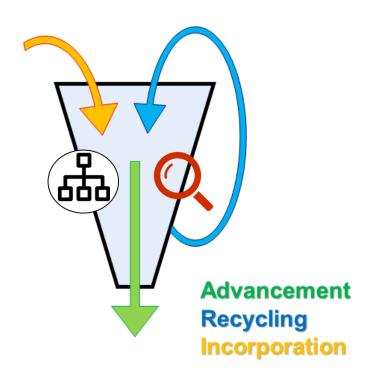
$$\begin{aligned}
 & \textit{Phe} = \textit{Env} + \textit{Gen} + \textit{G} \times \textit{E} \\
 & \textit{y} = \mu + Xb + Zu + Wa + e \\
 & \textit{b} \sim N(0, I\sigma_{b}^{2}) \\
 & \textit{u} \sim N(0, G\sigma_{a}^{2}) \\
 & \textit{a} \sim N \begin{pmatrix} G\sigma_{a1}^{2} & 0 & 0 \\ 0, & 0 & G\sigma_{a2}^{2} & 0 \\ 0 & 0 & G\sigma_{a(...)}^{2} \end{pmatrix} \\
 & e \sim N \begin{pmatrix} R_{1}\sigma_{e1}^{2} & 0 & 0 \\ 0, & 0 & R_{2}\sigma_{e2}^{2} & 0 \\ 0 & 0 & R_{3}\sigma_{e(...)}^{2} \end{pmatrix} \\
 & R_{i} = Z_{e_{i}}(\rho_{c_{i}} \otimes \rho_{r_{i}}) Z'_{e_{i}}
\end{aligned}$$

Single-stage is an alternative to two-stage analysis where spatially adjusted BLUEs are computed locally then fed to the (G)BLUP model



## **APPLICATIONS**





**Assessment** Classification

- Germplasm classification (PCA, Clustering, Unsupervised ML, F<sub>ST</sub>)
- Incorporation (GWAS, haplotype analysis)
- Genomic selection (BayesABC, Supervised ML, etc.)
- Recycling (Simulation and optimization)
- Quantitative assessment (Variance component analysis)



- Germplasm classification (*PCA, Clustering, Unsupervised ML, F<sub>ST</sub>*)
  - <u>Characterization</u> Characterize diversity using unsupervised learning methods.
  - Heterotic group Classify (if known) or infer (if unknown) heterotic groups on individuals and populations.
  - <u>Signatures of selection</u> Use F<sub>ST</sub> (or related methods) to identify signatures of selection, adaptation and domestication.
- Incorporation (GWAS, haplotype analysis)
- Genomic selection (BayesABC, Supervised ML, etc.)
- Recycling (Simulation and optimization)
- Quantitative assessment (Variance component analysis)



- Germplasm classification (PCA, Clustering, Unsupervised ML, F<sub>ST</sub>)
- Incorporation (GWAS, haplotype analysis)
  - <u>Trait discovery</u> Finding new QTLs via association analysis on breeding data and designed populations.
  - <u>Introduction of diversity</u> Screening non-elite (or elite from elsewhere) germplasm for pre-breeding.
  - Haplotype enrichment Assess genome of non-elite material to add diversity to regions where elite germplasm is fixed.
- Genomic selection (BayesABC, Supervised ML, etc.)
- Recycling (Simulation and optimization)
- Quantitative assessment (Variance component analysis)



- Germplasm classification (PCA, Clustering, Unsupervised ML, F<sub>ST</sub>)
- Incorporation (GWAS, haplotype analysis)
- Genomic selection (BayesABC, Supervised ML, etc.)
  - <u>F2 enrichment (WF)</u> Entire population is genotyped with few markers and selected for specific QTL (e.g. disease resistance)
  - <u>Pre-selection (WF/AF)</u> Entire population is genotyped and 0% is phenotyped. Selection is based on the genomic merit estimated a predefined estimation set that is either made by design or using breeding data.
  - <u>Test-and-shelf (WF/AF)</u> Entire population is genotyped and X% is phenotyped. Within-season selection is based on the genomic merit estimated with a genomic model from phenotyped individuals.
  - <u>Advancement (WF/AF)</u> Entire population is genotyped and phenotyped. Selection is based on the genetic merit of the individuals using one or more seasons of data from those individuals.
  - Product placement (AF) Similar to advancement but GxE takes the spotlight from G.
- Recycling (Simulation and optimization)
- Quantitative assessment (Variance component analysis)



- Germplasm classification (PCA, Clustering, Unsupervised ML, F<sub>ST</sub>)
- Incorporation (GWAS, haplotype analysis)
- Genomic selection (BayesABC, Supervised ML, etc.)
- Recycling (Simulation and optimization)
  - <u>Selection of parents</u> Selection of high BV individuals with complementary polygene or traits.
  - <u>Select combinations</u> Providing a set of candidate parents (100% genotyped), combinations are based on clustering, simulate crosses or predefined criterium (OHV or OPV).
- Quantitative assessment (Variance component analysis)



- Germplasm classification (PCA, Clustering, Unsupervised ML, F<sub>ST</sub>)
- Incorporation (GWAS, haplotype analysis)
- Genomic selection (BayesABC, Supervised ML, etc.)
- Recycling (Simulation and optimization)
- Quantitative assessment (Variance component analysis)
  - Heritability Narrow-sense and GxE (e.g. compound symmetry)
  - Genetic variance decomposition Classic (Vg = Va + Vd + Vi) and hybrid (Vg = V<sub>GCA1</sub> + V<sub>GCA2</sub> + V<sub>SCA</sub>)
  - **Genetic correlations** Across traits or within-trait across environments
  - Effective population size Eigen analysis of the G matrix
  - Genetic progress and rate of genetic gains Assess multiple years
  - Evaluate breeding strategies Simulations and retrospective studies to ask what if questions





## **CHALLENGES**



#### **KEY CHALLENGES**

- Improve accuracy with modeling + pop design + experimental design
- Better use of GxE and better understanding TPEs
- Use environment data (soil, weather, management) in genomic models
- Handle multi-parental crosses
- Collaborate effectively and breed consistently across programs
- Educate breeders on how to use genomic data
- Data management easy access to any type of data & visualization tools



#### ITERATIVELY TUNING BREEDING DESIGN

- Define the number of reps and locations for each breeding stage
- From which breeding stage to select parents to recycle
- At which stage to GxE outweighs G
- Strategies to increase heritability and optimize GS models



#### References in optimization procedures

- Rincent et al. (2012) Maximizing the reliability of genomic selection by optimizing the calibration set of reference individuals. Genetics, 192(2), 715-728.
- Isidro et al. (2015). Training set optimization under population structure in genomic selection. TAG 128(1), 145-158.
- Habier (2016). Improved molecular breeding methods. US20160321396A1.
- Ou and Liao (2019). Training set determination for genomic selection. TAG 132(10), 2781-2792.
- Brauner et al. (2019). Genomic prediction with multiple biparental families. TAG



Lecture

#### FOR THE BREEDERS

- Understand your germplasm
- Know your target environments
- Have clear breeding objectives



#### **Concluding Remarks**

- 1. GS is utilized differently for advancement, recycling and incorporations
- 2. Experimental settings and breeding design play key role in GS
- 3. Breeding pipeline is dynamic and constantly improved

#### Thank you for your attention!

Questions??

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