Mining, Understanding, and Utilizing Adaptive Alleles



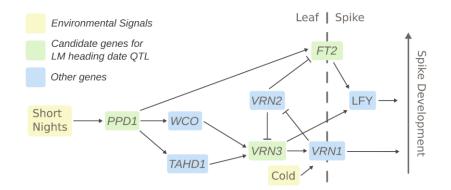
Heading Date

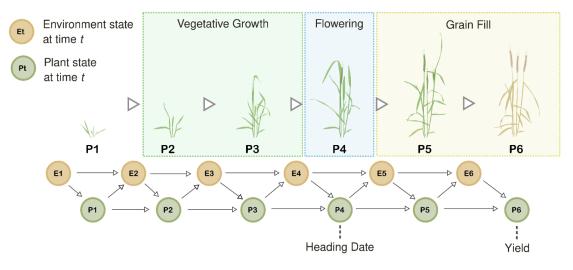
- Heading date variation indicator of variation in plant development rate
- RIL population LA96135 x MPV57 to seg for PH/HD genes
 - Large population: 348 RILs
 - o Known HD gene Ppd-D1
 - Novel variants in FT-2A and Vrn-A3
 - Mature PH genes Rht-D1

and Rht8

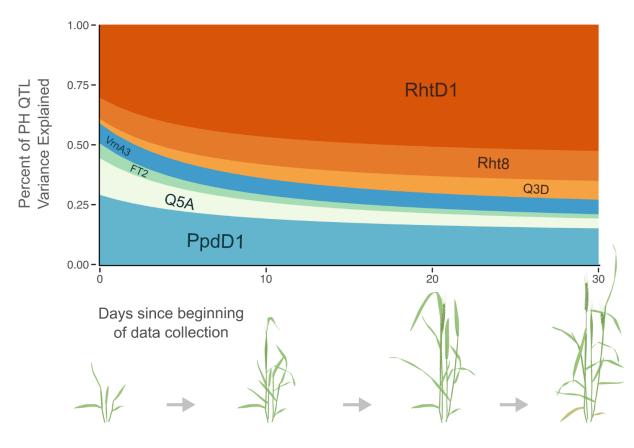
Mohammed Guedira





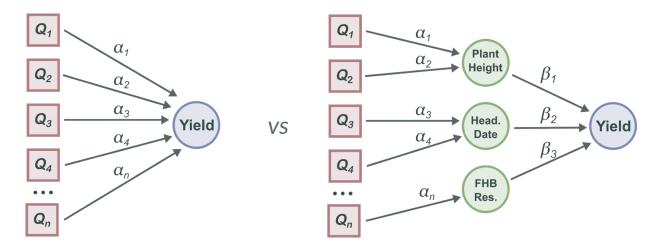


QTL Effects on Plant Growth



- Plant height on each day for each row plot estimated, variance associated with QTL
- Both sets of variants affect plant height in the observed range
- In general, heading date variants explain a comparatively larger proportion of phenotypic variation early on, and plant height variants more later on

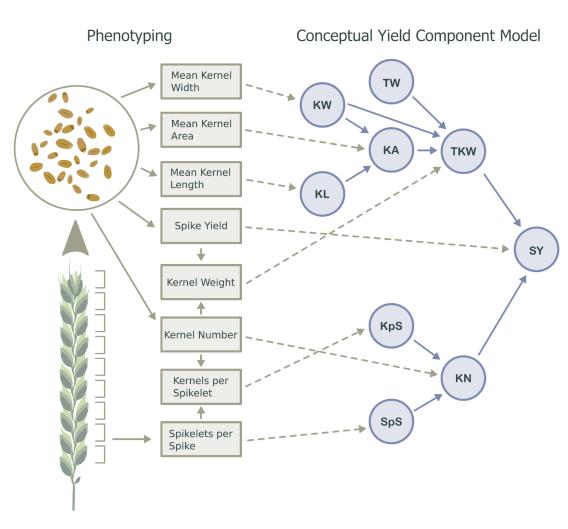
Framework - Break Yield QTL Up



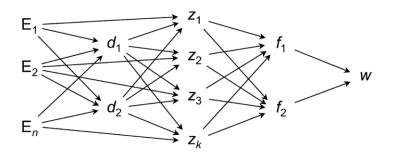
- Estimate a reasonable number of parameters per trait
- Understand mechanisms of yield QTL to use in breeding
 - *E.g.* some yield QTL are disease resistance QTL, which require strategy for use
- βs can represent correlations, "real" models (e.g. crop models), or environmental interactions (covariance between GxE of QTL effects for QTL affecting same trait)

Phenotyping Yield Components

- Focus on total per-spike yield
 - Easier to collect, tiller number has large management effect
- Spike yield broken up into kernel weight (TKW) and kernel number (KN); these both have components



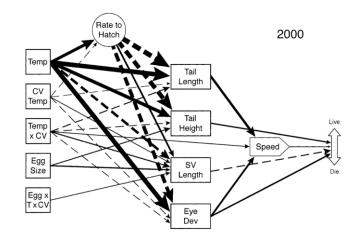
Path Analysis and Structural Equation Modeling



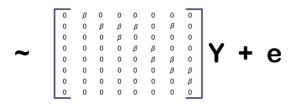
Environment → Development → Morphology → Performance → Fitness



- Fitness results from set of collected phenotypes, genotypes, and environmental variables meant to represent underlying causal processes.
- Variables can have direct effects, and indirect effects mediated by their effects on other variables

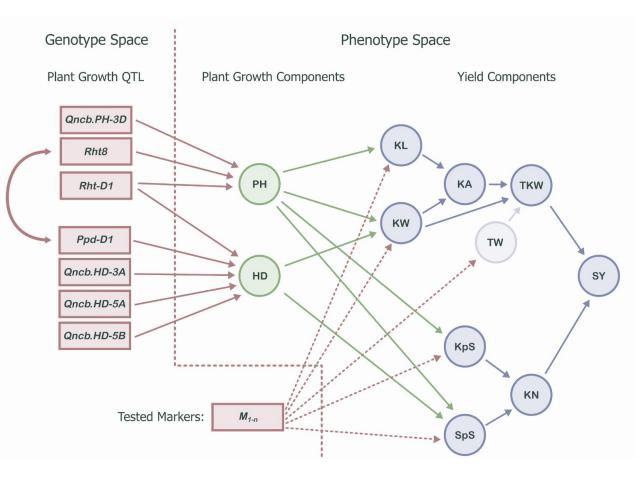


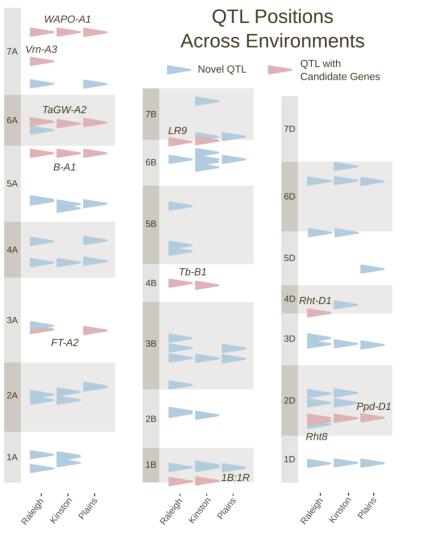
Environment 🔿 Development 🔿 Morphology 🔿 Performance 🔿 Fitness



Mapping Model

- Know causal relationships between phenotypes
- Genetic and non-genetic sources of correlations
- Test weight (kernel density) not observed (so test directly)

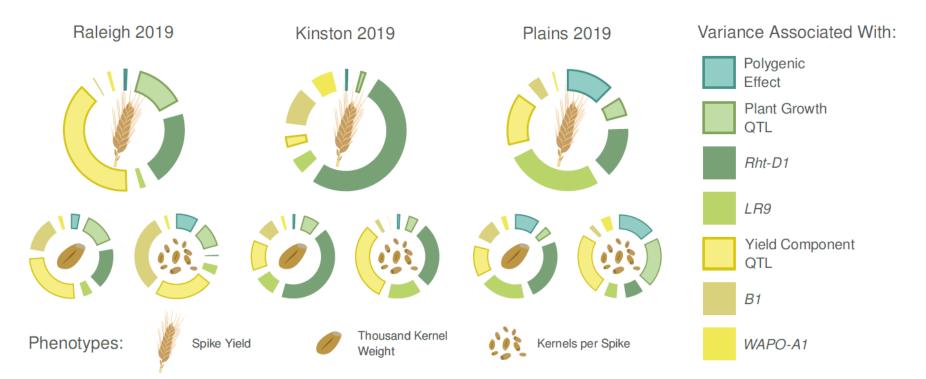




Allele Mining with Multivariate Mapping

- Positions of mapped QTL mostly consistent across environments
- QTL largely evenly distributed across genome
- Heading date/plant height QTL mapped in all three locations, but vary
 - Suggests direct in addition to mediated effects for some major QTL
- Some QTL "clusters" 2D, 6B

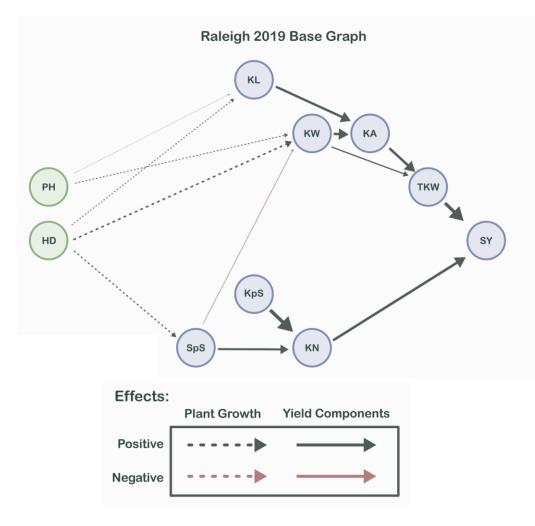
QTL Affect Spike Yield and Components



• Prediction accuracy in LASSO model for spike yield nearly doubles when only use mapped QTL r = 0.50 with only mapped QTL vs r = 0.28 when including all markers

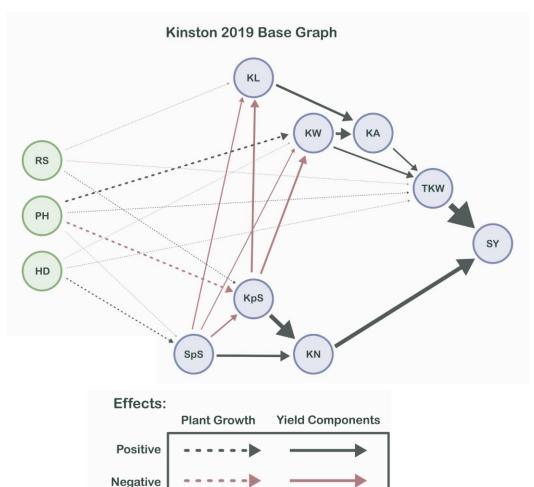
Base Graph

- Raleigh model fit with 10 phenotypes, 11 plant growth QTL, and 14 yield component QTL
- Only phenotype relationships shown here
- Size and color of arrows indicate size and direction of effect, respectively
- In Raleigh, little negative correlations between yield component traits



Base Graph

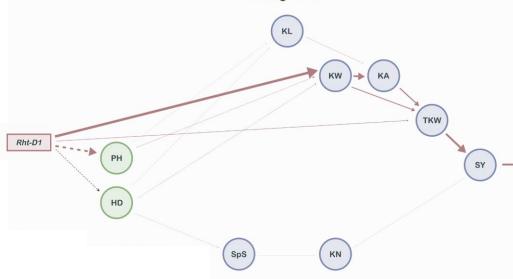
- Same model fit in Kinston, with addition of leaf rust score (RS) disease resistance phenotype
- Less effect of heading date on yield components, but greater effect of plant height
- More negative correlation between base yield components
- With source constraints, increasing kernel number decreases kernel size

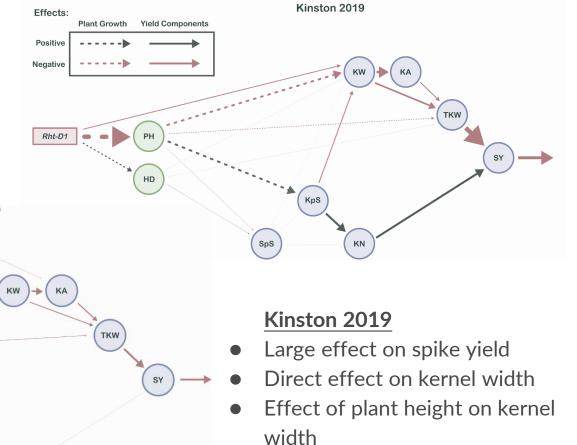


Rht-D1b

Raleigh 2019

- Small effect on spike yield
- Large direct effect on kernel width
- Plant height has a minimal effect on kernel width
 Raleigh 2019

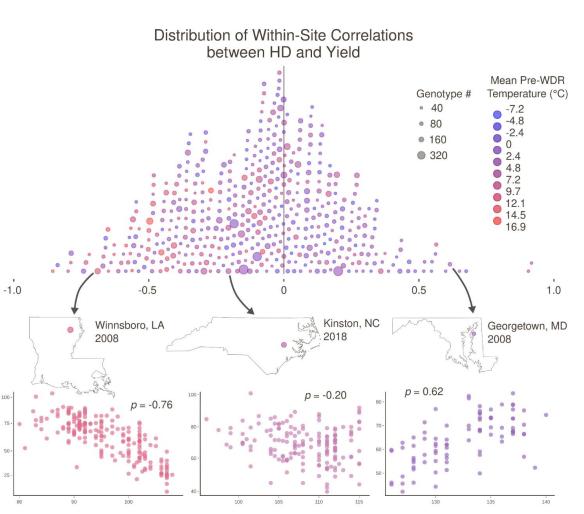




• Compensatory effect on KN

Understanding Mined Alleles

- Across > 350 siteyears, within-siteyear correlation between heading date and yield varies based on environmental factors
- Significantly higher variance in correlations than would be expected by random chance
- Suggests heading date underlies some GxE
 - How do we make use of mined alleles to predict GxE as function of env?

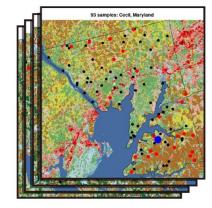


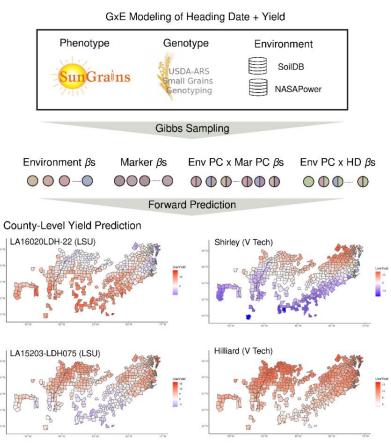


County-Level GxE Prediction

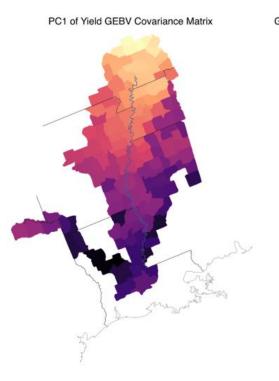
- Target population of environments is farmland (brown) within counties
- Sample soil and weather for forward prediction from SunGrains data

County Sampling and Land Use Characterization





How Do Alleles Drive GxE?



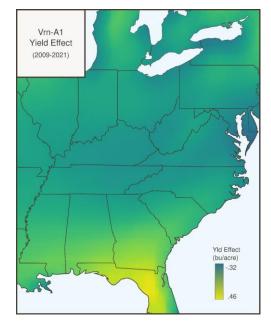
Genomic Estimated Reaction Norms of Louisiana Lines on PC1 Yield GEBVs

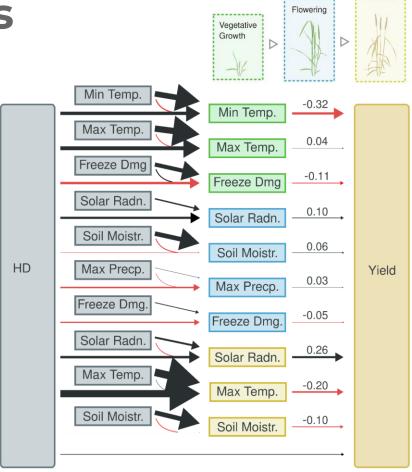
Informed Subjective Mega Environments for Delta Region

- Predict HD rank of all lines w/ markers
- Use HD x Weather interactions to help predict yield improves within-env accuracy
- HD x Weather interactions is primary driver of site-site predicted covariance
 - Improve prediction
 of HD, improve
 prediction of GxE
- Allele mine intermediate traits to improve GxE models

Mediated Yield Effects

- SEM of HD effects on yield as mediated by specific stress variables
- Total mediated effect estimation of Vrn-A1 earliness allele on yield across 10 years





Grain Fill

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USDA-ARS Small Grains Genotyping





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RECRUITING FOR FALL 2023!

