# Impact of climate change on *septoria tritici* blotch (STB)

An example of the use of a dynamic crop+disease model to study the effect of climate change

Disease

# STB

## Damage

The most important wheat disease in Europe

Average yield loss of 1.7t/ha

## Agronomic response

Choice of variety

## Chemical response

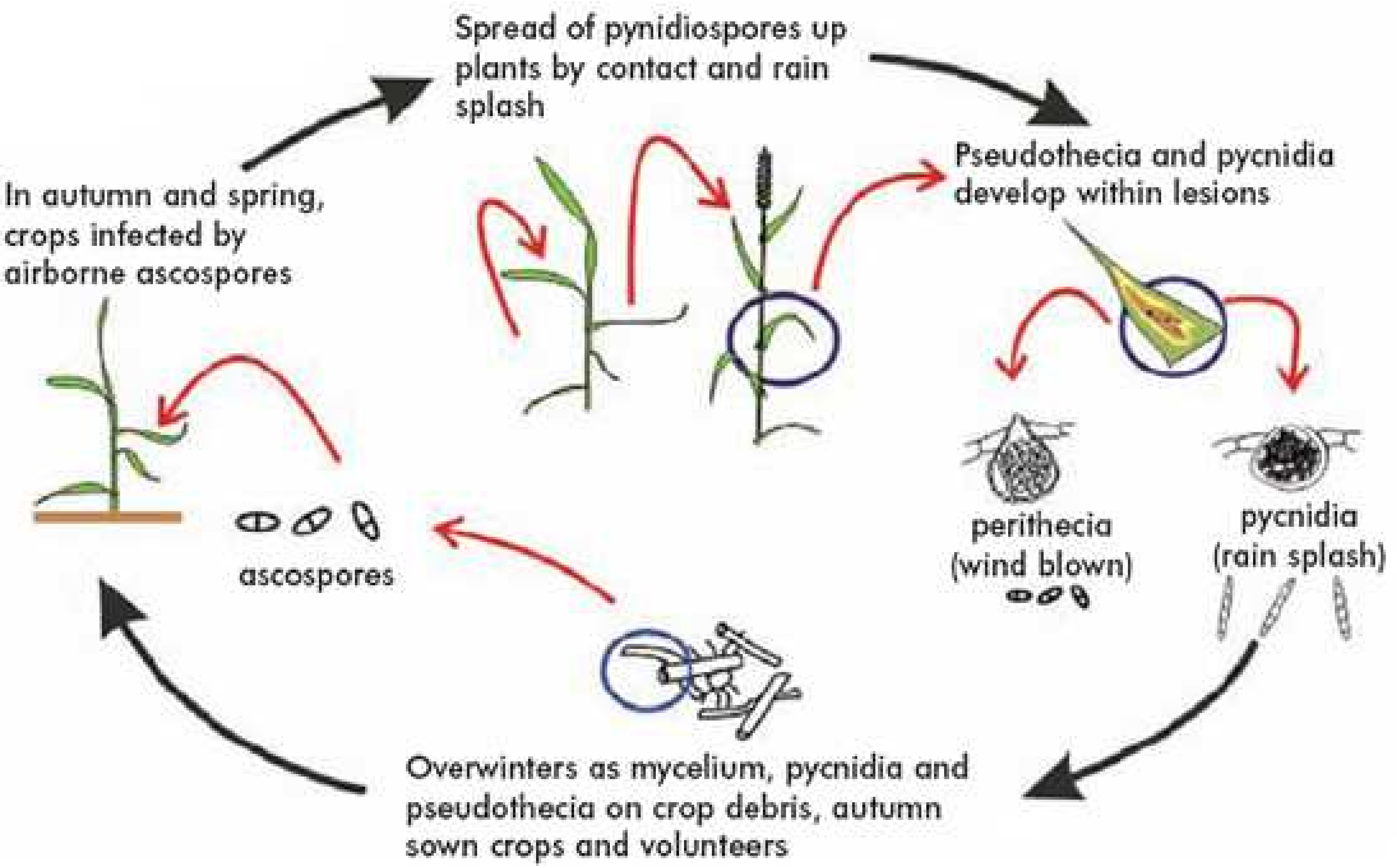
Preventive treatment or at start of outbreak

Emphasis on first treatment

Leaf severity: % of leaf area with necrotic symptoms

Effective severity: average over last 3 leaves
and over early grain filling

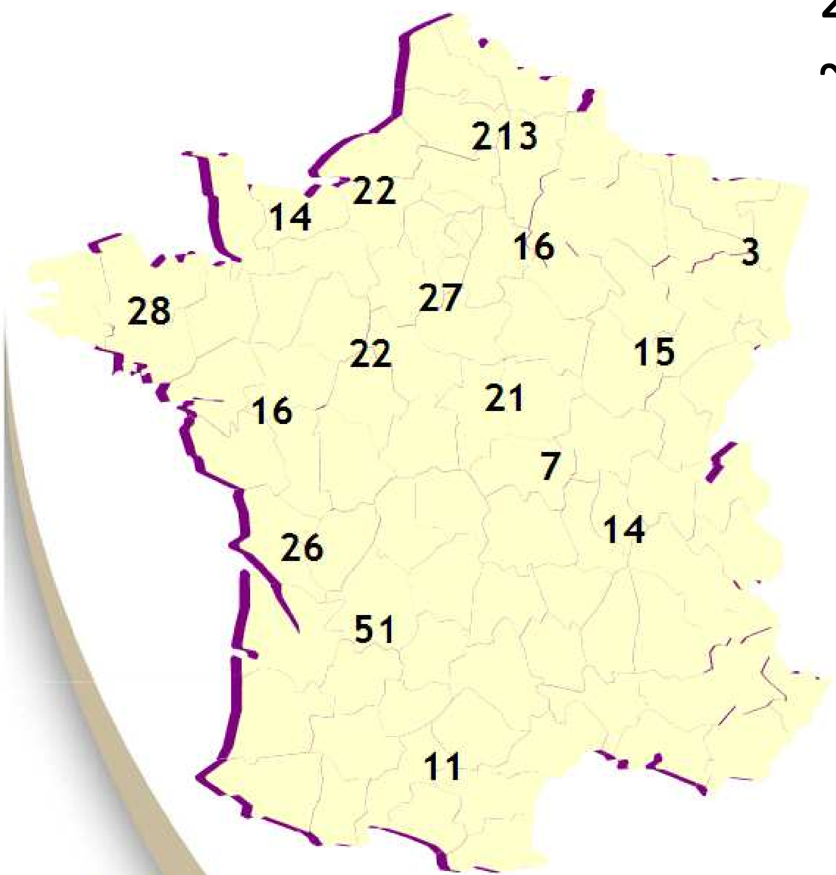
**DISEASE: Septoria tritici blotch (STB)**
**PATHOGEN: *Mycosphaerella graminicola***



# Possible effects of climate change

- temperature
  - higher temperatures affect winter accumulation of inoculum, reduce latency period and increase rate of lesion expansion
- rainfall
  - rainfall intensity affects winter accumulation of inoculum, affects inoculum viability and inoculum transfer by splash

# Data




20 years of experiments
~520 trials

Severity at 7-28 day intervals

Here:
8 trials for calibration
18 trials for evaluation
All trials for yield loss

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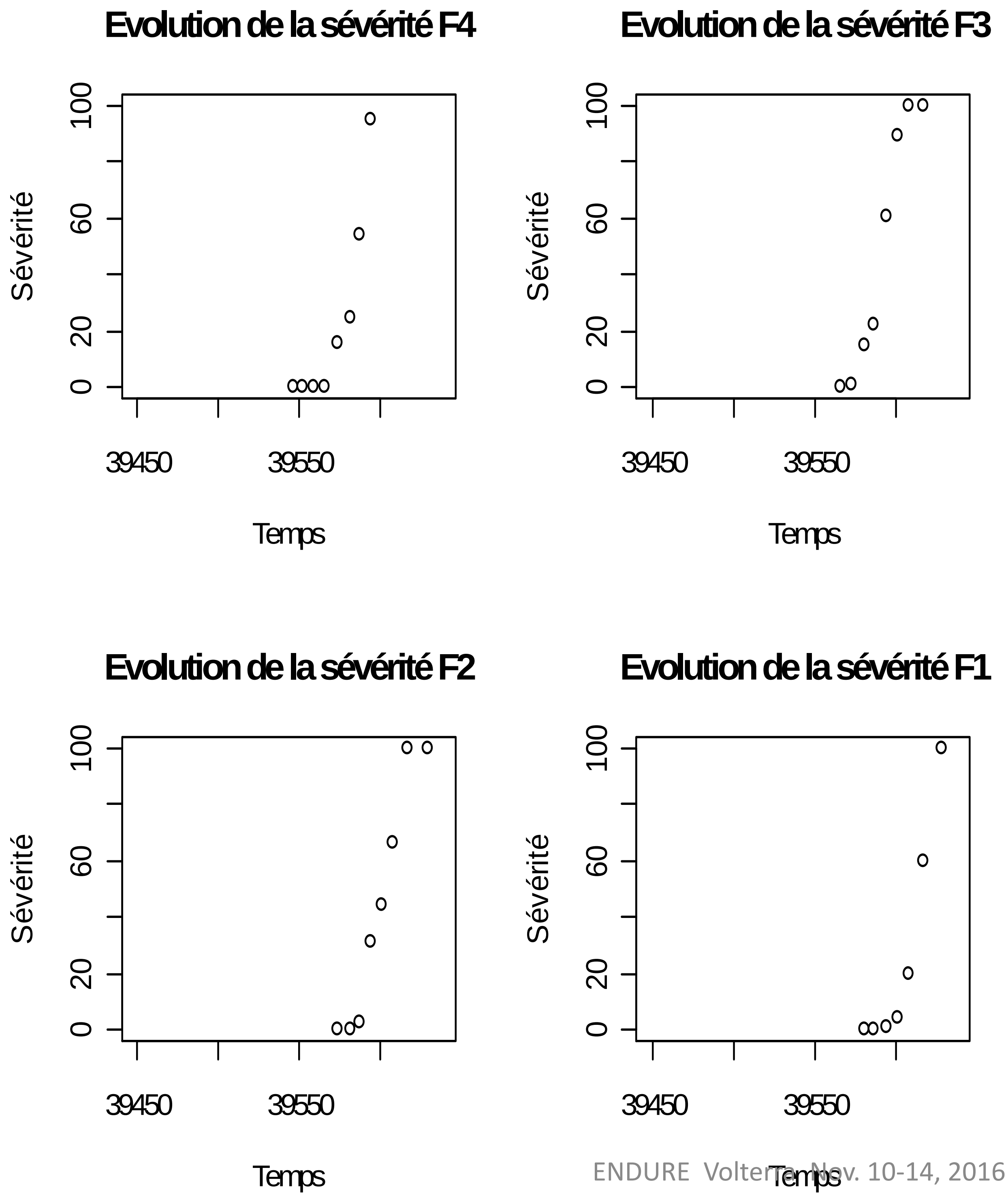


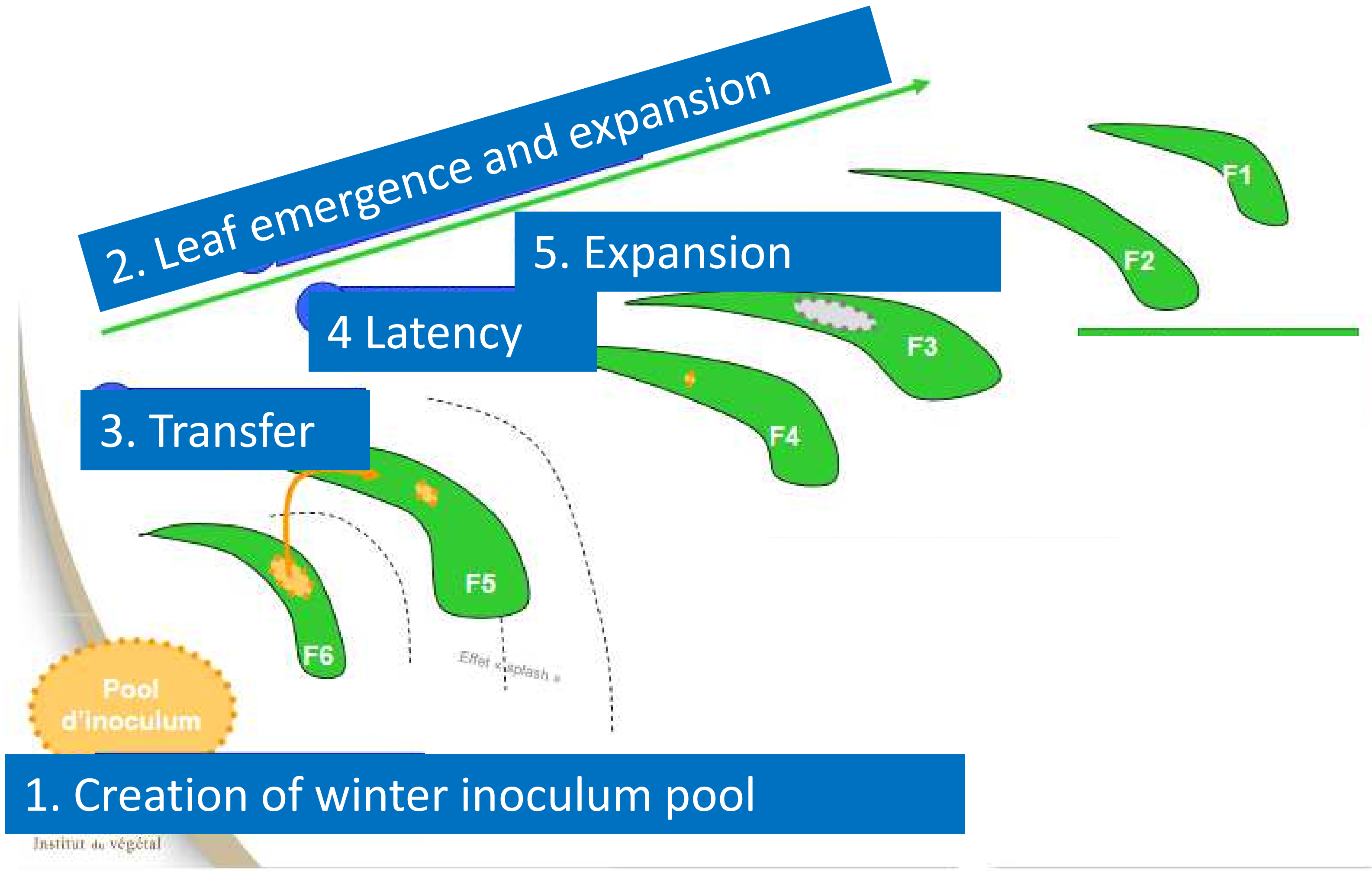

Data from 1 trial

F1 is flag leaf

# Data about damage

- At each location there are fully protected (+) and untreated (-) plots
  - $(Yield_{+}-Yield_{-})=Yield_{+}$ = relative yield loss

# The disease model


2. Leaf emergence and expansion
5. Expansion
4 Latency
3. Transfer
F1
F2
F3
F4
F5
F6
Effet « splash »
Pool
d'inoculum
1. Creation of winter inoculum pool
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# Leaf infection equations

$$U(t,l) = 1 - e^{-aY(t,l)}$$

$$F(t,l) = U_g e^{-kh_g(t)} + \sum_{j=l+1}^{M} U(t,j) e^{-kh_j(t)} + \rho U(t,l)$$

$$I(t,l) = L_V(t,l) L_C(t,l) R_{rain} F(t,l)$$

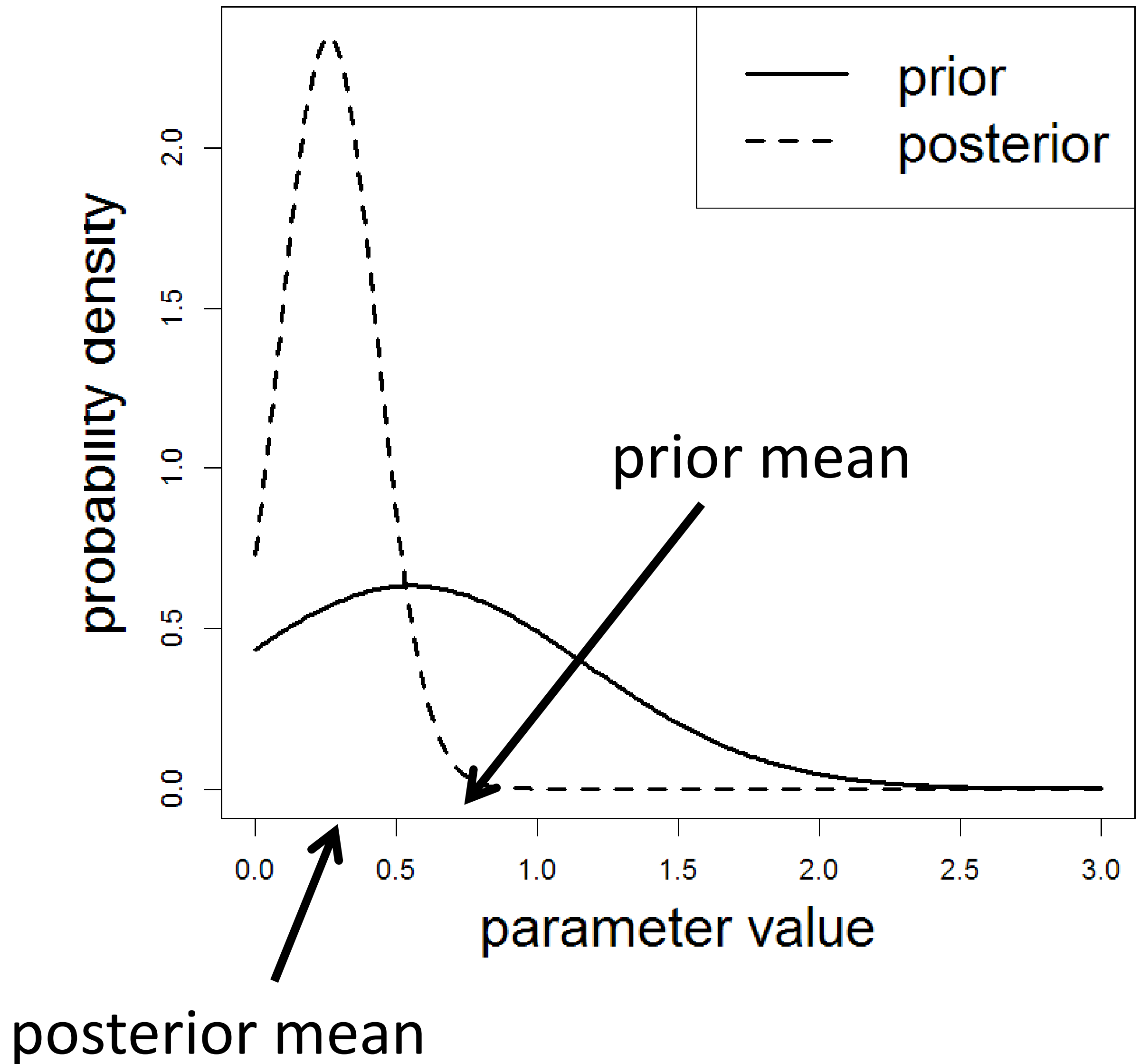
$$Y(t,l) = \sum_{i=1}^{t} I(i,l) y(T(t) - T(i))$$

- U(t,l) potential infections produced by leaf l, day t
- F = number of infections reaching leaf l, day t
  - from ground inoculum, other leaves, same leaf
- I(t,l) = successful infections on leaf l on day t
- Y(t,l) = % surface infected, leaf l, day t

# Parameter estimation

- Use Bayesian approach
  - Treat parameters as random variables
  - There is prior distribution (what we know before using data)
  - Result is posterior distribution (combining prior information and fit to data).

| Parameter | Prior mean | Prior std dev | Posterior Mean | Posterior std dev |
|---|---|---|---|---|
| | 8.25 | 3.90 | 8.89 | 2.32 |
| | 20.70 | 5.17 | 20.97 | 5.26 |
| | 50.50 | 28.58 | 5.42 | 3.75 |
| | 5.50 | 2.25 | 7.26 | 2.15 |
| | 2.50 | 2.25 | 2.16 | 2.17 |
| | 7.50 | 3.75 | 5.00 | 3.81 |
| | -0.35 | 0.08 | -0.38 | 0.07 |
| height | 0.55 | 0.63 | 0.26 | 0.17 |
| | 5.50 | 2.60 | 5.71 | 2.46 |
| | 0.047 | 0.028 | 0.030 | 0.015 |
| | 0.26 | 0.12 | 0.21 | 0.10 |
| | 2.50 | 2.25 | 2.53 | 2.29 |
| | 2.50 | 2.25 | 2.41 | 2.39 |
| | 1.53 | 0.74 | 1.44 | 0.43 |
| | 7.50 | 2.25 | 5.59 | 1.46 |
| | 1.65 | 0.08 | 1.63 | 0.08 |
| | 7.50 | 2.25 | 6.36 | 2.21 |


prior
posterior
prior mean
probability density
0.0
0.5
1.0
1.5
2.0
2.5
3.0
parameter value
posterior mean

# Calculation time

8 trials, 60000 model runs for each trial

Calculation time 5 days

(That’s why we only used a subset of the data)

# Damage model

- Use data on effective severity and damage
- Relative yield loss = 0.6*(effective severity)
  - 1% increase in severity increases relative yield loss by 0.6%

# Climate model

- A1B greenhouse gas emission scenario
  - Intermediate scenario
- 4 GCMs (climate models)
- Downscale

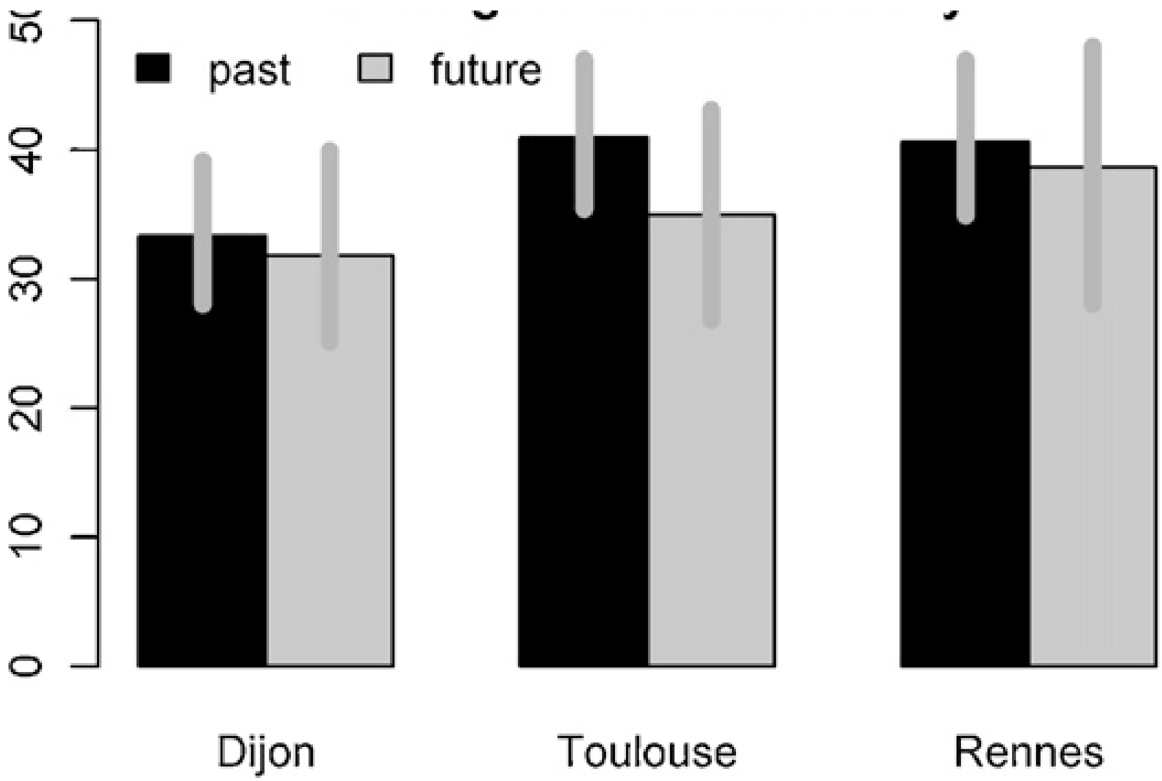
# Effect of climate change

- One wheat cultivar
- 2071-2099 compared to baseline 1971-1999
- 3 sites

- Run the model for each year, each site
  - with 4 climate models
  - with parameter vectors chosen from posterior
  - with model bias chosen from its distribution

Gives a distribution of results (uncertainty)

# Effective severity



# Conclusions

- Average of effective severity in future vs past:
  - Reduction of 2-6%
- Uncertainty is large compared to mean effect
  - Probability of reduction for Toulouse is 82%
  - Close to 50% at other locations
- Source of uncertainty
  - climate contributes more than model parameters
  - largest contribution is interaction

END