Alfalfa to get back into planetary boundaries

2025 world alfalfa congress
FRANCE REIMS-CHÂLONS

Technologies for alfalfa breeding and production

Session chair(s): Julier B. & Noushahi H.

Parallel session 5

FROM 03 › TO 06 nov. 2025

Alfalfa to get back into planetary boundaries

2025 world alfalfa congress
FRANCE REIMS-CHÂLONS

Multi-Omics Data Integration Improve the Accuracy of Prediction Models for Complex Traits in Non-dormant Alfalfa

Esteban Rios, PhD, and Pablo Sipowicz, PhD candidate

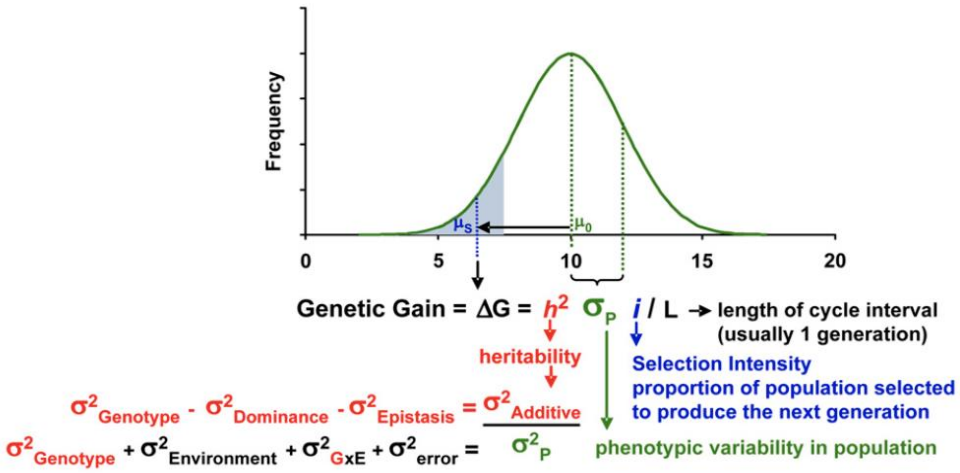
UF IFAS UNIVERSITY of FLORIDA

PLANT BREEDING

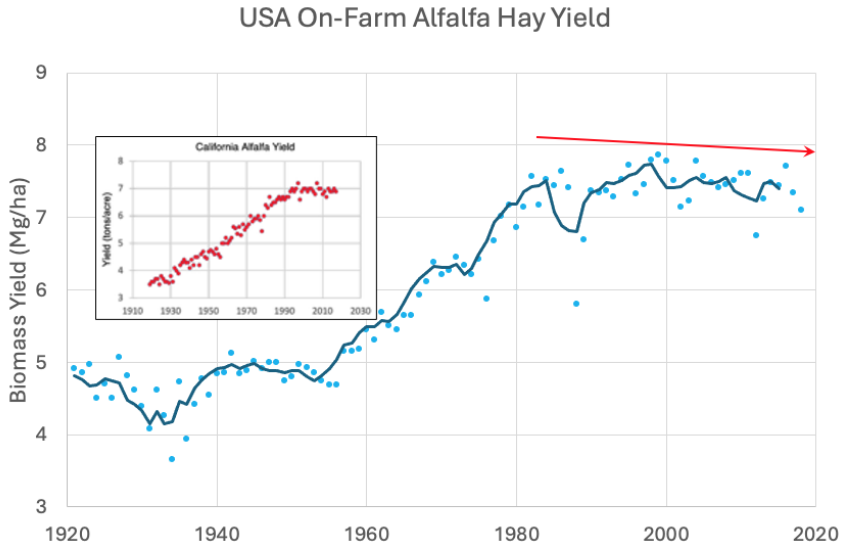
FORAGE BREEDING AND GENETICS

FROM 03 TO 06 nov. 2025

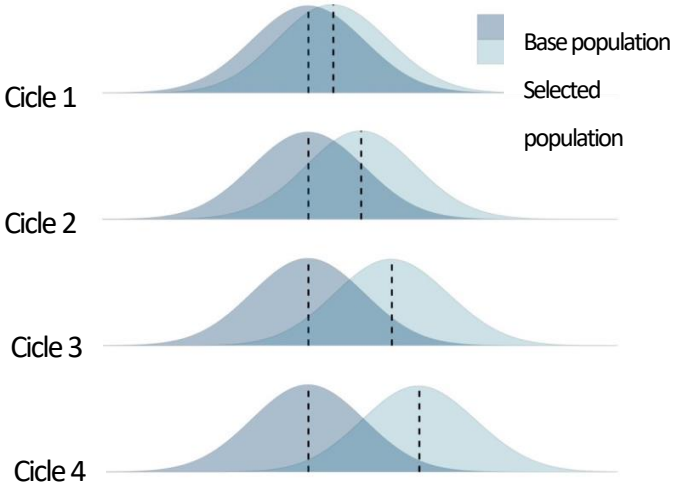
The goal in plant breeding / The reality in alfalfa breeding



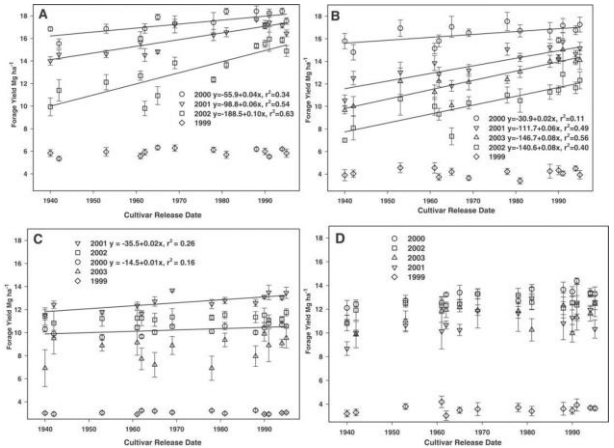
Moose and Mumm, 2008.



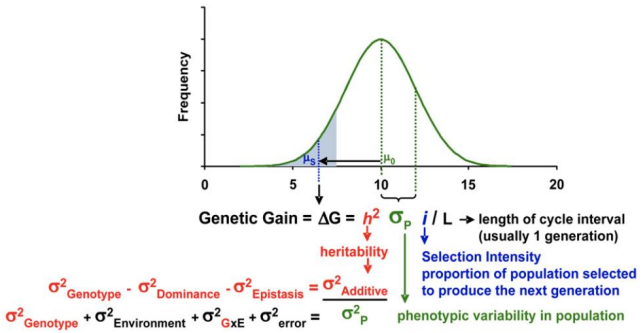
Source: Dr. Charles E. Brummer



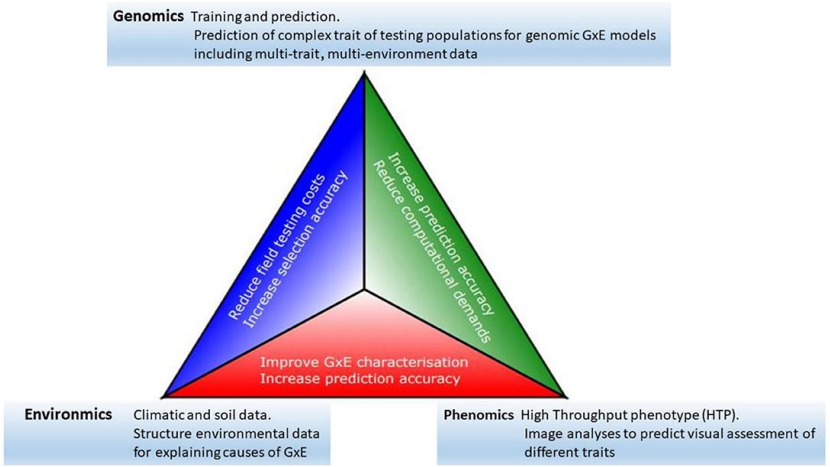

Crop Science
CSSA
Crop Breeding, Genetics & Cytology | Full Access
Five Decades of Alfalfa Cultivar Improvement: Impact on Forage Yield, Persistence, and Nutritive Value
JoAnn F. S. Lamb, Craig C. Sheaffer, Landon H. Rhodes, R. Mark Sulc, Daniel J. Undersander, E. Charles Brummer
First published: 01 March 2006 | https://doi.org/10.2135/cropsci2005.08-0236 | Citations: 106



The goal in plant breeding



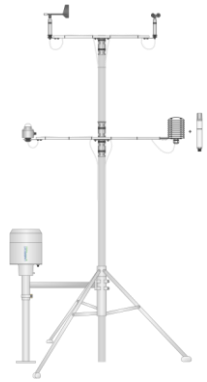
Moose and Mumm, 2008.



The modern plant-breeding triangle

Crossa et al., 2021

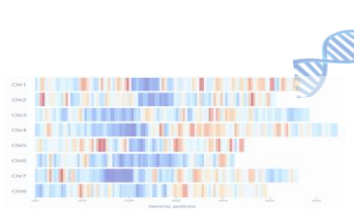
Enviromics



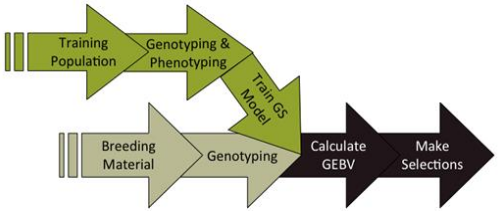
Costa-Neto et al., 2021

Phenomics

Rincent et al., 2018



Genomics



Meuwissen et al., 2001

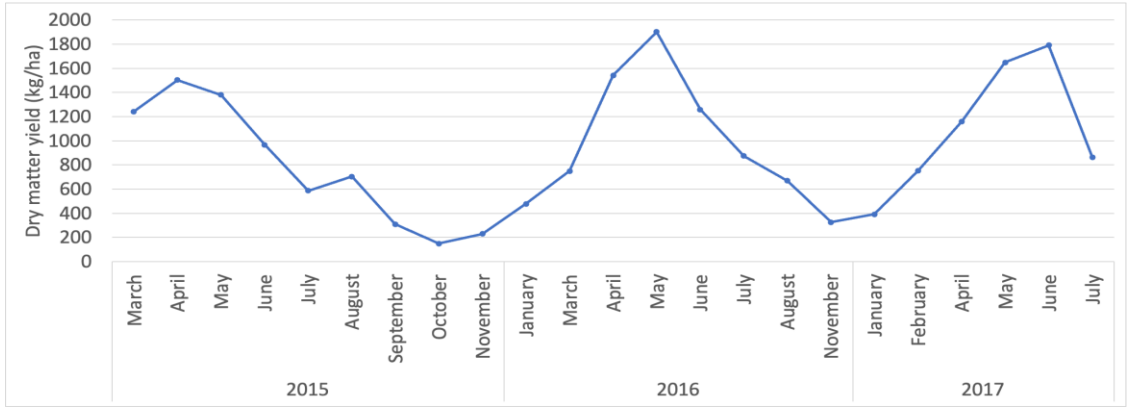
Alfalfa breeding in Florida

- Non-dormant cultivars developed in Florida:

  Florida 66 – adaptation to subtropical conditions

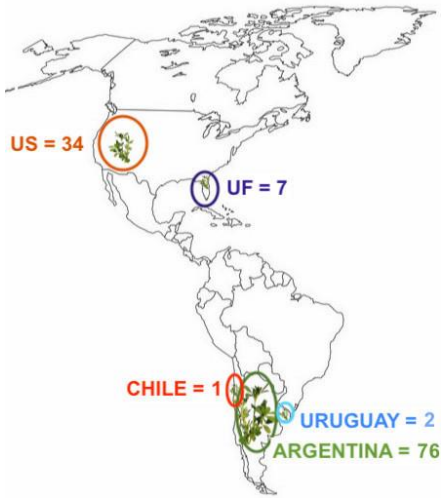
  Florida 77 – alfalfa aphid and yield

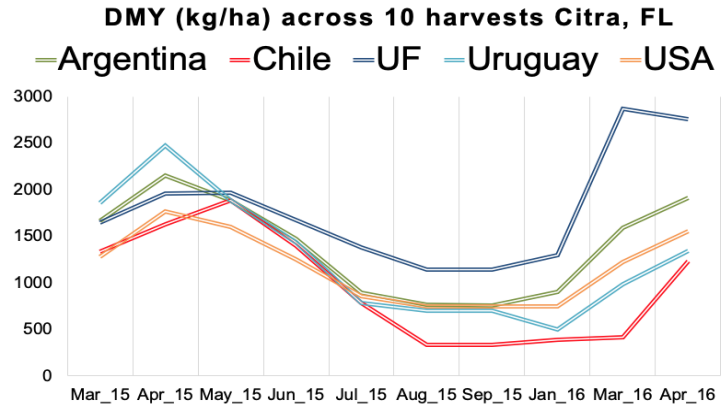
  Florida 99 – phytophthora, anthracnose, alfalfa aphid



- Program dropped in the 90's – Resumed in 2014

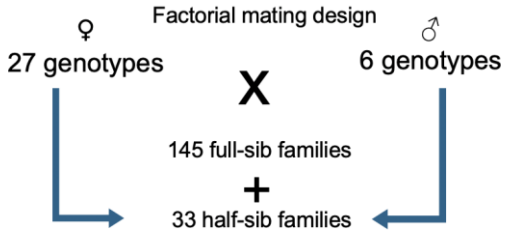
Alfalfa growing in Hillsborough County, Florida

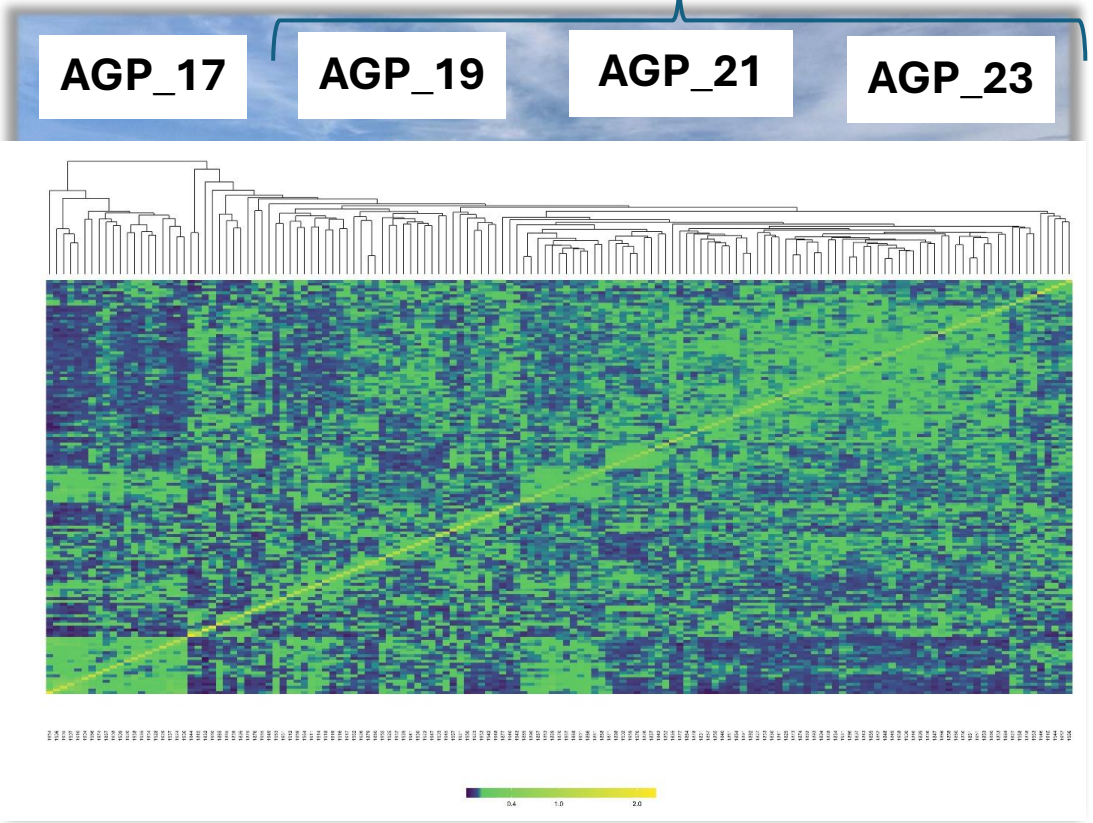




Acharya et al., 2020. https://doi.org/10.3390/agronomy10050742

Breeding populations and trials



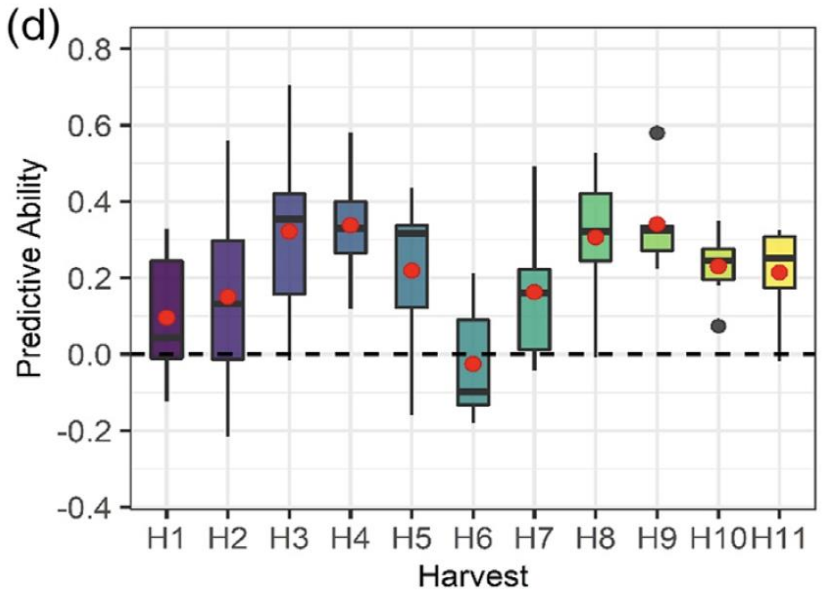


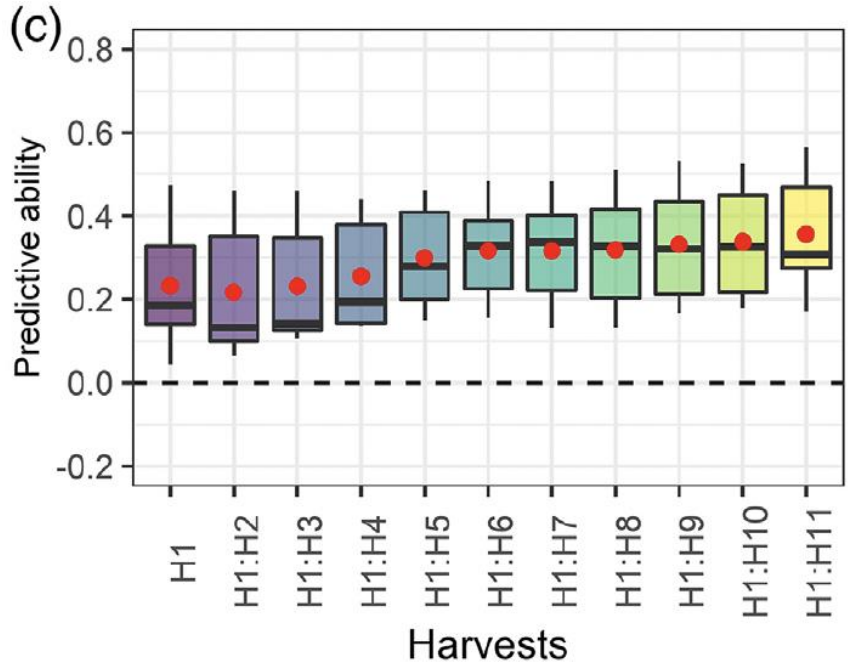
- Dry matter yield
- Persistence

Genomic prediction optimization

Dr. Mario Andrade
Postdoc

- Dry matter yield
- 114,000 SNPs – Capture-Seq
- G-BLUP in ASReml-R
- 10-fold cross-validation



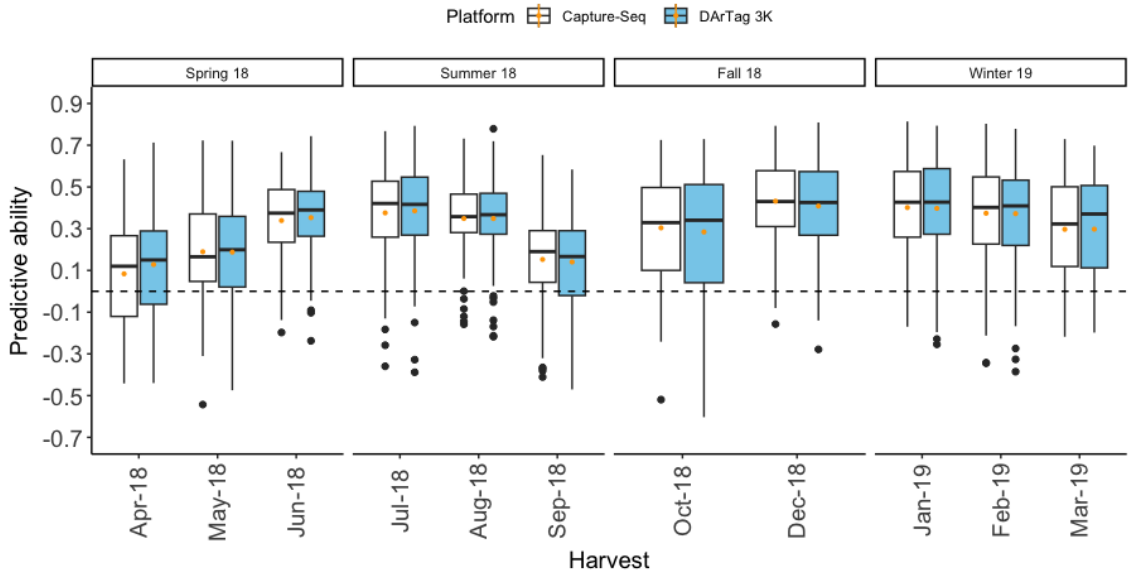


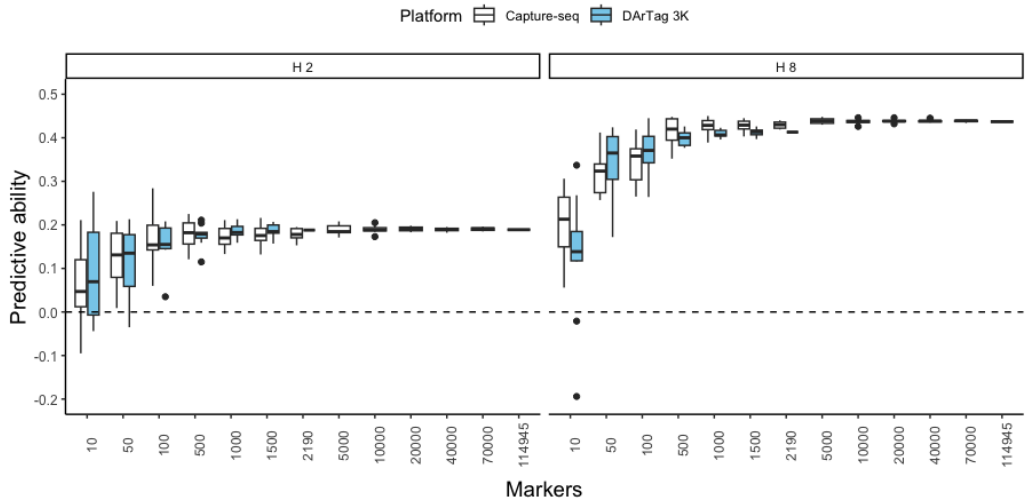
Andrade et al., 2022. The Plant Genome DOI: 10.1002/tpg2.20235

Genomic prediction optimization

Pablo Sipowicz
PhD candidate

- Dry matter yield
- 114,000 SNPs – Capture-Seq
- 2,200 SNPs - DArTag
- G-BLUP in ASReml-R
- 10-fold cross-validation





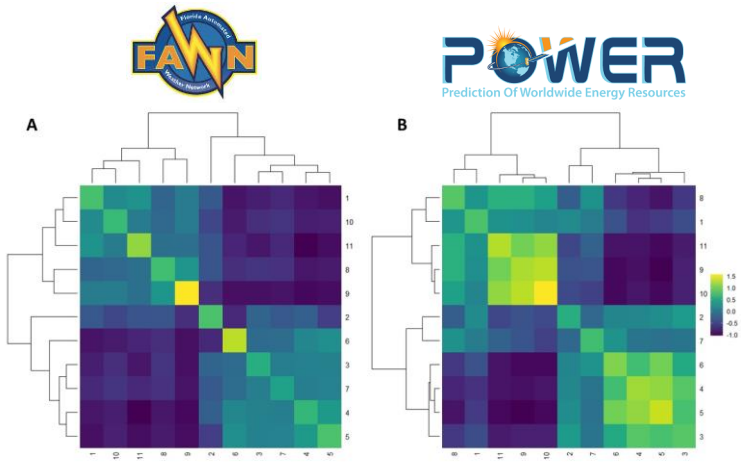
		Female			...	
	Male	1	2	3	...	27
		CW660	ExpLine1387	CW060097	...	WL1058
1	Alfalfa_NSY	x	x	x	...	x
2	Exp96	x	x	x	...	x
3	UF_Pers_2015	x	x	x	...	x
4	FL99_2006	x	x	x	...	x
5	Bulldog805	x	x	x	...	x
6	AmeriStand915	x	x	x	...	x

Sipowicz et al. 2025. The Plant Genome. DOI: https://doi.org/10.1002/tpg2.20526

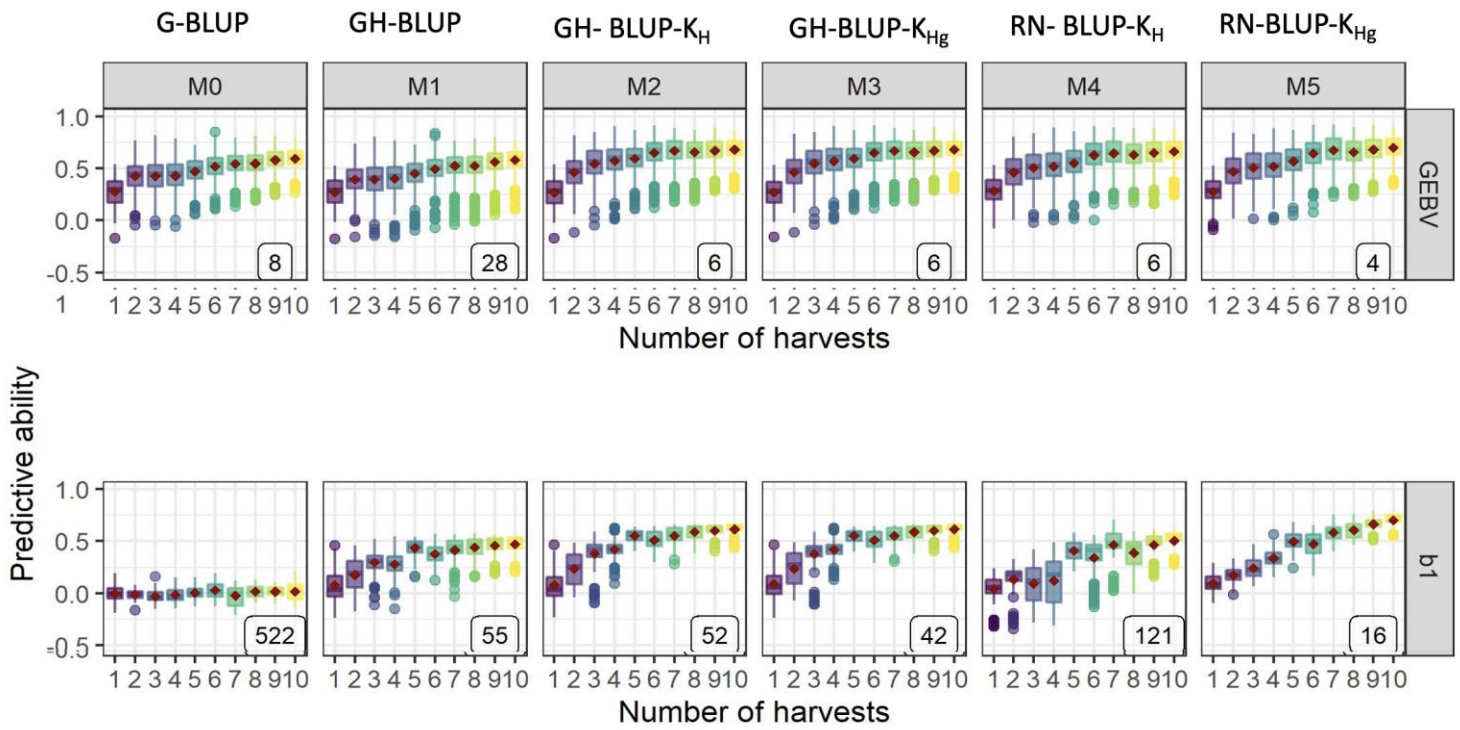
Genomic + Enviromic prediction optimization

- Dry matter yield and persistence
- 114,000 SNPs

Dr. Claudio Fernandes
Postdoc



Covariate	Stress by deficit	Lower sub-optimum	Optimum	Higher sub-optimum	Stress by excess	Reference
Daylight temperature	< 10°C	10°C to 24°C	25°C to 30°C	31°C to 34°C	> 34°C	Patterson (1993) Collino et al. (2005) Malik et al. (2018)
Night temperature	≤ 5°C	5°C to 14°C	15°C to 20°C	21°C to 25°C	>25°C	Robison et al. (1969) Patteson (1993)
Photoperiod	No leaf expansion < 10h	Linear leaf expansion 10h to 12.5h		Maximum leaf expansion >12.5h		Teixeira et al. (2007)
PAR	Linear interception <0.81			Maximum interception > 0.81		Teixeira et al. (2007)
LAI	< 3			> 3		
air-soil ratio temperature	No partitioning to the roots <0.8	Linear partitioning to the roots 0.8 to 1.3		Maximum partitioning to the roots >1.3		Teixeira et al. (2008)



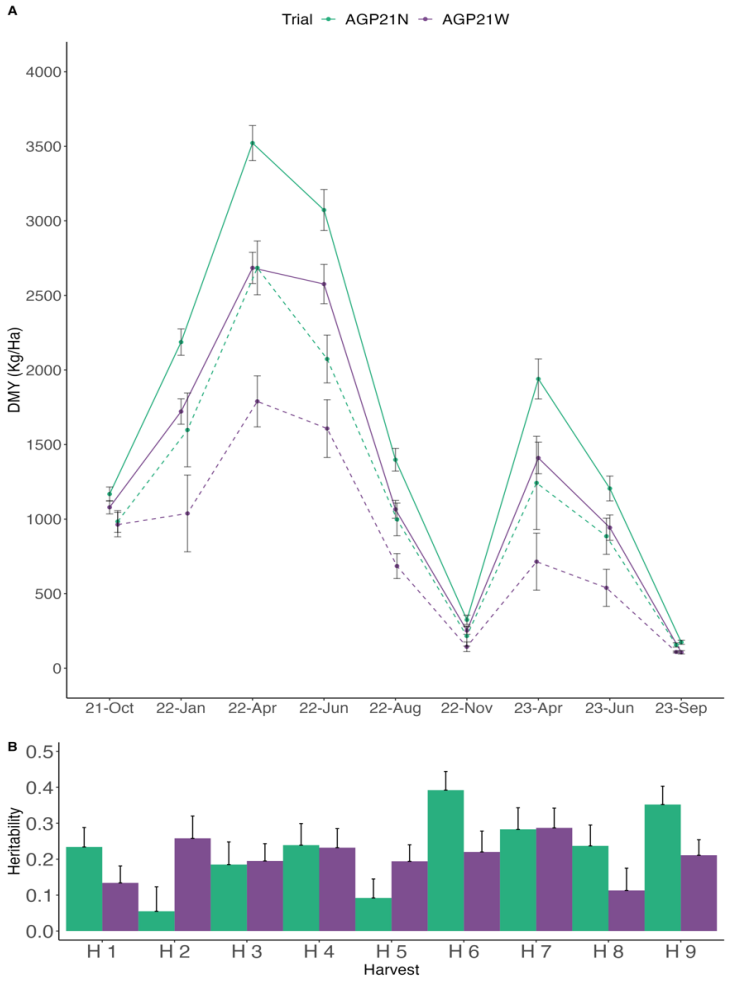
Dry matter yield

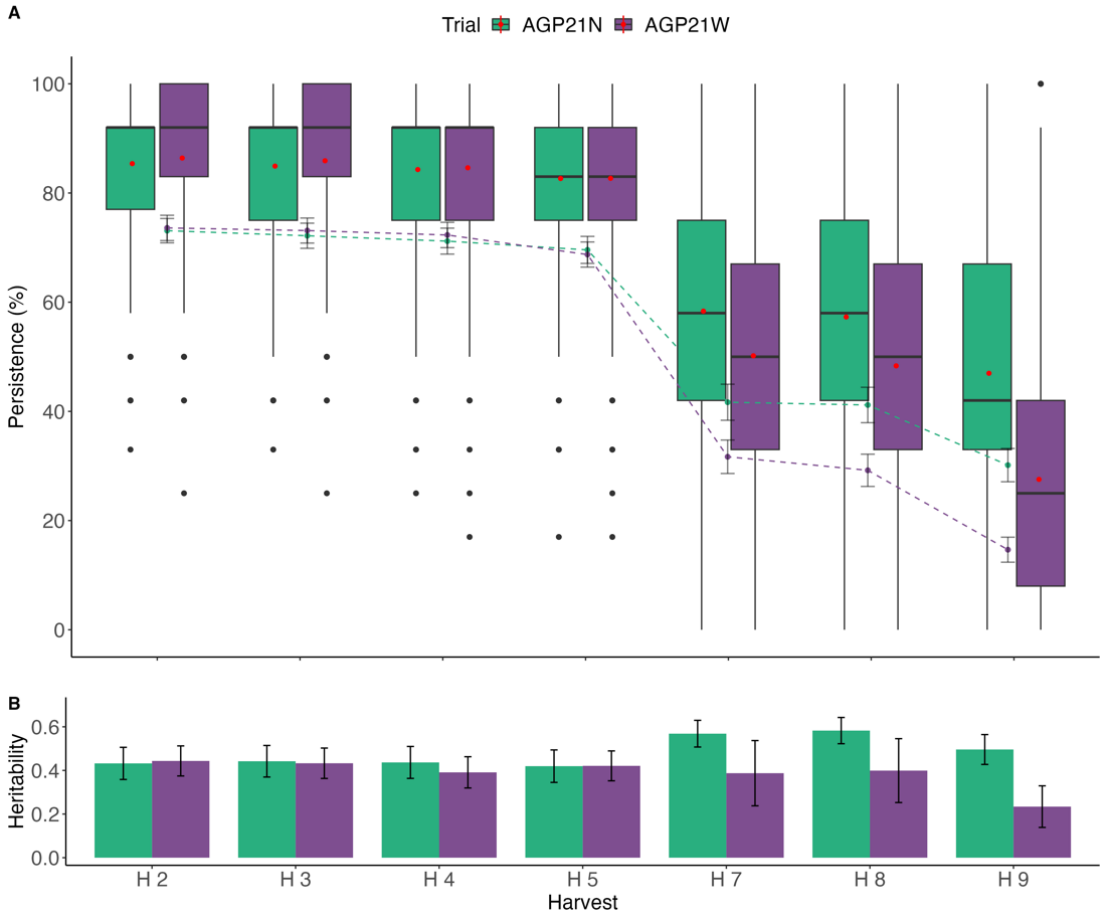
Persistence

Fernandes et al. 2023. The Plant Genome. http://dx.doi.org/10.1002/tpg2.20306

Genomic + Phenomic prediction optimization

Pablo Sipowicz
PhD candidate





Sipowicz et al. 2025. Under review

Genomic + Phenomic prediction optimization

Pablo Sipowicz
PhD candidate

Predictive ability for dry matter yield within each harvest and within fertility management using relationship matrix models based on:

- Genomic data (molecular markers) – red
- Phenomic data (hyperspectral sensor) – yellow
- Genomic + Phenomic data – orange

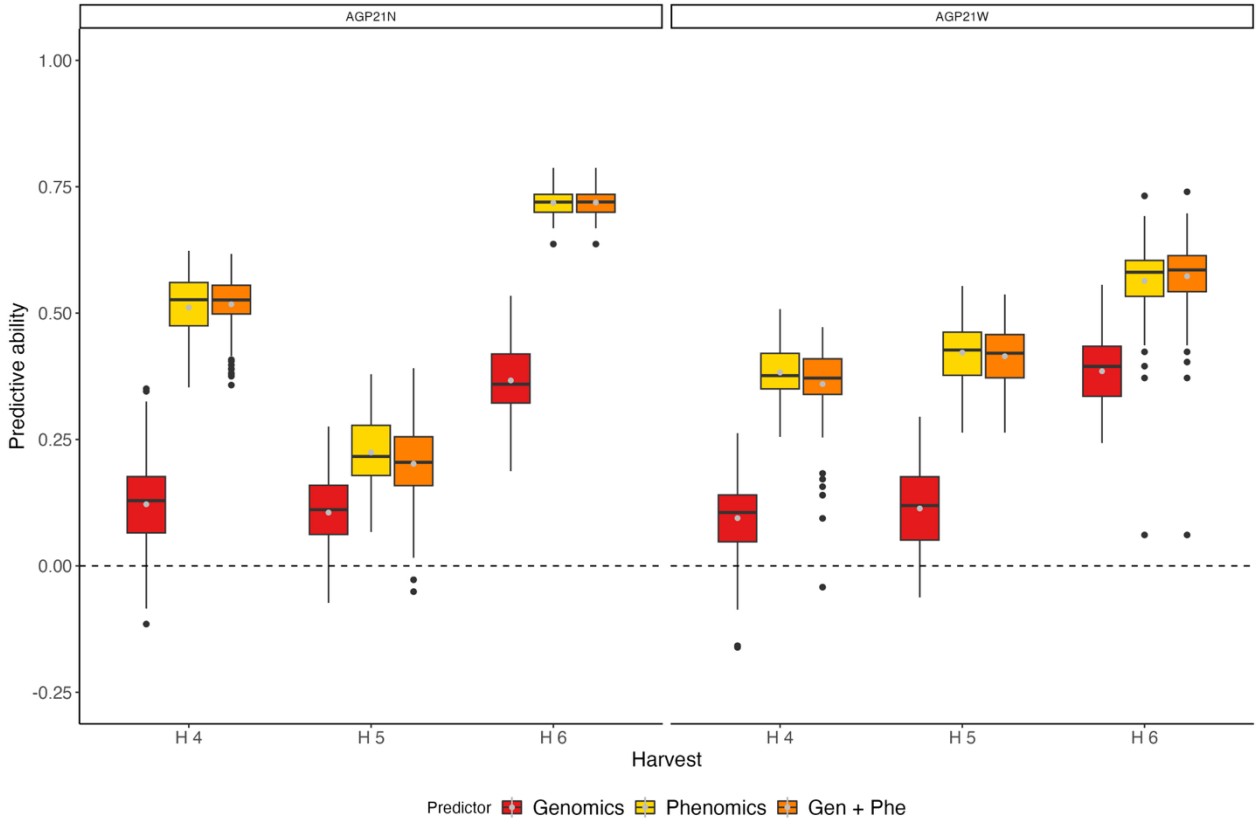
$$y = X\beta + Z_1 g + e \qquad y = X\beta + Z_1 p + e$$

$$g \sim N(0, G^{-1}\sigma_g^2) \qquad p \sim N(0, P^{-1}\sigma_p^2)$$

$$y = X\beta + Z_1 g + Z_2 p + e$$

$$p \sim N(0, P^{-1}\sigma_p^2)$$

$$g \sim N(0, G^{-1}\sigma_g^2)$$



Sipowicz et al. 2025. Under review

Genomic + Phenomic prediction optimization

Pablo Sipowicz
PhD candidate

Predictive ability for dry matter yield within each harvest and across fertility management using relationship matrix models based on:

- Genomic data (molecular markers) – red
- Phenomic data (hyperspectral sensor) – yellow
- Genomic + Phenomic data – orange

$$y = X\beta + Z_1 g + e \qquad y = X\beta + Z_1 p + e$$

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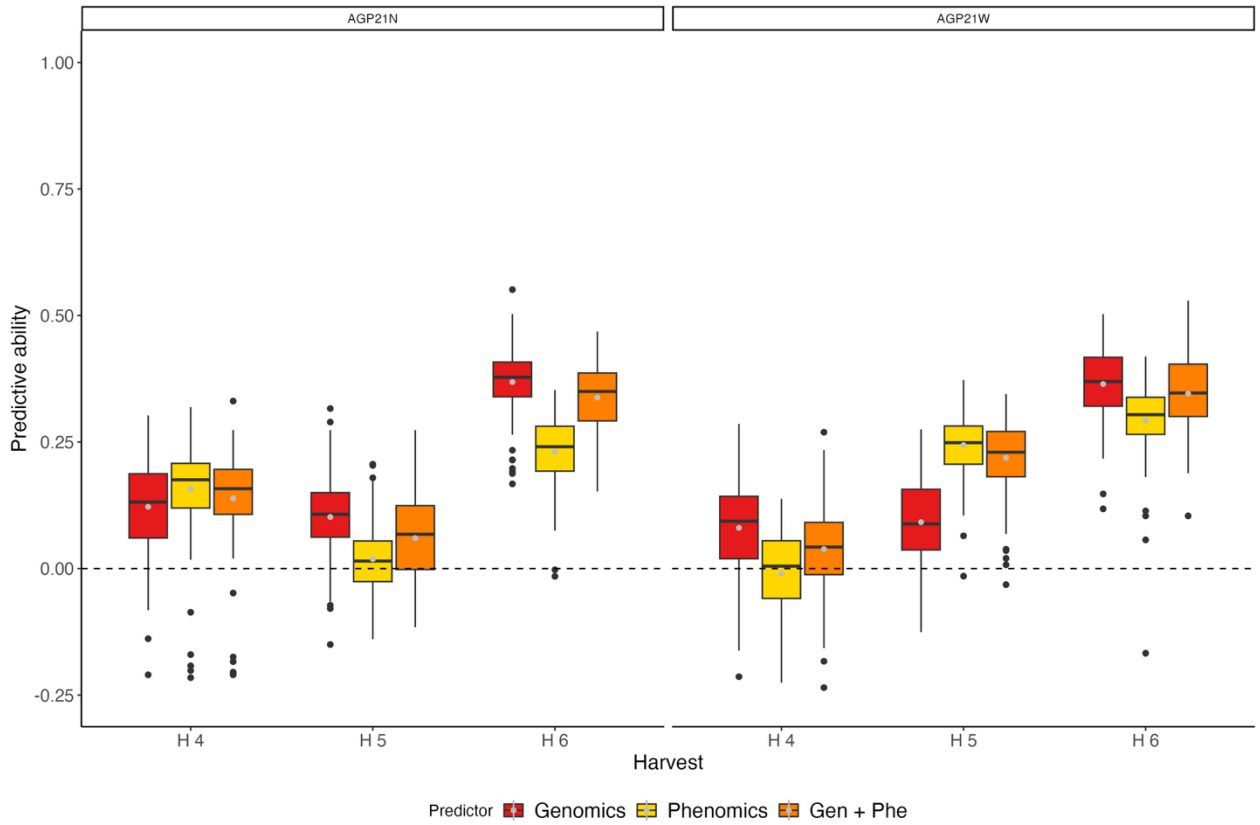

Sipowicz et al. 2025. Under review

Genomic + Phenomic prediction optimization

Pablo Sipowicz
PhD candidate

Predictive ability for persistence within each harvest and fertility management using relationship matrix models based on:

- Genomic data (molecular markers) – red
- Phenomic data (hyperspectral sensor) – yellow
- Genomic + Phenomic data – orange

$$y = X\beta + Z_1 g + e \qquad g \sim N(0, G^{-1}\sigma_g^2)$$

$$y = X\beta + Z_1 p + e \qquad p \sim N(0, P^{-1}\sigma_p^2)$$

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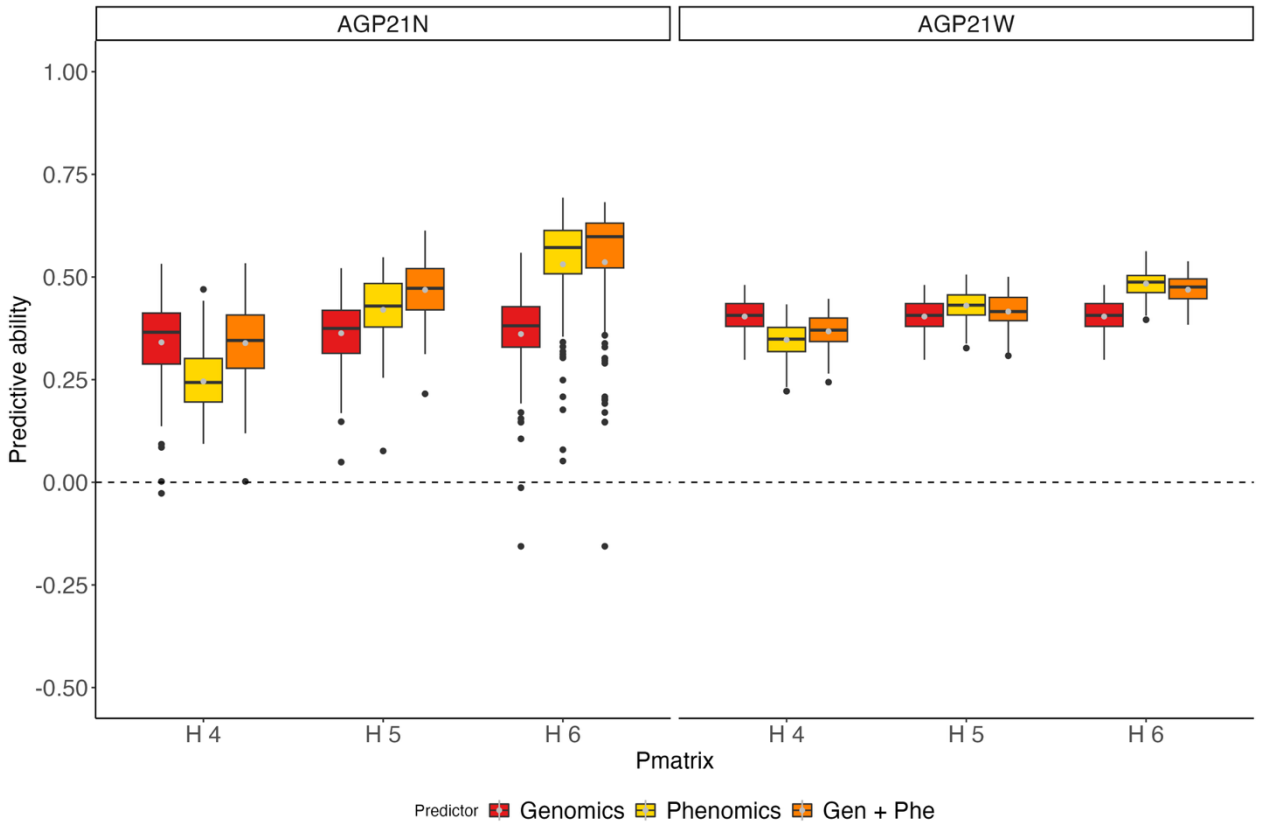
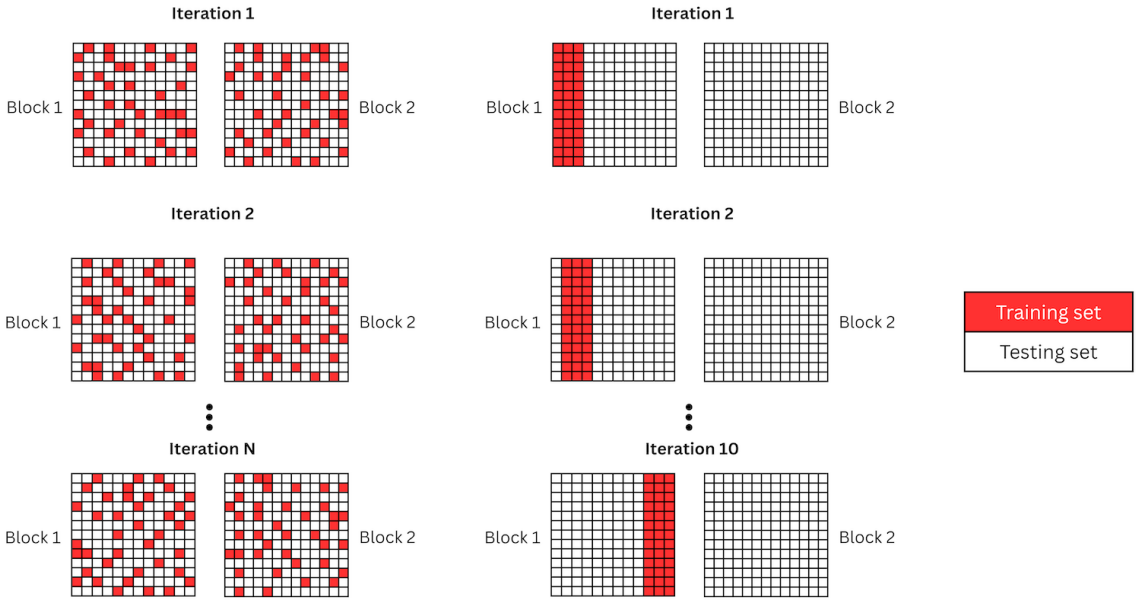
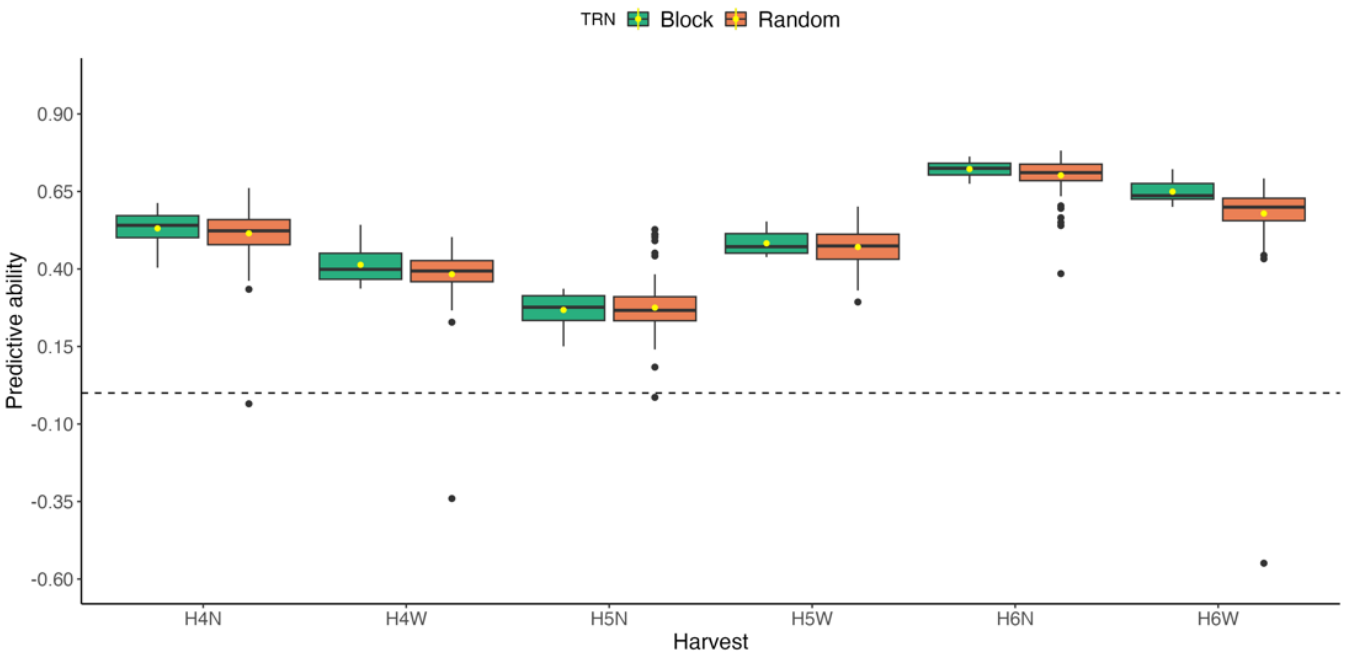


Sipowicz et al. 2025. Under review

Genomic + Phenomic prediction optimization





Sipowicz et al. 2025. Under review

Pablo Sipowicz
PhD candidate

Summary and concluding remarks

- Multi-omics data integration can lead to reductions in the number of harvests.
- Predict total annual yield and persistence six months before the end of the year.
- DArT Tag array presented similar results to Sequence Capture, reducing the cost of genotyping.
    - 1,000 markers achieved acceptable predictive ability.
- Phenomic selection had greater predictive ability than genomic selection when the models were trained within harvests and management.
- Phenomic selection is highly influenced by management and environment.
- Phenomic selection can be used to predict the phenotype of unharvested plots without randomly sampling fields.

Summary and concluding remarks

- Phenotypic selection resulted in improvements for dry matter yield and persistence in non-dormant alfalfa breeding for subtropical environments, but not for nutritive value (Lee et al., 2025).
- Can predictive breeding approaches lead to increases in genetic gain compared to phenotypic selection?
- THANKS to Dr. Brian Irish, USDA-ARS Alfalfa Curator for seed increases for the new breeding populations developed using predictive breeding!