Differences in growth features between species are driving cereal-legume intercrop yield.

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Increase plant diversity at the crop level?



Results from diversification experiments in ecology can lead to overly optimistic interpretations for agriculture [Cardinale2007, Loreau2021]

Diversification *per se* is not the cause of productivity increase [McGuire2023, Dee2023]

Cover crops

best mixture ~ best monoculture [Florence2020]

Intercrops

add a legume species, esp. in low N management, or extend the cropped time with relay cropping [Jones2023, McLaren2023]

System description (agronomy)

Concepts



Practice: Data curation and tidying



Production relative to :

Area (grain yield, Yi) Area and management land equivalent ratio = $\sum_{i=1}^{m} \frac{I(Y_i)}{S(Y_i)}$



Experiments in 5 countries, 2001-2017, ~ 600 units {location, year, management}, open-data [Gaudio2023, Mahmoud2024]

Measurements of performance (seeds, shoots), components (leaf area index) as a function of time (biomass, height, nitrogen content)

System description (ecology)



Aims and methods for modeling crop mixtures

Process-based models do not scale well from sole crop to less controlled and more species-varied crop stands [<u>Gaudio2019</u>].

Understand the determinants of canopy performance.

Statistical learning on features derived from our knowledge on crop ecology. Sort and prioritize relevant predictors.

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Overview of the modeling approach

Raw data	Durum wheat / legume intercrops Wheat / faba bean (n=39); wheat / pea (n=47) + sole crops ▼	
Data processing for modeling	Data pre-computation	
	Plant growth metrics Times series summary (biomass, height) → 2 parameters per time series (onset, inflexion)	Agricultural practices-related features Nitrogen nutrition index → 1 explanatory variable Cultivar identity → 2 explanatory variables
	V Dataset with raw and computed data	
	Multiple imputation \rightarrow 10 imputed versions of the dataset	
	\square	
	Interspecific indicators Interspecific differences within intercrops → 6 explanatory variables per model	Intraspecific indicators Intraspecific differences between inter- and sole-cropping conditions → 7 explanatory variables
▼ 16 explanatory variables		
Modeling approach	Models development 3 types of model: Linear Mixed-Effect (LME), Random Forest (RF), Mixed-Effect Random Forest (MERF) → 3 models (LME, RF, MERF) per species per imputed dataset	Models evaluation RMSE on training and test datasets
	▼ Variable selection (on RF-based models) Boruta method (sorting and prioritizing variable importance → 4-7 explanatory variables per model)

Balance data-driven and concept-driven approaches.

Features

Plant Traits (3) biomass, height, area ▼ Features (3) inflexion, asymptote, lag ▼ Metrics (2) relative distance in IC, between IC and SC

Management

crop nitrogen status [Louarn2021] cultivar modality

Environment

functional regression experiment modality

Model



Combine **random forest** non-linearity with within-experiment error structure from **linear mixed models** [Haijem2014]

ML is an accurate and useful method to study systems



Accuracy

Prediction error (RMSE, test) was twice lower for RF model (0.45 t.ha⁻¹) than for linear mixed-model (0.87 t.ha⁻¹).

Robustness

Harsh variable selection: variable permutation and binomial testing (<u>Kursa2010</u>). From 16 to 4-7 variables.

Random effects

E effects partly accounted in fixed effects.



Differences between species in mixture are key predictors.

1

2

3

4

5

6

7







wheat / pea

2

0.005

Competition

Most predictors had opposite effects on focal species, yet some asymmetry remains.

Genericity

Species and cultivar modality were not selected

Data science for studying diversified agrosystems

Modelling to ease the tension between generalisation and specialisation

Diversification is easy, mechanisms are not [McGuire2021]. Broad frameworks report **context-dependent** positive effects of diversification on productivity or stability [Dee2023, Lipoma2024].

For plants, traits-derived variables used as a signature of processes driving mixture functioning is a solid base for predictive models. For environment, we might need variables indicating stress patterns rather than practices and geography.

Work on the integration of scientific cultures [Enquist2024]

Separate (1) what can be explained through **processes**, (2) what can be explained with **data**, (3) what cannot be explained with a reductionist approach (**expertise**)



Thanks for the shared expertise and trials!

Design and experimentation

Laurent Bedoussac, Eric Justes, Etienne-Pascal Journet, Christophe Naudin, Henrik Hauggaard-Nielsen, Erik Steen Jensen, Elise Pelzer, Guénaëlle Corre-Hellou, Bochra Kammoun, Loic Viguier, Romain Barillot, Antoine Couëdel, Philippe Hinsinger

We're open!

Joint analysis of multiple experiments - a key consideration given the pressing need for consolidating results in the context of an increasingly variable and changing climate.

Thank you for you attention! Any questions?



