

June 28 2022

Agro-ecological modeling for sustainable crop production at field scale

David Makowski

What is a (mathematical) model?

Mathematical model = Tool to compute outputs Y from inputs X



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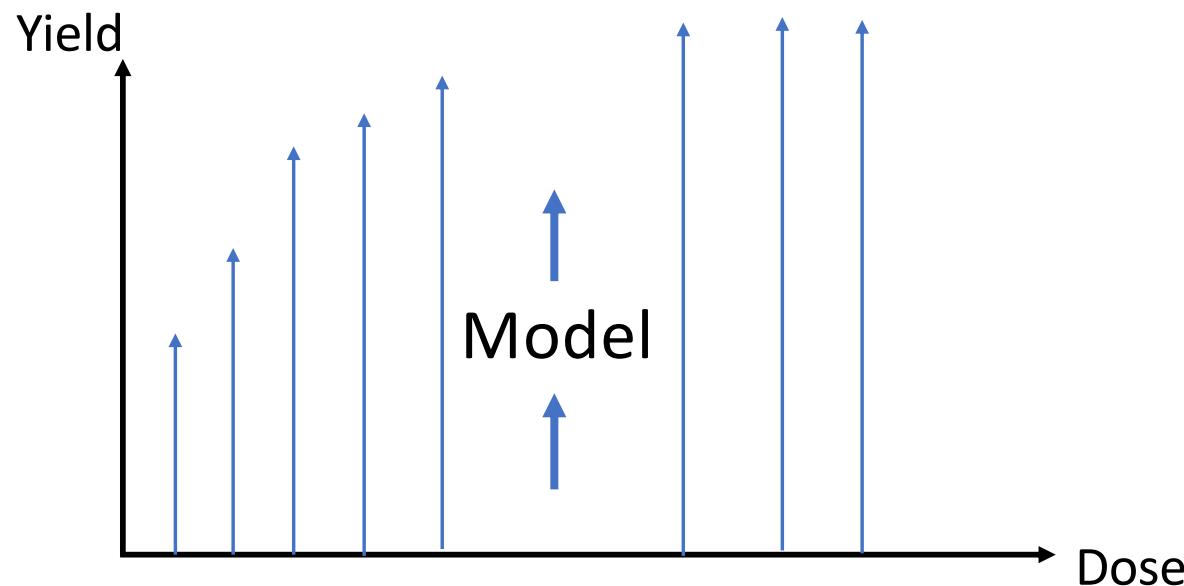
Wheat yield ← Model ← N fertilizer dose

What is a (mathematical) model?

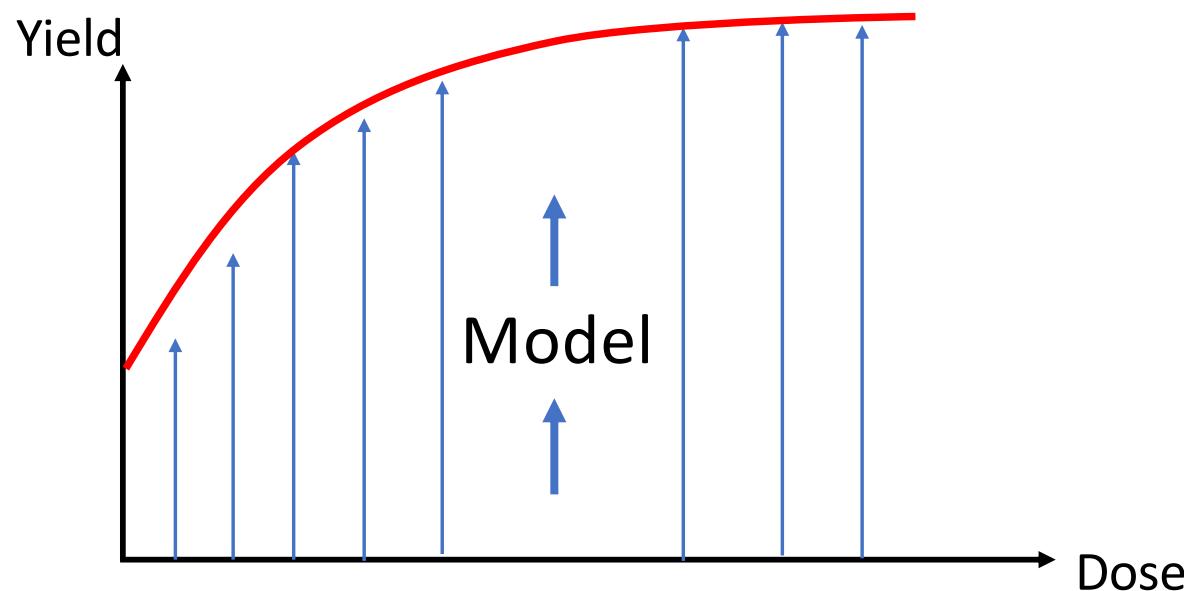
Mathematical model = Tool to compute outputs Y from inputs X

8 t ha⁻¹ ← Model ← 200 kg ha⁻¹

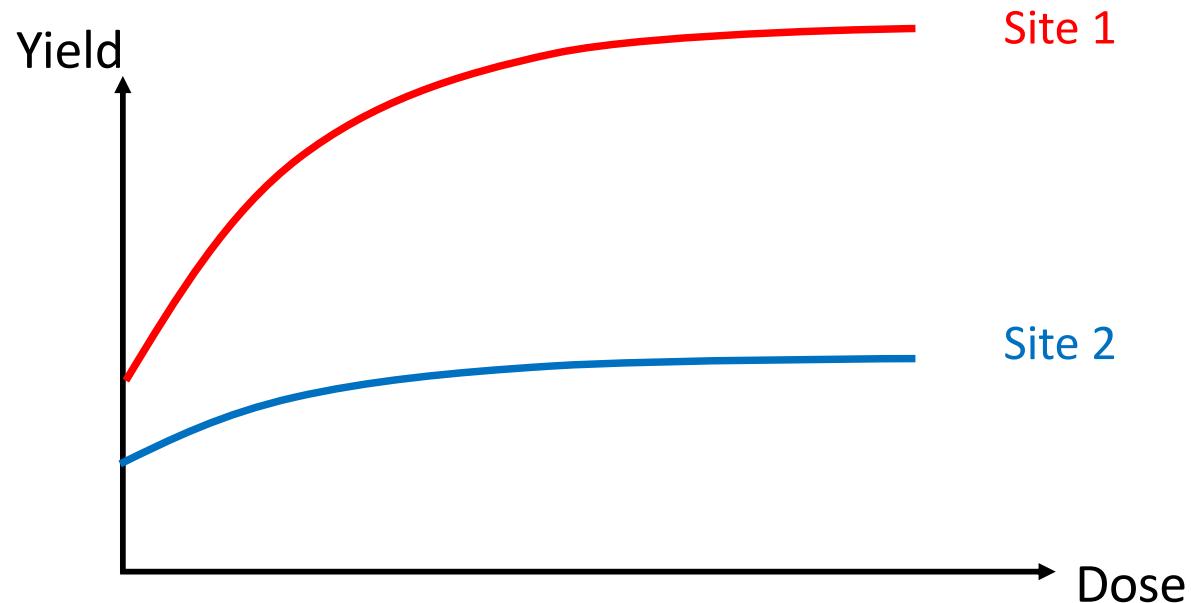
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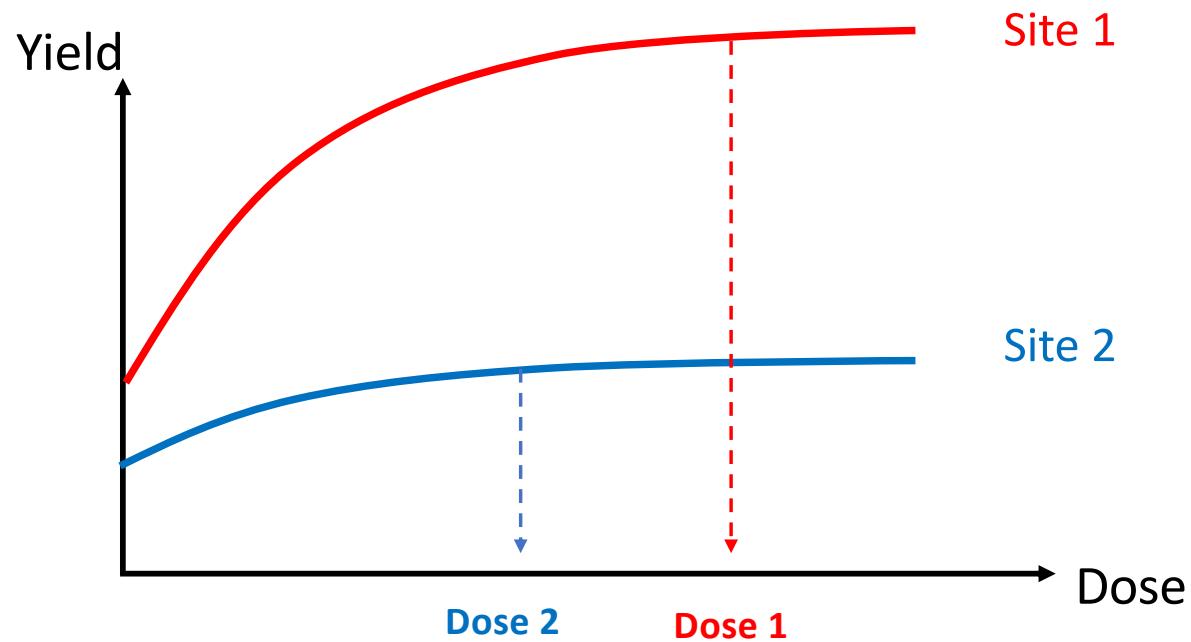
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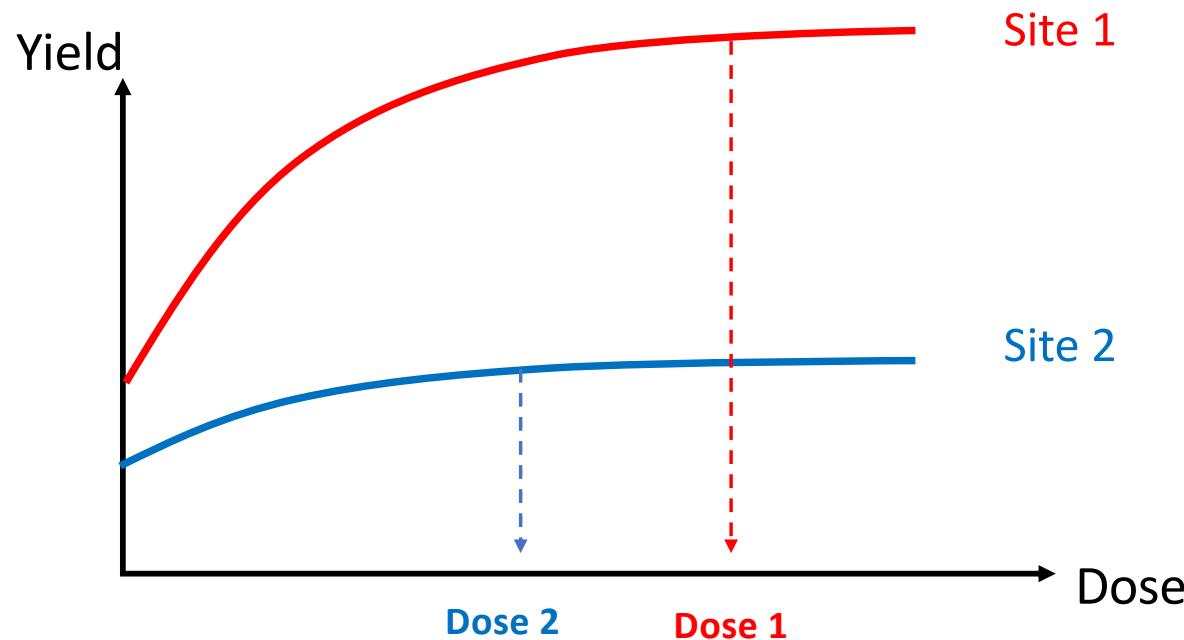


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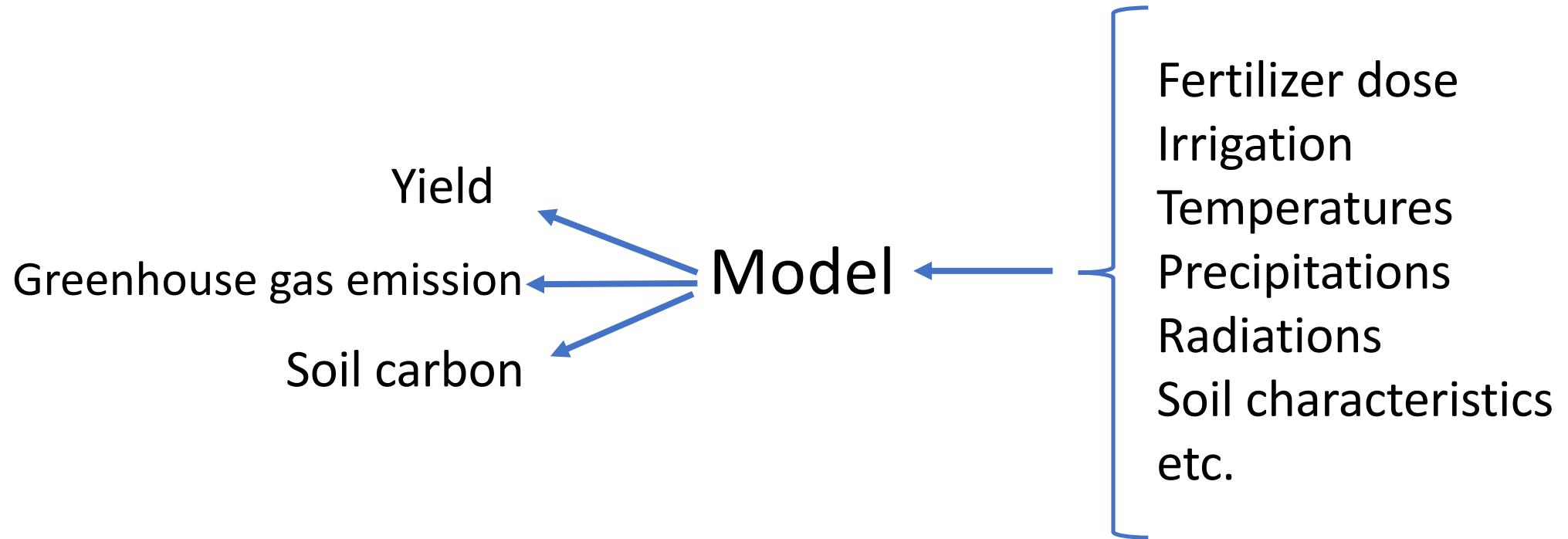
What is a (mathematical) model?

Model-based recommendations can contribute to chemical input use reduction



What is a (mathematical) model?

Mathematical model = Tool to compute outputs Y from inputs X



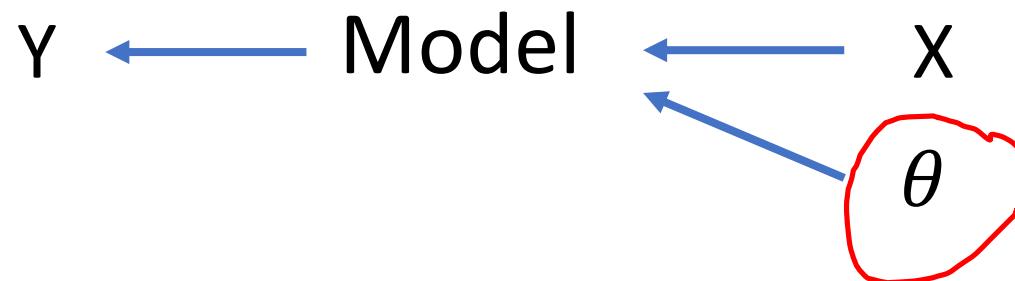
What is a (mathematical) model?

Mathematical model = Tool to compute outputs Y from inputs X
and parameters θ



What is a (mathematical) model?

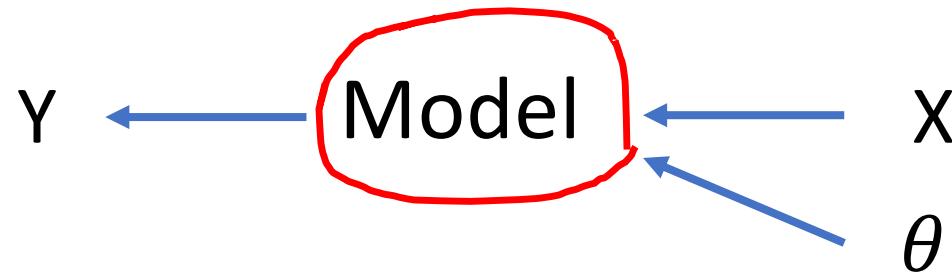
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Parameter values are unknown and need to be estimated
before running the model.

What is a (mathematical) model?

Mathematical model = Tool to compute outputs Y from inputs X
and parameters θ



A wide variety of models can be used to address a specific objective

Models can be very simple or... very complex

Model type	Example	Complexity
Linear model	$Y = \theta_1 + \theta_2 X$	1 input, 2 parameters

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Linear model	$Y = \theta_1 + \theta_2 X$	1 input, 2 parameters
Linear model	$Y = \theta_1 + \theta_2 X_1 + \theta_3 X_2$	2 inputs, 3 parameters

Models can be very simple or... very complex

Model type	Example	Complexity
Linear model	$Y = \theta_1 + \theta_2 X$	1 input, 2 parameters
Linear model	$Y = \theta_1 + \theta_2 X_1 + \theta_3 X_2$	2 inputs, 3 parameters
Nonlinear model	$Y = \theta_1[1 - \theta_2 \exp(-\theta_3 X)]$	1 input, 3 parameters

Models can be very simple or... very complex

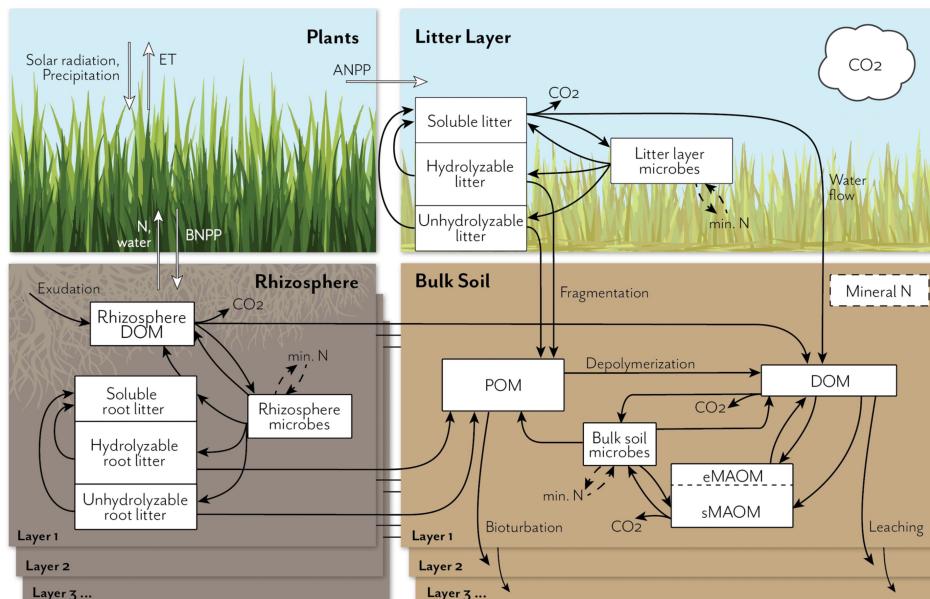
Model type

Example

Complexity

Mechanistic

model simulating carbon and nitrogen dynamics



~ 100

<https://doi.org/10.5194/bg-18-3147-2021>

Models can be very simple or... very complex

Model type

Example

Complexity

Mechanistic

~100

model simulating carbon and nitrogen dynamics

Equations	
Surface litter	
$\frac{dC_{ssoluble}}{dt} = -C_{ssoluble} * k_{soluble} * T_{eff} * W_{eff} * LCl_{eff} * MicCN_{eff} - C_{ssoluble} * k_{solubleLeach}$	$* W_{leach} + C_{shydro} * k_{shydro} * T_{eff} * W_{eff} * LCl_{eff} * MicCN_{eff}$
	$+ C_{unhydro} * k_{unhydro} * T_{eff} * W_{eff} * LCl_{eff} * MicCN_{eff} + C_{smiclitter} * k_{micDeath}$
	$+ frac{toSoluble}$
$\frac{dC_{shydro}}{dt} = -C_{shydro} * k_{shydro} * T_{eff} * W_{eff} * LCl_{eff} * MicCN_{eff} - C_{shydro} * k_{fragment} * T_{eff}$	$* W_{eff} + C_{smiclitter} * k_{micDeath} + frac{toUnhydro}$
$\frac{dC_{unhydro}}{dt} = -C_{unhydro} * k_{unhydro} * T_{eff} * W_{eff} * LCl_{eff} * MicCN_{eff} - C_{unhydro} * k_{fragment} * T_{eff}$	$* W_{eff} + C_{smiclitter} * k_{micDeath} + frac{toUnhydro}$
Note: unlike the soluble and hydrolyzable pools, no LCl_{eff} on unhydrolyzable pool decay.	
$\frac{dC_{smiclitter}}{dt} = -C_{smiclitter} * k_{micDeath} + C_{ssoluble} * k_{soluble} * T_{eff} * W_{eff} * LCl_{eff} * MicCN_{eff}$	$* CUE_{ssoluble}$
$\frac{dC_{CO_2}}{dt} = C_{ssoluble} * k_{soluble} * T_{eff} * W_{eff} * LCl_{eff} * MicCN_{eff} * (1 - CUE_{ssoluble})$	
Rhizosphere litter	
$\frac{dC_{ssoluble}}{dt} = -C_{ssoluble} * k_{solubleLeach} * LCl_{eff} + C_{rhydro} * k_{hydro} * T_{eff} * W_{eff} * LCl_{eff}$	$* MicCN_{eff} + C_{runhydro} * k_{unhydro} * T_{eff} * W_{eff} * MicCN_{eff} + C_{rmiclitter}$
	$+ k_{micDeath} * frac{toUnhydro}$
$\frac{dC_{rhydro}}{dt} = -C_{rhydro} * k_{hydro} * T_{eff} * W_{eff} * LCl_{eff} * MicCN_{eff} - C_{rhydro} * k_{fragment} * T_{eff}$	$* W_{eff} + C_{rmiclitter} * k_{micDeath} + frac{toUnhydro}$
$\frac{dC_{runhydro}}{dt} = -C_{runhydro} * k_{unhydro} * T_{eff} * W_{eff} * MicCN_{eff} - C_{runhydro} * k_{fragment} * T_{eff}$	$* W_{eff} + C_{rmiclitter} * k_{micDeath} + frac{toUnhydro}$
$\frac{dC_{RDOM}}{dt} = -C_{RDOM} * k_{soluble} * T_{eff} * W_{eff} * MicCN_{eff} - C_{RDOM} * k_{RDOMLeach} * WFPS^3$	$+ C_{ssoluble} * k_{solubleLeach} * LCl_{eff} + C_{endate} * k_{endate}$
Note: the decay rate of surface soluble litter $k_{soluble}$ is also used for RDOM.	
$\frac{dC_{rmiclitter}}{dt} = -C_{rmiclitter} * k_{micDeath} + C_{RDOM} * k_{soluble} * T_{eff} * W_{eff} * MicCN_{eff} * CUE_{RDOM}$	
$\frac{dC_{CO_2}}{dt} = C_{RDOM} * k_{soluble} * T_{eff} * W_{eff} * MicCN_{eff} * (1 - CUE_{RDOM})$	

<https://doi.org/10.5194/bg-18-3147-2021>

Models can be very simple or... very complex

Model type	Example	Complexity
Mechanistic	<p>Crop model WOFOST</p> <p>The diagram illustrates the WOFOST crop model. At the top, 'RADIATION' enters 'LIGHT INTERCEPTION', which is influenced by 'LEAF AREA'. This leads to 'POTENTIAL GROSS PHOTOSYNTHESIS'. A fraction 'Ta/Tp' leads to 'MAINTENANCE RESPIRATION'. The remaining energy goes to 'ACTUAL GROSS PHOTOSYNTHESIS'. This is used for 'CROP GROWTH (DRY MATTER)' and 'GROWTH RESPIRATION'. 'GROWTH RESPIRATION' is shown as a feedback loop back to 'ACTUAL GROSS PHOTOSYNTHESIS'. 'CROP GROWTH' is partitioned into 'ROOTS (ALIVE)', 'STEMS (ALIVE)', 'STORAGE ORGANS (ALIVE)', and 'LEAVES (ALIVE)'. Each of these pathways has a 'DEATH' arrow pointing to it. Below the diagram is a photograph of a corn crop.</p> <p>~100</p>	~100

Models can be very simple or... very complex

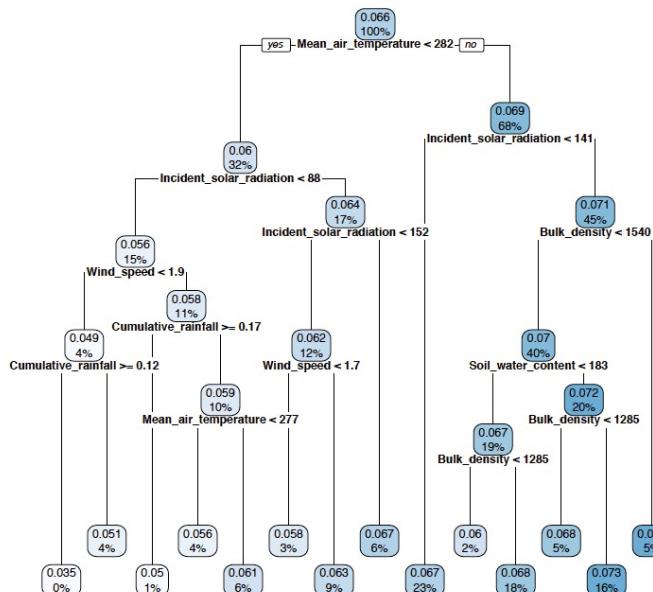
Model type

Example

Complexity

Machine learning

100, 1000 or more



Why modelling is useful for agro-ecology?

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« Agroecology seeks to optimize the interactions between plants, animals, humans and the environment while taking into consideration the social aspects that need to be addressed for a sustainable and fair food system »



Food and Agriculture
Organization of the
United Nations

**THE 10 ELEMENTS
OF AGROECOLOGY**
**GUIDING THE TRANSITION
TO SUSTAINABLE FOOD AND
AGRICULTURAL SYSTEMS**

Why modelling is useful for agro-ecology?

- Agroecology has multiple objectives
 - Improve soil health
 - Increase biodiversity
 - Input reduction (ex: fertilizer)
 - Improve resilience to climate change
 - Efficiency
 - Promote healthy diets
 - Etc.

<https://doi.org/10.1007/s13593-020-00646-z>

<https://www.fao.org/documents/card/fr/c/19037EN/>



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Why modelling is useful for agro-ecology?

- Agroecology promotes a great diversity of practices
 - Diversification of rotation
 - Agroforestry
 - Intercropping
 - Use of decision support tools to reduce inputs
 - No tillage
 - Etc.



Cocoa agroforestry system (Photo E. Malezieux)
DOI: 10.1051/agro:2007057

Why modelling is useful for agro-ecology?

- Agroecology has multiple objectives
- Agroecology promotes a great diversity of practices

→ Models = powerful tools to compare many practices for many objectives.

Why modelling at field scale?

- Many decisions are taken at the field scale
 - choice of crop species,
 - choice of cropping systems,
 - fertilization,
 - pest & disease control,
 - irrigation etc.

Why modelling at field scale?

- Many decisions are taken at the field scale
 - choice of crop species,
 - choice of cropping systems,
 - fertilization,
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 - irrigation etc.
- A lot of data is available at the field scale to assist in model development
 - trials in experimental stations,
 - on-farm experiments,
 - field observations,
 - expert knowledge (from farmers, advisors etc.)

Main steps in a modelling project

Step 1: Definition of the objective

Step 2: Data collection

Step 3: Definition of candidate models

Step 4: Model training with data (parameter estimation)

Step 5: Model testing with data (model evaluation)

Step 6: Model application

Example of modelling project:
N, P, K fertilization models for potato crops in Eastern Canada

<https://doi.org/10.1371/journal.pone.0230888>

PLOS ONE

RESEARCH ARTICLE

Site-specific machine learning predictive
fertilization models for potato crops in
Eastern Canada

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1 Department of Soils and Agrifood Engineering, Université Laval, Québec City, Quebec, Canada, **2** Quebec Research and Development Centre, Agriculture and Agri-Food Canada, Québec City, Quebec, Canada

Example of modelling project: N, P, K fertilization models for potato crops in Eastern Canada

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Random forest (RF) algorithm

The default parameters

```
In [43]: from sklearn.ensemble import RandomForestRegressor
```

```
In [44]: rf_reg = RandomForestRegressor(random_state = 1)
print('Parameters currently in use:\n')
pprint(rf_reg.get_params())
```

Parameters currently in use:

... . . . -

Data and code available!

https://github.com/rgoals/2019_Site-specific-potato-npk-model

Potato yield ← Model ←

- N, P, K doses
- Planting density
- Preceding crops
- Growing season length
- Temperature
- Precipitations
- Shannon diversity index
- Number of growing degree days
- Soil texture (0–20 cm) and carbon
- Soil types
- Soil pH
- Soil chemical composition

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Develop models to predict yields and calculate optimal N, P, K fertilizer doses for potato crops in Eastern Canada

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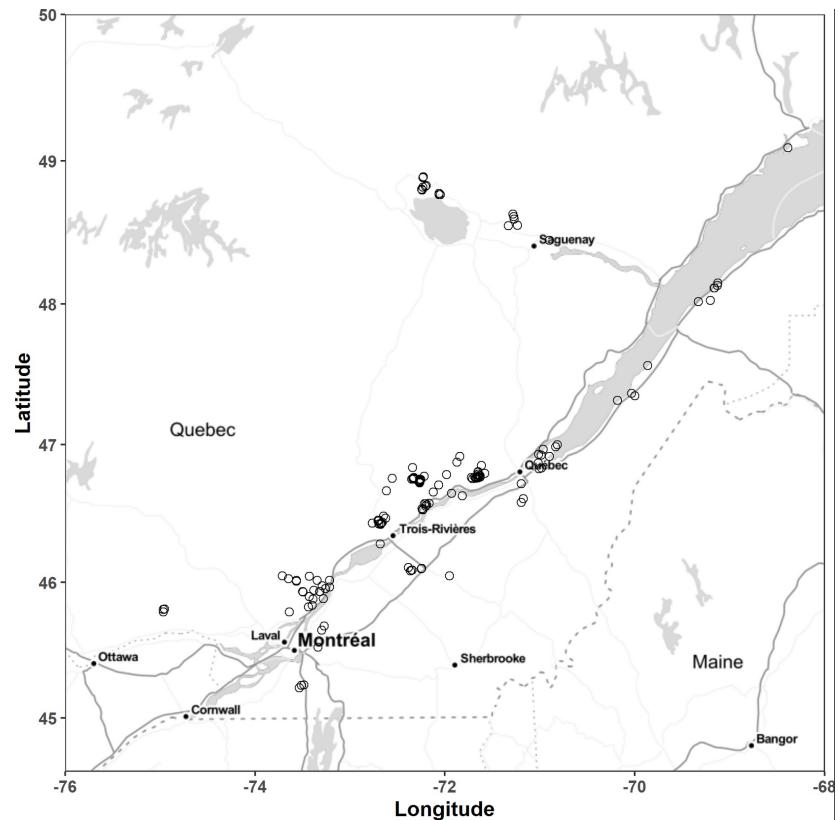
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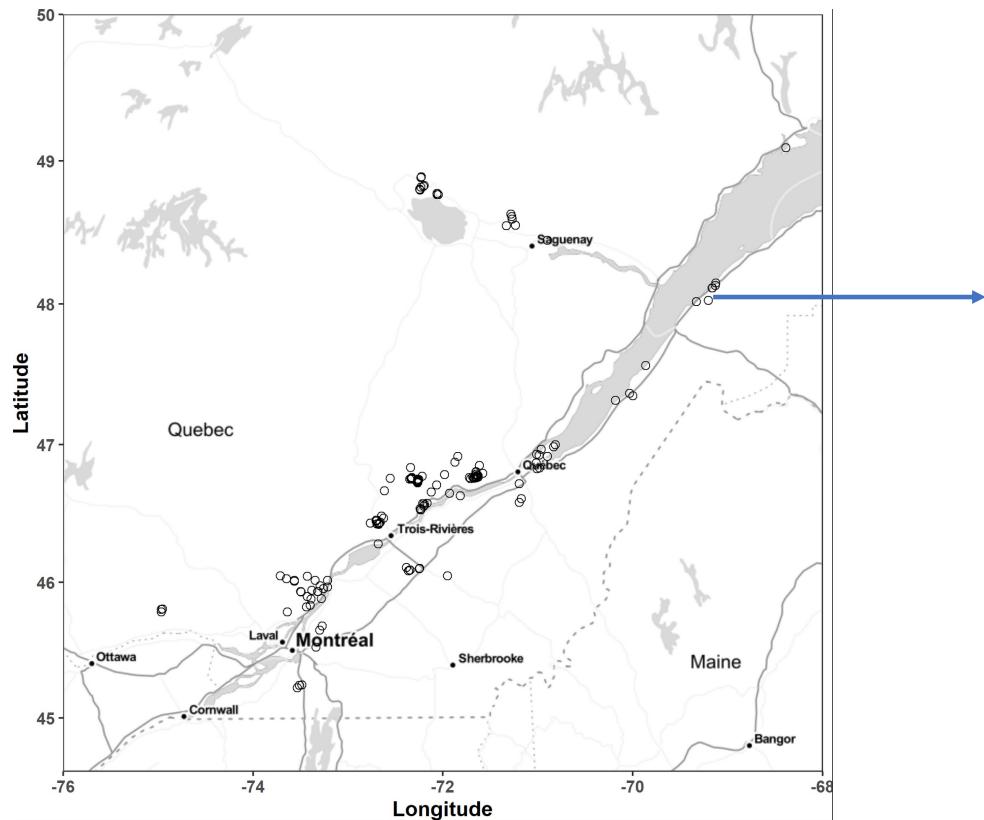
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237 field trials



<https://doi.org/10.1371/journal.pone.0230888>

237 field trials

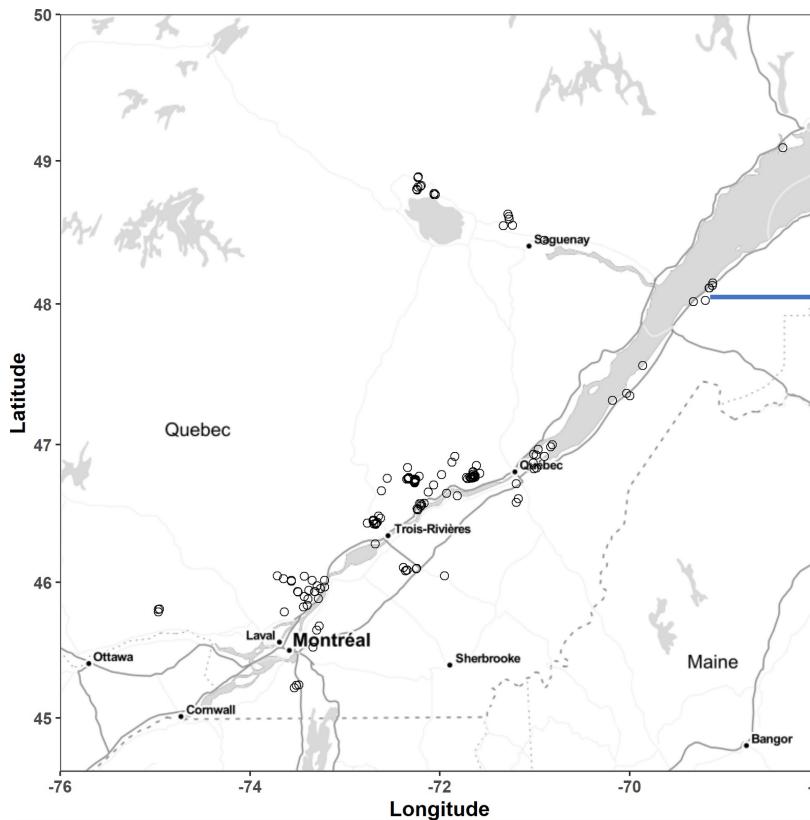


Dose 1	Dose 4
Dose 5	Dose 2
Dose 3	Dose 5
Dose 2	Dose 1
Dose 4	Dose 3

Yield measurement

<https://doi.org/10.1371/journal.pone.0230888>

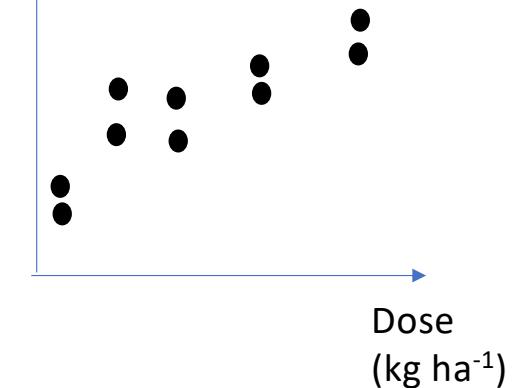
237 field trials



Dose 1	Dose 4
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Dose 2	Dose 1
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Yield measurement

Yield ($t \text{ ha}^{-1}$)



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Five models

1. Mitscherlich
2. KNN
3. Random forest
4. Neural network
5. Gaussian process

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Five models

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$$Y = A \ x(1 - e^{-R_N x(E_N + dose_N)})x(1 - e^{-R_P x(E_P + dose_P)})x(1 - e^{-R_K x(E_K + dose_K)})$$

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Standard machine learning models

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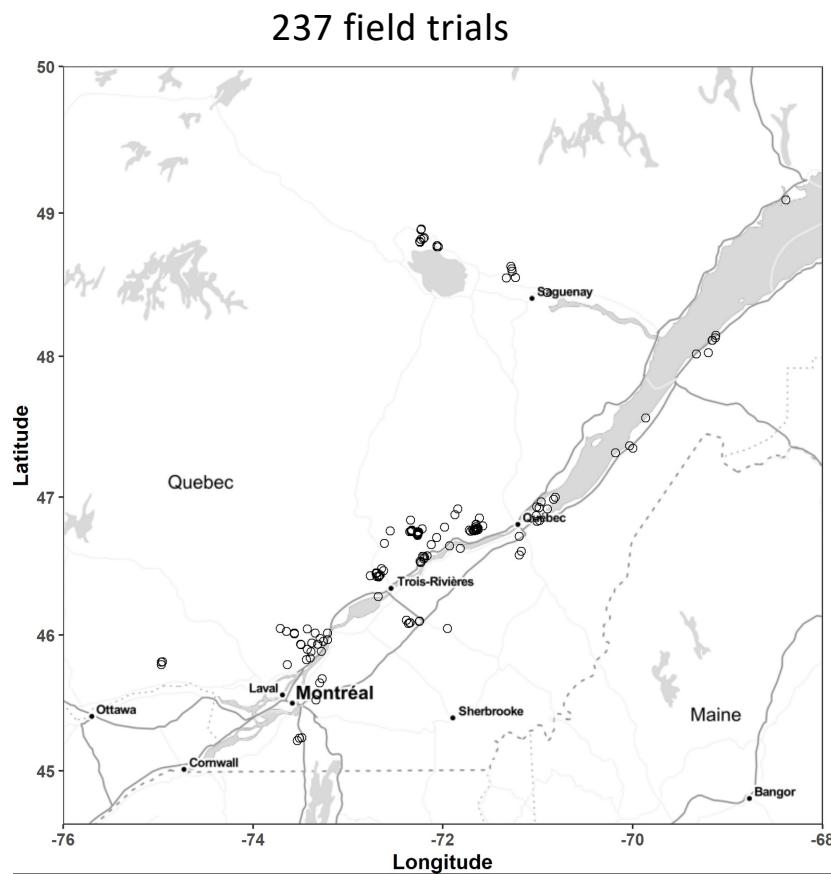
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Training dataset
60% of the trials

Parameter estimation
for the five models

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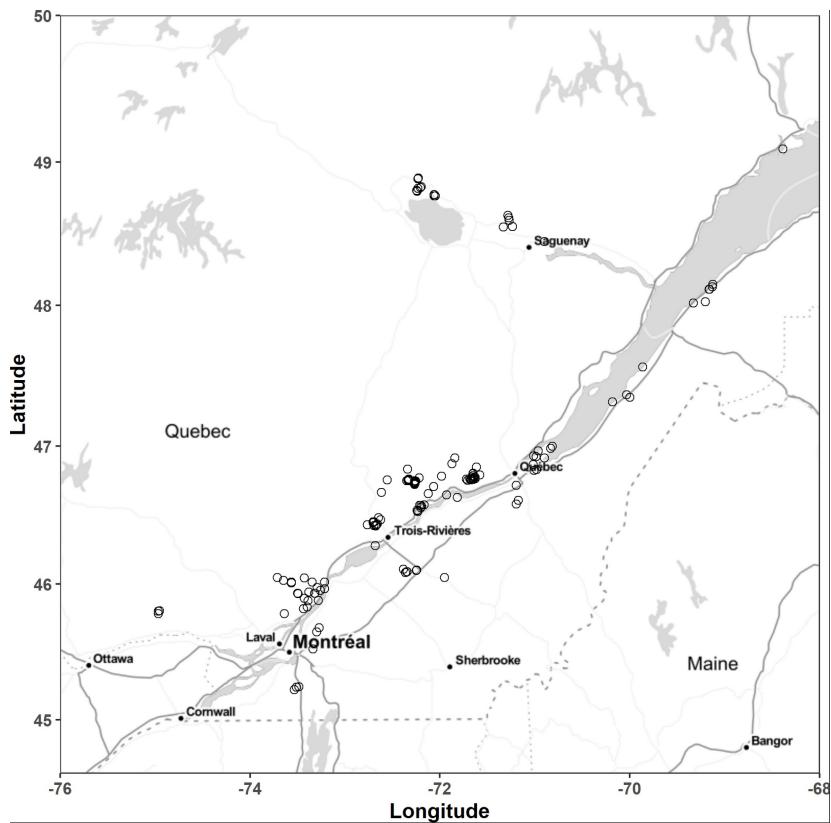
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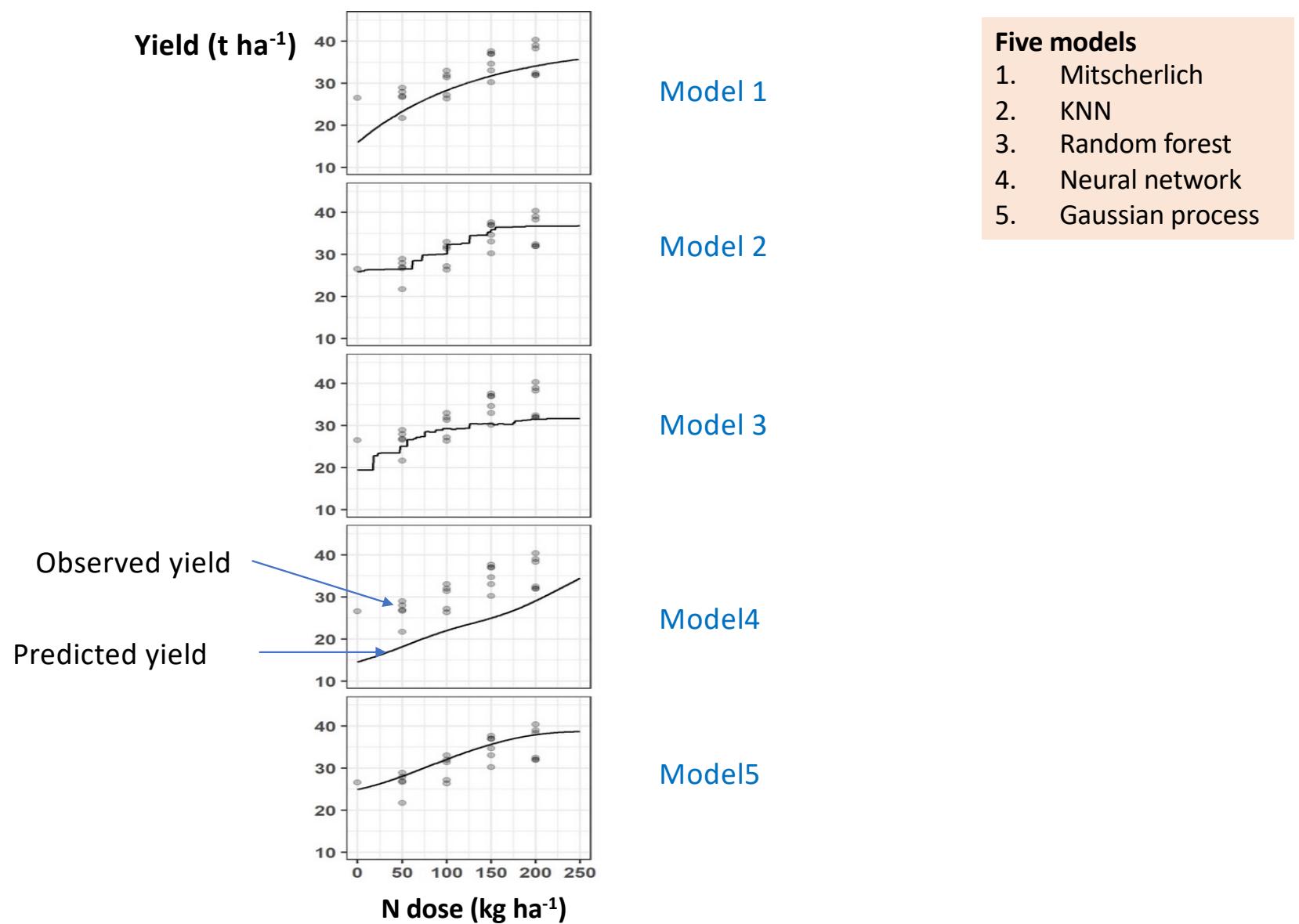
Step 6: Model application

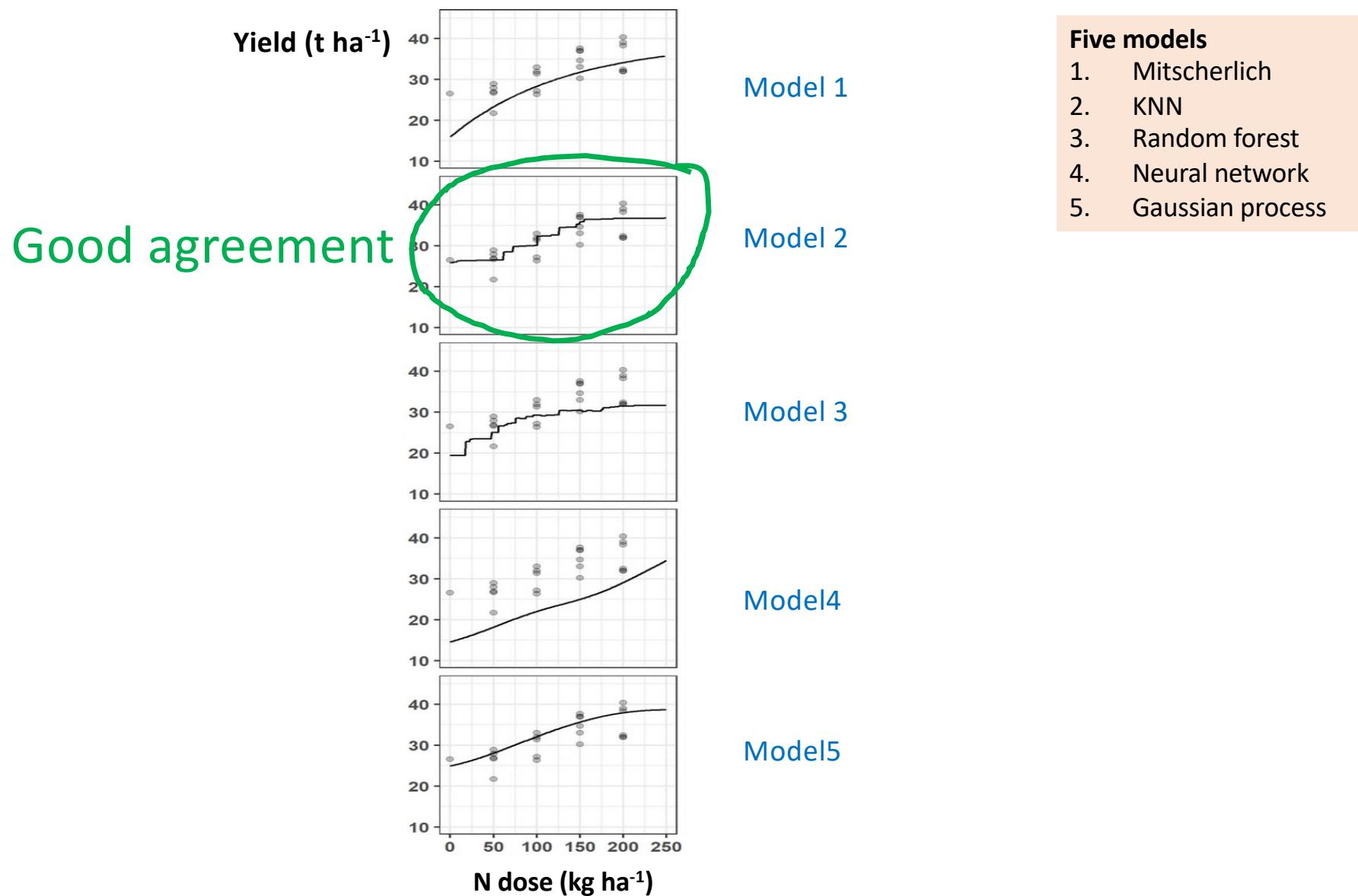
237 field trials



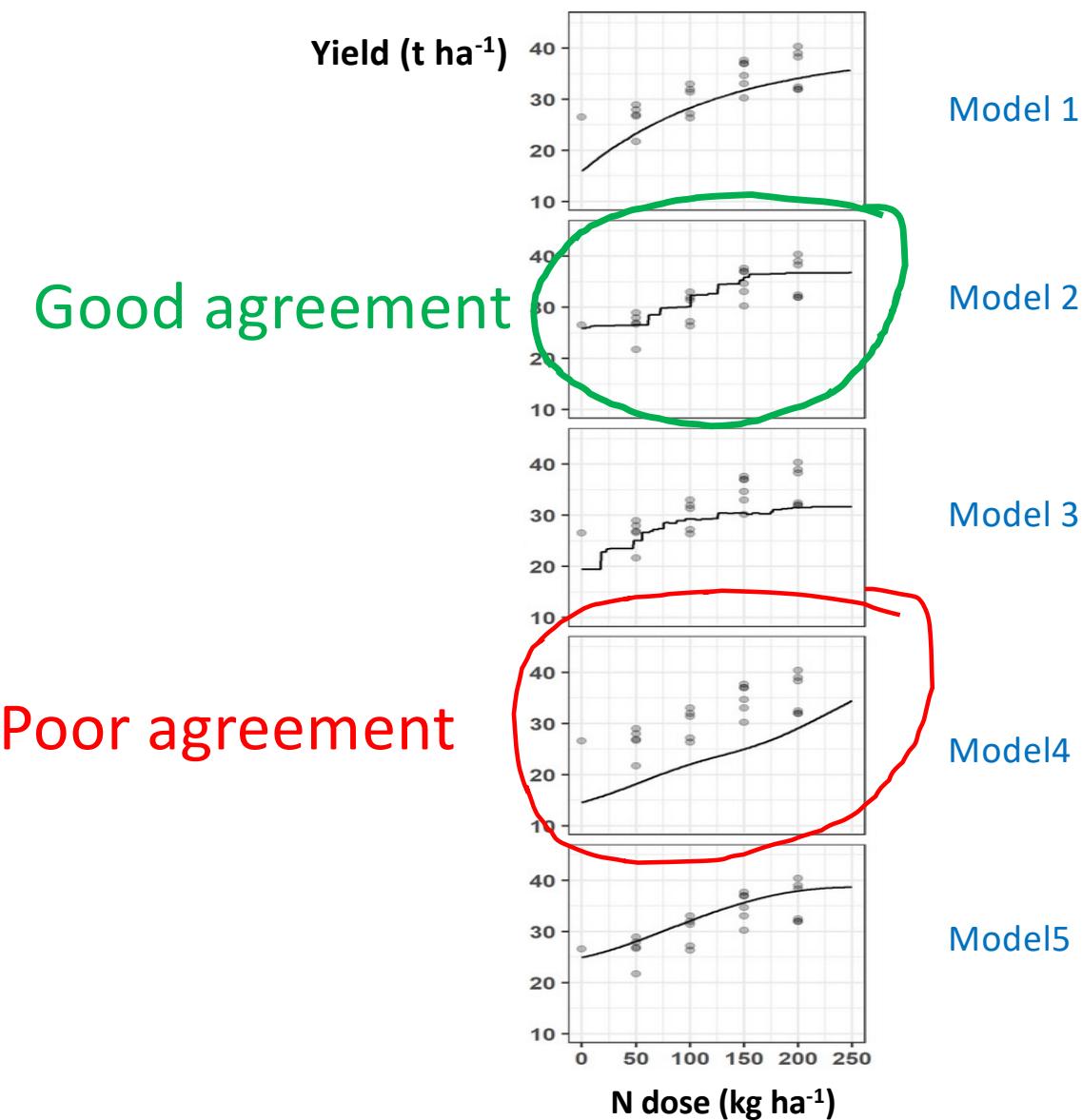
Testing dataset
40% of the trials

Evaluation of the
model performances



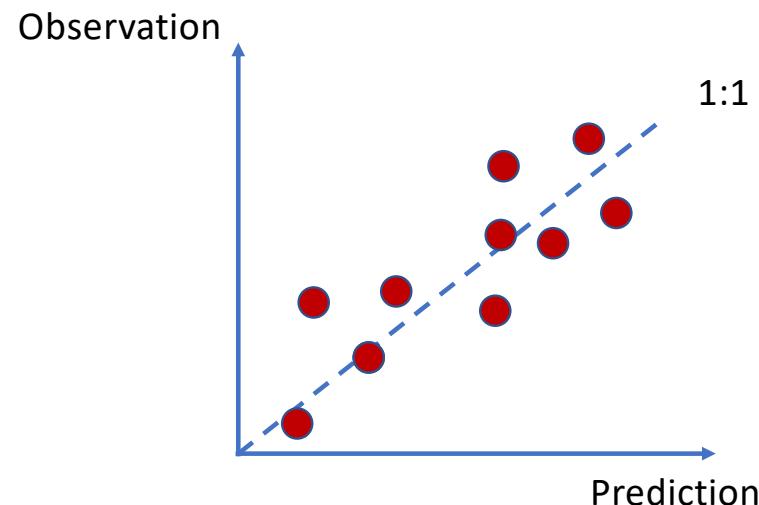


- Five models**
1. Mitscherlich
 2. KNN
 3. Random forest
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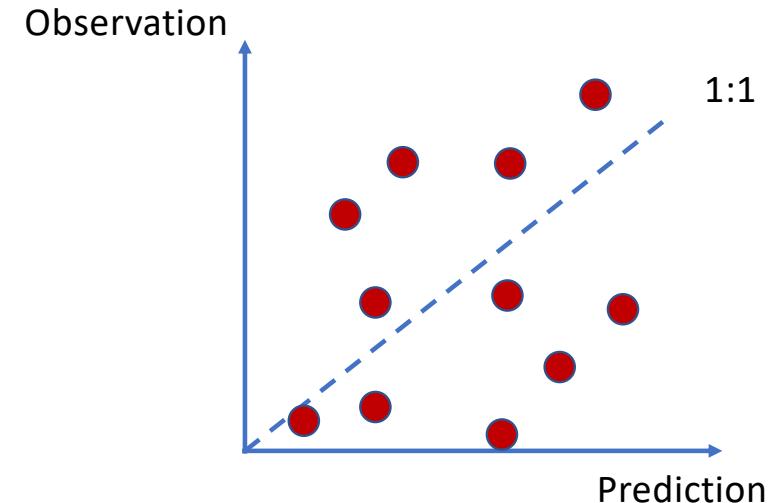
R^2 is a popular evaluation criterion

Good agreement



R^2 close to 1

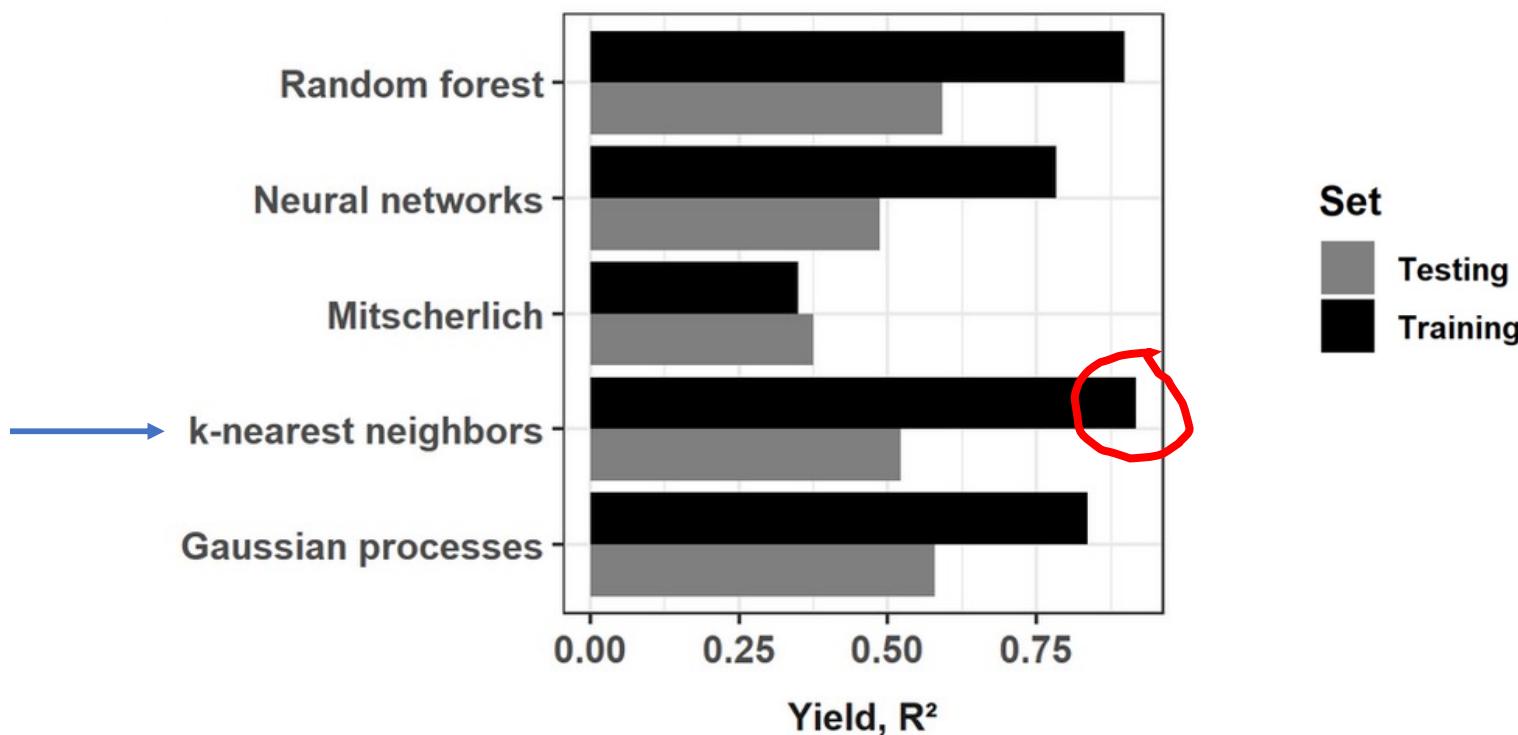
Poor agreement



R^2 close to 0

R^2

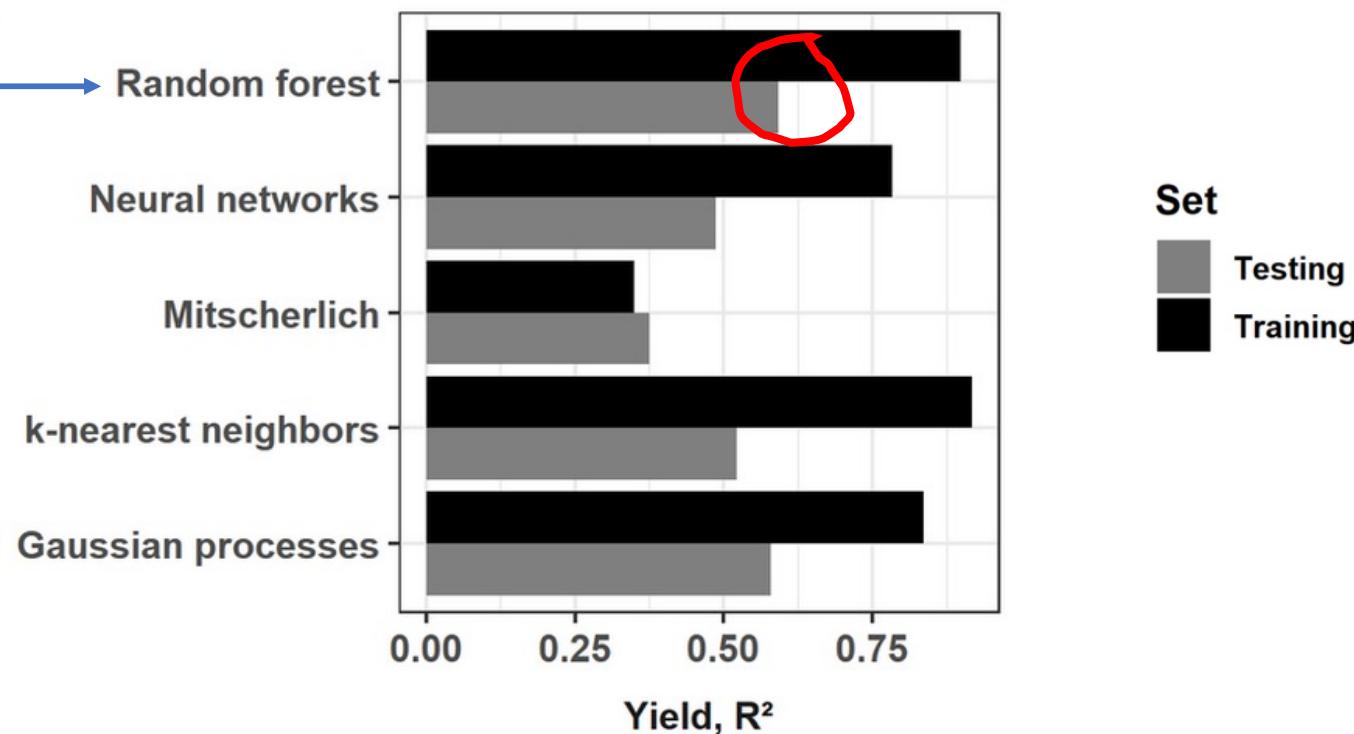
Best model
according to the
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<https://doi.org/10.1371/journal.pone.0230888>

R^2

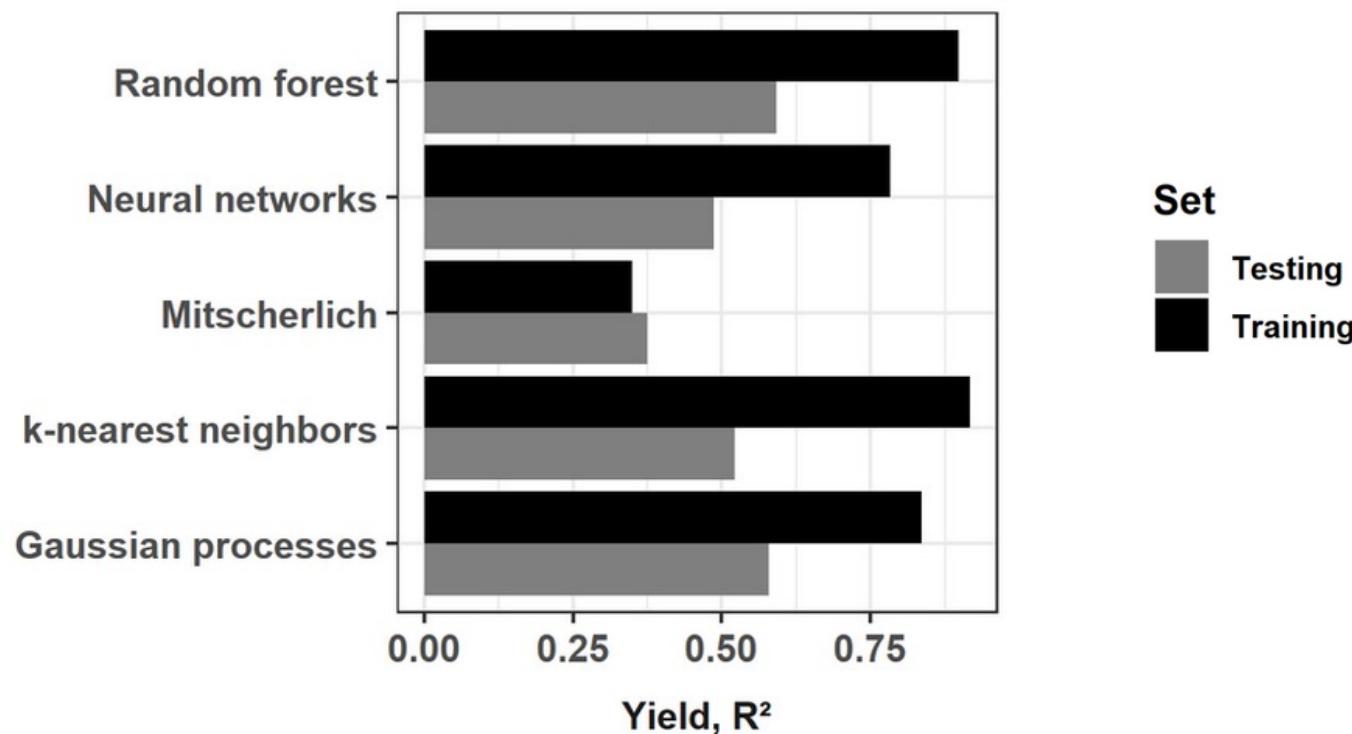
Best model
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R^2

Model performances are too optimistic according to the training dataset.

Important to use an independent test dataset !



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Step 1: Definition of the objective

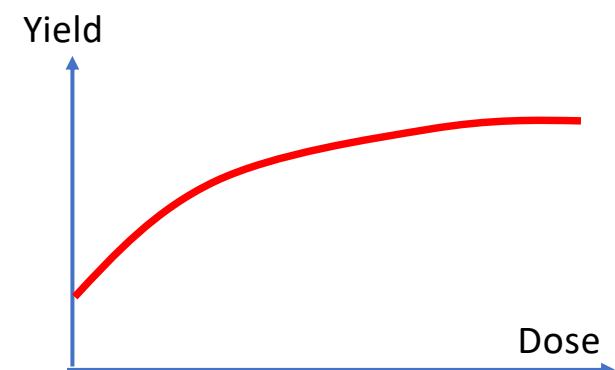
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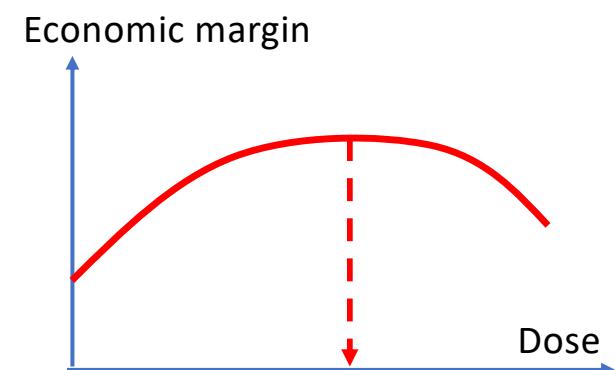
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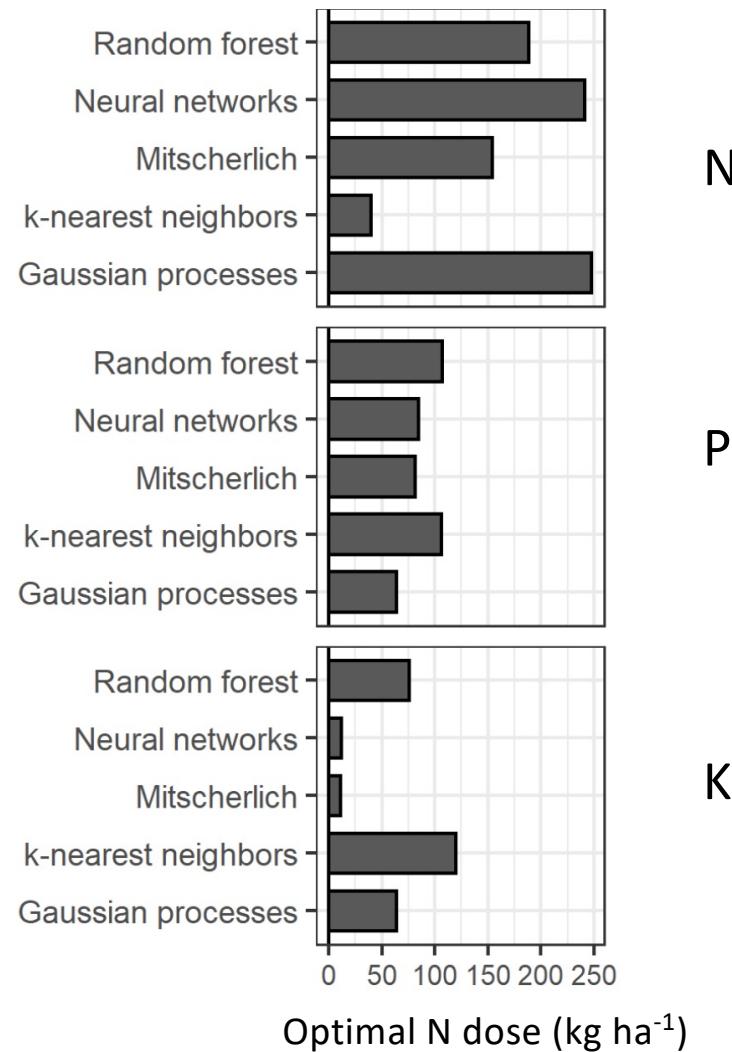
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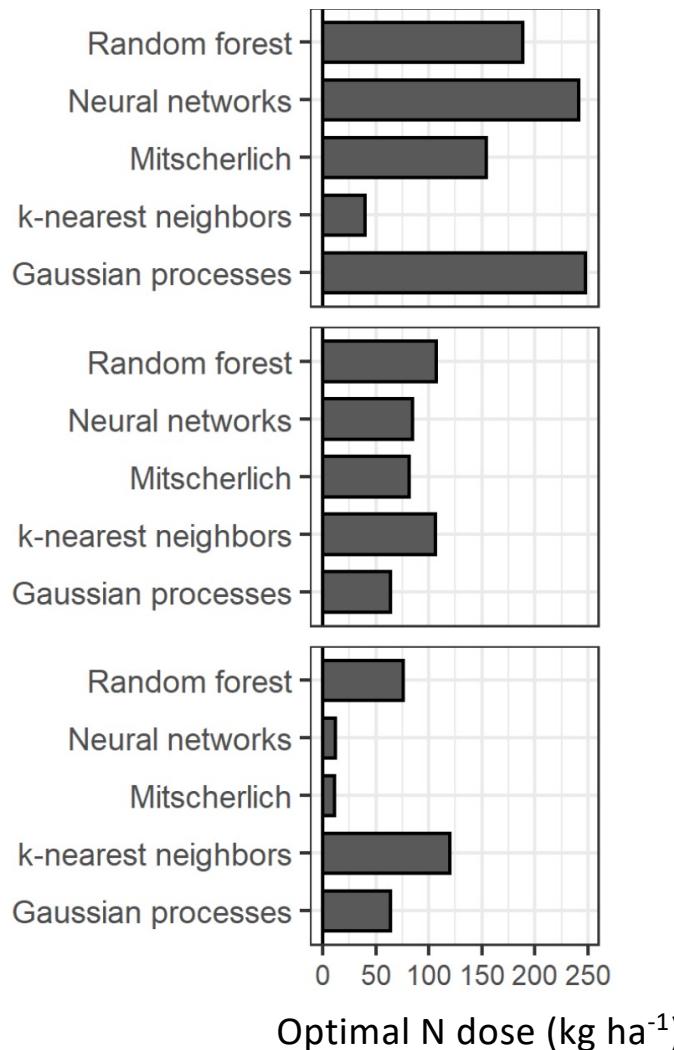
Step 6: Model application



Examples of optimal economic fertilizer doses at one site in Canada



Examples of optimal economic fertilizer doses at one site in Canada



Optimal doses are highly dependent on the selected model!

Why modelling is powerful?

- Models aggregate different sources of knowledge
- Useful for assessing & optimising farming practices
- Useful in foresight studies (ex: climate change)
- Support decisions of farmers, companies, policy makers

Why modelling can be dangerous?

- All models are wrong!
- Some models are not correctly evaluated
- Some models can lead to poor predictions and decisions

Why modelling can be dangerous sometimes?

- All models are wrong!
- Some models are not correctly evaluated
- Some models can lead to poor predictions and decisions
- Complex models can be fascinating... but can be highly uncertain.



Important to assess your models carefully!

Limit of modelling at field scale

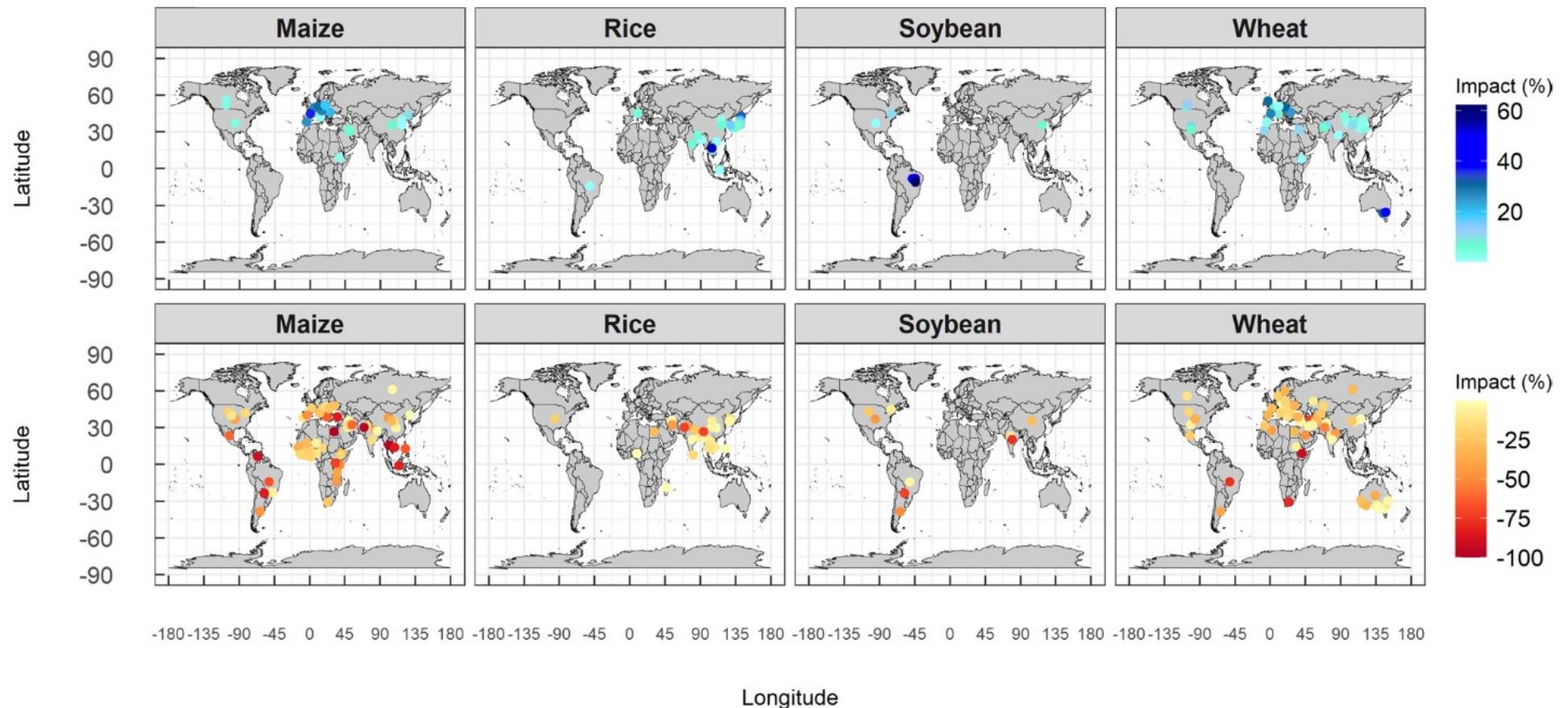
- Not the best scale to evaluate all economic and social impacts
- Not always the best scale to address global issues

BUT

Field-scale models can be upscaled at a larger scale.

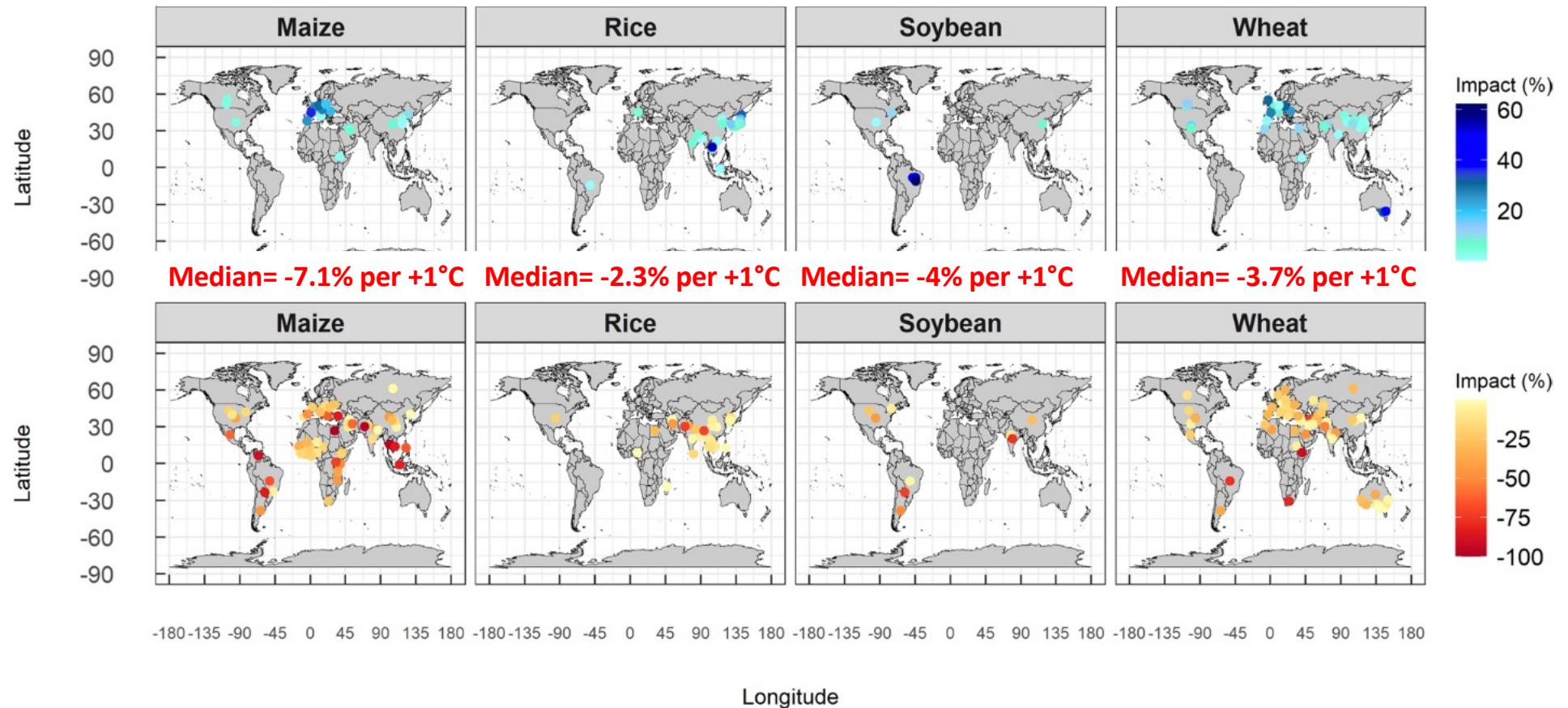
Simulated yield variations due to climate change

(a for scenario « RCP8.5 », time horizon 2050, baseline 2001-2010)



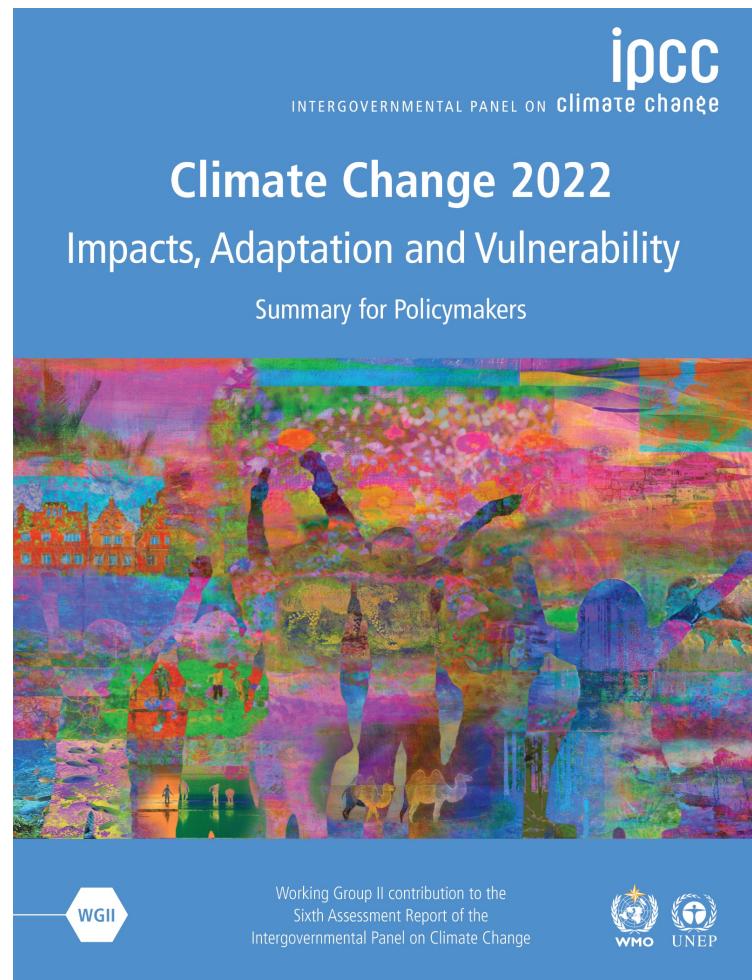
<https://doi.org/10.1038/s41597-022-01150-7>

Simulated yield variations due to climate change for scenario « RCP8.5 », time horizon 2050, baseline 2001-2010



<https://doi.org/10.1038/s41597-022-01150-7>

Crop model simulations are used in the IPCC reports on climate change



What you need to learn to be a good modeller

- Principles of agrosystem functioning

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- Potential sources of data (data on weather, soil, management, yields etc.)

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- Principles of agrosystem functioning
- Potential sources of data (data on weather, soil, management, yields etc.)
- Key modelling techniques
 - Statistics
 - Machine learning
 - Sensitivity/Uncertainty analysis
 - Data assimilation

What you need to learn to be a good modeller

- Principles of agrosystem functioning
- Potential sources of data (data on weather, soil, management, yields etc.)
- Key modelling techniques
- Coding

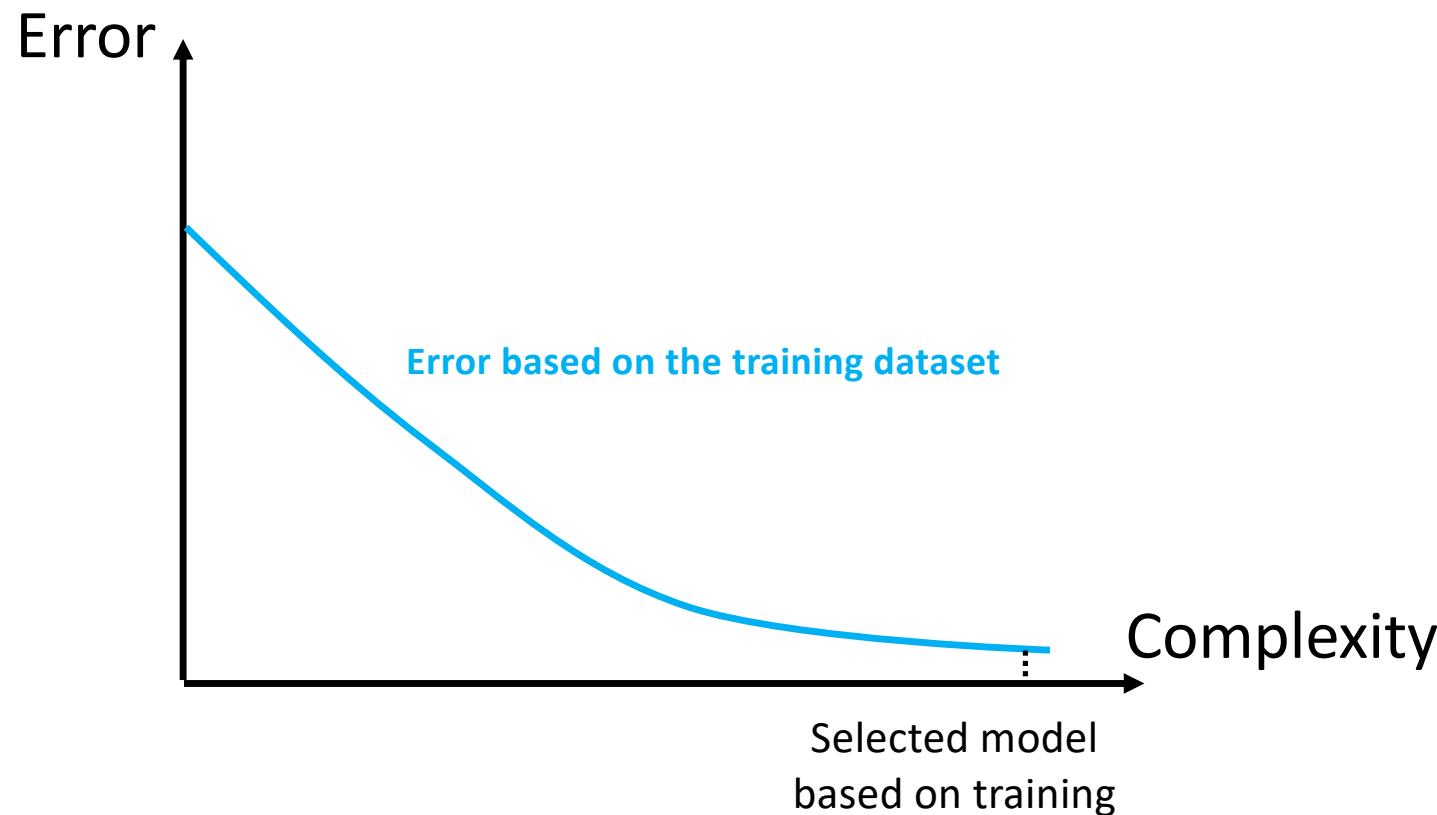
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- Key modelling techniques
- Coding
- Team work

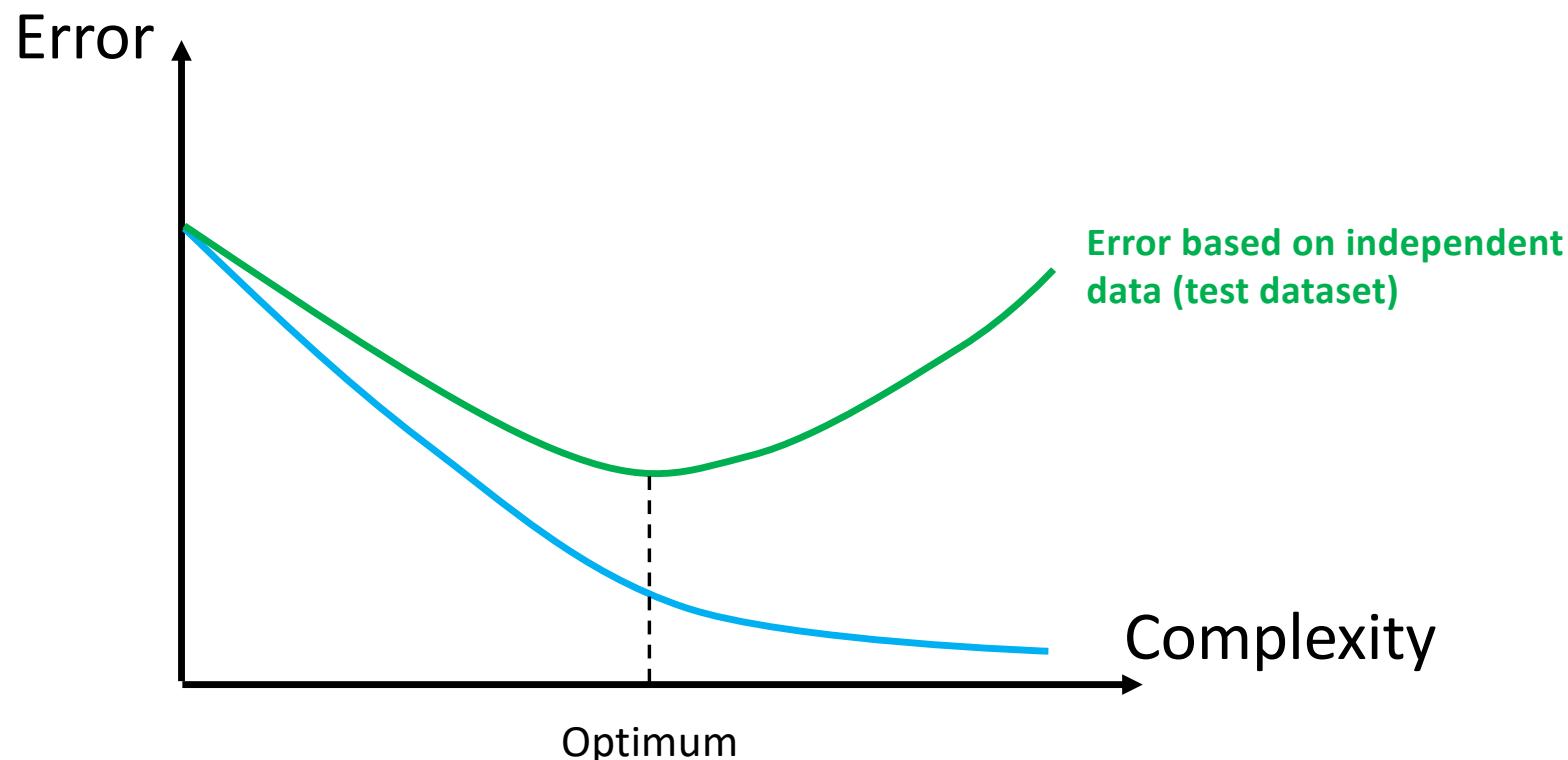
Check my github site for more lectures, data, and codes!

<https://github.com/davemakowski?tab=repositories>

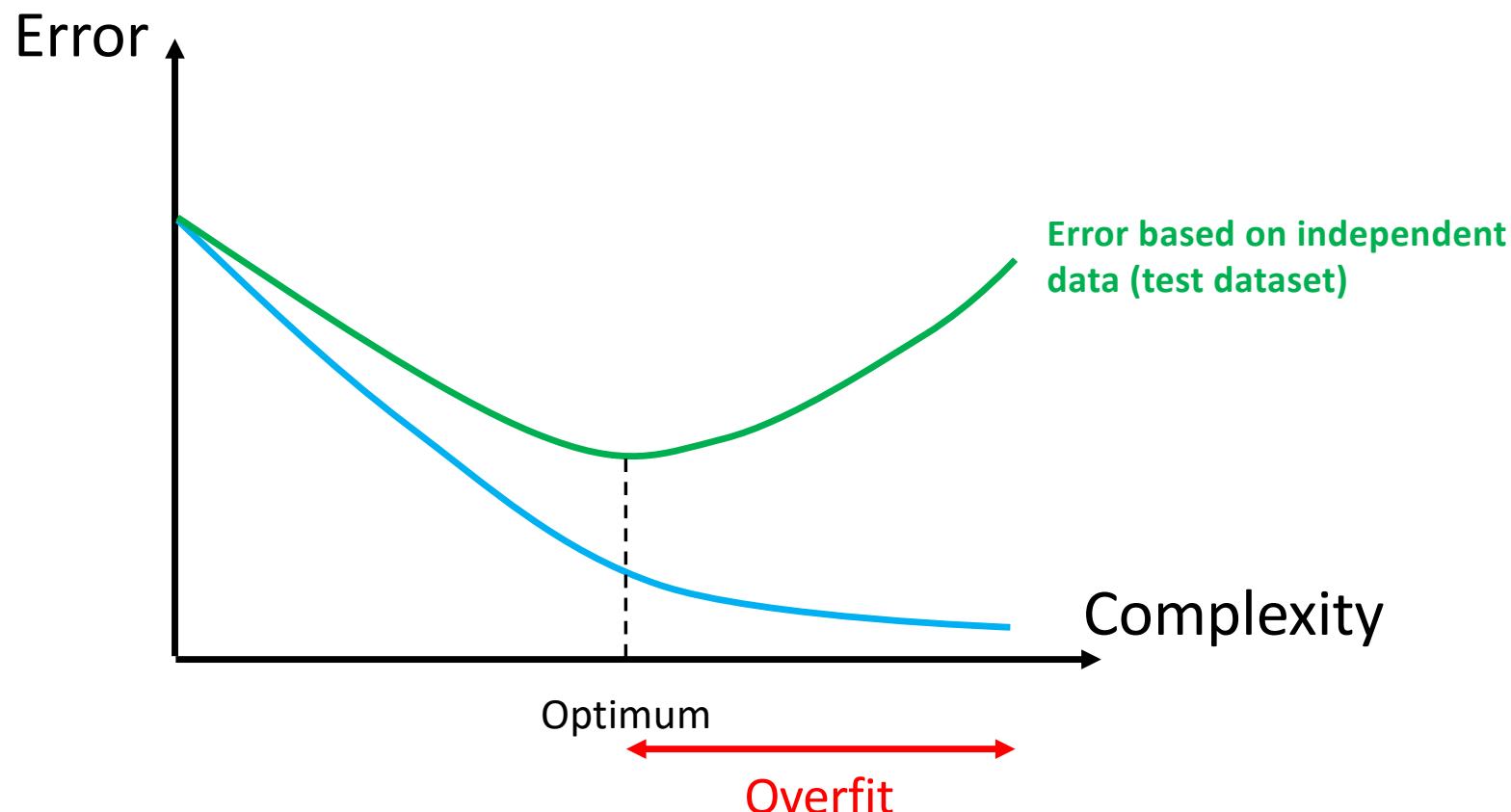
Model testing should be taken seriously to avoid risk of overfitting



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