



University of São Paulo
Escola Superior de “Luiz de Queiroz” College of Agriculture

HIGH THROUGHPUT PHENOTYPING ADJUSTED BY FINE ENVIRONMENTAL CHARACTERIZATION

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Motivation

Crop yield potential



Motivation

Crop yield potential

$$Y_p = S_t \cdot \varepsilon_i \cdot \varepsilon_c \cdot \eta$$

$$Y_p = \cancel{S_t} \cdot \varepsilon_i \cdot \varepsilon_c \cdot \cancel{\eta}$$

$$Y_p = \varepsilon_i \cdot \varepsilon_c$$

$$GY = \varepsilon_i \cdot \varepsilon_c$$

INDIRECT MEASUREMENT OF GY

Motivation

Crop yield potential

Issues of indirect measurement of GY:

1. Difficulty of measuring ε_i and ε_c ;
2. Influence of microenvironments;

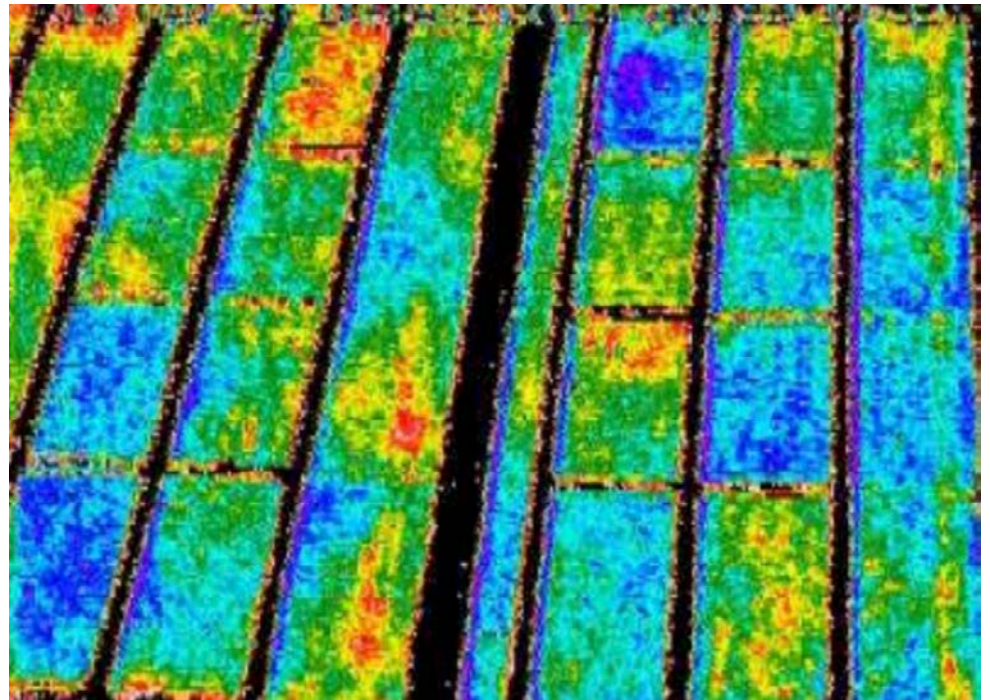
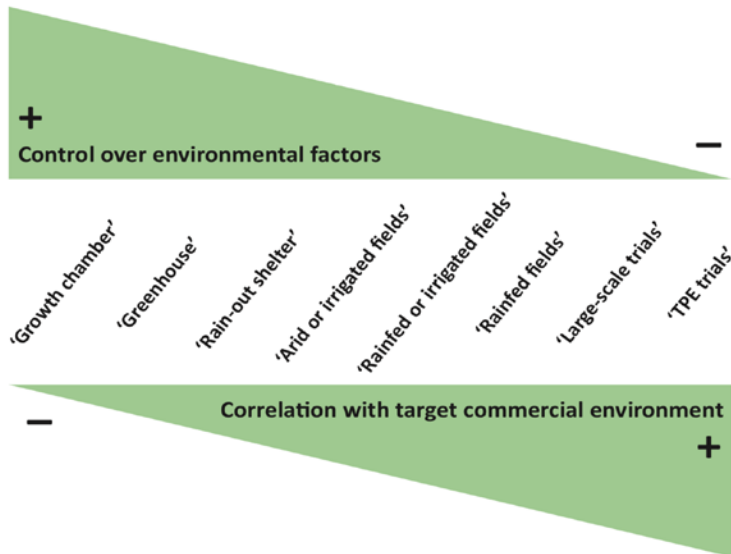
Solving problem 1: Image-based phenotyping;

Solving problem 2: ?

Motivation

Challenge

One of the greatest challenges of field phenomics is **dealing adequately with uncontrollable variation.**



Motivation

Objectives

Global

Evaluate the effect of the incorporation of environmental factors in HTP studies

Develop a low-budget
envirotyping platform

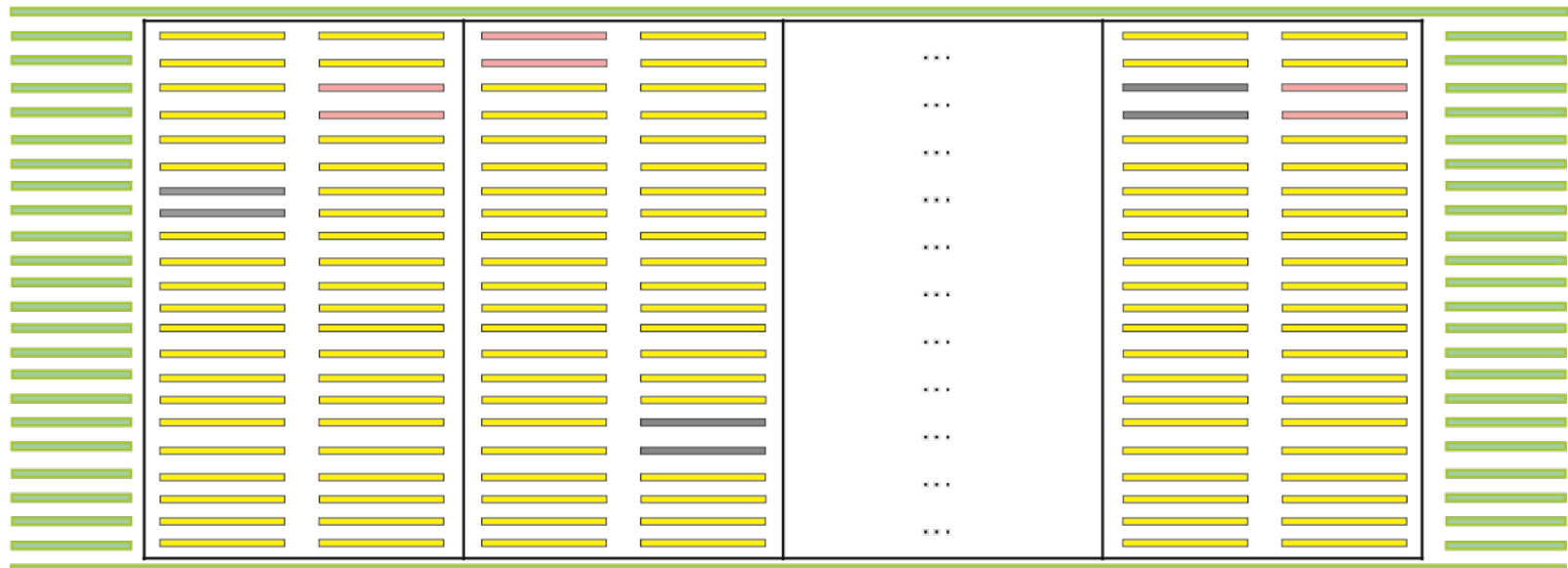
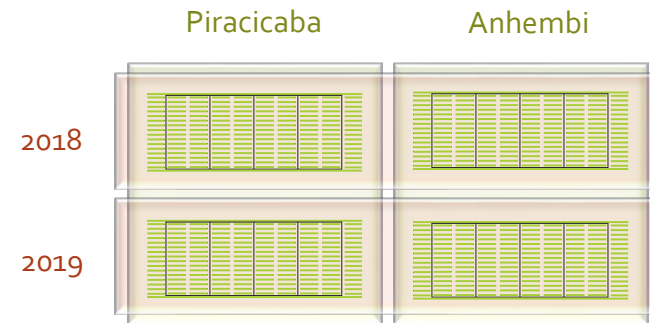
Verify the effect of
environmental factors
based correction of
conventionally and
high-throughput
evaluated traits

Identify remote and
quick yield-related
traits

M&M

Genetic material and experimentation

- 780 single-cross corn hybrids;
- 39 incomplete blocks;
- 2 checks.

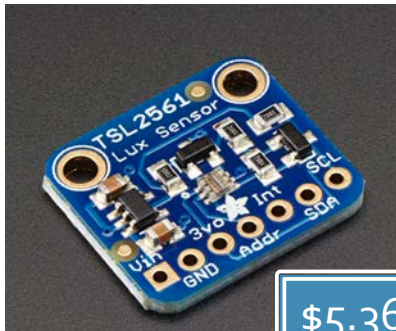


Regular treatments Border Checks

M&M

Fine environmental characterization (Temporal)

Lux sensor



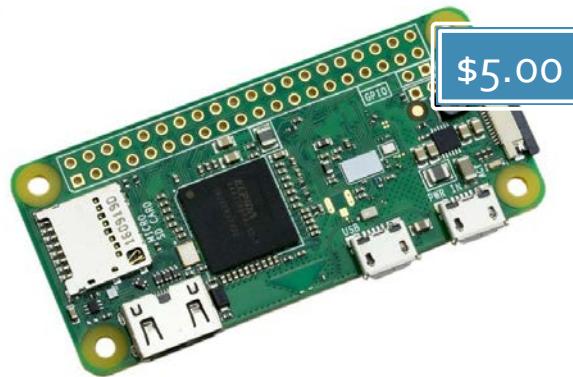
\$5.36

Soil humidity and temperature



\$44.96

Minicomputer



\$5.00

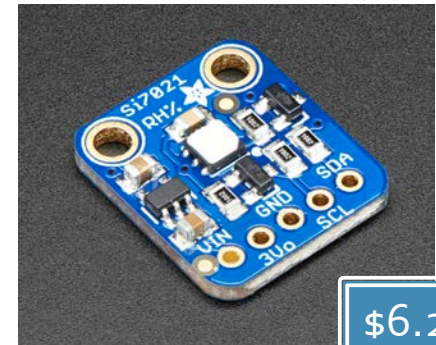
\$93.48

Ammonia sensor



\$31.90

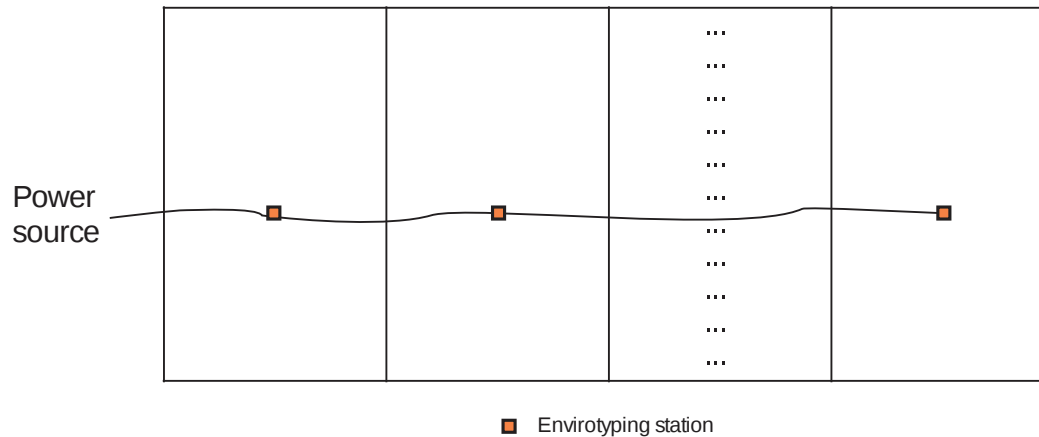
Air humidity and temperature



\$6.26

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Fine environmental characterization (Temporal)



TEMPORAL ENVIRONMENTAL COVARIATES:

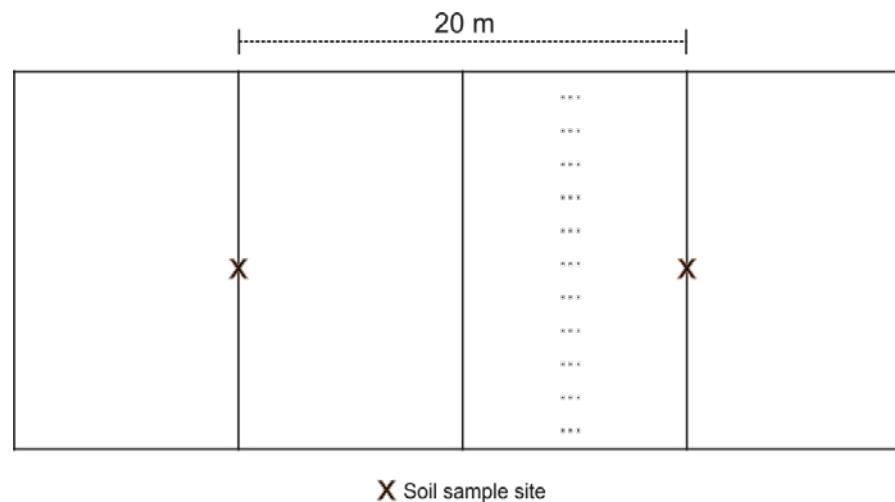
- **Soil temperature:** instant, season mean, maximum (season mean), range (season mean), flowering (mean);
- **Air temperature:** instant, season mean, maximum (season mean), range (season mean), flowering (mean), degree day (total);
- **Soil humidity:** instant, maximum (season mean), minimum (season mean), flowering (mean);
- **Air humidity:** instant, maximum (season mean), minimum (season mean), flowering (mean);
- **Ammonia content:** season sum (total loss);
- **Light intensity:** instant, season mean;

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Fine environmental characterization (Stable)

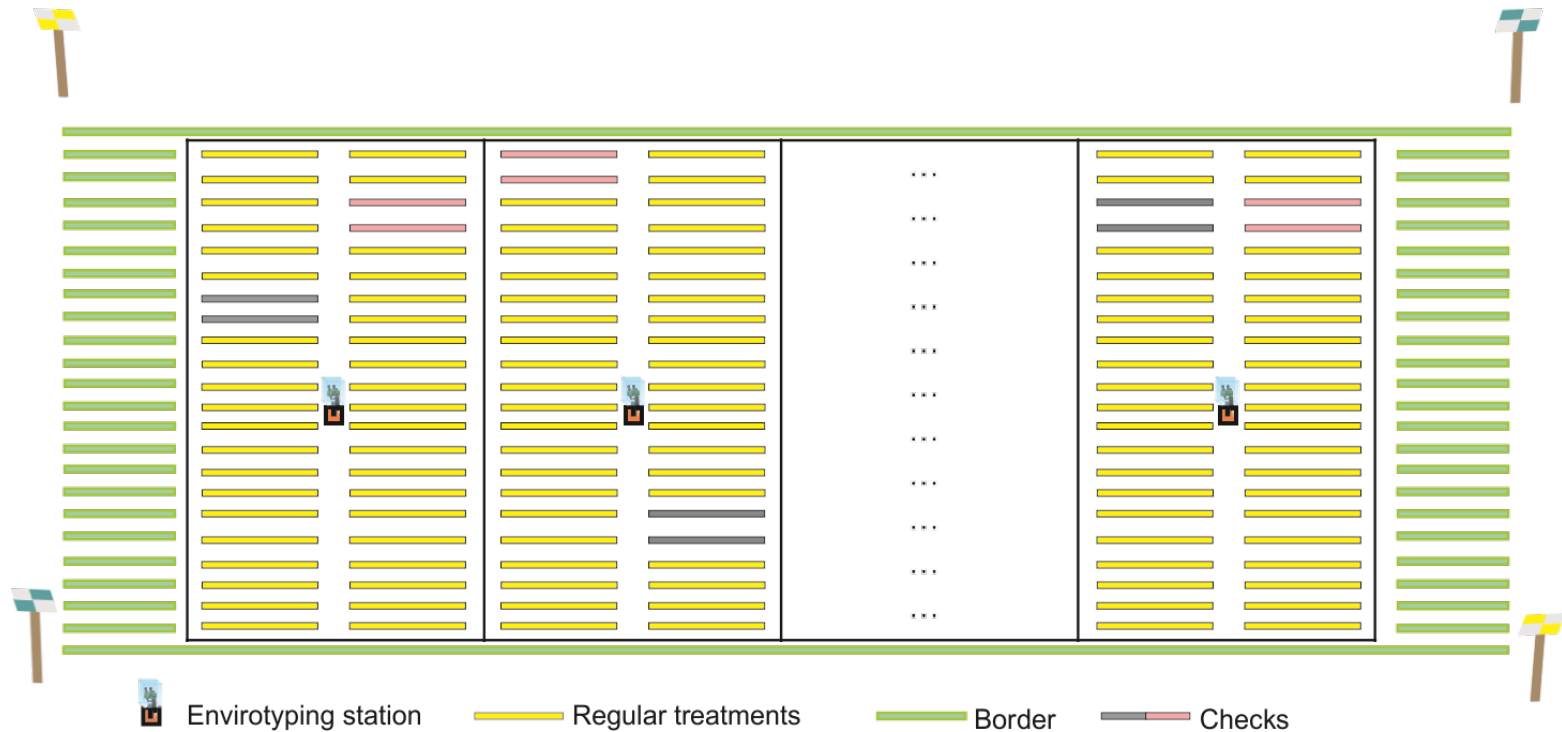
STABLE ENVIRONMENTAL COVARIATES:

- **Soil texture:** Sand, Silt and (Clay);
- **Chemical:** pH; Calcium, Magnesium and Aluminum



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Experiment representation



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High throughput phenotyping

Aerial imagery:

- Temporal resolution: V6, V12, VT, R3 e R6;
- Spatial resolution: 1 cm pixel⁻¹ (80% overlapping);

Software:



Equipment:



Canopy temperature
(CO₂ assimilation)

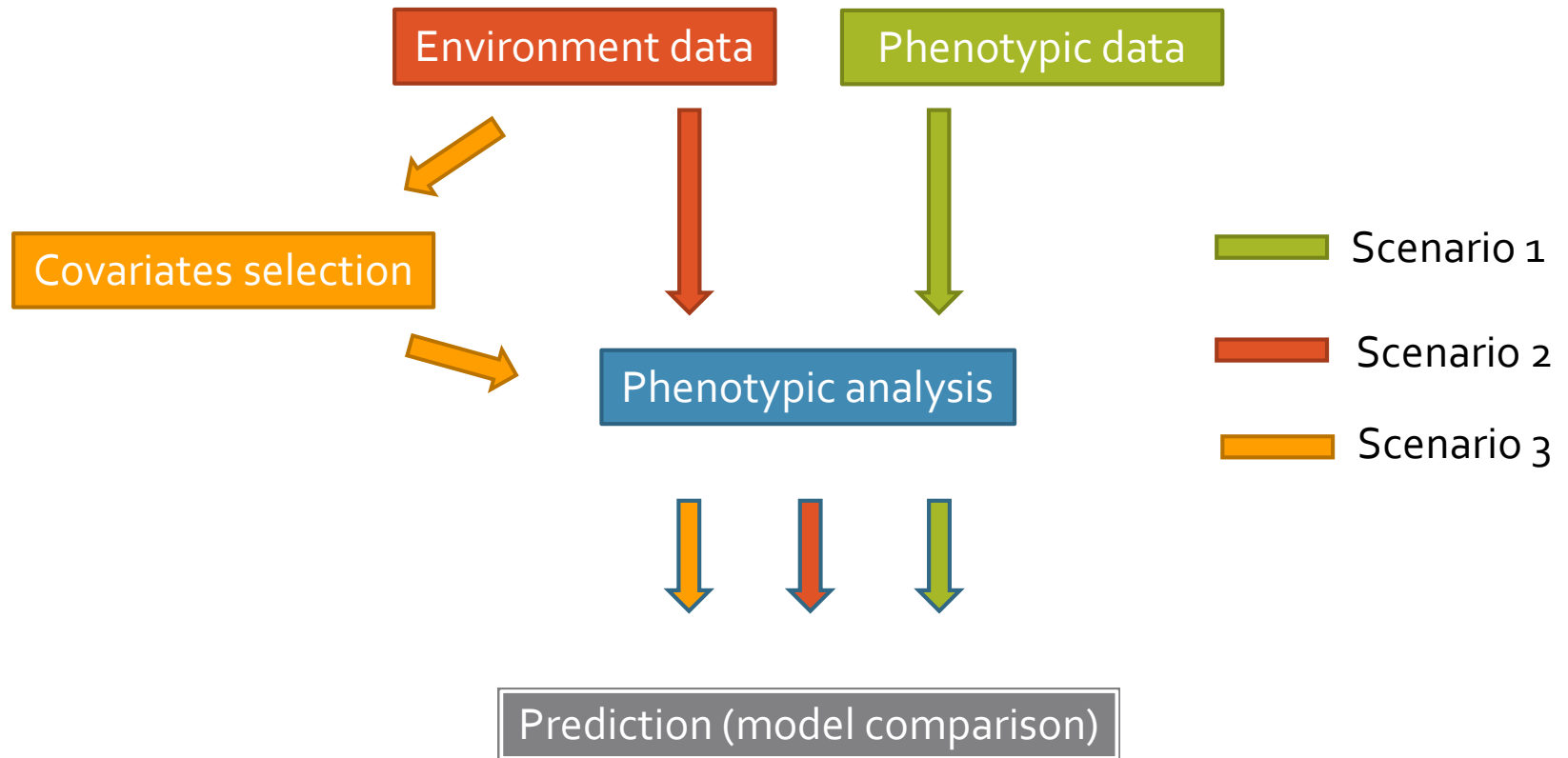
$$GNDVI = \frac{\rho_{NIR} - \rho_G}{\rho_{NIR} + \rho_G}$$

(LAI)

$$GY = \varepsilon_i \cdot \varepsilon_c$$

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Statistical analysis (Workflow)



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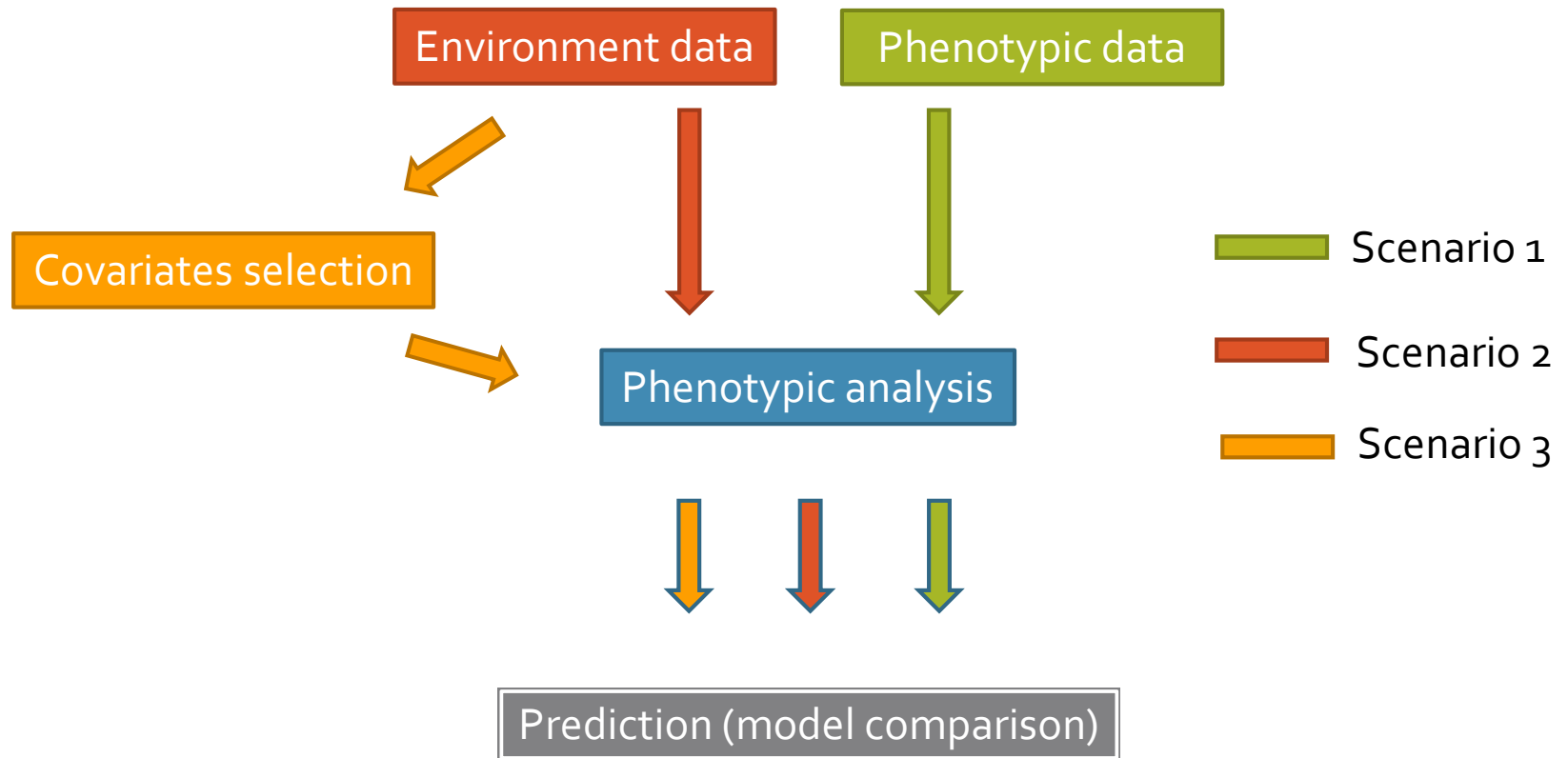
Statistical analysis

Covariates selection:

- Path analysis:
 - Dependent variables: GY, GNDVI and CT (each date);
 - Independent variables: environment covariates.

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Statistical analysis (Workflow)



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Statistical analysis

Covariates selection:

- Path analysis:
 - Dependent variables: GY, GNDVI and CT (each date);
 - Independent variables: temporal (1st Chain) and stable (2nd Chain) environment covariates.

Phenotypic analysis

- Analysis of GY, GNDVI and CT (each date);

Scenario 1

$$y = X\beta + Z\theta + \epsilon$$

Scenario 2

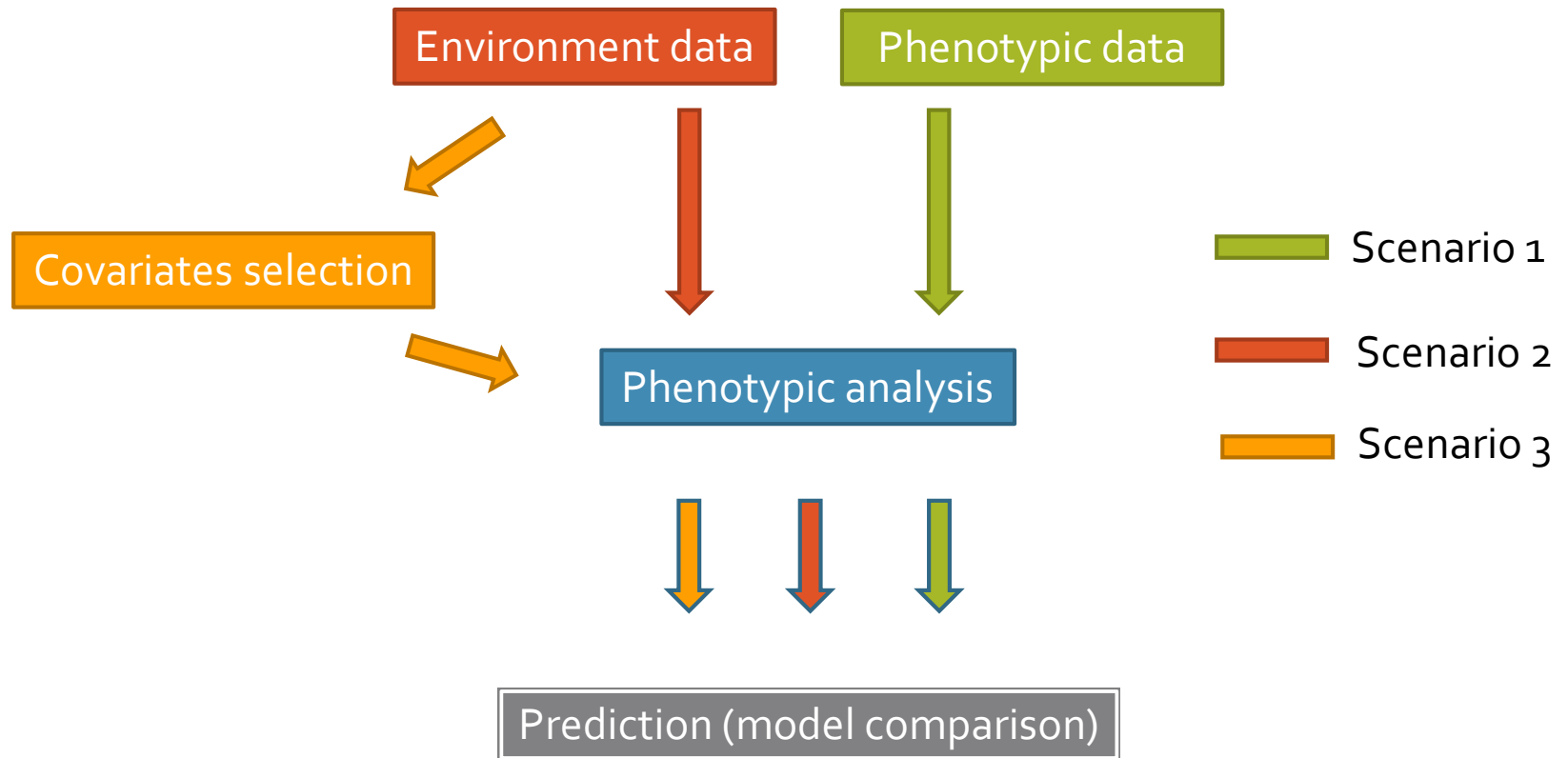
$$y = X\beta + Z\theta + T_1\tau_1 + \cdots + T_a\tau_a + \epsilon$$

Scenario 3

$$y = X\beta + Z\theta + S_1\alpha_1 + \cdots + S_s\alpha_s + \epsilon$$

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Statistical analysis (Workflow)



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Statistical analysis

Prediction:

Scenario 1

Scenario 2

Scenario 3

ESTIMATION (80%)

$$GY = \beta_0 + gndvi\beta_1 + thermal\beta_2 + \epsilon$$

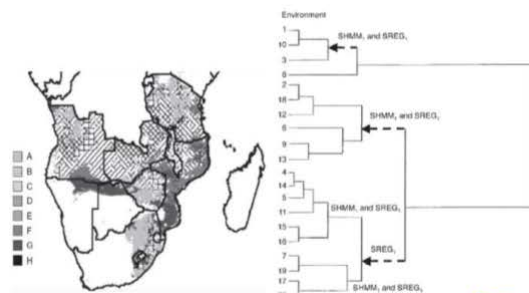
TESTING (20%)

$$\widetilde{GY} = gndvi\hat{\beta}_1 + thermal\hat{\beta}_2$$

$$r_{y,\tilde{y}} = cor(GY, \widetilde{GY})$$

Pearson & Spearman

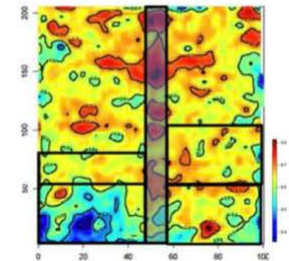
Remarks



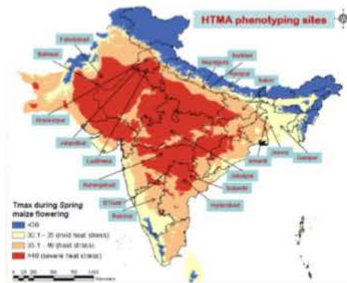
A Classification of environments



B Near-iso environments



C Control of experimental error



D Selection of experimental sites

Transcriptome data
461 microarray
(9 sets of 48hr samples
at 2hr interval, 0:00 &
12:00 samples at 1
week interval, etc.)

Models

Meteorological data
at every minutes
(air temperature,
global solar radiation,
relative humidity
etc.)

Parameter optimization &
Model selection for each gene

Summarization

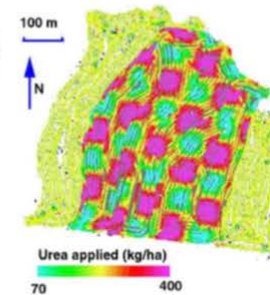
In-depth Analysis

Prediction

E Agronomic genomics



F Stress prediction



G Precision agriculture

Applications of envirotypic information

Remarks

At last:

- Local environmental variation contribute to the residual variance.
- Greater efficiency of genetic variation exploration;
- HTP and noise reduction;
- HTP and GY prediction.

References

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- LONG, Stephen P. et al. Can improvement in photosynthesis increase crop yields? Plant, Cell & Environment, v. 29, n. 3, p. 315-330, 2006.
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- XU, Yunbi. Envirotyping for deciphering environmental impacts on crop plants. Theoretical and Applied Genetics, v. 129, n. 4, p.653-673, 2016.

Thanks



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