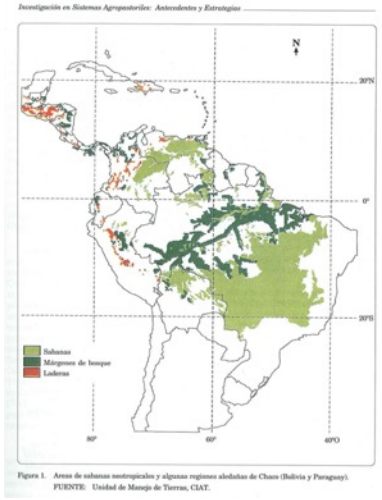


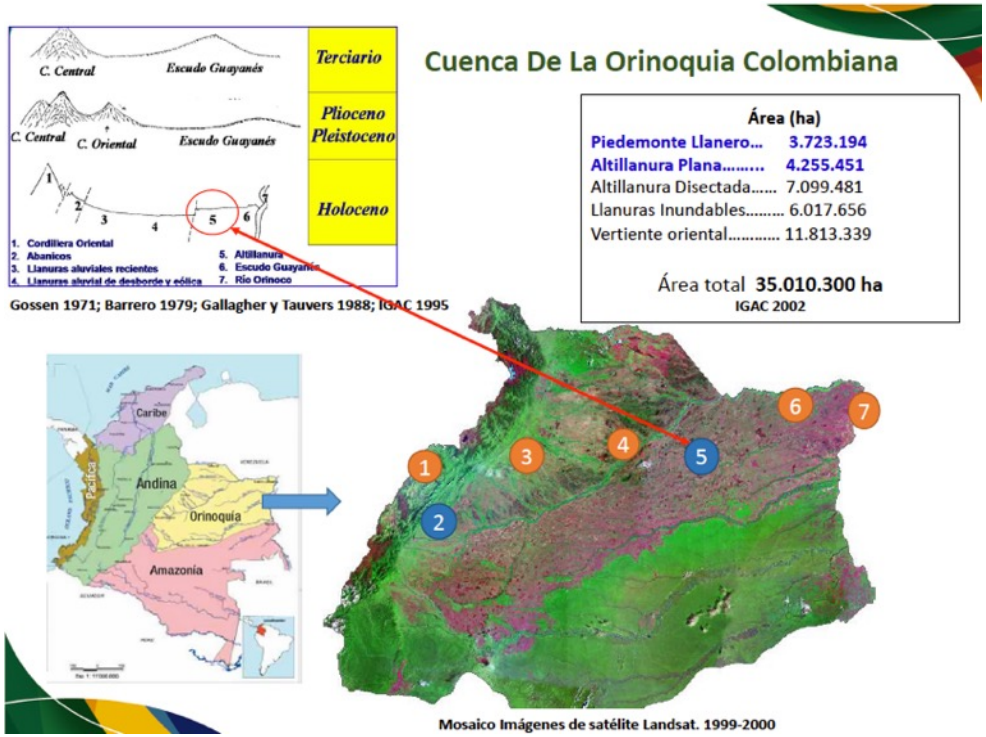
Genomic prediction for tolerance to Al in a synthetic population of upland rice

Cécile Grenier

Why Al tolerance?

In tropical South America, 85% of the soils are acidic and the production of most of staple crops is negatively impacted by acid soils





Aluminum (Al) is a metal naturally abundant in the soil, which, when pH values fall below 5.0, becomes highly phytotoxic by adopting a trivalent form (Al^{3+})

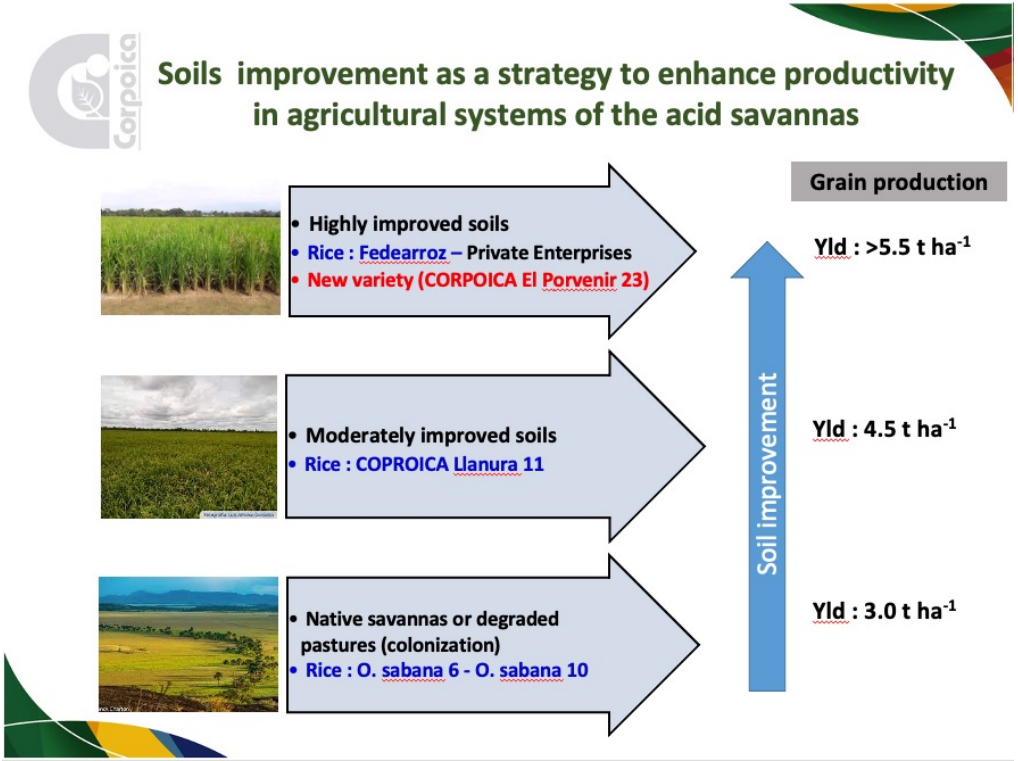


Why upland rice?

Upland rice (tropical japonica) is tolerant to acid soils an important component of rice-pasture cropping systems.

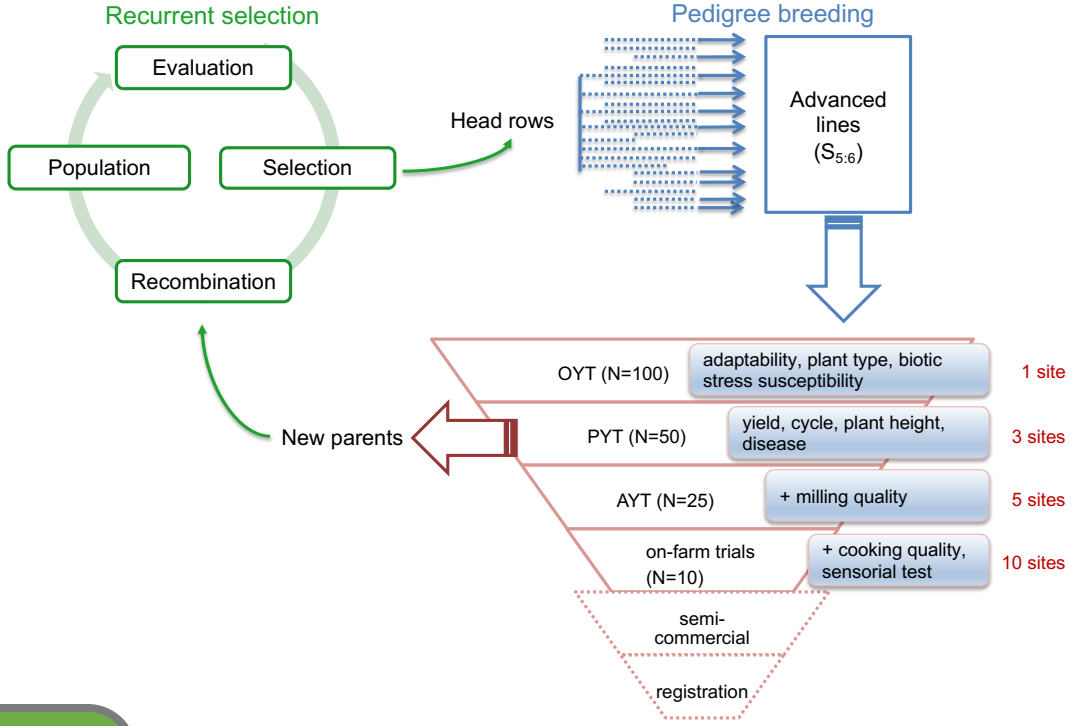
Rice-pasture cropping system, a productive option for the savannas

Since 1992 the Cirad-CIAT rice breeding program has worked on improving upland rice for the acid savannas of Colombia and LAC



The Cirad-CIAT rice breeding program





- Adaptation to upland conditions with acid soils (pH 4 - 5.2)
- Tolerance to water shortage
- Good yield
- Disease resistance (blast)

Variety benchmark

- Ozyzica sabana 6 (1991)
- Oryzica sabana 10 (1995)
- Corpoica llanura 11 (L-30) (2000-2011)



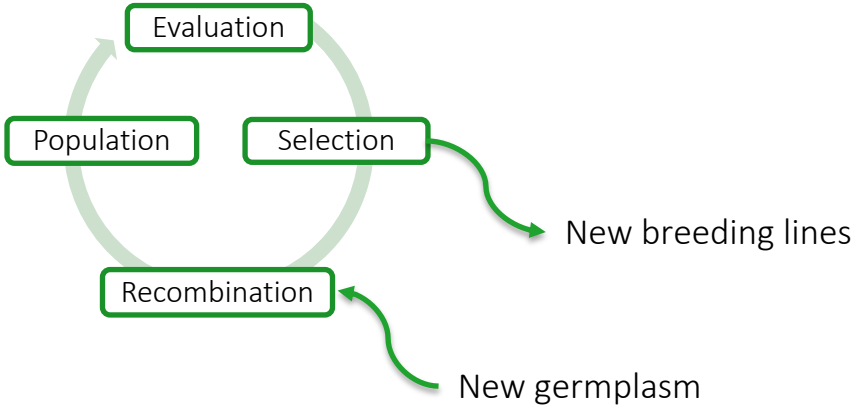
Why Recurrent Selection on synthetic populations?

To combine many required trait of interest.

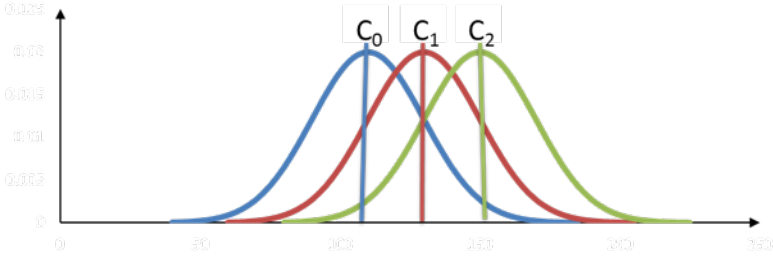
Synthetic populations can thus be improved with a particular focus for adaptation to the savanna soils.

The recurrent selection method of plant breeding carries the advantage to target the improvement of quantitative traits such as those usually controlling adaptative characters.

Recombination among best progenies to improve the population value



Mean value increased without compromising the genetic variability





Why Genomic Prediction aided RS?

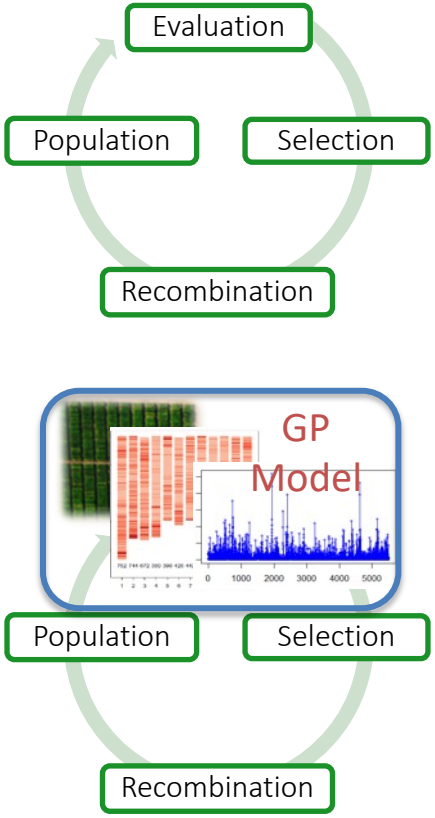
Accelerate the development of elite material

Operate more precise selection

Save cost in the breeding program

Increase genetic gain

$$\Delta G_{Yr} = \frac{i_{Ns} . r_{g\hat{g}} . \sigma^2{}_A}{L}$$

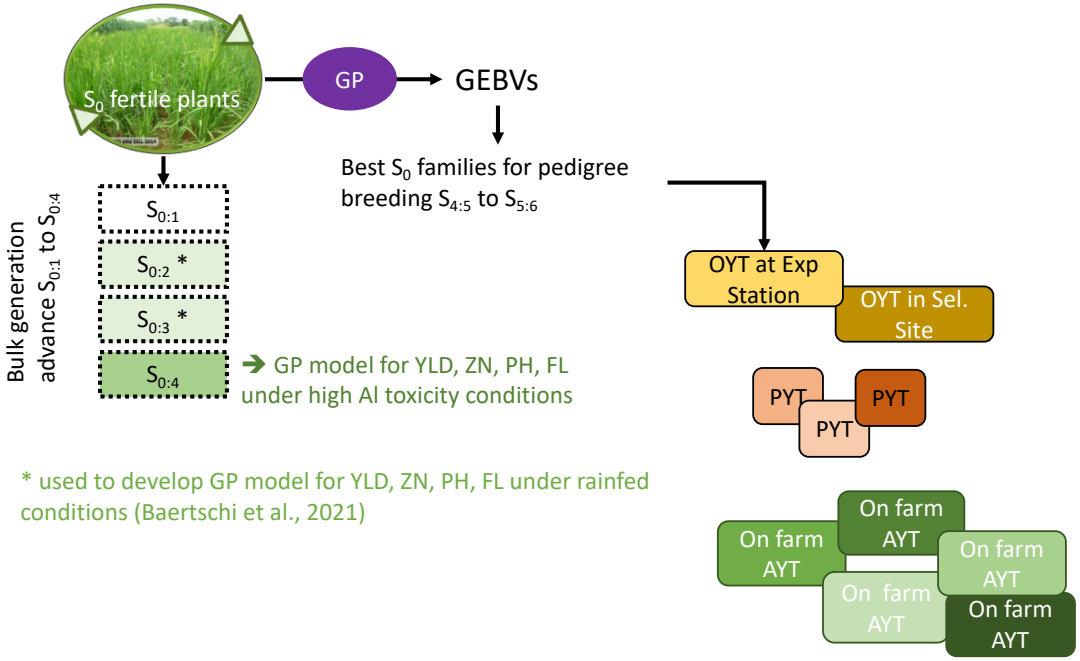




Our approach

Families derived from a synthetic population which is the base of the upland rice breeding program

Tropical japonica germplasm derived from the recombination of elites upland rice from Asia, Africa and Latin America and three decades of recombination



* used to develop GP model for YLD, ZN, PH, FL under rainfed conditions (Baertschi et al., 2021)

PCT27 generated from the mixture of for population (Baertschi et al., 2021)
Genotyping performed at S_0 generation
334 advanced generation families ($S_{0:4}$) randomly drawn from the PCT27

Experimental set up

334 $S_{0:4}$ lines (grey colour)

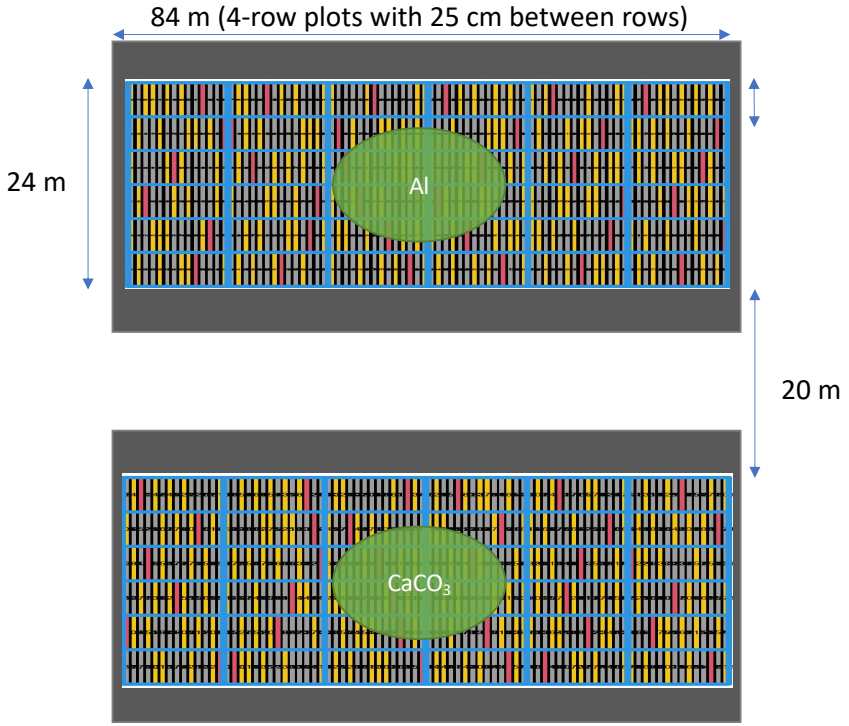
+ 25% repetitions = 84 $S_{0:4}$ lines (yellow colour)

+ 50 $S_{0:2}$ lines (for cross year comparisons & GxE-Genomic Prediction)

+ 6 checks repeated 6 times (red colour)

➔ 504 plots (6 ranges with 6 blocks of 14 plots)

4 3m long row
25 cm between rows
Sowing density: 1 g/m



Data Analysis

BLUEs estimation using mixed linear model

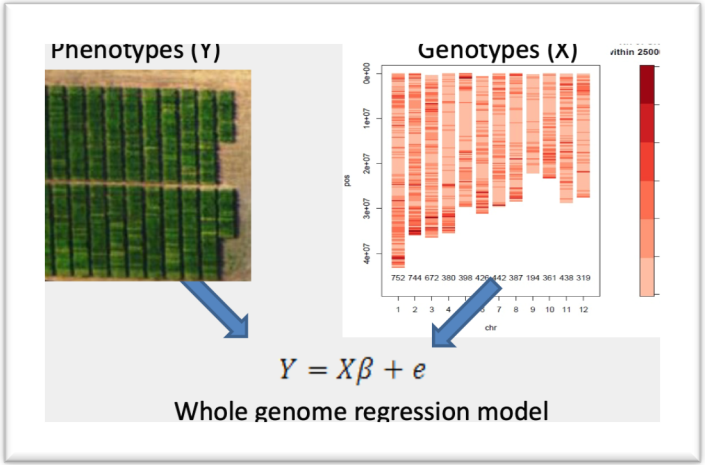
Calibration model (BGGE R-CRAN) by Gustavo de los Campos & Paulino Perez-Rodriguez)

pTst <- 0.3

folds <- 100

nIter <- 70000; burnIn <- 2000

➔ GEBVs



Predictive ability (PA) = r (GEBVs, BLUEs) from fold 1 to 100

BGGE – the Bayesian linear mixed models (Granato et al., 2018)

Model	Main genetic effect of line across environments	Genotype × environment interaction (G×E)
MM	$\mathbf{Z}_u\mathbf{K}\mathbf{Z}_u'$	
MDs	$\mathbf{Z}_u\mathbf{K}\mathbf{Z}_u'$	$(\mathbf{Z}_u\mathbf{K}\mathbf{Z}_u')\circ\mathbf{Z}_E\mathbf{Z}_E'$
MDe	$\mathbf{Z}_u\mathbf{K}\mathbf{Z}_u'$	$\begin{bmatrix} 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & \mathbf{K}_j & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 \end{bmatrix}$ for each environment j $(j = 1, \ldots, m)$

SM : single-environment, main genotypic effect model -- fits the data for a single environment, and only one kernel is produced

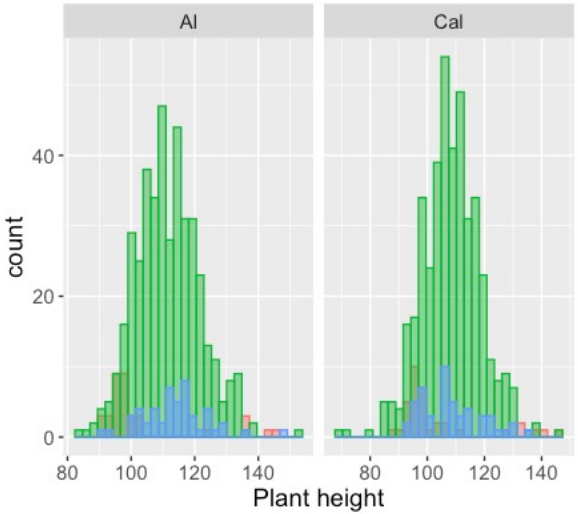
MM : multi-environment, main genotypic effect model -- considers the main random genetic effects across environments.

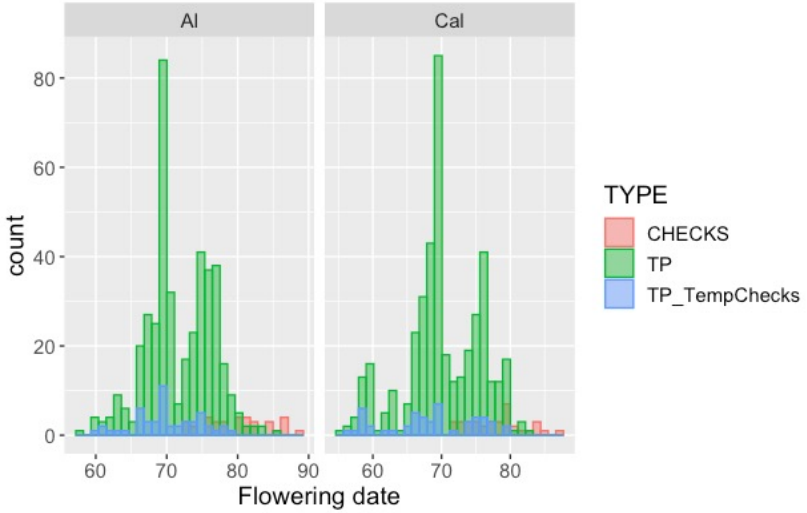
MDs : multi-environment, single variance GxE deviation mode -- extension of MM by adding the random interaction effect of environments with genotype information.

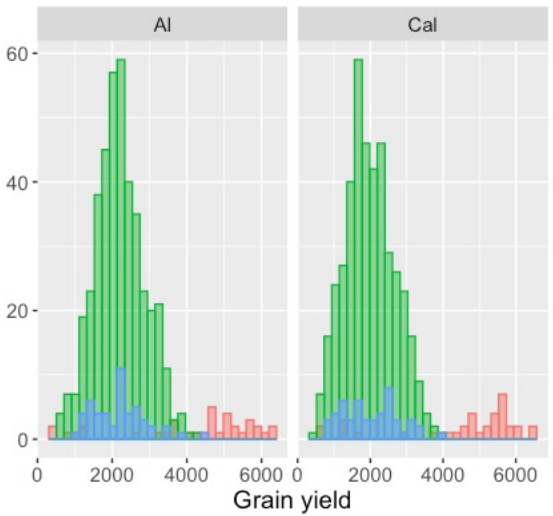
MDe : multi-environment, environment-specific variance GxE deviation model -- separates the genetic effects into the main genetic effects and the specific genetic effects (for each environment).

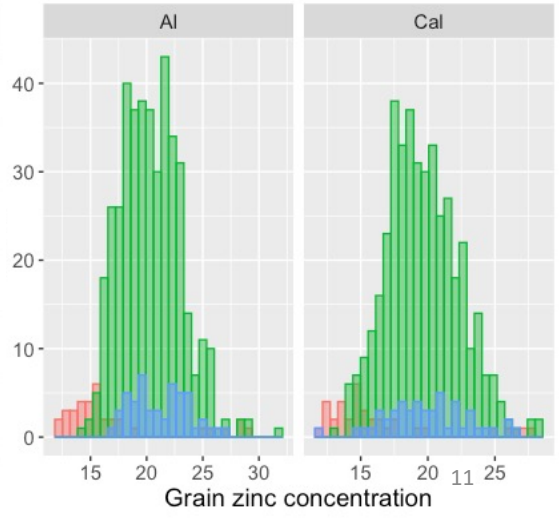
$\mathbf{Z}_u$ is a known incidence matrix that relates the genotypes to the observations in the environments

Trait distribution in the whole set









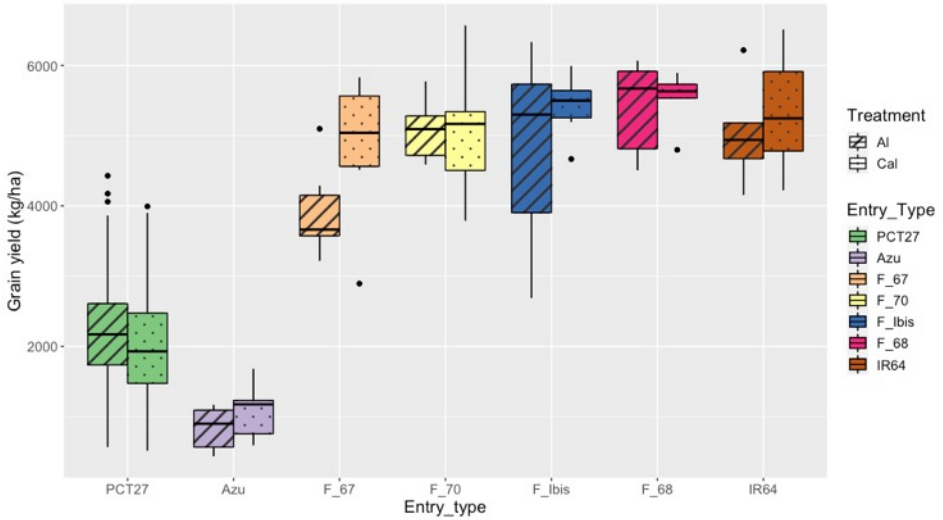


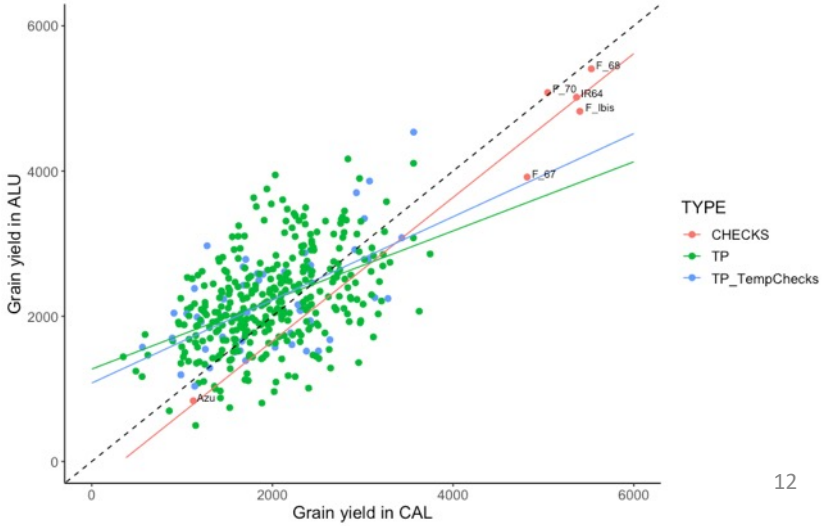
Effect of treatment on grain yield

Greater general performance of indica rice under any treatment

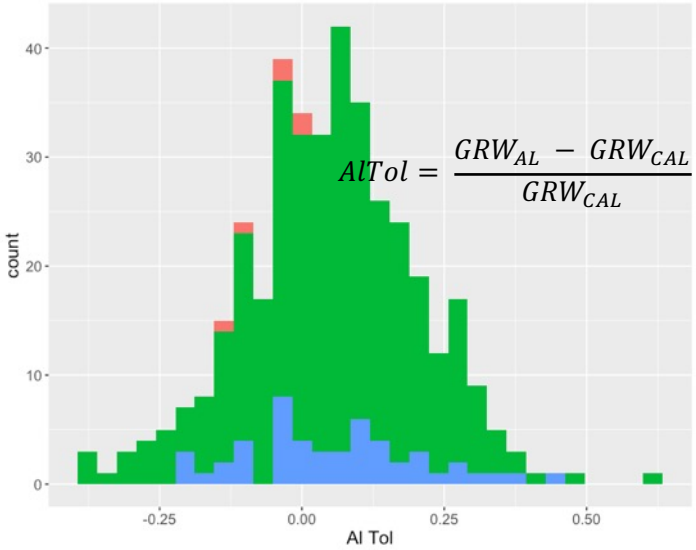
Only within the PCT27 grain yield significantly greater under Al than Cal

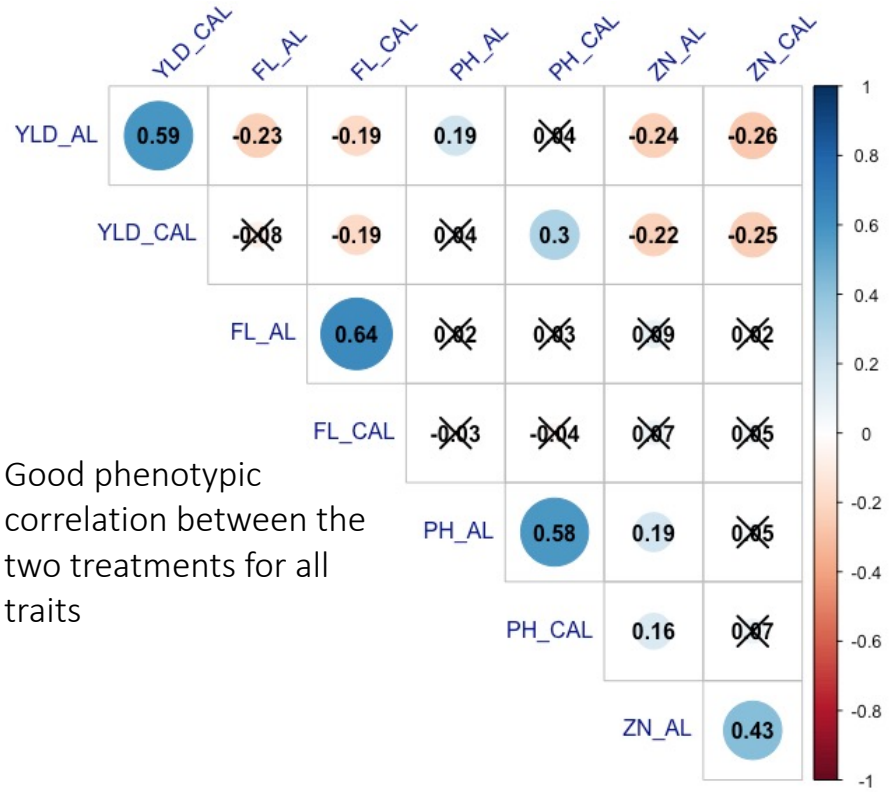
→ Upland rice families have lower yield than the indica rice but tolerance to aluminum seems to exist in this set of germplasm





High trait correlation and variability in AlTol index

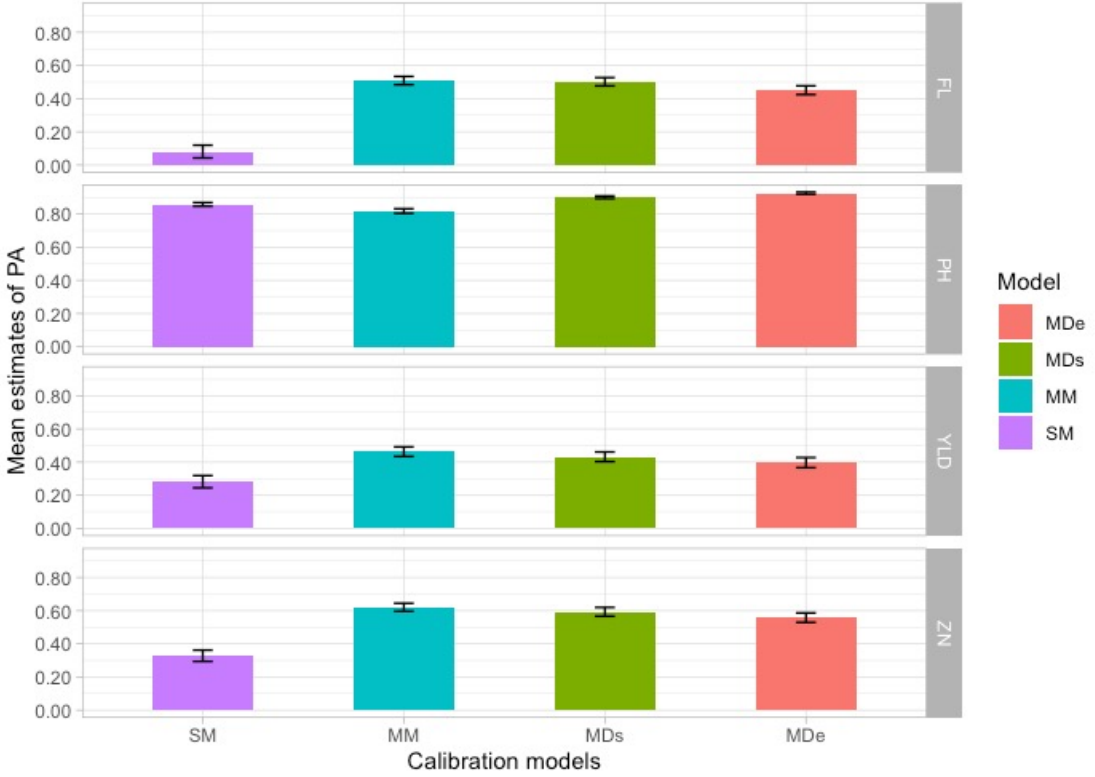




Good phenotypic correlation between the two treatments for all traits

Potential to exploit AlTol among the families

GP on the 334 $S_{0:4}$ families for trait in Al condition



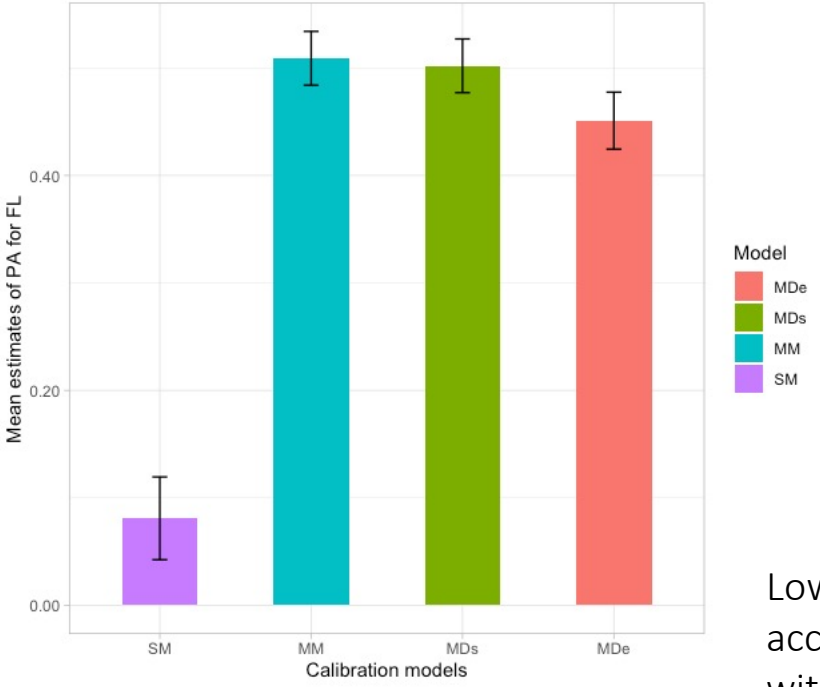
Predictive ability as the Pearson correlation between predicted values (GEBVs) and the estimated values (BLUEs)

Large variation in PA according to the traits

Considering GxE has different impact on the PA

Generally better PA when using the data from both sites to calibrate the model

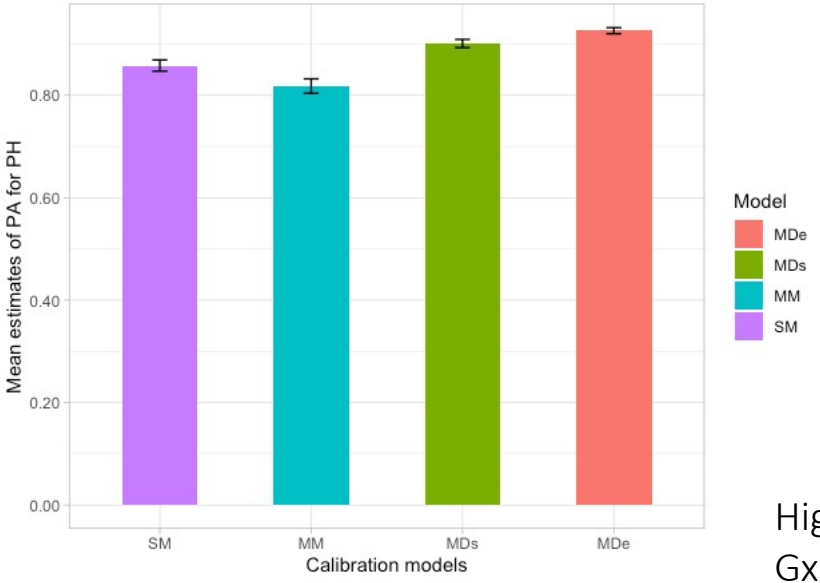
High PA for FL considering multisite models

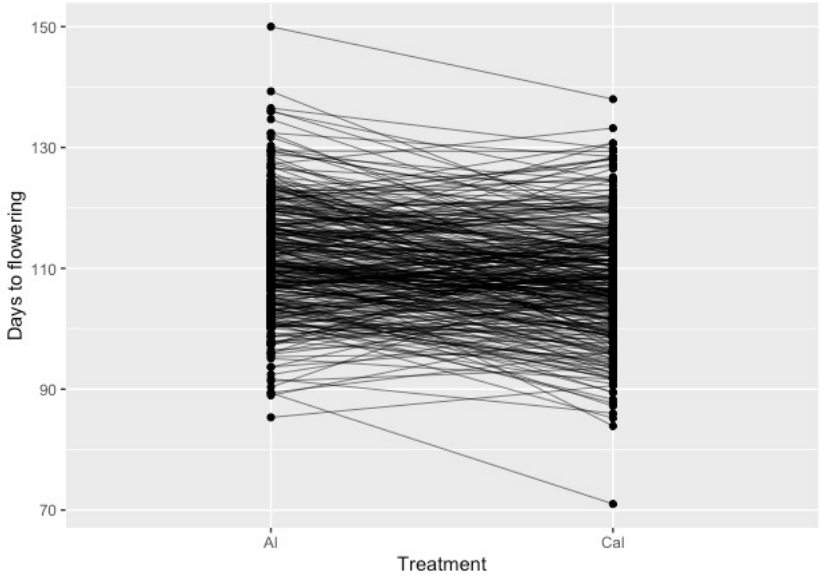


FL	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
DESIGN	383	18837.1	49.18	18.7591	0.051905	.
SITE	1	652.9	652.91	249.0299	0.003992	**
DESIGN:SITE	383	4688.9	12.24	4.6695	0.192681	
SITE:R	10	476.2	47.62	18.1612	0.053289	.
SITE:C	156	1497.1	9.6	3.6603	0.238695	
Residuals	2	5.2	2.62			

Low PA with the single-environment, best when accounting for the GxE and genotypic as main effect or with single GxE variance effect

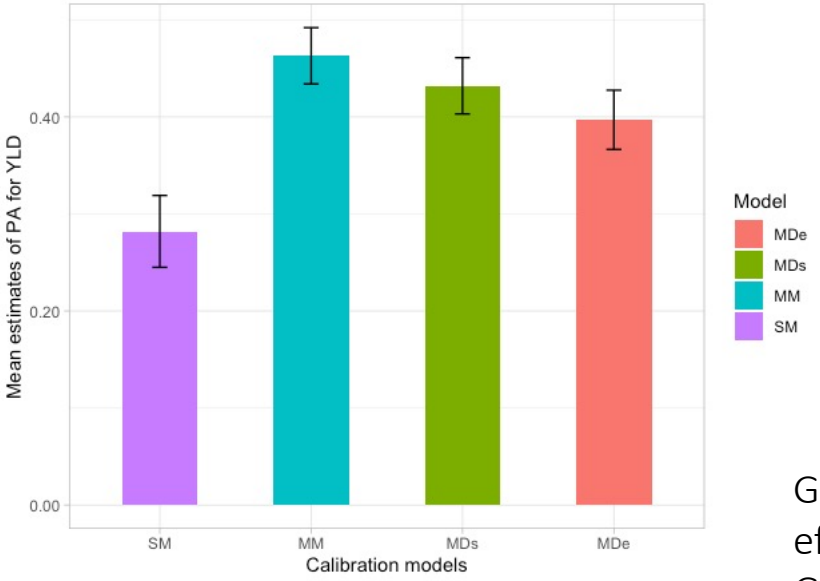
High PA for PH with any models





High PA regardless of the model probably due to the low GxE contribution and high phenotypic correlation between sites

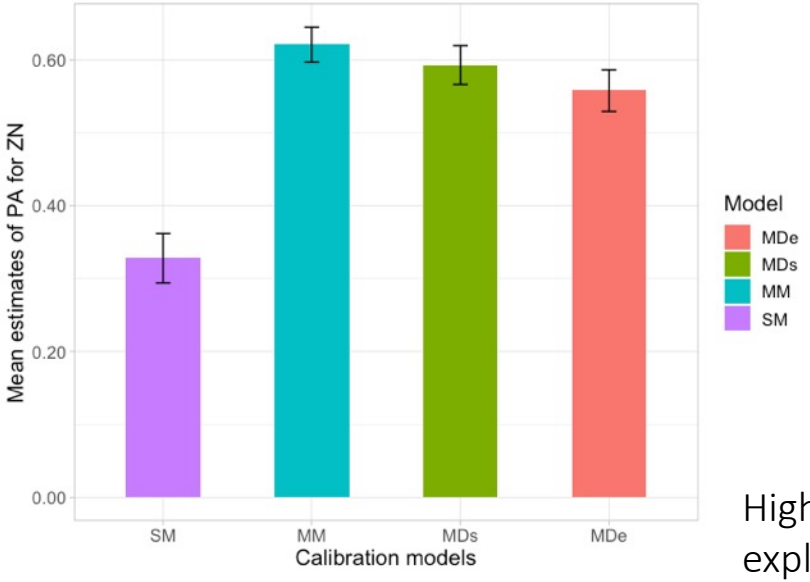
Good PA for YLD with main genetic effect

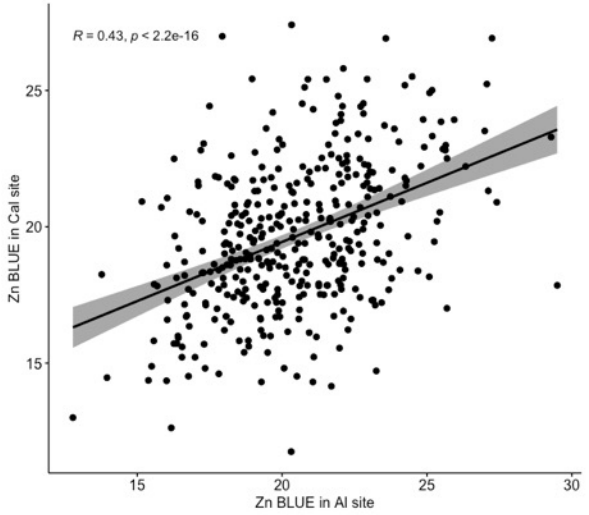


	Groups	Variance	Std.Dev.	σ^2_{ge}/σ^2_g
FL	DESIGN:SITE	1.9938	1.412	0.13
	DESIGN	15.0419	3.8784	
	Residual	4.0519	2.0129	
PH	DESIGN:SITE	2.51E-12	1.58E-06	4E-14
	DESIGN	55.97	7.48	
	Residual	32.16	5.67	
YLD	DESIGN:SITE	0	0	**0.00**
	DESIGN	212260	460.72	
	Residual	149032	386.05	
ZN	DESIGN:SITE	1.3394	1.1573	1.22
	DESIGN	1.0947	1.0463	
	Residual	4.2442	2.0602	

Greater PA with multi-environment, main genotypic effect model probably because variance explained by GxE remains low compared to the genetic variance

Good PA of ZN with multisite model





Trait	H^2_Al	H^2_Cal
FL	0.733	0.743
PH	0.568	0.396
GRW	0.566	0.513
YLD	0.598	0.486
ZN	0.647	0.634

High PA for ZN with GxE and main genotypic effect explained as high H^2

Discussion

Although lower in productivity than the indica rice the potential of japonica is important to consider for acid soils.

Japonica rice can have a function for degraded soil restauration, crop rotation with pasture/leguminous.

Japonica rice can bring interesting gene to high yielders indica rice.

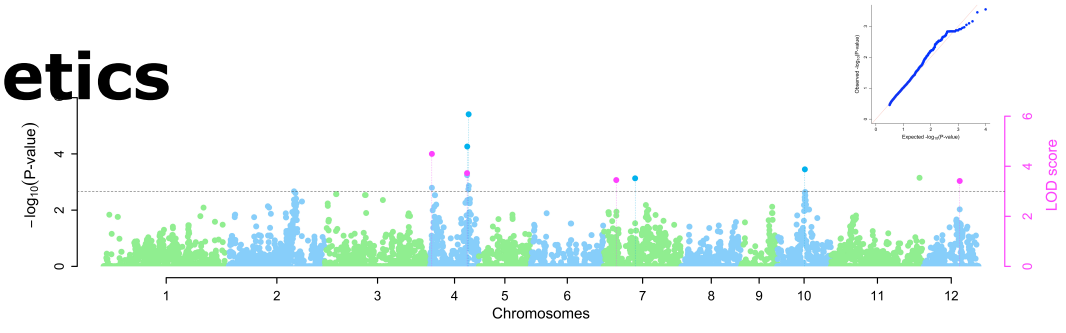
Good perspective to increase genetic gain in the breeding program through genomic prediction aided recurrent selection.



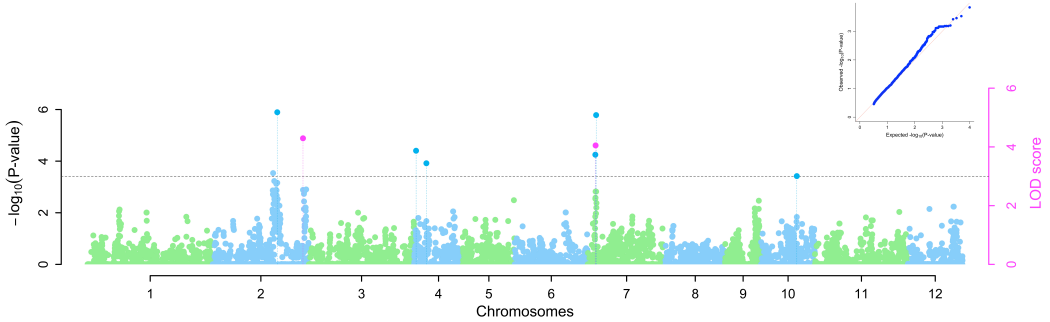
Next step -- Genetics

The GWAS combined with the genomic prediction could potential improve the fixation of certain key genes

Need of more markers (GBS pending) to detect more closely the responsible genetic control



YLD in AL



YLD in CAL

Finer evaluation of GP and estimate on intra family variance to further the optimization of the breeding scheme to adaptation to acid soils



Next steps -- Connections

The 50 elite lines evaluated for drought and Al tolerance are derived from populations which conformed PCT27. Validation of genetic control in the 50 lines can be done on this larger population

→ direct application of MAS with targeted regions / combination of GP and single marker MAS to combine several traits of interest

→ discovery of new mechanisms (under more quantitative control)

General poor performance of the tropical japonicas for lack of resistance to RHBV

→ should be taking advantage of the work on other P6 for general improvement of upland rice

Population available for further phenotyping of quantitative traits and that is of direct use for breeding

→ consider a subset for phenotyping climate resilient traits



Acknowledgments

All the co-authors and even further than the group who have collaborated to this work

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The funding CRP GRiSP, Rice and Harvest Plus for the development of the population and the genotyping of S_0, and Omicas for the field phenotyping and advanced generation sequencing