

The oil palm

- > world major oil crop
- one cultivated species, Elaeis guineensis



> allogamous (monoecious with male and female cycles)

female

> vegetative multiplication difficult



Selection criteria:



Average bunch weight (ABW), Bunch number (BN)



Fruits to bunch ratio (F/B), Pulp to fruits ratio (P/F), Oil to pulp ratio (O/P)

Height increment (INC)

Bunch production (FFB)

Oil extraction rate (OER)

Breeding populations:

Distant populations with narrow genetic bases

Deli

La Mé



Genomic selection

Method of MAS (Meuwissen et al 2001):

- Training population phenotyped and genotyped
- Dense genotyping of the whole genome
- All markers effects estimated simultaneously
- No test of significance of marker effects
- Selection on markers alone (GEBV) in test population

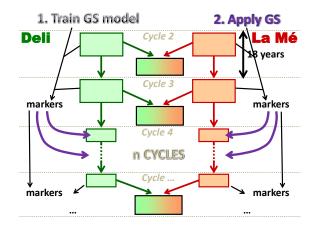
"Selection on genetic values predicted from markers could substantially increase the rate of genetic gain in animals and plants"

Genetics 157: 1819–1829 (April 2001)

Prediction of Total Genetic Value Using Genome-Wide Dense Marker Maps

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Could we increase the rate of genetic gain in oil palm breeding with genomic selection?

<u>Hypothesis</u>: Progeny-tested individuals could be used to train a GS model that could be applied to predict breeding values of individuals of the same populations

With:

- Narrow genetic base / Low effective size
- Small training populations
- Small number of markers
- Multiallelic markers

<u>Hypothesis</u>: Progeny-tested individuals could be used to train a GS model that could be applied to predict breeding values of individuals of the same populations

→ Will be checked by measuring the accuracy of GS in a cross-validation study with real data

Genetic gain per year =

Intensity * Accuracy * σ_a

Generation interval

With accuracy = r(TBV, EBV) and current accuracy $\sim 0.8\,$

Materials and methods

Plant material:

Deli: 131 individualsLa Mé: 93 individuals









Materials and methods

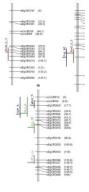
Molecular data:

235 SSR (Billotte et al 2005; Tranbarger et al 2011)

 $^{\sim}$ 1 SSR / 7.4 cM

Phenotypic data:

- 1. Progeny tests, 10 quantitative traits
- 2. Estimated breeding values (BLUP)
- Deregressed and used in a weighted analysis to derive genomic estimated breeding values (Garrick et al 2009)



Materials and methods

5-fold cross-validation:

- 1/ Individuals (genotyped and phenotyped) divided into 5 groups to make <u>training population (4 groups)</u> and <u>test population (5th group)</u>
 - → 5 replicates
- 2/ Estimation of allelic effects
- 3/ Calculation of GEBV for test individuals
- 4/ Calculation of accuracy of genomic selection in test population

Materials and methods

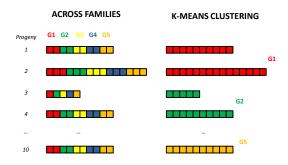
Definition of groups for training and test populations:

2 methods, in order to get a range of accuracy of GS:

- 1. Lower bound: CLUSTERING (Saatchi et al 2011)
- Calculate matrix of additive genetic relationships between individuals,
- Use K-means clustering to make 5 groups
- → Increases within-group relationships / Decreases betweengroup relationships (groups represent subpopulations)
- 2. Upper bound: ACROSS FAMILIES
- Each family is randomly divided into 5 groups
- → Maximizes relationships between training and test populations

Materials and methods

Definition of groups for training and test populations:



Materials and methods

Statistical methods to estimate GEBV:

Group of method	Method	Marker effects	Comments	Reference
Mixed Model	ABLUP	no	Control	Henderson 1975
Mixed Model	BLUP	yes	gi ~ N(0, Vm)	Meuwissen et al 2001
Mixed Model	GBLUP	no	Estimate GEBV	Henderson 1975, Eding and Meuwissen 2001
Bayes	BRR	yes	gi $\sim N(0, \sigma^2_{BR})$	Perez et al 2010
Bayes	BL	yes	gi \sim N(0, $\tau_i * \sigma_e^2$)	Perez et al 2010
Semi-parametric	RKHS	no	Estimate GEBV	Gianola et al 2006, Heslot et al 2012

→ Some methods better suited for traits with many small effect genes, others for traits with major genes + small effect genes

Accuracy:
$$r_{\text{GEBV,TBV}} = \frac{\hat{\sigma}_{\text{DEBV,GEBV}}}{\sqrt{\sigma_a^2 \, \hat{\sigma}_{\text{GEBV}}^2}}$$
 (Saatchi et al 2011)

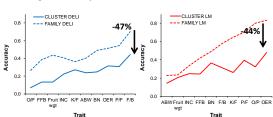
Results

- > Factors with the strongest effect on accuracy:
 - (1) TRAINING MODE,
 - (2) TRAIT, POPULATION
 - (3) TRAIT * POPULATION INTERACTION
- ➤ No effects of statistical method, no statistical method * trait interaction

Results

Effect of training mode on accuracy:

→ Range of accuracy for GS



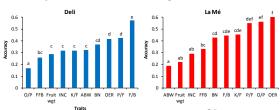
... Effect of training mode related to a_{max} :

family → cluster, -22% 1.1 0.86 family → cluster, -18% 0.93 0.77

Results

Effect of trait on accuracy:

Accuracy varies with a factor 3 according to trait (very low to very high)

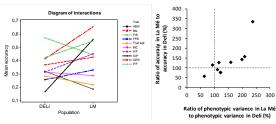


Due to genetic architecture of each trait?

(number of QTLs, distribution of QTL effects, distribution of QTL along genome versus distribution of SSRs, LD between markers and QTLs)

Results

Effect of trait * population interaction on accuracy:



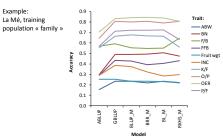
Due to differences in genetic architecture between populations and traits?

Related to differences in phenotypic variance

Results

Effect of statistical method on accuracy:

No effect, no interaction with trait



... contradictory with trait effect and trait * population interaction

→ Too small number of phenotypic records?

Conclusions

Some traits with very low accuracy

→ bigger training populations / more markers

More **studies required** before implementing GS in our oil palm breeding program...

- Effect of increasing training population size ?
- Rate of decrease of accuracy over generations ?
- Accuracy between experimental designs?
- Genetic architecture of traits in each population ?

...

Some answers in 2013 (simulations)

and 2014 (more real data: 2 experimental designs, 2 generations

+ GBS genotyping)

