Keynote Presentations: 1st EWRN Workshop

Keynote N°3

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Contribution of models to the assessment of risks associated with wireworm infestation and damage

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igepp

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European Wireworm Research Network, 1st workshop – Oslo – 7 July 2024

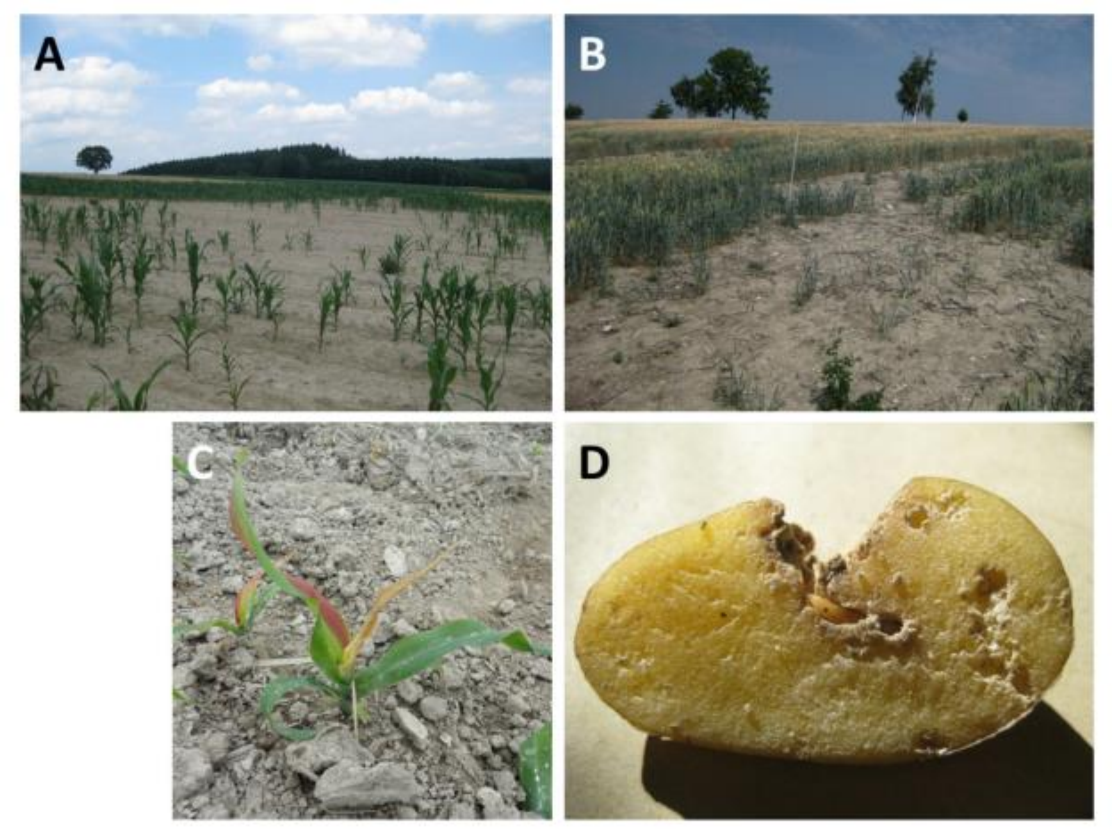
Context

- Drive toward a greener European agriculture with reduced inputs as part of The European Green Deal

- Resurgence of the threat posed by wireworms and increase in crop damage (e.g. maize, potatoes, vegetables)

- Mandatory[1] application of the principles of IPM

→ risk assessment can promote IPM strategies [Furlan et al., 2017][2] in view to reduce the dependence to and use of chemical pesticides



Poggi *et al.*, 2021. Agriculture, 11 (5), 436

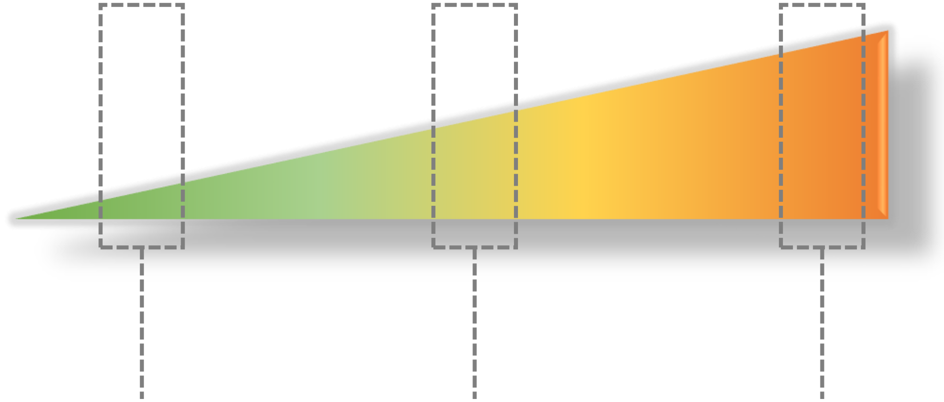
Assessing the risk associated with wireworm infestation and the potential damage to crops can benefit from statistical and mathematical modelling

[1] UE Directive 128/2009/EC
[2] Furlan et al., 2017. Crop Protection 97, 52-59

Diversity of modelling approaches

data-driven

knowledge-driven
(mechanistic)

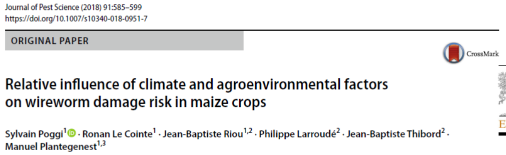


Regression models

Latent variable models

Reaction-diffusion models

ILLUSTRATIONS



Journal of Pest Science (2018) 91:585–599
https://doi.org/10.1007/s10340-018-0951-7

ORIGINAL PAPER

CrossMark

Relative influence of climate and agroenvironmental factors on wireworm damage risk in maize crops

Sylvain Poggi[1] · Ronan Le Cointe[1] · Jean-Baptiste Riou[1,2] · Philippe Larroudé[2] · Jean-Baptiste Thibord[2] · Manuel Plantegenest[1,3]

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Data-based regression models

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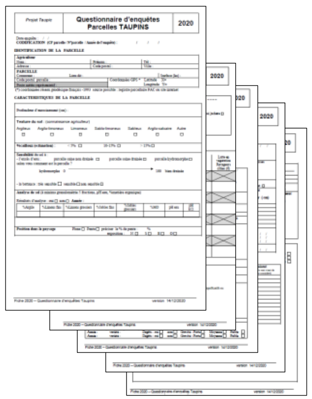
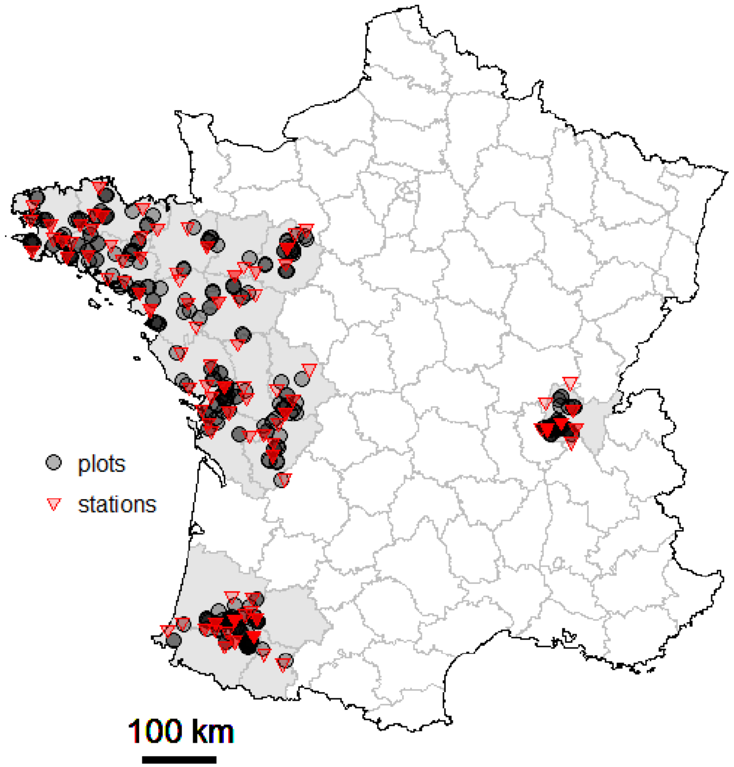
336 survey data (2012-2014)



ARVALIS Institut du végétal

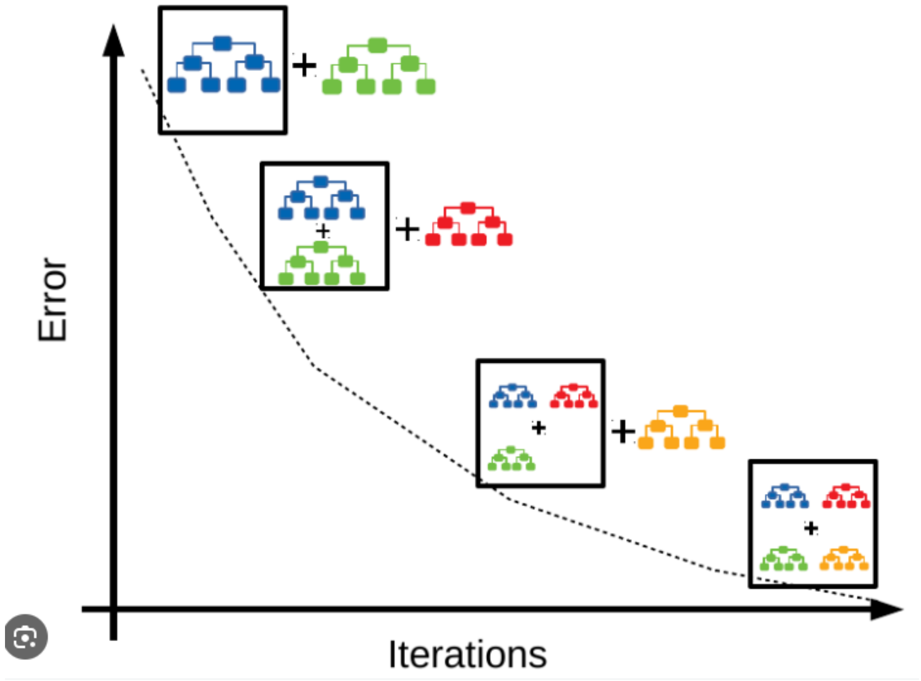


37 explanatory variables (X)

- Presence of wireworms and identity of predominant species
- Weather conditions
- Soil characteristics
- Agricultural practices
- Field history
- Local landscape features

Response variable (y)
Rate of damaged plants along 3 transects (3*10 metres) randomly chosen

DATA → MODEL → RISK FACTORS → CLASSIFIER & DSS



$$y = f(X,\varepsilon)$$

- $y \in [0,1]$: rate of damaged plants
- $X \in R^n$: covariates
- ε : some kind of error
- $f : R^n \rightarrow [0,1]$: some kind of function

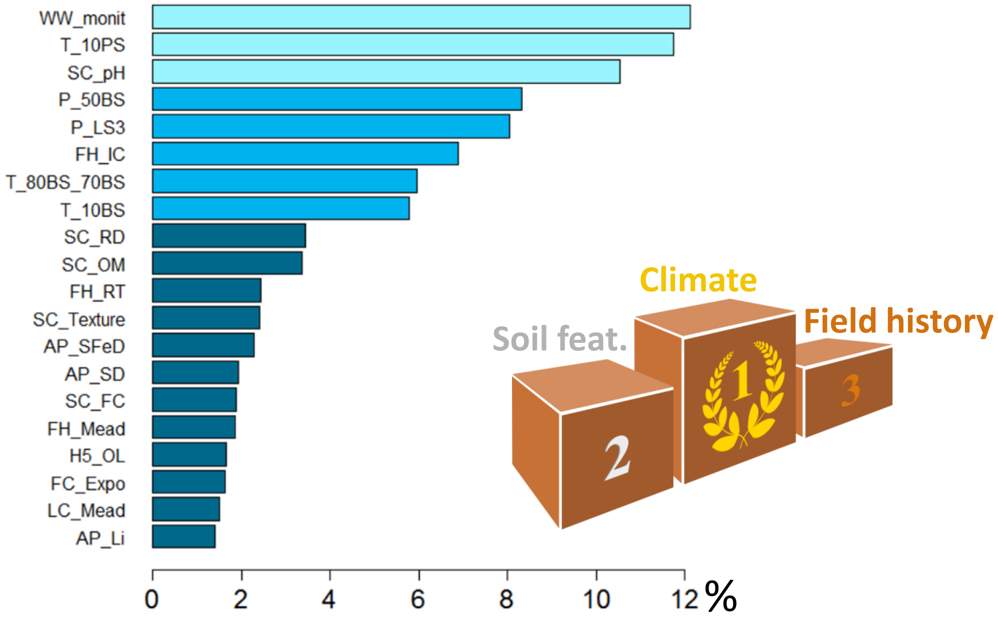
Boosted Regression Trees (*machine learning*)

Stochastic, nonlinear regression model inheriting the strengths of regression trees and boosting

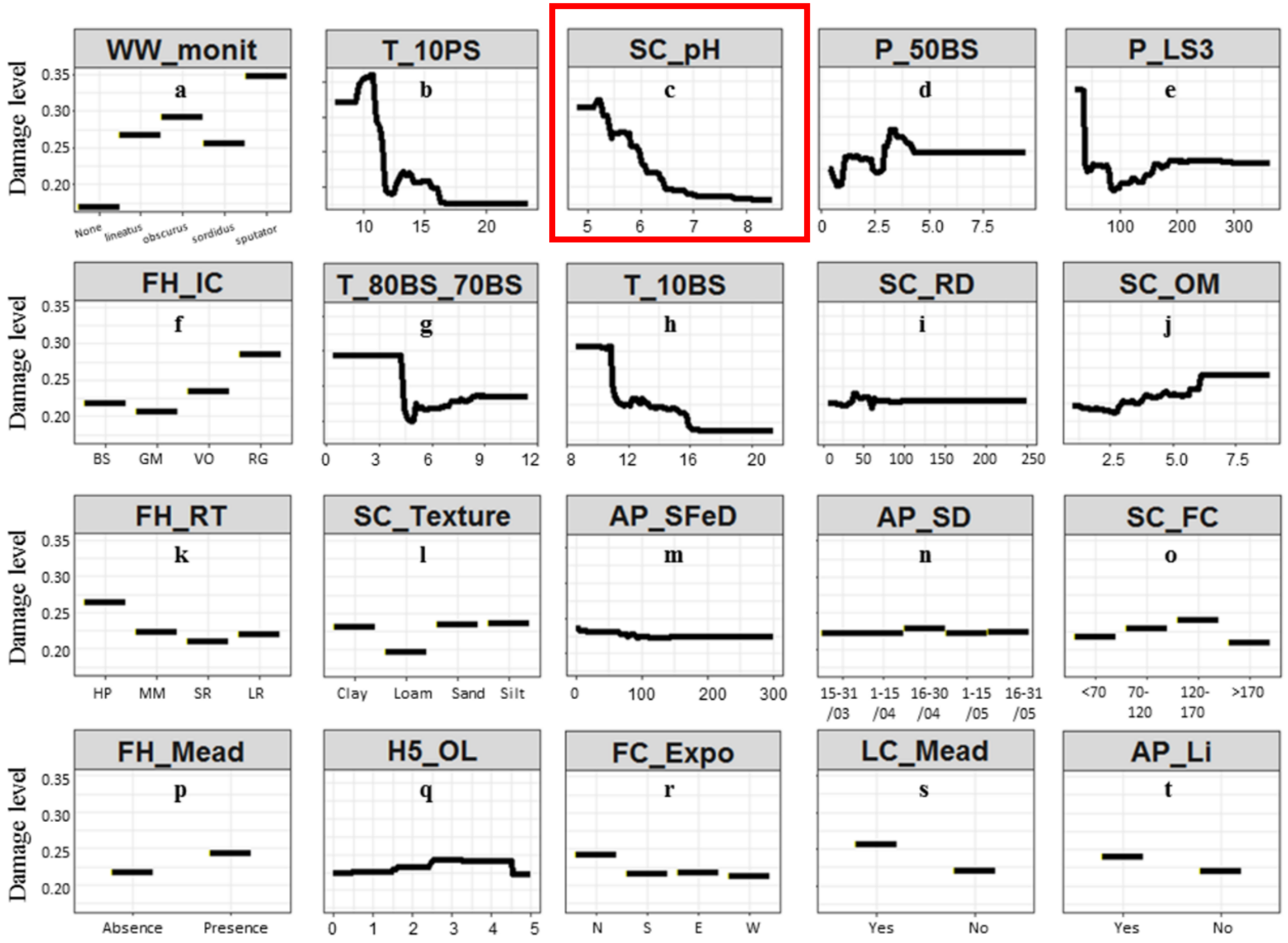
DATA | MODEL | RISK FACTORS | CLASSIFIER & DSS

Data-based regression models

Relative influence of variables



Marginal effects of the main influential variables



DATA → MODEL → RISK FACTORS → CLASSIFIER & DSS

Data-based regression models

Given the **economic threshold** 15%[3], observed field status is

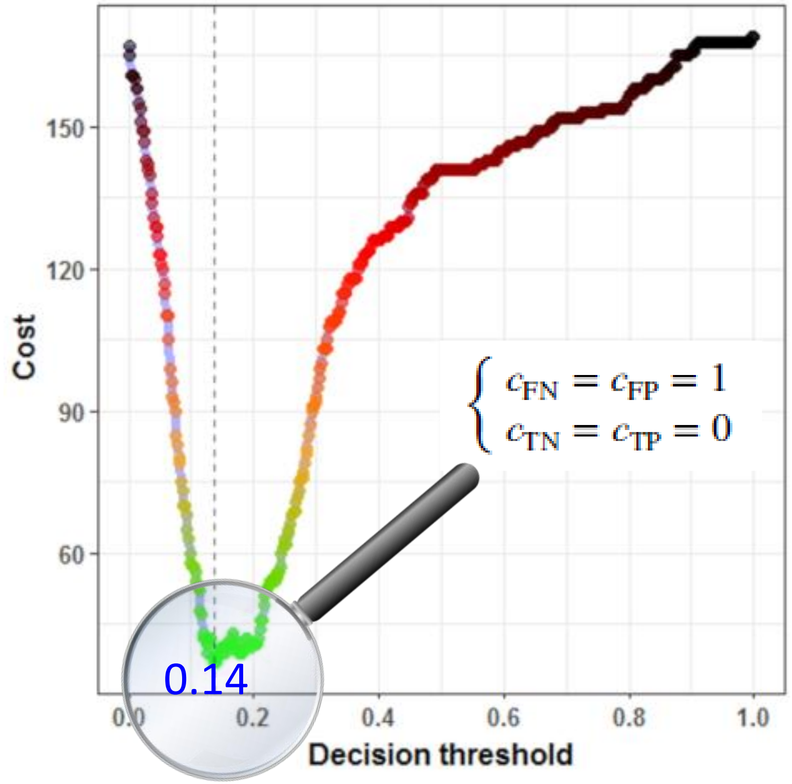
167	169	(336)
undamaged ("negative")	*damaged* ("positive")	

➡ Downgrade BRT model in a **binary classifier** with 4 possible outcomes: **TN, TP, FN, FP**

- Define an "expected cost" function:

$$C(D_{\text{dec}}) = c_{\text{FN}} \times P(\text{FN}) + c_{\text{FP}} \times P(\text{FP}) + c_{\text{TN}} \times P(\text{TN}) + c_{\text{TP}} \times P(\text{TP})$$

- Infer the decision threshold D_{dec} that minimizes the expected cost



[3] Furlan et al., 2017. Environ Sci Pollut Res 24, 236-251

DATA | MODEL | RISK FACTORS | CLASSIFIER & DSS

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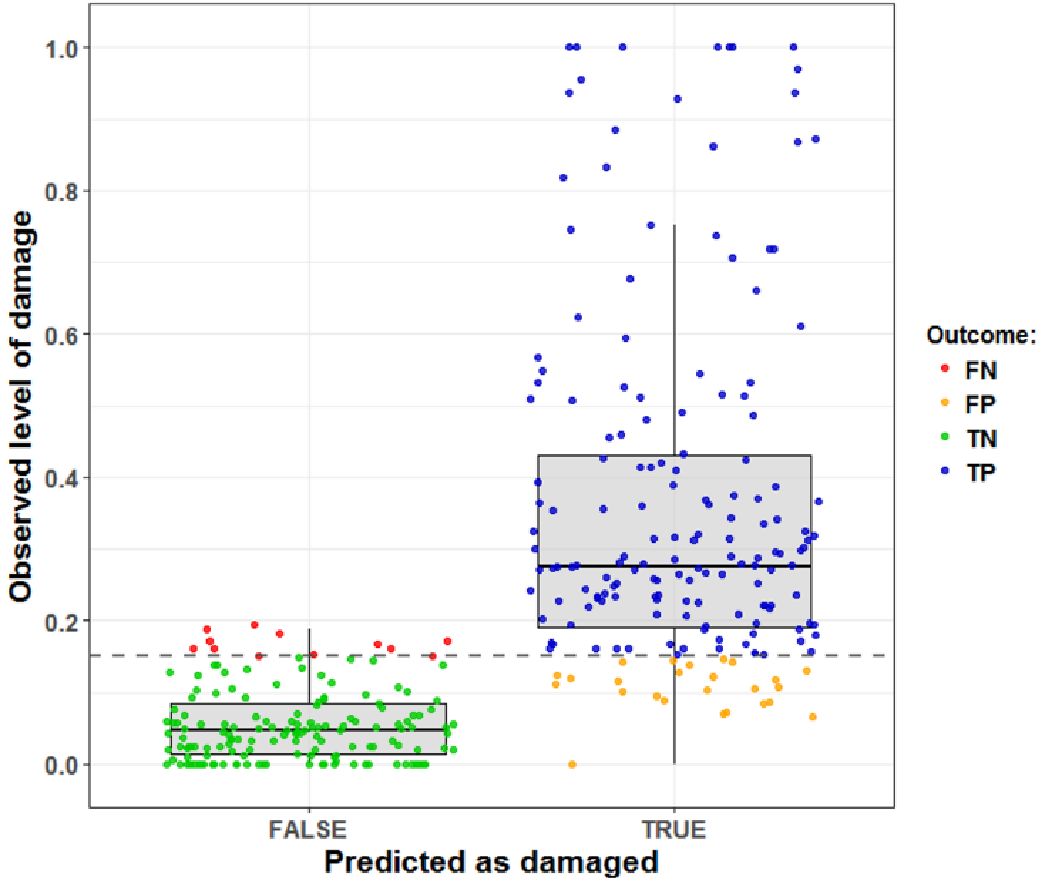
Performance of the binary classifier

Classification error:	11%	
Sensitivity	93%	Probability of (risk) detection
Specificity	85%	Probability of false alarm 15%
False Negative (FN)	~4%	
False Positive (FP)	~7%	



DATA → MODEL → RISK FACTORS → CLASSIFIER & DSS

CONCLUSION PART ONE

- Identification and ranking of the main risk factors for wireworm damage
- Proof of concept of a DSS for risk management
- Further requirements:

  - inform the binary classifier with real economic costs (incl. treatment, yield loss)

  - compare forecast with a set of test data

LIMITATIONS

- Approach dependent on data quality: how informative? How representative? Etc.
- “Black-box model”, i.e. no consideration of mechanisms at stake

PERSPECTIVE

- Apply this methodology to the wireworm/potato system (project TAUPIC, coord. inov3PT)

Latent variable models

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419 maize fields with different levels of infestation

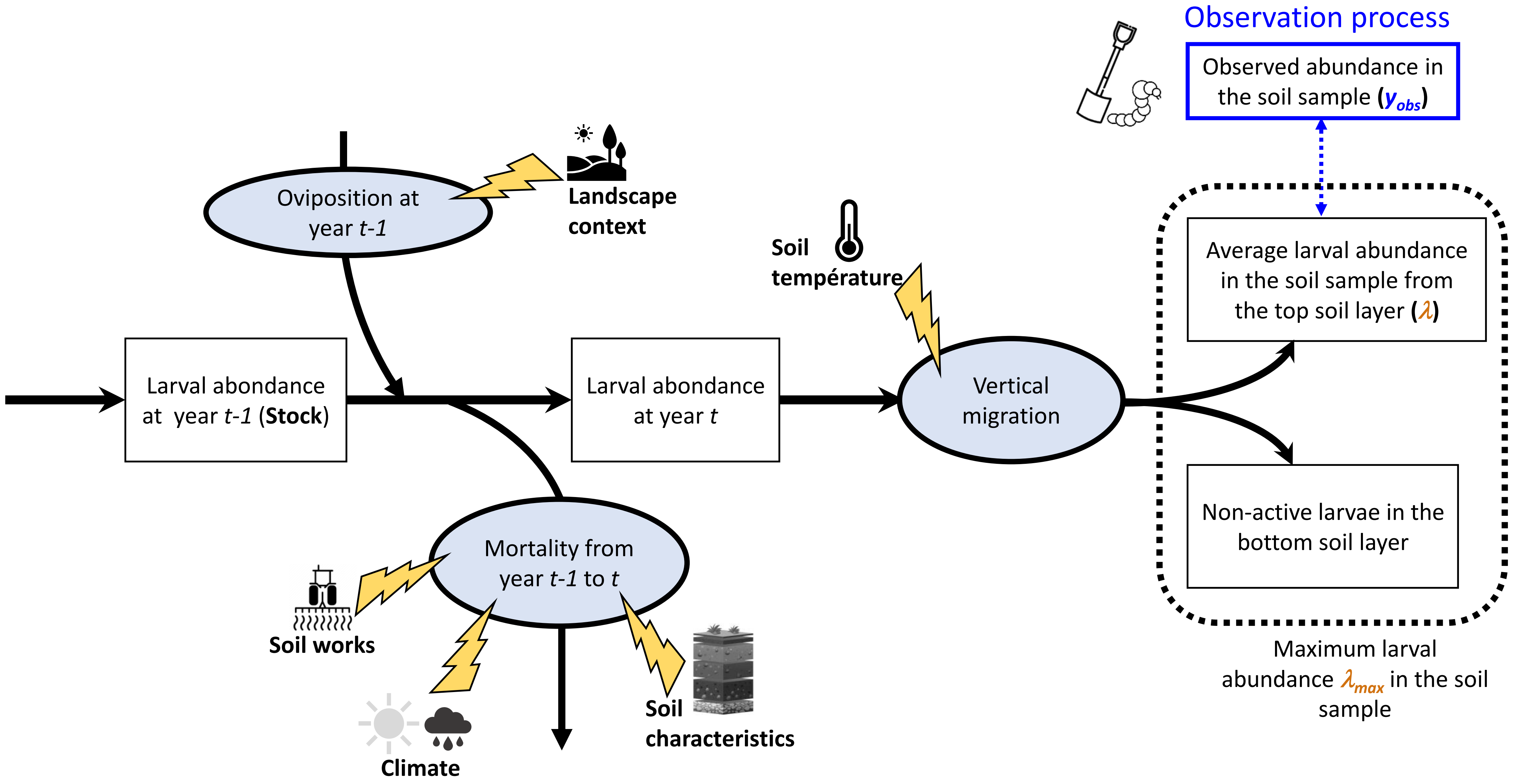
15 explanatory variables (***X***)

Response variable $\boldsymbol{y_{obs}}$: wireworm abondance

→ *Pooled soil samples obtained from 3 randomized spade holes (20x20x20 cm^3) in each field*

MOTIVATION FOR HIERARCHICAL BAYESIAN MODELLING

- Appropriate framework for risk assessment: random variable with credible intervals
- Incorporate biological/ecological expertise
- Address the uncertainty associated with field sampling: observations (pest abundance in soil samples) are described as realisations of a stochastic process


Observation process
Observed abundance in the soil sample (y_{obs})
Oviposition at year *t-1*
Landscape context
Soil température
Average larval abundance in the soil sample from the top soil layer (λ)
Larval abondance at year *t-1* (**Stock**)
Larval abondance at year *t*
Vertical migration
Non-active larvae in the bottom soil layer
Mortality from year *t-1* to *t*
Soil works
Climate
Soil characteristics
Maximum larval abundance λ_{max} in the soil sample

Latent variable models

$\boldsymbol{i}: field\ id$

$$y_{obs_i} \sim P(\lambda_i)$$

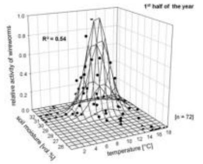
$$\log(\lambda_i) = VM(T_i) * \left(\sum_k \alpha_k * X_{quanti\,(i,k)} + \sum_l \beta_{l, X_{quali\,(i,l)}} + C \right)$$

Latent variable models

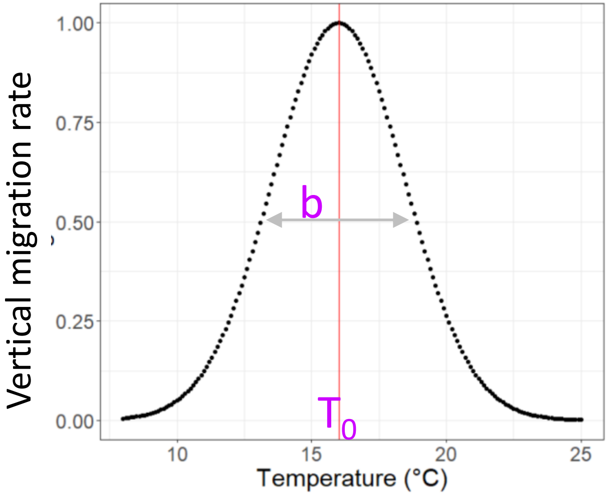
$$y_{obs_i} \sim P(\lambda_i)$$

$\boldsymbol{i}$: *field id*

$$\log(\lambda_i) = VM(T_i) * \left(\sum_k \alpha_k * X_{quanti\,(i,k)} + \sum_l \beta_{l, X_{quali\,(i,l)}} + C \right)$$



Jung et al., 2014. J Appl Entomol 138, 183-194



$\mathbf{i}$: $field\ id$

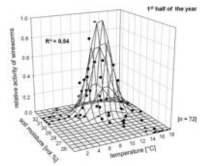
$$y_{obs_i} \sim P(\lambda_i)$$

Larval counting process

⬍

Poisson distribution with parameter λ

$$\log(\lambda_i) = VM(T_i) * \left(\sum_k \alpha_k * X_{quanti\,(i,k)} + \sum_l \beta_{l,X_{quali\,(i,l)}} + C\right)$$



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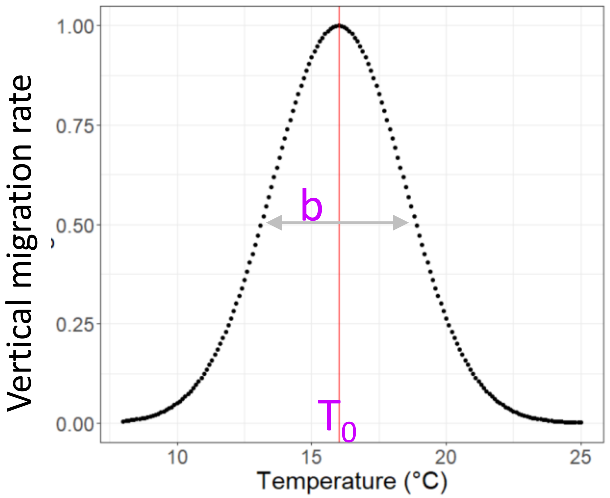

Latent variable models

$y_{obs_i} \sim P(\lambda_i)$

Larval counting process

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Poisson distribution with parameter λ

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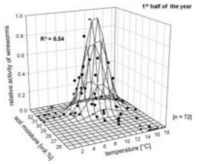

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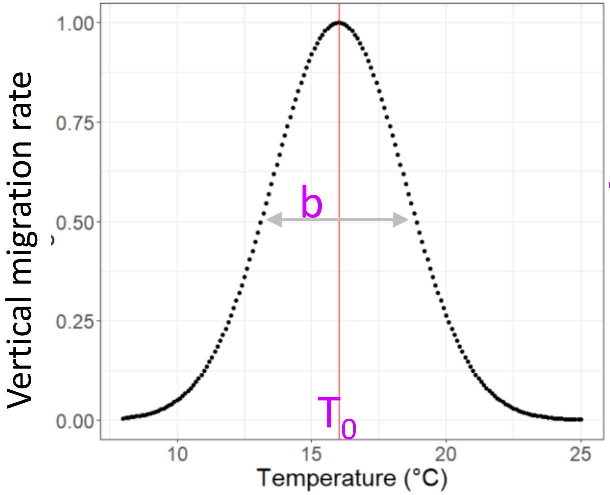
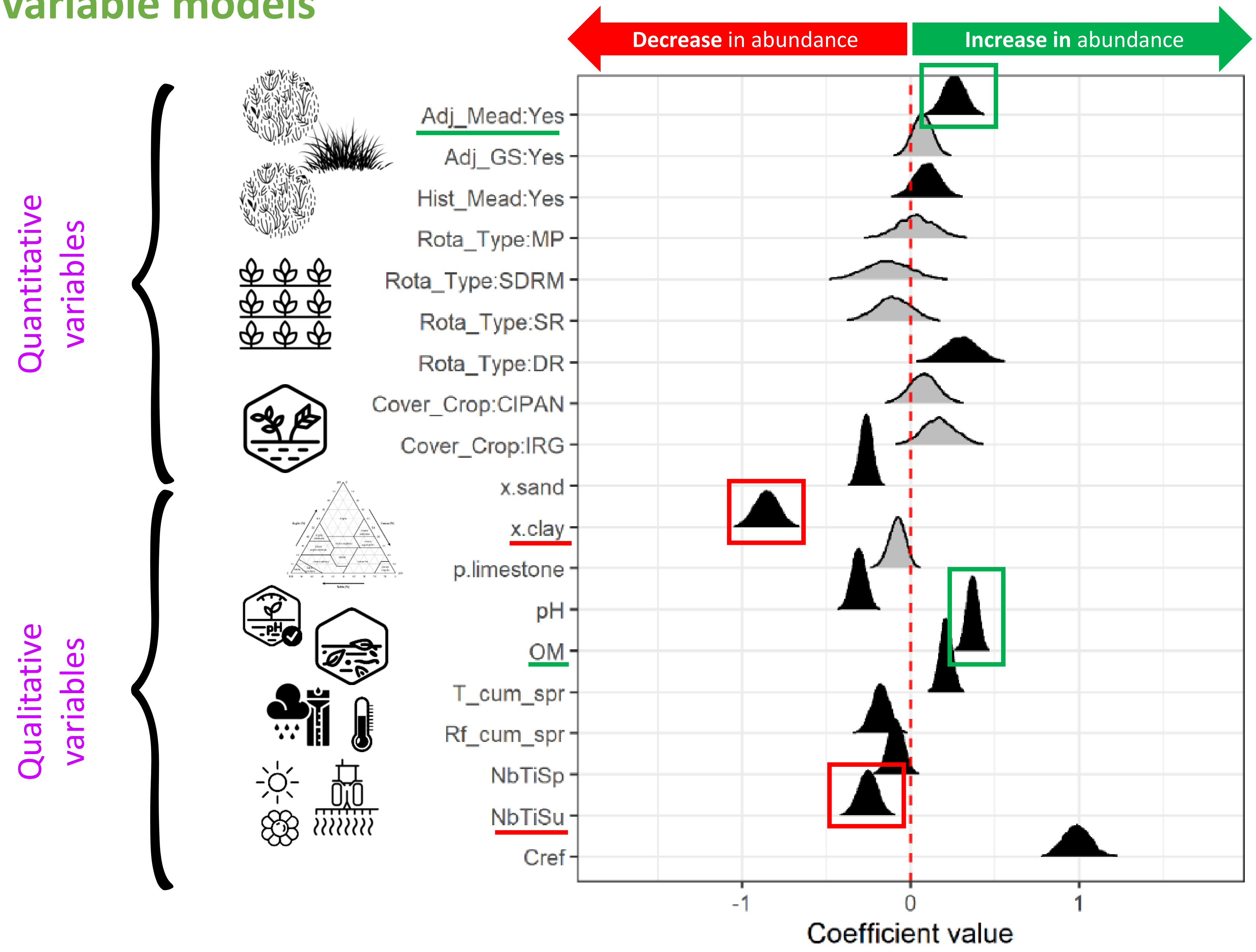


Parameter inference using a MCMC algorithm → posterior distributions

α_k, β_l : standardized coefficients

Latent variable models



CONCLUSION PART TWO

- Model outcomes show good agreement with current knowledge from literature and field expertise in terms of the effects of variables on wireworm abundance
- Fairly good predictive capacity (cf. publication)
- Ongoing test step before encapsulating as a DSS for the implementation of IPM strategies

PERSPECTIVES

- Incremental improvement with better biological and ecological knowledge (processes at stake)
- Conceptual framework that can be adapted to a wide range of similar situations involving other crops and pests

Mechanistic models

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MOTIVATIONS

- Explicitly describe the main processes at stake → e.g. can inform model with pest life traits (incl. dispersal)
- Derive a framework for combining (i) a spatially explicit and mechanistic model describing the pest population dynamics in both aerial and soil compartments involved along its life cycle, and (ii) spatiotemporal representations of various landscape contexts → ***in silico* experiments**
- Focus: examine the role of grassland arrangements in field colonisation and implications for pest management

Mechanistic models

Biological and ecological hypotheses

Larvae only move vertically ('in z')

Adults are mobile in the agricultural landscape ('in x and y')

Adults lay eggs, disperse in space and then die

Larvae develop and emerge at maturity

Larval mortality depends on their density and the quality of the habitat in which they are found

Etc.

Mathematical formalism

(choice of the modelling approach)

Mechanistic approach:

- Explicit consideration of biological and ecological processes
- Modelling the pest population dynamics
- Spatially explicit

Understanding the processes governing population dynamics (at ≠ stages)

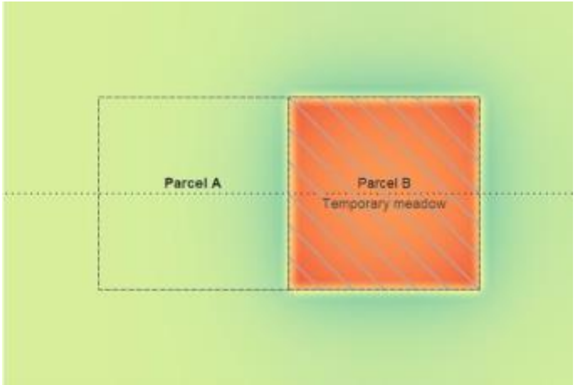
Discrimination between local and non-local processes (reproduction vs. immigration, mortality vs. emigration)

Sensitivity of responses to different processes

Software development

Model parameterisation

***In silico* experiments**



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Aboveground population

Reaction-diffusion-advection model

$$\begin{cases} \partial_t A(x,t) = \tau B(x,t,m_c) + D\Delta A(x,t) - \vec{u}(x,t)\cdot\nabla_x A(x,t) - \mu_A A(x,t) \\ \partial_t B(x,t,m) = -\tau B(x,t,m_c) + \pi A(x,t) - c\,\partial_m B(x,t,m) - \mu_B \big(B(x,t,m)/K(x,t)\big)^\beta B(x,t,m) \end{cases}$$

Belowground population

Key processes

- **Emergence**
- **Diffusion**
- **Advection**
- **Mortality**
- **Oviposition**
- **Maturation**

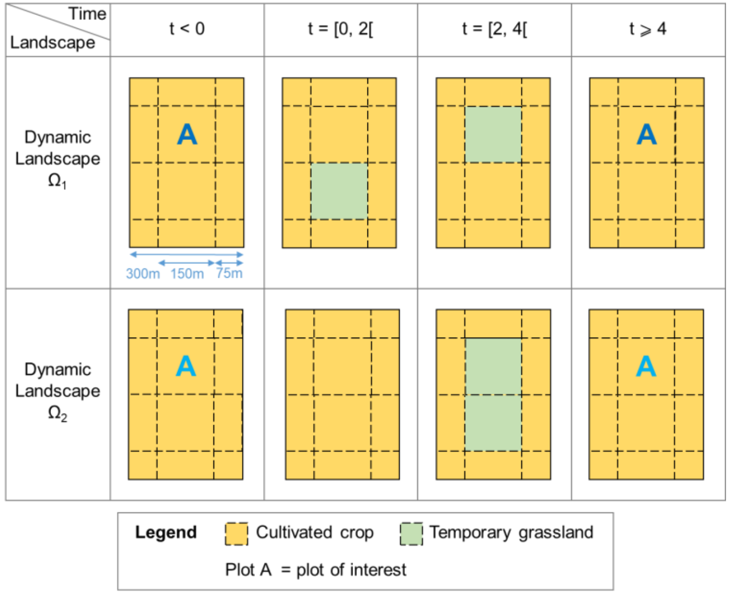
x: location in 2D space
t: time dimension
m: maturity dimension
m_c: critical maturity for emergence
K: carrying capacity
K_M=120 ind/m²
K_G=2000 ind/m²

Mechanistic models

Simplistic dynamic landscapes

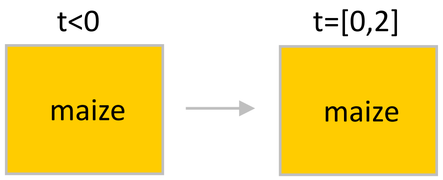
t<0: maize → t=[0,2]: maize

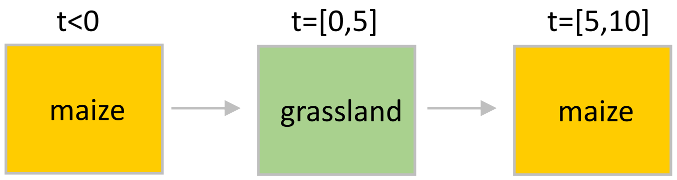
t<0: maize → t=[0,5]: grassland → t=[5,10]: maize

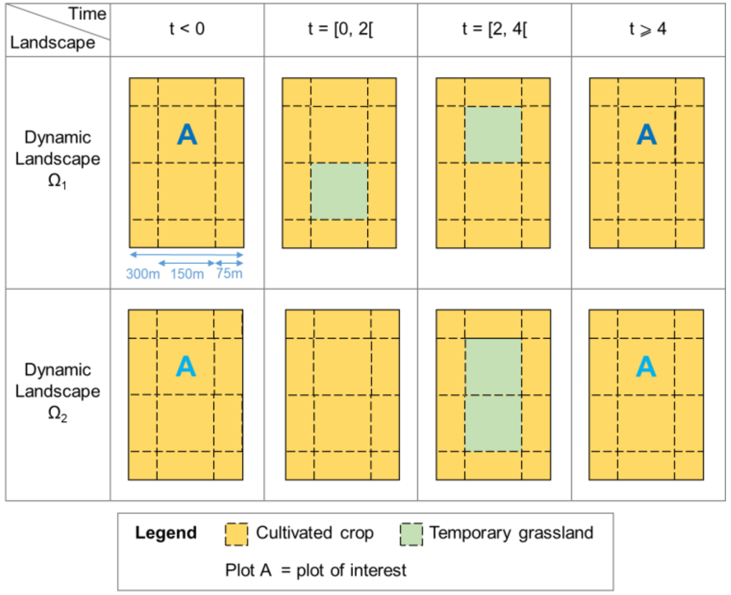


Mechanistic models

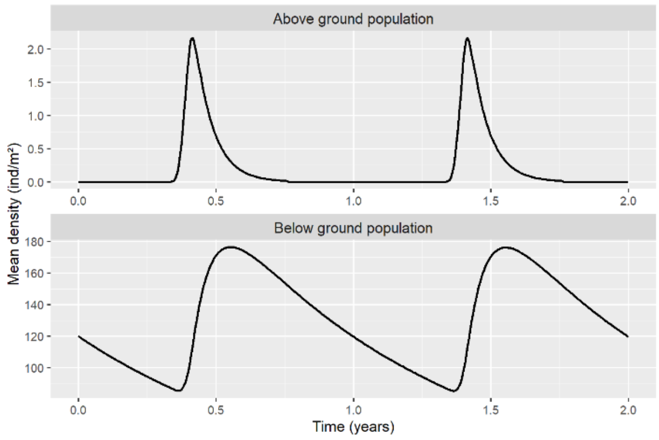
Simplistic dynamic landscapes







Model outcomes



Confirmation of expected population dynamics

Mechanistic models

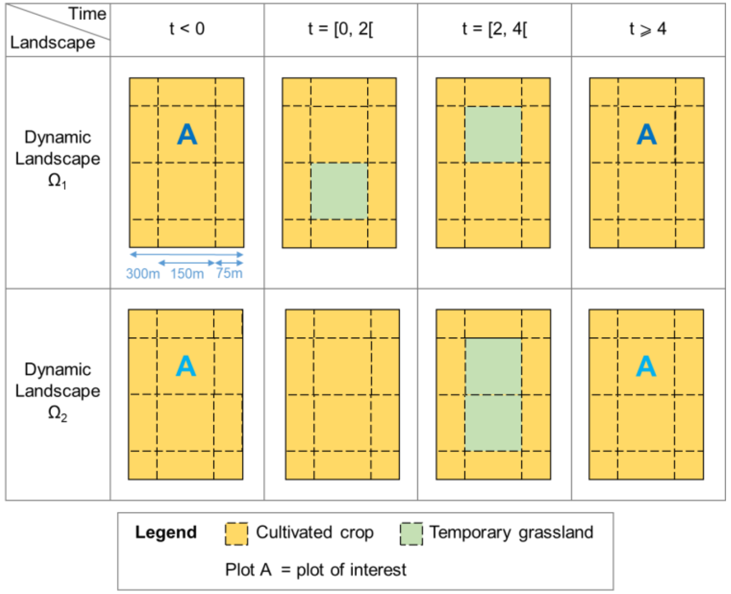
Simplistic dynamic landscapes

t<0 → t=[0,2]

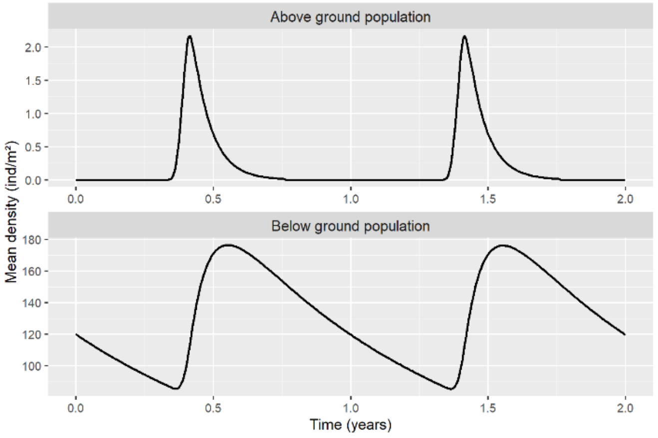
maize → maize

t<0 → t=[0,5] → t=[5,10]

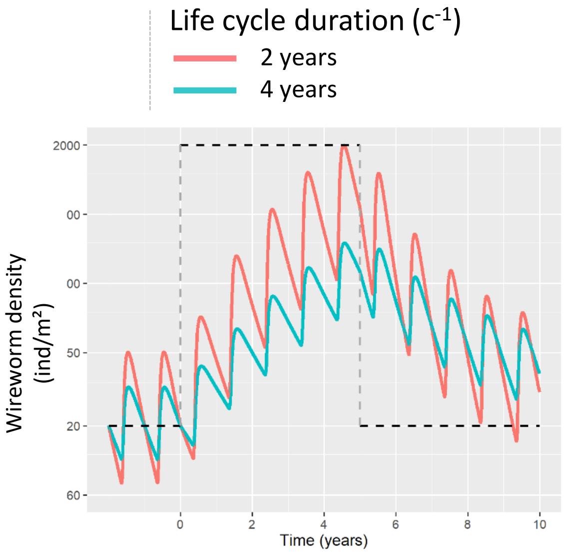
maize → grassland → maize



Model outcomes



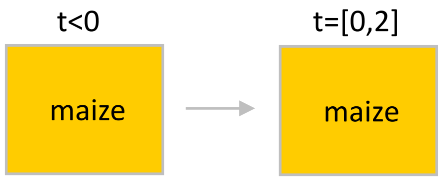
Confirmation of expected population dynamics

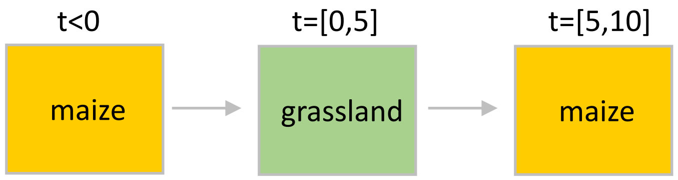


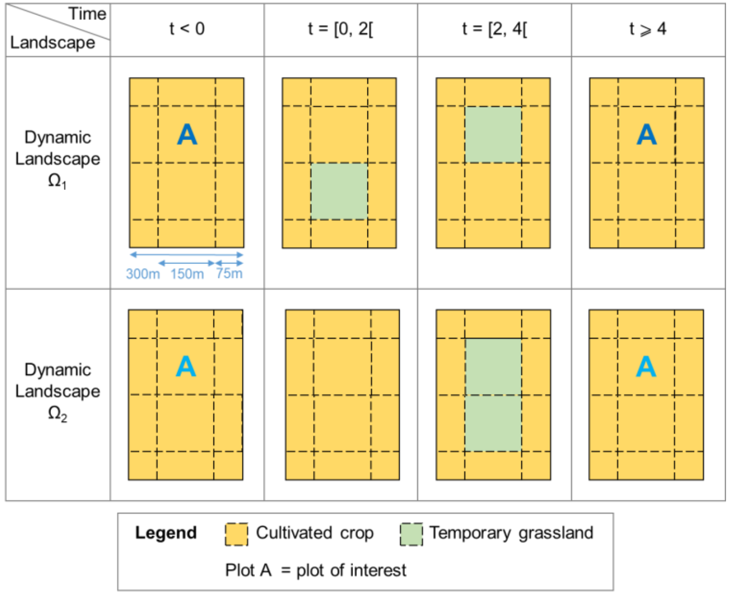
Effect of long vs. short life cycle

Mechanistic models

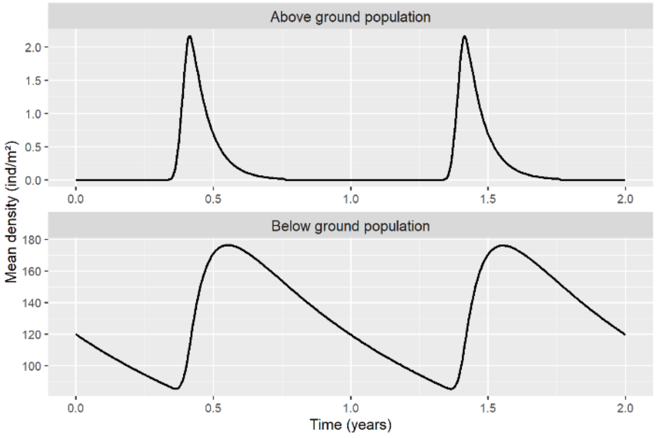
Simplistic dynamic landscapes

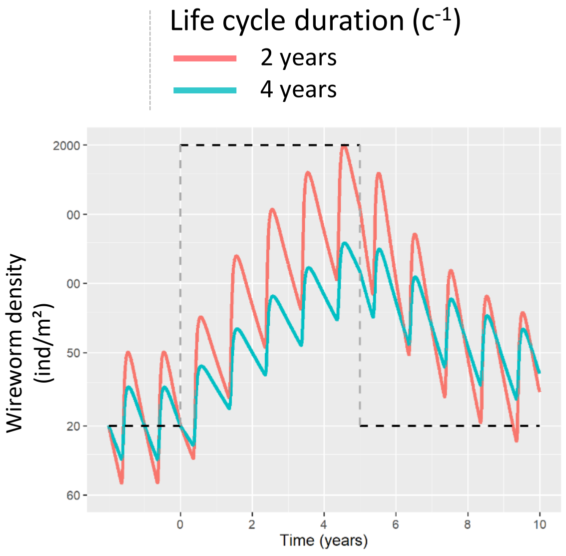


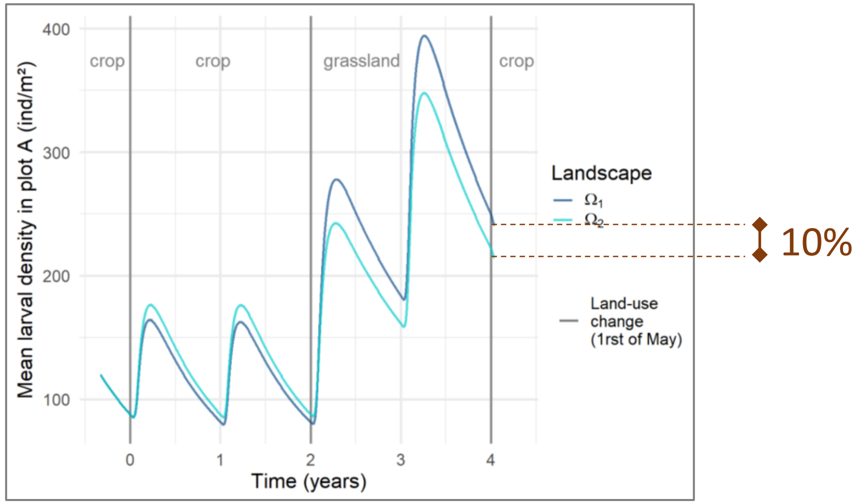




Model outcomes







Confirmation of expected population dynamics

Effect of long vs. short life cycle

Same composition over the period under study but contrasted spatial configurations ⇒ significative effect on wireworm infestation

CONCLUSION PART THREE

- Explicit consideration of processes at stake
- *In silico* exploration of landscape manipulation (effect of land-use legacy, neighbourhood, or their interaction)

Also:

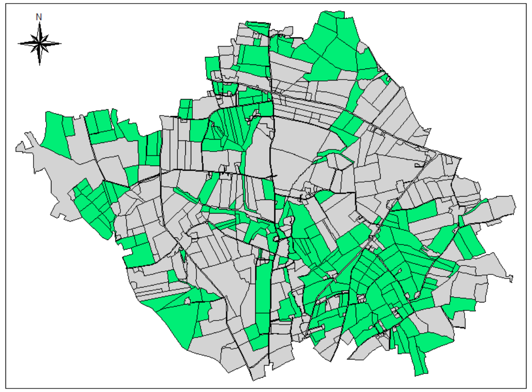
- understanding dispersal mechanisms may help design effective pest management strategies
- Example of a case study: the role of grassland on pest populations (pseudo-sink vs. source)

LIMITATION

- Parameterisation step based on published literature, sometimes rudimentary or dated

PERSPECTIVE

- Explore suppressive patterns in simplified but realistic agricultural landscapes, generated under agronomic constraints at the farm or landscape scales



GENERAL CONCLUSION

MODELLING CAN PROVIDE TOOLS FOR THE IDENTIFICATION AND RANKING OF MAIN RISK FACTORS ALSO FOR THE DESIGN OF DECISION SUPPORT SYSTEMS

- Enrich datasets ; Share standardized protocols for data collection at long-term and larger spatial scale

IMPROVING KNOWLEDGE ON THE BIOLOGY AND ECOLOGY OF WIREWORMS/CLICK BEETLES WILL BENEFIT TO MODELS (AND VICE VERSA)

- Click beetle dispersal ; Species-specific life traits ; Relationship between wireworm infestation and crop damage (species-crop economic threshold, etc.)

MECHANISTIC MODELS DESERVE GREATER ATTENTION SINCE THEY ARE USEFUL SIMULATION TOOLS

- Knowledge-hungry models that must be informed by some critical pest traits, land-use characteristics and their interaction
- Explore scenarios of land-use manipulation to design potential suppressive landscape contexts ; Study the relative contribution of local vs. landscape factors to wireworm colonisation

AKNOWLEDGEMENTS

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Maize farmers who accepted to participate in the survey and all the people who collected field data.

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