

# High throughput phenotyping and its role in a strategy for improving complex traits

Fred van Eeuwijk & EU-SPICY consortium

PhenoDays, Wageningen, October 2011



# Smart tools for Prediction and Improvement of Crop Yield

New genotype-to-phenotype models  
at the intersection of  
genetics, physiology and statistics



# Aim EU project SPICY (KBBE-2008-211347)

- **Predictive models** for phenotypic variation in complex traits
  - Take into account
    - a range of environmental conditions
    - multiple traits
    - developmental time
  - Use as input
    - molecular marker variation
      - DNA polymorphisms
    - environmental inputs
      - temperature, humidity, light, nutrients, ...
    - genomic information
      - gene expression, metabolites, proteins, ...
    - intermediate phenotypes / approximate phenotypes
      - image analysis, fluorescence measurements

# SPICY participating organizations & PI's

- Wageningen University (WU) – WP 0/2/3/4
  - F.A. van Eeuwijk
- Plant Research International (PRI) – WP 0/2/3/4
  - A. Dieleman
- Institut National de la Recherche Agronomique (INRA) – WP 1/3
  - A. Palloix
- Flemish Institute for Biotechnology (VIB) – WP 1/5
  - M. Vuylsteke
- Estación Experimental de la Fundación Cajamar (EEFC) WP 2/4
  - J. Magán
- Budapest University of Technology and Economics (BME) – WP 2
  - A. Barócsi
- Scottish Crop Research Institute (SCRI) – WP 2
  - C. Glasbey
  
- 0 = coordination; 1 = genomics; 2 = phenotyping; 3 = modeling; 4 = validation; 5 = dissemination

# Industrial Advisory Board

## ■ Participating companies

- ENZA
- LemnaTec
- Limagrain
- Monsanto
  - De Ruiter
  - Seminis
- Nunhems
- Ramiro Arnedo
- Rijk Zwaan
- Syngenta

## ■ Tasks

- At start project
  - Discussing aims and deliverables
- During project
  - Discussing results in relation to current developments in the European breeding industry & suggesting improvements



- MAIN MENU
- ▶ Home
  - ▶ Project
  - ▶ Partners
  - ▶ Agenda
  - ▶ Output
  - ▶ Intranet

WELCOME TO THE SPICY WEB

Welcome

This website was generated to provide both the scientific community and the general public background information about the SPICY project.

The aim of the **Smart** tools for **Prediction** (and) **Improvement of Crop Yield** project is to develop a suite of tools based on molecular breeding to help breeders in predicting phenotypic response of genotypes for complex traits like yield under a range of environmental conditions.

The project particularly focuses on developing tools for predicting phenotypic performance (growth, yield) of a genotype by means of an integrated gene-to-phenotype model, thereby reducing the effort of phenotyping new genotypes. This will be achieved by extending a crop growth model with a separation between species specific and genotype (variety, line) specific parameters and the development of smart tools for integrating QTL analysis with crop growth models. In addition, gene expression studies will try to identify genes within the QTL while imaging and fluorescence tools will be developed for fast and automated large scale phenotyping.



SPICY is supported by the European Community and funded by the KBBE FP7 programme. (Grant agreement number *KBBE-2008-211347*)

# Philosophy of SPICY

- Dissect complex traits (yield) with context dependent variation into **component traits** that
  - do not show strong context dependencies
    - no QTLxE, no QTLxQTL, no QTLxQTLxE
  - can be integrated with environmental information over the growing season to produce yield
    - which Genotype-to-Phenotype (G2P) model to use?
  - have relatively simple genetic basis
    - few additive genes/QTLs

# G2P models, more generally

- G2P models predict the phenotypic performance of organisms on the basis of genetic, genotypic, genomic and environmental information
- G2P models help in defining strategies for improvement of plant performance

# Some G2P models (ignoring error variation)

- $P = G + E + G \times E$

- $G \times E$  = genotype by environment interaction

- $P = G + \beta Z$

- $Z$  = environmental quality

- $P = f(\mathbf{G}, \mathbf{Z})$

- $f$ : non-linear function
- $\mathbf{G}$ : vector of genotype related parameters
- $\mathbf{Z}$ : environmental triggers/ inputs

- $P_t = \int f_t(\mathbf{G}_t, \mathbf{Z}_t) dt$

- as above, but now with integration over time to account for development

# Some QTL models as G2P models

- $P = \text{QTL} + \text{residual G} + \text{error}$
- $P = \sum \text{QTL} + \sum (\text{QTL} \times \text{QTL}) + \text{residual G} +$ 
  - $E +$
  - $\sum (\text{QTL} \times E) + \text{residual G} \times E +$
  - $\text{error}$
- $P = \text{QTL} + \text{residual G} +$ 
  - $E +$
  - $\text{QTL} \times E_{(\text{environmental covariable})} + \text{residual QTL} \times E +$
  - $\text{residual G} \times E +$
  - $\text{error}$

# QTL by Environment interaction: genetic basis GEI

- Model for fitting environment-specific QTL effects;
  - $P = E + GGE = E + \Sigma(QTL_E) + \varepsilon$ 
    - GGE random
    - $VCOV(\varepsilon) = VCOV(GGE) =$  factor analytic
- Eco-physiological QTL model
  - Regression of environment specific QTL on environmental information
  - $QTL_E = QTL(Z_E) + \delta$

# G2P models

- Statistical genetic models (REML and Bayesian mixed models)
  - multi-trait multi-environment QTL models/ hierarchical models
  - models for QTL x E, QTL x QTL, QTL x genetic\_background
- Crop growth models
  - ordinary differential equation models
  - mechanistic model with modules for morphology, leaf area, photosynthesis, assimilate partitioning, nutrient dynamics and fruit growth dynamics
- Integration of statistical genetic and crop growth models
  - express individual physiological parameters in crop growth models in terms of underlying QTLs
  - impose network relations on multi-trait QTL models using prior physiological knowledge (Bayesian belief networks)

# SPICY: phenotyping and molecular tools

- New phenotyping tools:
  - Image analysis tool (BIOSS and WUR)
  - Fast fluorescence tool (Univ Budapest)
- Role of image analysis/ fluorescence
  - Provide proxies to physiological components
  - Provide G2P inputs with high heritability (cf. correlated response theory)
  - Give details of the growing process over time to help in development of G2P models (provide a genotype specific movie)
- New molecular tools:
  - Approaches for finding candidate genes (INRA + VIB)
    - bio-informatic strategies on gene data bases of related species
  - eQTL mapping & genetic pathway reconstruction
    - co-localization of QTLs for gene expression, eQTLs, and QTLs for physiological parameters

# Phenotyping experiments

## ■ Genotypes

- RIL-population, 149 genotypes
- Parents: Yolo Wonder, CM 334
- F1



## ■ Two locations

- Netherlands (Wageningen) & Spain (Almería)

## ■ Two seasons

- Spring & Autumn



# Relevant measurements

## ■ Crop measurements

- Plant weight (stem, leaves, fruit; initial and final)
- Number of internodes
- Leaf area (initial and final)
- Fruit harvest (number, weight)



## ■ Environment

- Temperature
- Radiation

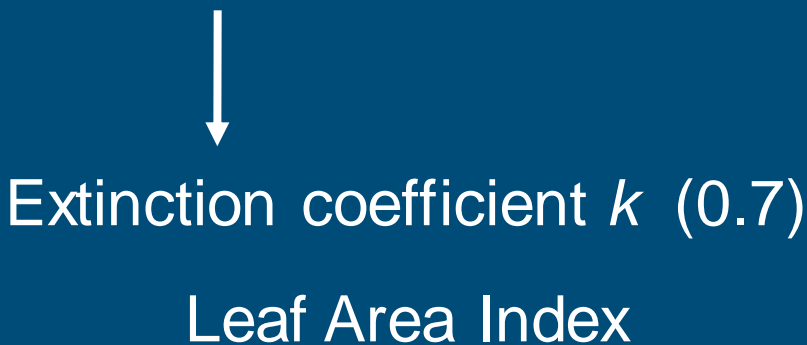


# 'Simulating' yield from identified QTLs

Yield of sweet pepper ( $\text{g m}^{-2}$ )

Maaïke Wubs  
Ep Heuvelink

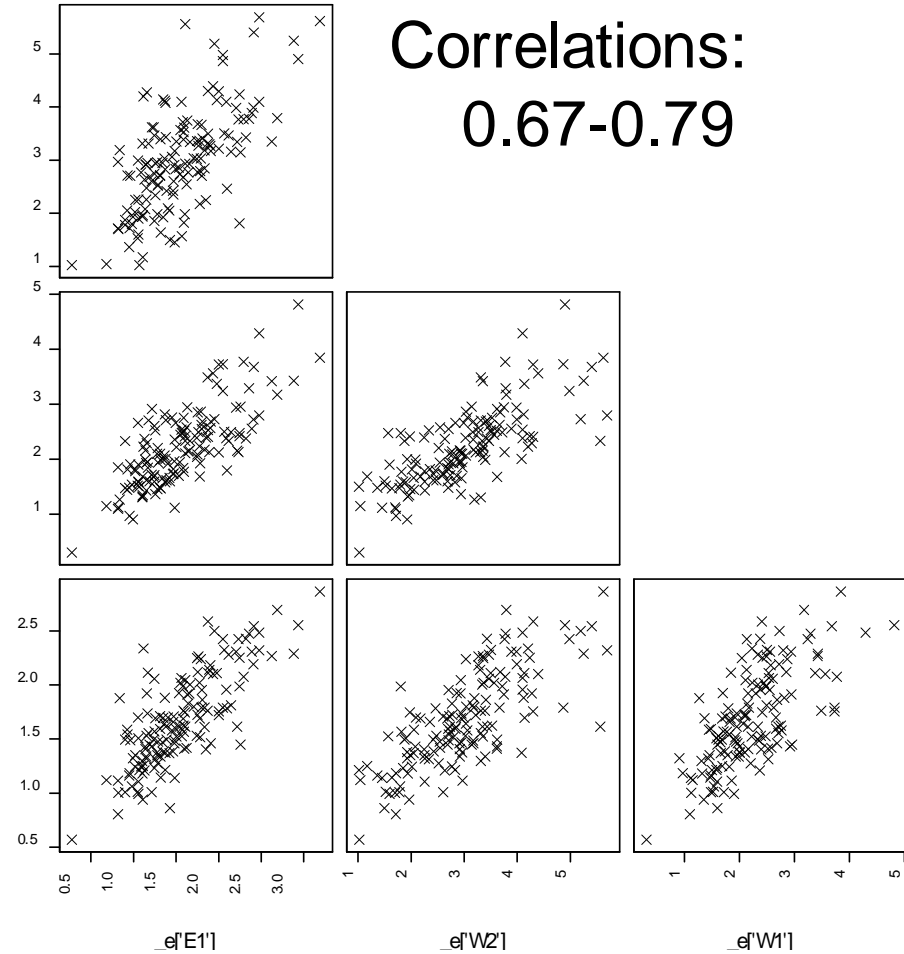
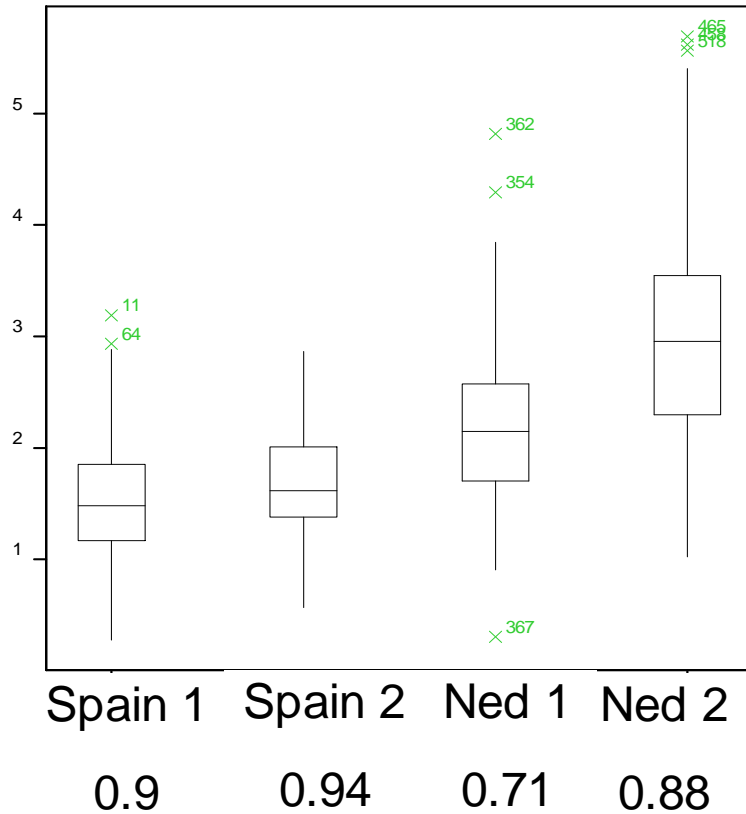
Yield = total biomass production \* Partitioning into fruits



$$I_{\text{int}} = I_0 * (1 - e^{-k * LAI})$$



# Leaf development rate



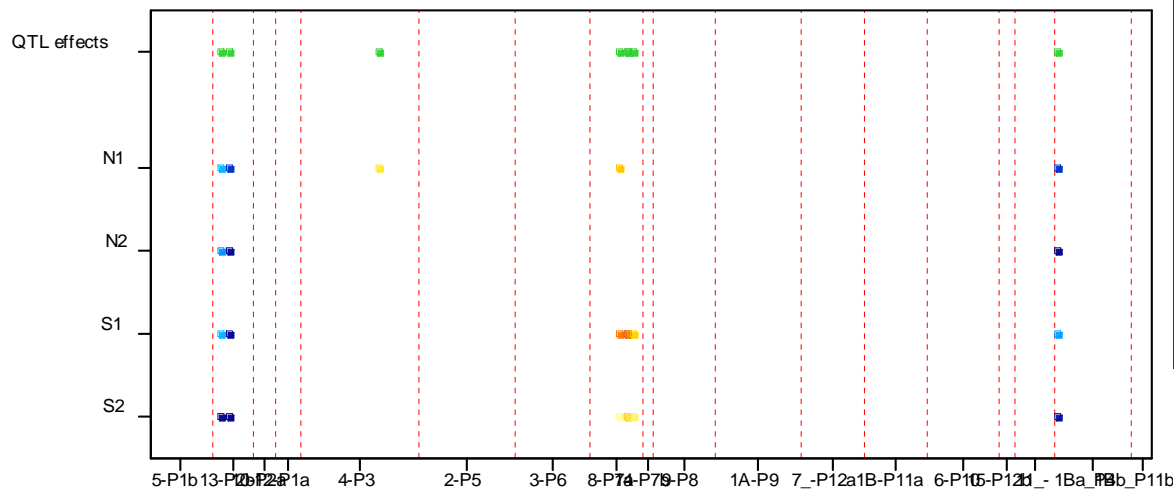
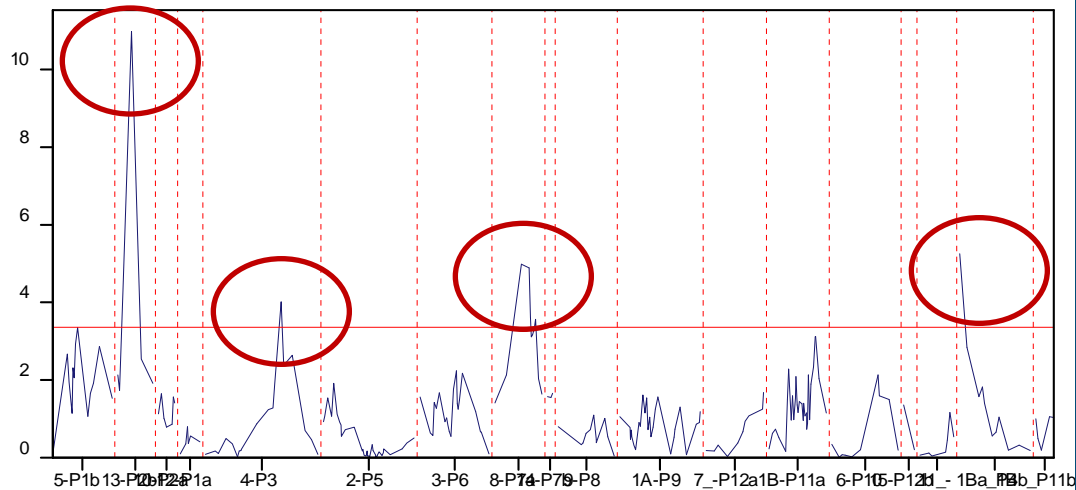
# G2P models for yield and its components

- yield =
  - environment +
  - env. specific QTLs +
  - residual G and GxE +
  - error
  
- yield component =
  - environment +
  - QTL +
  - residual G +
  - error

# QTL analysis on crop model parameters

## Leaf area development rate (\*1000)

LAI\_rate Additive effects in lower plot



Chromosomes

Multi-  
environment  
QTL analysis



# Effect of QTL's in different environments

Leaf area development rate

- Average fitted value 2.11
- Effect env. from -0.65 to 0.79

QTL	S1	S2	N1	N2
1 (P2b)	-0.16 (0.04)	-0.23 (0.03)	-0.21 (0.05)	-0.33 (0.07)
2 (P7a)	0.14 (0.04)	0.06 (0.03)	0.13 (0.05)	0.02 (0.07)
3 (P4)	-0.10 (0.04)	-0.13 (0.03)	-0.21 (0.05)	-0.35 (0.07)
4 (P3)	-0.05 (0.04)	0.02 (0.03)	0.08 (0.05)	-0.09 (0.07)

Variance explained by QTL's

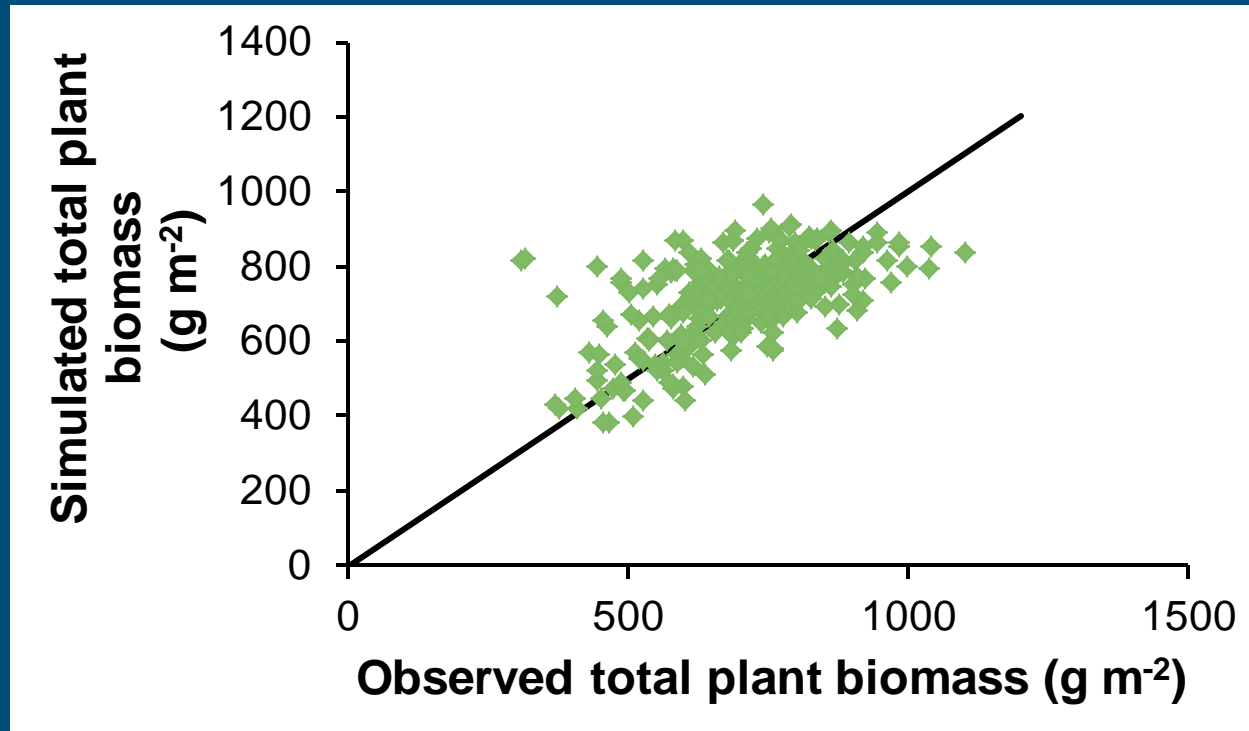
N1 24%      N2 24%

S1 23%      S2 33%

# Yield component traits

- Model parameters have high heritabilities and high genetic correlations
- QTL analysis
  - Analysis of leaf area dev. rate was successful
  - Other two parameters:
    - Not very high scores in QTL profiles
    - Effect of the QTL's is not very large

# Predicting yield from crop growth model using 'real' QTLs



Predictions Spain 2 from QTLs identified in Spain 2  
Rank correlation 0.54

# Crop growth simulation: Scenario studies

## Radiation

### 3 realizations (years) in Spain:

- 1994 - minimum average between 1991 and 2008
- 2008 - median average between 1991 and 2008
- 2000 - maximum average between 1991 and 2008

+

### 3 realizations (years) in The Netherlands:

- 1998 - minimum average between 1996 and 2008
- 2007 - median average between 1996 and 2008
- 2003 - maximum average between 1996 and 2008

36 Environments

## Average Temperature

### 3 levels:

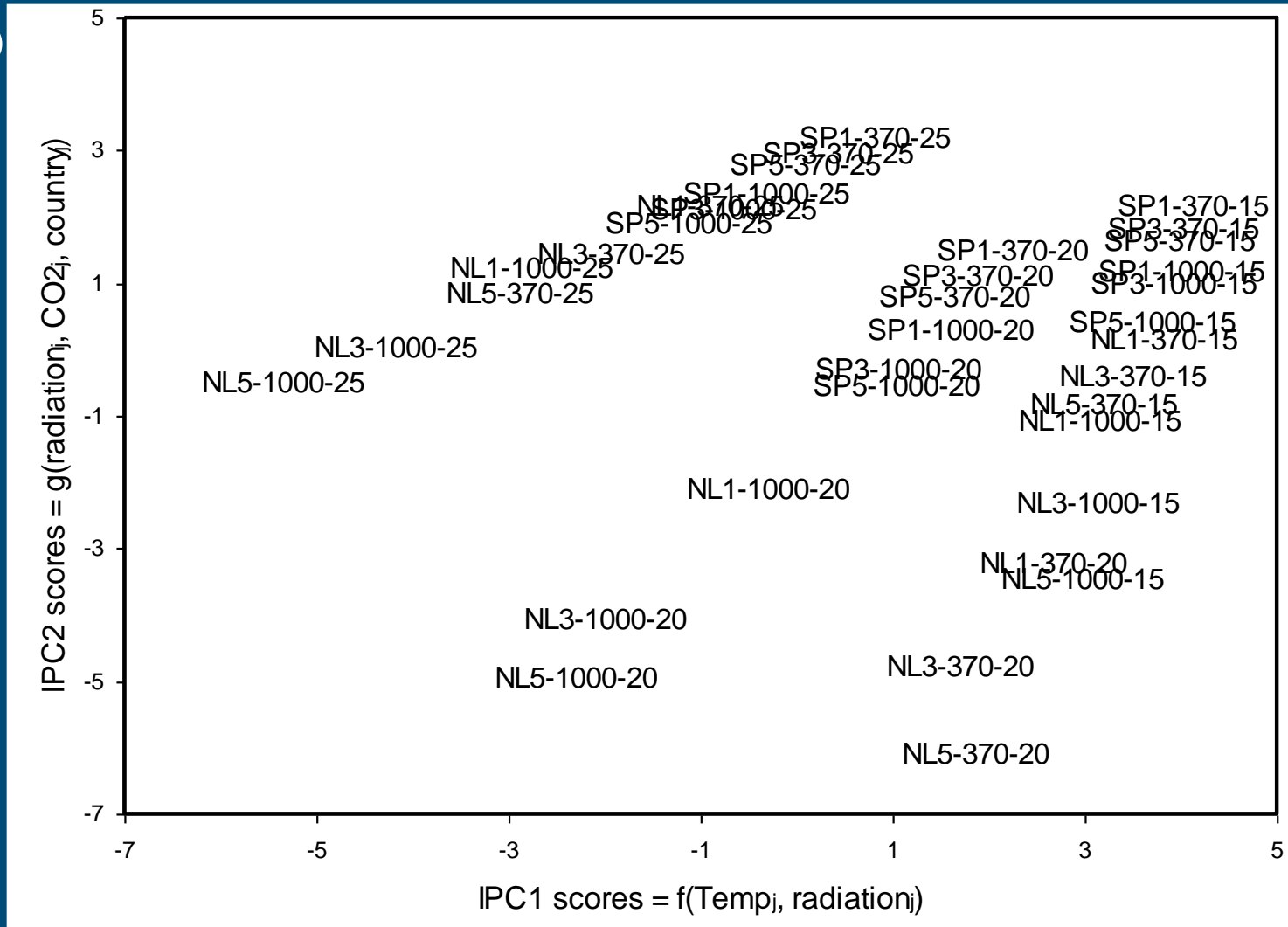
- 15°C
- 20°C
- 25°C

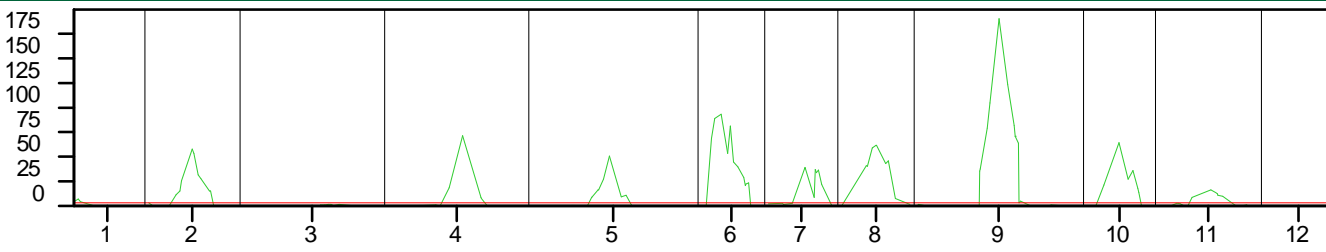
## CO<sub>2</sub> levels

- 370 ppm – open environment
- 1000 ppm – closed greenhouse

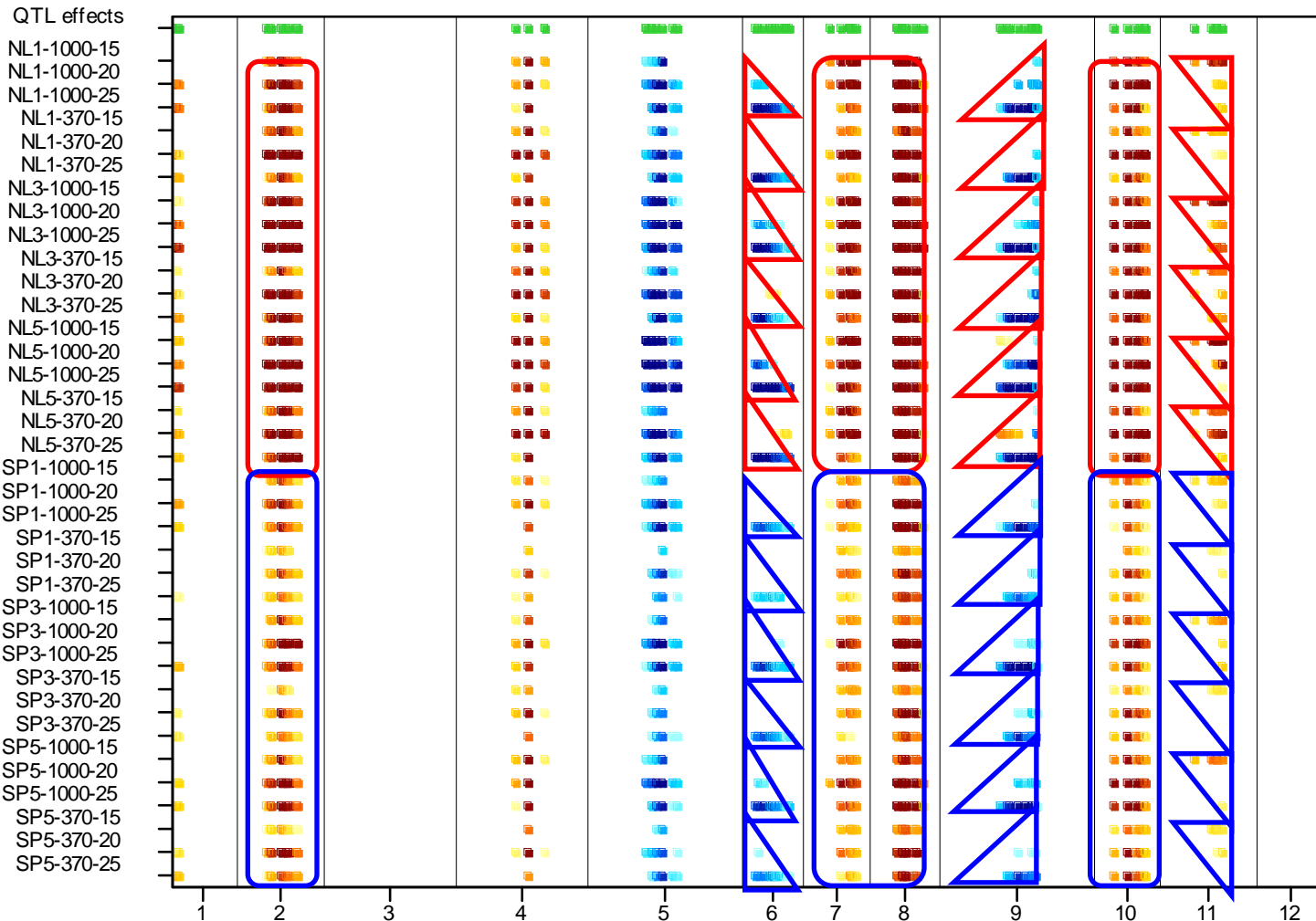
# GxE analysis on simulated yield (AMMI2)

bip





k LUE b FTF FDMC w LUE LUE w LUE z



NL

Spain

QTL analysis for yield simulated from crop growth model with additive QTLs for physiological traits

Chromosomes

# Results scenario study in pepper

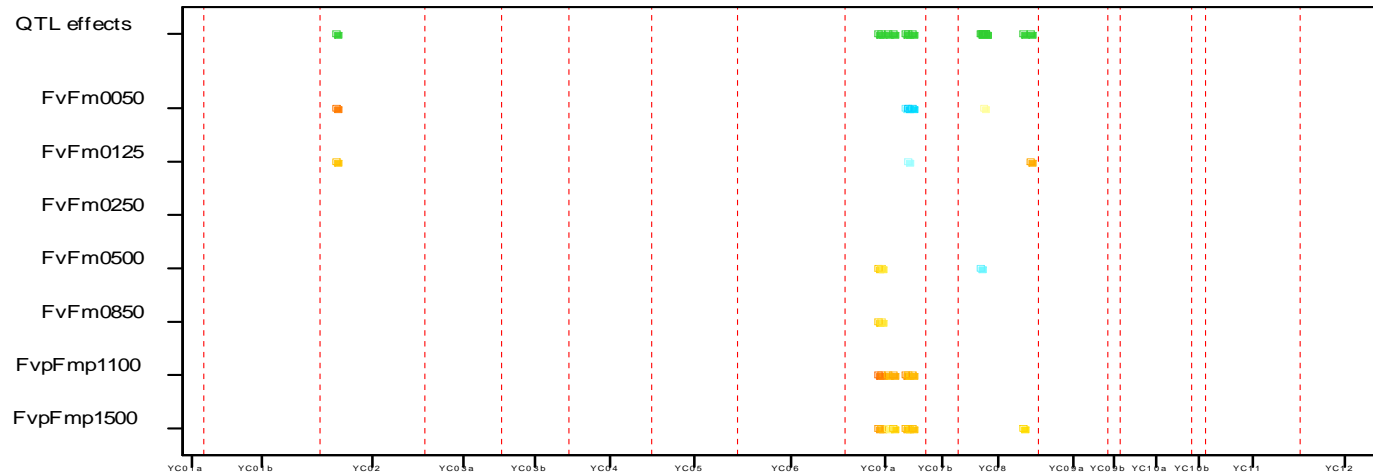
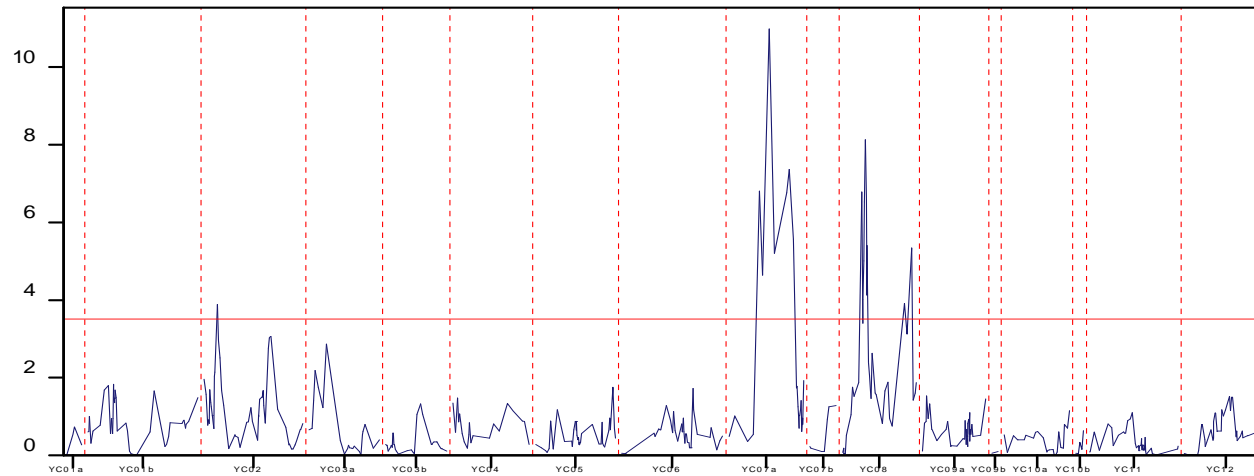
- Crop growth model containing 7 genotype specific parameters (components) could produce GxE and QTLxE
- QTLs for yield appeared there were QTLs for components were simulated
- Patterns of QTLxE for yield could be understood given knowledge of location and effect of QTLs for yield components and environmental variables

# Fluorescence traits

- Can we find QTLs for fluorescence traits?
- Do these QTLs co-locate with physiologically interesting QTLs?

# Mapping fluorescence traits | $Fv' / Fm'$

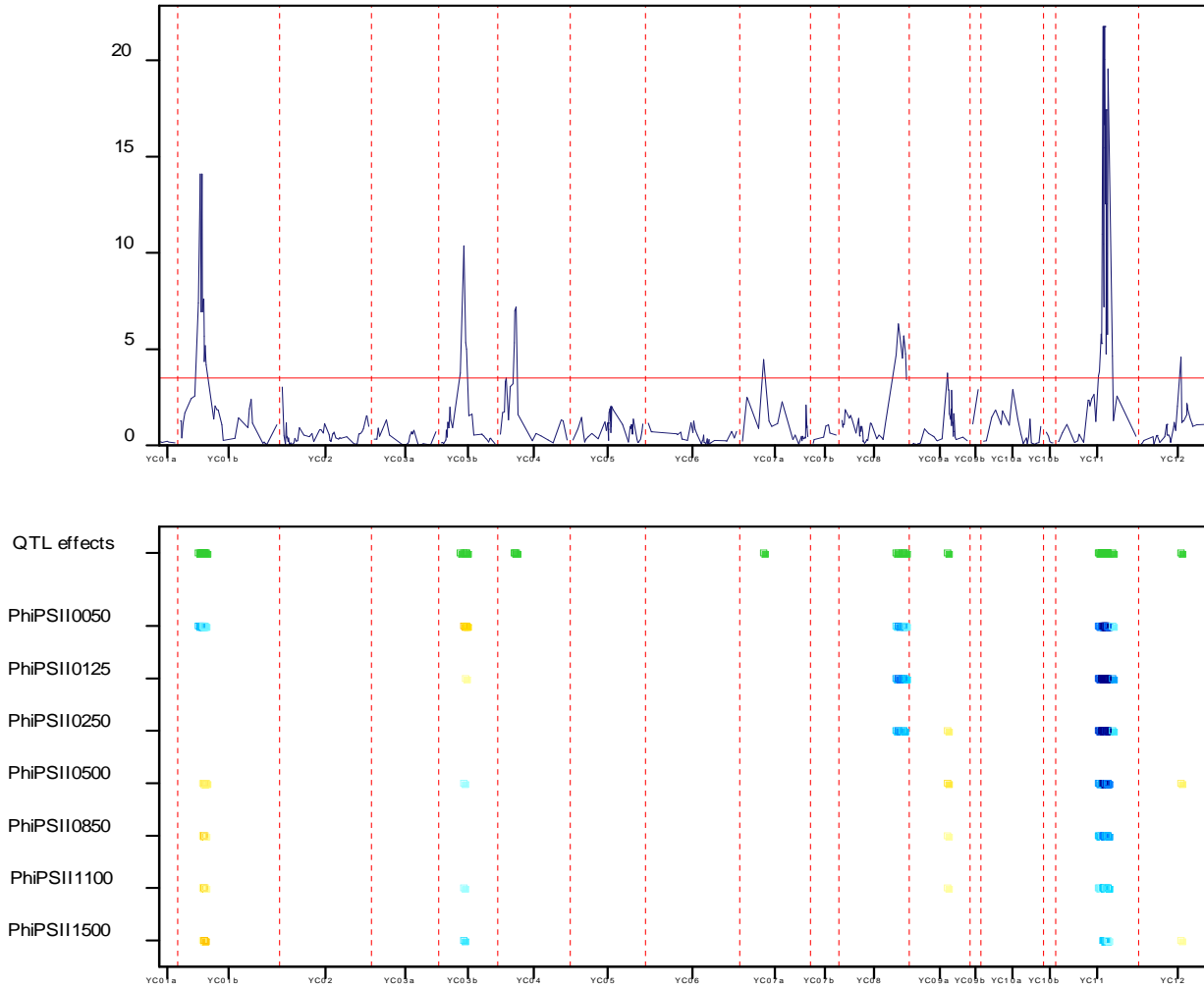
Test profile and additive effects: `_traits`



Chromosomes

# Mapping fluorescence traits PhiPSII

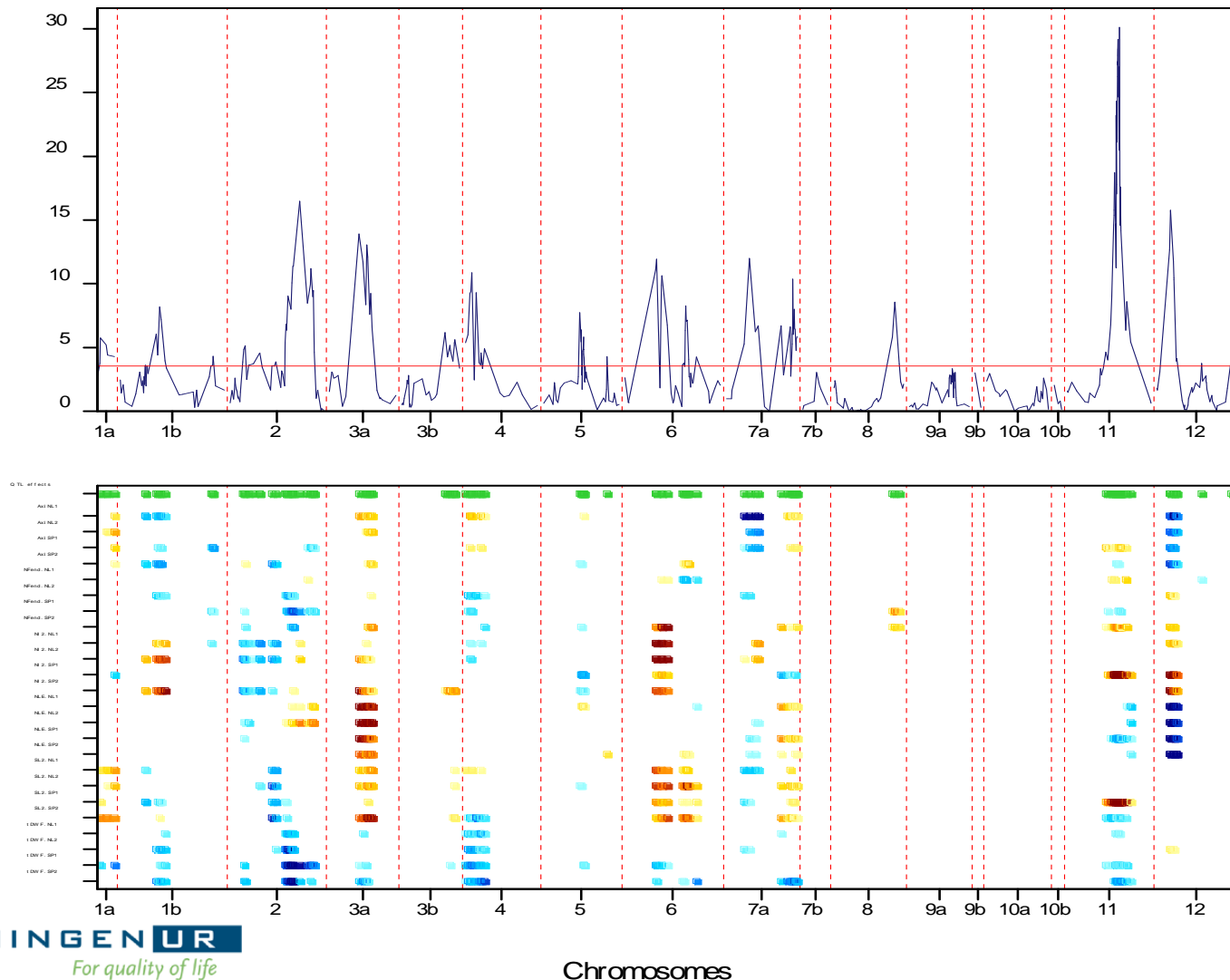
Test profile and additive effects: \_traits



Chromosomes

# Mapping plant physiological traits: Search for co-location with fluorescence traits

Test profile and additive effects: Stem



# Image analysis

**Find summaries of spatial/spectral characteristics of images which:**

- **Correlate with physiological features (leaf area, fruit weight etc)**
- **Show consistent differences between genotypes: heritability**

# Measuring plant characteristics

Barcode reading finds the position of each plant and reads its ID number.

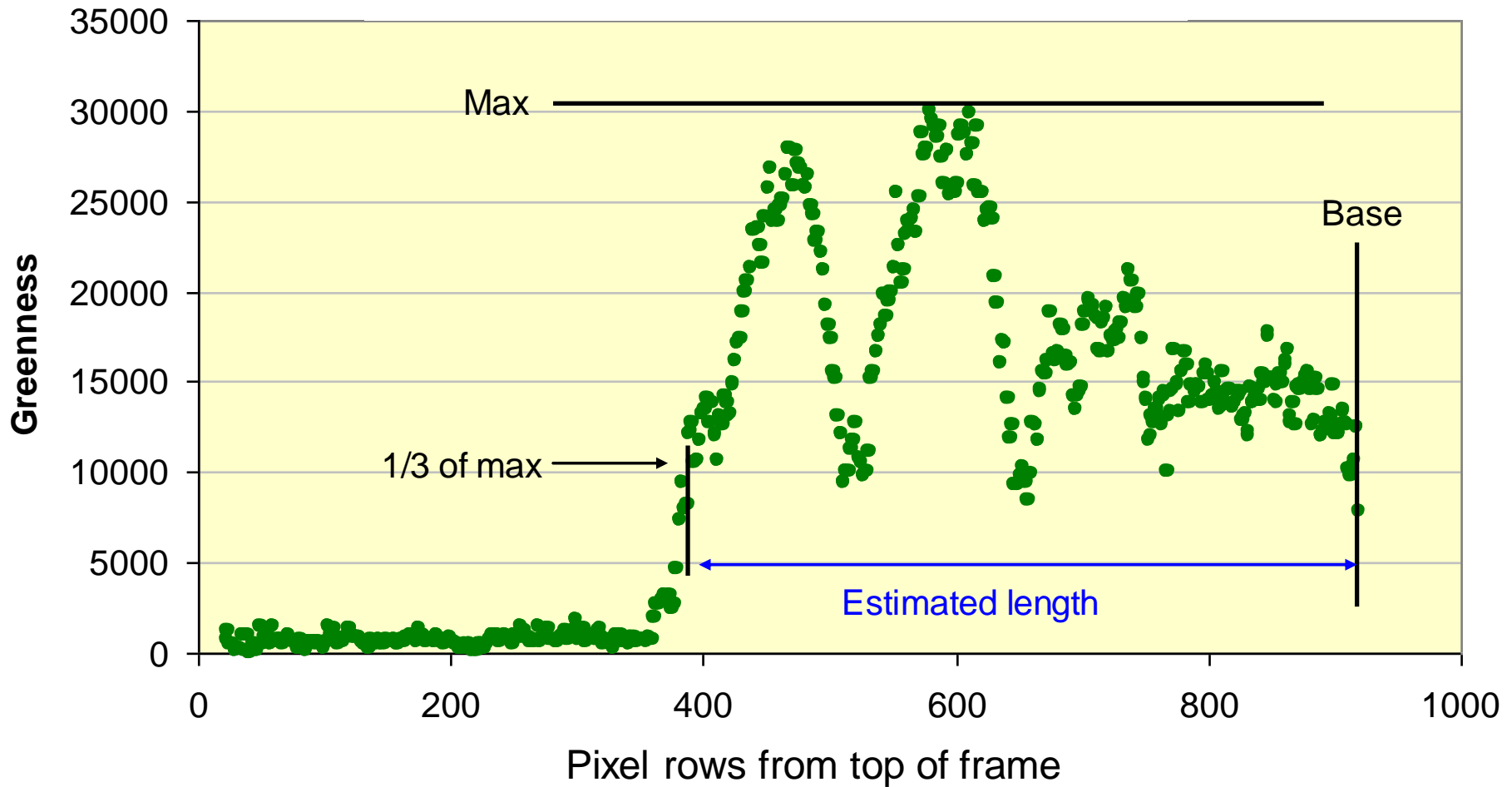
This allows us to draw a frame around the plant.



# Estimating height

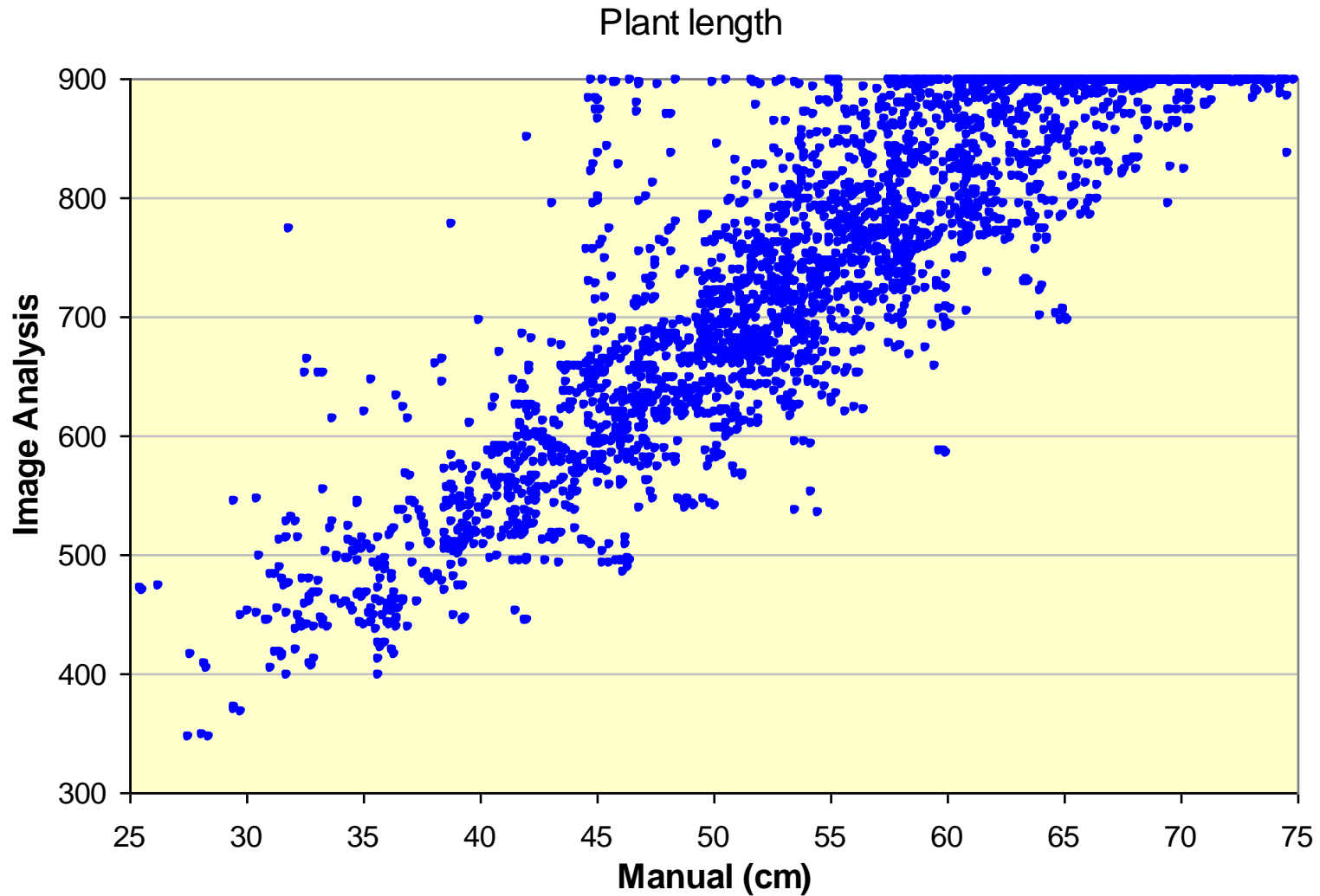


Sum of pixel greenness ( $G - 0.5B - 0.5R$ )





# Automatic vs manual



**Correlation = 0.86**

Manual length (sum of length 1 and 2) versus first estimate by image analysis



# Consistent differences between genotypes

## Manual length

### Error: plant

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
genotyp	151	251646	1666.53	<b>34.904</b>	< 2.2e-16 ***
Residuals	738	35236	47.75		

### Error: Within

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Residuals	2077	1.5789e-26	7.6016e-30		

## Automatic length

### Error: plant

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
genotyp	153	61549300	402283	<b>31.214</b>	< 2.2e-16 ***
Residuals	1639	21123263	12888		

### Error: Within

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Residuals	4273	6287244	1471.4		

# Discriminant analysis

- **Data: red, green and blue spectrum (256 traits/intensities)**
- **Discriminant analysis constructs combinations of variables that best separate genotypes**

# Spectral histogram discriminant functions

## First discriminant function

### Error: plant

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
genotype	153	16845.9	110.104	38.831	< 2.2e-16 ***
Residuals	1639	4647.3	2.835		

### Error: Within

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Residuals	4273	1264.7	0.29597		

## Second discriminant function

### Error: plant

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
genotyp	153	7384.5	48.265	16.059	< 2.2e-16 ***
Residuals	1639	4925.9	3.005		

### Error: Within

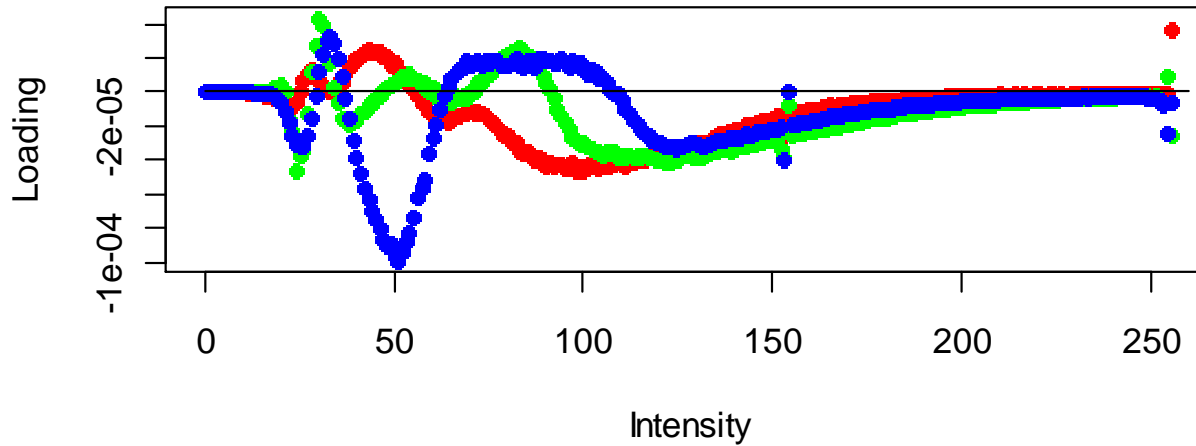
	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Residuals	4273	986.14	0.23078		

# Spectral histogram discriminant functions

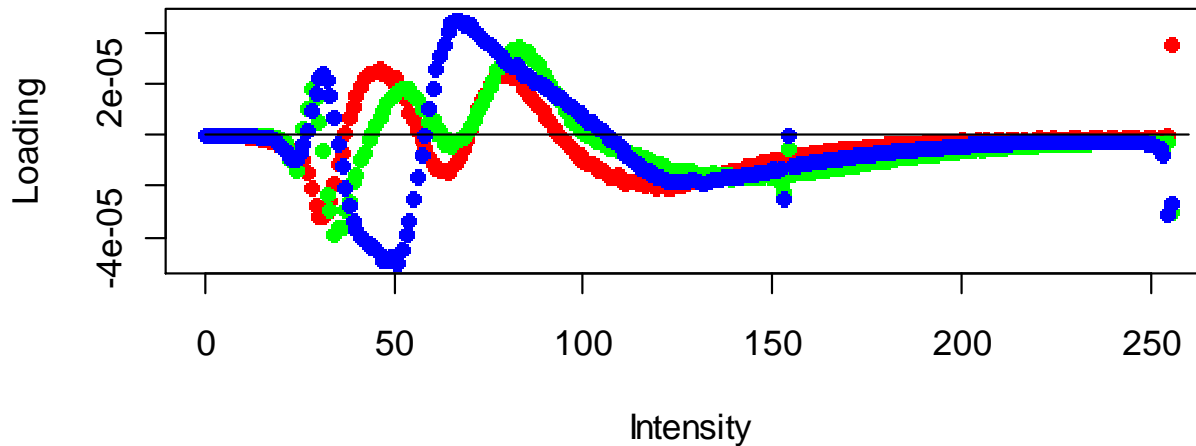
## What do they mean?



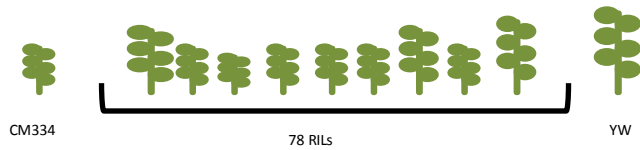
1st discriminant function



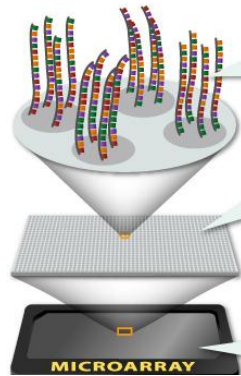
2nd discriminant function



# Which genes can be identified behind QTLs? eQTL mapping

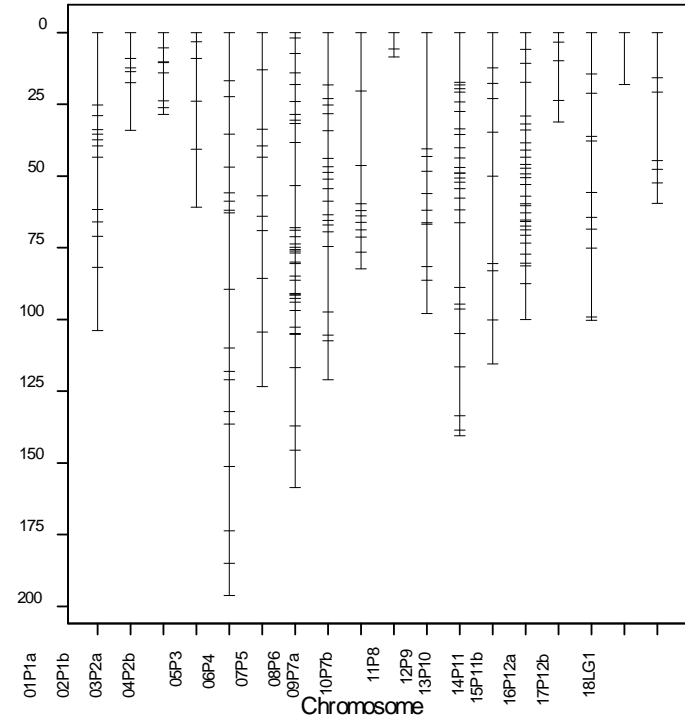


expression  
data

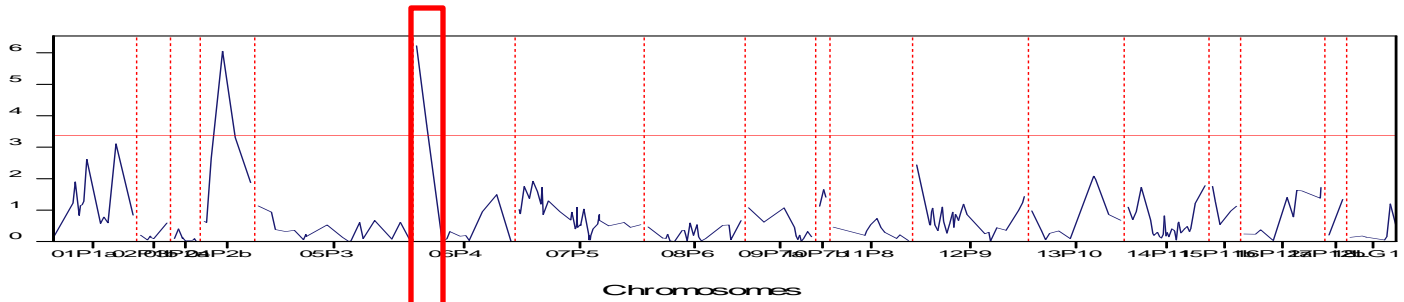


42779 probesets

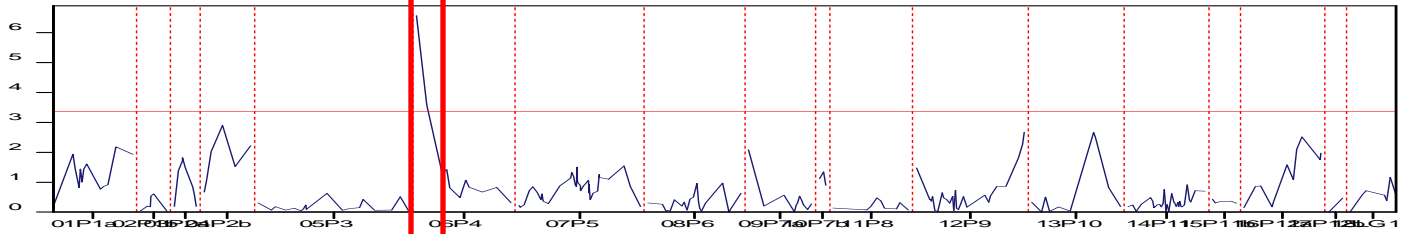
+



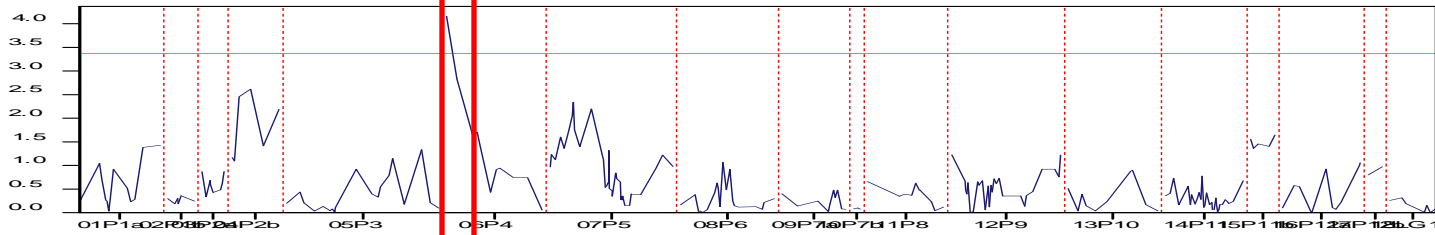
Physiol.  
QTL



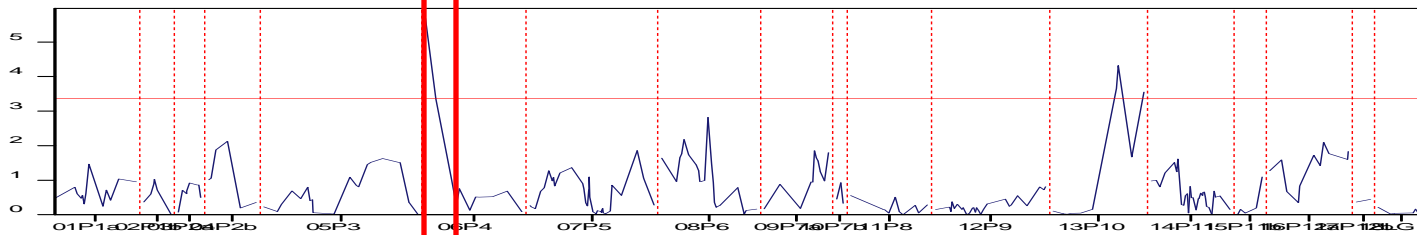
gene1



gene2

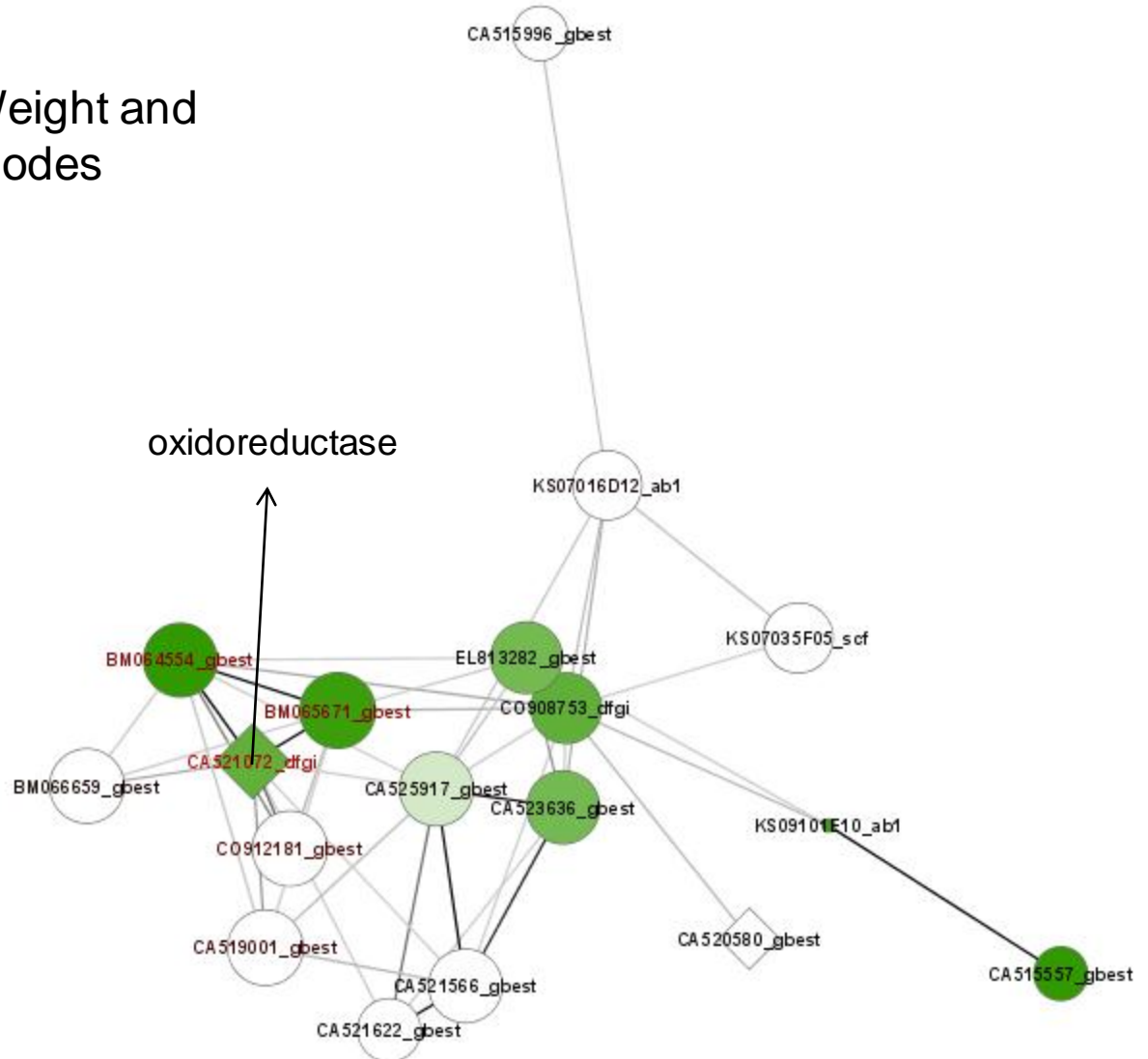


gene3



# P3 (46 cM)

QTLs for Fruit Weight and  
Number of Internodes



# Final remarks

- Within context SPICY project a 3-5 day course/meeting will be organized on G2P modelling in general in spring 2011
- A special symposium on G2P modelling / crop growth modelling / genetics will be held 2 september 2012 in Hohenheim
- EU-DROPS project led by Francois Tardieu is another project with a strong G2P modelling component in it, comparing statistical and physiological approaches