Séminaire MIAT
22 octobre 2021

Étude de l'évolution des résistances aux fongicides chez *Zymoseptoria tritici,* quantification de ses déterminants à grande échelle

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Introduction – Agricultural systems need to be more sustainable

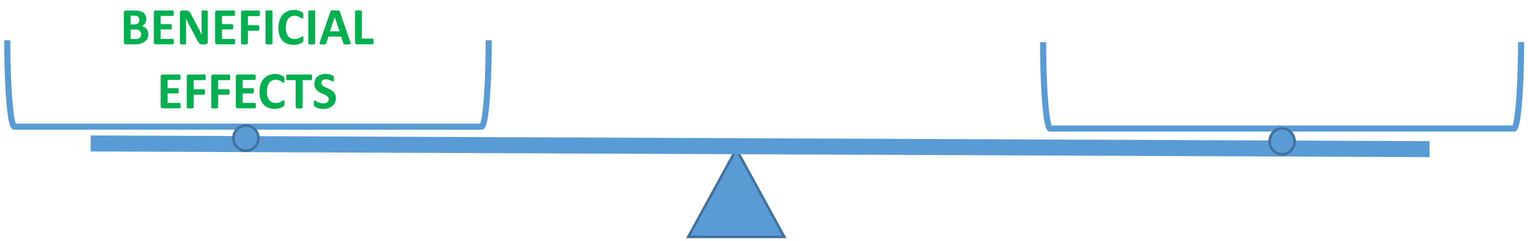
Widespread use of **plant protection products** (PPP) in agriculture

Fungicides

Herbicides

Insecticides

Increased **productivity** and potential **yield** of crops, harvest **quality** and **stability**



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Soil, water and air **pollution**, negative impact on **biodiversity**, **human health**, **resistance** build up

BENEFICIAL EFFECTS

UNINTENDED EFFECTS

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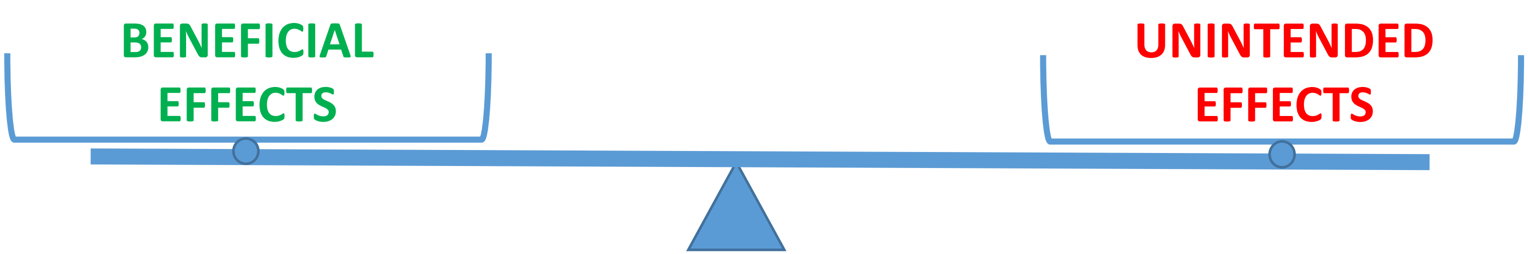


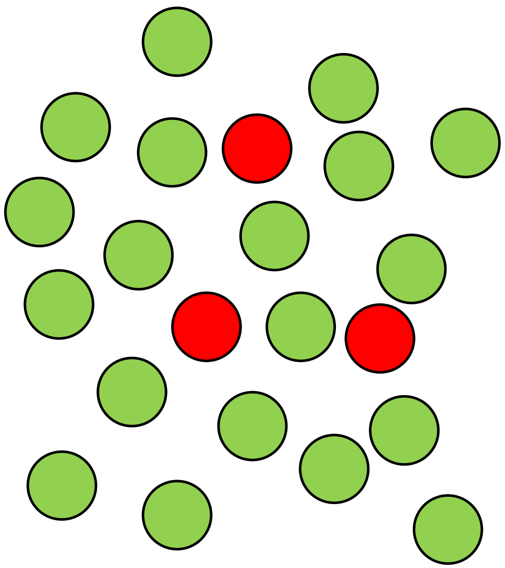
Development of public policies towards a better use and a reduction of PPP

ÉCOPHYTO
RÉDUIRE ET AMÉLIORER L'UTILISATION DES PHYTOS

Introduction – The resistance phenomenom is inescapable

Resistance is defined as a **heritable and stable trait** in an organism, resulting in a **decrease** of the organism's **sensitivity to a biocidal** active substance

Population **before selection**
(G_t)



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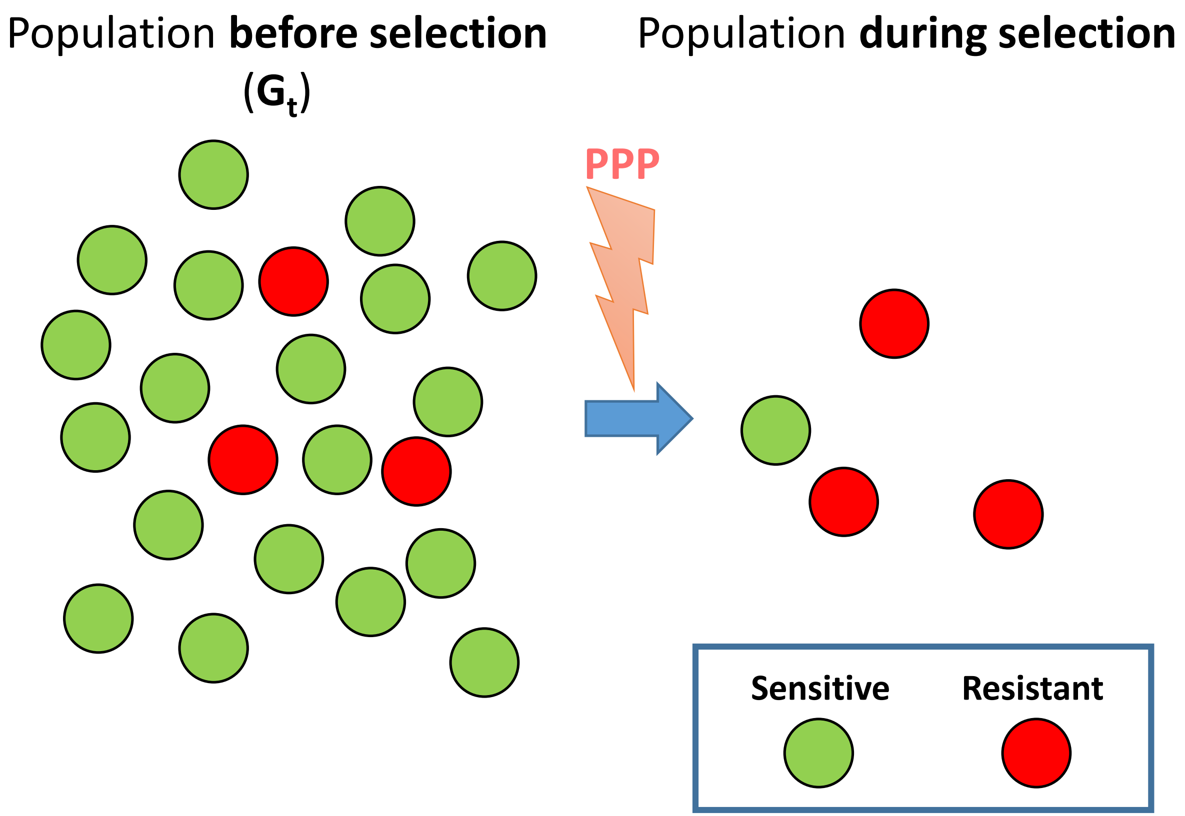

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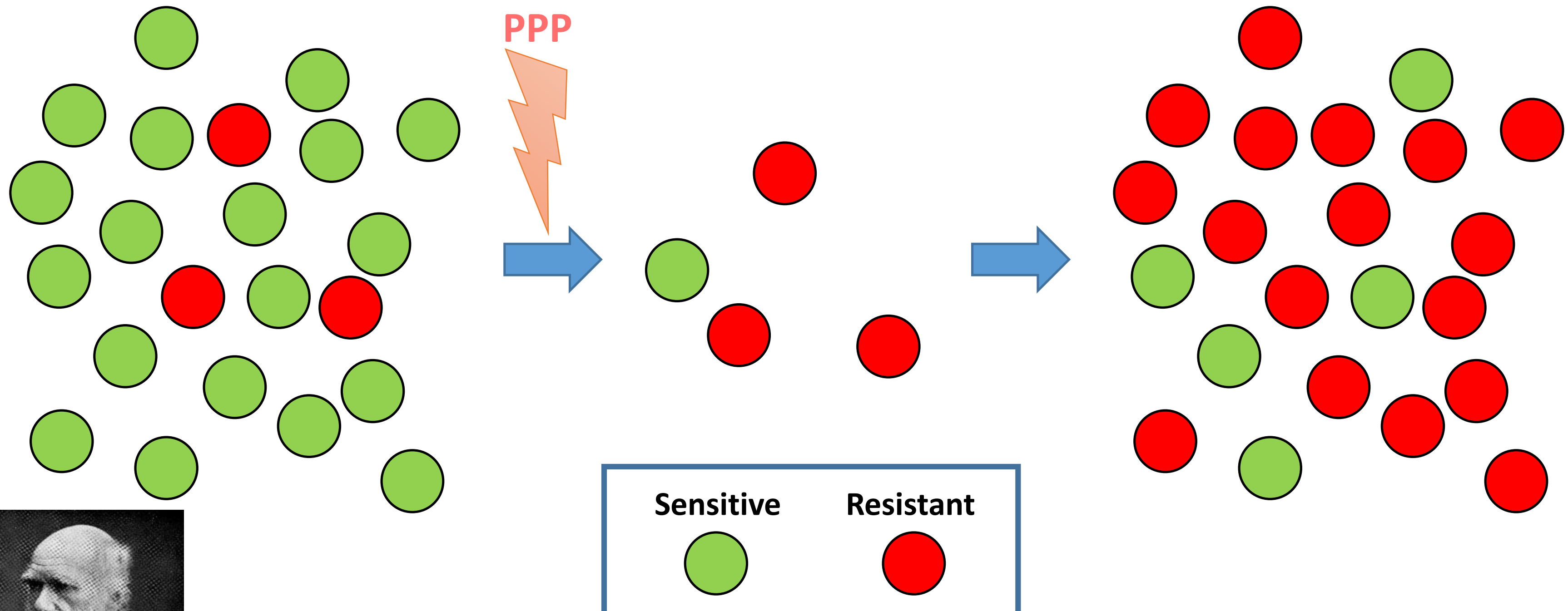
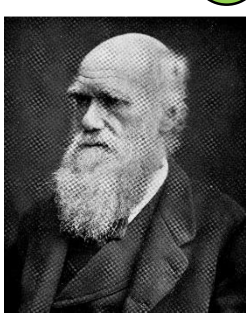
Population **before selection** (**G_t**) | Population **during selection** | Population **after selection** (**G_{t+1}**)




Darwin, C. (1859).
On the origin of species

The existence of a selection pressure will inevitably lead to the selection of adapted phenotypes in populations

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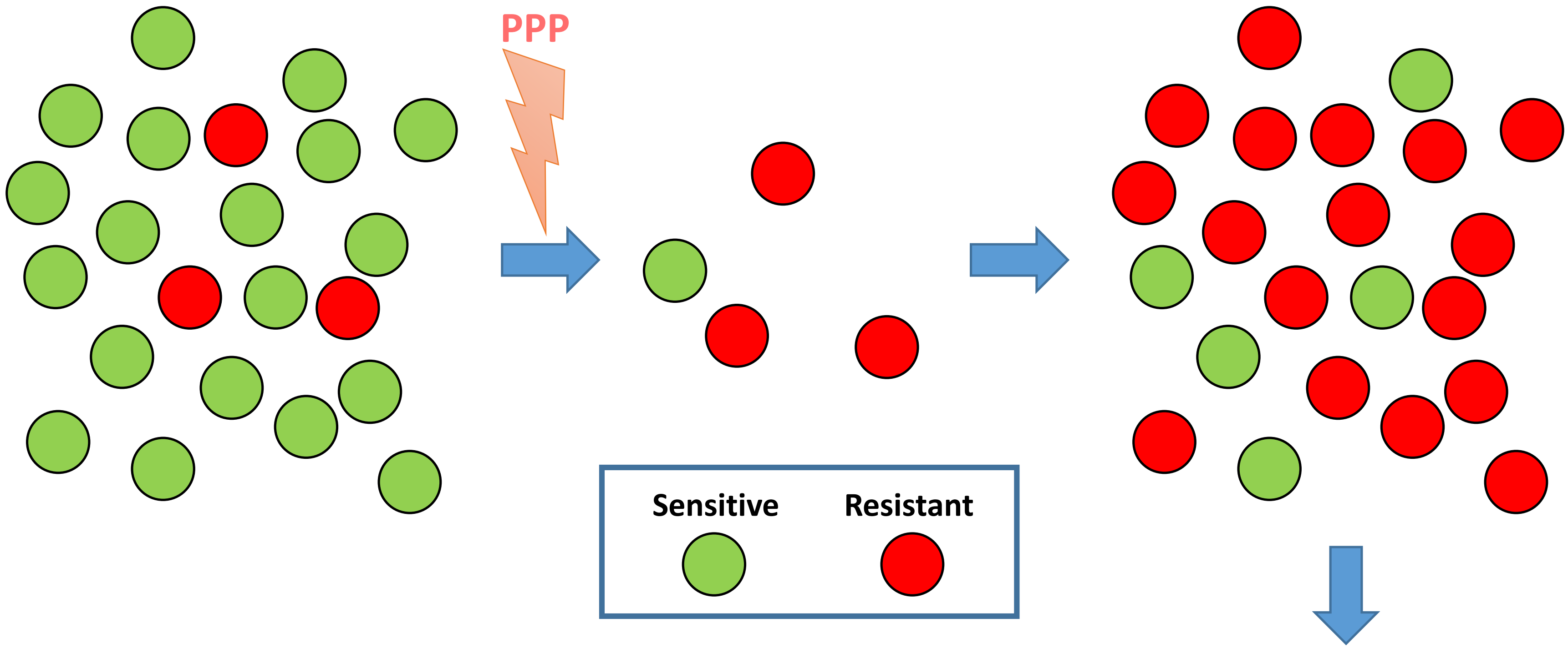

May lead to resistance in practice and to an increase in PPP use

Introduction – Anti-resistance strategies rely on the heterogeneity of the selection

Alternative control methods: Cultivar tolerance, Prophylactic measures, Biocontrol, …

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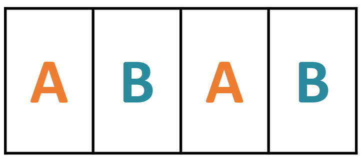
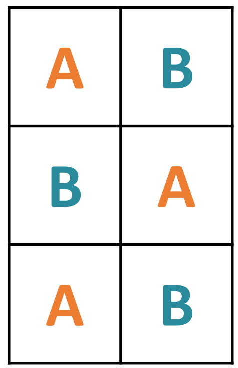
Changes in PPP use:

Alternation



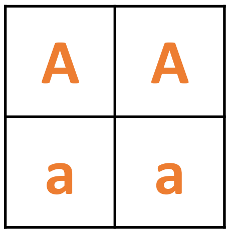
Temporal heterogeneity

Mosaic



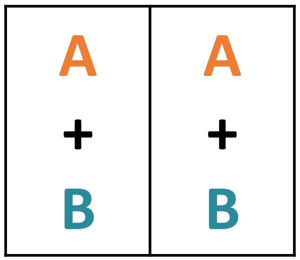
Spatial heterogeneity

Dose modulation



Intensity heterogeneity

Mixture



Heterogeneity within spray

Rex Consortium. (2013). *Trends in ecology & evolution*

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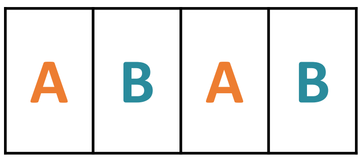

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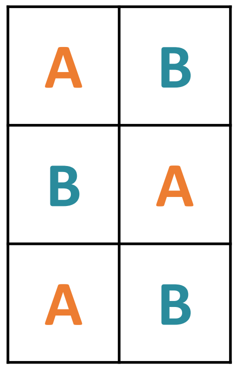

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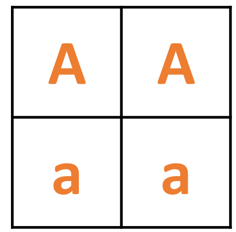

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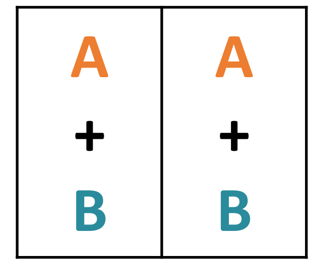

Heterogeneity within spray

Mixing fungicides:
Most recommended and used in cereal crops

(FRAC, FAO, French & European guidelines)

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Alternative control methods: Cultivar tolerance, Prophylactic measures, Biocontrol, …

Changes in PPP use:

Alternation

A	B	A	B

Temporal heterogeneity

Mosaic

A	B
B	A
A	B

Spatial heterogeneity

Dose modulation

A	A
a	a

Intensity heterogeneity

Mixture

A + B	A + B

Heterogeneity within spray

How effective? At which scales?
Which doses? Mixtures composition?

➢ **Lack of study concerning empirical approach at large spatiotemporal scales**

Introduction – *Zymoseptoria tritici* is a major pathogen

- **Ascomycete fungus responsible for septoria tritici blotch**


(Photos - F. Suffert - INRA)

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- **Ascomycete fungus responsible for septoria tritici blotch**
- **Main disease on wheat: 18 q/ha (25%)**

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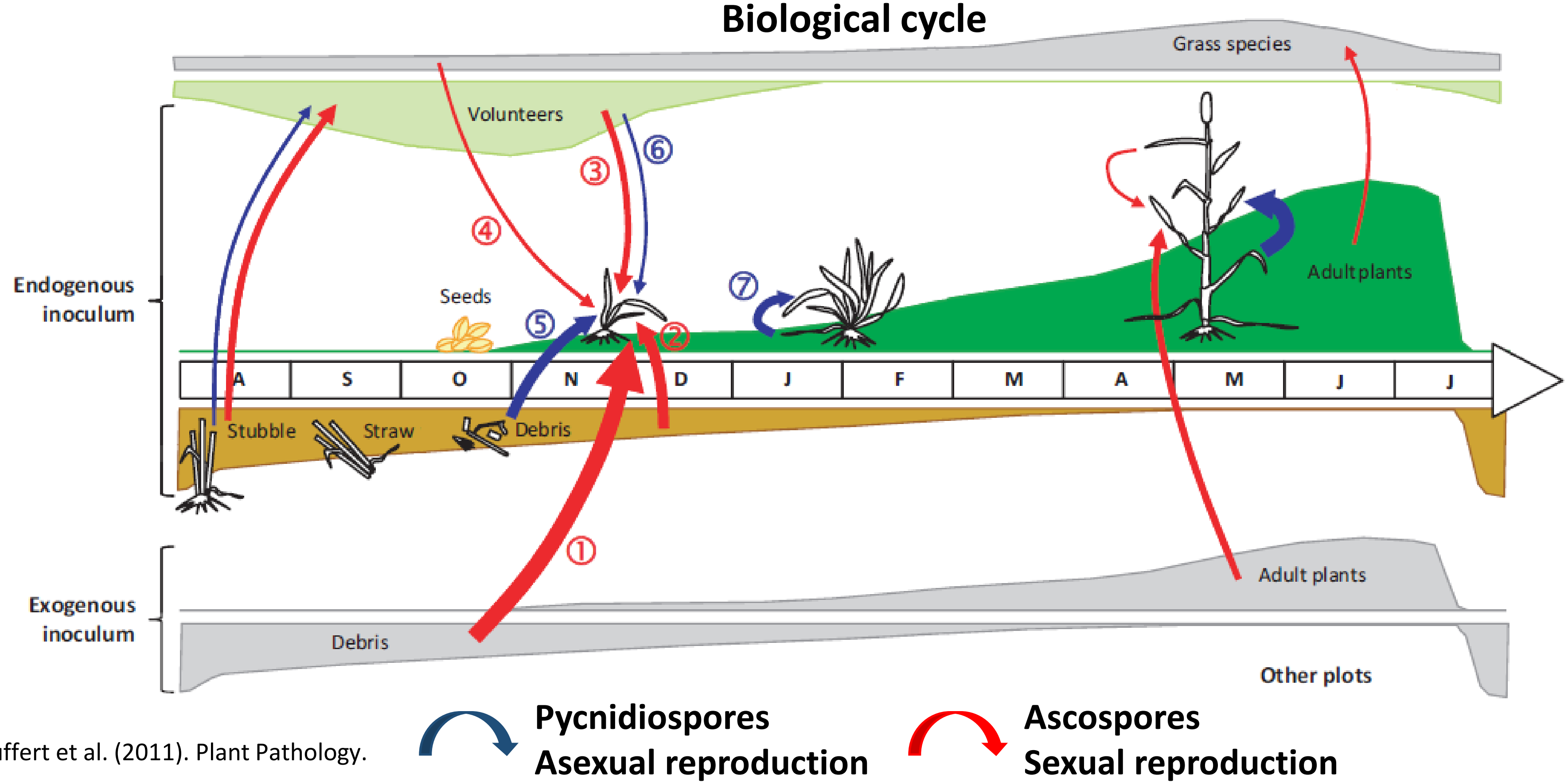
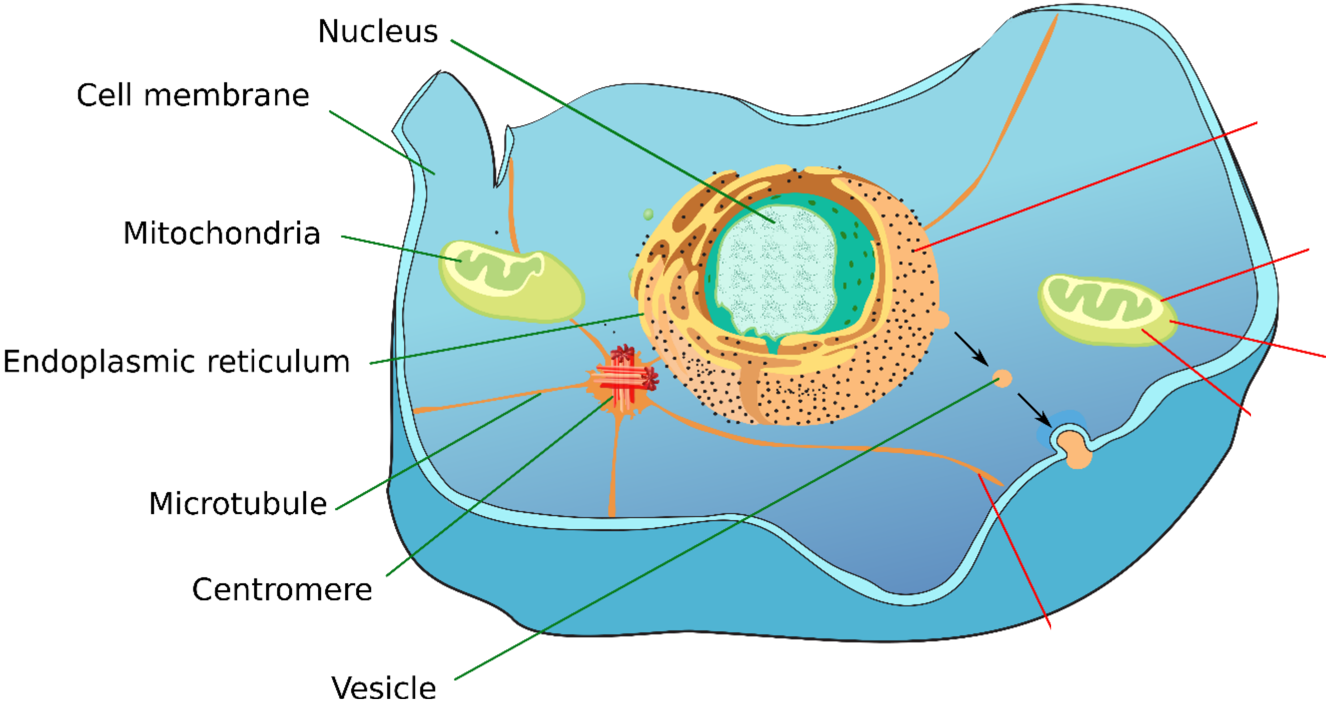
Biological cycle



Suffert et al. (2011). Plant Pathology.

Introduction – A great diversity of fungicides to control *Z. tritici*

- **5 fungicide modes of action (MoA)**



Multisites: respiration inhibitors
1980's

(FRAC, frac.info)

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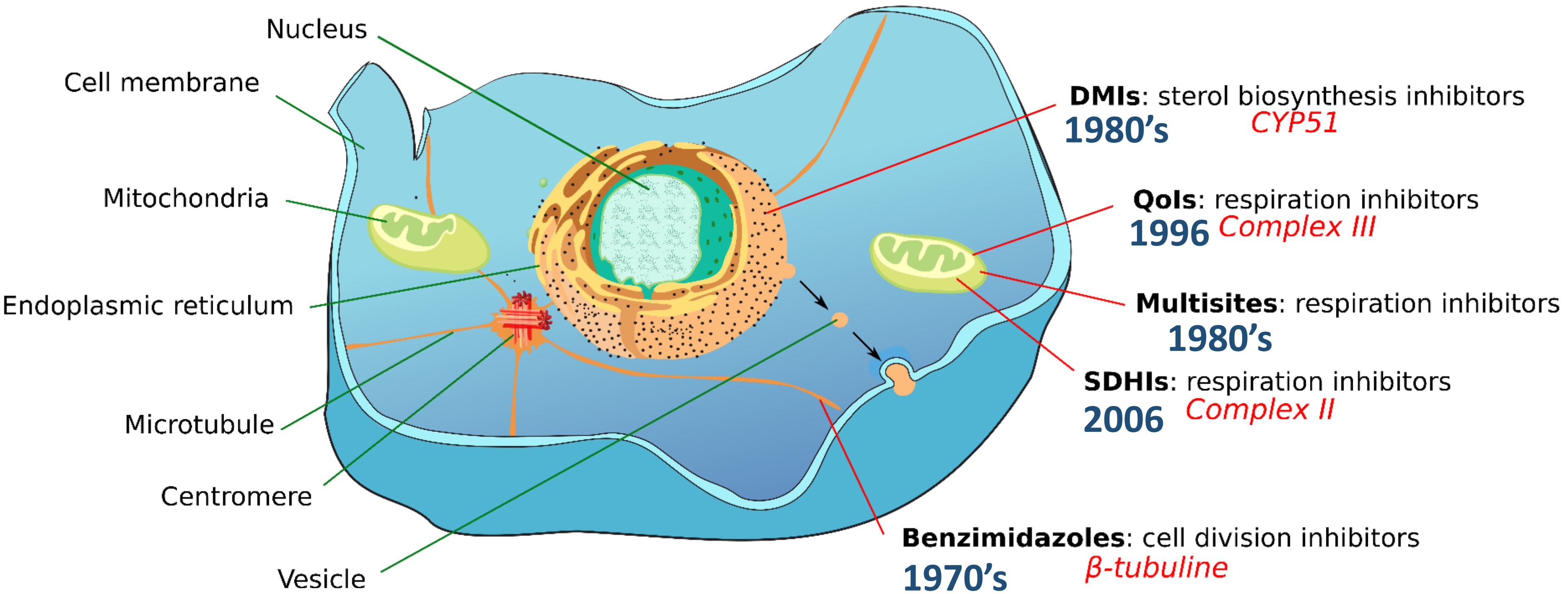

(FRAC, frac.info)

Introduction – A great diversity of resistance mechanisms in *Z. tritici*

- **5 fungicide modes of action (MoA)**
- **Resistance to all unisite fungicides**

Benzimidazoles (**BenR** / BenS)
QoIs or **Str**obilurins (**StrR** / StrS)
SDHIs or **Car**boxamides (**CarR** / CarS)
DMIs or **Tri**azoles (**TriR** / TriS)

Introduction – A great diversity of resistance mechanisms in *Z. tritici*

Qualitative R
Quantitative R

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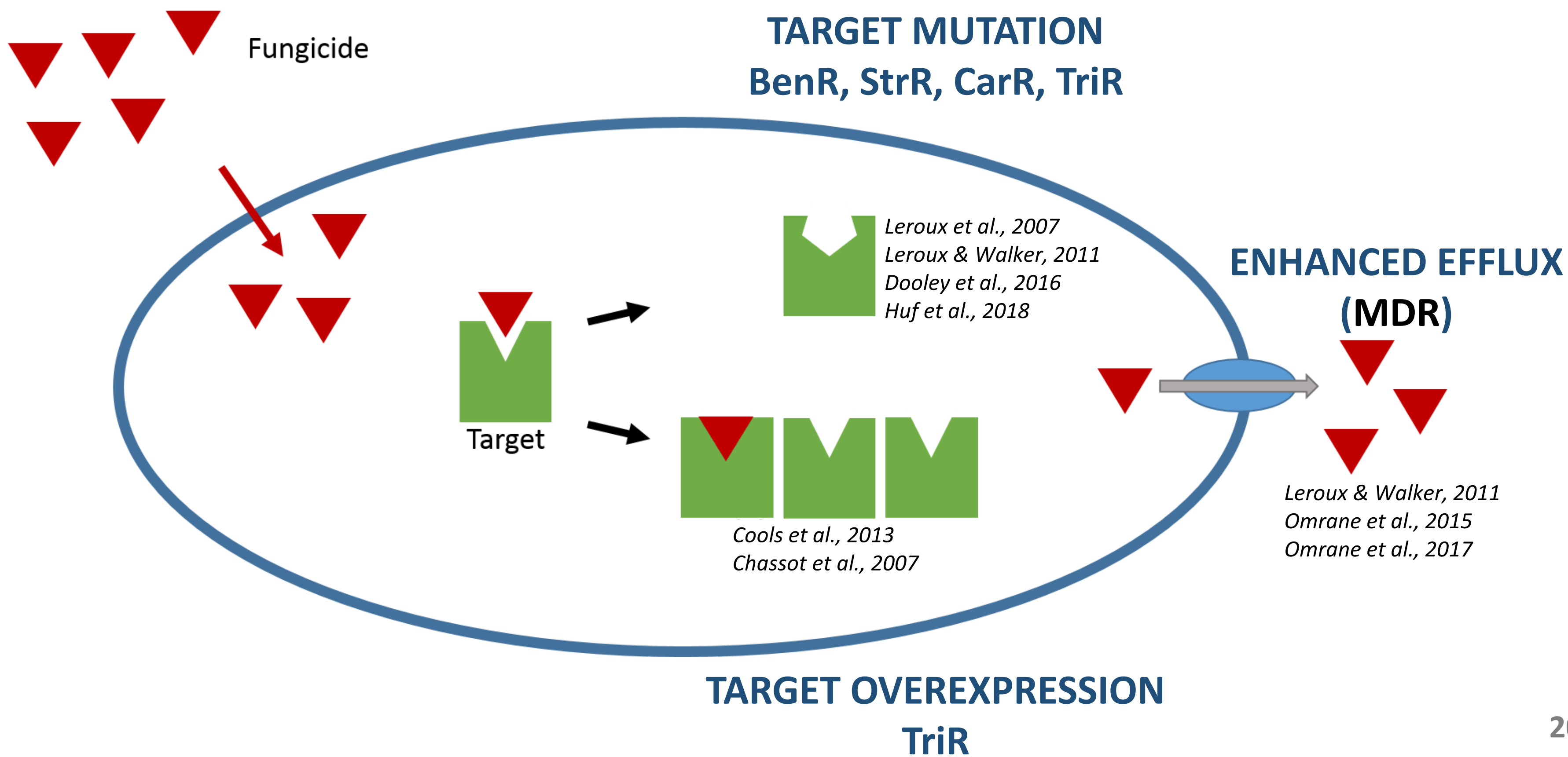

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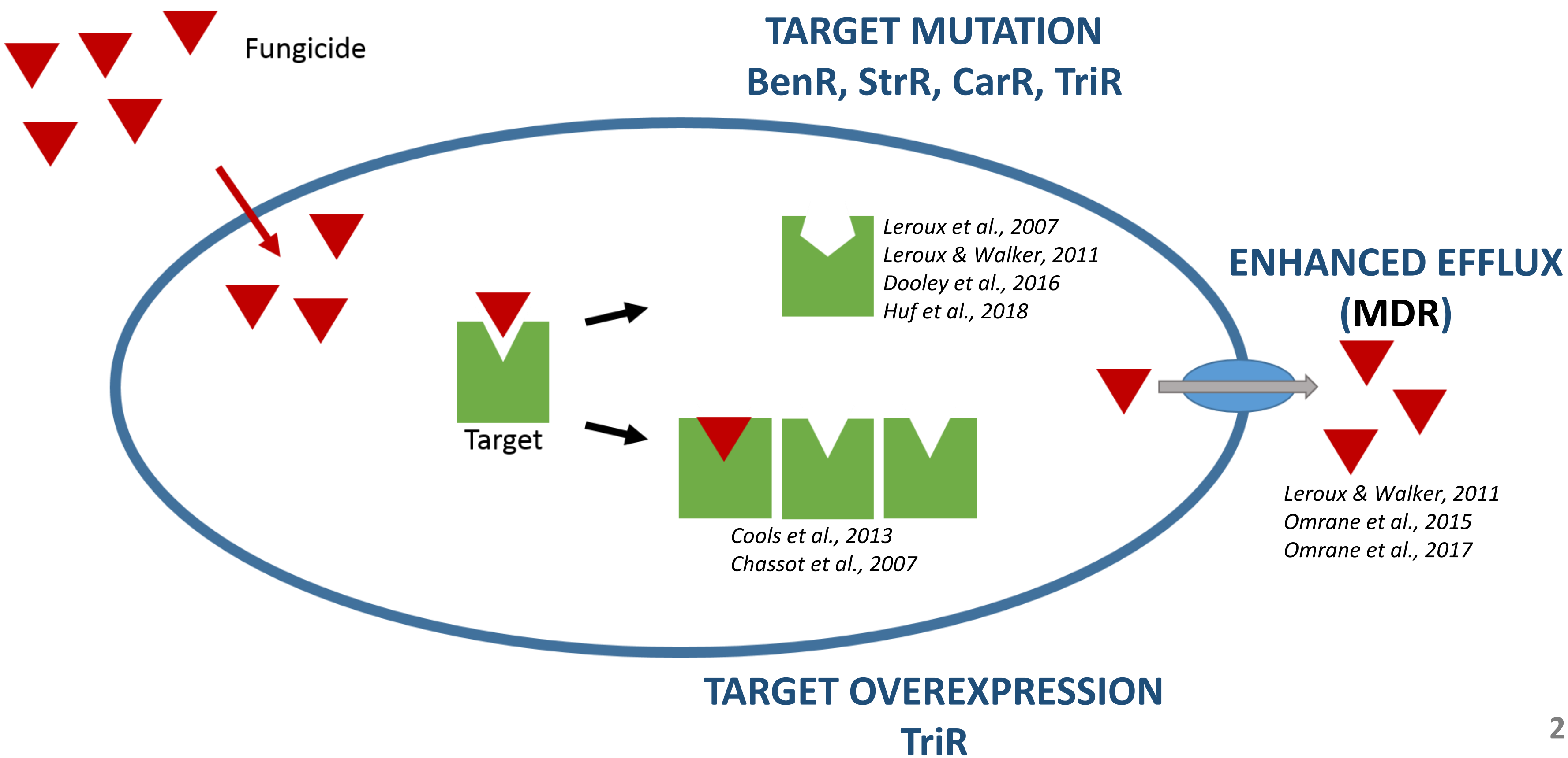
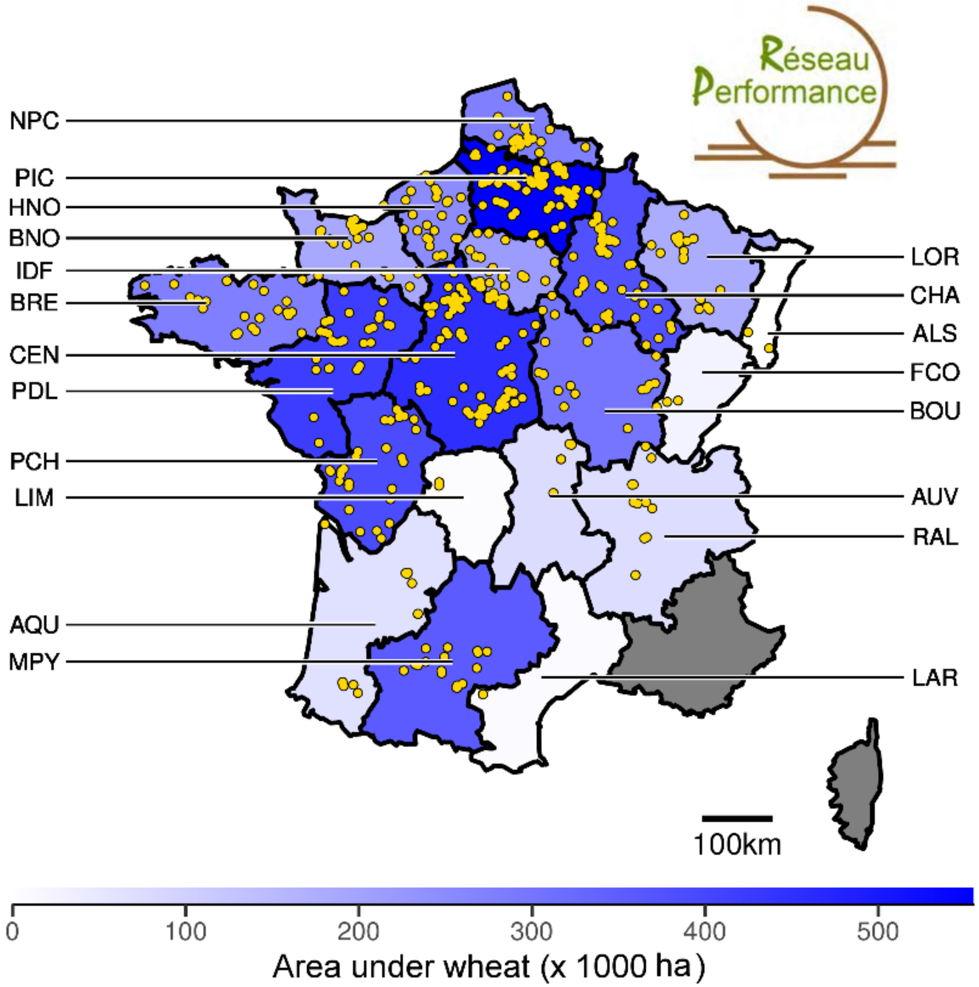
  - DMIs or **Tri**azoles (**TriR: LR → MR → HR**)
- **Need for a reliable resistance monitoring**



Introduction – The *Performance* network compiled a unique dataset



- **Since 2004**
- **70 locations monitored yearly**
- **Up to 10 different sprayed strategies + 1 unsprayed plot**

Garnault et al. (2019). Pest management science.

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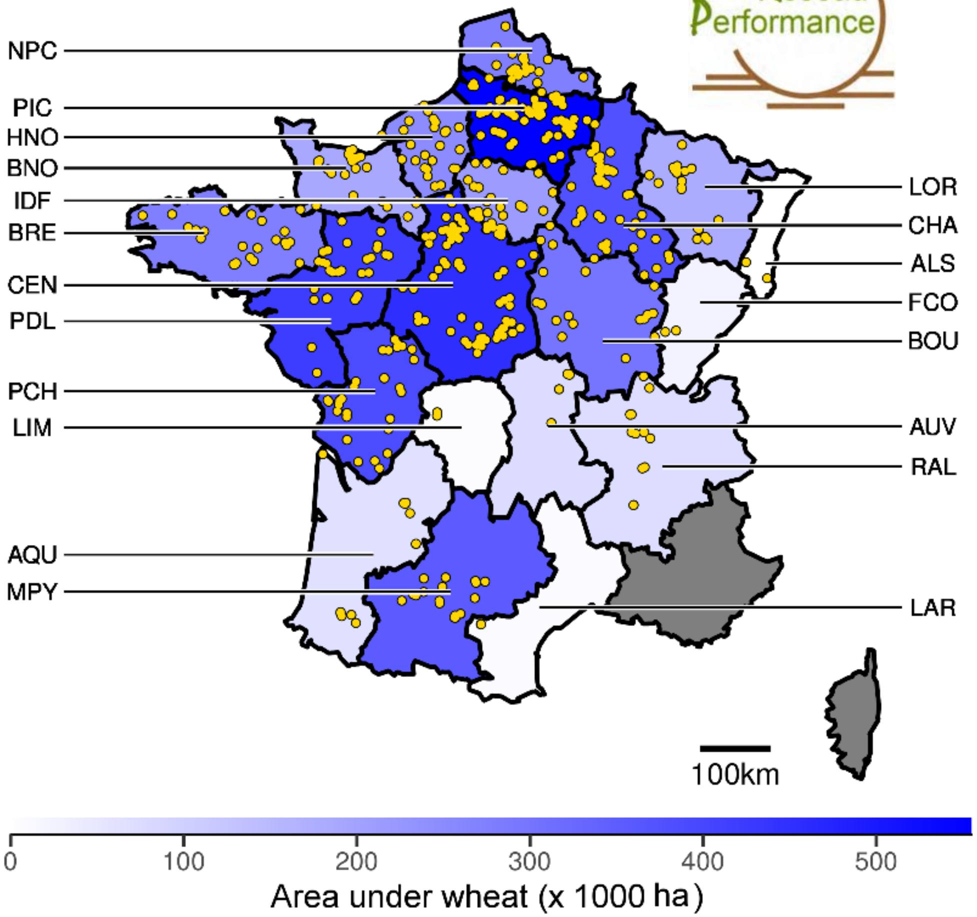

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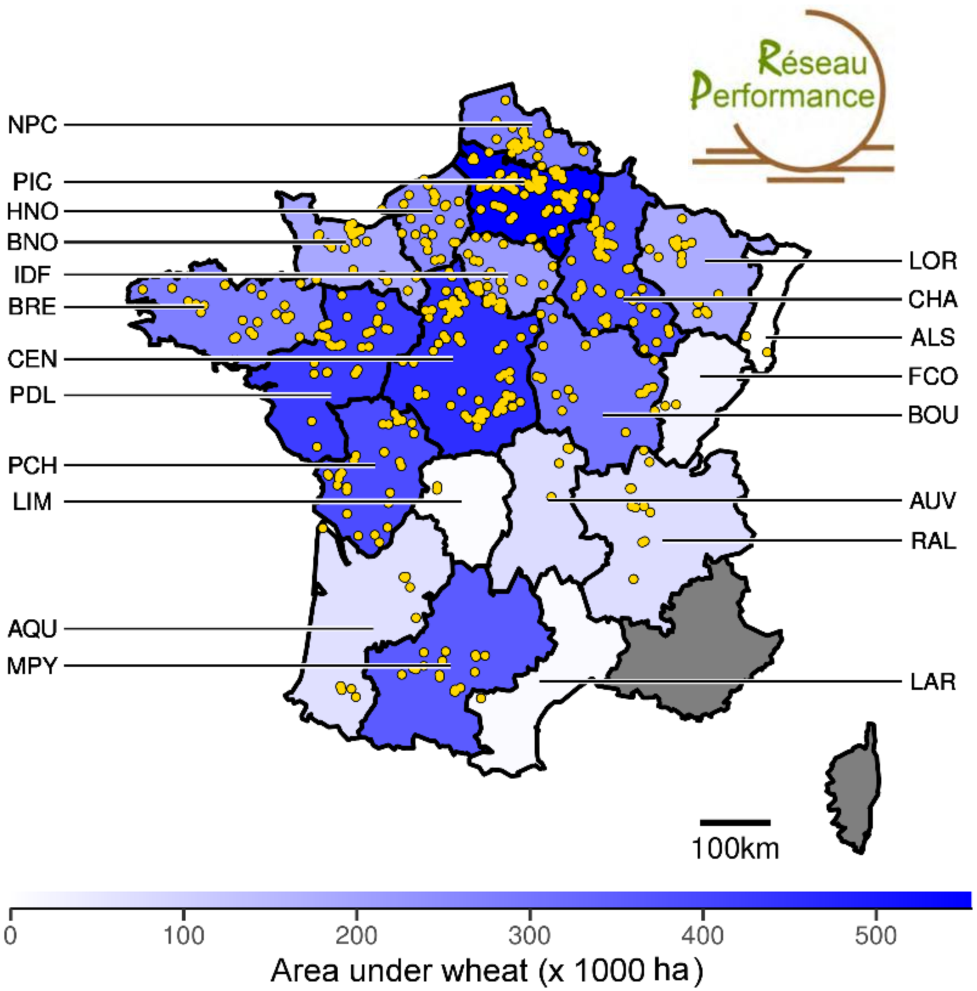

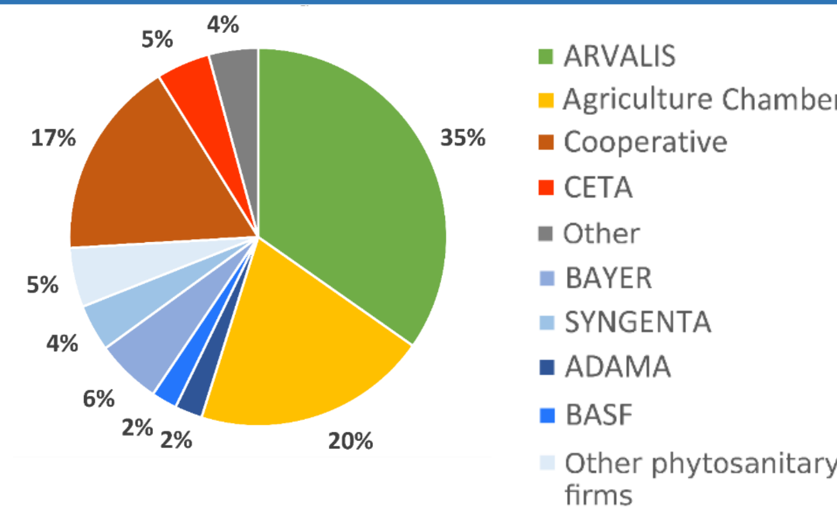

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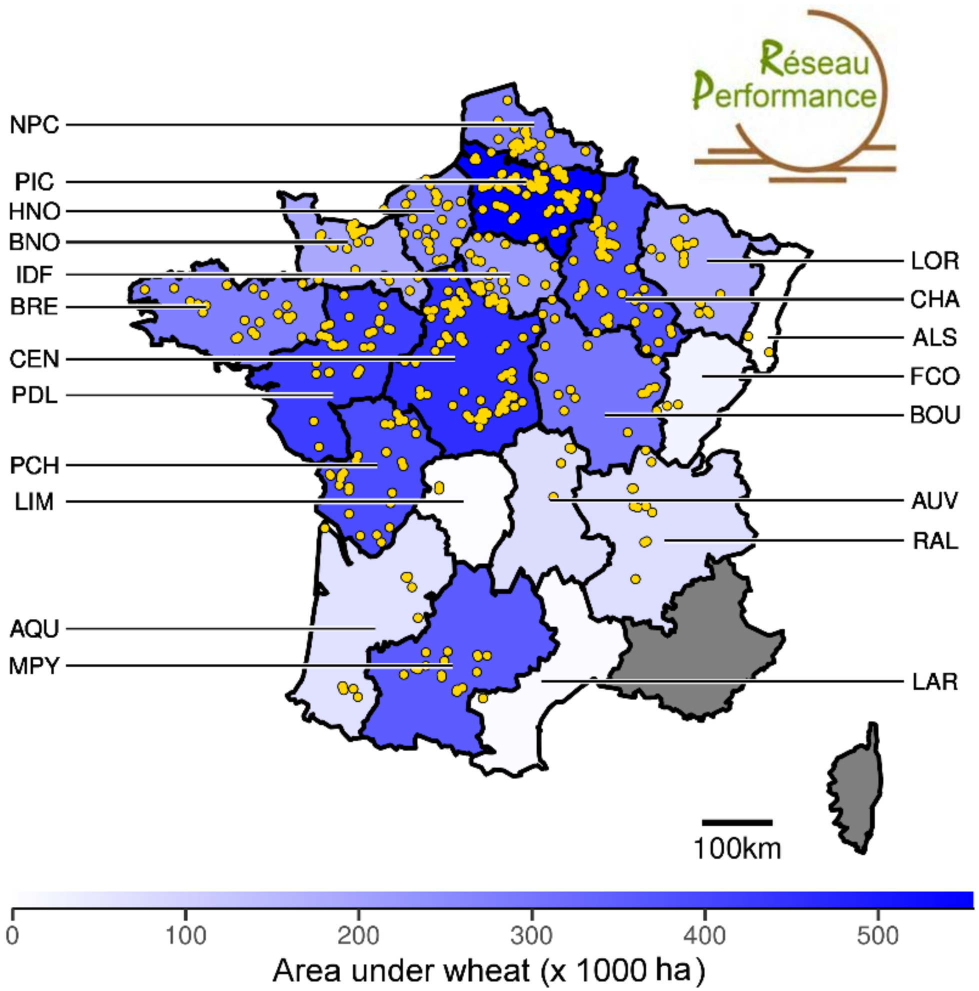

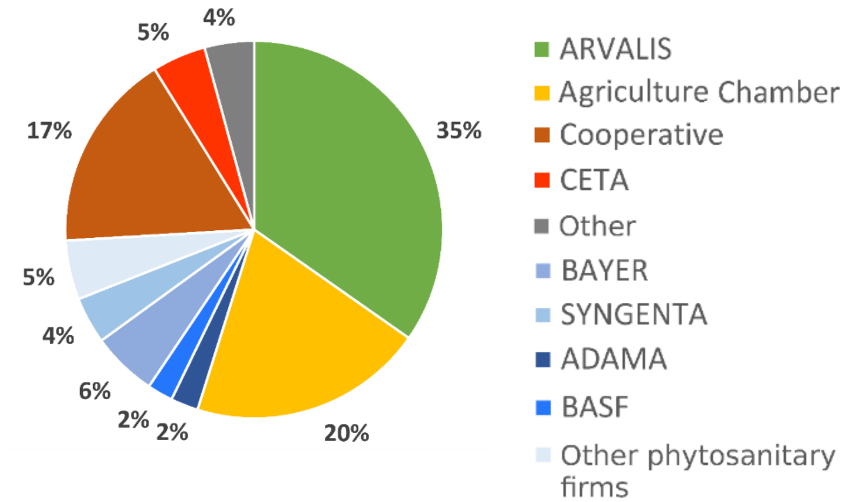

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➢ **A unique dataset: time and space scales, exhaustiveness of resistances**

Garnault et al. (2019). Pest management science.

Questions and approaches

- **How resistance evolves on large time and space scales?**

  Section 1 - Historical review and quantification of resistance dynamics to fungicides in the French *Z. tritici* populations

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  Section 2 - Quantification of the effect of regional fungicides uses on resistance frequencies

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- **What are the determinants of resistance evolution at the regional scale?**

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- **How anti-resistance strategies modulate resistance evolution at the plot scale?**

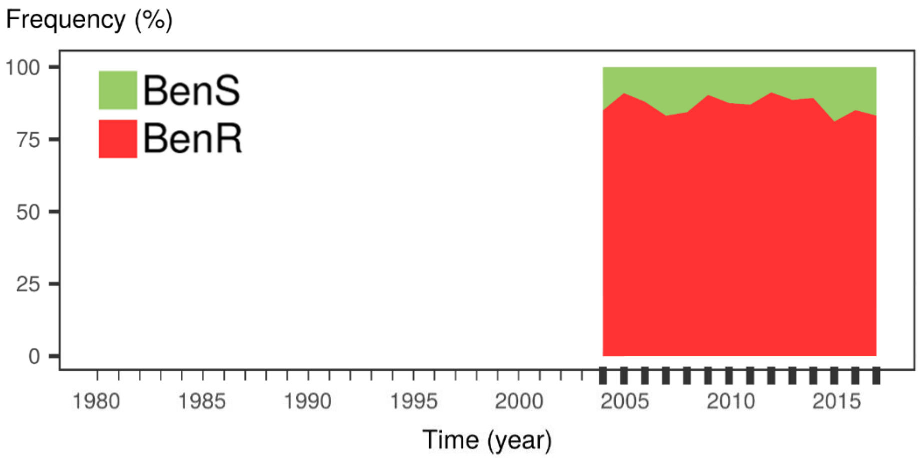
  Section 3 - Quantification of the effect of mixing fungicides

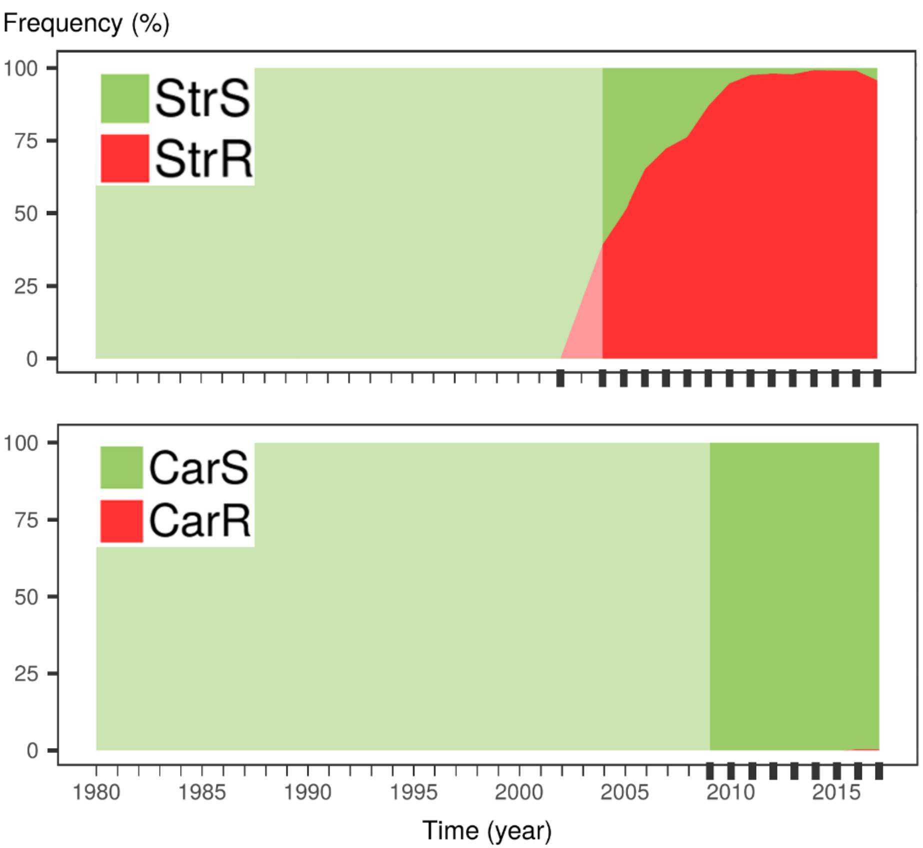
Section 1 – Explored data

Variable to be explained

Resistance frequencies observed in unsprayed fields

"Biological spore traps": resistance frequency before any selection





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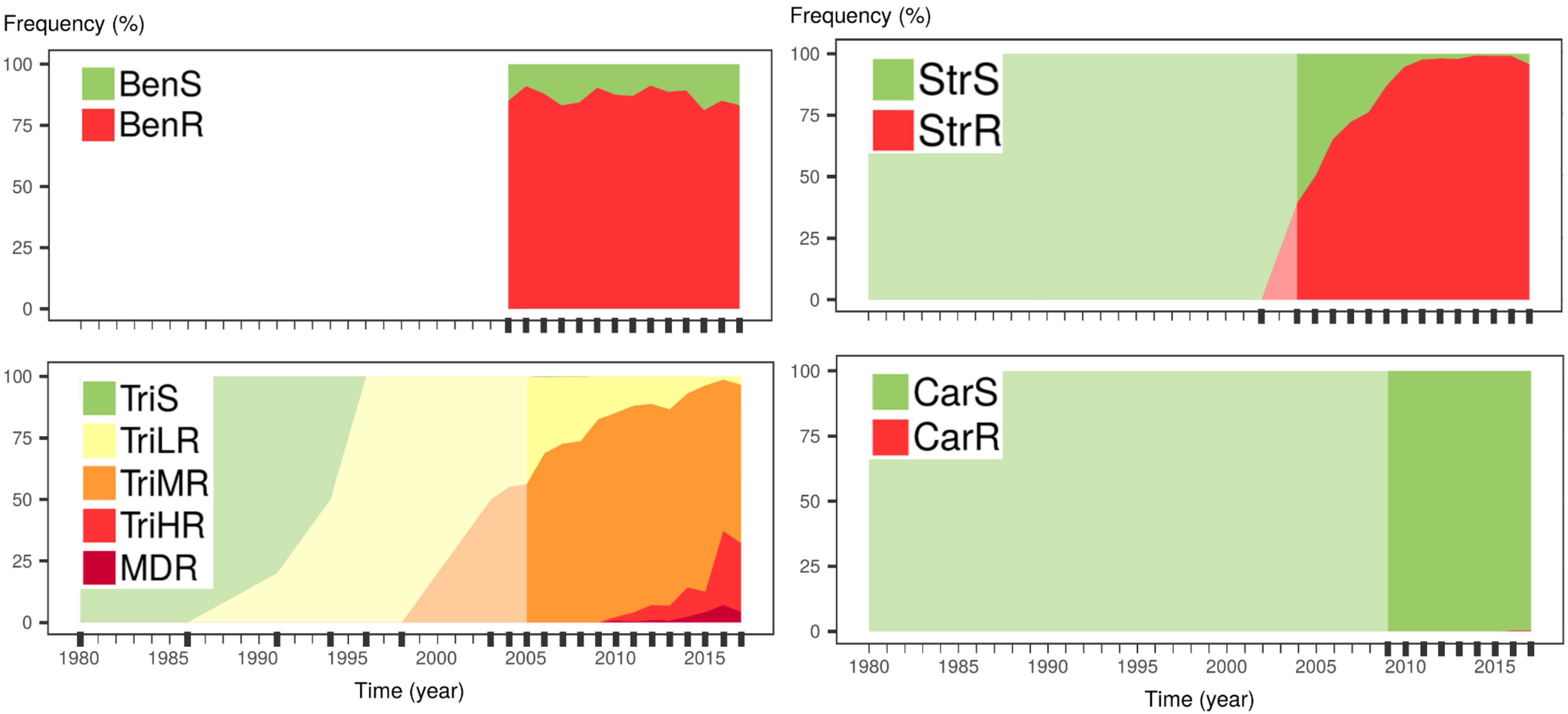

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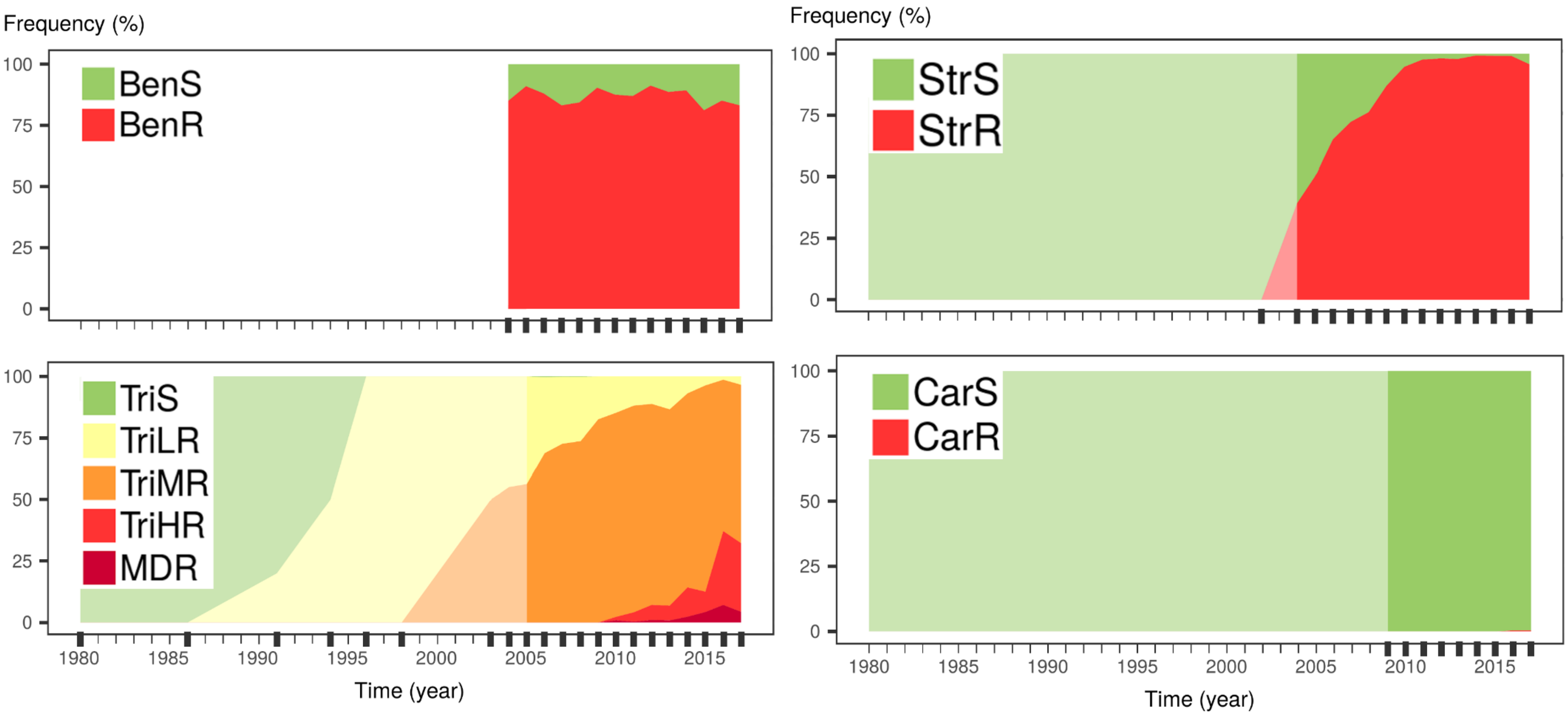


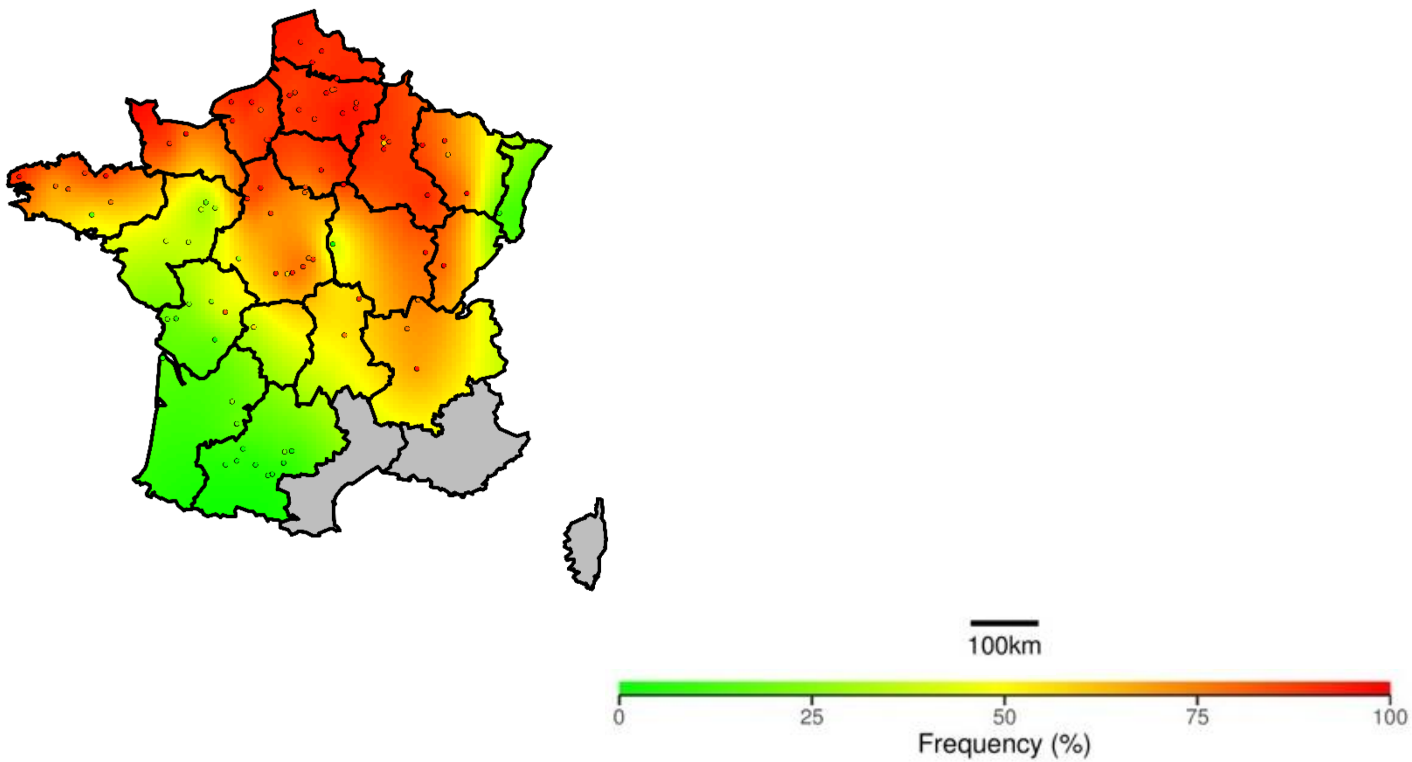
Explanatory variables

Year and Region

Garnault et al. (2019). Pest management science.

Mapping of the annual resistance status:
Are spatial structures stable over time?

Spatial kriging
(variogram estimation)

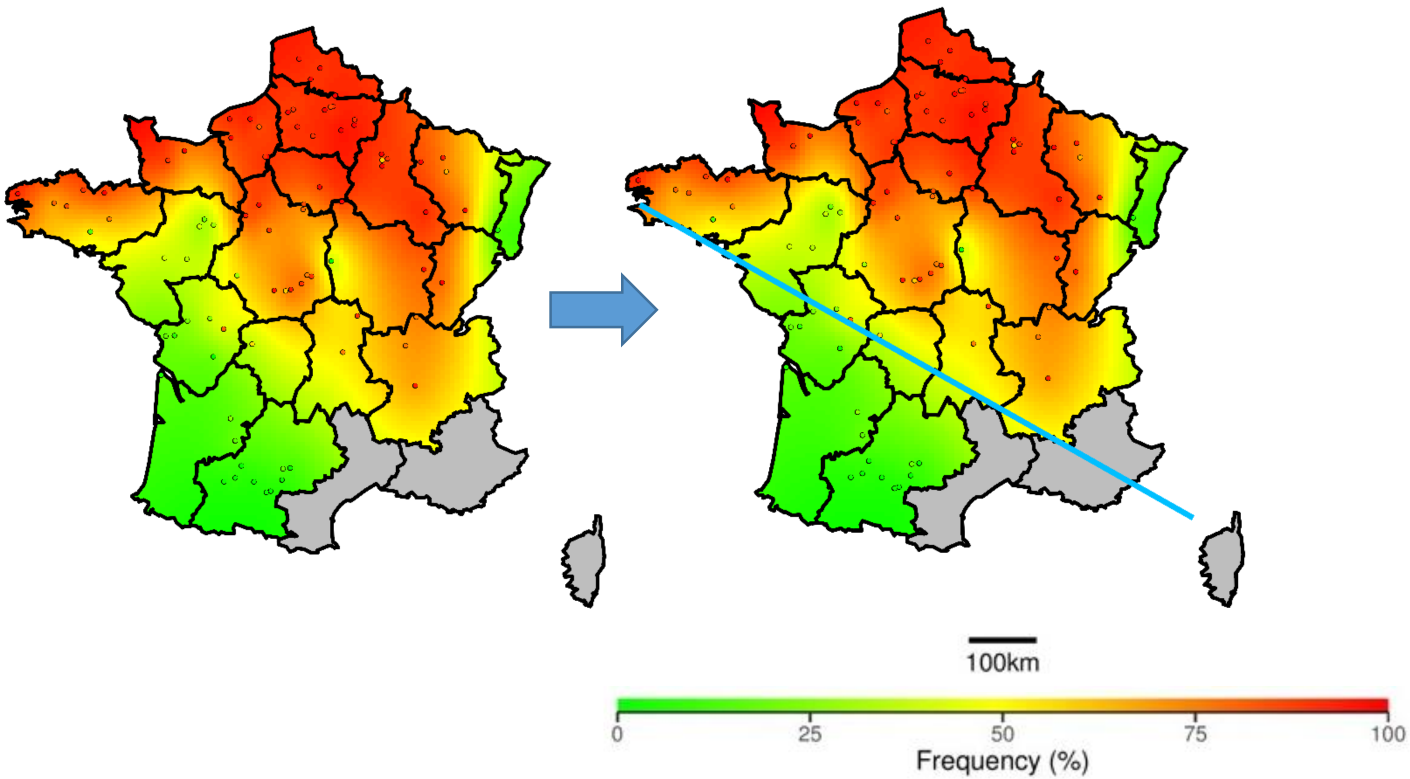


Garnault et al. (2019). Pest management science.

Section 1 – A spatial analysis highlighting contrasted dynamics

Mapping of the annual resistance status:
Which are the geographical zones with higher frequencies?

Spatial kriging (variogram estimation) + **Spatial partitioning (decision trees)**

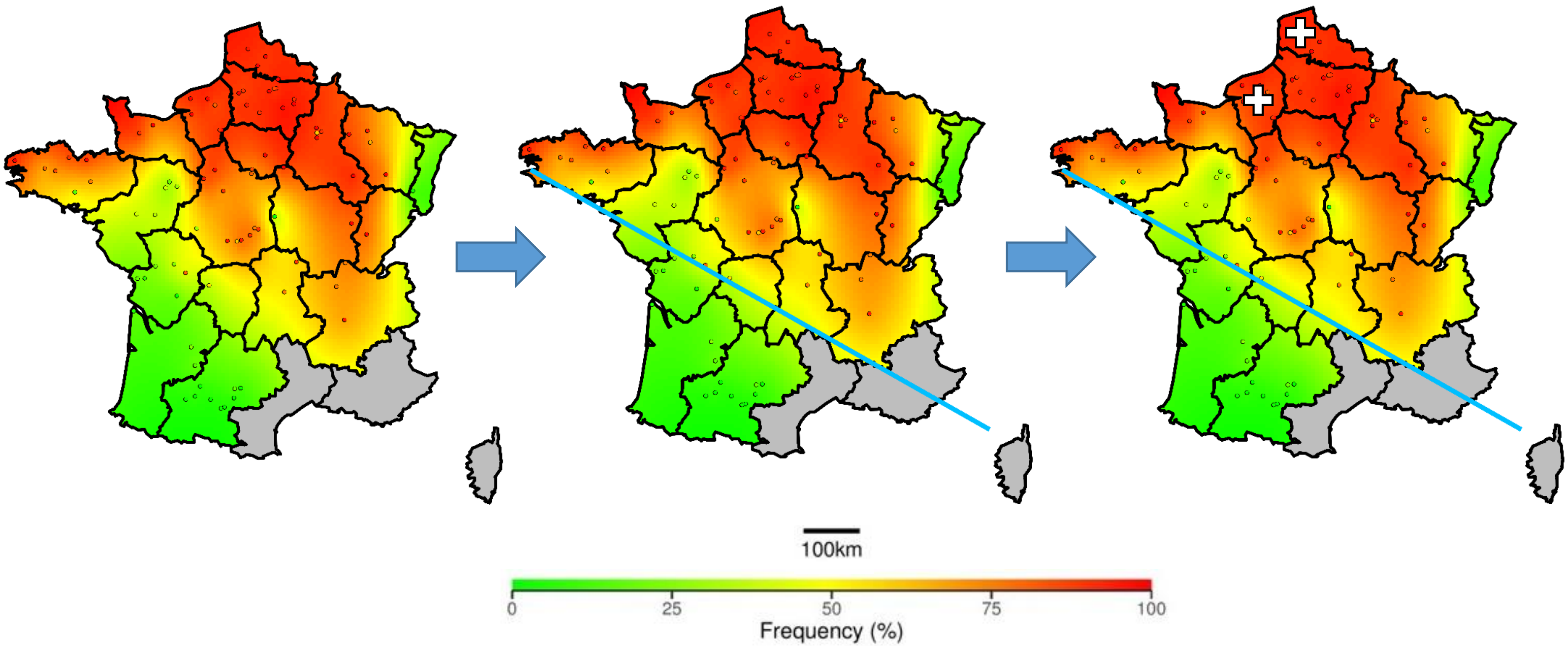


Garnault et al. (2019). Pest management science.

Section 1 – A spatial analysis highlighting contrasted dynamics

Mapping of the annual resistance status:
Which are the years/regions with higher/lower frequencies compared to the average?

Spatial kriging (variogram estimation) + **Spatial partitioning (decision trees)** + **0-1 inflated GLM (Year x Region)**



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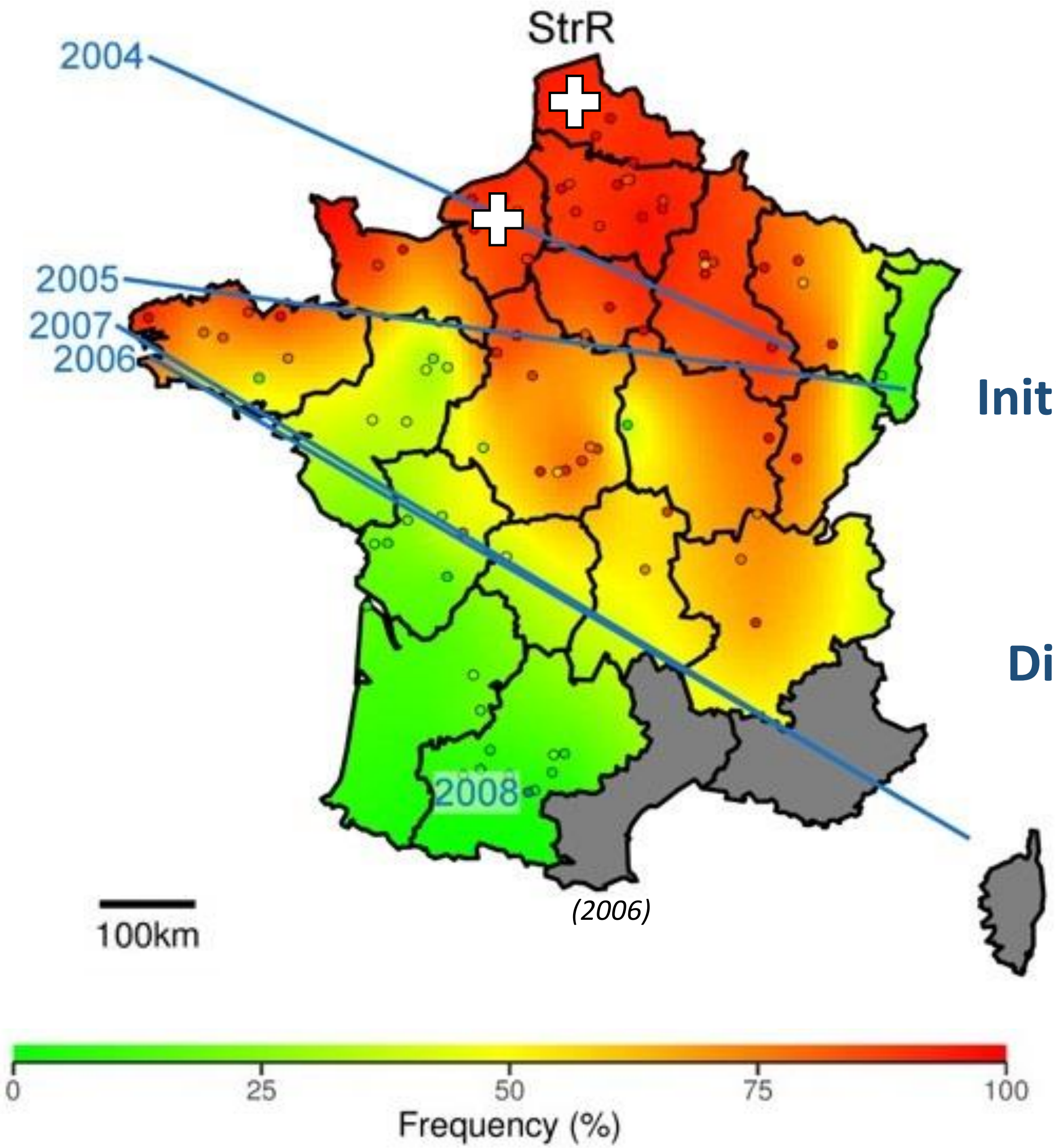
Section 1 – Dynamic spatial structure for the StrR phenotype

QoI resistance



Initially found in Northern regions

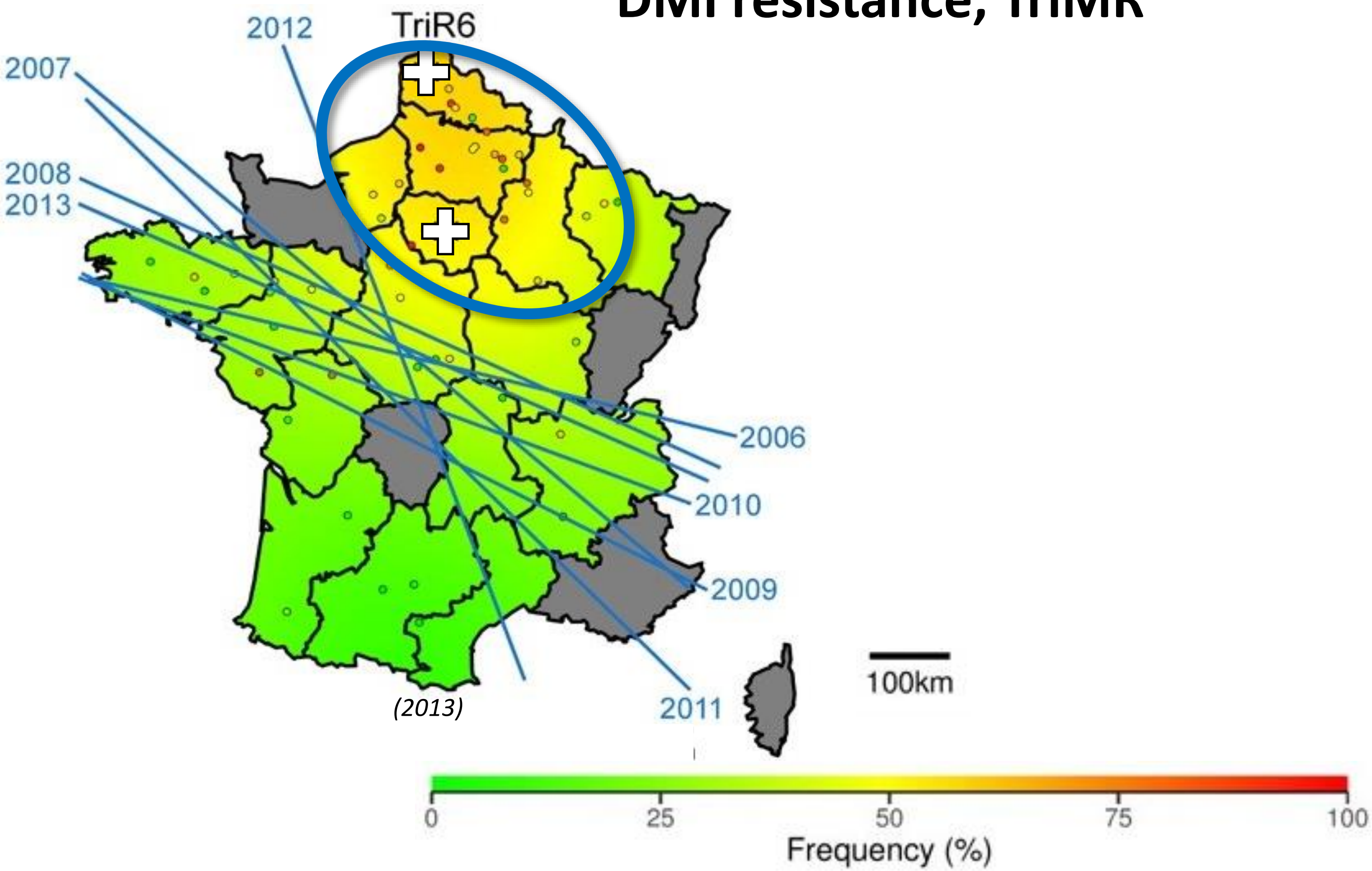
Progression front structure

Dispersal capacity: 150 km/year

Garnault et al. (2019). Pest management science.

Section 1 – Stable spatial structures for the TriR6 and TriR7-R8 phenotypes

DMI resistance, TriMR



Higher frequencies of TriR6 in Northern / North-Eastern regions

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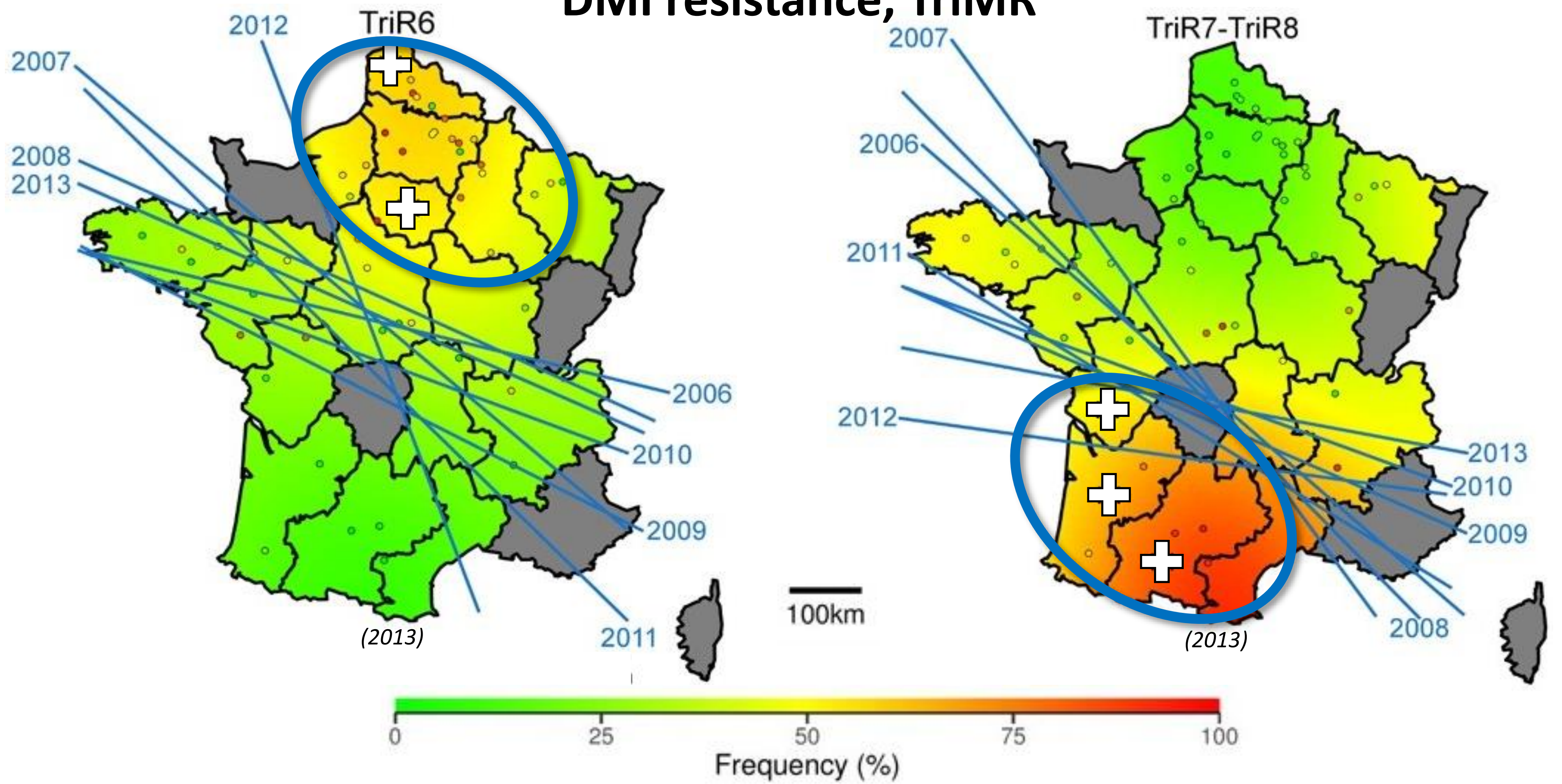

Higher frequencies of TriR6 in Northern / North-Eastern regions

Higher frequencies of TriR7-TriR8 in Southern / South-Western regions

Garnault et al. (2019). Pest management science.

Section 1 – Modelling resistance growth

Represents the counting protocol and the three main evolution stages of resistance

$$Y \begin{cases} = 0 & \text{with probability } \pi_0 \\ \sim \mathcal{B}(100, p) & \text{with probability } 1 - \pi_0 - \pi_{100} \\ = 100 & \text{with probability } \pi_{100} \end{cases}$$

$\Rightarrow$ **Selection**

Garnault et al. (2019). Pest management science.

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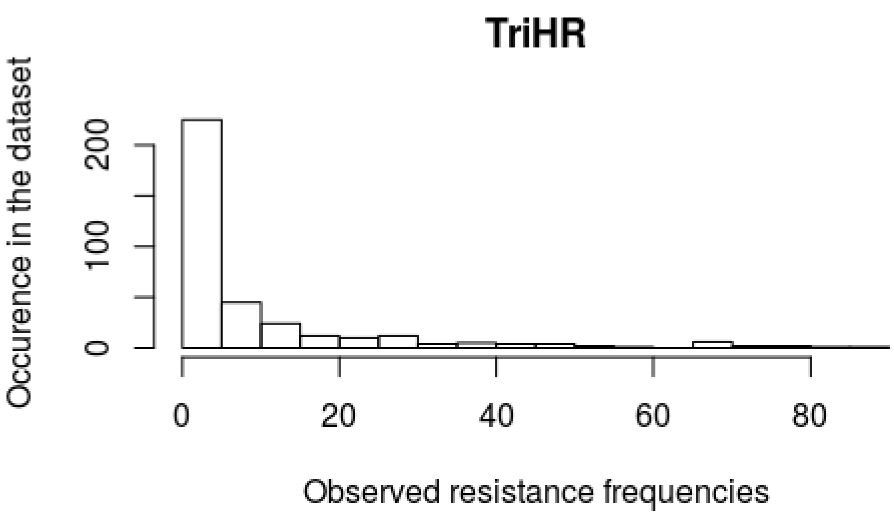
Emergence

Selection



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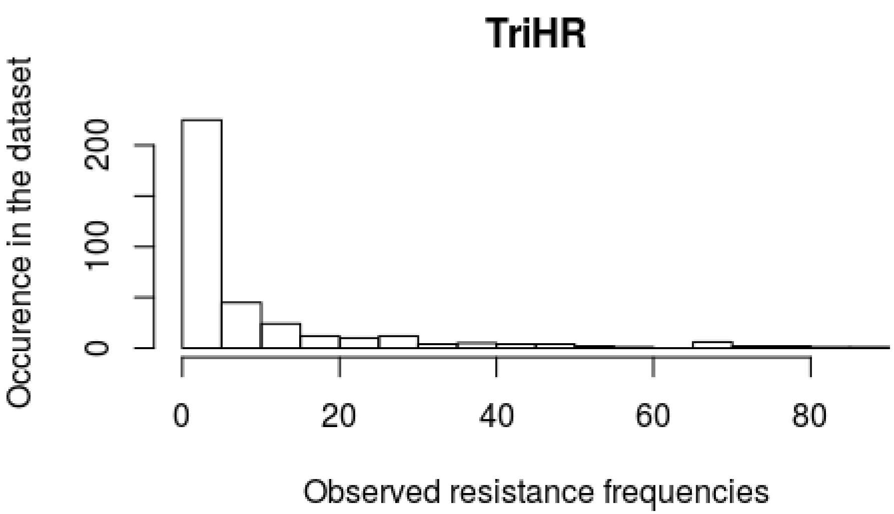
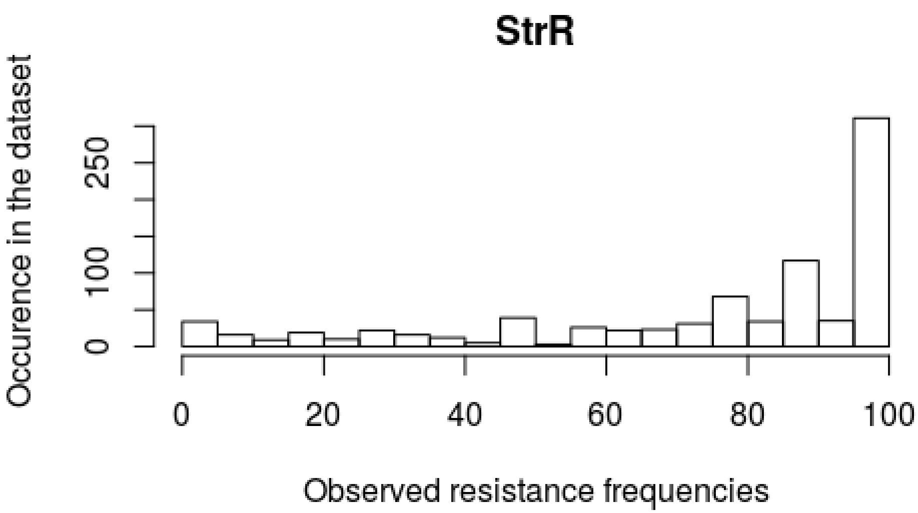
Emergence

Selection

Generalization





Garnault et al. (2019). Pest management science.

Section 1 – A dynamic approach to study relative fitness

Population dynamics approach: Hartl & Clark, 1997

Resistant phenotype $R(t) = R_0 \omega_R^t$

Sensitive phenotype (wild type) $\mathrm{S}(t) = S_0 \omega_S^t$

$\omega = \frac{\omega_R}{\omega_S}$ **the relative fitness**

How many times faster resistant individuals grow compared to others

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$$\omega = \frac{\omega_R}{\omega_S}$$ **the relative fitness**

How many times faster resistant individuals grow compared to others

$$p_{R(t)} = \frac{R(t)}{R(t) + S(t)}$$

$$logit(p_{R(t)}) = \ln\left(\frac{p_{R(t)}}{1 - p_{R(t)}}\right) = \ln\left(\frac{R(t)}{S(t)}\right) = \ln\left(\frac{R_0 \omega_R^t}{S_0 \omega_S^t}\right)$$

$$= \ln\left(\frac{R_0}{S_0}\right) + \ln\left(\frac{\omega_R^t}{\omega_S^t}\right) = \ln\left(\frac{R_0}{S_0}\right) + \ln\left(\frac{\omega_R}{\omega_S}\right)^t = \ln\left(\frac{R_0}{S_0}\right) + t * \ln\left(\frac{\omega_R}{\omega_S}\right)$$

$$\boxed{logit(p_{R(t)}) = \mu + \beta * t \qquad with\ \mu = \ln\left(\frac{R_0}{S_0}\right)\ and\ \beta = \ln(\omega)}$$

Garnault et al. (2019). Pest management science.

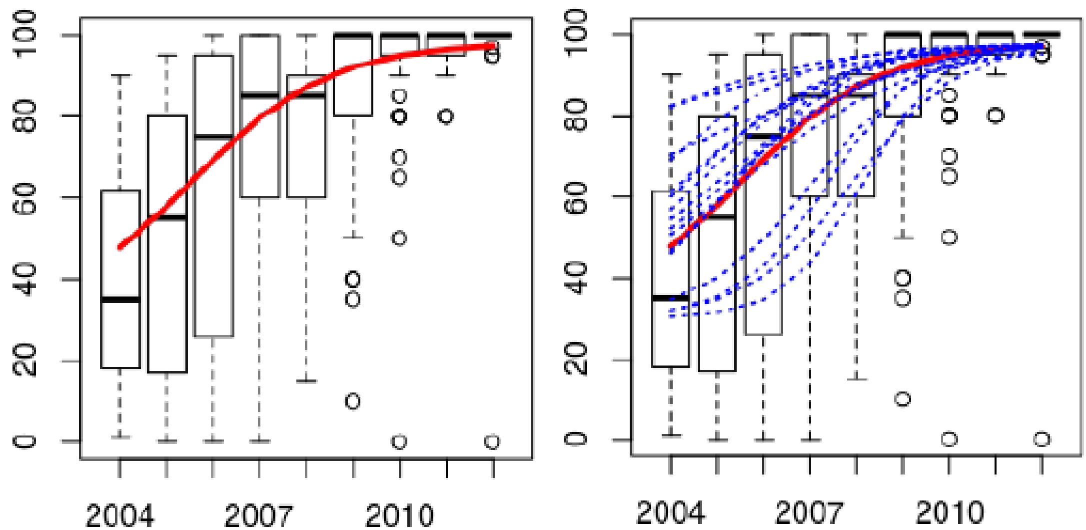
Section 1 – A model to estimate apparent relative fitness

$$Y \begin{cases} = 0 & \text{with probability } \pi_0 \\ \sim \mathcal{B}(100, p) & \text{with probability } 1 - \pi_0 - \pi_{100} \\ = 100 & \text{with probability } \pi_{100} \end{cases}$$

$$\begin{aligned} logit(p_{ijln}) = \; & (\mu + \alpha_i) \\ & + (\beta + \eta_i) * (l - 1) \end{aligned}$$

Initial frequencies (*l=1*): global + regional

Growth rates: global + regional



Garnault et al. (2019). Pest management science.

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$logit(p_{ijln}) = (\mu + \alpha_i)$	**Initial frequencies (*l=1*): global + regional**
$+ (\beta + \eta_i) * (l - 1)$	**Growth rates: global + regional**
$+ \delta_j$	**Sampling date effect**
$+ \varepsilon_{ijkln}$	**Overdispersion**

$$\text{where } \varepsilon_{ijln} \underset{iid}{\sim} \mathcal{N}(0,\ \sigma^2)$$

Garnault et al. (2019). Pest management science.

Section 1 – A model to estimate apparent relative fitness

$$
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$$

$$
\begin{aligned}
logit(p_{ijln}) = \;& (\mu + \alpha_i) && \textbf{Initial frequencies } (\textbf{\textit{l=1}})\textbf{: global + regional} \\
& + (\beta + \eta_i) * (l - 1) && \textbf{Growth rates: global + regional} \\
& + \delta_j && \textbf{Sampling date effect} \\
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& \text{where } \varepsilon_{ijln} \underset{iid}{\sim} \mathcal{N}(0,\ \sigma^2)
\end{aligned}
$$

A model that can estimate relative fitness of resistance phenotypes from their frequency evolutions

$$
\boxed{logit(p_{i,\,j,\,l,\,\cdot}) = logit(p_{i,\,j,\,l-1,\,\cdot}) + (\beta + \eta_i)}
$$

- **Bayesian framework, MCMC algorithms, non-informative priors**

Garnault et al. (2019). Pest management science.

Section 1 – A method to test variance parameters

$$logit(p_{i,\,j,\,l,\,.}) = logit(p_{i,\,j,\,l-1,\,.}) + (\beta + \eta_i)$$

We define for region parameters as $\eta_i \sim \mathcal{N}(0, \sigma_\eta^2)$, which is equivalent to the contrasts « sum = 0 » in frequentist models

➢ **How to test significance of variance parameters (variance hyperparameters or random effects) ?**

Section 1 – A method to test variance parameters

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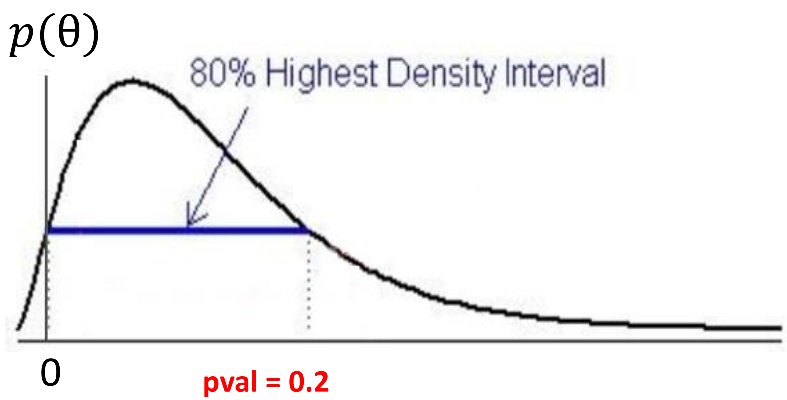
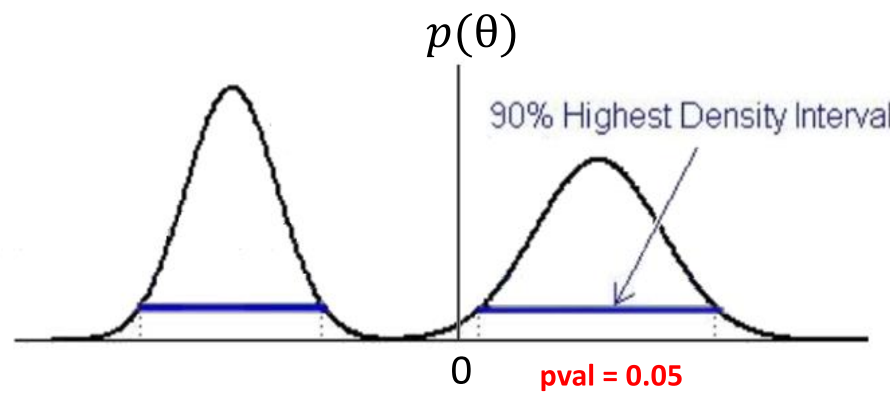
Pvalues are computed using **credible intervals of parameters posterior densities**



pval = 0.2



pval = 0.05

(HDInterval - R package, 2018)

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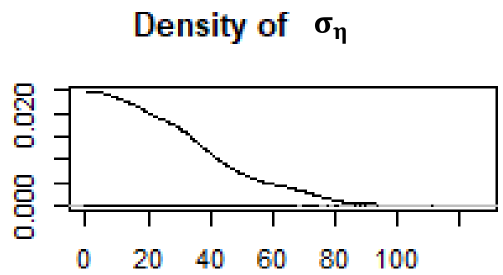
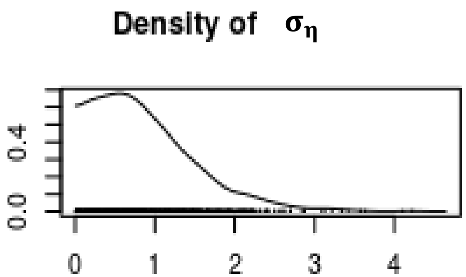
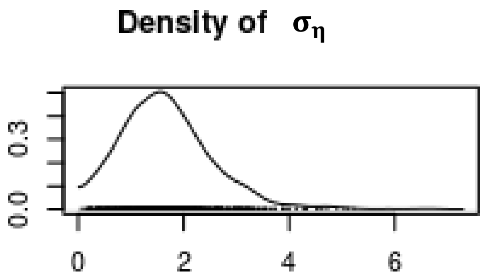
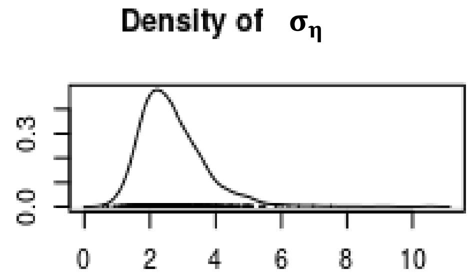


Model convergence







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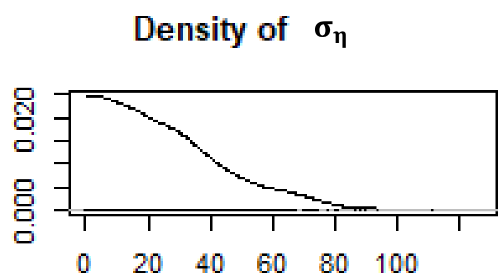

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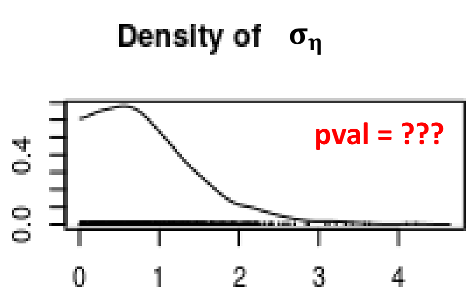

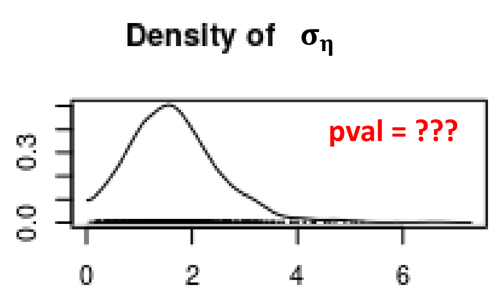

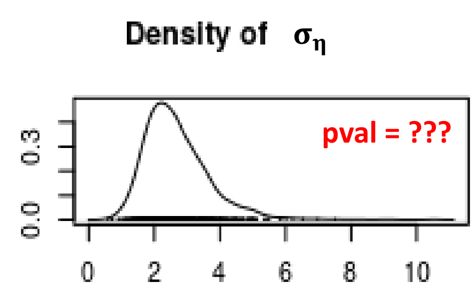

Section 1 – A method to test variance parameters

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- **How to test significance of variance parameters (variance hyperparameters or random effects) ?**

$$\boxed{\eta_i = \sigma_\eta * \eta_i'}$$

avec $\eta_i' \sim \mathcal{N}(0, 1)$

Section 1 – A method to test variance parameters

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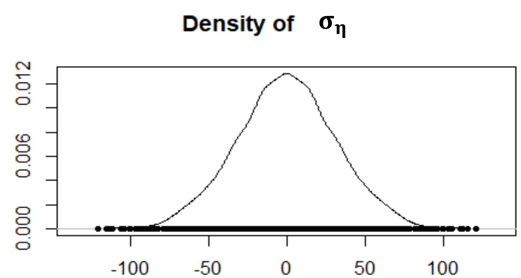
$$\boxed{\eta_i = \sigma_\eta * \eta'_i}$$

avec $\eta'_i \sim \mathcal{N}(0, 1)$



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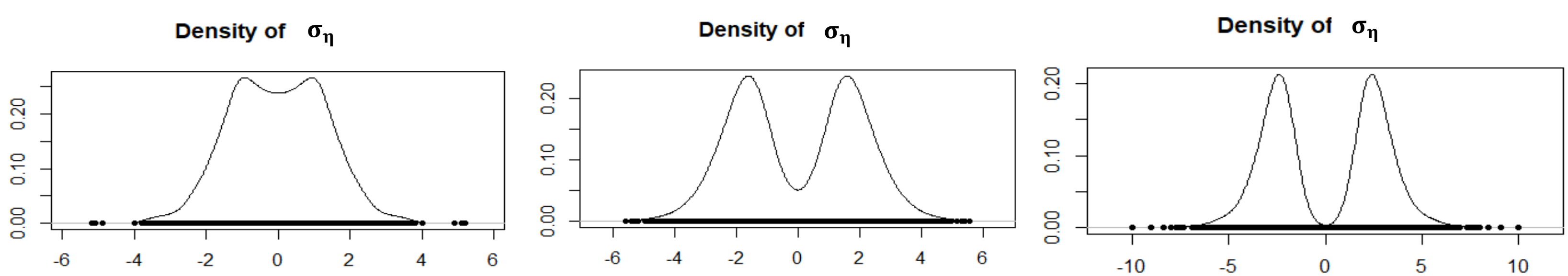

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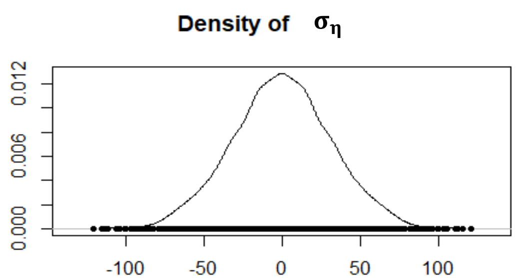

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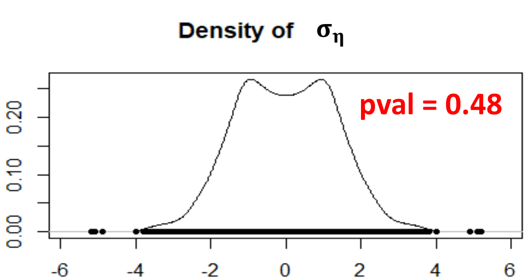
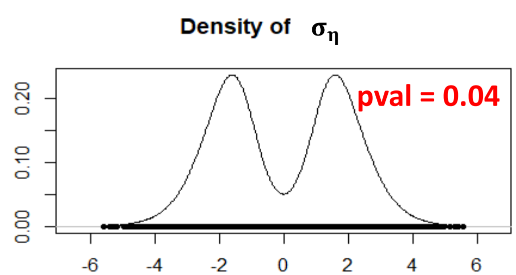
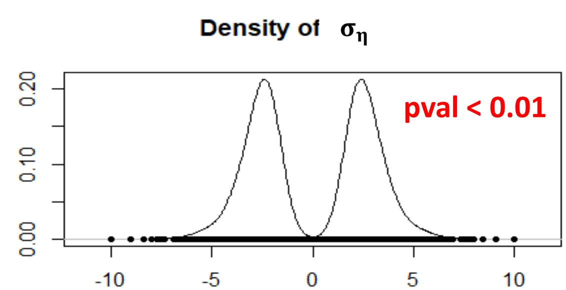
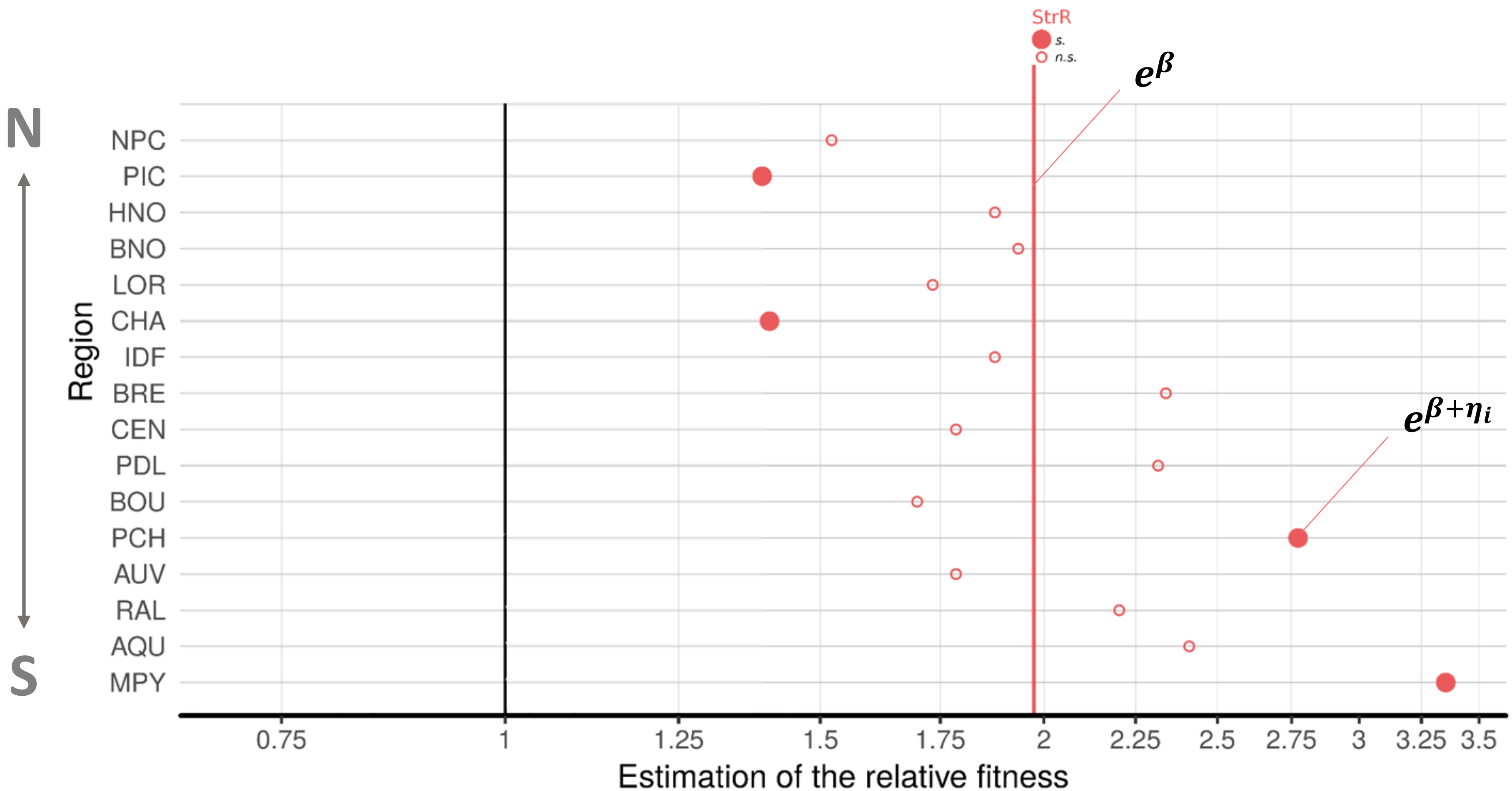






Section 1 – Apparent fitness estimated from the dynamic model



Garnault et al. (2019). Pest management science.

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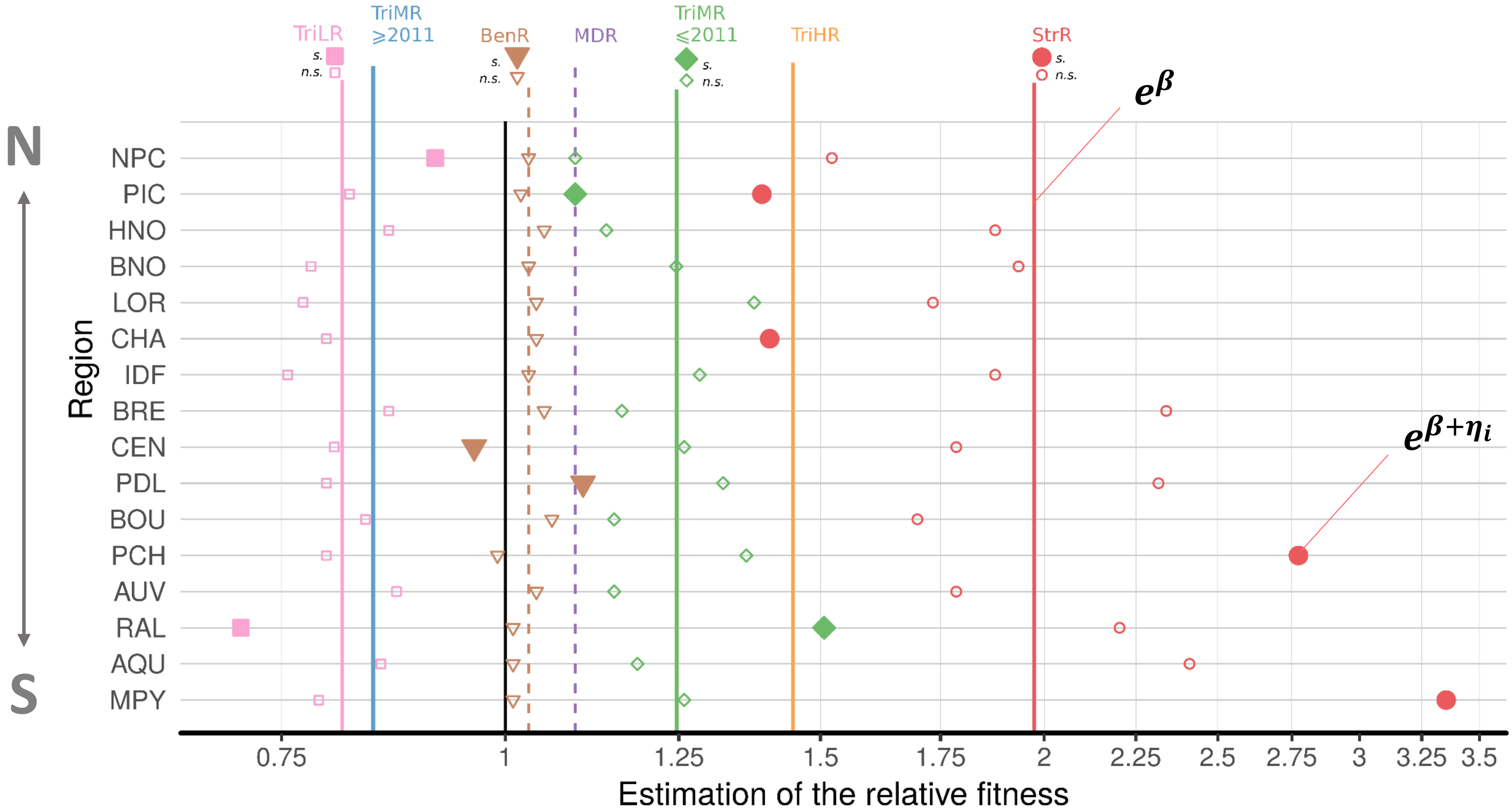

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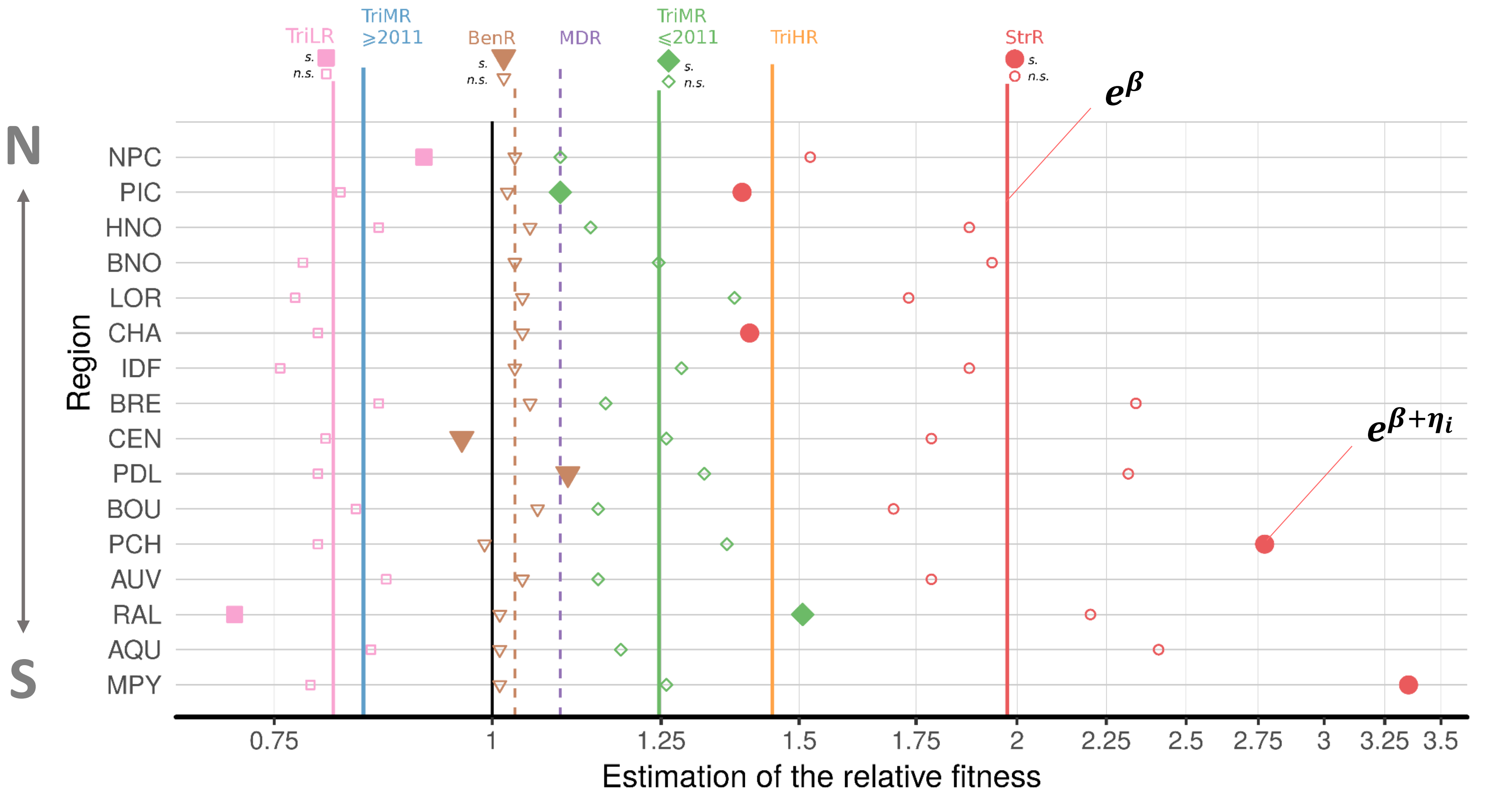
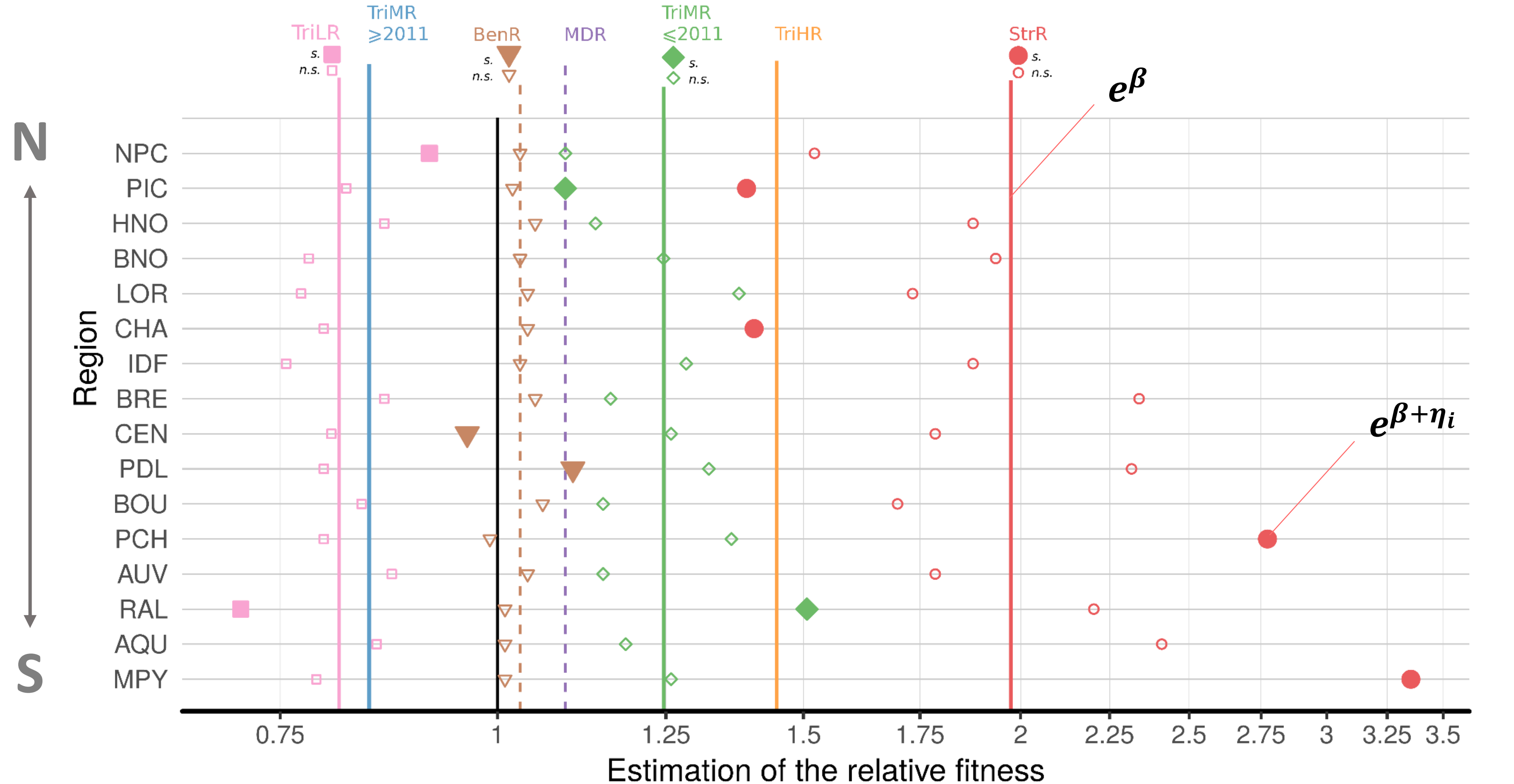


Evolution speeds differ among resistance phenotypes

Garnault et al. (2019). Pest management science.

Section 1 – Apparent fitness estimated from the dynamic model



Evolution speeds differ among resistance phenotypes

Evolution speeds differ among regions for a given resistance phenotype

Garnault et al. (2019). Pest management science.

Section 1 – Key points

- **Progression front structure (QoI resistance, previously described on a West-to-East gradient by Torriani *et al.*, 2009)**
- **Stable and strong regionalization of resistance (DMI resistance)**
- **Constrated growth speeds among phenotypes**
- **Contrasted growth speeds among regions for a given phenotype**
- **Significant difference between spring and summer samples highlight intra-annual evolution**

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➢ **Regional scale is interesting for resistance management**

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➢ **Regional scale is interesting for resistance management**

➢ **Which factors modulate the selection at the regional scale?**

Section 2 – Adressed question

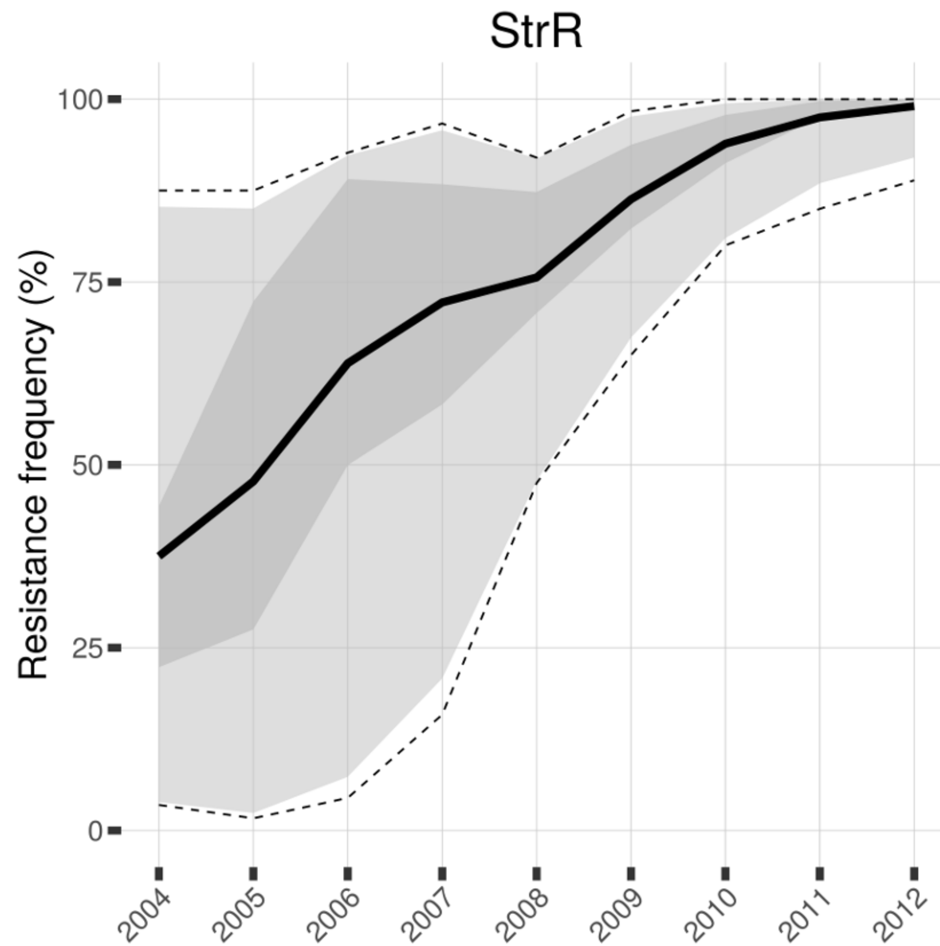
- **Section 2 -** The regional drivers of resistance dynamics

Selection pressure | Genetic drift | Migration

➢ **Can regional fungicides uses explain resistance frequencies?**

Variable to be explained

Resistance frequencies observed in unsprayed plots



Garnault et al. (2020). New Phytologist.

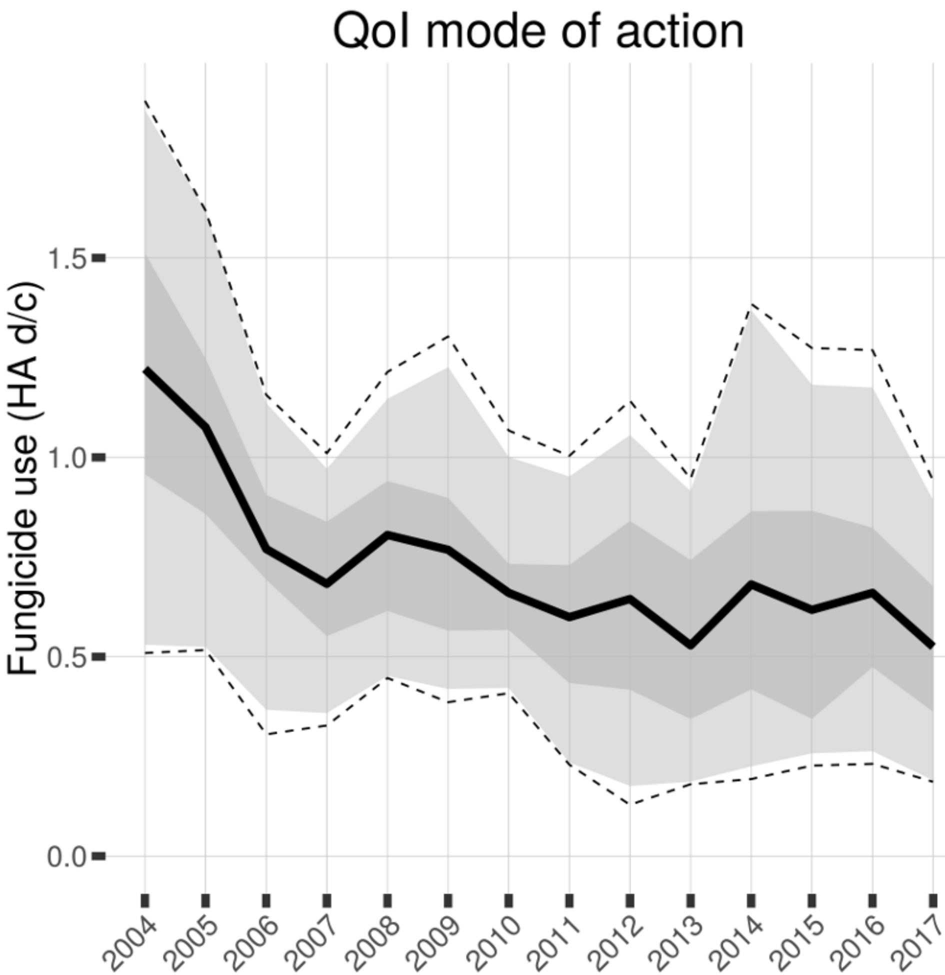
Section 2 – Explored data

Variable to be explained

Resistance frequencies observed in unsprayed plots

Explanatory variables

Selection pressure intensity: use of anti-septoria fungicides



Garnault et al. (2020). New Phytologist.

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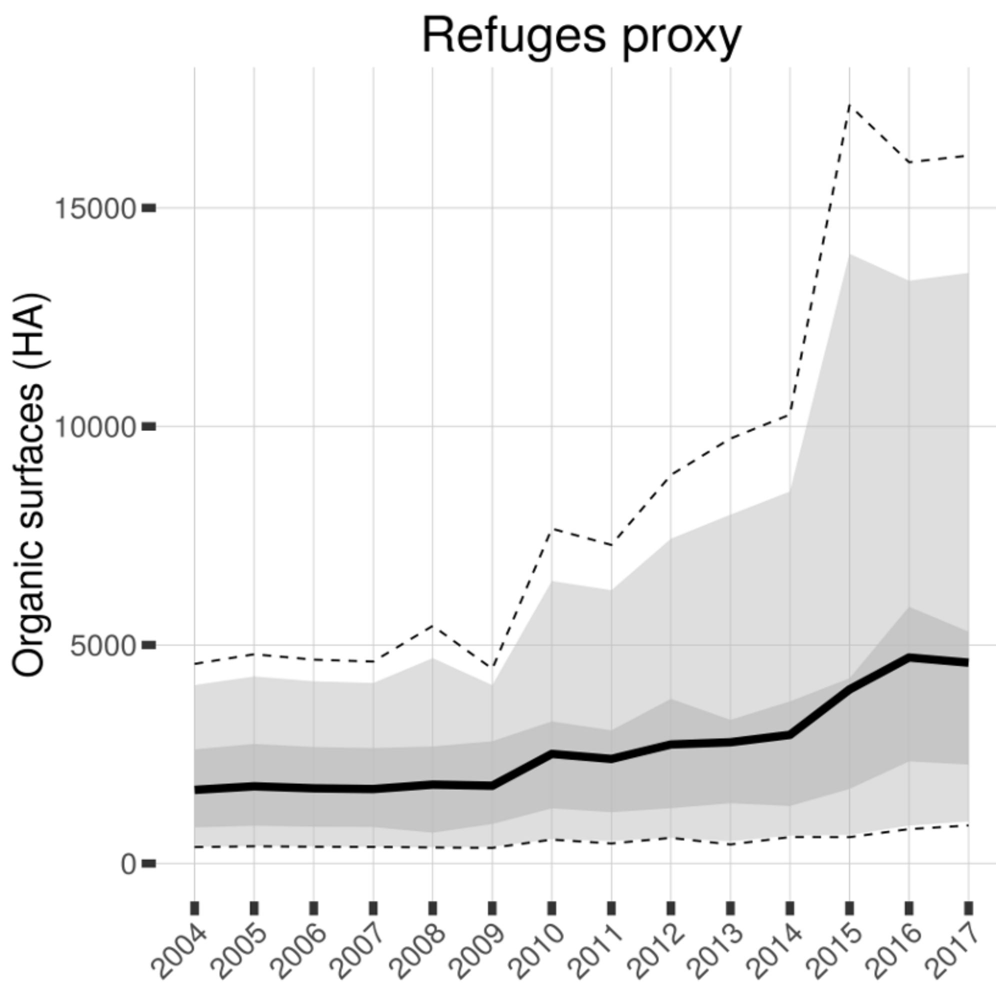
Selection pressure intensity: use of anti-septoria fungicides

Selection pressure heterogeneity: surfaces under organic wheat



Garnault et al. (2020). New Phytologist.

Section 2 – Explored data

Variable to be explained

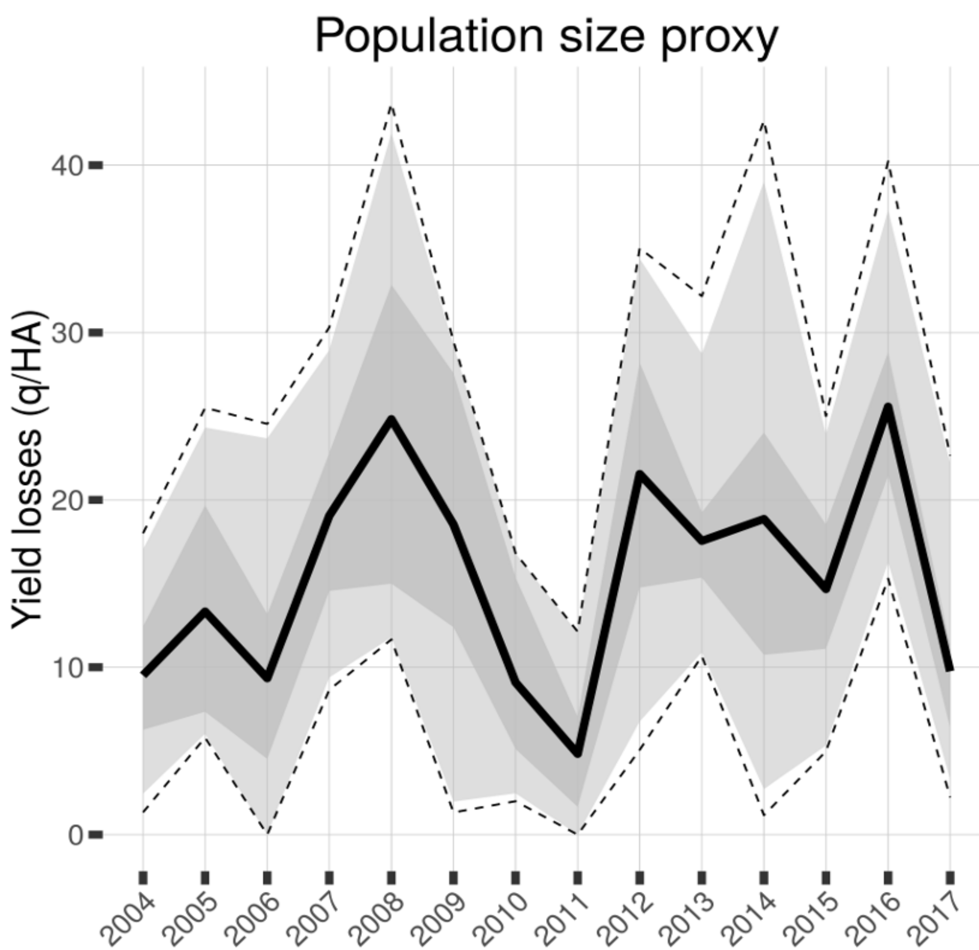
Resistance frequencies observed in unsprayed plots

Explanatory variables

Selection pressure intensity: use of anti-septoria fungicides

Selection pressure heterogeneity: surfaces under organic wheat

Population size proxy: Potential yield losses



Garnault et al. (2020). New Phytologist.

Section 2 – Adding explanatory factors to the dynamic model

$$logit(p_{i,\,j,\,l,\,\cdot}) = logit(p_{i,\,j,\,l-1,\,\cdot}) + (\beta + \eta_i)$$

$$\beta$$

Constant growth

$$+ \sum_{m=1}^{M} \nu_m * F_{m,\,i,\,j,\,l-1,\,\cdot}$$

Selection pressure

- Associated MoA
- $\nu_m > 0$ (StrR, TriMR)

Garnault et al. (2020). New Phytologist.

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$$+ \sum_{m=1}^{M} \nu_m * F_{m,\,i,\,j,\,l-1,\,\cdot}$$ **Selection pressure**

$$+ \rho * P_{i,\,j,\,l-1,\,\cdot}$$ **Population size**

Garnault et al. (2020). New Phytologist.

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$+ \kappa * R_{i,\,j,\,l-1,\,\cdot}$ **Refuges**

Garnault et al. (2020). New Phytologist.

Section 2 – Adding explanatory factors to the dynamic model

$$logit(p_{i,j,l,\cdot}) = logit(p_{i,j,l-1,\cdot}) + (\beta + \eta_i)$$

β **Constant growth**

Variable selection
(Kuo & Mallick, 1998)

$+ \sum_{m=1}^{M} \nu_m * F_{m,i,j,l-1,\cdot}$ **Selection pressure**

$+ \rho * P_{i,j,l-1,\cdot}$ **Population size**

$+ \kappa * R_{i,j,l-1,\cdot}$ **Refuges**

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Constant growth

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(Kuo & Mallick, 1998)

$$\left\{ \begin{array}{l} + \sum_{m=1}^{M} \nu_m * F_{m,\,i,\,j,\,l-1,\,\cdot} \\ + \rho * P_{i,\,j,\,l-1,\,\cdot} \\ + \kappa * R_{i,\,j,\,l-1,\,\cdot} \end{array} \right.$$

Selection pressure

Population size

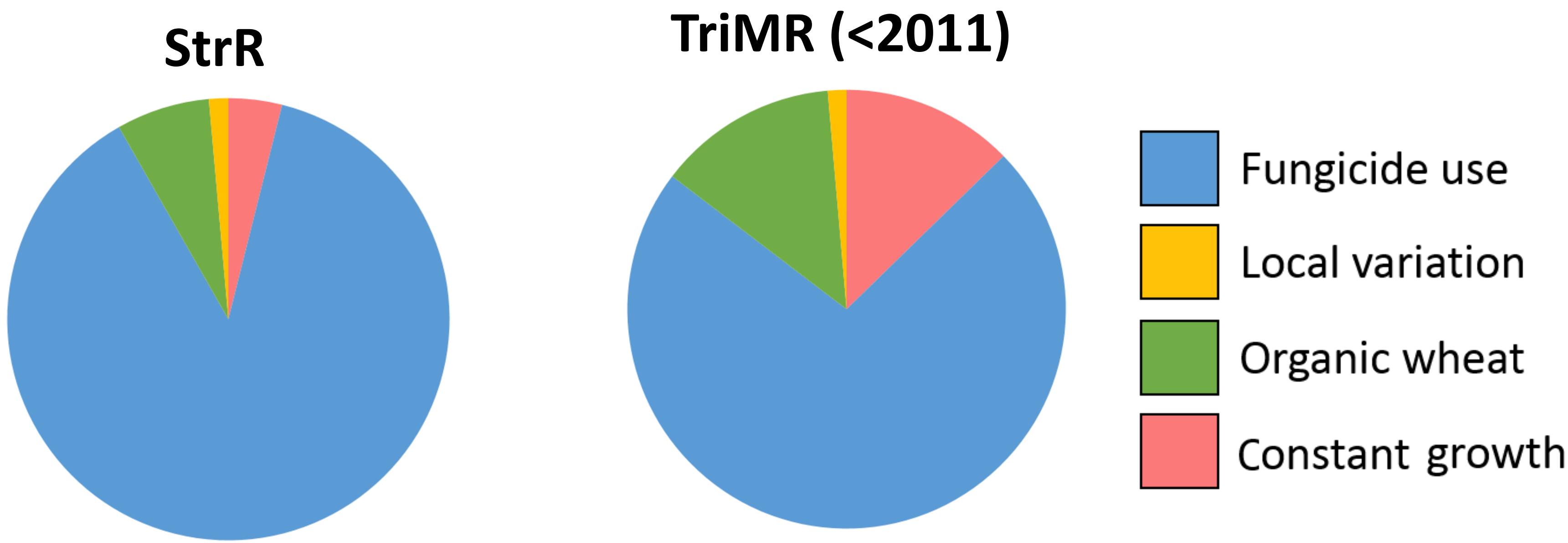
Refuges

β is an integrative parameter: fitness cost (migration?, …)

Garnault et al. (2020). New Phytologist.

Section 2 – Regional fungicide use is the most important factor

The loss of explained variance induced by removing the factor from the model.



Yield losses effect was never selected

Regional fungicide use is the major factor in models: 42% to 88%

Garnault et al. (2020). New Phytologist.

Section 2 – Frequency change induced by active substances

Parameter		StrR	TriMR <2011
Constant growth (β)		- 3.71 *	- 4.12 ·
Selection pressure (ν_m)			
QoIs	Kresoxym-methyl	4.23 ***	
	Pyraclostrobin	3.28 **	
DMIs	Cyproconazole		x
	Epoxiconazole		4.94 **
	Prochloraz		x
	Tebuconazole		x
Refuges (κ)		3.26 ***	

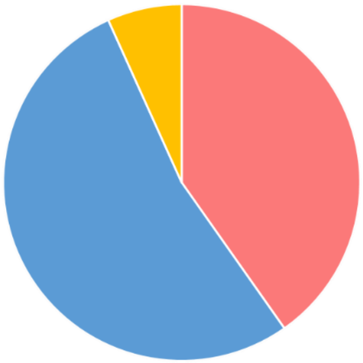
Selected actives substances are pioneers and most used fungicides

Constant growth are negative ➔ resistance cost ?

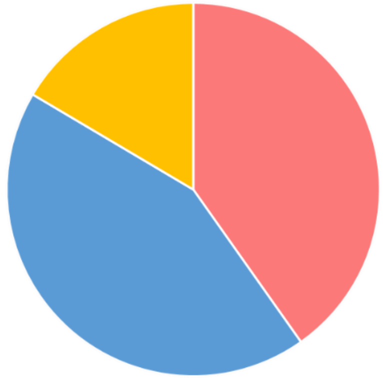
Garnault et al. (2020). New Phytologist.

Section 2 – Link between resistance factors and fungicide effects

TriR6



TriR7-TriR8



Fungicide use

Local variation

Constant growth

	TriLR	TriMR		TriHR
		TriR6	TriR7-TriR8	
Pyrifenox				
Prochloraz				
Epoxiconazole				
Propiconazole				
Fluquinconazole				
Tebuconazole				
Metconazole				
Difenoconazole				
Prothioconazole				

Leroux & Walker (2011). Pest management science.

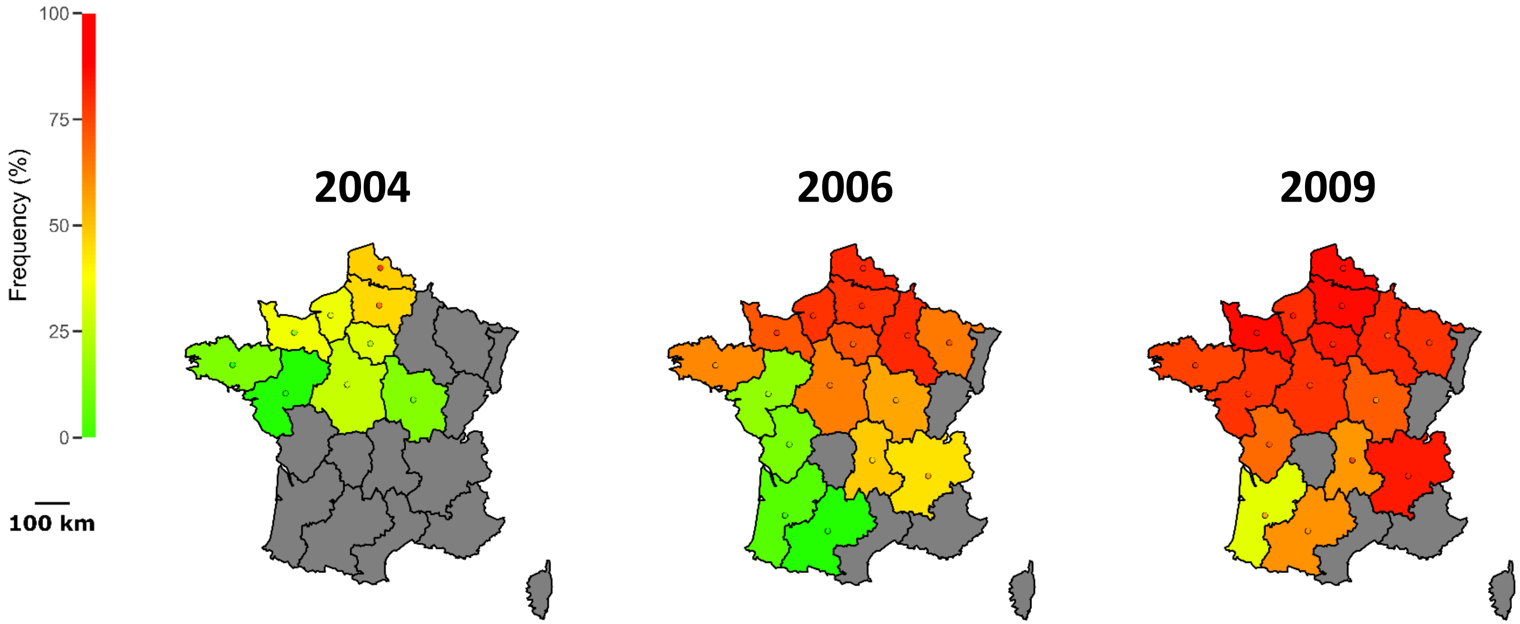
Resistance factor			
Sensitive	Low	Medium	High

Parameter		TriR6	TriR7-TriR8
Constant growth (β)		4.96 ***	1.52 ·
Selection pressure (ν_m)			
DMIs	Cyproconazole	x	2.46 **
	Epoxiconazole	x	x
	Prochloraz	**3.7 *** **	**-3.95 *** **
	Tebuconazole	-11.35 ***	2.6 *

Garnault et al. (2020). New Phytologist.

Section 2 – Prediction quality for the StrR phenotype

The model can estimate the average regional frequencies of resistances



StrR predicted frequencies

Garnault et al. (2020). New Phytologist.

Section 2 – Prediction quality for the StrR phenotype

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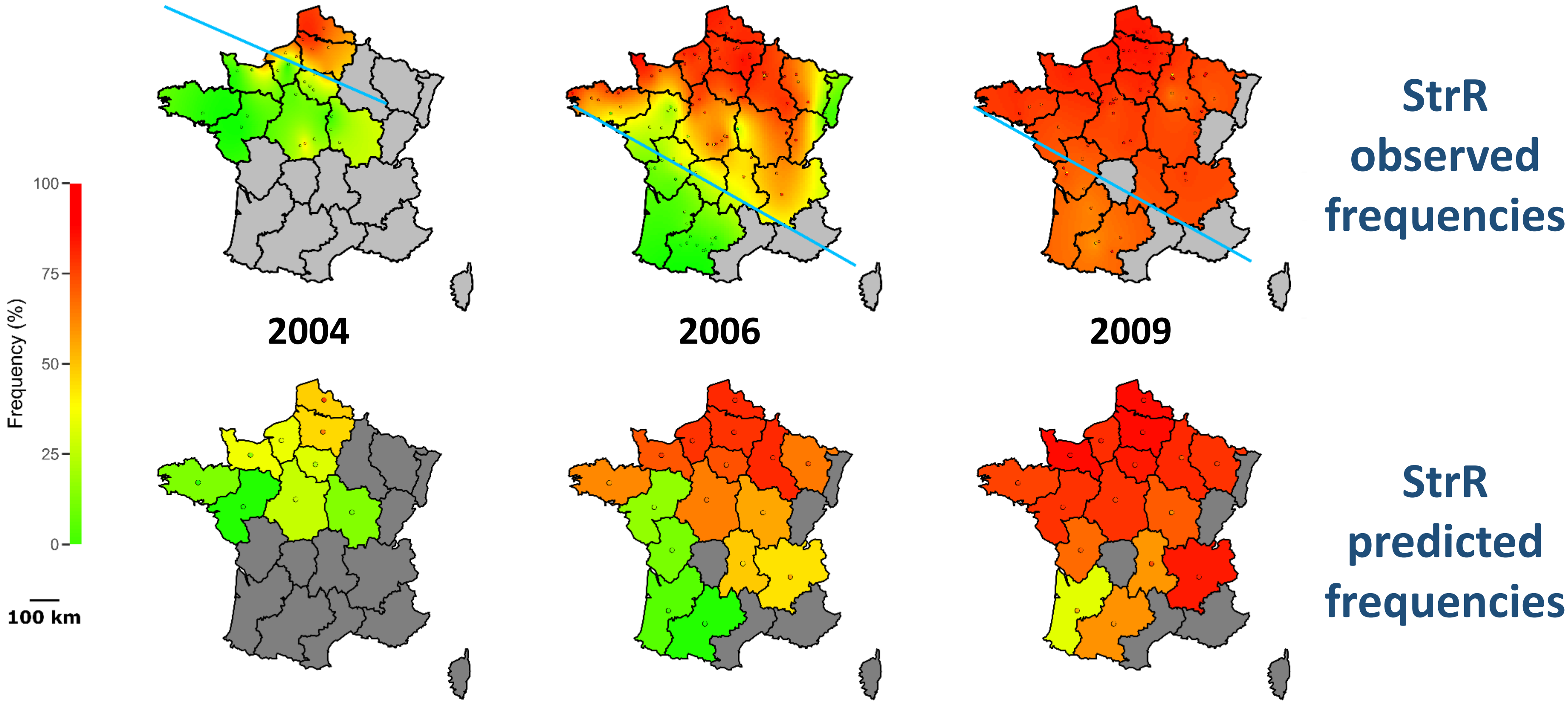


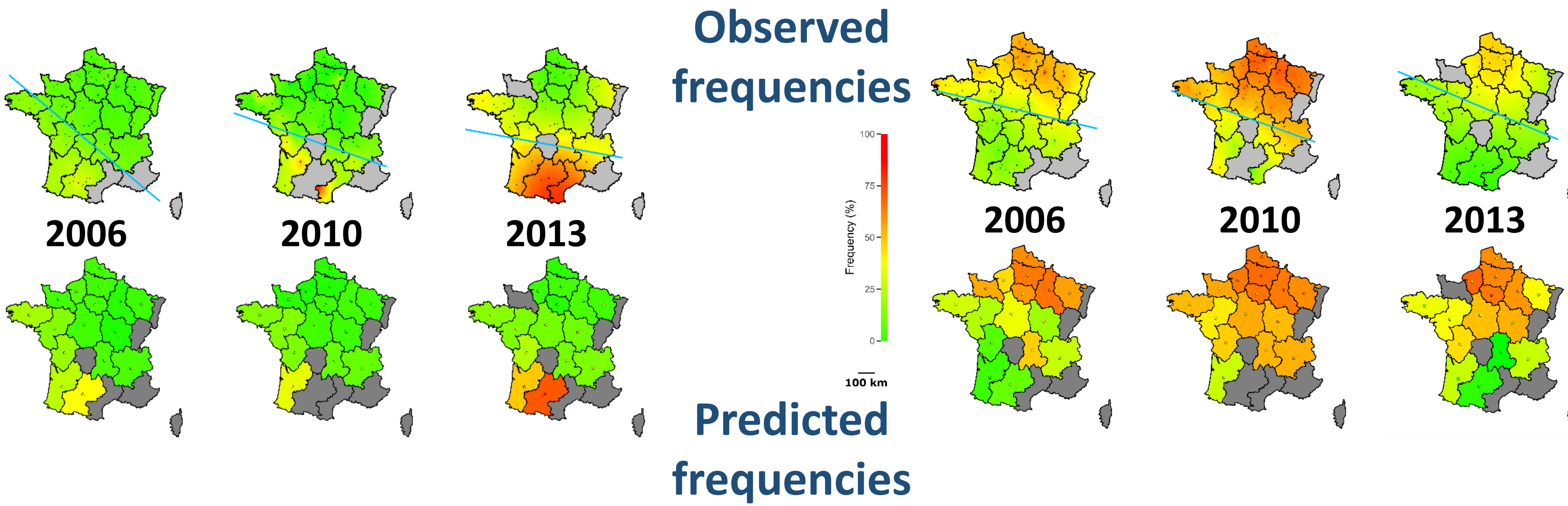
➢ **The model is able to recreate the North-South progression front**

Garnault et al. (2020). New Phytologist.

- The model is also able to represent the constant regionalization of TriR6 and TriR7-TriR8 phenotypes

TriR7-TriR8

TriR6



Garnault et al. (2020). New Phytologist.

Section 2 – Key points

- Regional fungicide use is the most important driver of resistance evolutions

- Estimated fungicide effects at the regional scale can in general be linked to resistance factors of phenotypes determined at the laboratory scale

- Model predictions are consistent with field observations

- Yield losses/Population size is not a constraining factor

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- Regional fungicide use is the most important driver of resistance evolutions

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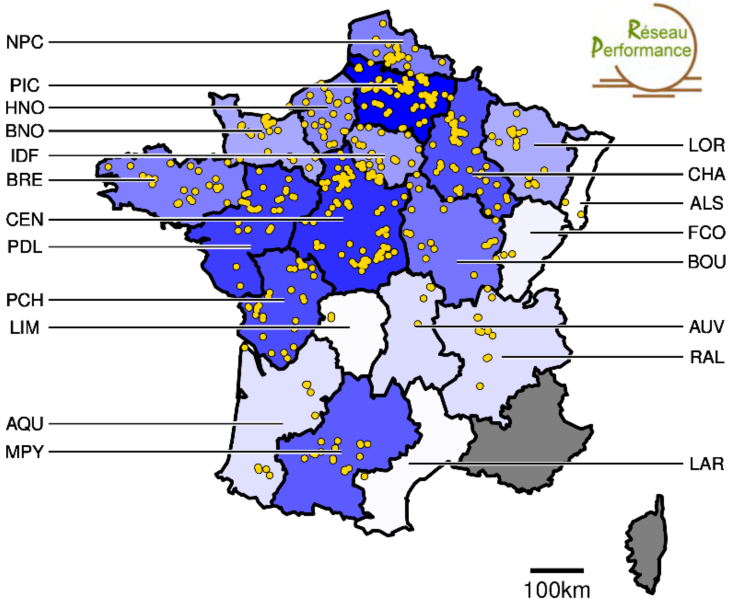
➢ **The use of fungicides at the regional scale can be modulated to manage resistance evolution**

Conclusions

- **National monitoring data at large scales, a original approach:**
  - **Phenotype frequency**
  - **Time (>10 years)**
  - **Space (France)**



Conclusions

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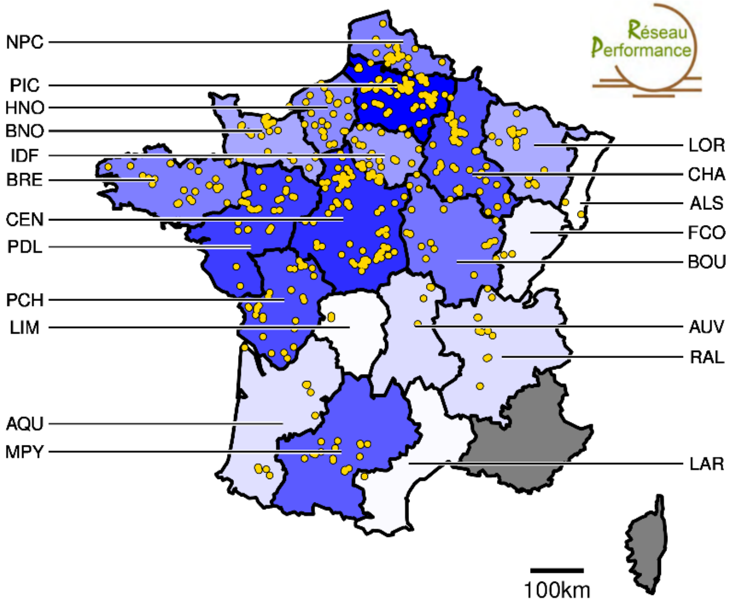


- **Large scale monitoring is an asset for:**
  - **The short-term recommandation**
  - **The long-term comprehension of resistance dynamics**
  - **The implementation of reliable and sustainable strategy of resistance management on large scales**

Outlooks

Outil *CartoFreq*

Importation des fichiers :

Importer un CSV

C:/Users/maxim/Documents/BIOGER&MalAGE/CartoFreq/data/Frequences_CSV/Septo 2004-2020 - Corrige - Allege.csv

Données pluri-annuelles

Afficher les statistiques annuelles

Fréquence :

TriR7.R8

Année :

2013

Modalité :

TNT

Région	TriR7.R8.2013.TNT	n
FRANCE	33.60	120
AQU	77.50	2
AUV	50.00	1
BNO	21.25	4
BOU	69.62	8
BRE	37.78	9
CEN	44.09	11
CHA	30.00	8

Tableau | Cartographie | Prédiction

Show 100 entries

ligne	annee	code_essai	commune	numero_depar
2	2004	2004-VIMY	VIMY	62
3	2004	2004-VIMY	VIMY	62
4	2004	2004-VIMY	VIMY	62
5	2004	2004-VIMY	VIMY	62
6	2004	2004-VIMY	VIMY	62
7	2004	2004-VIMY	VIMY	62
8	2004	2004-LURY SUR ARNON	LURY SUR ARNON	18
9	2004	2004-LURY SUR ARNON	LURY SUR ARNON	18
10	2004	2004-BERRY BOUY	BERRY BOUY	18
11	2004	2004-BERRY BOUY	BERRY BOUY	18
12	2004	2004-STE SOLANGE	STE SOLANGE	18
13	2004	2004-STE SOLANGE	STE SOLANGE	18
14	2004	2004-STE SOLANGE	STE SOLANGE	18

Outlooks

Outil *CartoFreq*

Fréquence représentée :

TriR7.R8

Année représentée :

2013

Modalité représentée :

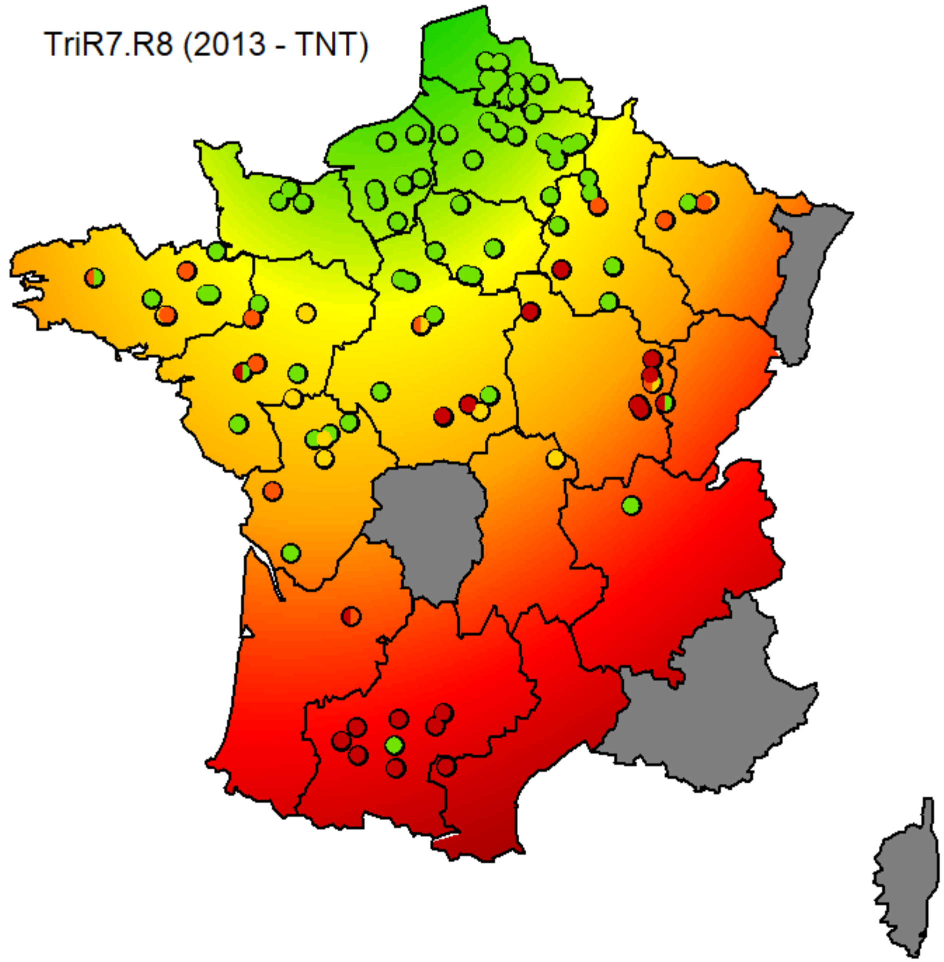
TNT (n=120)

Exporter la légende au format PDF

Soumettre

Exporter la carte au format PDF

Tableau | Cartographie | Prédiction



Outlooks

Outil *CartoFreq*

Sélection des données modélisées :

Fréquence prédite :

TriHR

Plage temporelle d'apprentissage :

2009 2012 2020

Indice de confiance souhaité :

1 2 10

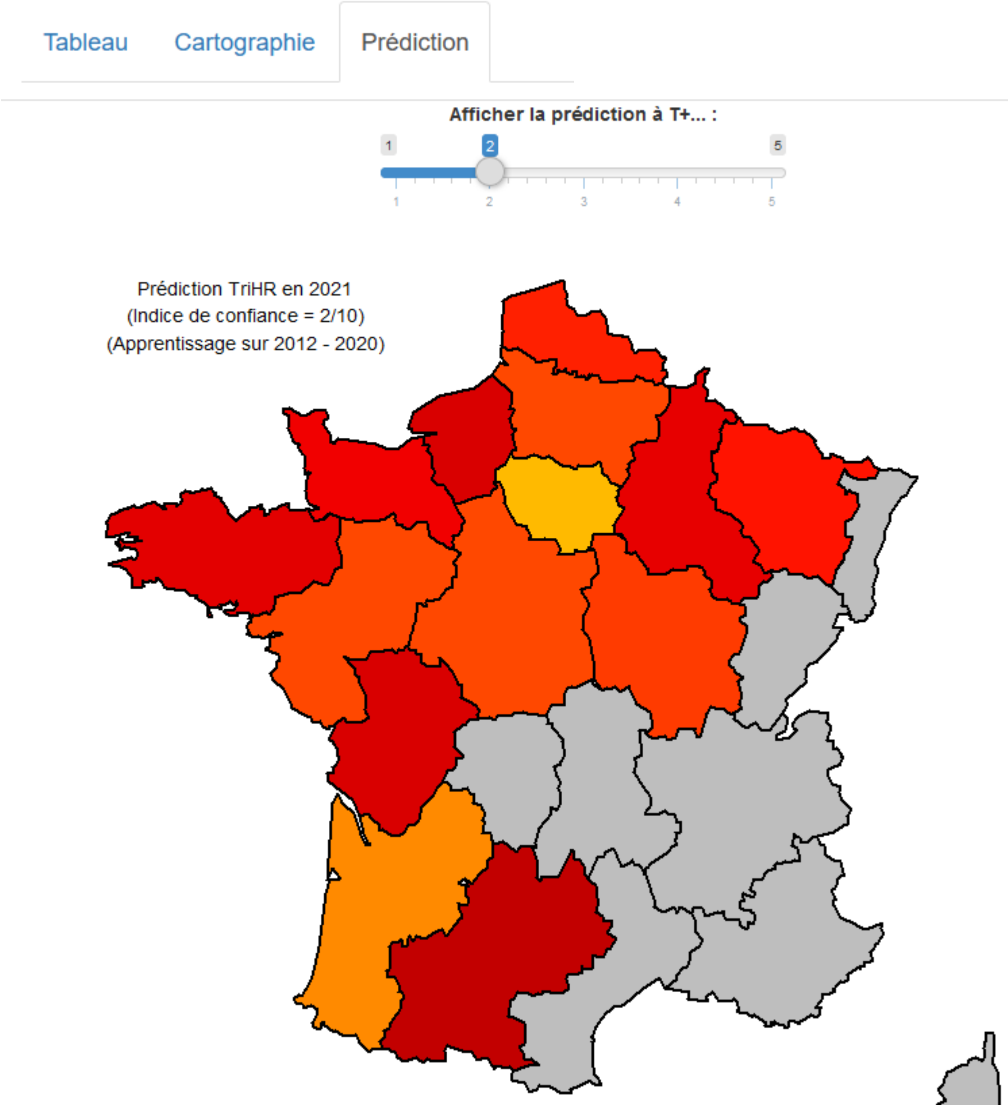
Importation de variables explicatives :

Importer un Panel

Résultats du modèle :

pseudo-R² = 0.462

Paramètre	Estimation	Ecart.type	P.value	Signif.
FRANCE	0.438	0.029	0.000	***
AQU	-0.112	0.119	0.349	
BNO	-0.105	0.071	0.141	
BOU	0.093	0.127	0.467	
BRE	-0.066	0.059	0.265	
CEN	0.020	0.061	0.748	
CHA	0.009	0.065	0.895	
HNO	-0.028	0.060	0.642	



Outlooks

Outil *CartoFreq*

Sélection des données modélisées :

Fréquence prédite :

StrR

Plage temporelle d'apprentissage :

2004 – 2006 (2020)

Indice de confiance souhaité :

1 – 2 – 10

1 2 3 4 5 6 7 8 9 10

Importation de variables explicatives :

Importer un Panel

C:/Users/maxim/Documents/BIOGER&MaIAGE/CartoFreq/data/UtilisationFongicide_1990-2019.csv

Choix des variables explicatives :

SOMME.QoI (100%)

Résultats du modèle :

pseudo-R^2 = 0.286

Paramètre	Estimation	Ecart.type	P.value	Signif.
Growth constant	-1.156	0.167	0.000	***
SOMME.QoI	1.436	0.127	0.000	***

Soumettre

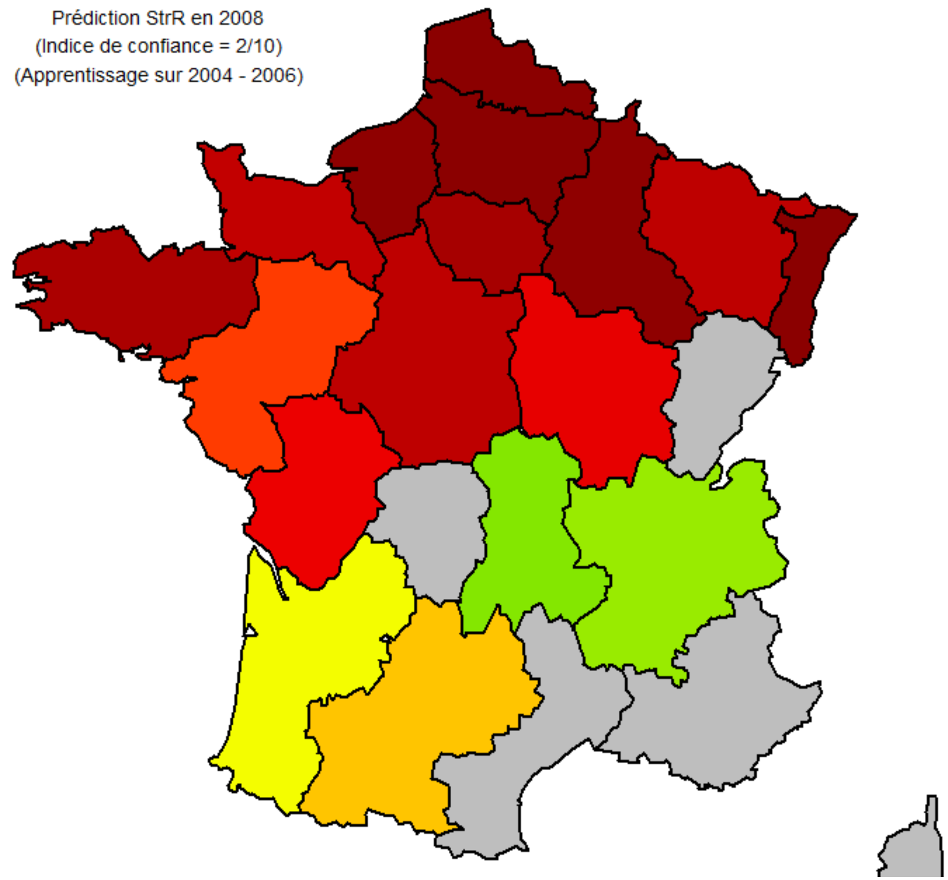
Exporter la prédiction au format PDF

Tableau | Cartographie | Prédiction

Afficher la prédiction à T+... :

1 – 2 – 5

1 2 3 4 5



Outlooks

Outil *CartoFreq*

Sélection des données modélisées :

Fréquence prédite :

StrR

Plage temporelle d'apprentissage :

2004 2006 2020

Indice de confiance souhaité :

1 2 10

1 2 3 4 5 6 7 8 9 10

Importation de variables explicatives :

Importer un Panel

C:/Users/maxim/Documents/BIOGER&MaIAGE/CartoFreq/data/UtilisationFongicide_1990-2019.csv

Choix des variables explicatives :

SOMME.QoI (100%)

Résultats du modèle :

pseudo-R² = 0.286

Paramètre	Estimation	Ecart.type	P.value	Signif.
Growth constant	-1.156	0.167	0.000	***
SOMME.QoI	1.436	0.127	0.000	***

Soumettre

Exporter la prédiction au format PDF

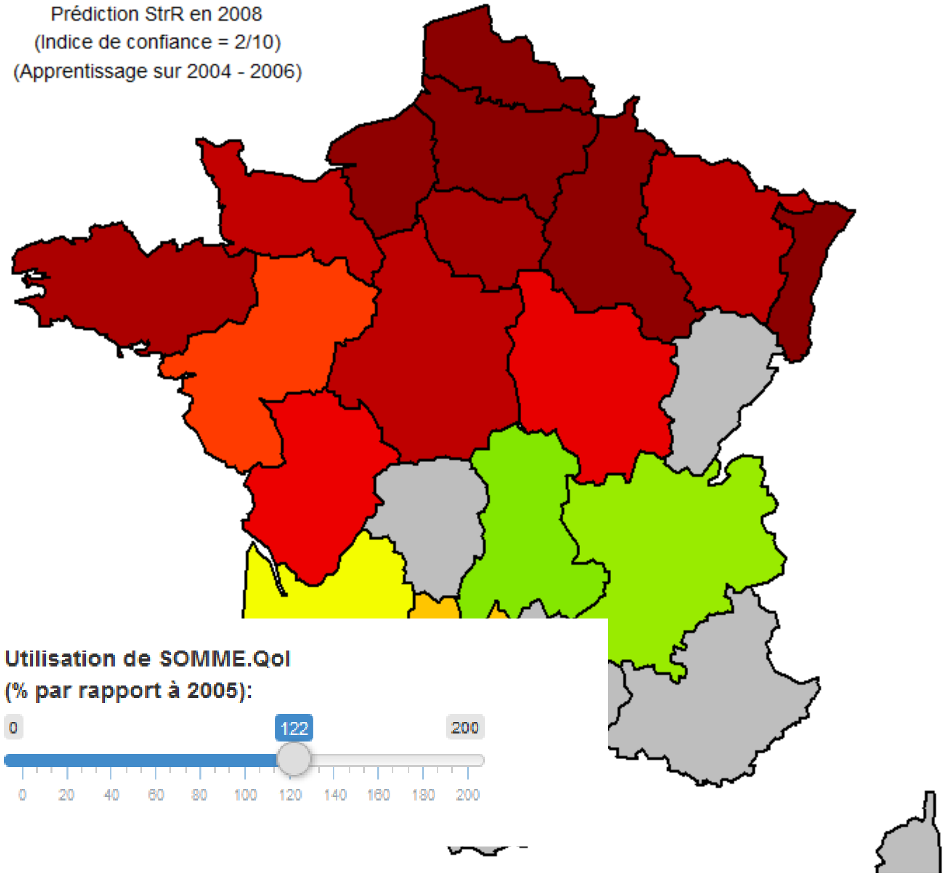
Tableau | Cartographie | Prédiction

Afficher la prédiction à T+... :

1 2 5

1 2 3 4 5

Prédiction StrR en 2008
(Indice de confiance = 2/10)
(Apprentissage sur 2004 - 2006)



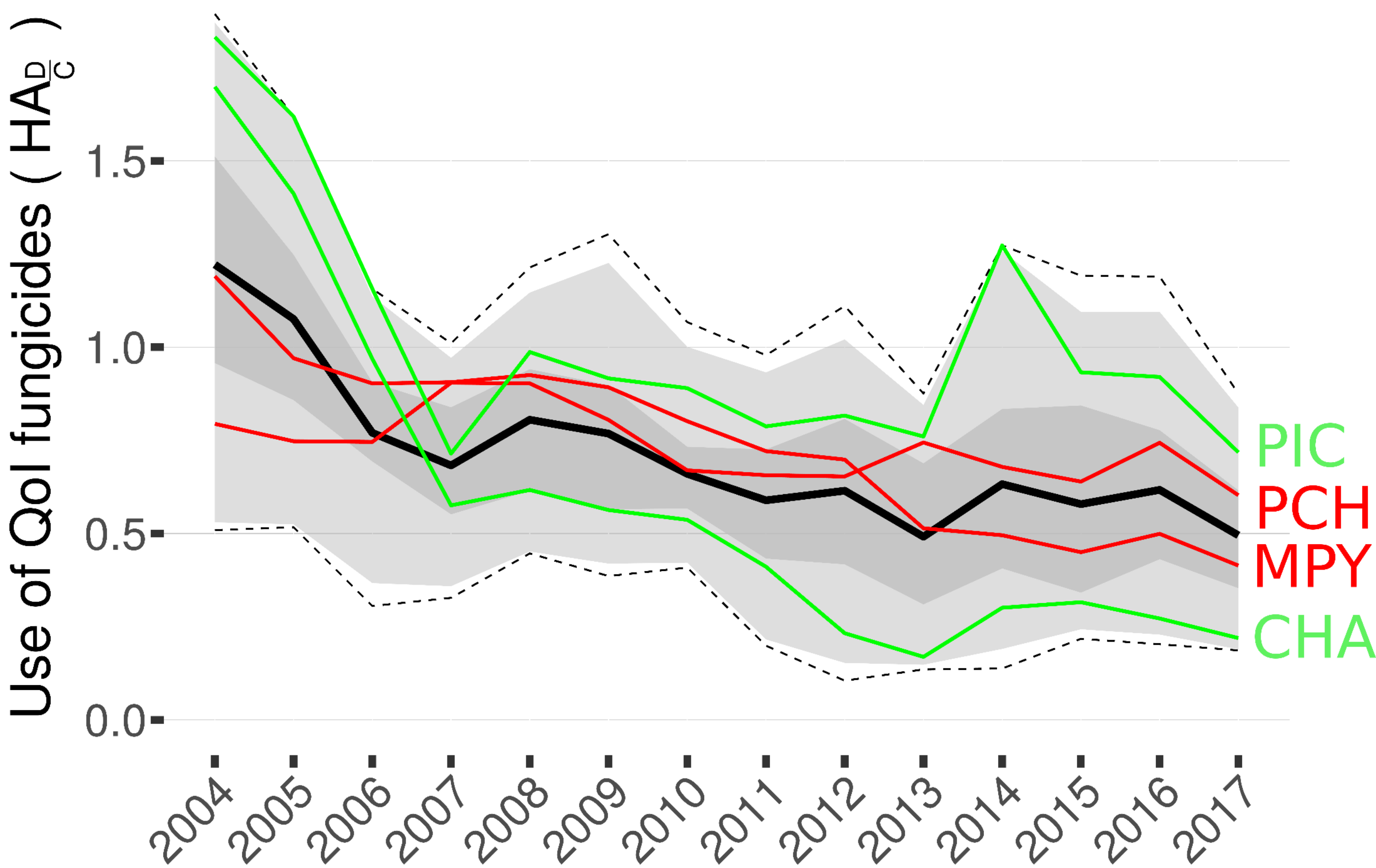
Utilisation de SOMME.QoI (% par rapport à 2005):

0 122 200

0 20 40 60 80 100 120 140 160 180 200

Thank you for your attention

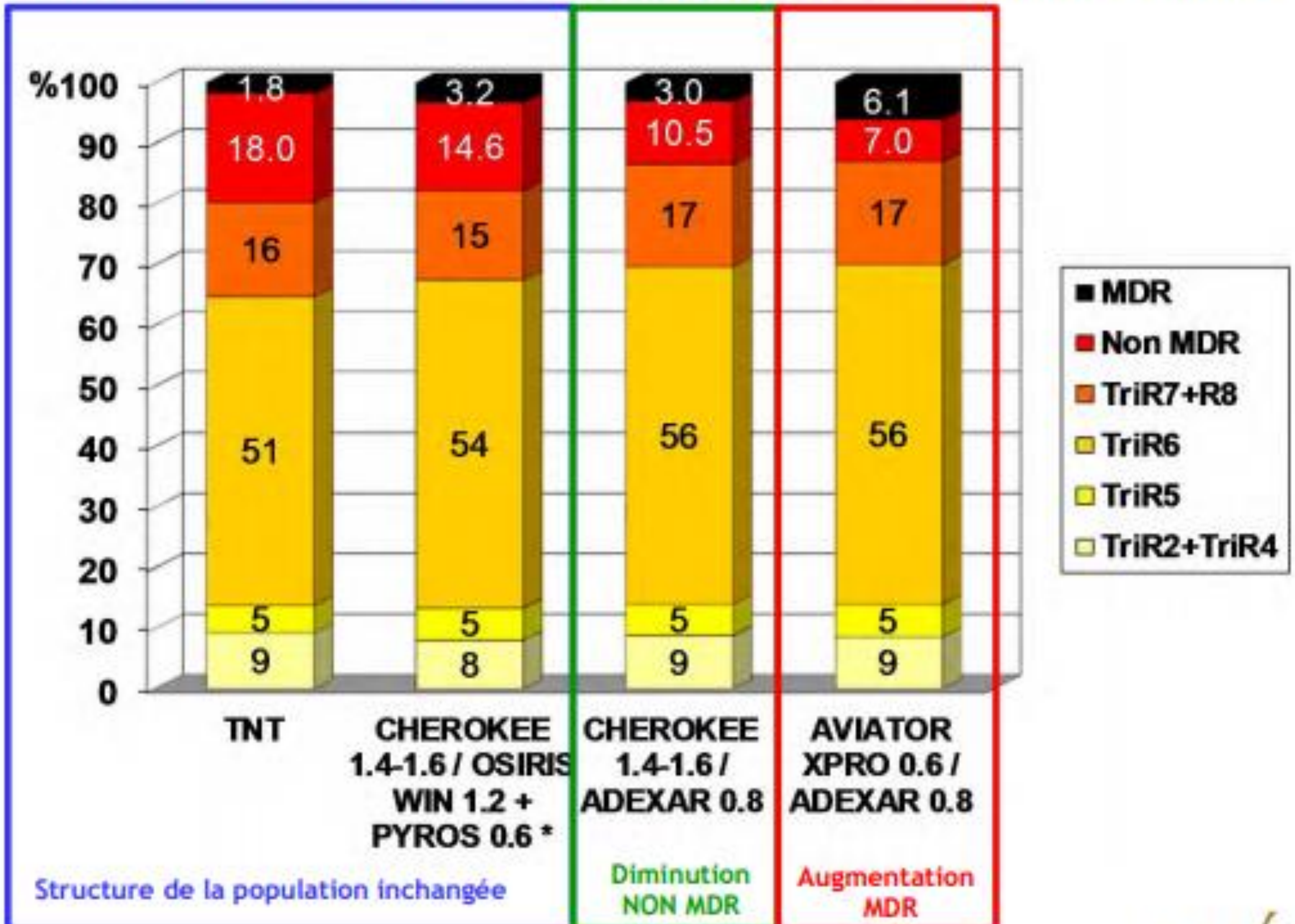
(Photo – G. Couleaud - ARVALIS)



Use of QoI fungicides ($HA_{\frac{D}{C}}$)
0.0
0.5
1.0
1.5
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
PIC
PCH
MPY
CHA

Pression de sélection en fonction des traitements

33 essais 2013 - 2012 (11 + 22) avec Non MDR > 0 dans les témoins



* OPUS NEW 0.75 + PYROS EW 0.7 en 2012

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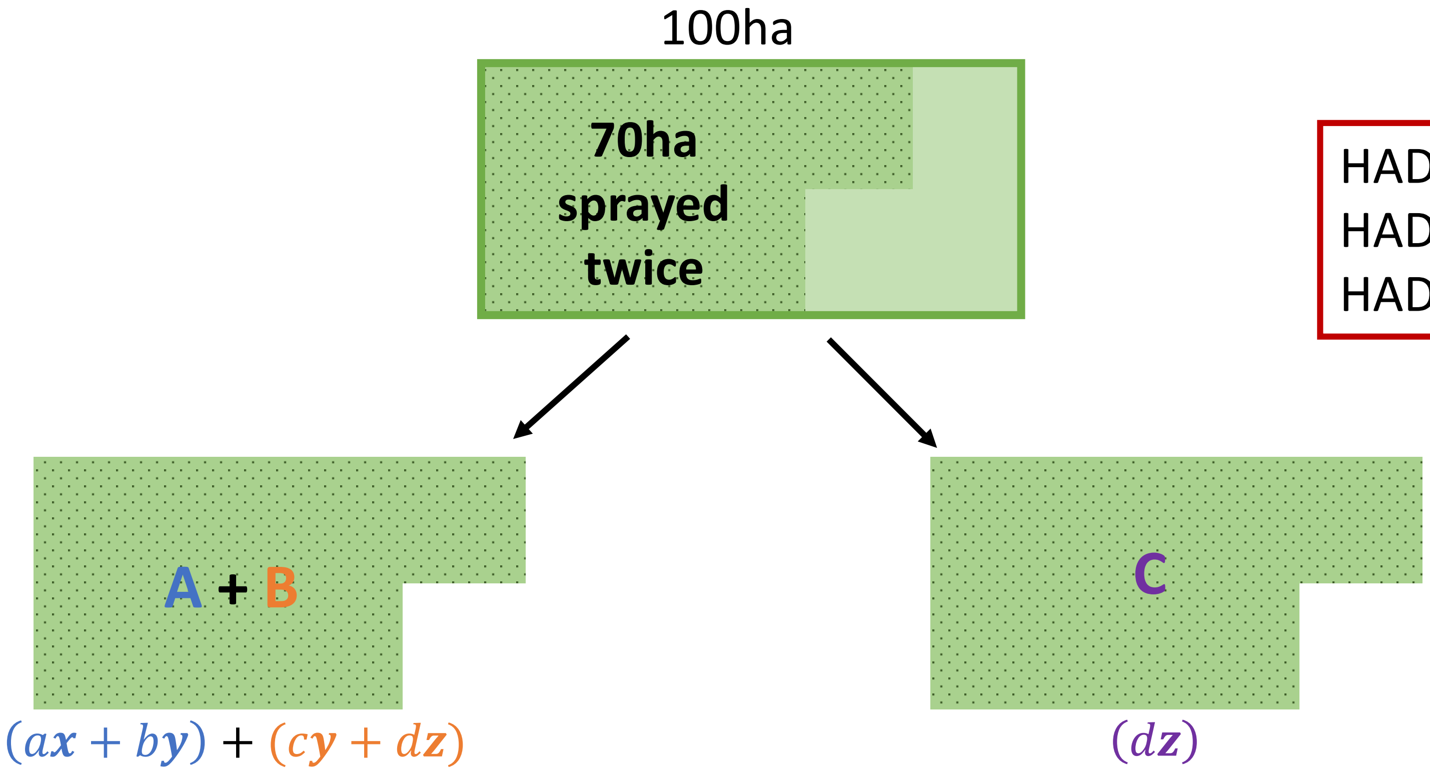
Deployed hectares



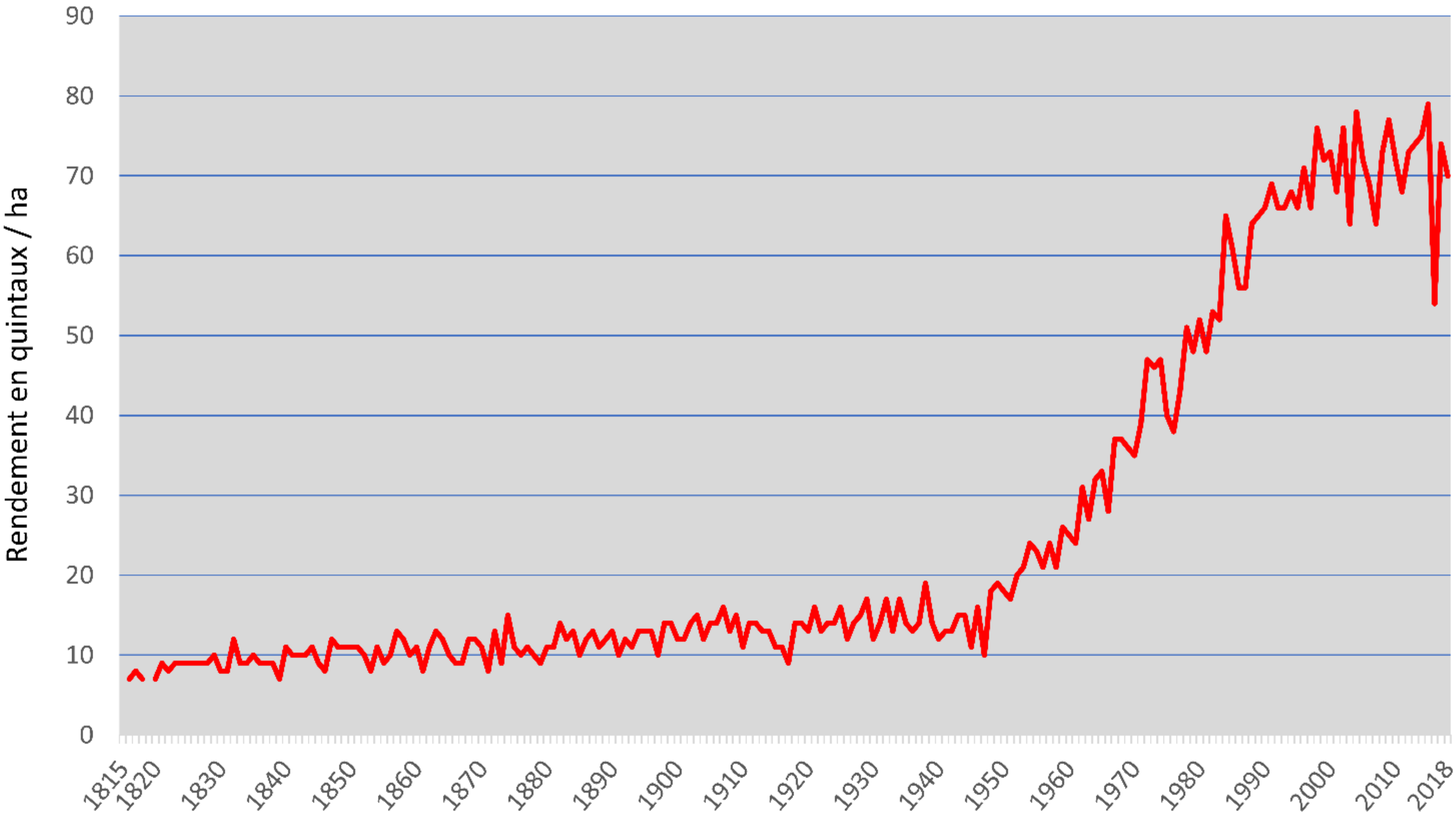
HAD$\boldsymbol{x}$ = 70ha
HAD$\boldsymbol{y}$ = 70x2 = 140ha
HAD$\boldsymbol{z}$ = 70x2 = 140ha

Expected frequency change

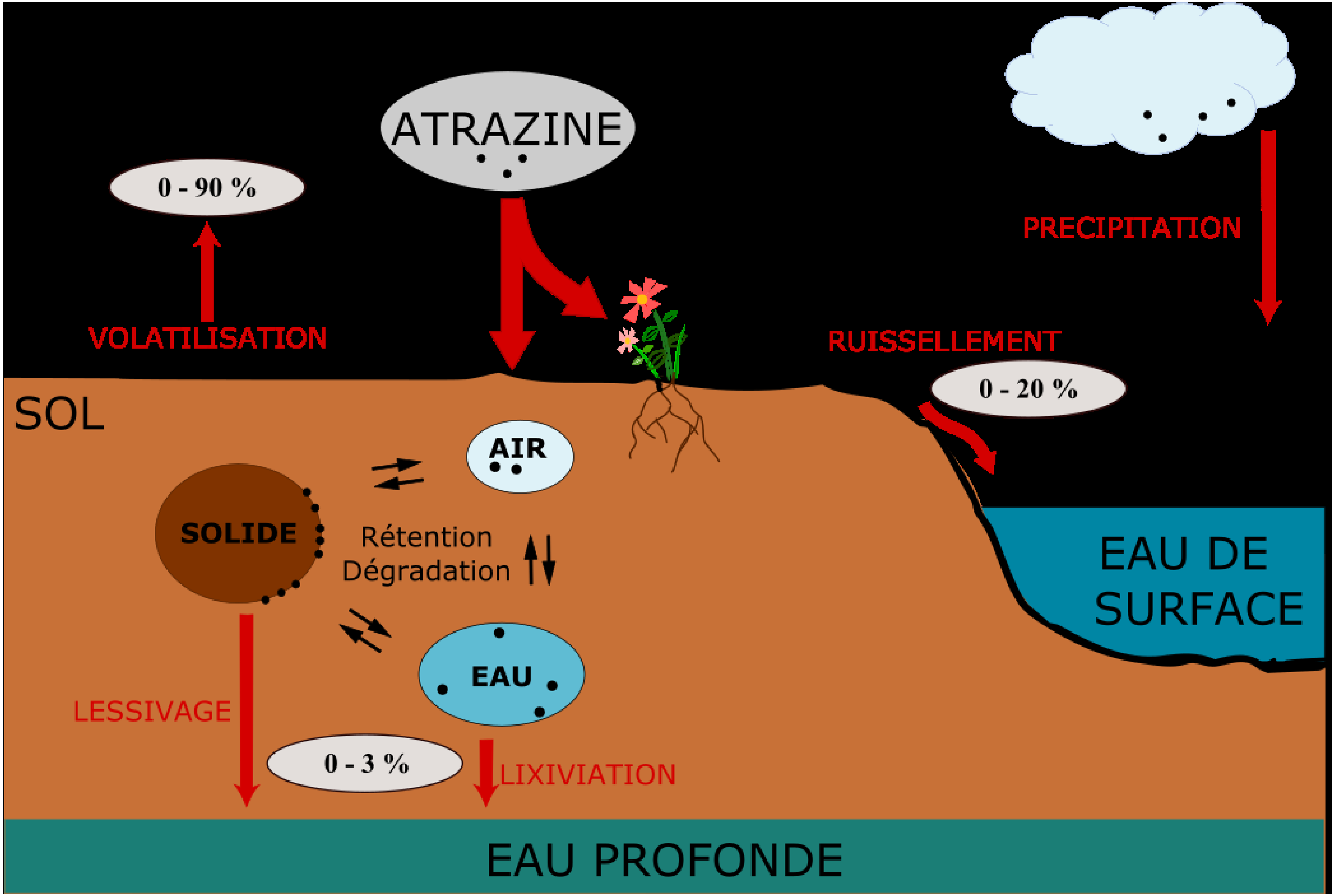
$$EFC_{\theta} = 100 * (p^e - \bar{p})$$

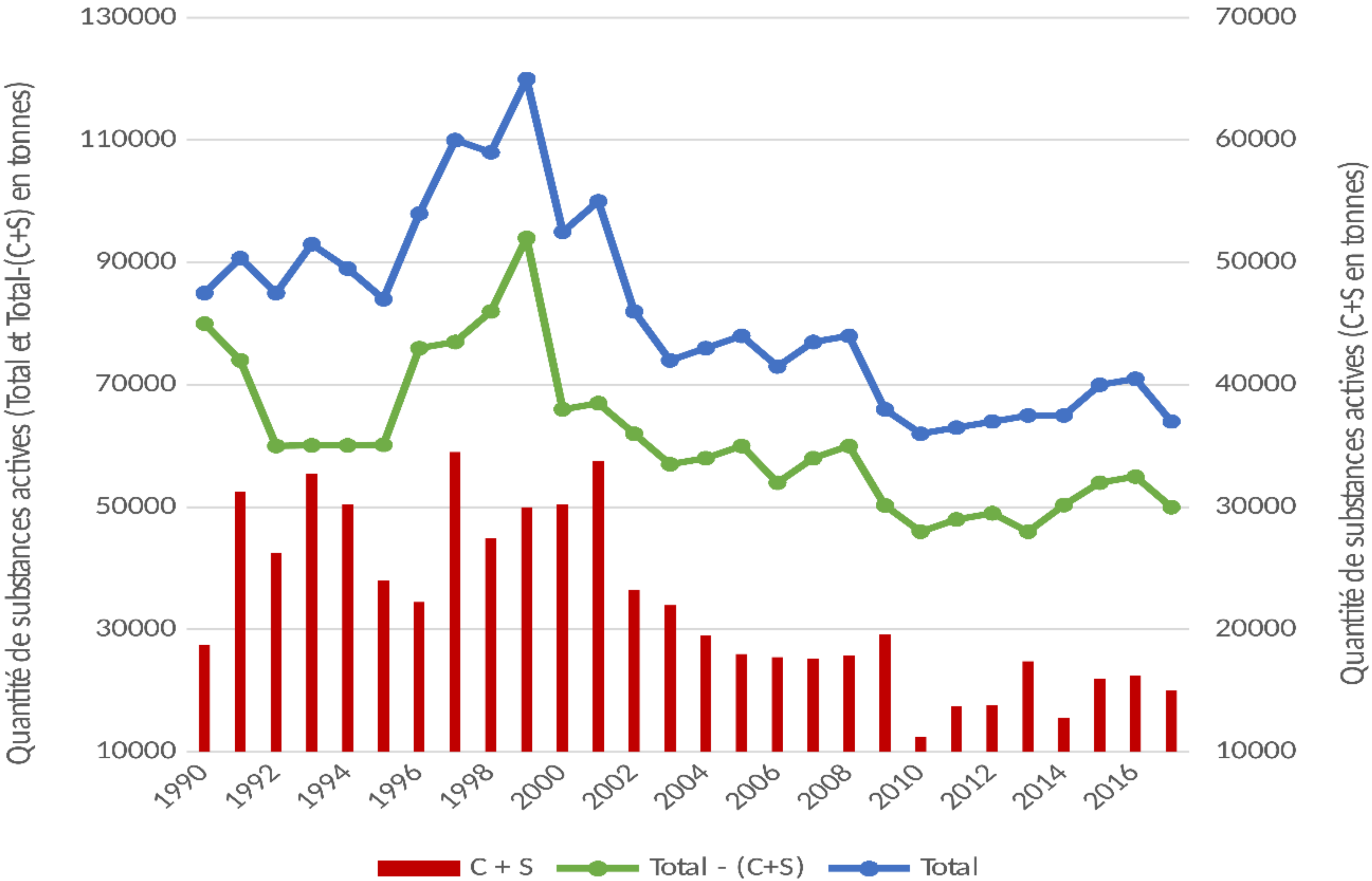
$$logit(p^e) = logit^{-1}(\bar{p}) + \hat{\theta} * \overline{X_{\theta}}$$

$$\bar{p} = \frac{\bar{Y}}{100}$$

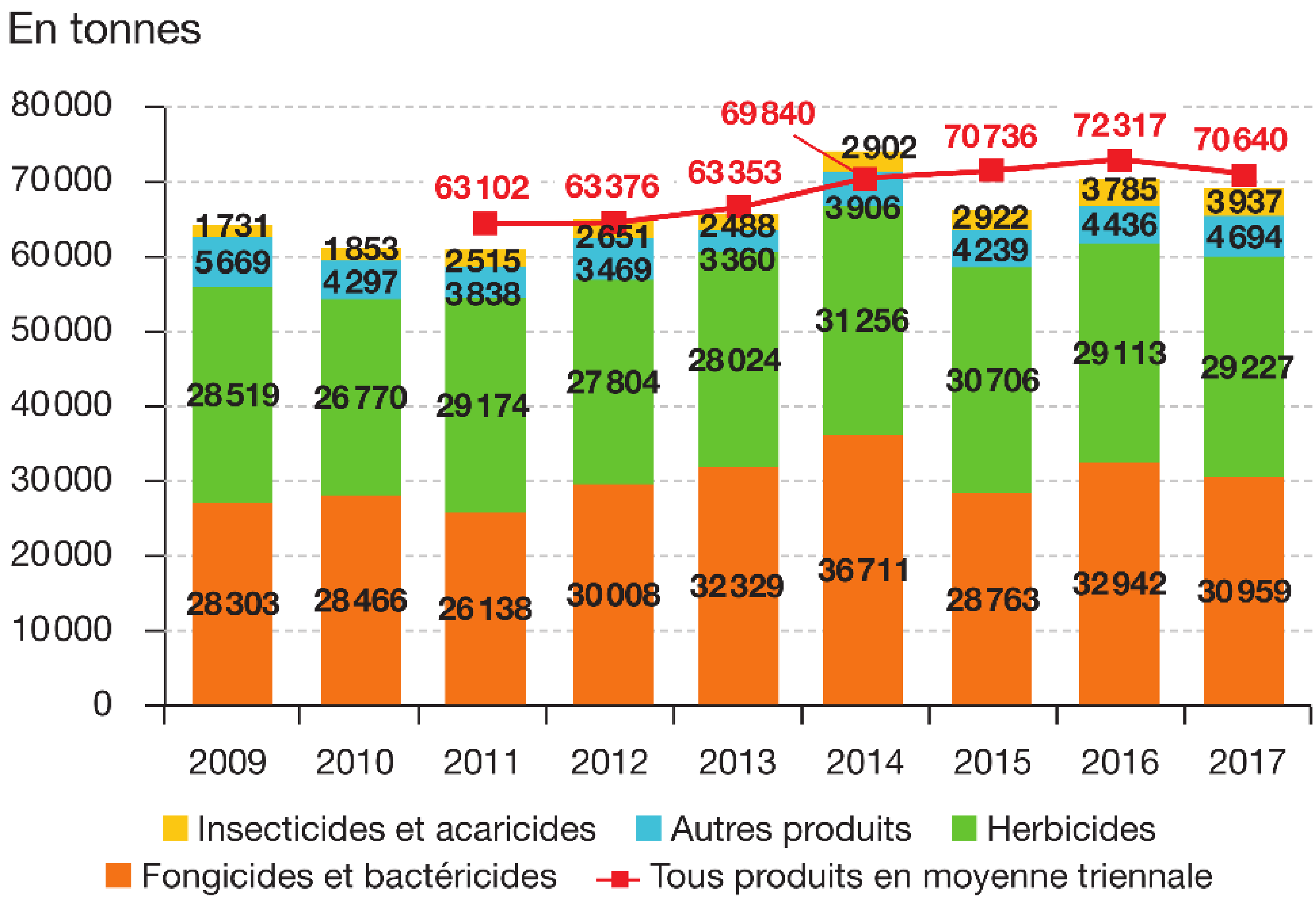


Sources: Statistiques Ministère de l’agriculture 1913,
Tableaux rétrospectifs. GNIS & Unigrains.

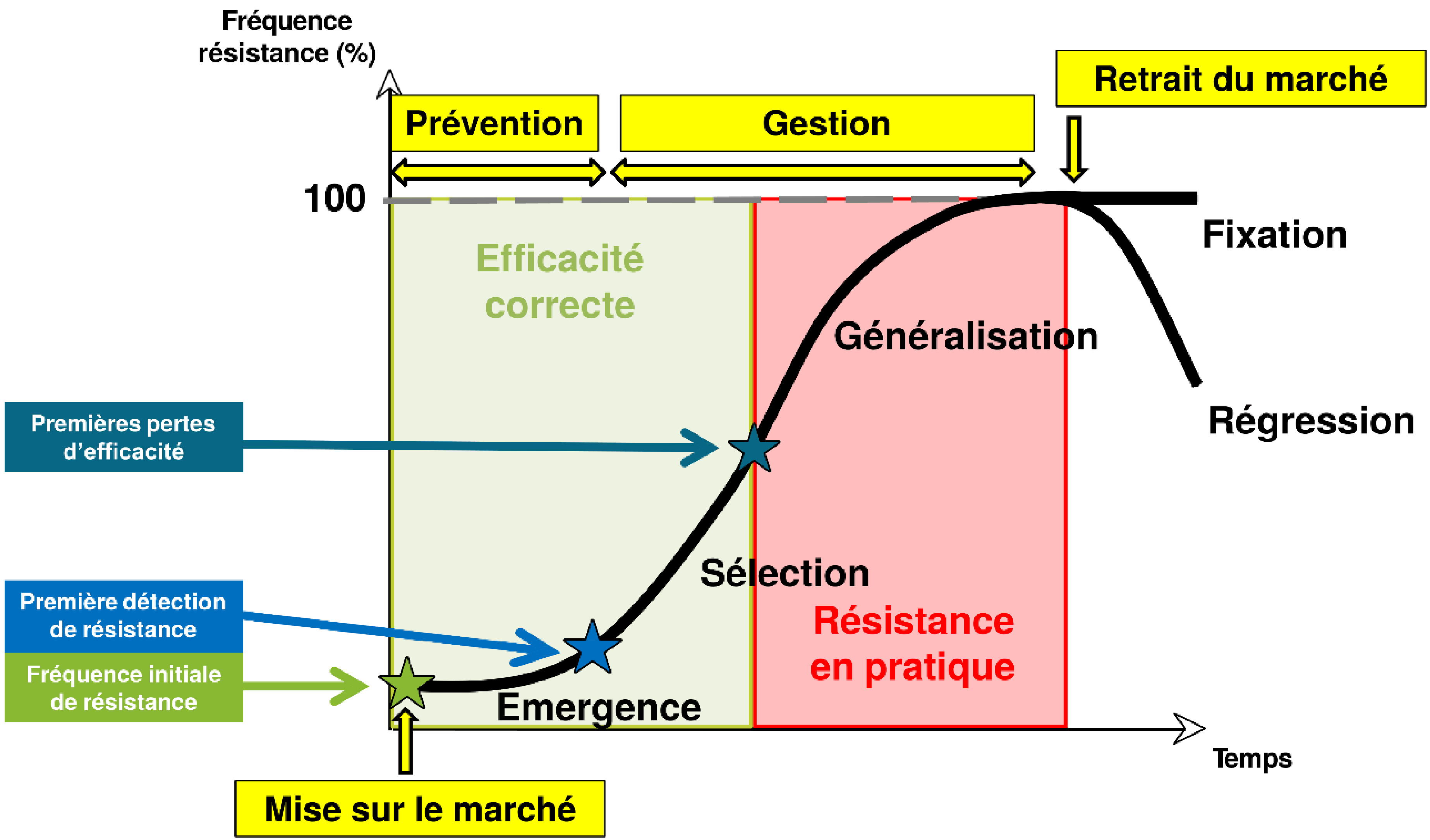

ATRAZINE
0 - 90 %
VOLATILISATION
PRECIPITATION
RUISSELLEMENT
0 - 20 %
SOL
AIR
SOLIDE
Rétention
Dégradation
EAU
EAU DE SURFACE
LESSIVAGE
0 - 3 %
LIXIVIATION
EAU PROFONDE



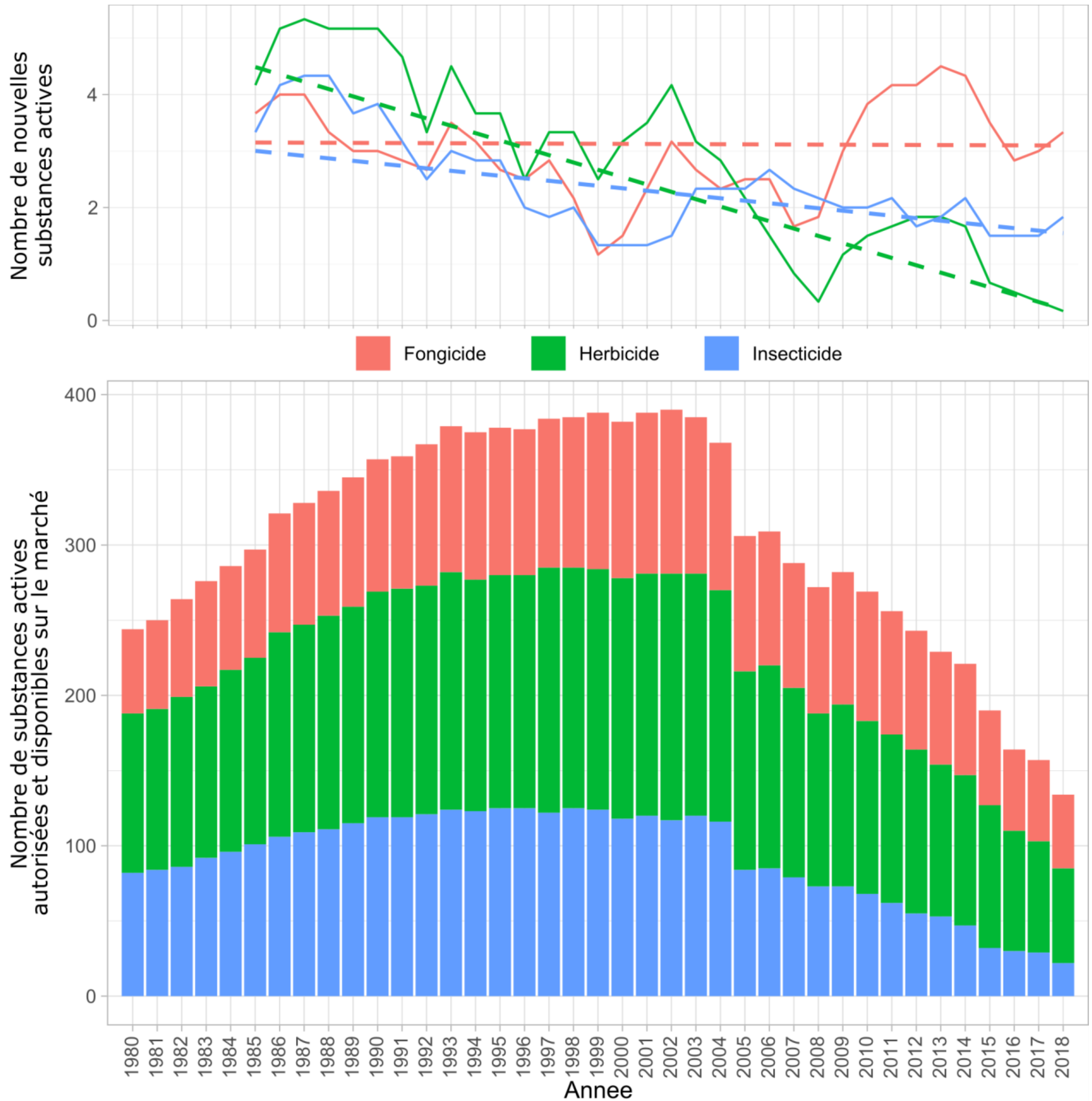
130000
110000
90000
70000
50000
30000
10000
70000
60000
50000
40000
30000
20000
10000
Quantité de substances actives (Total et Total-(C+S) en tonnes)
Quantité de substances actives (C+S en tonnes)
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010
2012
2014
2016
C + S
Total - (C+S)
Total

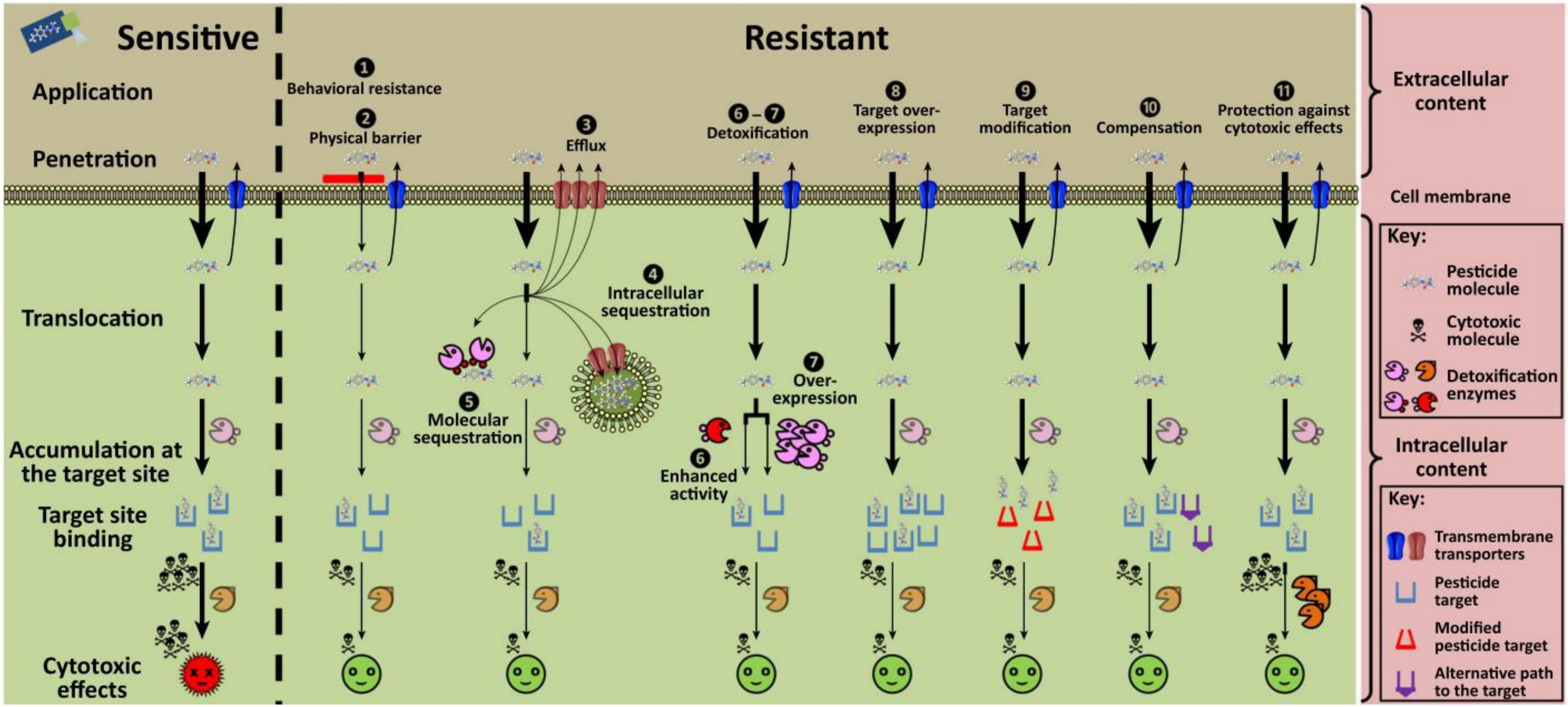


Source : *BNV-D, données sur les ventes au code commune Insee des distributeurs, extraites le 13 novembre 2018. Traitements : SDES, 2019*

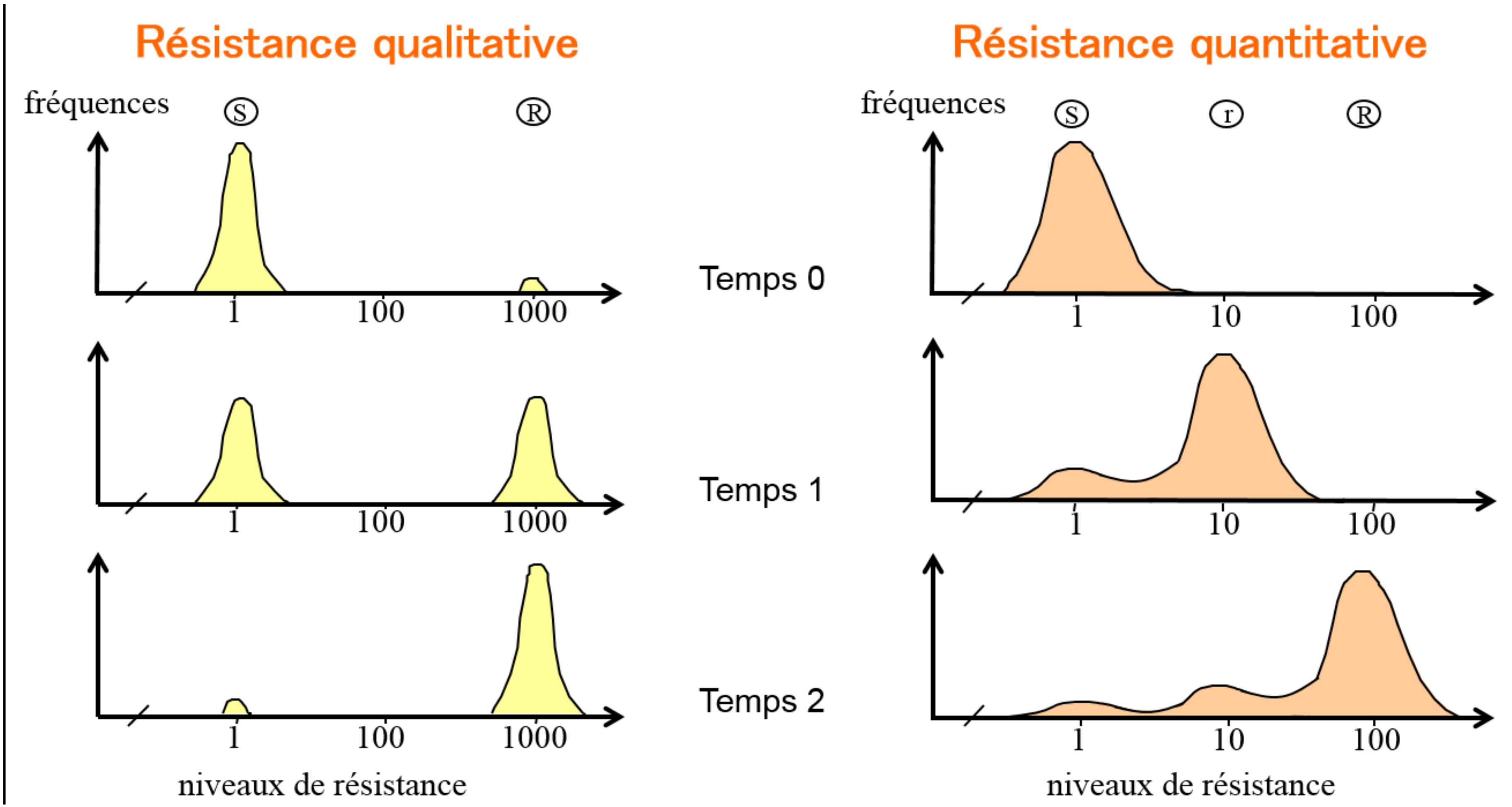


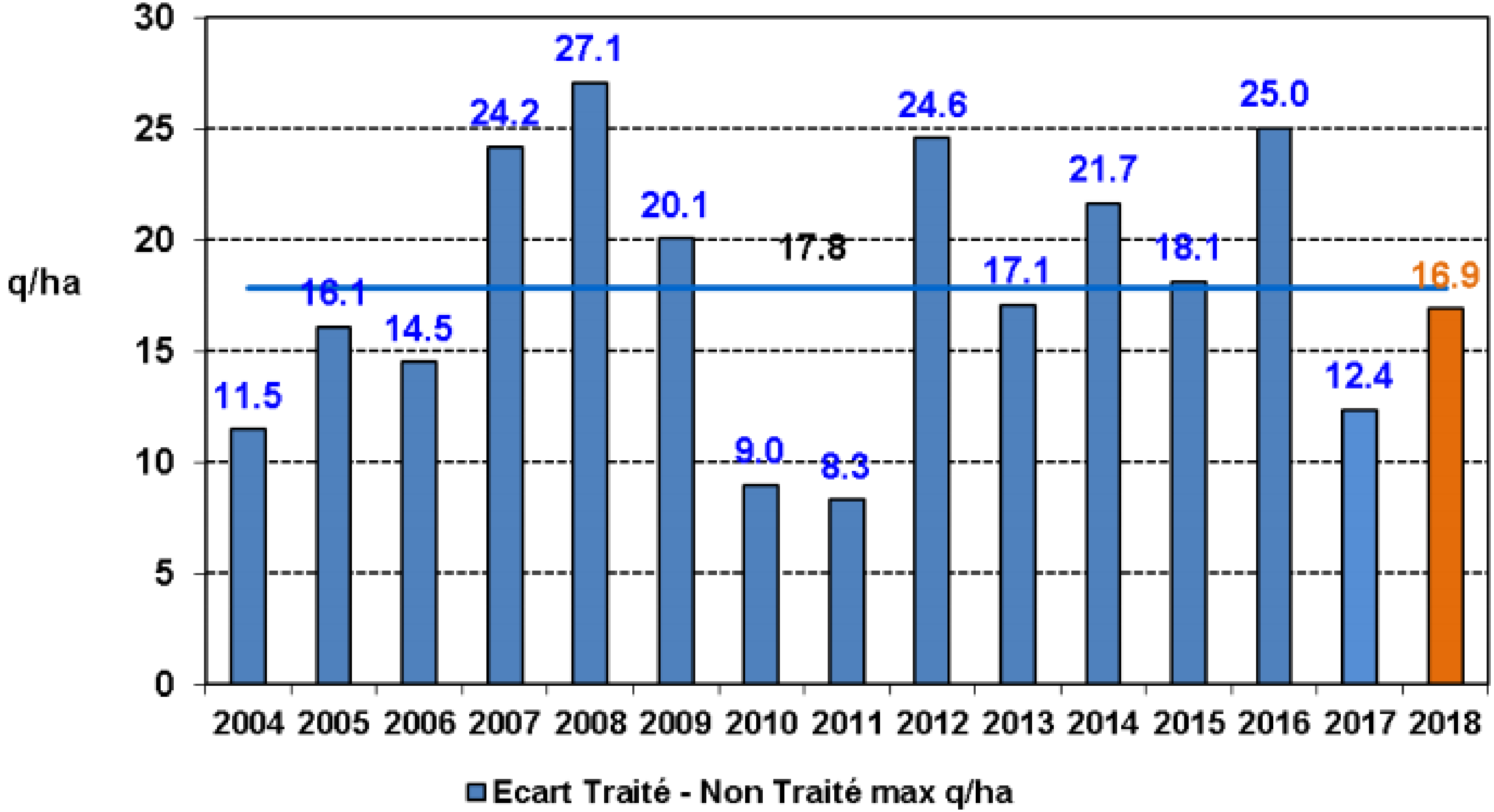
Fréquence résistance (%)
Retrait du marché
Prévention
Gestion
100
Efficacité correcte
Fixation
Généralisation
Premières pertes d'efficacité
Régression
Sélection
Première détection de résistance
Résistance en pratique
Fréquence initiale de résistance
Emergence
Temps
Mise sur le marché


Nombre de nouvelles substances actives
0
2
4
Fongicide
Herbicide
Insecticide
Nombre de substances actives autorisées et disponibles sur le marché
0
100
200
300
400
1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018
Annee



Sensitive
Resistant
Application
Penetration
Translocation
Accumulation at the target site
Target site binding
Cytotoxic effects
1 Behavioral resistance
2 Physical barrier
3 Efflux
4 Intracellular sequestration
5 Molecular sequestration
6 – 7 Detoxification
7 Over-expression
6 Enhanced activity
8 Target over-expression
9 Target modification
10 Compensation
11 Protection against cytotoxic effects
Extracellular content
Cell membrane
Key:
Pesticide molecule
Cytotoxic molecule
Detoxification enzymes
Intracellular content
Key:
Transmembrane transporters
Pesticide target
Modified pesticide target
Alternative path to the target


Résistance qualitative
Résistance quantitative
fréquences
S
R
r
1
10
100
1000
Temps 0
Temps 1
Temps 2
niveaux de résistance



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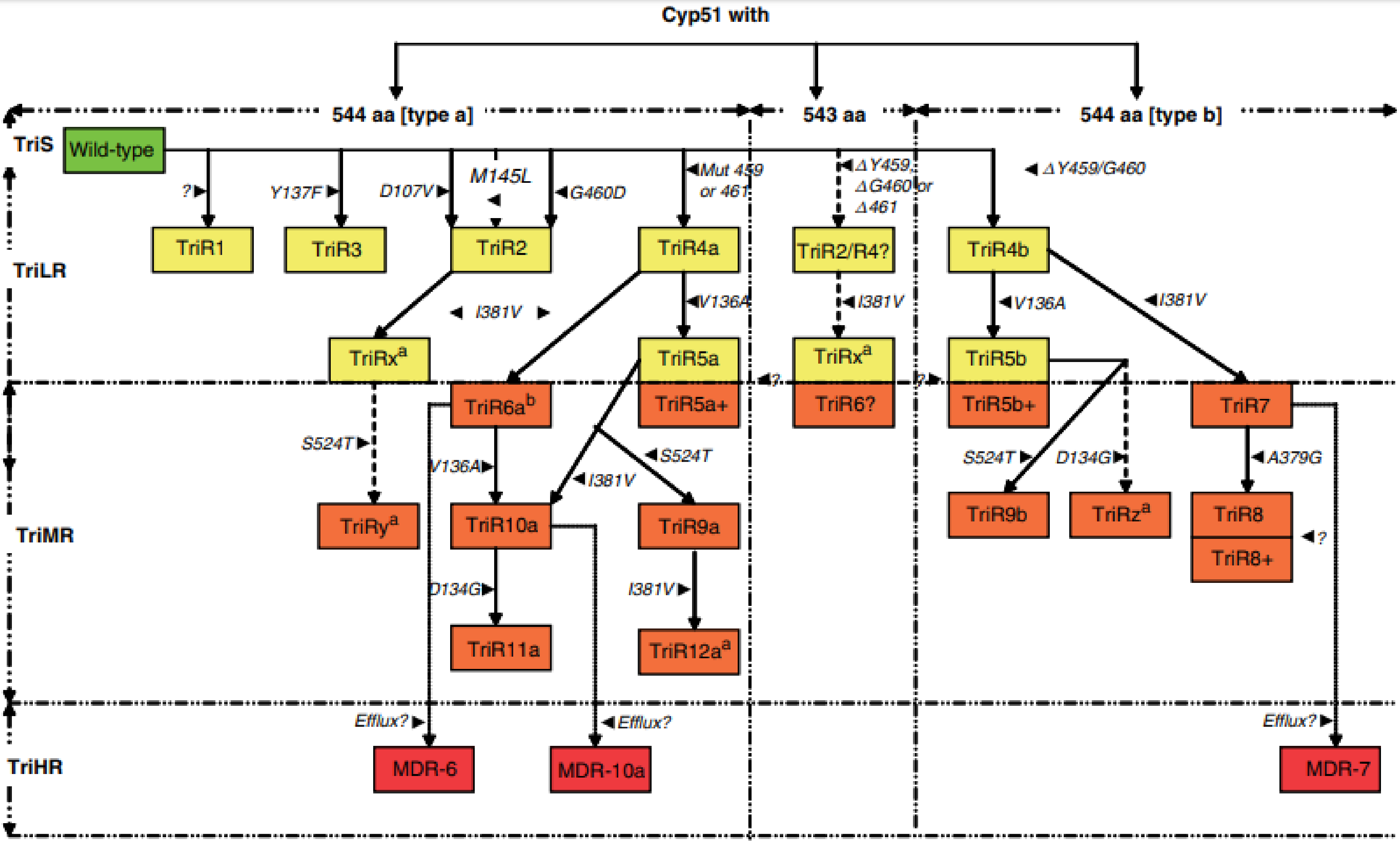

Leroux & Walker (2011). Pest management science.