Big data, small explanatory power?

Experiences with cereal yield variability across the globe

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Big data – the end of traditional agronomy?

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- ❑ **Hope:** Big data can be the backbone of *ex-ante* policy assessments and can help prioritize management interventions to meet food availability and environmental targets in the future.

- ❑ **Doubt:** To which extent can actual yields in farmers’ fields be predicted for different crops, farm types and farming systems across the world?

Objective

Assess the performance of statistical and machine learning techniques to predict actual yields in time and space, based on a wide range of biophysical and management factors.

> 10k field x year combinations

Maize and wheat in Ethiopia

Sample: 6350 fields
Year: 2009/10 & 2013
Field size: < 1.5 ha
Source: CIMMYT Surveys

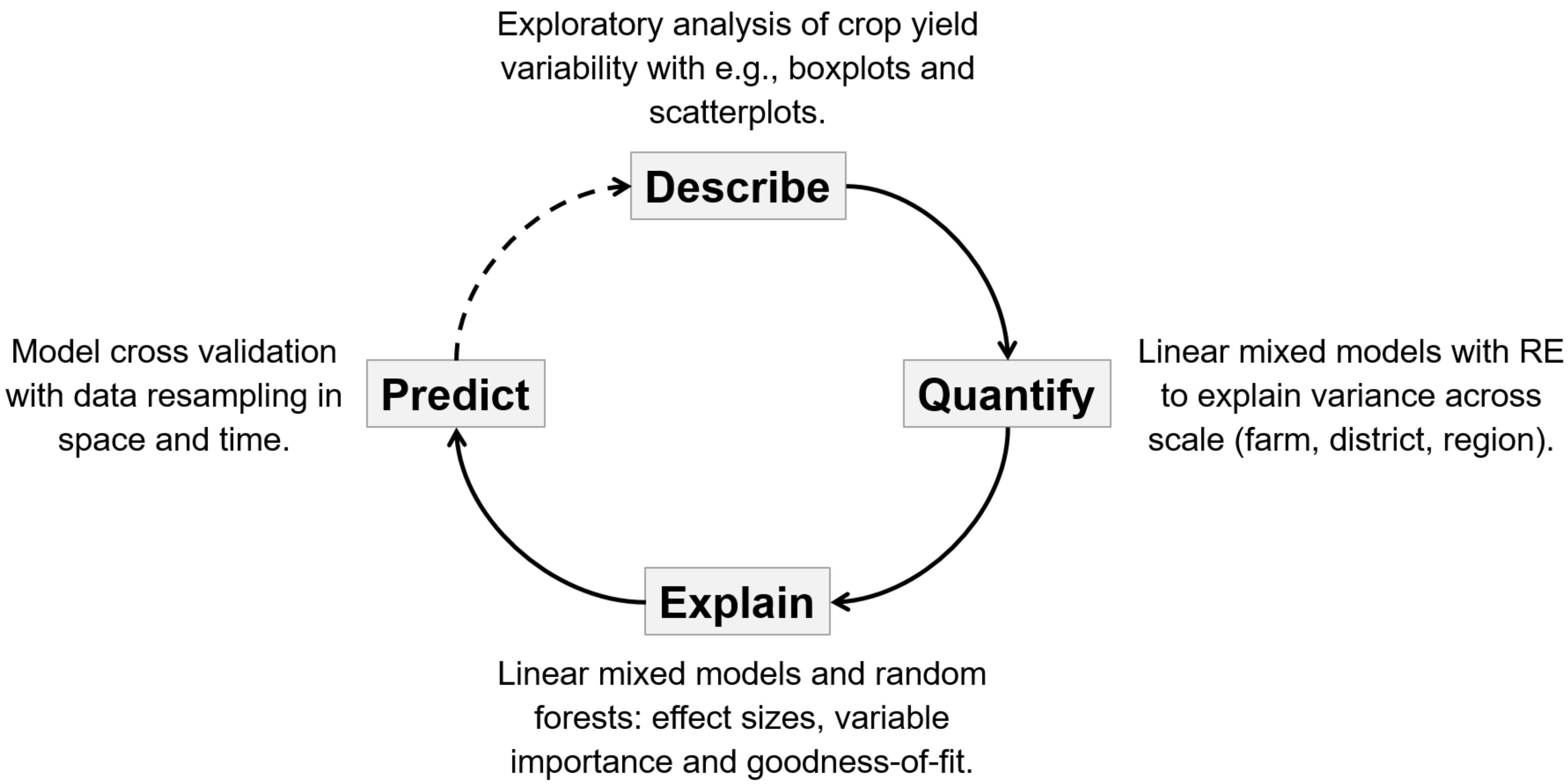
Rice in Central Luzon, Philippines

Sample: 2000 fields
Year: 2014 WS and DS
Field size: < 1.3 ha
Source: IRRI Surveys

Wheat and barley in the Netherlands

Sample: 1770 fields
Year: 2015 – 2017
Field size: < 7.9 ha
Source: Agrovision Records

Methodological framework



Exploratory analysis of crop yield variability with e.g., boxplots and scatterplots.

Describe

Quantify

Linear mixed models with RE to explain variance across scale (farm, district, region).

Explain

Linear mixed models and random forests: effect sizes, variable importance and goodness-of-fit.

Predict

Model cross validation with data resampling in space and time.

Delaune et al.
Submitted (EJA)

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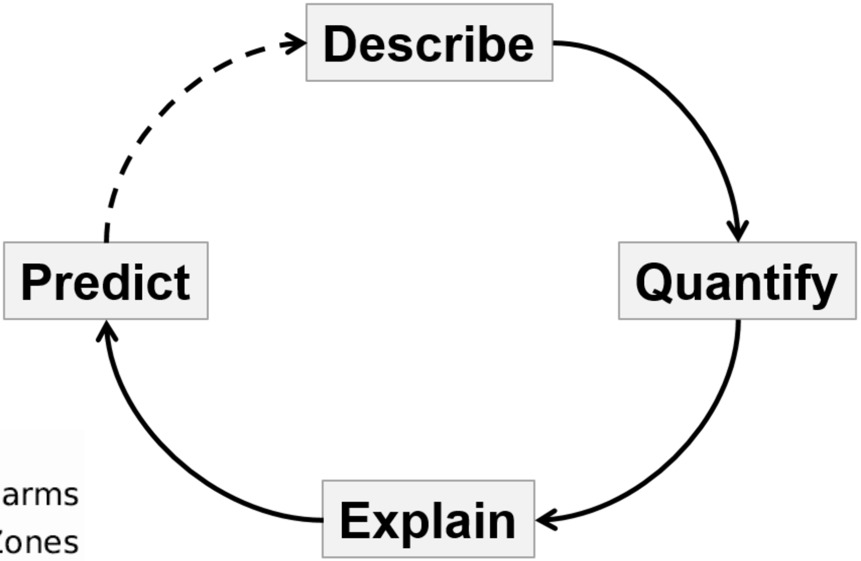

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🟦 Pooled data

🟧 Cross-validation_Farms

🟩 Cross-validation_Zones

🟥 Cross-validation_Years

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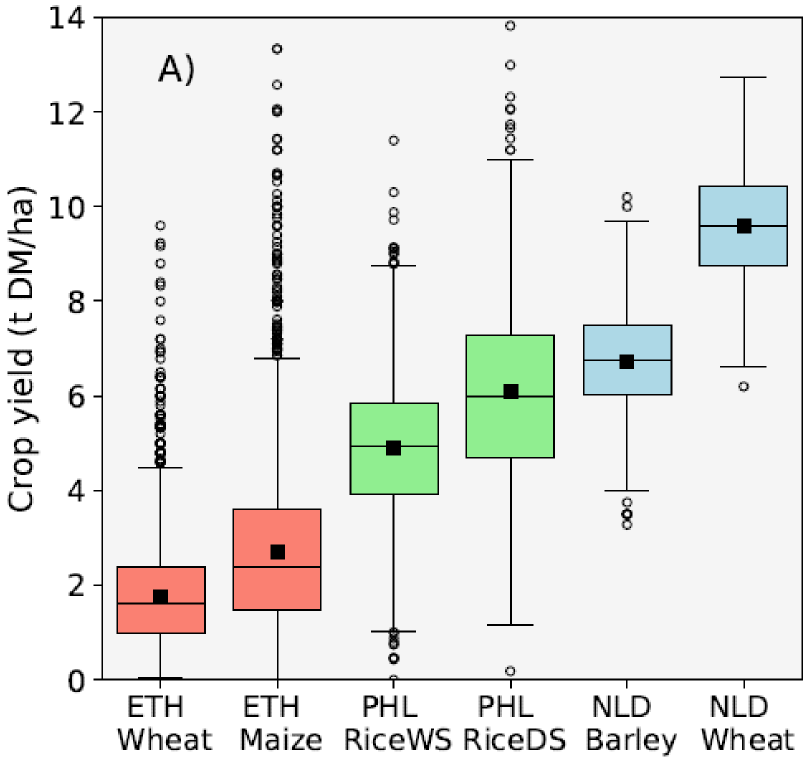
Yield variability and sources of variation



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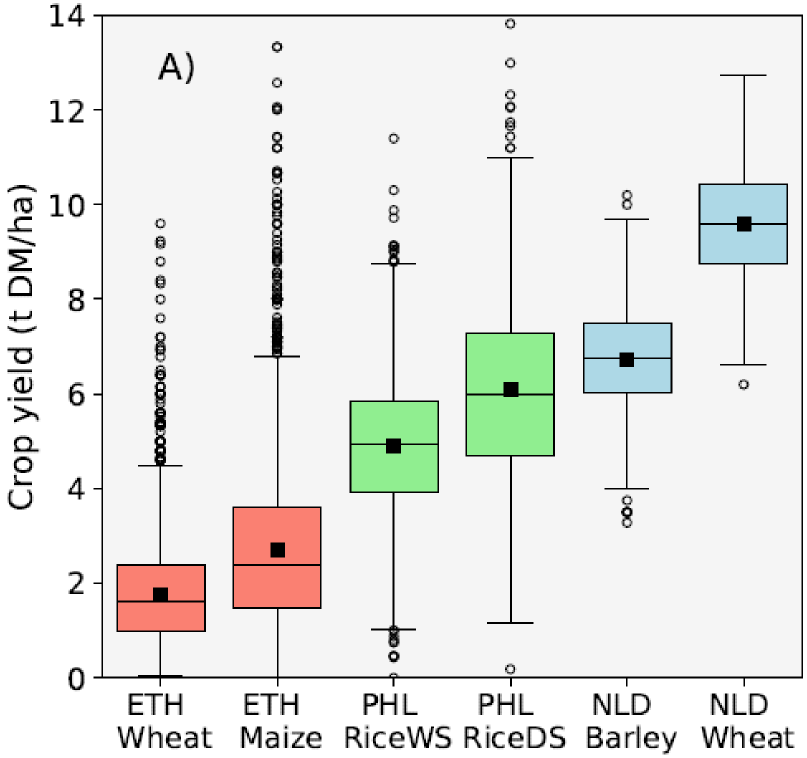

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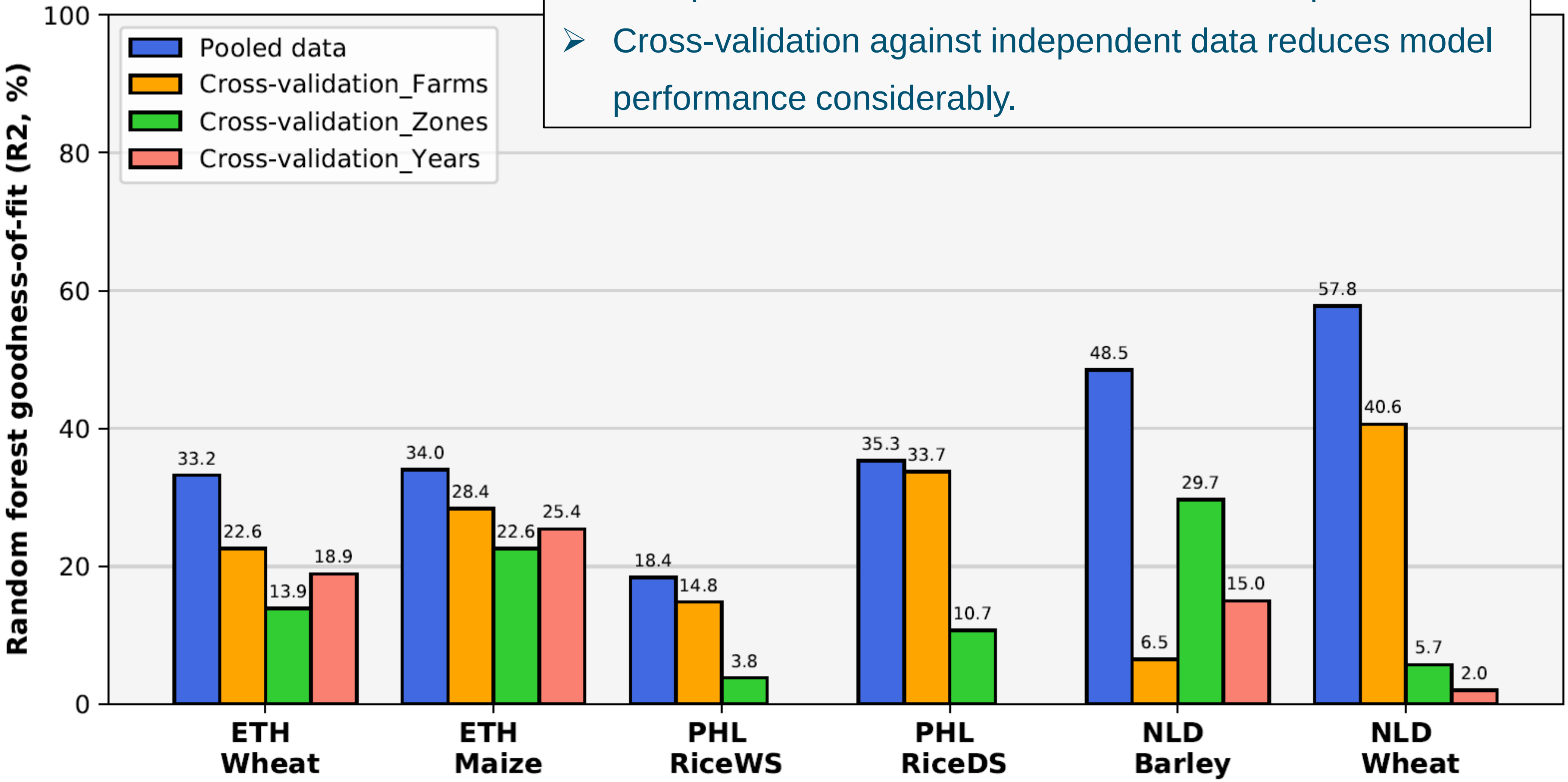
- Most yield variation is explained by **farm random effects** rather than by district or region random effects.

Model performance (R^2)

- ➢ Best performance achieved in the model with pooled data;
- ➢ Cross-validation against independent data reduces model performance considerably.



Conclusions

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- Improved data collection and robust agronomic frameworks are needed to materialize agronomy-at-scale approaches based on big data.

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