# Using Statistical Model Checking in a Process for Evaluating and Calibrating a Model of Tropical Forest Dynamics

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Université de la Guyane



## Outline

- Studying a Forest Model
  - Forest of Paracou
  - A Forest Model
  - A Process to Evaluate and Calibrate it
- Some challenges, experiments and questions as a newcomer
  - on the models and properties involved
  - on the process

#### Amazonian forest



#### Amazonian forest



Paracou, French Guyana Forest dynamics model Model Evaluation

#### Amazonian forest

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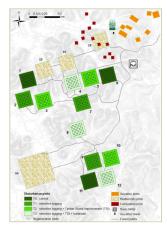
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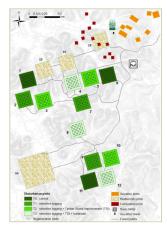
### The plots



▶ 16 permanent plots (fifteen 6.25 ha plus one 25 ha) have been censused every 1-2 years for more than 35 years.

Paracou, French Guyana Forest dynamics model Model Evaluation

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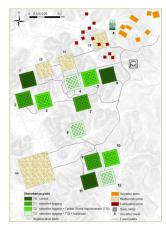


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Paracou, French Guyana Forest dynamics model Model Evaluation

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 some regions not always accessible

 $\label{eq:https://paracou.cirad.fr/website/miscellaneous/pretty-pictures/inventory-measurement$ 

#### Decades of Data

More than just counting trees

- ID
- geolocalisation
- family, genus and species when possible
- circumference

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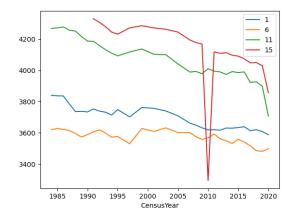
#### around 80-120 k entries for each plot

Forest	Plot Plo		ubPlot	TreeP-idTree		Yfield	Xutm	Yutm		Lon	Family	Genus	Species	BotaSource	Bo+idVe	m VernName	Comm Censu	sYear)	
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Paracou	- 4	6,25	1	1 89068		125,	285844,84375		5,27080011367798		7 Sapotaceae	Pradosia	cochlearia	Bota		102 kimboto	0	1985	
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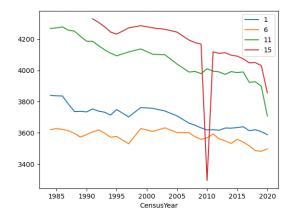
## Number of trees

▶ Number of trees : reference plots (No logging)



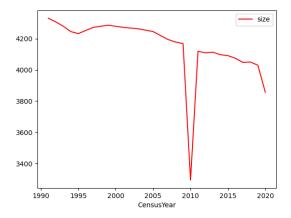
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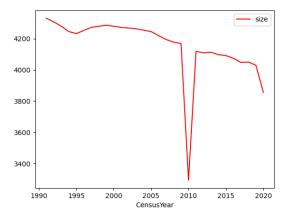


plot 15 wasn't always fully reachable

## Number of trees : The case of plot 15

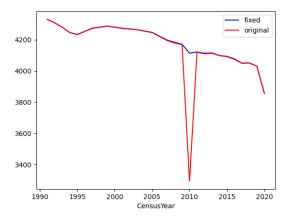


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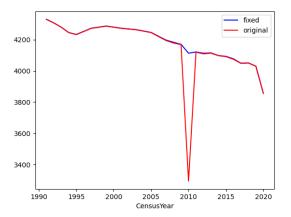
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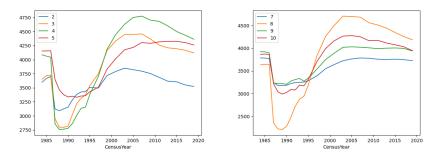
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A tree is alive between any two dates where it has been noted alive Correction under 1‰ for the other plots

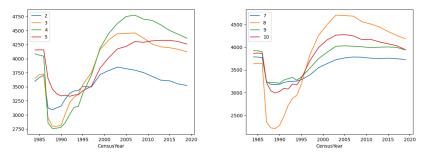
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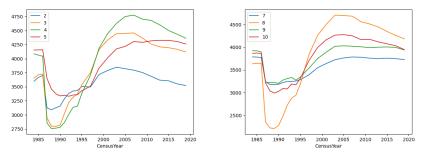
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Different recovery rates, sometimes failing to reach the starting point

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The regrowth is what we want to model.

## Model Properties

Properties we want for the model

- close enough to the data
- as few parameters as possible
- preferably identifiable parameters
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#### Problem

relevant models in the litterature are age-structured : Young trees vs Mature trees which can produce seeds

## First Model

Antonovsky and Korzukhin (1990) :

 $u \rightsquigarrow \mathsf{young}$  trees,  $v \rightsquigarrow \mathsf{mature}$  trees

$$\begin{cases} \dot{u} = \rho v - \gamma(v)u - fu, \\ \dot{v} = fu - hv. \end{cases}$$

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 $\begin{array}{lll} \rho & \leadsto & \mbox{recruitment (birth) rate,} \\ f & \leadsto & \mbox{aging rate,} \\ h & \leadsto & \mbox{mortality,} \\ \gamma(v) & \leadsto & \mbox{competition} \end{array}$ 

$$\gamma(v) = a(v-b)^2 + c.$$

Widely studied and the basis of many forest dynamics models

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#### Three parameter regimes

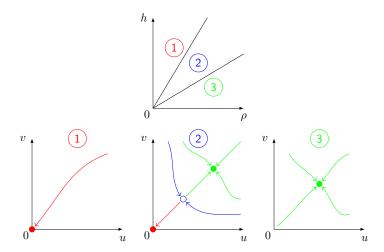
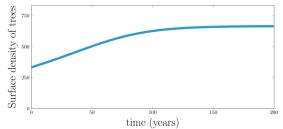


Figure – Three possible dynamics : dying forest, healthy forest or coexistence between persistence and extinction

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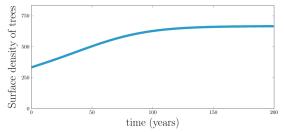
#### Overall shape for most parameter values



Model with *linear* aging rate.

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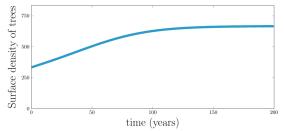


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 $\blacktriangleright$  The oscillation seen post logging is absent using the linear aging term  $\pm fu$ 

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## Overall shape for most parameter values



Model with *linear* aging rate.

- $\blacktriangleright$  The oscillation seen post logging is absent using the linear aging term  $\pm fu$
- ▶ Intuition : reaching maturity is also a kind of competition
  - bounded by a maximal tree density
  - fiercer among youngs

 $\blacktriangleright \operatorname{Replacing} \pm fu$  with

$$fu \times v \times (T_{max} - (u+v)).$$

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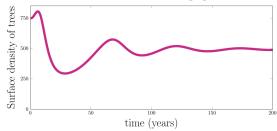
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▶ Replacing  $\pm fu$  with

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▶ × $v \rightsquigarrow$  maturing is lower when v diminishes. ▶ × $(T_{max} - (u + v)) \rightsquigarrow$  maturing is bounded by the maximum density.



Model with **nonlinear** aging rate.

# Evaluating the model

Now that we have a more promising candidate model, we want to see how it behaves :

- can it fit the data?
- can common (or close enough) values of parameters fit all the plots ?
- can we determine regions of interest in the parameter space?
- can we observe strong correlation between parameters (hint at simplification)

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# Fitting the data - Properties and measure

#### Qualitative

the simulation stays within D% of the data, except for a maximum of K outliers.

#### Quantitative

average distance to the data (as %), number of outliers

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Finding a plausible range for each parameter.

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Then we need to discretize the space

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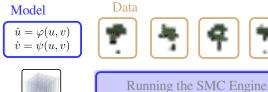
# **Evaluation Process**

ModelData $\dot{u} = \varphi(u, v)$  $\phi(u, v)$  $\dot{v} = \psi(u, v)$  $\phi(u, v)$ 

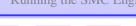


Model Evaluation

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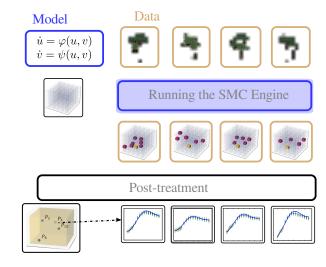






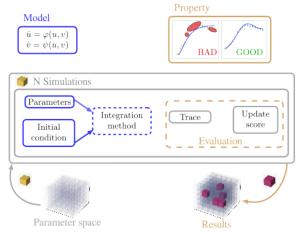
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Paracou, French Guyana Forest dynamics model Model Evaluation

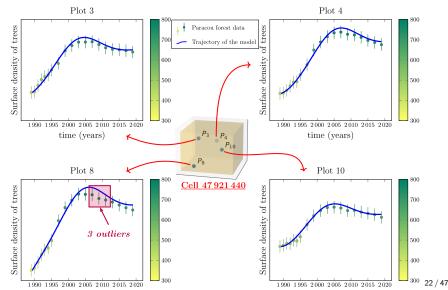
## **Evaluation Process - SMC**



N is determined based on precision guarantees. score is the % of good simulations

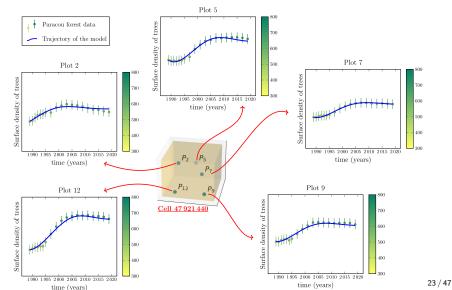
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### Results on the base plots



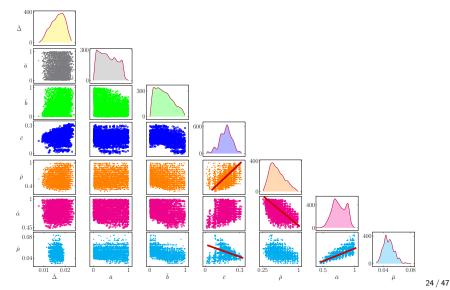
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### Results on the control plots

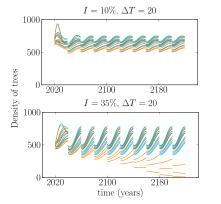


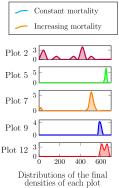
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## The overall picture



# Example of applications





On model verification On the process Partial data Experiment : pretending to zoom in

# First Impressions

#### Coming from Sofware Engineering Verification

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"Real world models" are different beasts.

On model verification On the process Partial data Experiment : pretending to zoom in

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#### My preliminary conclusion

The fitting property inside a biologist's brain is complex and somehow unpredictable

On model verification On the process Partial data Experiment : pretending to zoom in

# Properties are complex as well

#### My preliminary conclusion

The fitting property inside a biologist's brain is complex and somehow unpredictable

distance and outliers are only a part of the equation.

There's something about shape , but how to capture it efficiently?

**On model verification** On the process Partial data Experiment : pretending to zoom i

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- How to match "non abstract parameters" with data?
  - could Young/Old distribution be inferred from the data?
  - use GPS data to get finer grained info about density?
- Even params that are supposed to be reflected in the data (birthrate) won't be a perfect fit (variability +abstraction). how far can they go from their real counterparts? They should be correlated enough to let us make predictions

On model verification On the process Partial data Experiment : pretending to zoom in

# First impression

The process from a user perspective

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- 6. sigh and start again

On model verification On the process Partial data Experiment : pretending to zoom in

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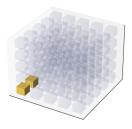
# What could be improved

- to detect errors and stop wasting resources scary failure numbers in HPC
- to exploit preliminary information
- to make decisions, change plans
- which results could be more useful to get first?

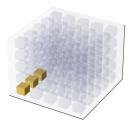
On model verification On the process Partial data Experiment : pretending to zoom in



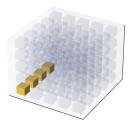
On model verification On the process Partial data Experiment : pretending to zoom in



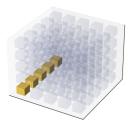
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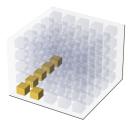
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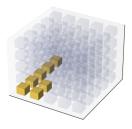
On model verification On the process Partial data Experiment : pretending to zoom in



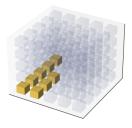
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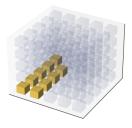
On model verification On the process Partial data Experiment : pretending to zoom in



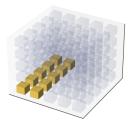
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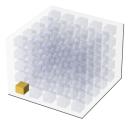
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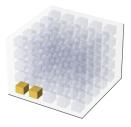
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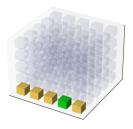


On model verification On the process Partial data Experiment : pretending to zoom in



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# On traversal - Simple variation



Good news : low expectations

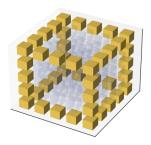
On model verification On the process Partial data Experiment : pretending to zoom in

### On traversal - Educated guesses?



On model verification On the process Partial data Experiment : pretending to zoom in

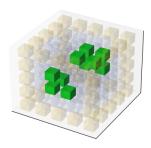
### On traversal - Educated guesses?



# Out of normal range - Check if false positives

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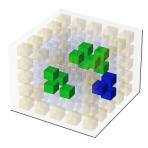
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Out of normal range - Check if false positives Two probable ecological niches

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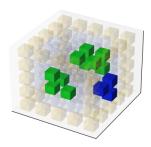
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Out of normal range - Check if false positives Two probable ecological niches Less likely

Allow prioritization without loss or redundancy. Cost vs Precision

# Getting the size right

#### Computing cost/time vs

cell sizes : vs parameter sensitivity number of simulations : precision computing the property and additionnal statistics

### Space : disk/network usage vs

storing information about visited cells : % match, avg distance, data reached, std. dev., best results found

# A few strategies

- Stopping simulations before the end (depends on traces length/cache misses)
- not running all simulations if the result won't probably reach expectations
- filter or aggregate results to save space
- getting partial results to test hypotheses on more effective discretisation
- exploiting more info about intra-cell variability (quasi random instead of the costly Sobolov indices)

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If the first 10 simulation failed and we want 90% match for good cells, how much is it worth continuing considering the precision we aim for ?

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MaxSPRT will drastically reduce the number of simulations But we want some info even on sub optimal regions, especially if the variability is high

- We configured Max SPRT to be a little more tolerant than our match threshold
- We keep additionnal info for the best simulation for each "interesting enough "cell

### Pretending to zoom in - a hint

- We have a derived property comparing results from different simulations.
- We also kept the position and rewards for the best simulation found in each "interesting enough" cell.

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- We have a derived property comparing results from different simulations.
- We also kept the position and rewards for the best simulation found in each "interesting enough" cell.

We can use this to partially answer the question "would we have found smaller common cells if we used a finer grained discretization ?"

Which is another way to select a subset of cells where it could be intersting to zoom in first.

On model verification On the process Partial data Experiment : pretending to zoom in

### Pretending to zoom in - how

- compute distances between best parameters of each cells
- use them to determine the "virtual size" of a cell which would have contained them all.
- sort them
- select the "smallest" virtual cells

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we know we're missing out a lot but looking for these small cells is a matter of seconds, not hours or days.

### Pretending to zoom in - limitations

- Larger cells make room for best individual fits

   were getting worse and worse solutions when reducing the
   "virtual" size of the cell
- filtering out too much alters the distribution ~> the selection cease to be representative of good solutions

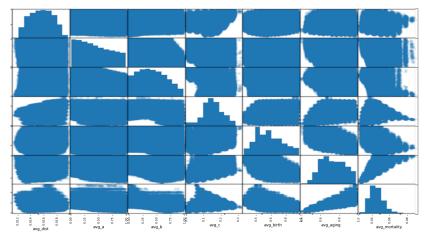
### Pretending to zoom in - limitations

- Larger cells make room for best individual fits

   were getting worse and worse solutions when reducing the
   "virtual" size of the cell
- To know where to stop we must consider
  - simulation scores (don't get too bad)
  - global parameter distribution for "good" cells

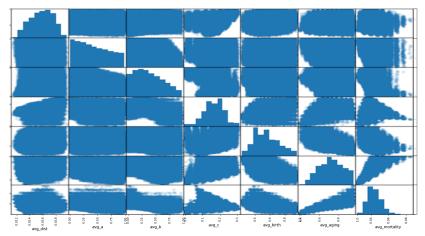
On model verification On the process Partial data Experiment : pretending to zoom in

### The original distribution



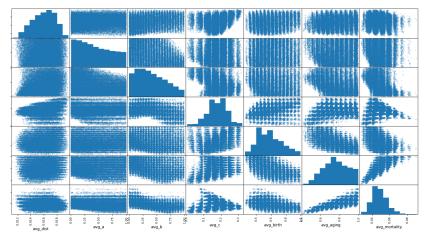
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### First quartile



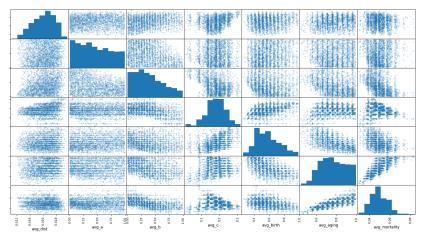
On model verification On the process Partial data Experiment : pretending to zoom in

### First decile



On model verification On the process Partial data Experiment : pretending to zoom in

### First centile



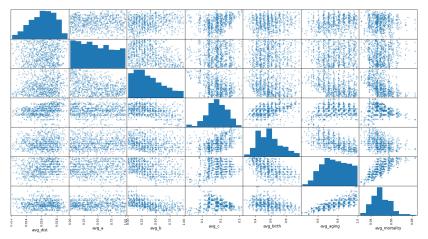
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### First millile

1 Same Brand Barry						
					, dan	
					A STATISTICS	
avg_dist	52 05 05 0 avg_a	8 57 95 50 avg_b	avg_c	avg_birth	avg_aging	avg_mortality

On model verification On the process Partial data Experiment : pretending to zoom in

### First 3 milliles



On model verification On the process Partial data Experiment : pretending to zoom in

# virtual zoom

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  - only gives a brief impression of what smaller cells would do

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Automating it would require

- finding good criteria wrt distance and distribution
- different virtual cell size (distance functions)

Keep in mind that differents splits strategies change the precision (the size of the subcells becomes heterogeneous)

# Conclusion

An interesting use case Plenty of future work

- the quest for good models is neverending
- optimization and trade offs (vs guaranties)
- useful and low cost metrics
- exploration strategies
- data mining, clustering

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I guess some might be seen as peripheral to the topic, but I believe that automating boring computations and put the user in charge of more meaningful decisions is a worthy goal.