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Arnaud Bensadoun, Herve Monod, Frédérique Angevin, David Makowski,
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Modeling of gene flow by a Bayesian approach: A new perspective for decision support

Arnaud Bensadoun

Joint work with:

Hervé Monod, Frédérique Angevin, David Makowski and Antoine Messéan

GMCC 2013 - Lisbon
12-15 November 2013



Outline

- 1 Introduction
 - Context
 - Objectives
- 2 Materials and Methods
 - Dispersal model
 - Observation model
 - Types of data
- 3 Results
 - Parameter estimation
 - Overall variability
 - Goodness of fit
 - Uncertainty quantification
- 4 Discussion and Perspectives

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Context and Challenges

EU Commission provides recommendations for coexistence measures:

- To base decisions on scientific results.
- To take specific measures depending on the species and varieties and regional context.

How to set up coexistence measures in practice?

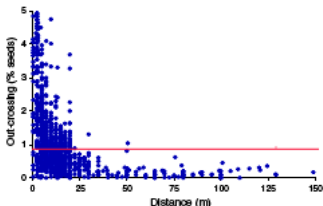
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EU Commission provides recommendations for coexistence measures:

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How to set up coexistence measures in practice?

- Statistical approach.



⇒ Easy to implement from a regulatory point of view.

⇒ Difficult adaptation to local contexts → Not proportional to the risk

Figure: Cross pollination rate as a function of distance. *Source:* Riesgo et al., 2010

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- Statistical approach.
- **Modelling approach** considering the effects of landscape characteristics, climate and agricultural practices to set up coexistence measures adapted to local climatic and agronomic factors.

⇒ Proportionality principle.

⇒ More difficult to implement under a regulatory framework.

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Challenges

⇒ Adapt coexistence rules to the diversity of possible situations.

⇒ Incorporate variability and uncertainty in decision making.

Knowledge and Objectives

- Knowledge about the risks of mixing and in particular on gene flow.
⇒ Databases gathering results of field experiments (e.g. SIGMEA).
- Generic models of pollen dispersal and Cross Pollination Rate (CPR) at the landscape scale, for instances:
 - ⇒ MAPOD (Angevin et al., 2008) for maize.
 - ⇒ GeneSys (Colbach et al., 2001) for rapeseed.

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Objectives of the study

- Integrate variability and uncertainty in decision making.
 - Probabilistic prediction rather than single value:
⇒ Associate confidence interval to any CPR prediction.
 - Quantify prediction uncertainty.
- Enable adaptability of models to information level.
 - Development of simplified and flexible models.
 - Quantify the benefit of adding input data.



Relevance of the Bayesian approach

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Individual Dispersal Functions

Individual dispersal function: $\gamma(d_s)$

A probability density function describing the probability that a pollen grain fertilises an ovule at a distance d_s from its emission point.

Individual Dispersal Functions

$$\gamma(d_s) = \begin{cases} K \times e^{-a_1 d_s} & d_s < D \\ K \times e^{-a_1 D - a_2 d_s} & d_s \geq D \end{cases} \quad (1)$$

(Source: Damgaard et al., 2005)

Where:

- $d_s = \sqrt{x^2 + y^2}$

⇒ **Distance model.**

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Where:

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- $d_s = \sqrt{x^2 + y^2} \times (1 - \theta_v \cos(\omega - \omega_0))$,

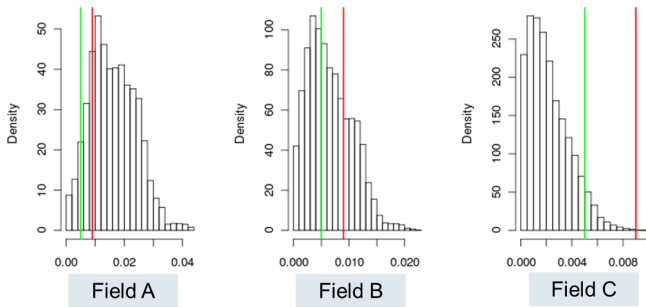
ω_0 the main wind direction,

and ω the angle between the vector donor/receptor and the horizontal axis.

⇒ **Distance+Wind model.**

Bayesian Framework

Model parameters are random variables, so is the prediction:



⇒ Requires the definition of a probabilistic model linking the observations to the model parameters.

Observation model

Natural observation model for counts of rare events

⇒ Poisson model:

$$Y_s \sim \mathcal{P}(K\mu'_s) \quad (2)$$

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But highly variable observations AND over-representation of zeros

⇒ Zero-Inflated Poisson model:

$$Y_s \sim ZIP(1 - q_s, K\mu'_s) \quad (3)$$

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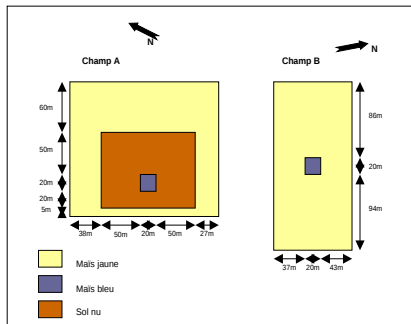
$$Y_s \sim ZIP(1 - q_s, K\mu'_s) \quad (3)$$

Taking into account the remaining variability

⇒ Normal model for the Poisson model expectation :

$$\mu'_s \sim \mathcal{N}(\gamma(d_s), \sigma^2) \quad (4)$$

Types of data



(Source: Klein et al., 2003)



(Source: Messeguer et al., 2006)

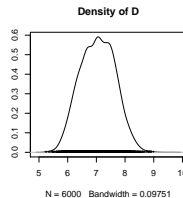
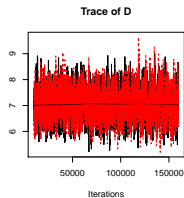
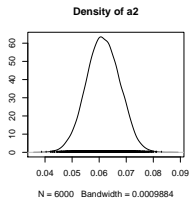
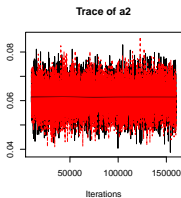
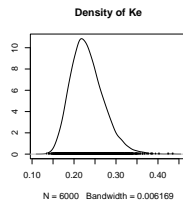
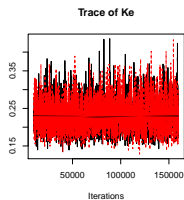
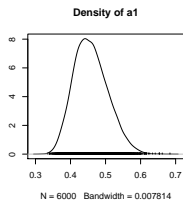
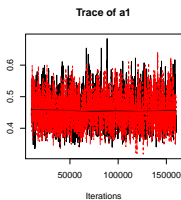
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Parameter estimation

- Method: Monte Carlo Markov Chain (MCMC)
- Software for estimation and inference: JAGS
- Convergence to posterior distribution: OK

$$\gamma(d_s) = \begin{cases} K \times e^{-a_1 d_s} & d_s < D \\ K \times e^{-a_1 D - a_2 d_s} & d_s \geq D \end{cases}$$



Overall variability

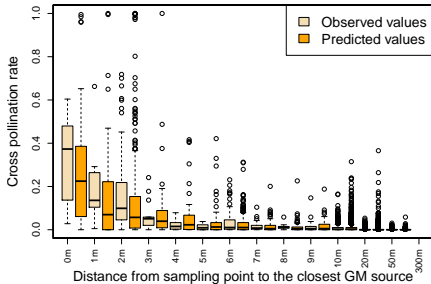


Figure: Boxplots of observed and predicted cross-pollination rates as a function of distance to the closest GM source.

⇒ Both models reflect the overall variability well.

⇒ The observation model ($ZIP + Normal$ expectation) is sufficient to reproduce this variability.

Goodness of fit

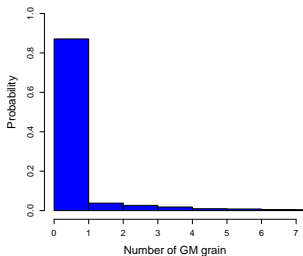
Criterion	Model	
	Distance	Distance + Wind
<i>CRPS</i>	-2.720	-2.400 ✓
<i>Correlation</i>	0.696	0.746 ✓
<i>Efficiency</i>	0.465	0.536 ✓
<i>RMSE</i>	14.234	13.254 ✓
<i>ROC</i>	0.813	0.863 ✓

Table: Criteria values calculated with mean predictions for the two models

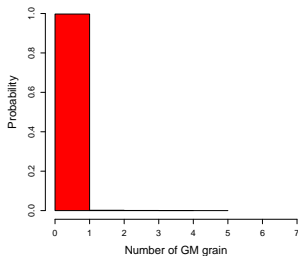
⇒ **Distance+Wind** model outperforms **Distance** model either on absolute error (RMSE, efficiency, correlation) or on quality of decision (ROC).

Uncertainty quantification

**Histogram of a
Distance model Prediction**



**Histogram of a
Distance+Wind model Prediction**



- Both models predict the observed value as the more likely.
- **Distance+Wind** model gives more precise predictions.

⇒ Incorporate wind effect reduce uncertainty prediction.

⇒ Better description of the situation increases the accuracy of prediction.

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Discussion and Perspectives

Discussion

- High uncertainty and/or unavailability of input that must be taken into account.
- High uncertainty in predictions that need to be assessed.

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- Bayesian methods allows for probabilistic predictions.
 - ⇒ Overall variability well reflected.
 - ⇒ Provide better understanding of prediction uncertainty.
- Substantial benefit of a better description of the situation.
 - ⇒ Decrease of absolute error.
 - ⇒ Decrease of prediction uncertainty.
- Probabilistic predictions provide better insight into the risk for decision makers.
 - ⇒ Decisions may adapt to the level of risk aversion.

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Perspectives

- Extension to *Multi-source* situations.
- Incorporate the effect of flowering delay.
- Refine the individual dispersal function.

Thanks for listening

Any questions?



Life is like a Markov chain, you never know what you're gonna get