

Linking genome wide association studies (GWAS) and genomic selection (GS) to better utilize natural variation in rice

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Rice: a mosaic of diversity



Most is rice produced on farms < 1 ha in size.
92% consumed w/in country where produced.
Consumer quality preferences diverse & inelastic.

Building a road map of natural variation in rice



- How much genetic variation is there in *O. sativa*, how is it partitioned and where is it found?
- How can we use that diversity to identify genotype-phenotype associations for traits of interest?
- How can we efficiently select on favorable alleles at thousands of loci across the genome to increase the overall rate of genetic gain in rice improvement?

How is diversity organized in *O. sativa*?

Two major varietal groups

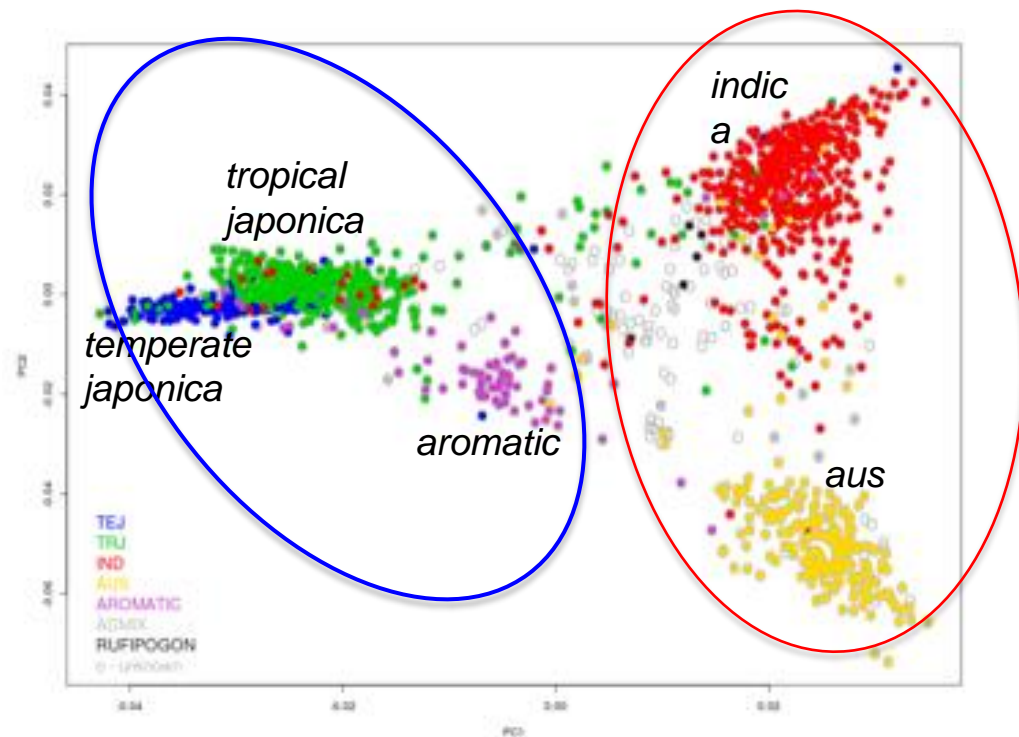
Five genetic sub-populations

- **JAPONICA**

- *tropical japonica*
- *temperate japonica*
- *aromatic (Group V)*

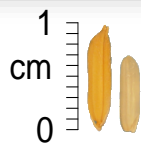
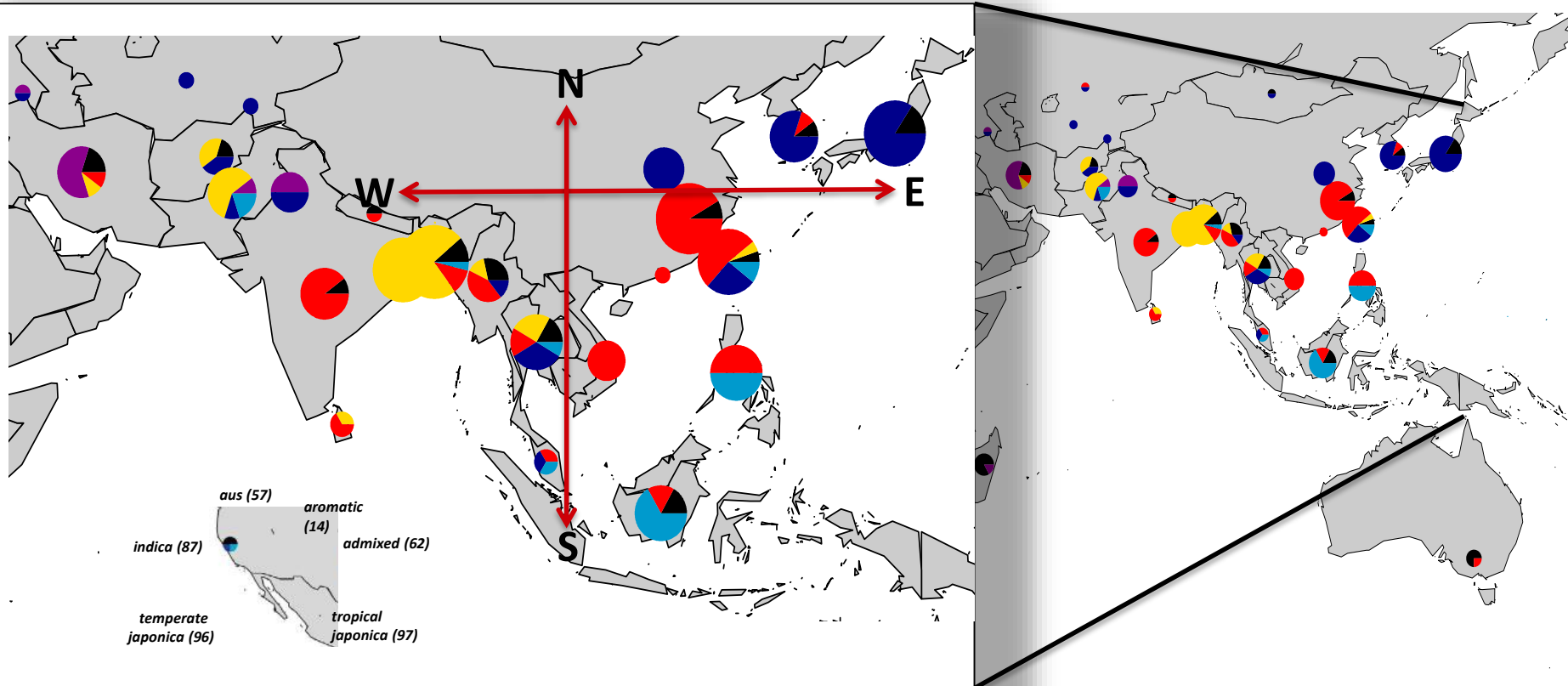
- **INDICA**

- *indica*
- *aus*



McCouch et al. (2016) Open access resources for genome-wide association mapping in rice. Nature Comm. 7:10532

Geographic distribution of rice subpops



indica



aus



temperate japonica

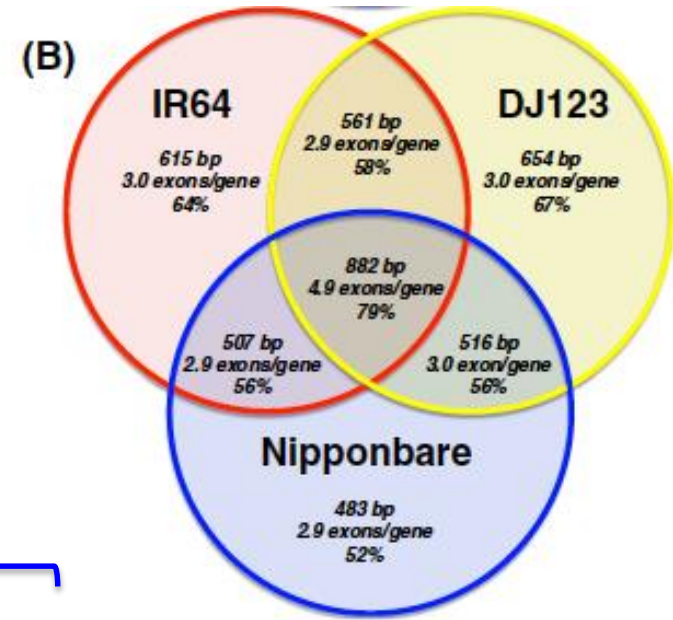
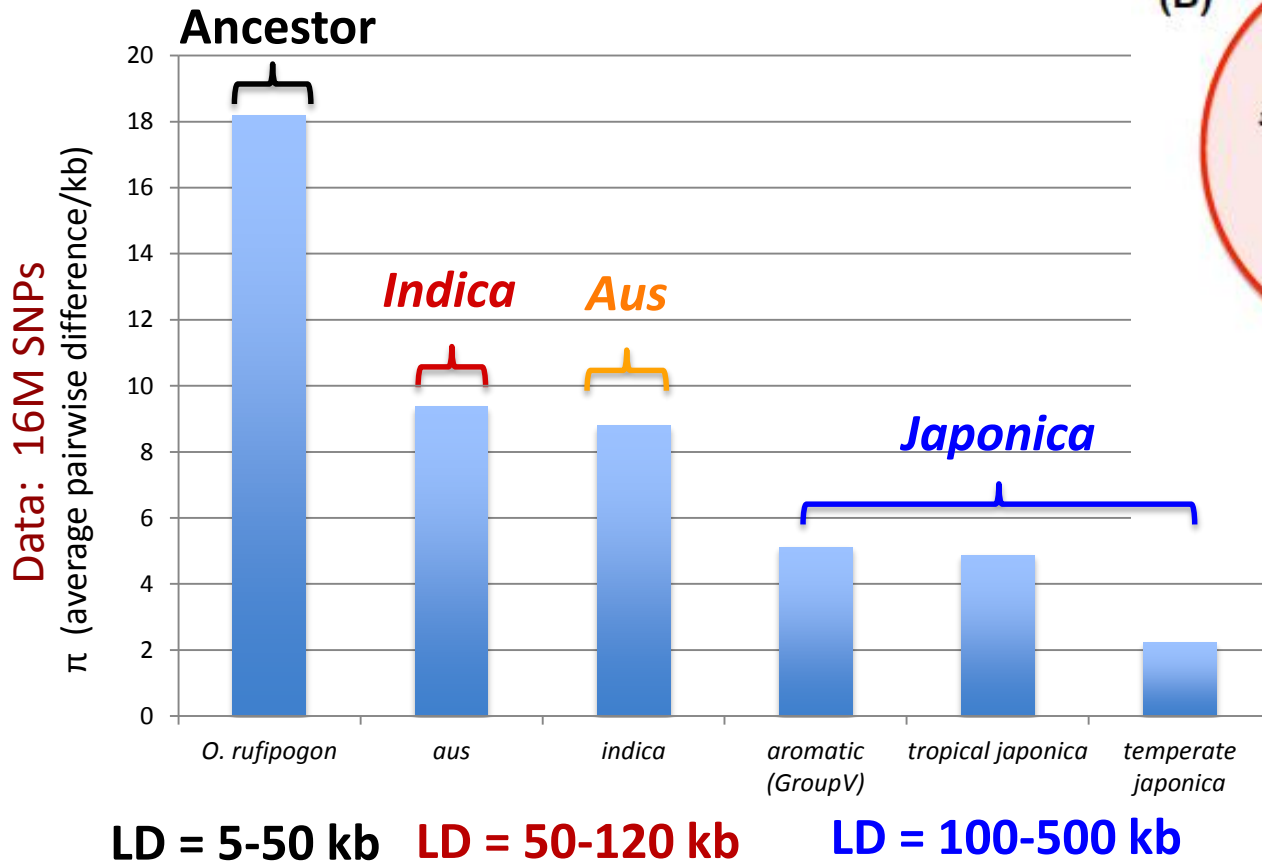


aromatic



tropical japonica

Variation within & between subpopulations

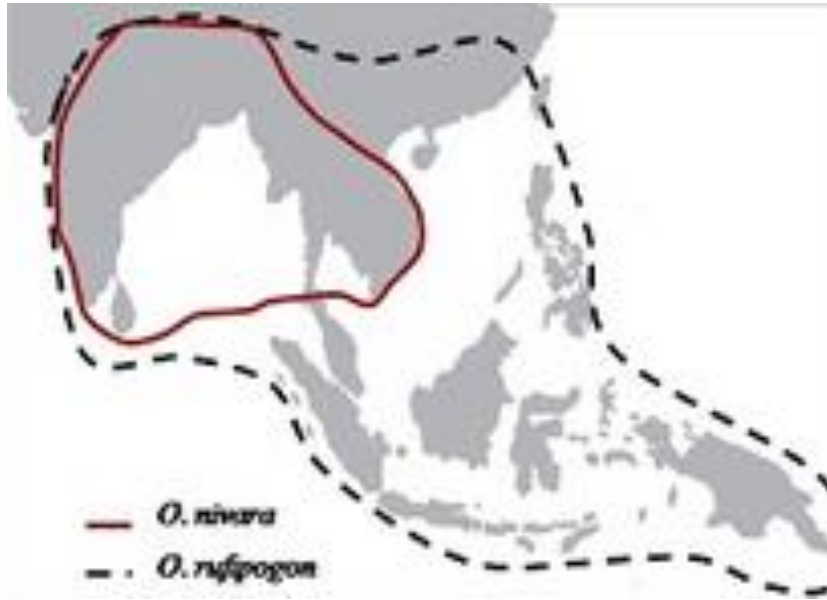


Gene Space

- Median CDS length
- Av No. Exons
- % InterPro/homology

Oryza rufipogon species complex

Inbreeding annuals and outcrossing perennials



Features

Habitat

Life history

Photoperiod

Breeding system

Seed dispersal

O. rufipogon

Deep water

Perennial

Sensitive

Outcrossing

Less efficient

O. nivara

Seasonally dry

Annual

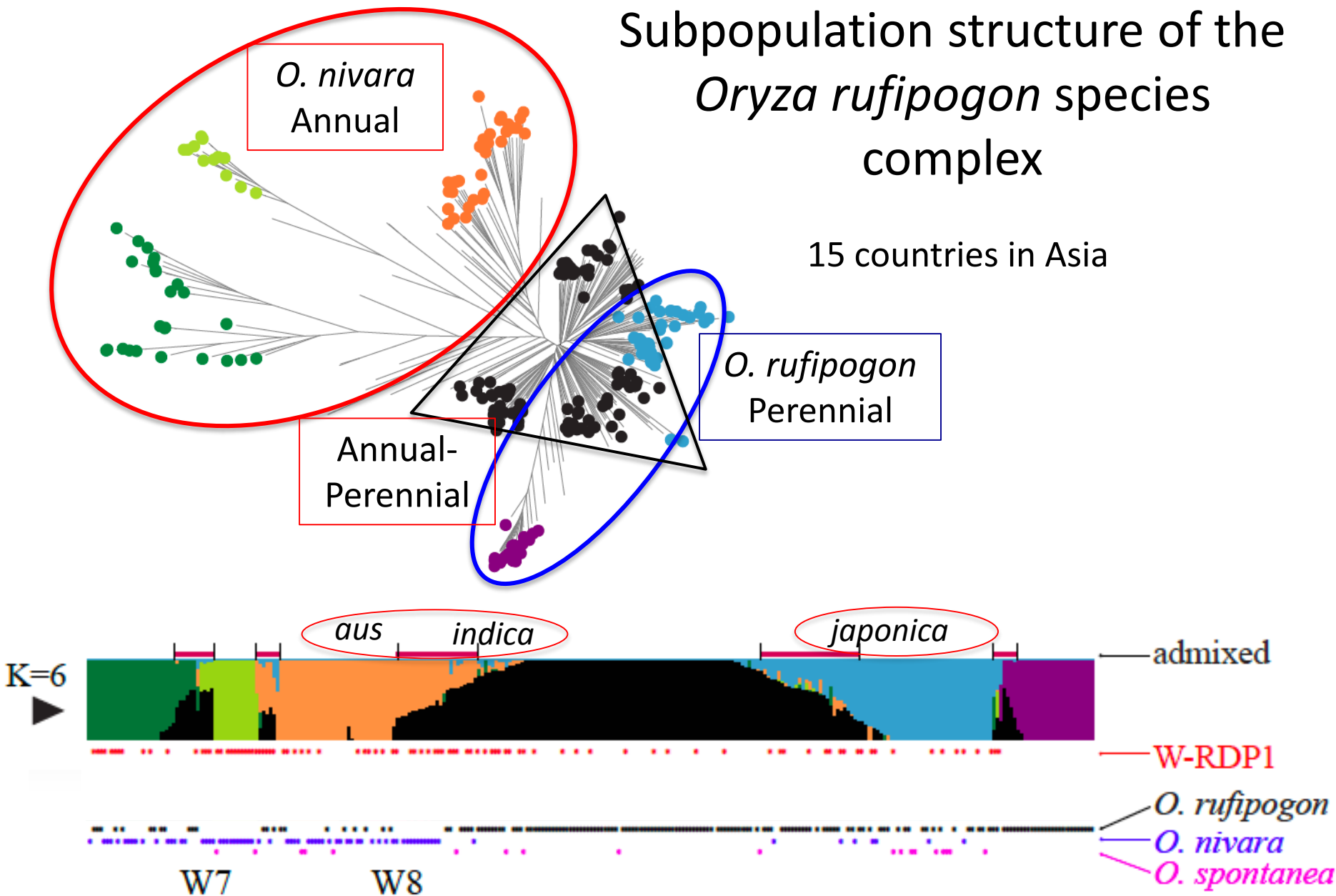
Insensitive

Selfing

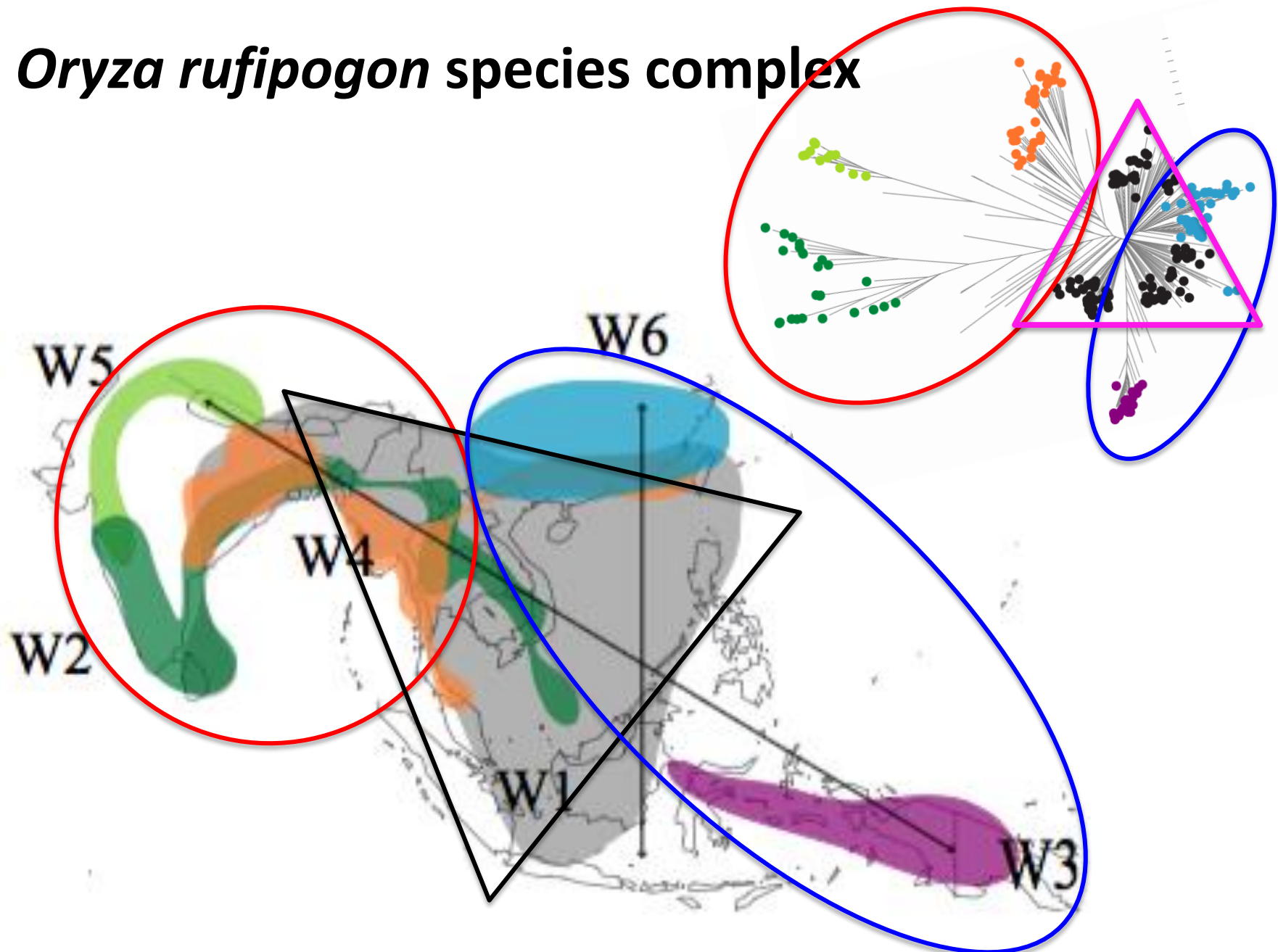
More efficient

Subpopulation structure of the *Oryza rufipogon* species complex

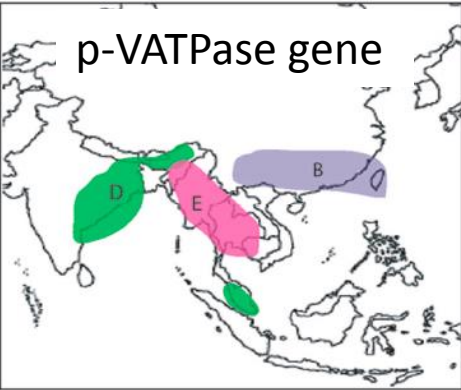
15 countries in Asia



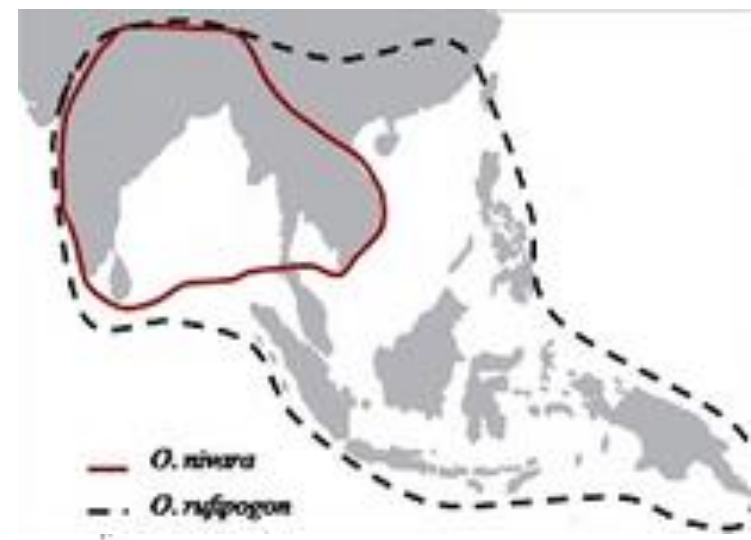
Oryza rufipogon species complex



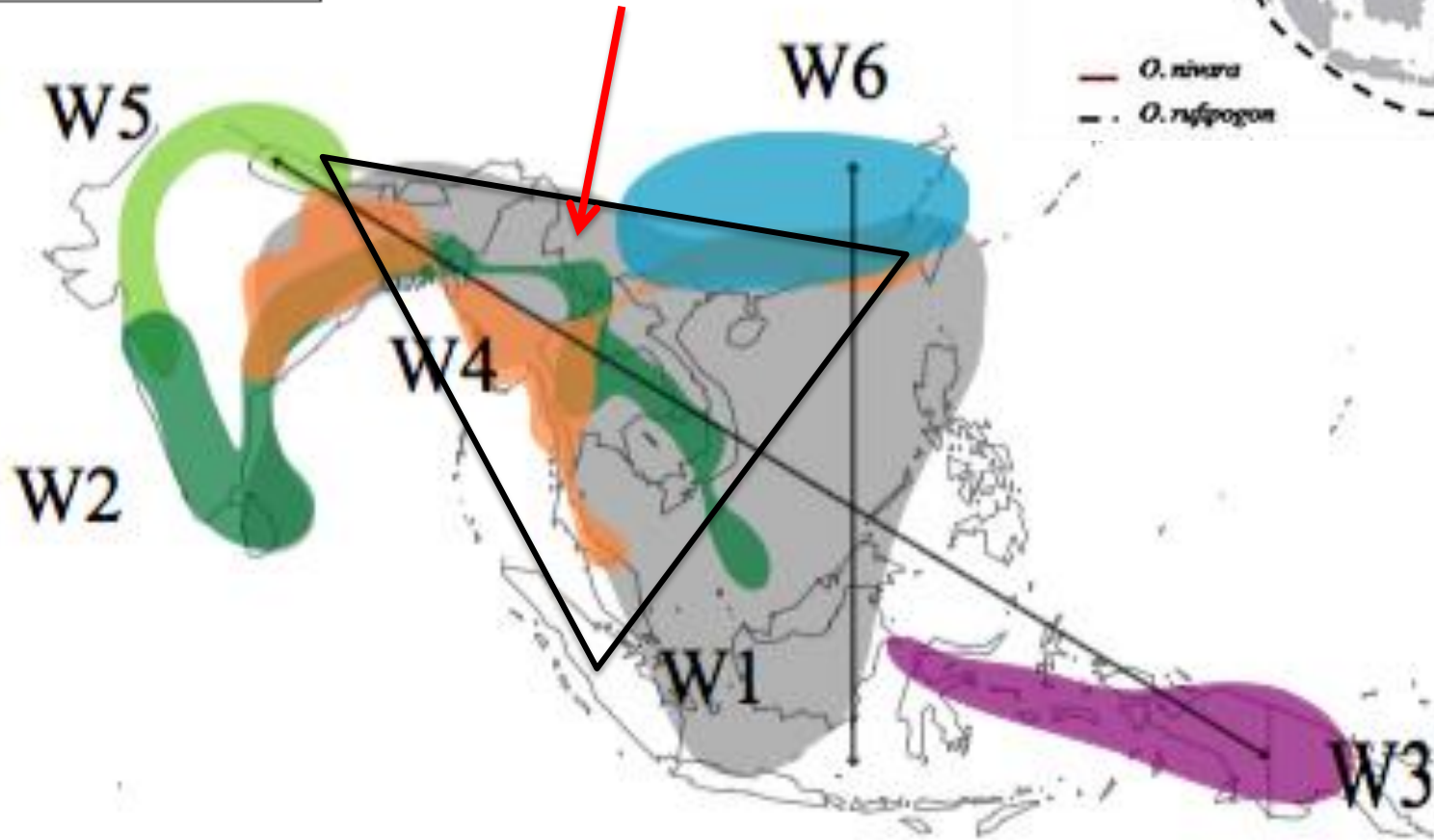
Kim/ Jung et al. (2016) Population Dynamics Among six Major Groups of the *Oryza rufipogon* Species Complex, Wild Relative of Cultivated Asian Rice. RICE 9:56



Londo et al. (2006)
PNAS 103(25): 9578



Greatest diversity



Kim/ Jung et al. (2016) Population Dynamics Among six Major Groups of the *Oryza rufipogon* Species Complex, Wild Relative of Cultivated Asian Rice. RICE 9:56



Arkansas, USA

Los Baños, Philippines



GWAS diversity panel

Rice Diversity Panel 1 “RDP1” (USDA)

~400 *O. sativa*

- 87 *indica*
- 57 *aus*
- 97 *tropical japonica*
- 96 *temp. japonica*
- 14 *aromatic*
- 49 *admix*
- 100 *wilds (O. rufipogon)*

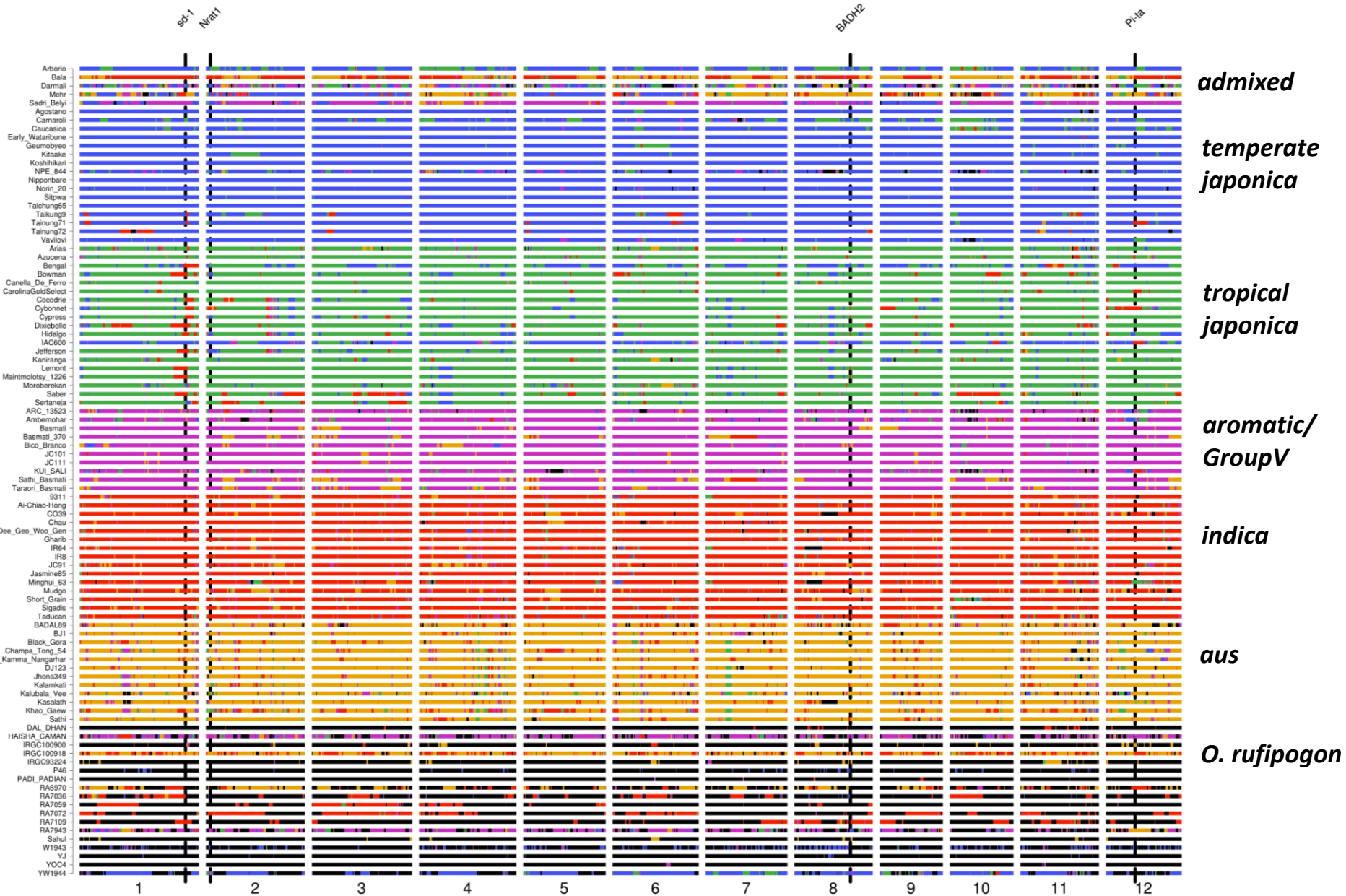
Rice Diversity Panel 2 “RDP2” (IRRI)

~1200 *O. sativa*

- 571 *indica*
- 203 *aus*
- 428 *tropical japonica*
- 152 *temp. japonica*
- 83 *aromatic*
- 7 *admix*

**Total: ~1600 homozygous *O. sativa* accessions
genotyped with 700,000 SNPs**

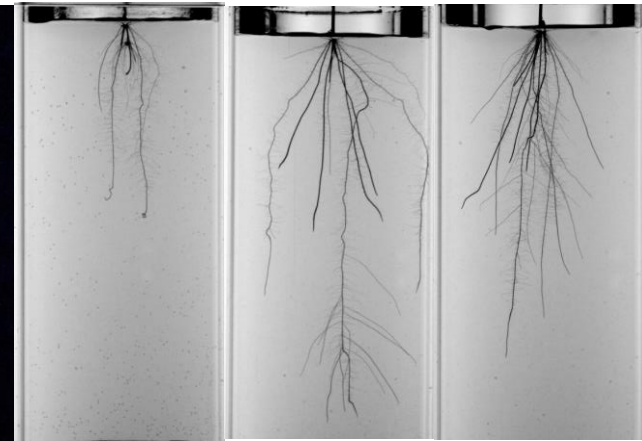
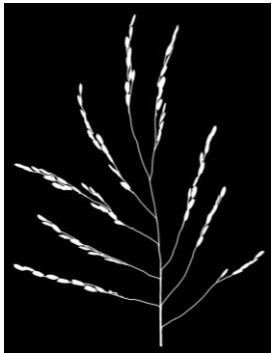
SNP catalogue & admixture atlas



Phenotypic Evaluation

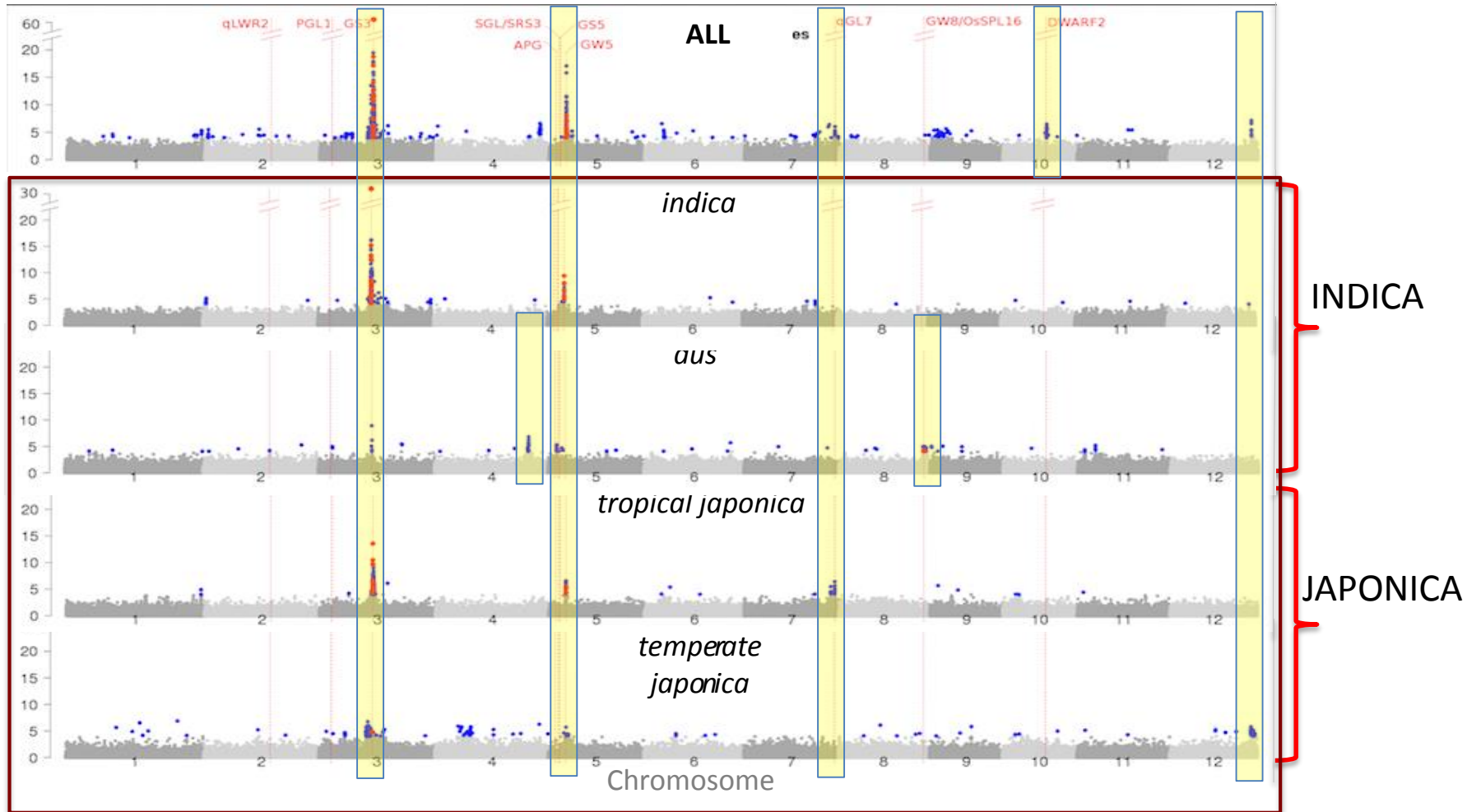
multiple locations, environments, collaborators

- Whole plant phenotypes in the field
- Seed & grain quality characters
- Disease and insect resistance
- Abiotic stress tolerance
- Root and panicle phenotypes
- Ionomics



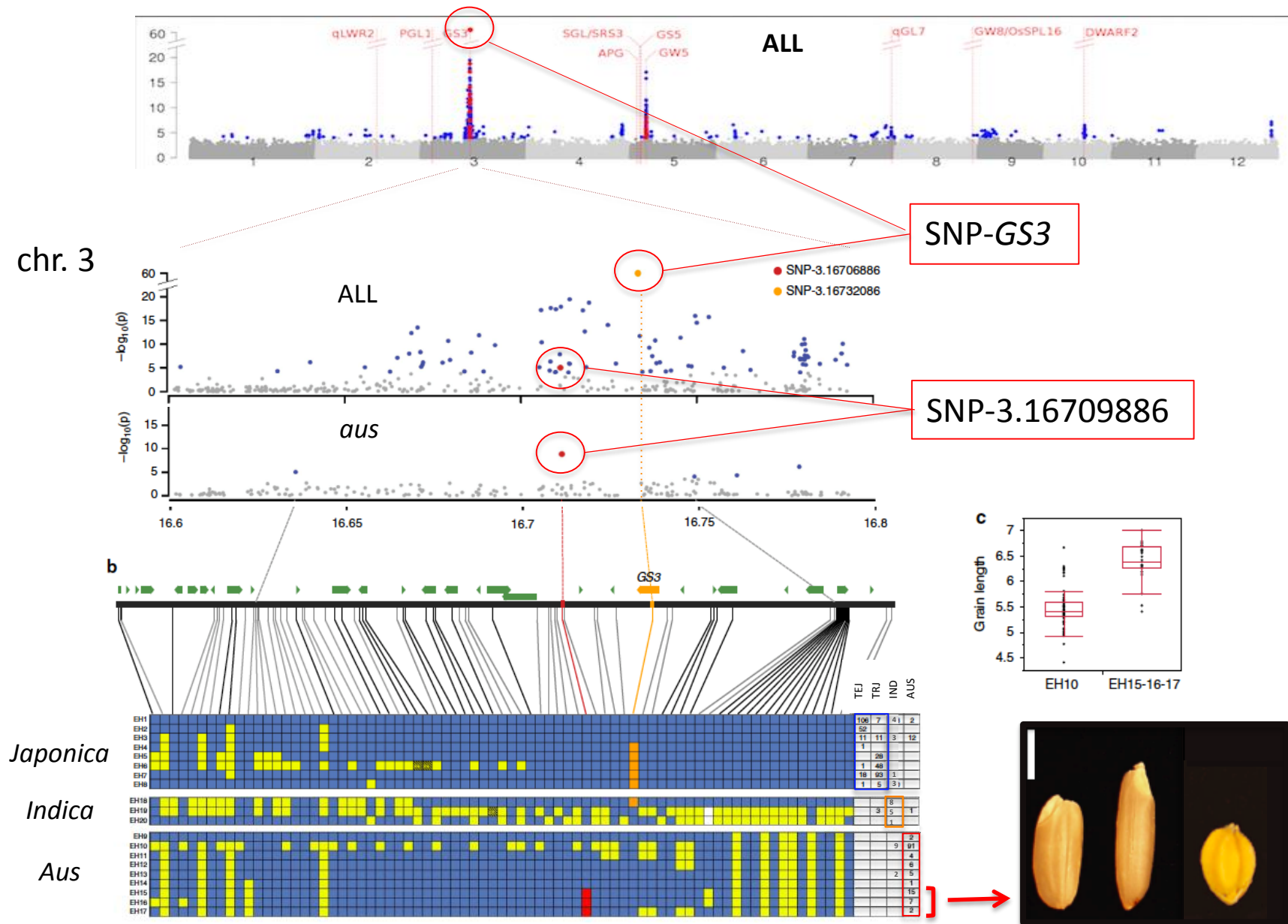
GWAS=> evidence of subpopulation-specific variation

Ex: grain length



McCouch et al., (2016) Open access resources for GWAS in rice. Nat.Comm.

Subpopulation-specific alleles – isolated or shared?



McCouch et al., (2016) Nat.Comm.,

Takano-Kai/Jiang et al., (2013) Breeding Science

Isolated pockets of diversity persist in the hills & valleys



Many local varieties are maintained within a community, some are shared only through traditional networks, others are traded

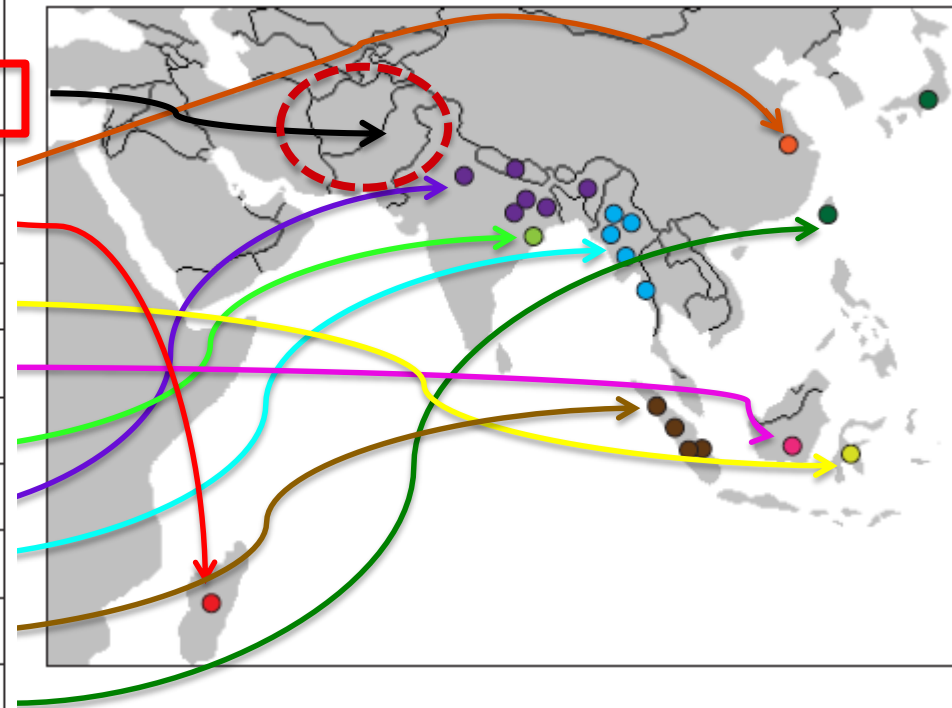


Diverse origins of fragrance



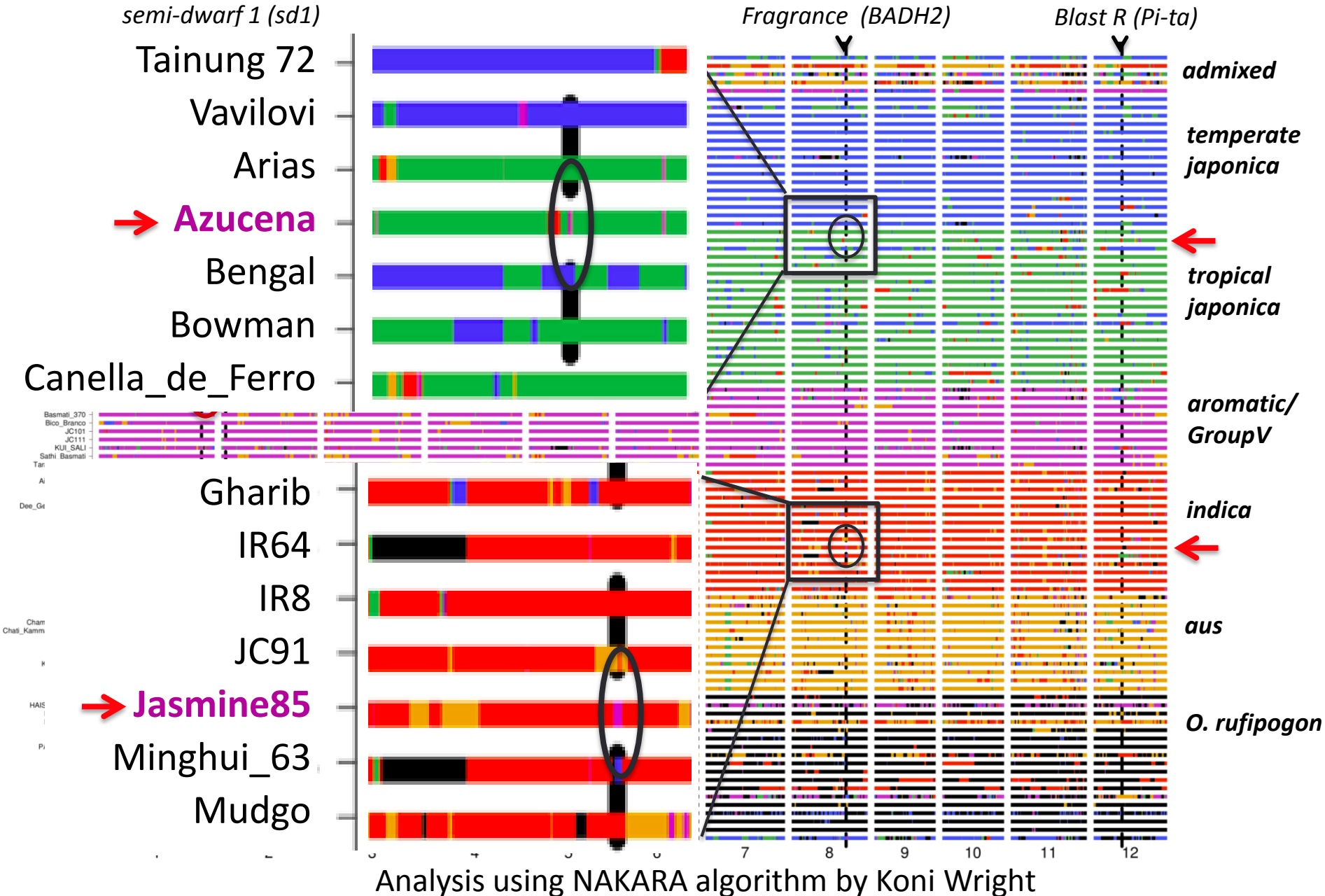
Multiple *BADH2* alleles in locally adapted landraces

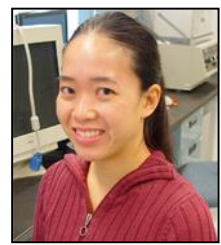
| BADH2 allele | Mutation | N | Sub-populat'n | Aroma [2AP] |
|-----------------|---------------|-----|---|-------------|
| Wild Type | | 149 | ALL | < 0.05 |
| <i>badh2.1</i> | FNP | 93 | Group V (aromatic) <i>indica</i> <i>tropical japonica</i> | 0.70 ± 0.41 |
| <i>badh2.2</i> | 7bp deletion | 1 | <i>tropical japonica</i> | 0.66 |
| <i>badh2.3</i> | 2bp deletion | 1 | <i>tropical japonica</i> | 0.74 |
| <i>badh2.4</i> | 1bp insertion | 1 | <i>tropical japonica</i> | 0.59 |
| <i>badh2.5</i> | 1bp deletion | 1 | <i>indica</i> | 0.70 |
| <i>badh2.6</i> | G→T SNP | 1 | <i>aus</i> | 0.41 |
| <i>badh2.7</i> | 1bp insertion | 6 | <i>aus</i> | 0.43 ± 0.17 |
| <i>badh2.8</i> | 3bp insertion | 5 | Group V (aromatic) | 0.36 ± 0.14 |
| <i>badh2.9</i> | G→T SNP | 6 | <i>tropical japonica</i> | 0.18 ± 0.08 |
| <i>badh2.10</i> | C→T SNP | 2 | <i>tropical japonica</i> | 0.35 |



Predominant allele from *basmati* found in ~65% of aromatic accessions today

Population structure & admixture in *O. sativa*





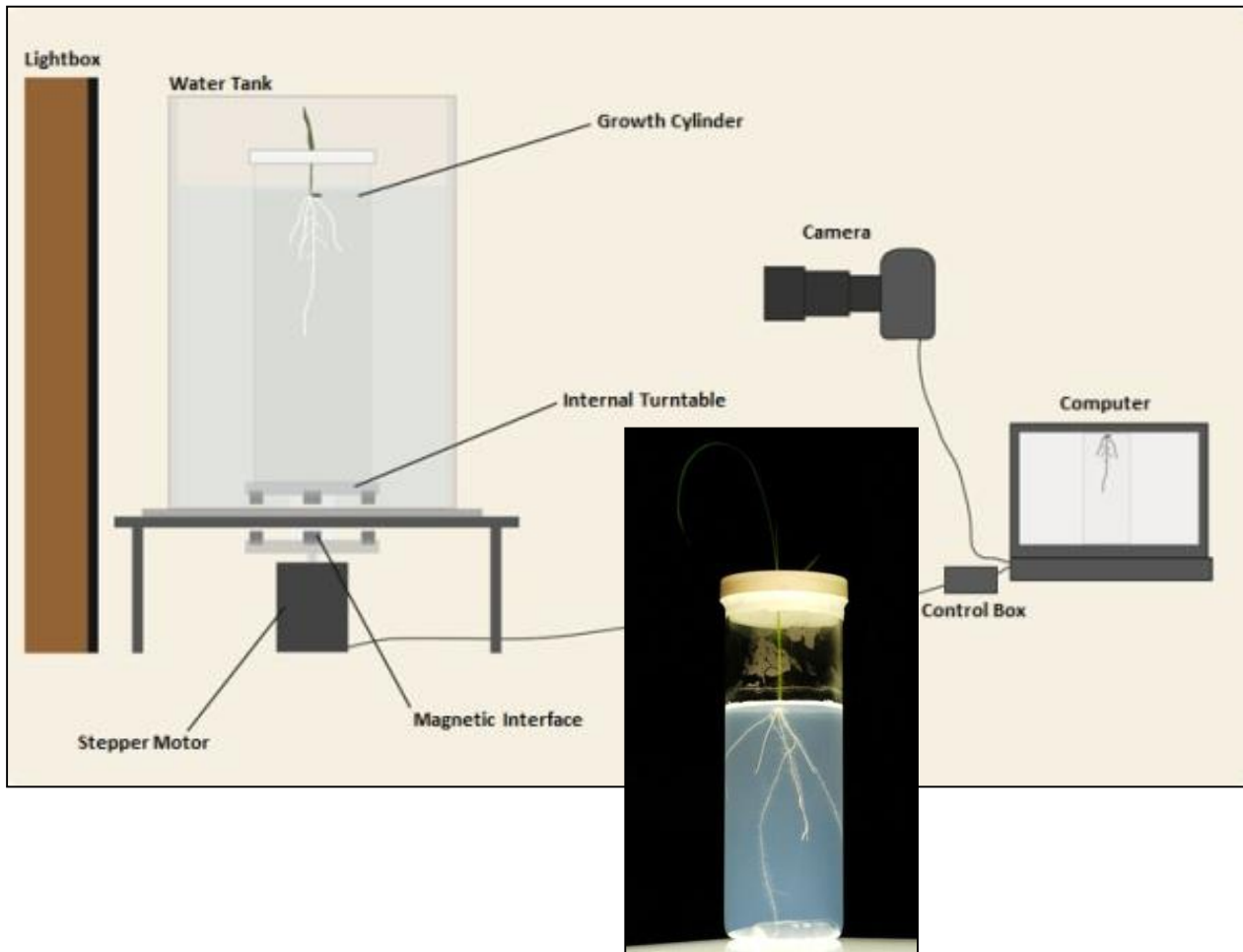
Janelle Jung

3D Root System Architecture

3D Phenotyping Platform



Randy Clark



- **Image & Analysis**
 - Sequence of 40 images per plant
 - Imaged at Day 3, 6, 9,
 - RootReader3D Software

3D Root System Architecture (RSA)

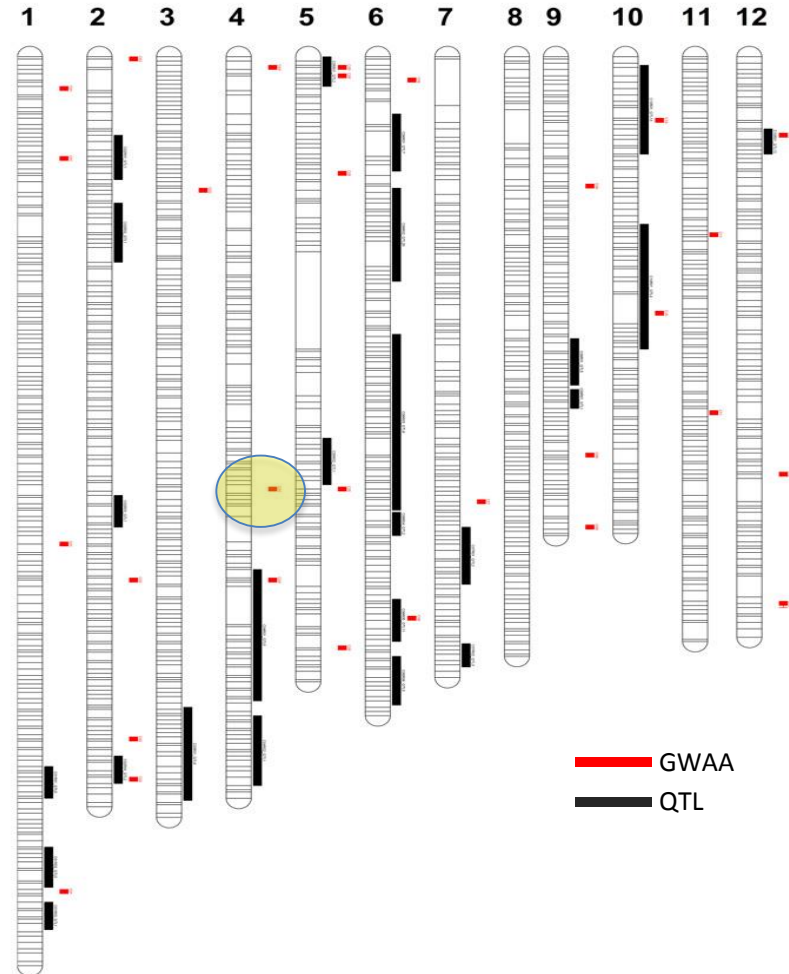
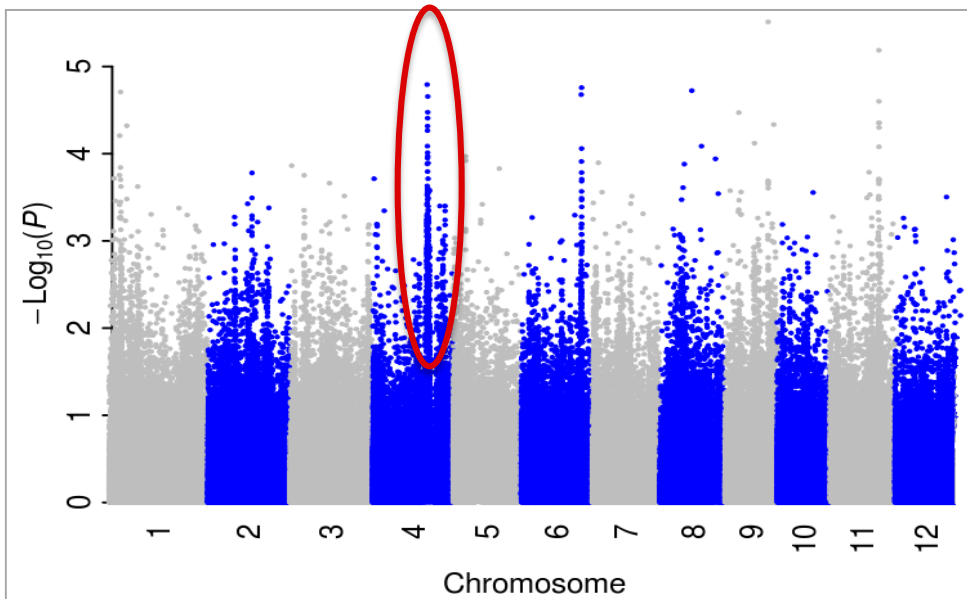


Randy Clark

Genome Wide Association Analysis

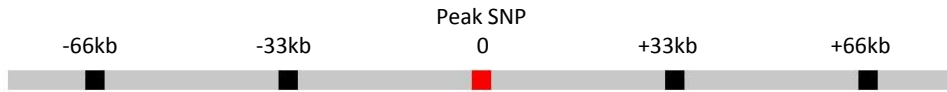
- 380 individual single trait analyses:
 - 13 traits x 3 days x 4 subpopulations
- Significant regions found for each analysis.
- Global, local and dynamic characteristics

Region significantly correlated with rooting depth in *indica*

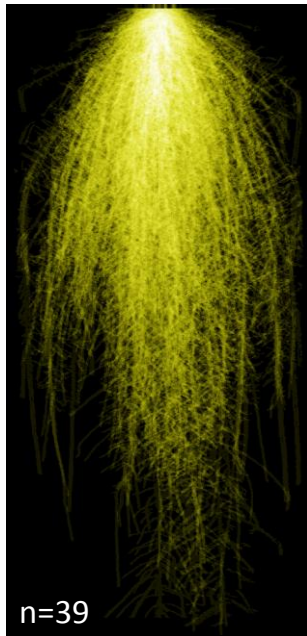


GWAS for Root System Architecture

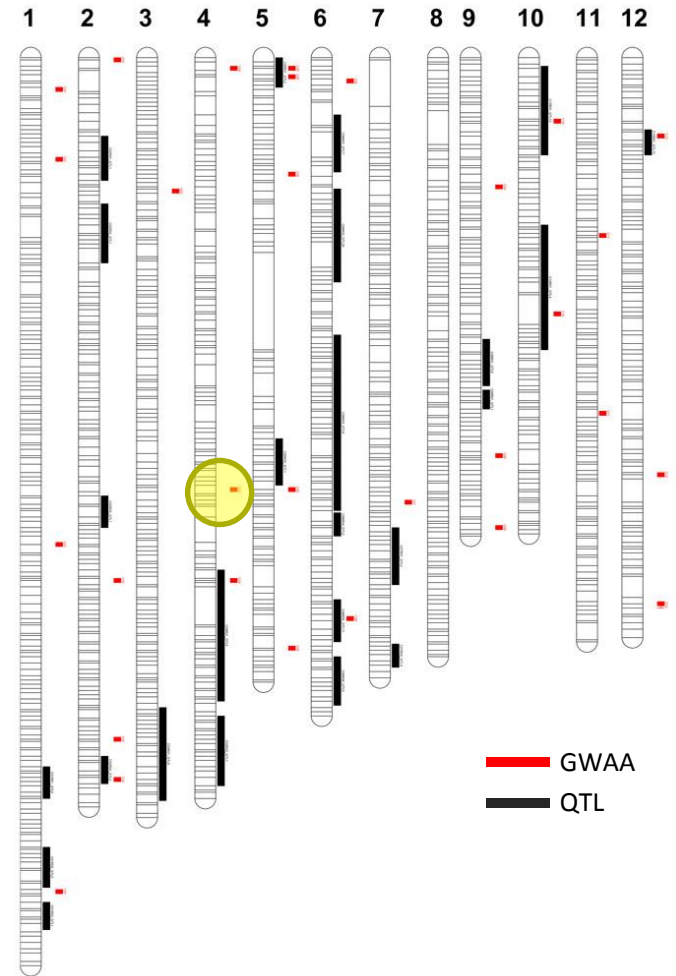
Indica subpopulation



“A”
SNP Allele

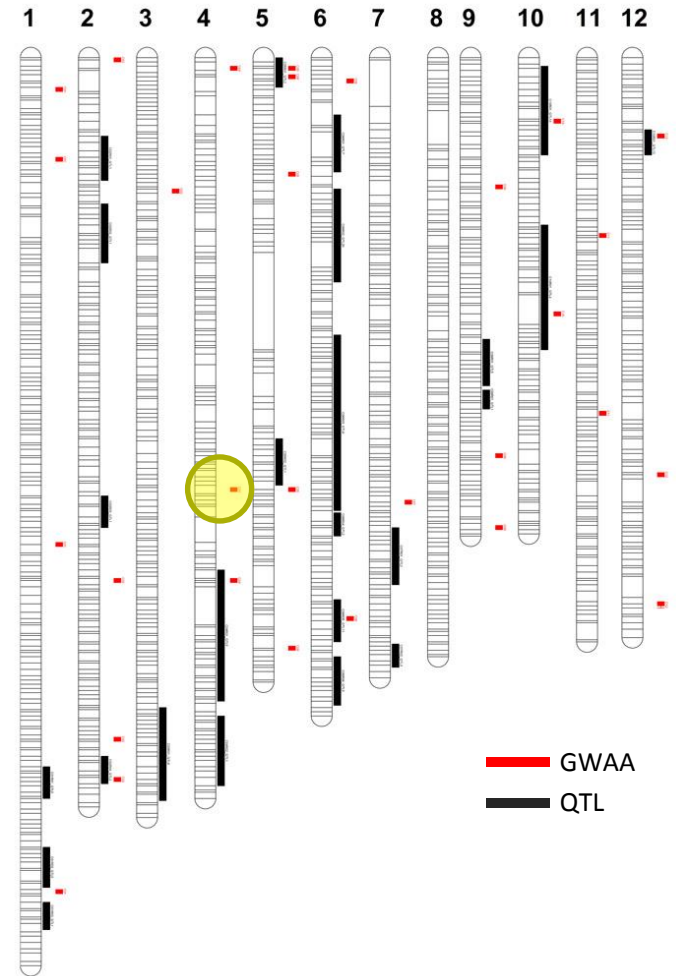
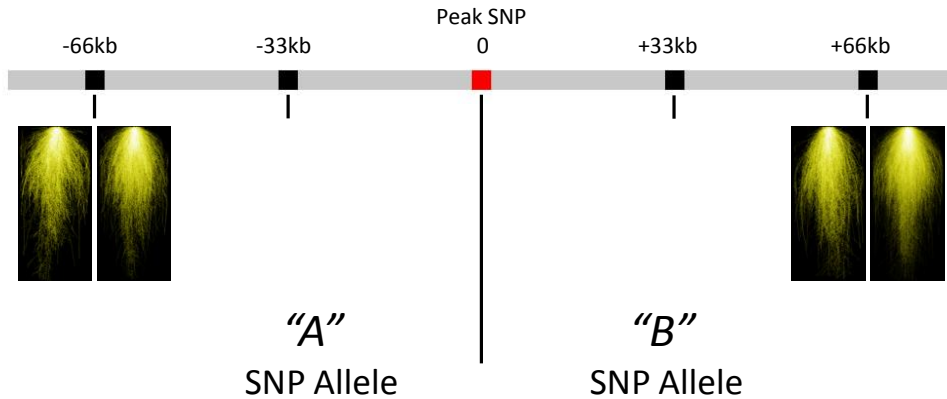


“B”
SNP Allele



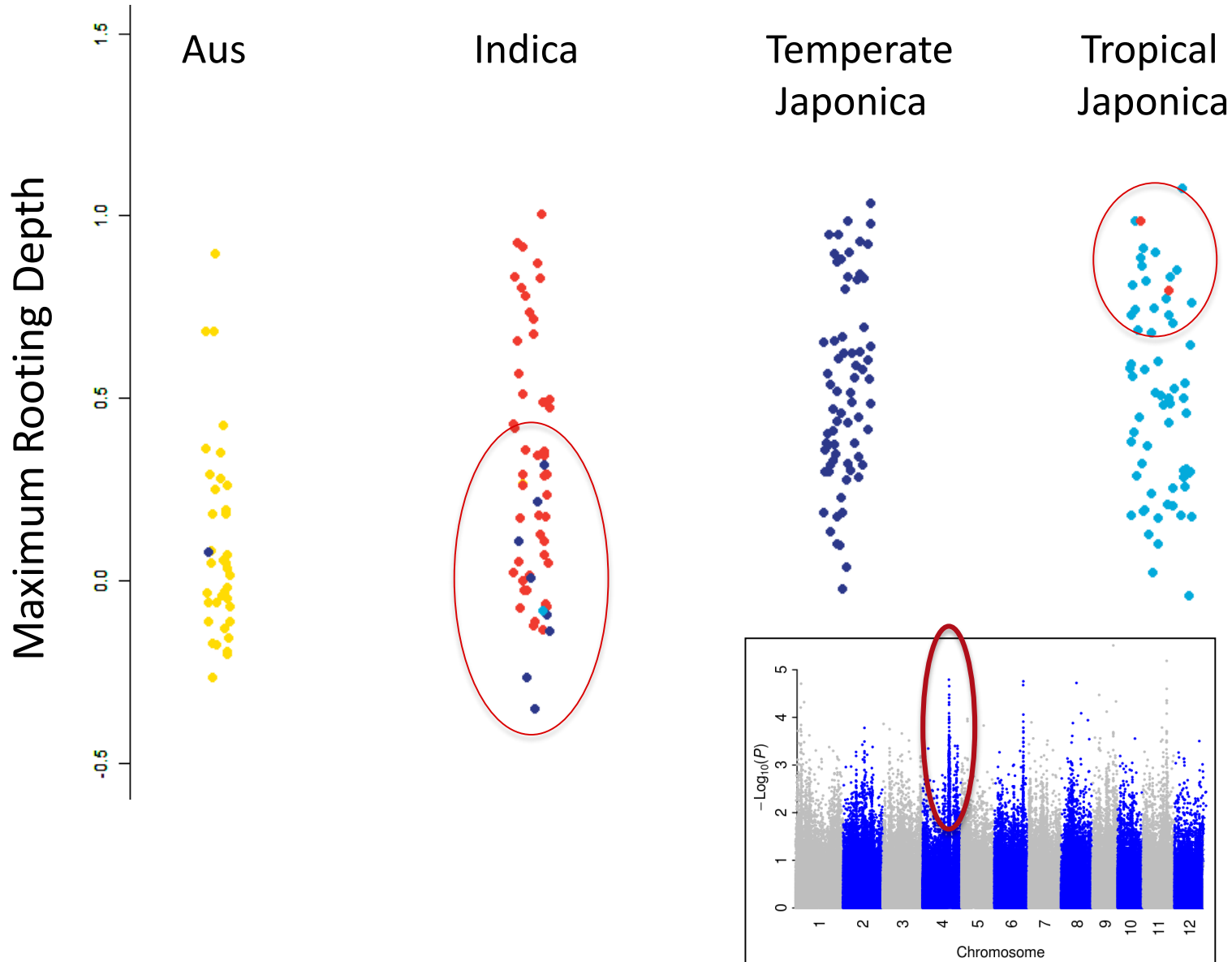
GWAS for Root System Architecture

Indica subpopulation



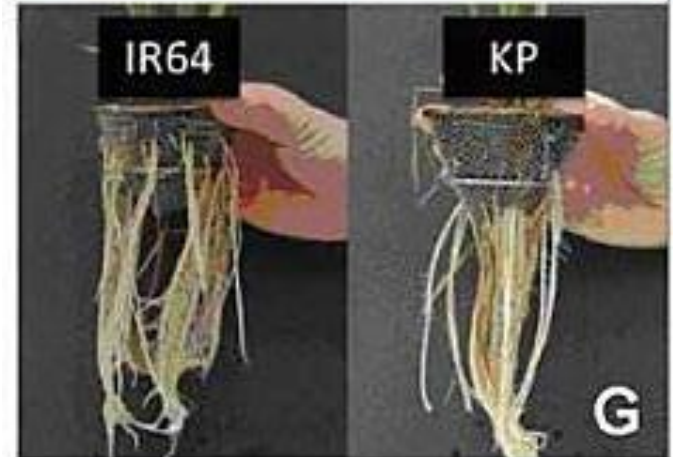
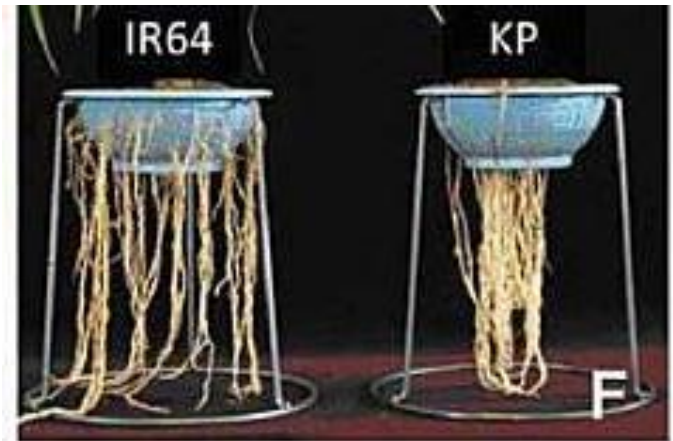
GWAA
QTL

Sub-population introgression at target SNP



Co-localization of genes/QTLs - field & hydroponics

DRO1 & *Pistol1*, rice genes controlling root system architecture => enhance yield under drought & phosphorus uptake in low-fertility soils



Uga et al. (2011) TAG;

Gamuyao et al. (2012) Nature

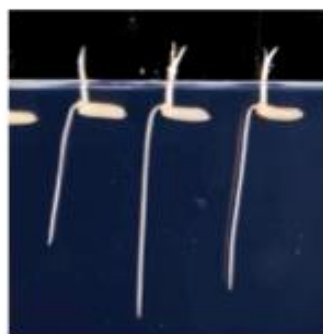


***DRO1* = single bp deletion in exon 4 changes root angle & enhances grain yield under drought**

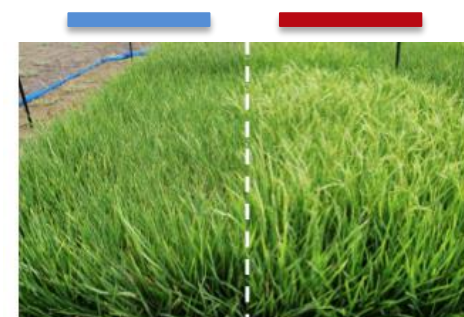
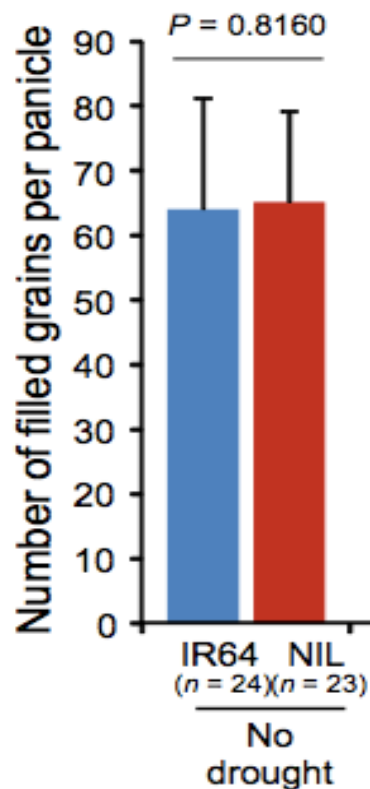
Marker-assisted selection (MAS) => NILs



1 (RNAi)



3 (KPg-Mc)



IR64

IR64-Dro1



IR64

IR64-Dro1

DRO1 expression positively correlated with root gravitropism, abundant in root meristems, responsive to auxin, localized to plasma membrane when introduced into protoplasts.

MAS vs Genomic Selection

Large-effect loci effectively targeted by MAS in rice;
what about the many small-effect QTLs?

Yield

Grain quality

Disease and insect resistance

Plant architecture

Flowering time

Heat /cold tolerance

Submergence / drought tolerance

Micronutrient deficiency / toxicity



Developing GS models in rice

IRRI, Philippines

331 advanced *indica* inbred lines from the irrigated rice breeding program

Replicated Yield Trial (RYT):

4 years: 2009-2012

2 seasons: dry and wet

IRRI, Los Baños, Philippines

73K SNPs (GBS)

11 traits

INIA, Uruguay

311 tropical *japonica* elite

Uruguayan varieties

- 12 half-sib families

Replicated Yield Trial (RYT)

- 3 years: 2010-2012

- Treinta y Tres, Uruguay

40K SNPs (GBS)

8 traits

Heritabilities & Prediction Accuracies

| IRRI (tropics) | | |
|----------------|---------|--------|
| Trait | Season | h^2 |
| YLD | DS 2012 | 0.3213 |
| PH | DS 2012 | 0.3546 |
| FL | DS 2012 | 0.4378 |

| Trait | Training Population | Validation Population | Statistical Method | Accuracy |
|-----------|---------------------|-----------------------|----------------------------|----------|
| Yield | 2009-2011 all | 2012 DS | RR-BLUP | 0.3044 |
| Plant Ht | 2009-2011 DS | 2012 DS | Random Forest | 0.3411 |
| Flowering | 2009-2011 DS | 2012 DS | Multiple Linear Regression | 0.6270 |

Accuracy of models used for GS (IRRI)

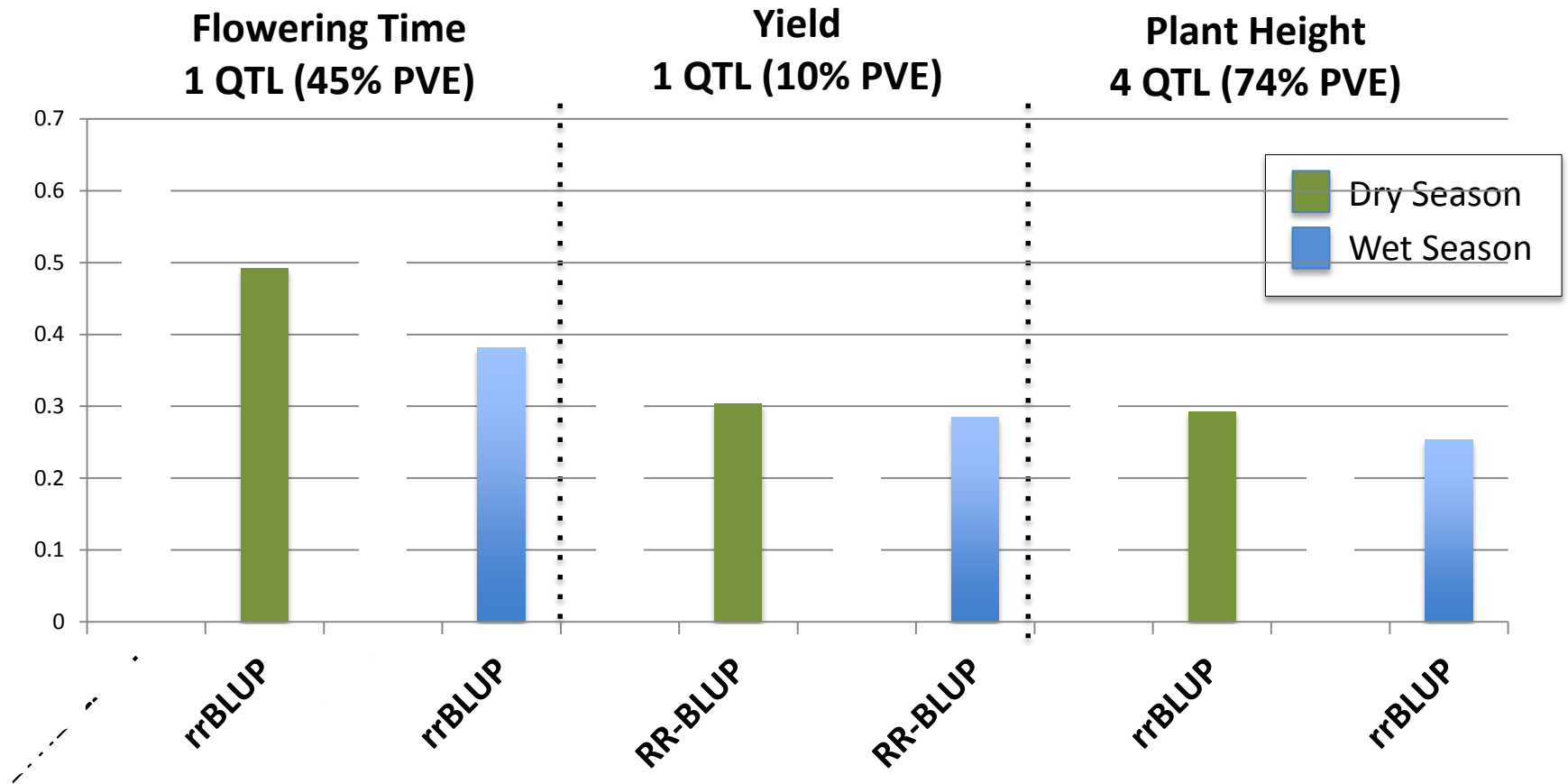
Spindel et al. PLoS Genetics (2015)

1. **RR-BLUP** – linear, parametric & frequentist
2. **Reproducing Kernel Hilbert Spaces (RKHS)** – linear, semi-parametric
3. **Random Forest** – machine learning
4. **Bayesian Lasso** – linear, parametric & Bayesian
5. **Multiple Linear Regression (MLR)** – a subset of significant markers chosen to fit a linear model
6. **Pedigree** –kinship BLUP used with pedigree A-matrix alone

| Trait | VP | stat method | accuracy |
|-------|---------|----------------------|----------|
| YLD | 2012 DS | ^A RR-BLUP | 0.3044 |
| YLD | 2012 DS | ^A RKHS | 0.2596 |
| YLD | 2012 DS | ^A RF | 0.2458 |
| YLD | 2012 DS | ^B ped | 0.2146 |
| YLD | 2012 DS | ^C BL | 0.1358 |
| YLD | 2012 DS | ^D MLR | -0.0599 |
| YLD | 2012 WS | ^A RF | 0.3136 |
| YLD | 2012 WS | ^A RR-BLUP | 0.2852 |
| YLD | 2012 WS | ^A RKHS | 0.2399 |
| YLD | 2012 WS | ^B ped | 0.1904 |
| YLD | 2012 WS | ^C BL | 0.0876 |
| YLD | 2012 WS | ^D MLR | 0.0095 |
| FL | 2012 DS | ^D MLR | 0.6270 |
| FL | 2012 DS | ^A RF | 0.6093 |
| FL | 2012 DS | ^A RR-BLUP | 0.4919 |
| FL | 2012 DS | ^A RKHS | 0.4865 |
| FL | 2012 DS | ^C BL | 0.4536 |
| FL | 2012 DS | ^B ped | 0.3997 |
| FL | 2012 WS | ^D MLR | 0.5400 |
| FL | 2012 WS | ^A RF | 0.4187 |
| FL | 2012 WS | ^A RKHS | 0.3872 |
| FL | 2012 WS | ^A RR-BLUP | 0.3808 |
| FL | 2012 WS | ^C BL | 0.3237 |
| FL | 2012 WS | ^B ped | 0.2071 |

GS Prediction Accuracies

5-fold cross-validation (CV)

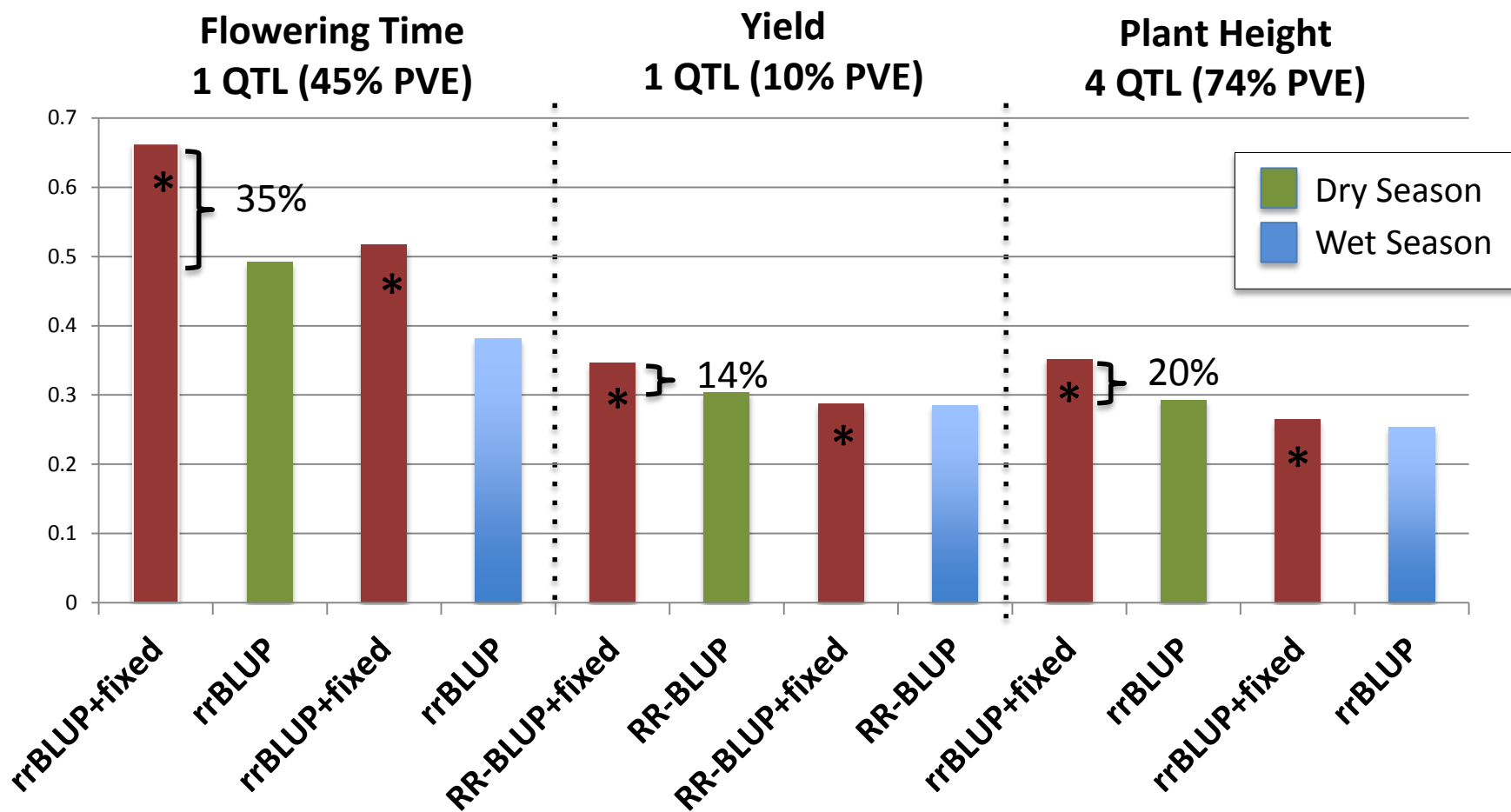


Prediction accuracies equivalent to trait heritabilities (h^2)



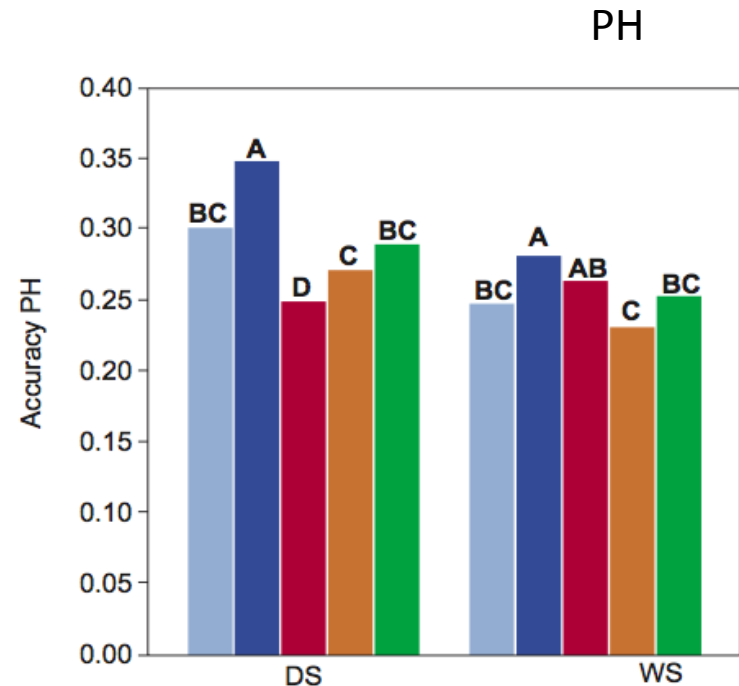
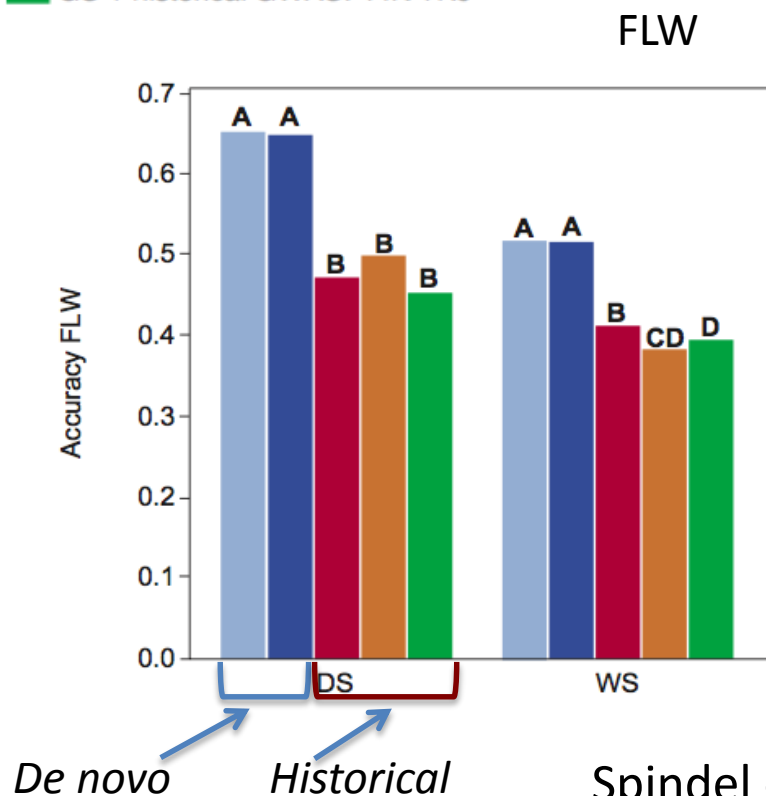
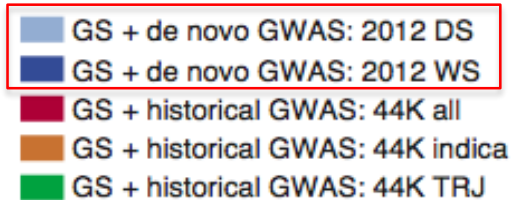
GS Prediction Accuracies

significantly improved using GWAS information



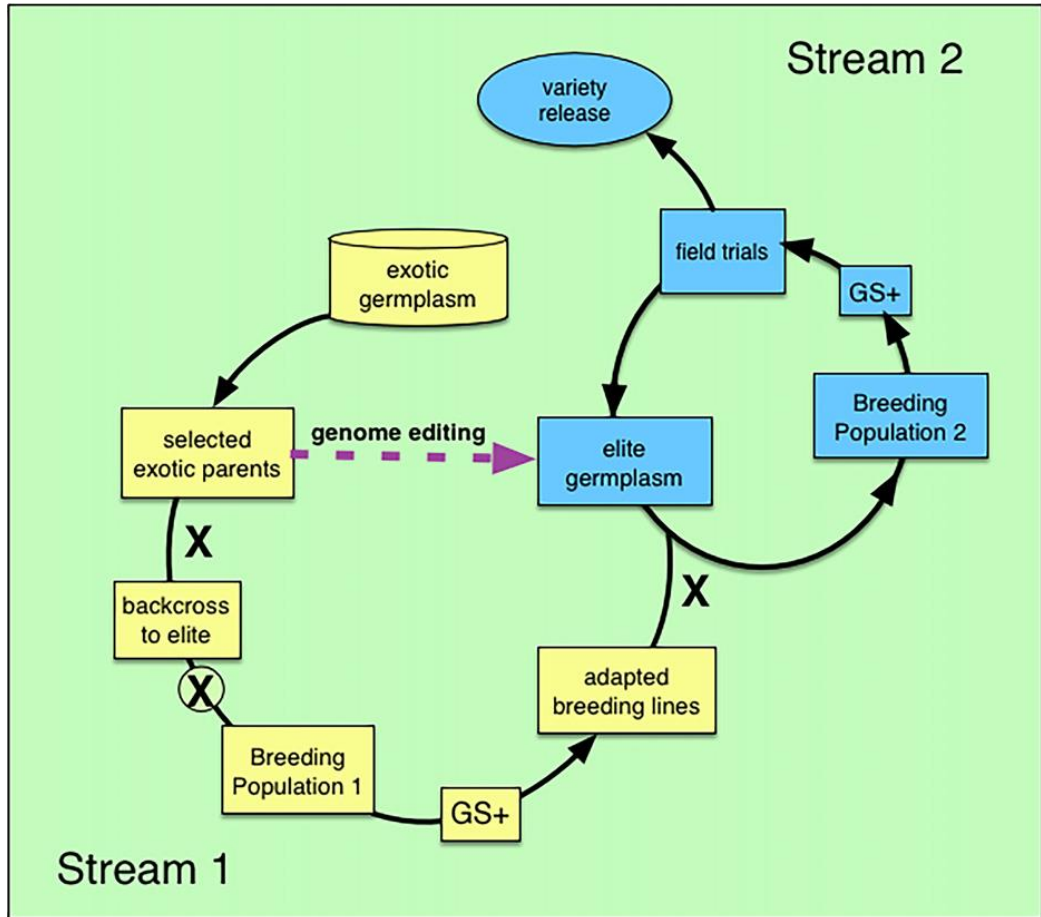
GS + *de novo* GWAS versus GS + historical GWAS

de novo GWAS on breeding population better than blindly using “candidate genes” from literature



Spindel et al. Heredity (2016)

GWAS + GS => facilitate/ accelerate introgression of 'exotic' variation into elite breeding pools



Linking GWAS & GS to better utilize natural variation in rice?

- GWAS is helping develop a Genotype => Phenotype road map to accelerate trait /gene discovery in rice
- Genetic architecture of most complex traits in rice involves alleles of large effect (GWAS) and genes of small effect (GS); different genes/ alleles important in different populations (wild & cultivated)
- Use of *de novo* GWAS + GS => weights alleles of large effect and enhances accuracy of genome-wide prediction.

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