

# Genomic evaluation based on selected variants from imputed whole-genome sequence data in Australian sheep populations

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# Background

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- Multi-breed & Crossbred Population.
- high  $N_e$ , Esp in Merino (*~850 J. Kijas 2011*).
- Smaller size of shared haplotypes.

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  - slightly better prediction within breed (~2.3%)
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- Results of using HD genotypes in sheep population *Moghaddar et al 2017*
  - slightly better prediction within breed (~2.3%)
  - no or very small improvement from across breed information.
- **Whole Genome Sequence data** provides new opportunities.
  - It potentially covers the causal mutations
  - Marker variants in high LD with causal mutation

# Background

## Objective

**To test whether selected variants from WGS data improve genomic prediction accuracy of Australian sheep populations**

## - Phenotypes:

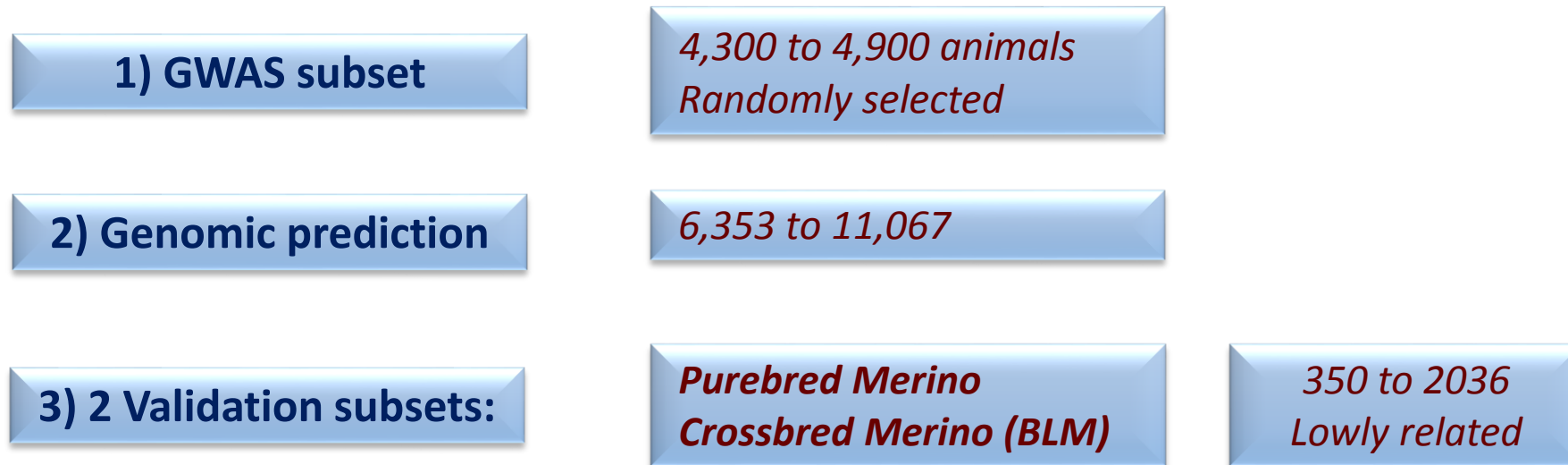
- Combined research and industry datasets
- 6 traits on growth and eating quality traits (2008 to 2015 drops).

Trait Name	Trait	Reference set	Mean	SD
Post Weaning Weight	PWT (kg)	29,025	46.70	13.11
PW Eye Muscle Depth	PEMD (mm)	24,871	26.34	4.65
Carcass Eye Muscle Depth	CEMD (mm)	16,418	29.56	4.85
Carcass Fat	CFAT (mm)	16,284	4.04	2.27
Intra Muscular Fat	IMF (%)	13,518	4.35	1.14
Shear Force day 5 ageing	SF5 (Newtons)	15,494	25.3	14.05



## - Phenotypes:

- Pre-corrected for environmental and non-direct additive effect.
- Phenotypes were divided into 3 non-overlapping data subsets:



## - Genotypes:

- **50k genotypes:** 35,980 *33% imputed from 12k*
- **HD genotype:** 2,266 *key animals*
- **WGS:** 726 animals *10x coverage*  
*Sheep-CRC and Sheep Genome DB (Daetwyler et al., 2017)*

## - Genotype Imputation:

- 50k  $\longrightarrow$  HD  $\longrightarrow$  WGS
- *MiniMac Imputation  $R^2 \geq 0.4$ ,*
- *Final WGS set: 31,154,249 variants S. Bolormaa et al WCGALP-2018*

- **Selected Variants:**
- **Based on GWAS on sequence data:**
  - Only GWAS data subset *N. Duijvesteijn et al WCGALP-2018*
  - $-\text{Log}(\text{P\_Value}) \geq 3$
  - Pruning: ( $LD \geq 0.95$ , 100kb windows , *~4,500 variants*)
  - Other (P\_Value) threshold tested on one trait.

- **Genomic prediction:**

- **GBLUP performed based on:** *MTG2 program (Lee et al 2016).*

- *1) Routine 50k genotypes.*

- *2) Whole Genome Sequence data*

- *3) Selected Sequence Variants*

- *3) 50k + Sel\_Seq*

- *1) Fitted as one variance component.*

- *2) Fitted as two variance components jointly.*

- MTG2 program (Lee et al 2016).*

- **Prediction accuracy:**

- $r(GBV, Phen)/h$

- **Bias of prediction:**

- $[1 - RegCoeff, \dots]$

## Heritability estimates based on 50k, WGS and 50k + Selected Variants

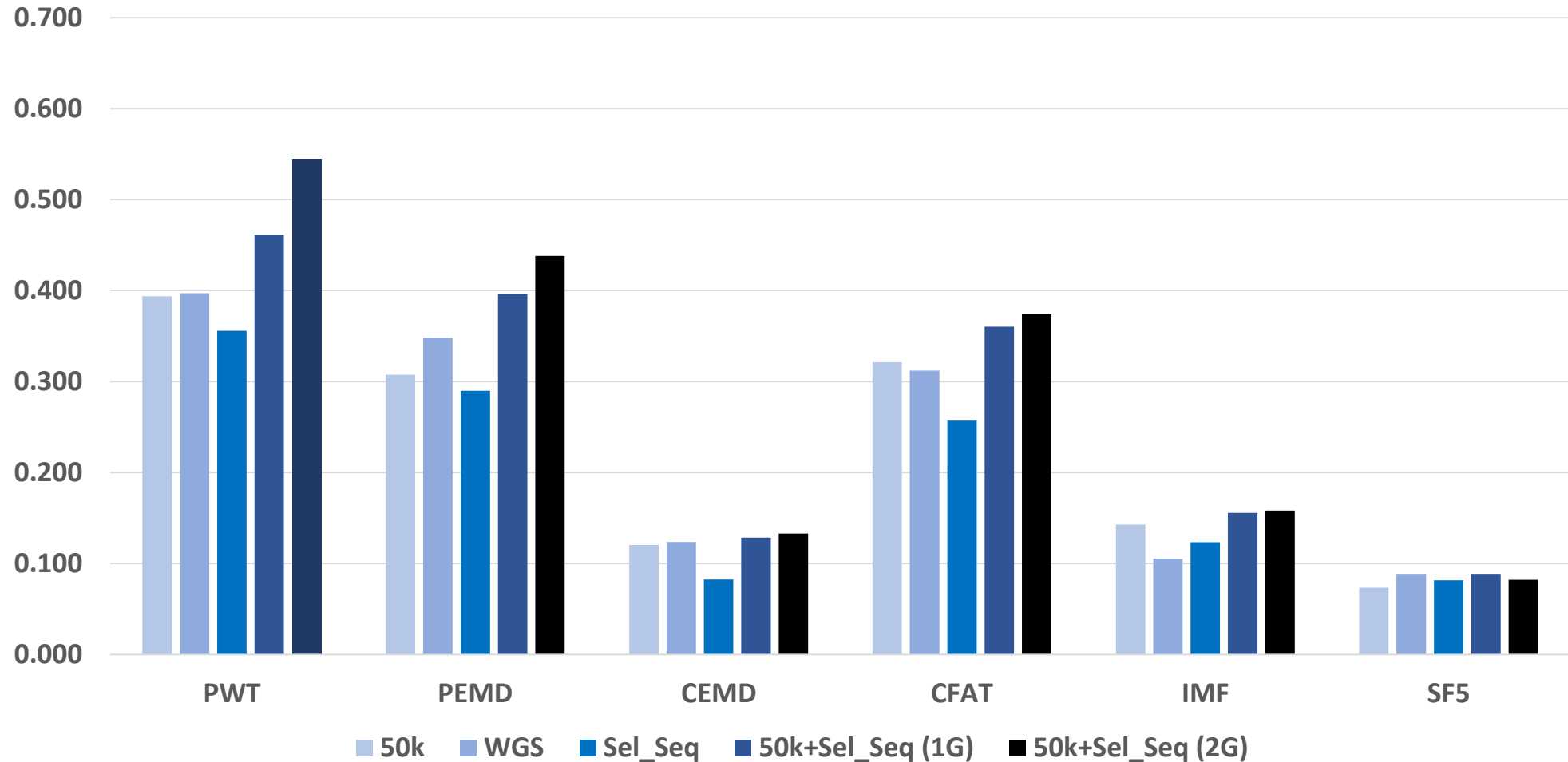
Trait	Size	$h^2$ , 50k	$h^2$ , WGS	$h^2$ (50k , Sel-Variants)
<b>PWT (kg)</b>	11,067	0.21	0.25	0.16 , 0.06
<b>PEMD (mm)</b>	9,715	0.23	0.26	0.19 , 0.09
<b>CEMD (mm)</b>	7,714	0.16	0.19	0.14 , 0.03
<b>CFAT (mm)</b>	7,635	0.19	0.21	0.13 , 0.07
<b>IMF (%)</b>	6,353	0.38	0.42	0.33 , 0.07
<b>SF5 (Newtons)</b>	7,392	0.24	0.29	0.14 , 0.11

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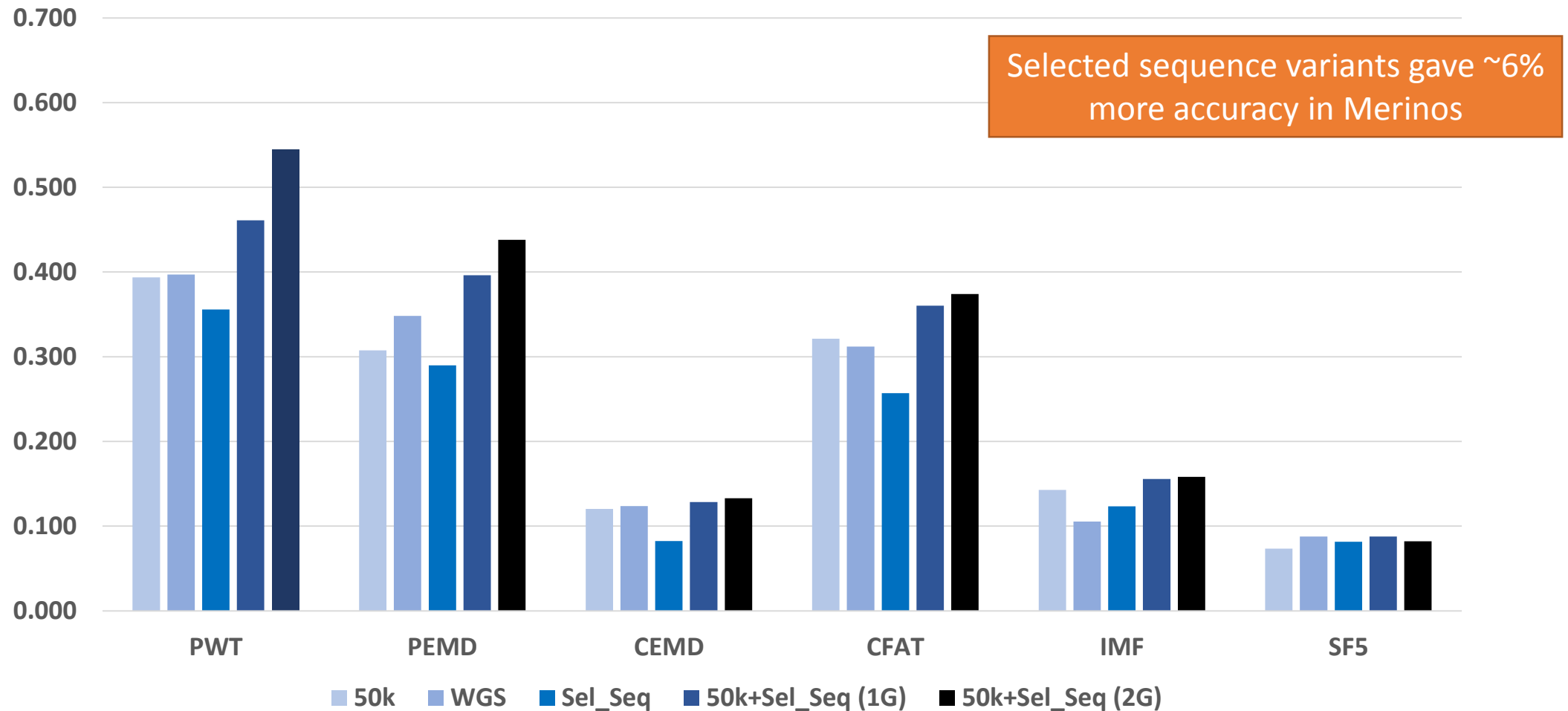
# Results

Accuracy of Genomic prediction in purebred Merinos



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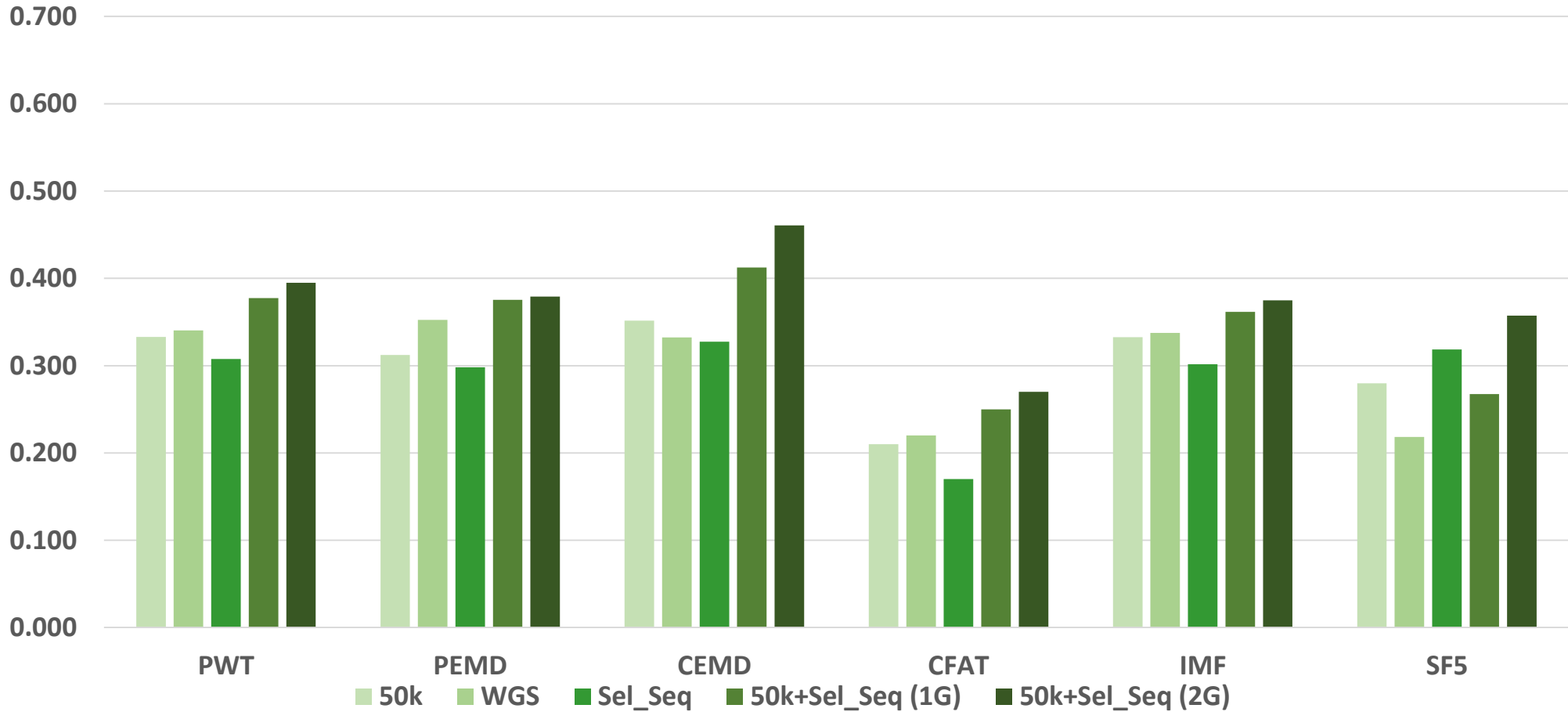
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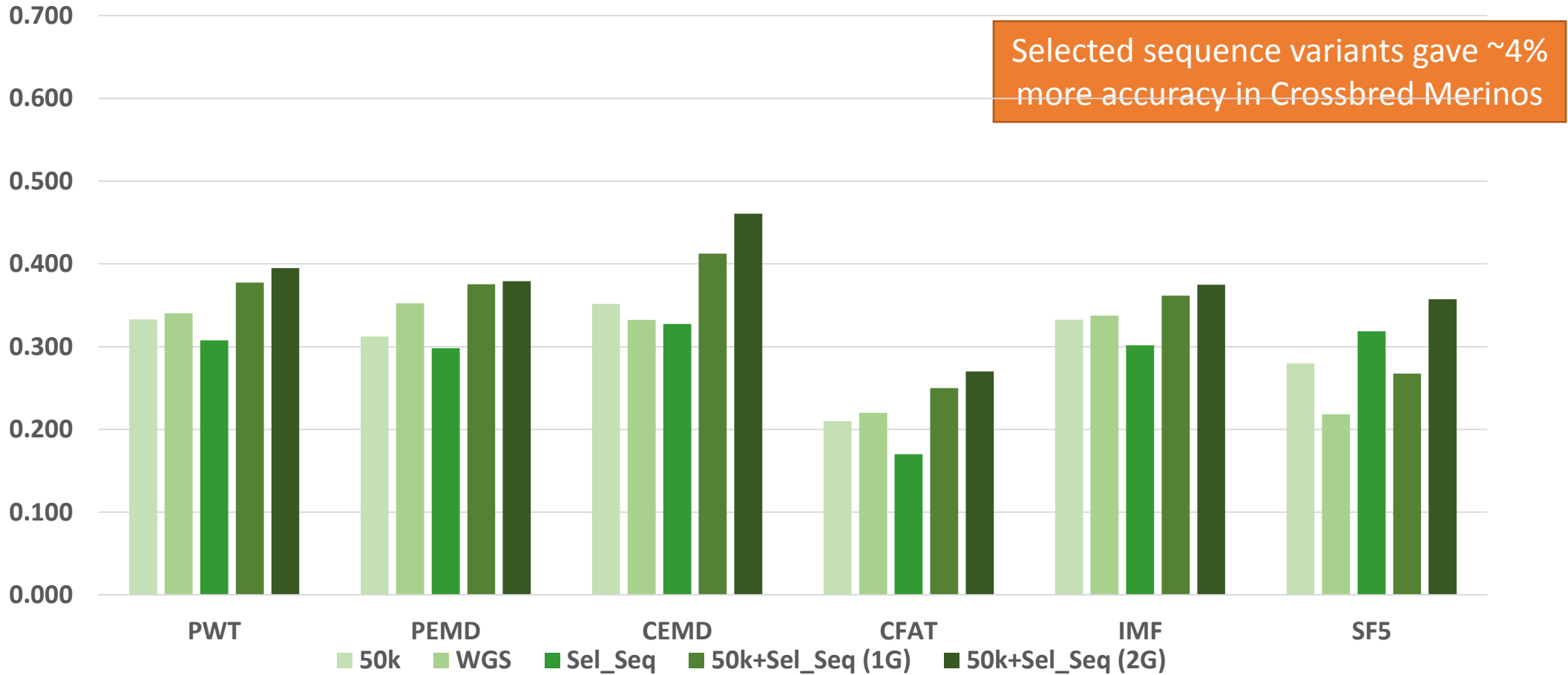
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Accuracy of Genomic prediction in Crossbred Merino (BL x Mer)



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Regression coefficient of adjusted phenotypes from GBV in **purebred** and **crossbred Merino** validation sets

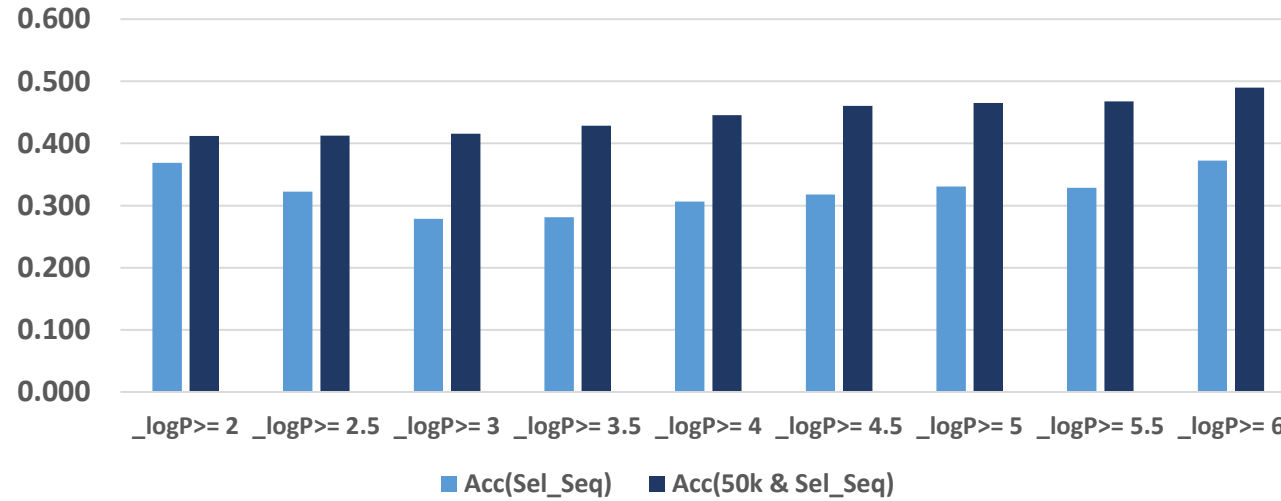
Trait	Purebred Merinos				Crossbred Merinos			
	50k	WGS	Sel-Variants <sup>1</sup>	50k+Sel-Variants	50k	WGS	Sel-Variants	50k+Sel-Variants
PWT	0.92	0.91	1.14	1.06	0.89	0.89	0.80	0.88
PEMD	0.87	0.90	0.74	0.88	0.92	0.95	0.68	0.84
CEMD	0.89	0.88	0.70	0.77	1.14	1.00	0.69	1.62
CFAT	1.06	1.10	0.61	0.91	0.36	0.72	1.44	1.07
IMF	0.51	0.49	0.44	0.50	0.85	0.88	0.84	0.88
SF5	0.34	0.46	0.61	0.35	0.64	0.56	1.44	0.65

<sup>1</sup>: Selected sequence variants,  $-\text{Log}P \geq 3$

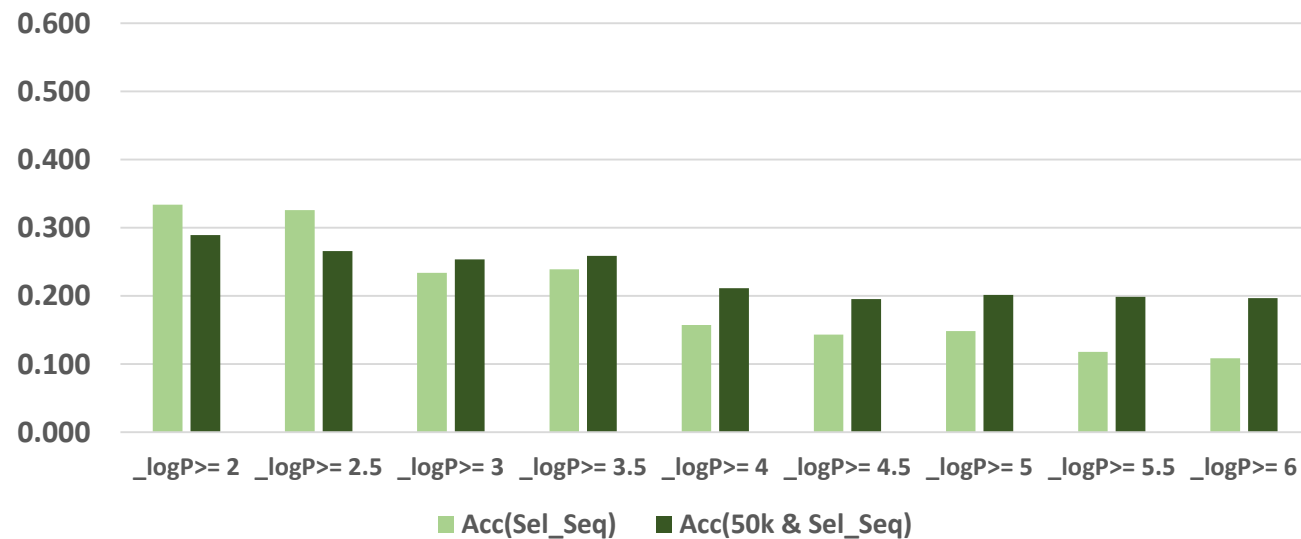
# Results

Genomic prediction of CFAT using selected variants based on **different GWAS threshold**

**Purebred Merinos**



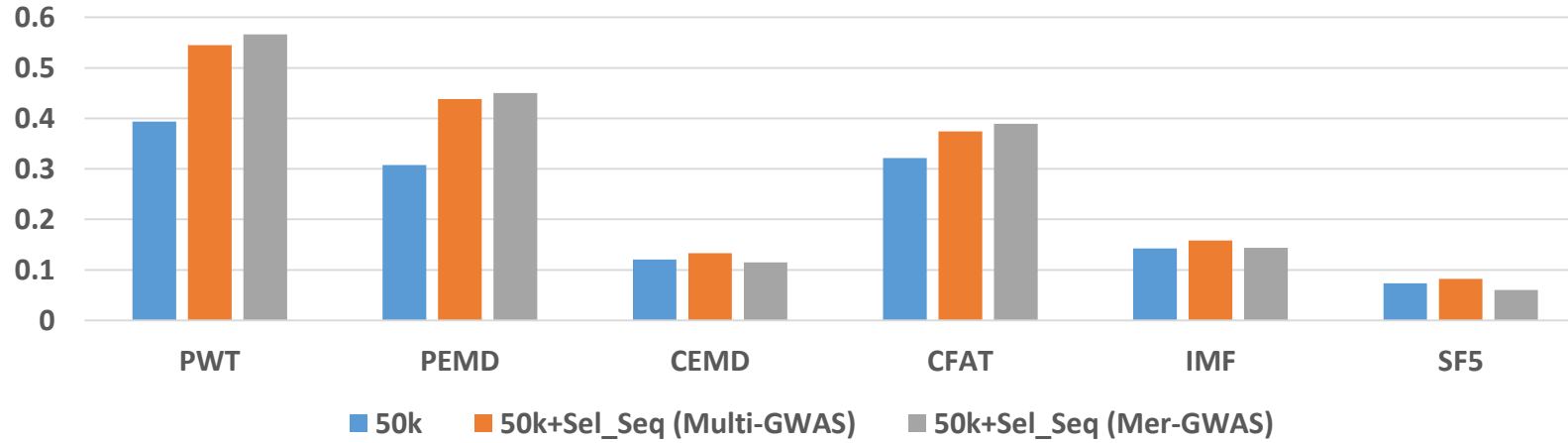
**Crossbred Merinos**



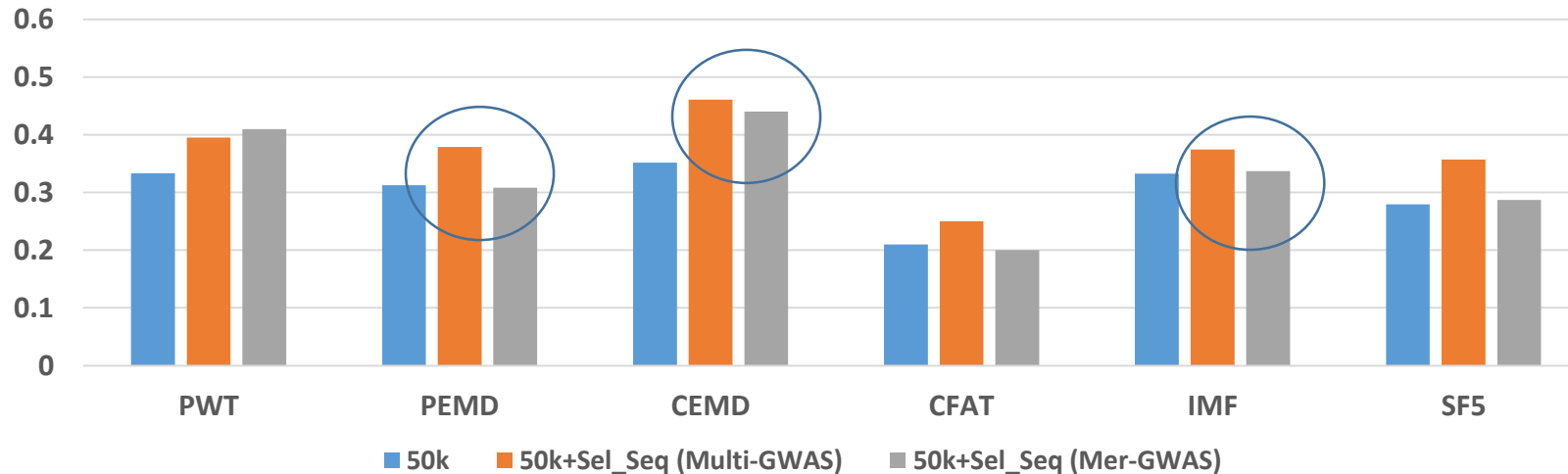
# Results

## Multi-breed GWAS vs single breed GWAS

prediction accuracy for **Merinos** using Multi-breed GWAS vs Merino GWAS



Prediction accuracy for **BLM** using Multi-breed GWAS vs Merino GWAS



# Conclusions

- **Genomic prediction accuracy increased substantially by using selected sequence variants.**
- **Multi-breed GWAS outperformed single breed GWAS.**
- **Stronger threshold on selected variant didn't persistently improved the accuracy between different traits and purebred or crossbred animals**
- **GBLUP methods can accommodate the selected variants by fitting them as a separate variance component and to avoid double counting of part of additive genetic variance.**

# Acknowledgements

- *Sheep CRC*
- *AGBU*
- *UNE*
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*Thanks*

