# Predictive Ability of Genomic Estimated Family Values (GEFV)

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families, such as most outbreeding forage species. A significant drop in genotyping costs as one sample per family is needed would allow the application of GWFS in minor higher for GEFV in both populations, even after standardizing GEFV predictions to be comparable to GEBV. Results revealed great potential for using GWFS in breeding programs that select Bayes-B using the package BGLR in R and models were validated using 10-fold cross validations. Predicted ability, computed by correlating phenotypes with GEBV and GEFV, was always averaged across replicates for all the individuals and allele frequency was computed for each SNP. Marker effects were estimated at the individual (GEBV) and family (GEFV) levels with CCLONES, 5000 polymorphic loci and two traits (oligogenic and polygenic). In both populations, phenotypic and genotypic data was pooled at the family level in silico. Phenotypes were tree stiffness and lignin content) and genotyped using an Illumina Infinium assay with 4740 polymorphic SNPs, and ii) a simulated population that reproduced the same pedigree as (Pinus taeda L.) populations: i) the breeding population CCLONES composed of 63 families (5-20 individuals per family), phenotyped for four traits (stem diameter, stem rust susceptibility, costs. Besides, breeding and selection is performed at the family level in some crops. We aimed to study the implementation of genome-wide family selection (GWFS) in two loblolly pine Genomic selection (GS) has been used to compute genomic estimated breeding values (GEBV) of individuals; however, it has only been applied to animal and major plant crops due to high

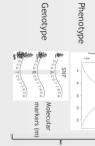
# Introduction

breeding animals and major crops that can invest in high costs is used to compute GEBV of individuals (Figure 1), but it has only been applied ťo

Figure 1. GS scheme to predict breeding values of individuals

ning population



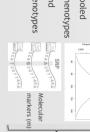


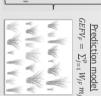


at the family level and GWFS could be implemented in these crops (Figure 2). some plant crops such as most outbreeding forages, breeding and selection is performed

Figure 2. GWFS scheme to predict breeding values of families

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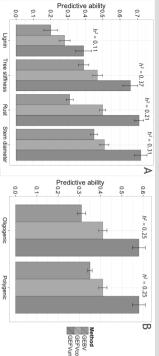
experimental breeding population CCLONES (Resende population (de Almeida Filho et al., 2016). We aimed to study the implementation of GWFS in two loblolly pine populations: the et al., 2012) and a simulated

Results

Predicted ability was always higher for GEFV in both populations and all traits, even without correcting (GEFVuncor) to get the individual accuracy via family selection. phenotypes and the GEBV and GEFV, using the correction factor (10.5) (GEFVcor) and Predicted ability was obtained through simple correlation analysis between the observed

pine breeding population CCLONES (A) and of two traits with different genetic Figure 3. Predictive ability of four traits with different heritability in the loblolly

standardizing GEFV to be comparable to GEBV (Figure 3 A and B).



architecture in a simulated population (B).

**Materials and Methods** 

- Predictive ability for individual and family GS models was computed using two populations: The loblolly pine experimental breeding population CCLONES (Comparing Clonal Lines resulting in 4740 polymorphic SNPs. were phenotyped and genotypic data was obtained using an Illumina Infinium assay, On Experimental Sites), composed of 63 full-sib families (5 to 20 individuals per family). traits (stem diameter, stem rust susceptibility, tree stiffness and lignin content)
- 2. A simulated population that had similar genetic properties as CCLONES. Initially, effects, and ii) polygenic: 1000 QTL were used and their additive effects were sampled a gamma distribution with rate 1.66 and shape 0.4, with positive or negative QTL from a standard normal distribution. simulated with different genetic architectures: i) oligogenic: 30 QTL were sampled from used in this study. The simulated genome had 5000 polymorphic loci and two traits were used in a mating design that reproduced the same pedigree as CCLONES (G2), which was generate the first breeding generation (G1). From G1, 42 individuals were selected the 10% highest phenotypic values from G0 were selected and randomly mated population with effective size ( $N_e$ ) of 10000 and mutation rate of 2.5  $\times$  10.8. Secondly, diploid individuals were created (G0) by randomly sampling 2000 haplotypes from a to

factor (/0.5, the parentage between full sibs) was imposed to GEFV to get the to compare the predictive ability computed with individual and family models, a correction  $\equiv$ accuracy via family selection los Campos, 2014) in R and models were validated using 10-fold cross validations. In order (GEBV) and family (GEFV) levels with Bayes-B using the package BGLR 1.0.4 (Pérez and de frequency was computed for each SNP. Marker effects were estimated at the individual Phenotypes were averaged across replicates for all the individuals per family and allele both populations, phenotypic and genotypic data was pooled at the family level in silico individua

## Conclusion

perennial ryegrasses. GWFS models revealed great potential for using GWFS in breeding programs that select alfalfa (Medicago sativa L.), families to develop cultivars, as is the case of most outbreeding forage and annual (Lolium multiflorum Lam.) and species (L. pere perenne such as

especially in those that phenotyping is performed at the plot level. instead of n samples per family would enable the application of GWFS in The significant drop in genotyping costs in GWFS, as one sample per family is needed minor crops,

prediction in a pine breeding and simulated population. Submitted. Muñoz, M. Kirst and M.F. R. Resende Jr. de Almeida Filho, J., J. F. Guimarães Rodrigues, F. Fonseca e Silva, M. D. The contribution of dominance to V. Resende, phenotype

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