Modeling the tree scale variability of carbon and water fluxes in clonal *Eucalyptus* plantations

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Introduction: *Eucalyptus* plantations in Brazil

30m height
at 6 years

→ Among the most productive plantation in the world (Gross Primary Production (GPP) > 3.5 kgC/m²/y)

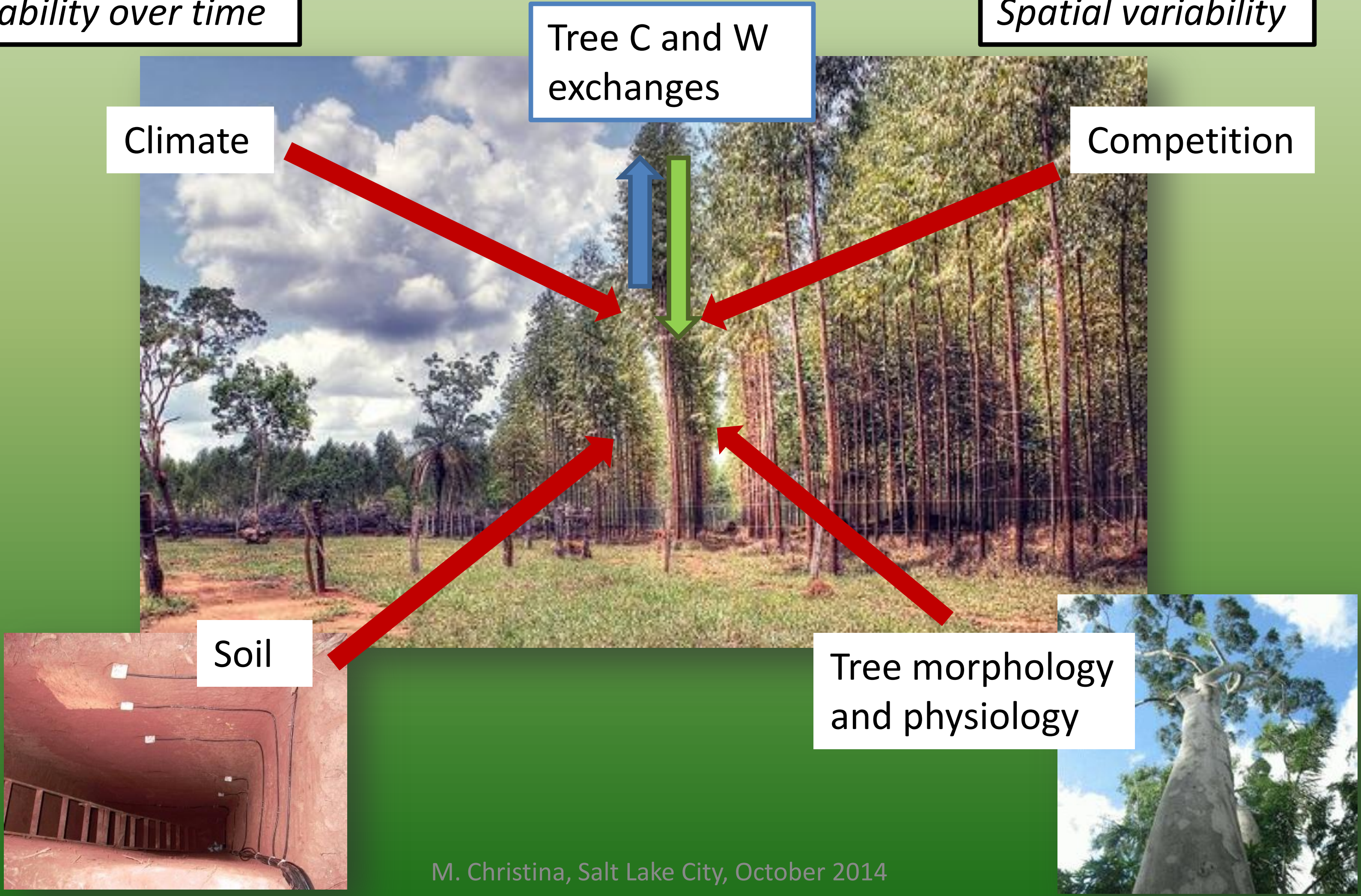
→ Considerable use of water (Transpiration (TR) ~ total rainfall (> 1500 mm/y) after canopy closure)

Introduction: Understanding the processes controlling water and carbon exchanges with atmosphere at the **tree scale**

Uncertainty coming from the variability of the ecosystem characteristics

Variability over time

Spatial variability



Objectives

→ To gain insight into the temporal and spatial variability of tree GPP and transpiration in *Eucalyptus* plantation

→ To quantify the influence of climate, biological drivers and competition on the daily variability of tree GPP and transpiration through process-based modeling

→ To provide simple predictive model of GPP and transpiration at the tree scale

Temporal and spatial variability of tree GPP and transpiration in *Eucalyptus* plantation

Material & Method

C and W exchange variability predicted by MAESPA model, in *Eucalyptus* plantations

Study site

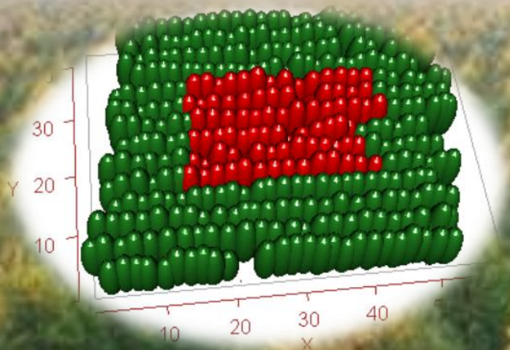
Site: EUFLUX Itatinga-SP, Brazil
200ha *E. grandis* plantations

Continuous eddy-covariance measurements

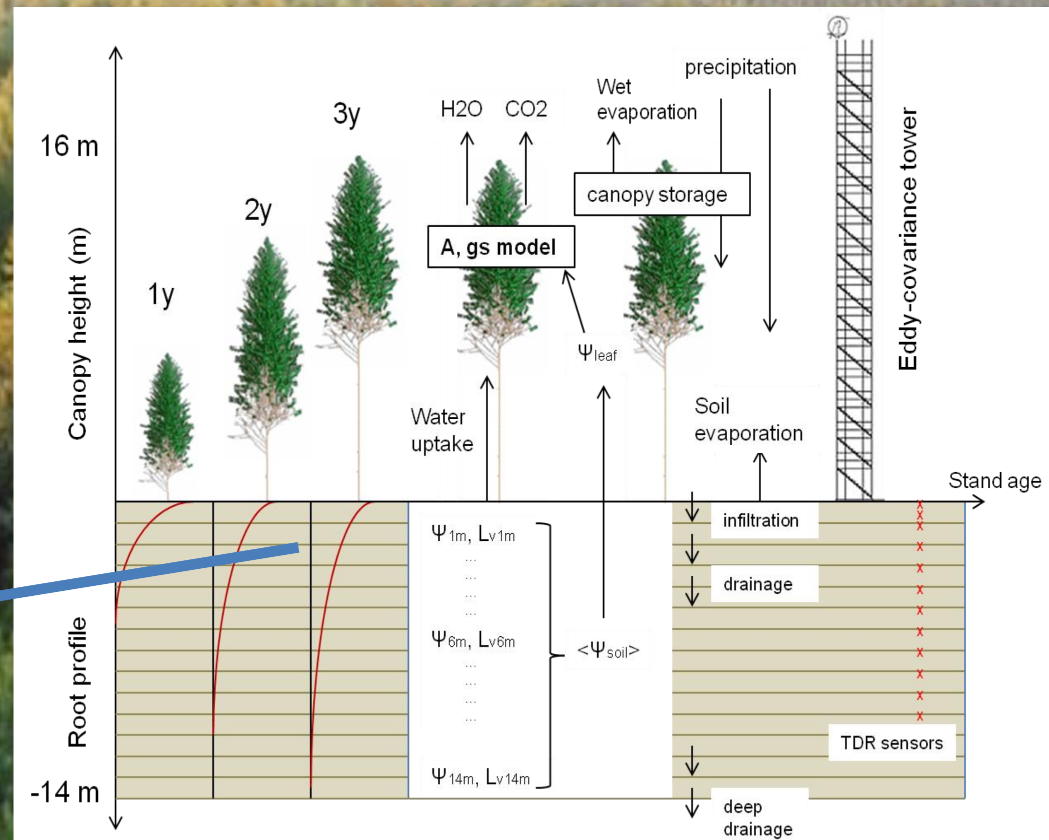
Continuous SWC and soil T measurements

Process-based modeling

Site: EUFLUX Itatinga-SP, Brazil
200ha *E. grandis* plantations



MAESPA model (Duursma & Medlyn 2012, Wang & Jarvis 1990)

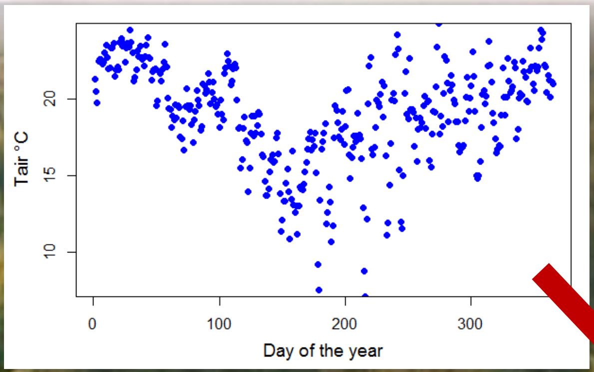


Validation at the stand scale
- Latent heat flux over the first 3 years after planting
- SWC down to 10m depth over the first 3 years
- Light interception (Gap fraction)

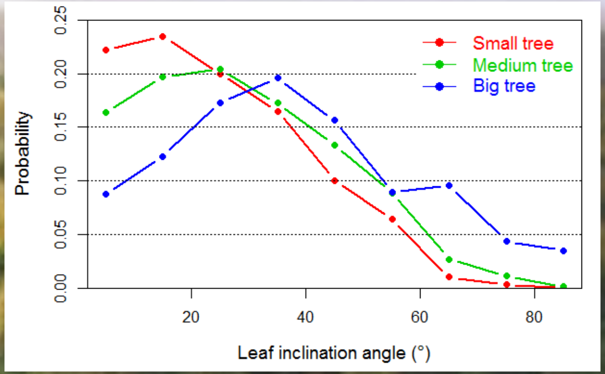
A model coupling water and carbon balances at the tree scale

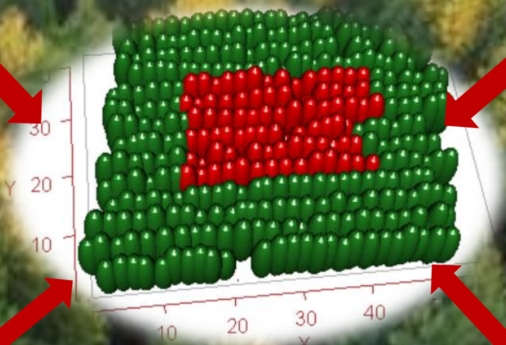
Sources of model parameter variability in clonal *Eucalyptus* plantation

Climate variability
(ex air T)



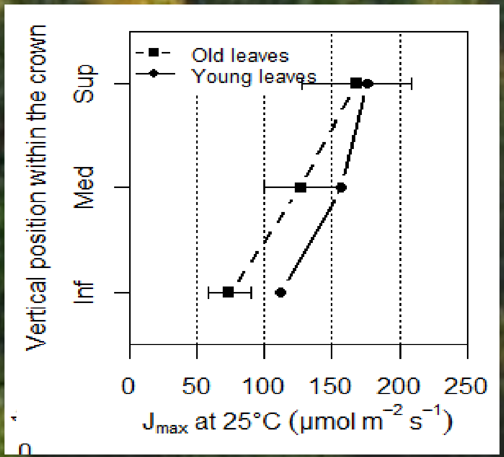
Variability with tree size
(ex Leaf angle)



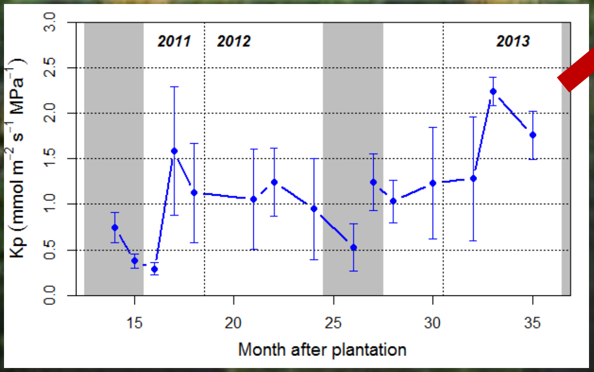


MAESPA representation

Variability with crown position
(ex Jmax)

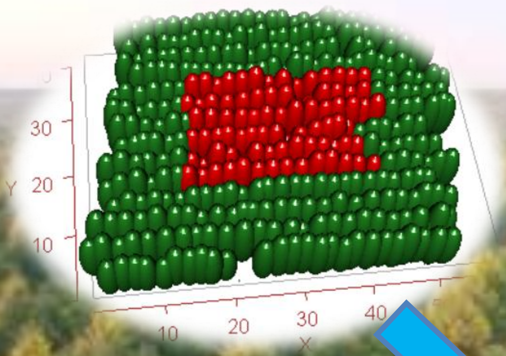


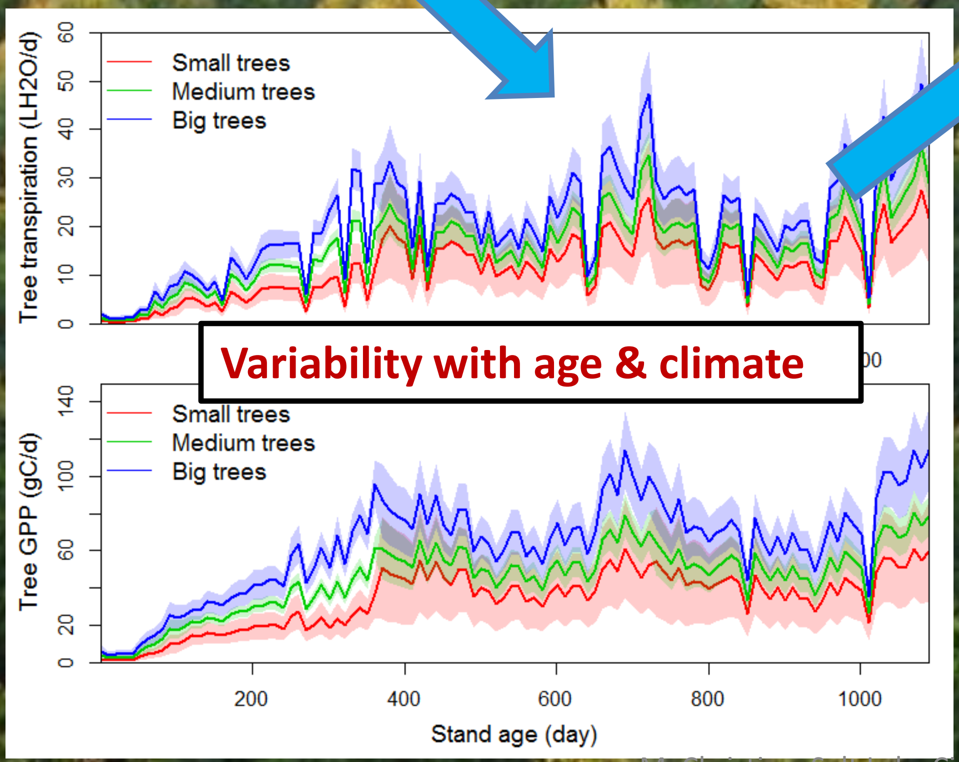
Variability with tree age
(ex plant conductivity)

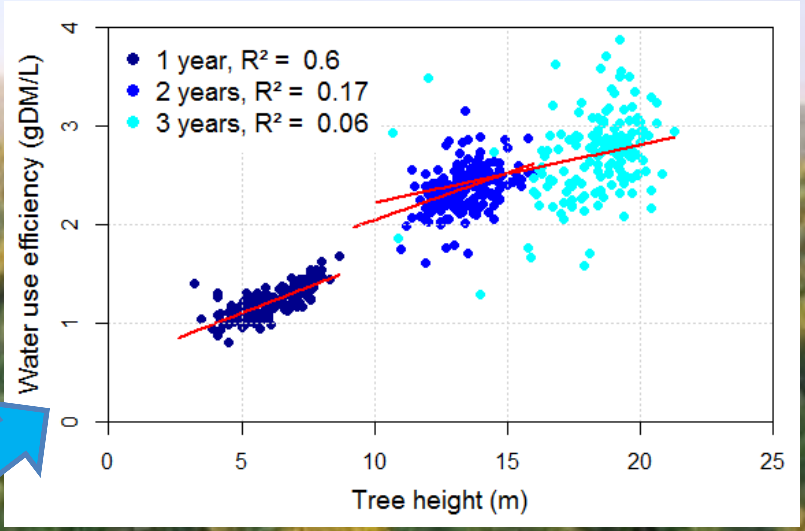


A model requiring a large set of parameters

Tree GPP and transpiration variability in clonal *Eucalyptus* plantation, predicted by the MAESPA model





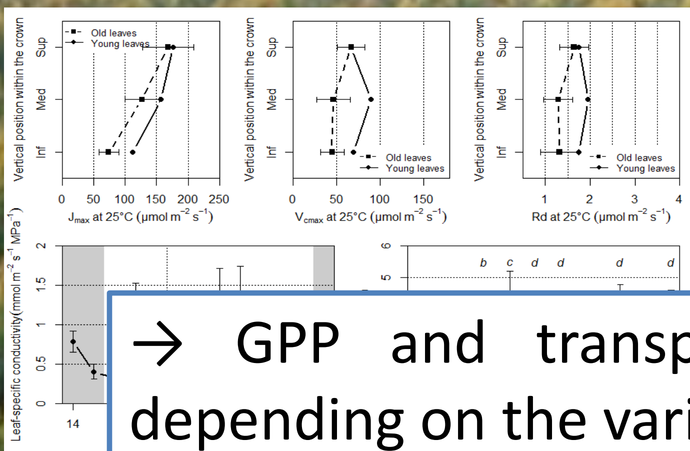


Variability with age & social status

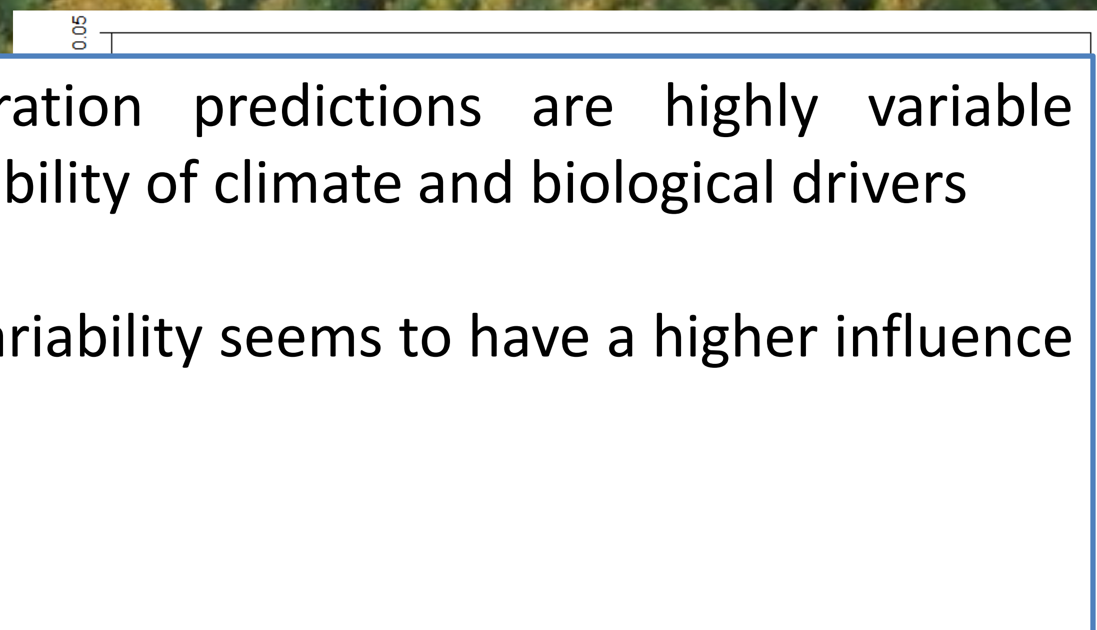
Variability with age & climate

Impact of parameters variability on GPP and transpiration predictions, First observations

→ Do we have to take into account the natural variability of parameters ?



Ex : Variation in GPP if we do not take into account the variability of photosynthetical parameters



→ GPP and transpiration predictions are highly variable depending on the variability of climate and biological drivers

→ Some parameters variability seems to have a higher influence than others

But :

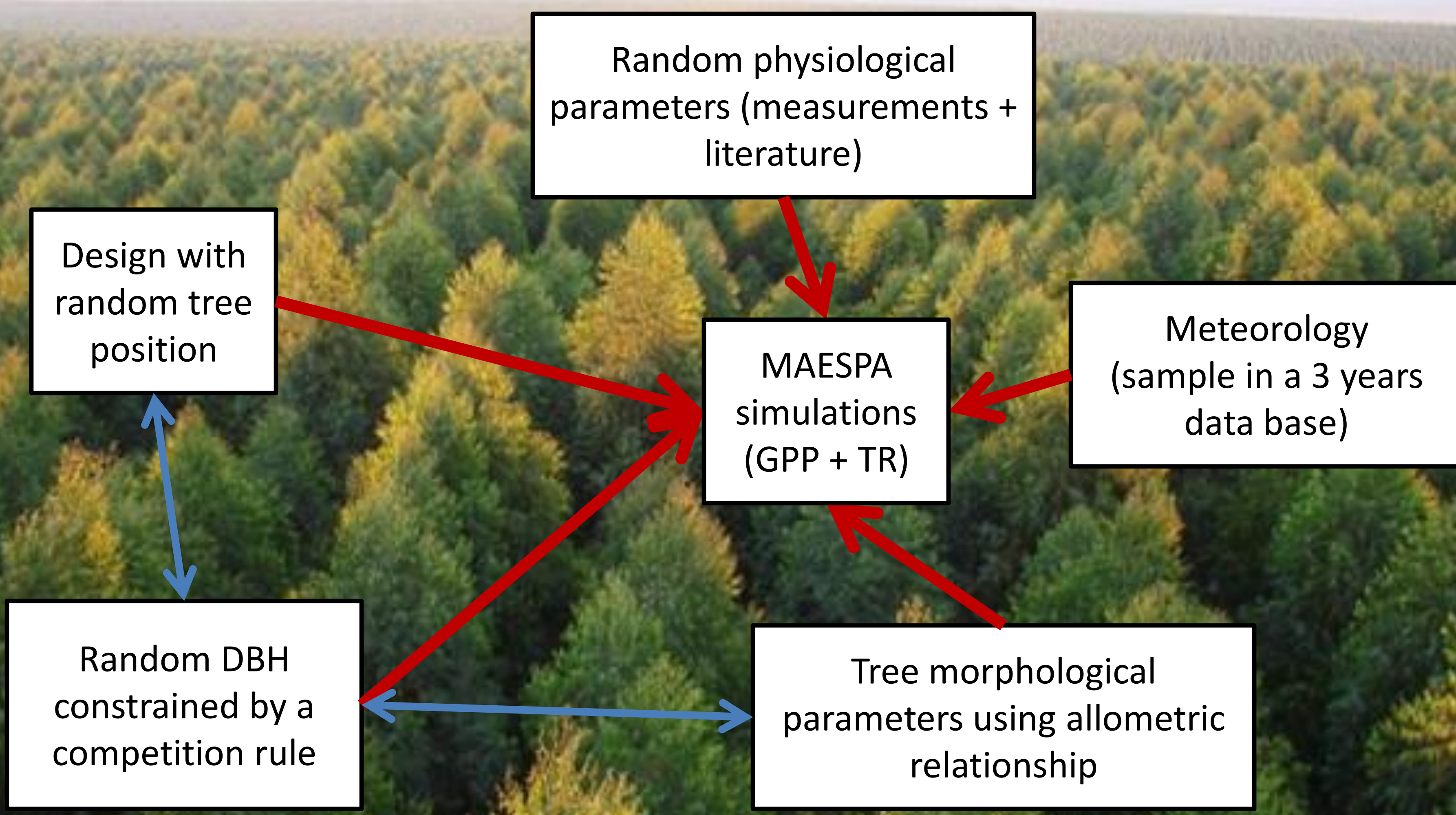
→ How can we quantify their influence ? How do they interact ?

Influence of climate, biological drivers and competition on the daily variability of tree GPP and transpiration through process-based modeling

M**eta-modeling** and **sensitivity** analyses to tackle this issue

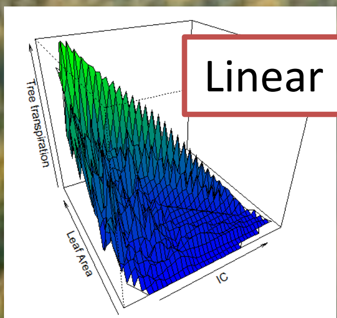
Construction of random *Eucalyptus* plantations

→ Sampling of 1000 random design: Latin Hypercube method

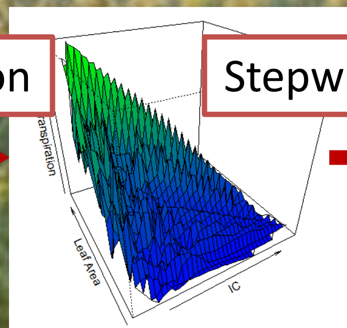


Building of a polynomial meta-model for daily predictions

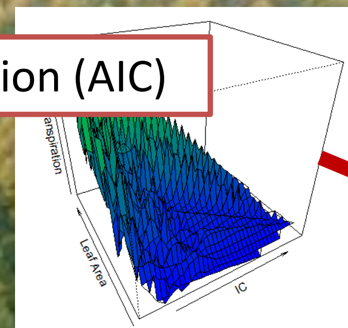
→ Approximation of a complex model with a simple one
→ Use of aggregated variables in place of complexe variables



Linear regression



Stepwise regression (AIC)



Sensitivity analysis

MAESPA model
40 parameters for the target tree
N=3000 simulations

>100 parameters for neighbor trees

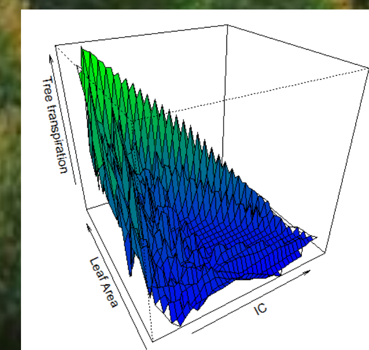
Hourly climate data
SWC at each depth

Meta-model 1
40 parameters

Hegyi's competition indice (CI, 1974)

Daily climate data
Average SWC

Meta-model 2
30 parameters

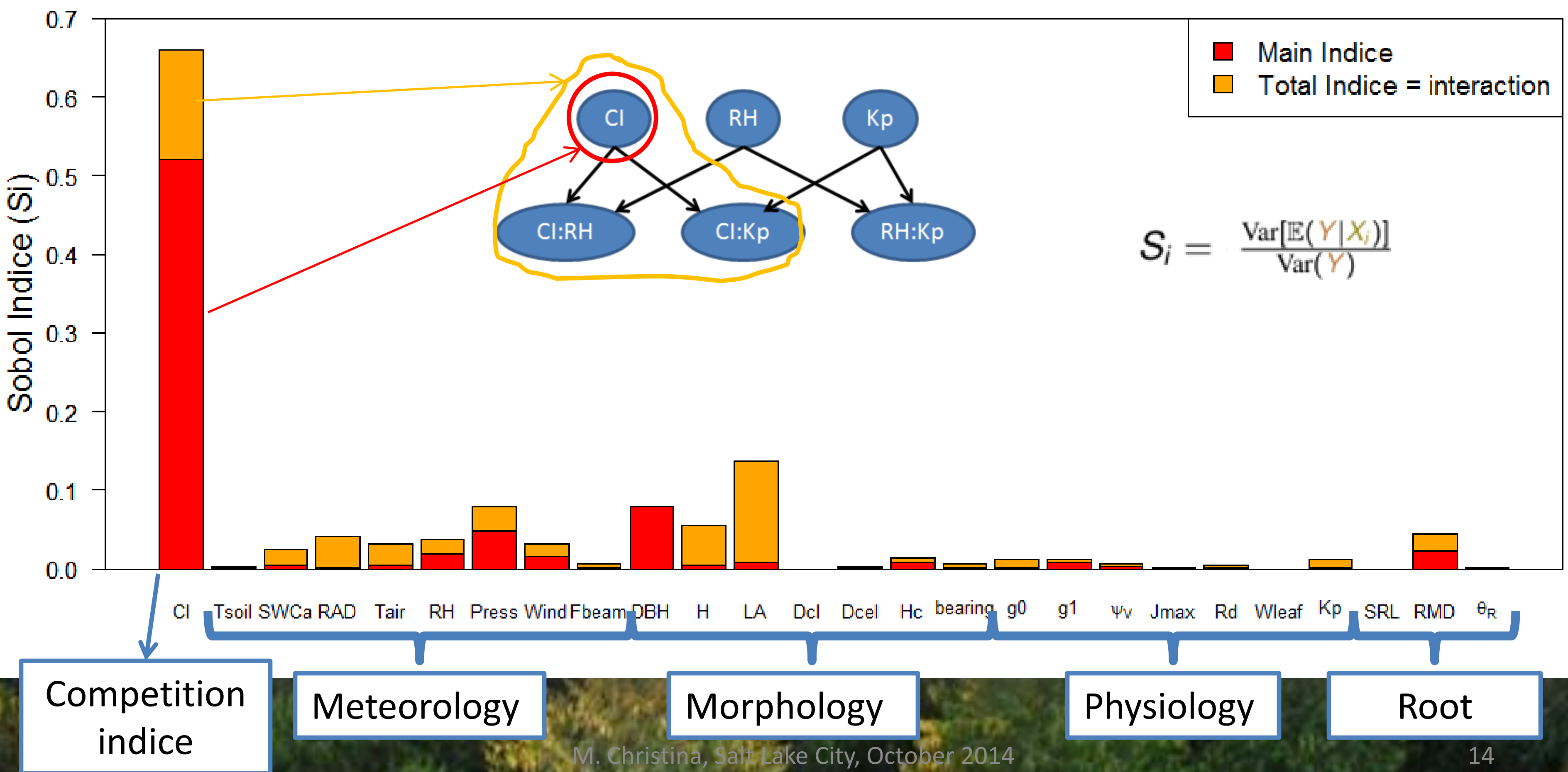


Meta-model 3
10 parameters

Sensitivity analysis of the meta-model 2, for transpiration

→ Use of Sobol indices to rank the parameters based on the model sensitivity
→ Possible approach to simplify the model

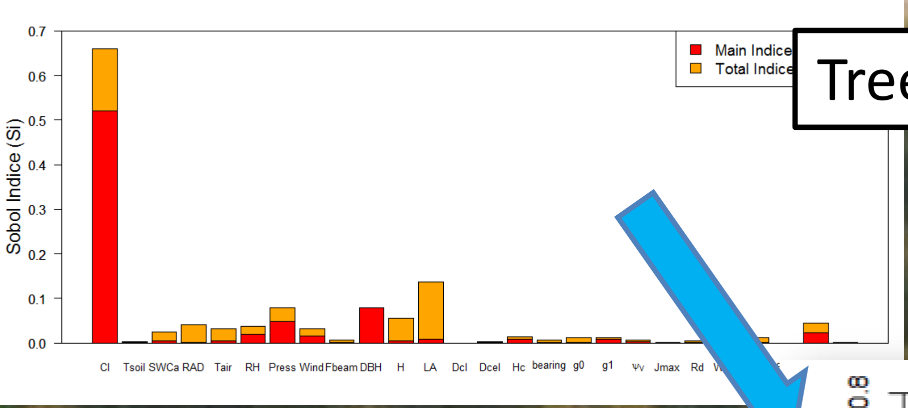
Tree transpiration, meta-model 2



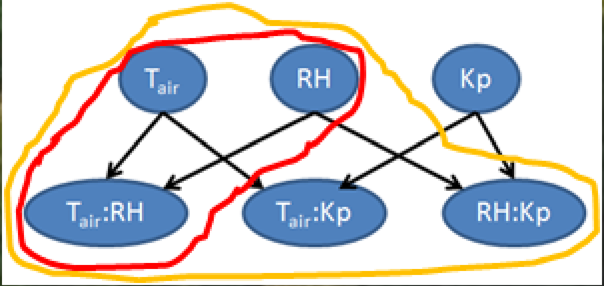
$$S_i = \frac{\mathrm{Var}[\mathbb{E}(Y|X_i)]}{\mathrm{Var}(Y)}$$

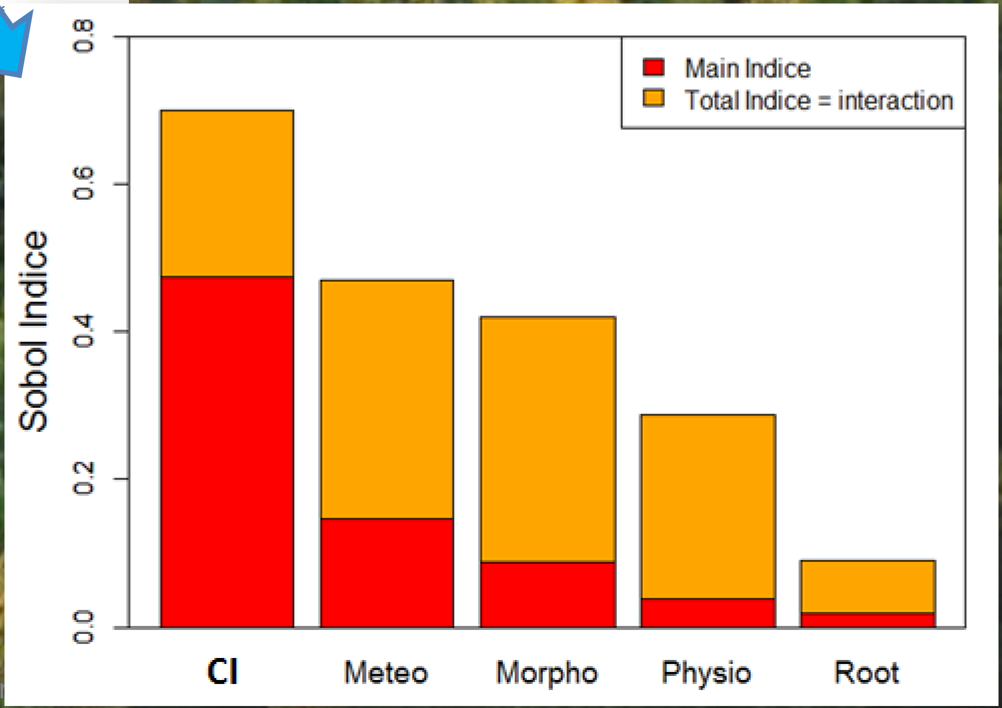
Sensitivity analysis of the meta-model 2, for transpiration

→ Sensitivity for a group of parameters
→ To distinguish climate, biological drivers and competition effects



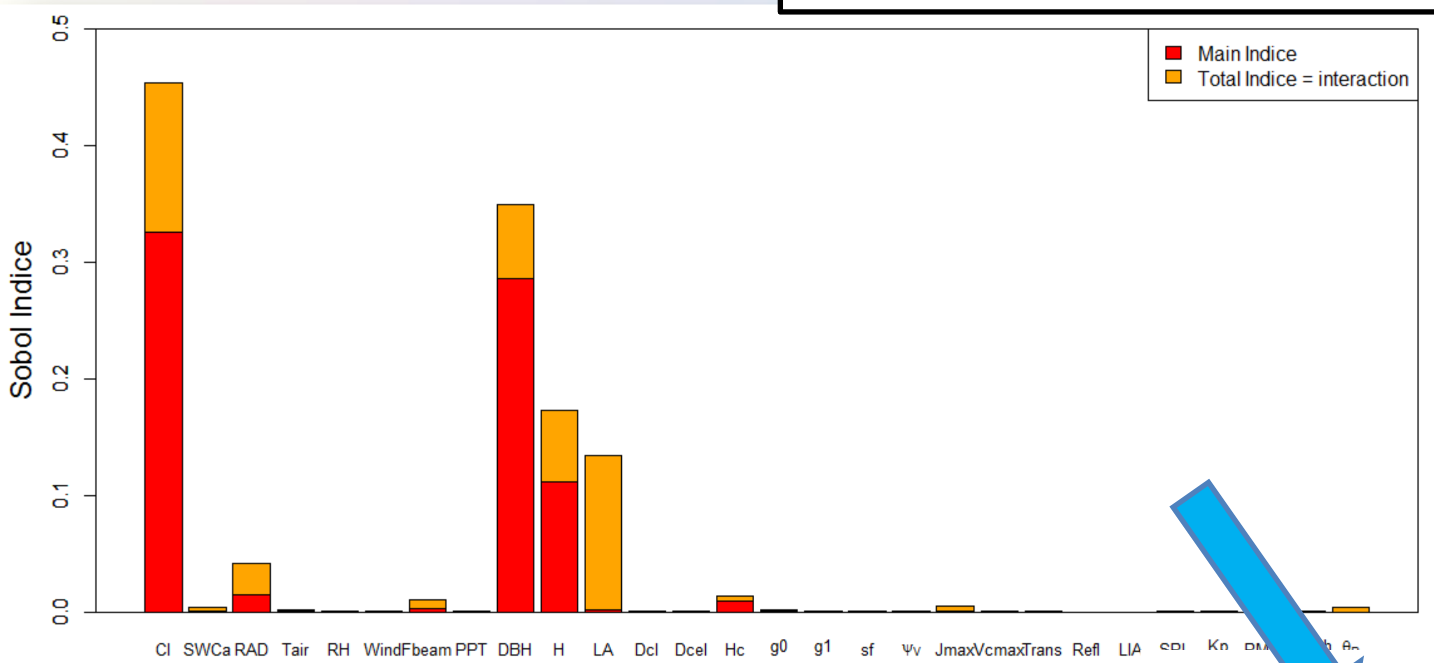
Tree transpiration, meta-model 2

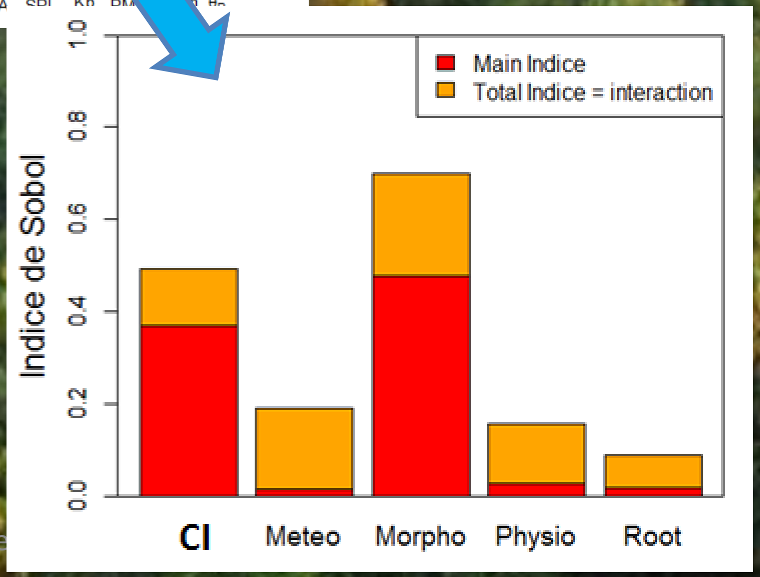




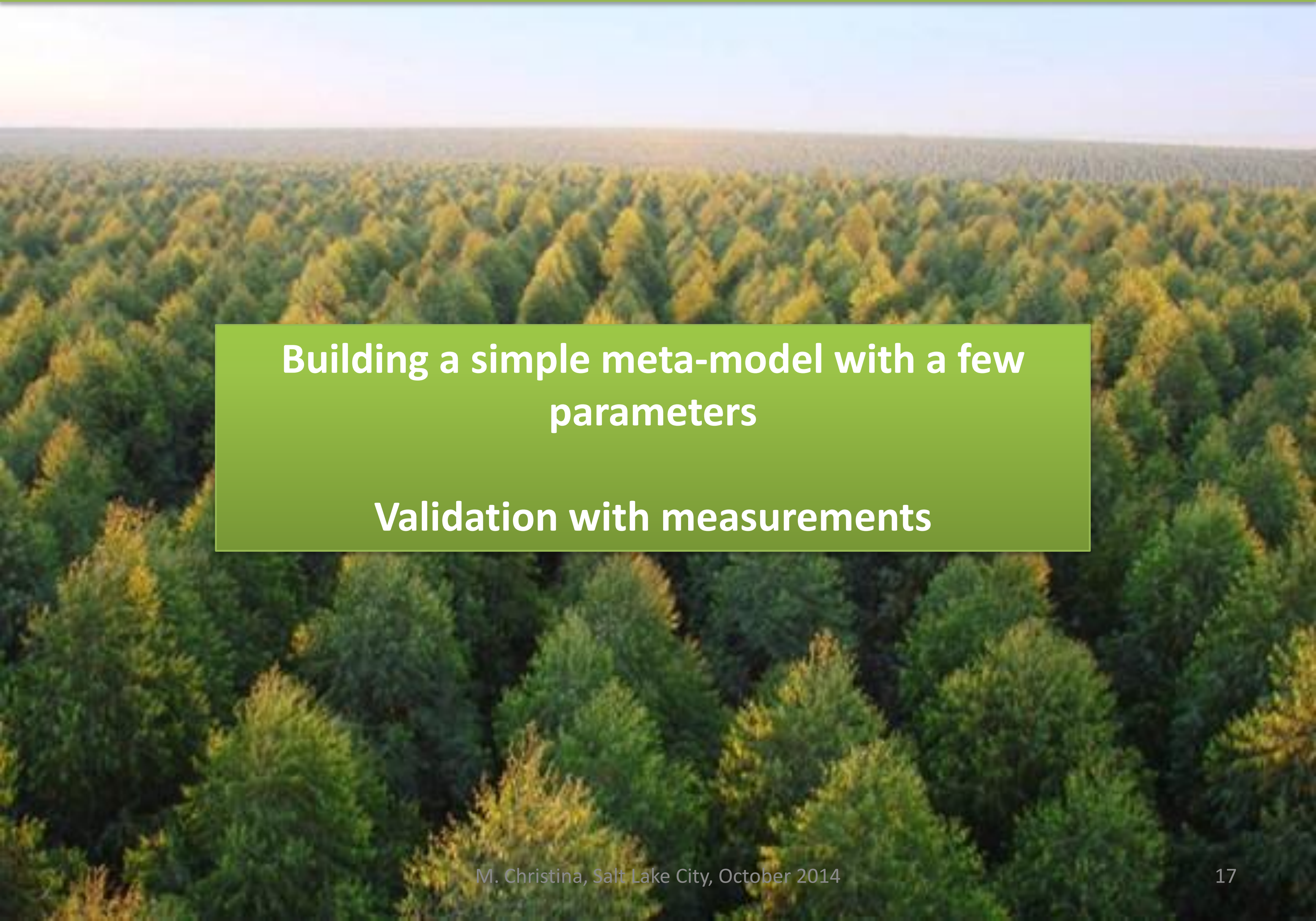
Sensitivity analysis of the meta-model 2, for GPP

Tree **GPP** meta-model 2, $R^2 = 0.89$





Simple predictive model of GPP and transpiration at the tree scale

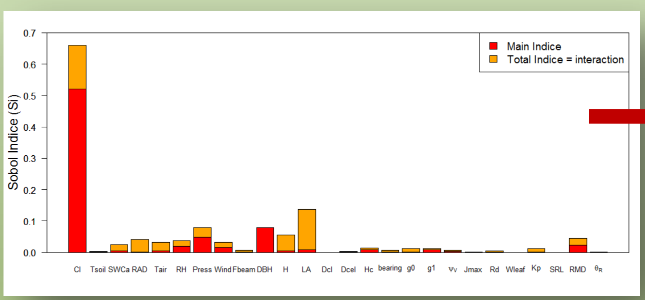


Building a simple meta-model with a few parameters

Validation with measurements

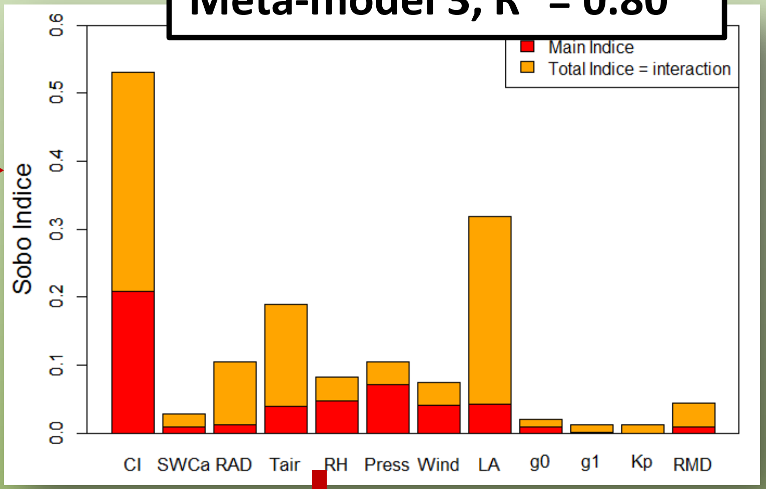
Simplified meta-model validation with sapflow measurements

Meta-model 2, R^2 = 0.85



Simplification based on Sobol indice values

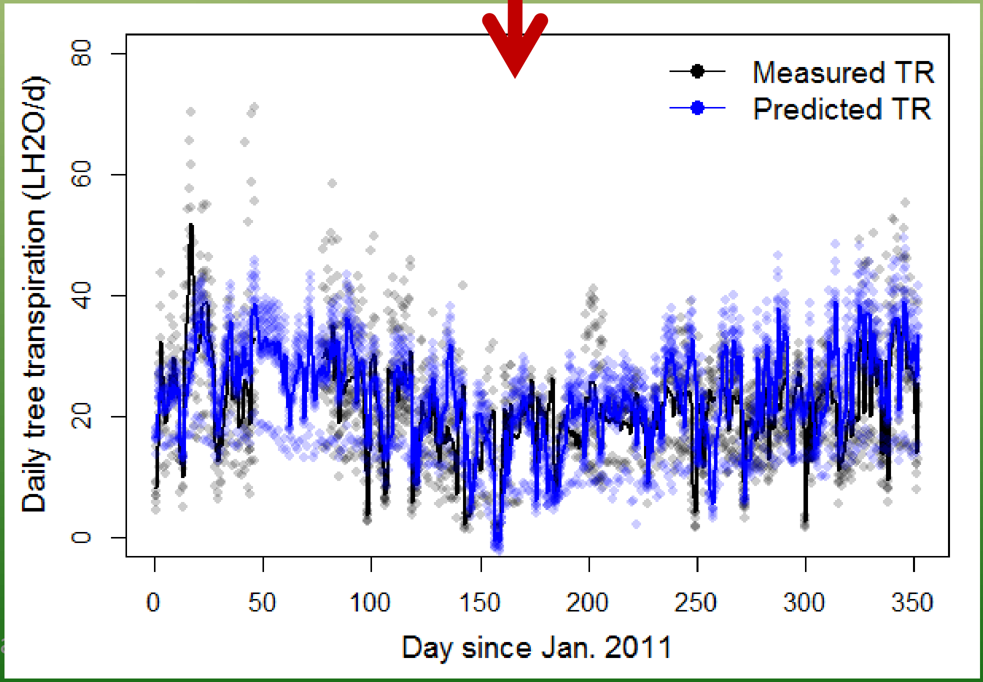
Meta-model 3, R^2 = 0.80



Site: Rainfall exclusion SP, Brazil

3ha *E. grandis* plantations

10 trees sap flux measurements over one year



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Simplified meta-model validation with sapflow measurements

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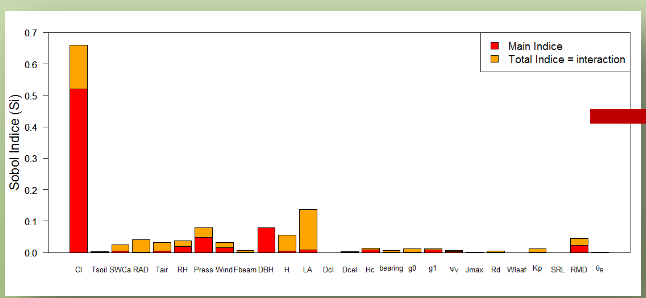

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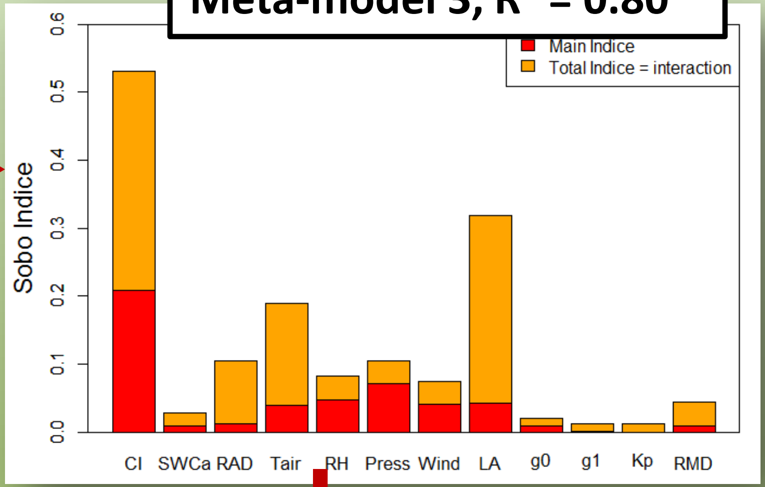
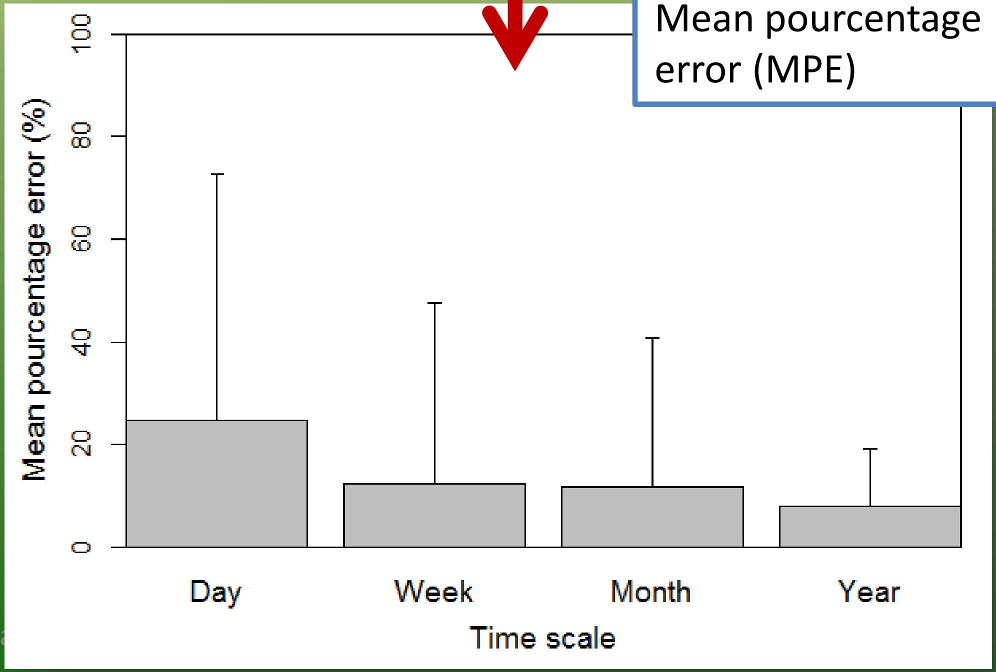


Site: Rainfall exclusion SP, Brazil
3ha *E. grandis* plantations
10 trees sap flux measurements over one year

Mean pourcentage error (MPE)



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CONCLUSION

→ Tree transpiration and gross photosynthesis are highly variable depending on tree traits, morphology and climate

→ Tree transpiration is driven by inter tree competition and the interaction between meteorology and tree traits in *Eucalyptus* plantations.

→ Tree GPP is essentially controlled by inter-tree competition and morphological tree traits.

→ Meta-modeling approaches provide good estimates of GPP and transpiration, at the tree and the stand scales, which could be useful for gap filling or showing tendencies.

Applications:

For example, use of simulated WUE and LUE for individual trees to optimize planting designs in mixed-species stands.


Thank you for your attention