GHG Breakfast Club

FOR POSTDOC & PhD

25 March 2022

3DForMod

Combining remote sensing and 3D forest modelling to improve tropical forests monitoring of greenhouse gases emissions

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FACCE ERA-GAS MONITORING & MITIGATION OF GREENHOUSE GASES FROM AGRI- AND SILVI-CULTURE

IRD Institut de Recherche pour le Développement FRANCE

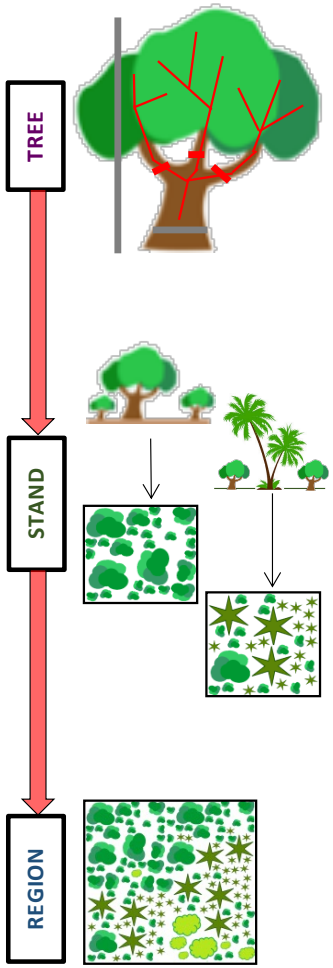
AMAP

WAGENINGEN UNIVERSITY & RESEARCH

UNIVERSITY OF TAMPERE

YAOUNDE UNIVERSITY

Project main objectives



Non-destructive approaches for tree-level biomass estimation (TLS, QSM, etc.) :

$AGB_{Tree} = f$ (Volume, Density)

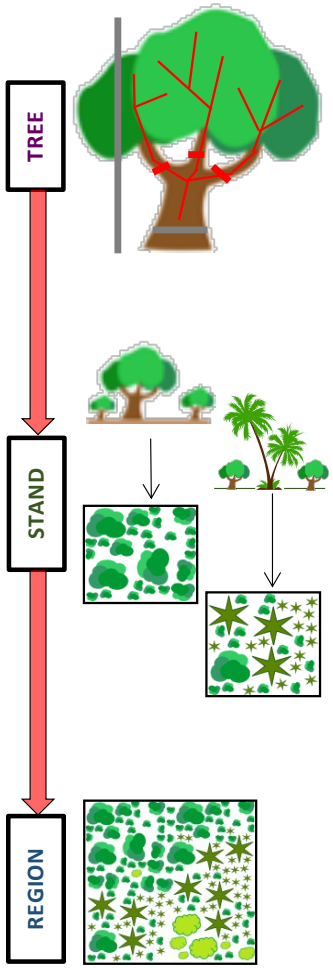
Allometric and RS models to link sensor and field data (plot-level):

$\Sigma AGB_{Tree} = f$ (RS signal)

Model inversion for large-scale biomass mapping:

f^{-1}(RS signal) = AGB

Project main objectives



Non destructive approaches for tree-level biomass estimation (TLS, QSM, etc.) :

$AGB_{Tree} = f$ **(Volume, Density)**

Allometric and RS models to link sensor and field data (plot-level):

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What is the actual performance of large-scale forest biomass mapping models?

Model inversion for large-scale biomass mapping:

f^{-1}**(RS signal) = AGB**

nature COMMUNICATIONS

ARTICLE

Check for updates

https://doi.org/10.1038/s41467-020-18321-y OPEN

Spatial validation reveals poor predictive performance of large-scale ecological mapping models

Pierre Ploton[1✉], Frédéric Mortier[2,3], Maxime Réjou-Méchain[1], Nicolas Barbier[1], Nicolas Picard[4], Vivien Rossi[5], Carsten Dormann[6], Guillaume Cornu[2,3], Gaëlle Viennois[1], Nicolas Bayol[7], Alexei Lyapustin[8], Sylvie Gourlet-Fleury[2,3] & Raphaël Pélissier[1]

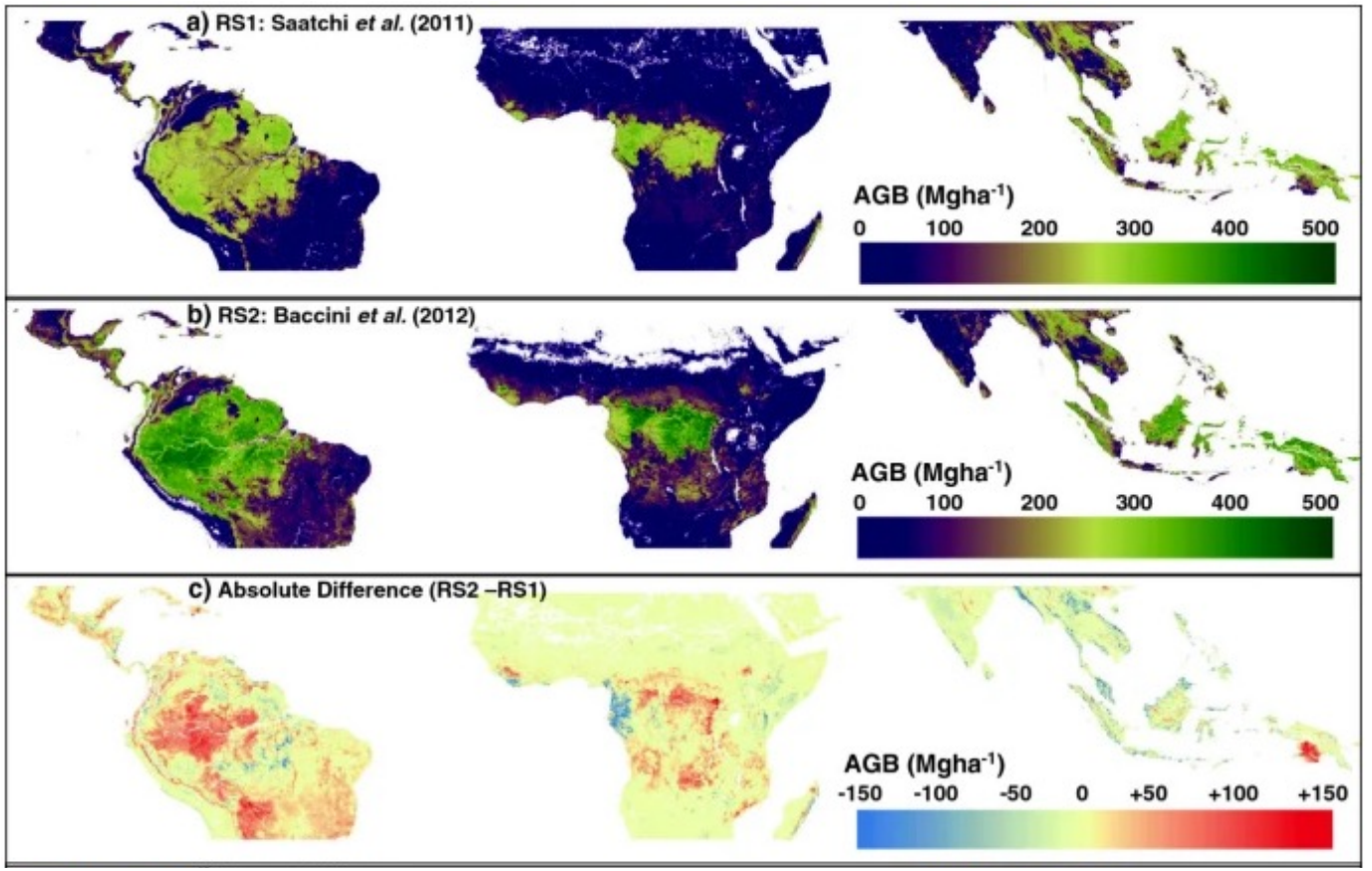
Mitchard *et al. Carbon Balance and Management* 2013, **8**:10
http://www.cbmjournal.com/content/8/1/10

CARBON BALANCE AND MANAGEMENT

RESEARCH Open Access

Uncertainty in the spatial distribution of tropical forest biomass: a comparison of pan-tropical maps

Edward TA Mitchard[1*], Sassan S Saatchi[2], Alessandro Baccini[3], Gregory P Asner[4], Scott J Goetz[3], Nancy L Harris[5] and Sandra Brown[5]

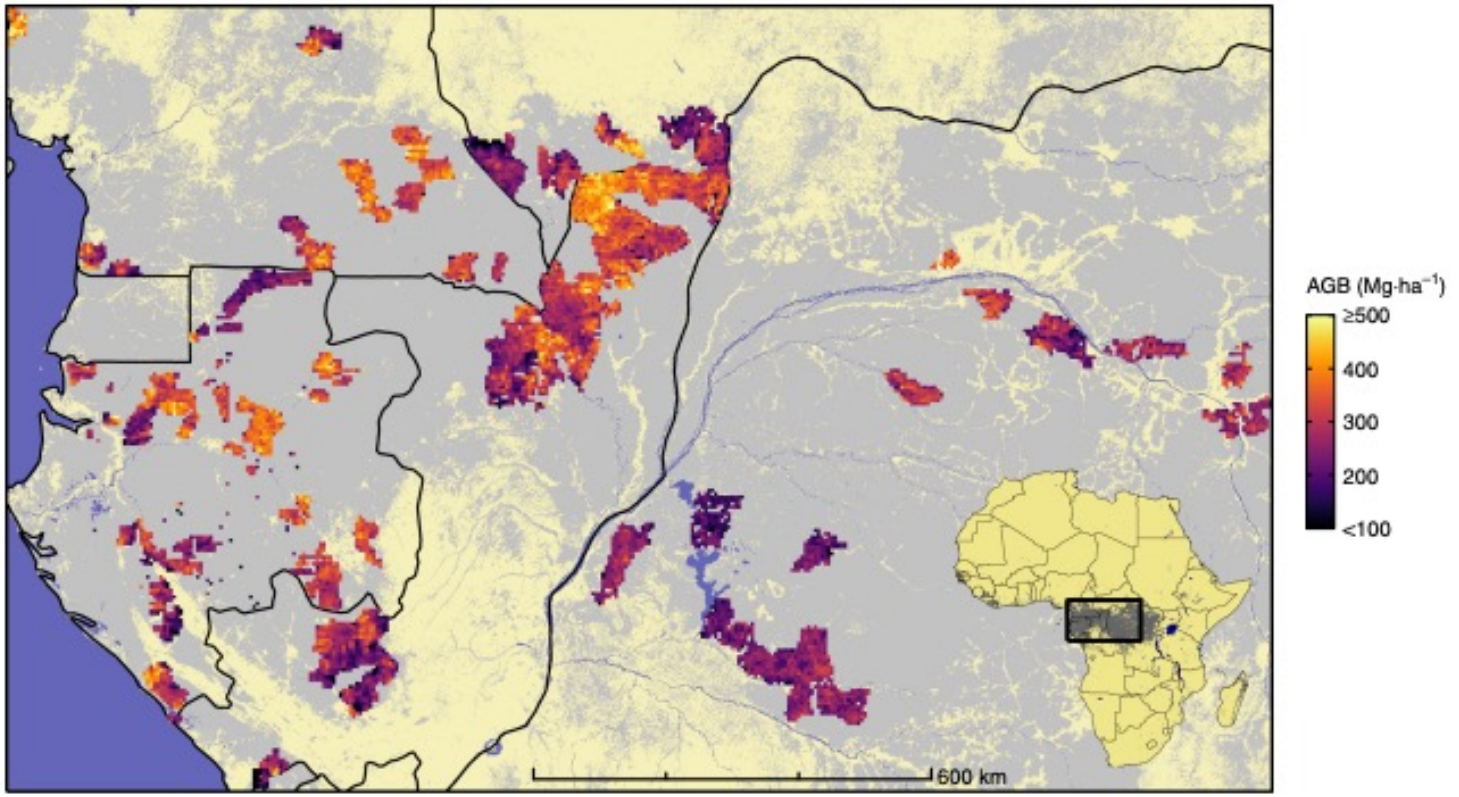


Commercial forest inventories from Central Africa (2000-2010): c. 100 000 ha; 1.8 Million trees

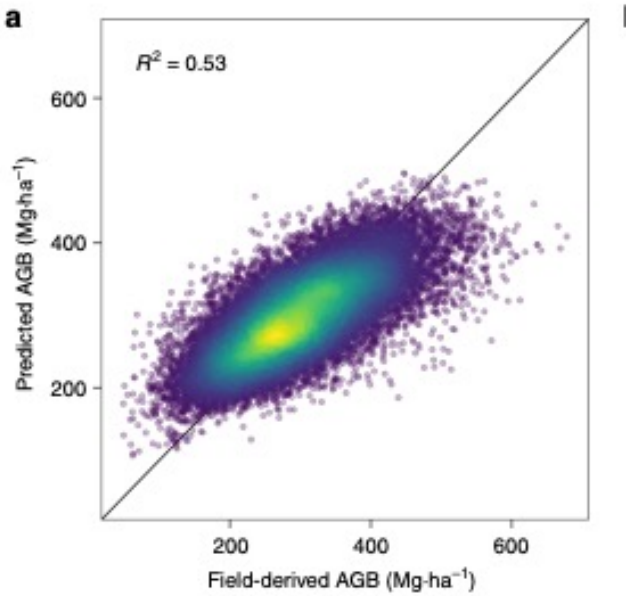
Above-Ground Biomass (AGB)
in 60 000 1-km^2 pixels

RF model with 22 predictors variables:
- Environmental layers (climate, topography, etc.)
- RS-derived vegetation indices (MODIS)

Wall-to-wall AGB map
at 1-km resolution

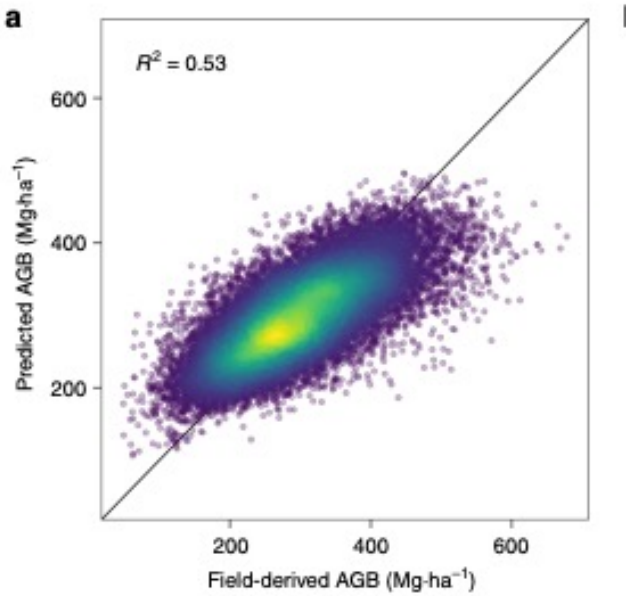


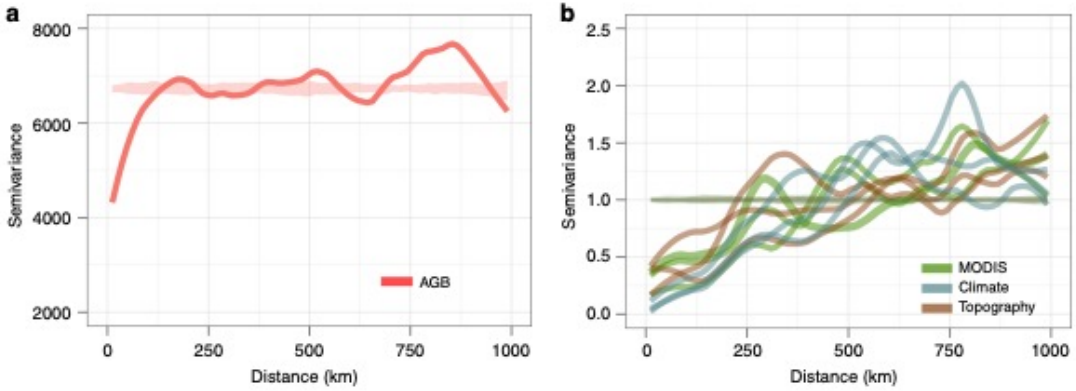
Random K-fold cross-validation
with 10% randomly selected test pixels



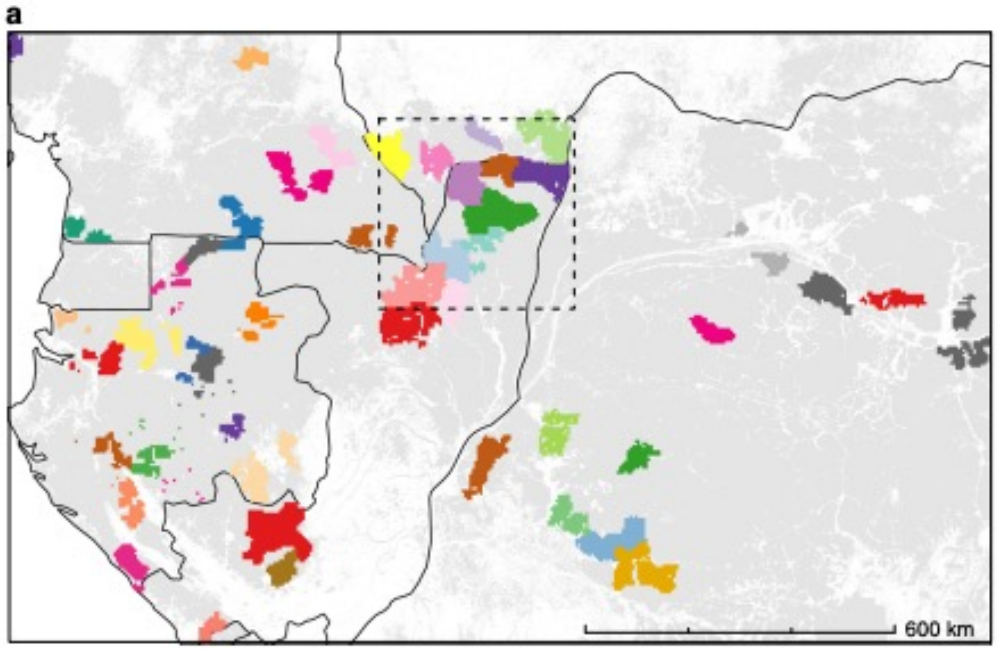
Random K-fold cross-validation
with 10% randomly selected test pixels

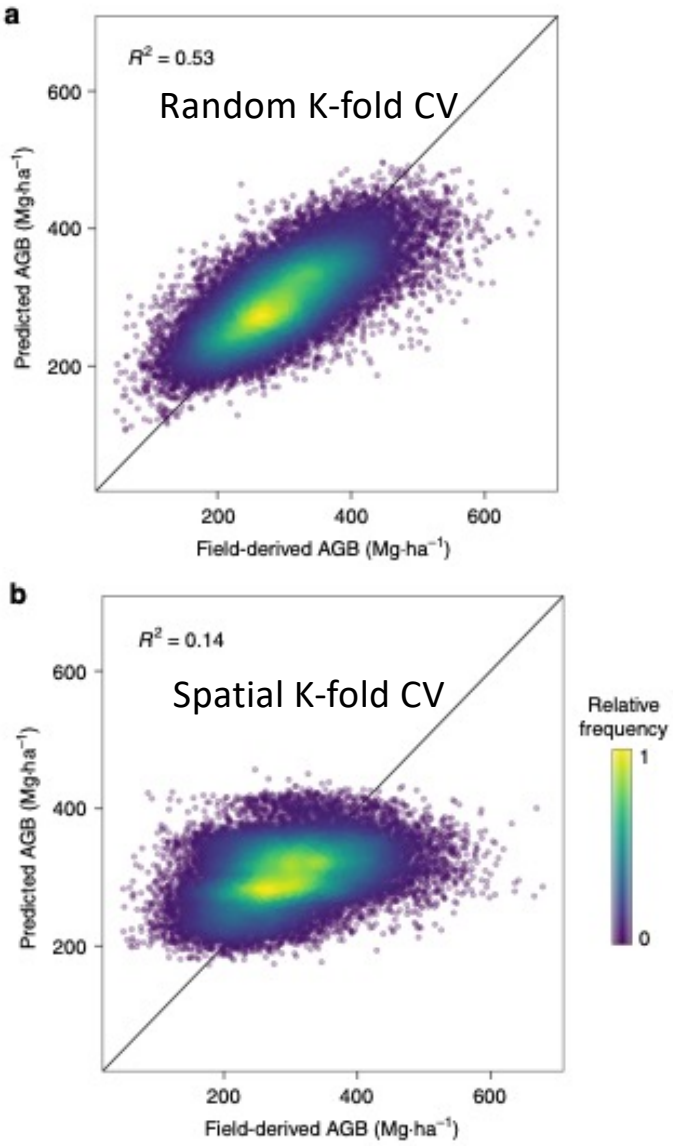
Spatial autocorrelation violate
independence between observations





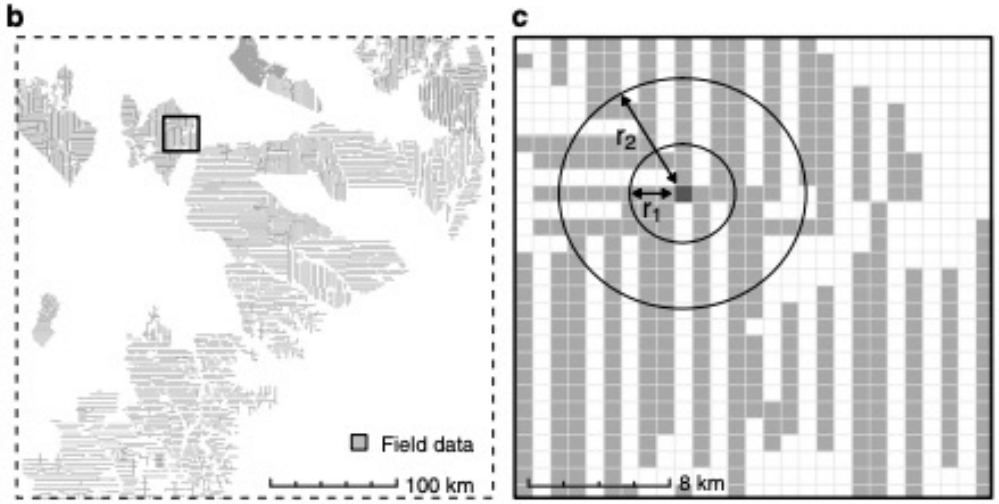
Spatial K-fold cross-validation (blocking)

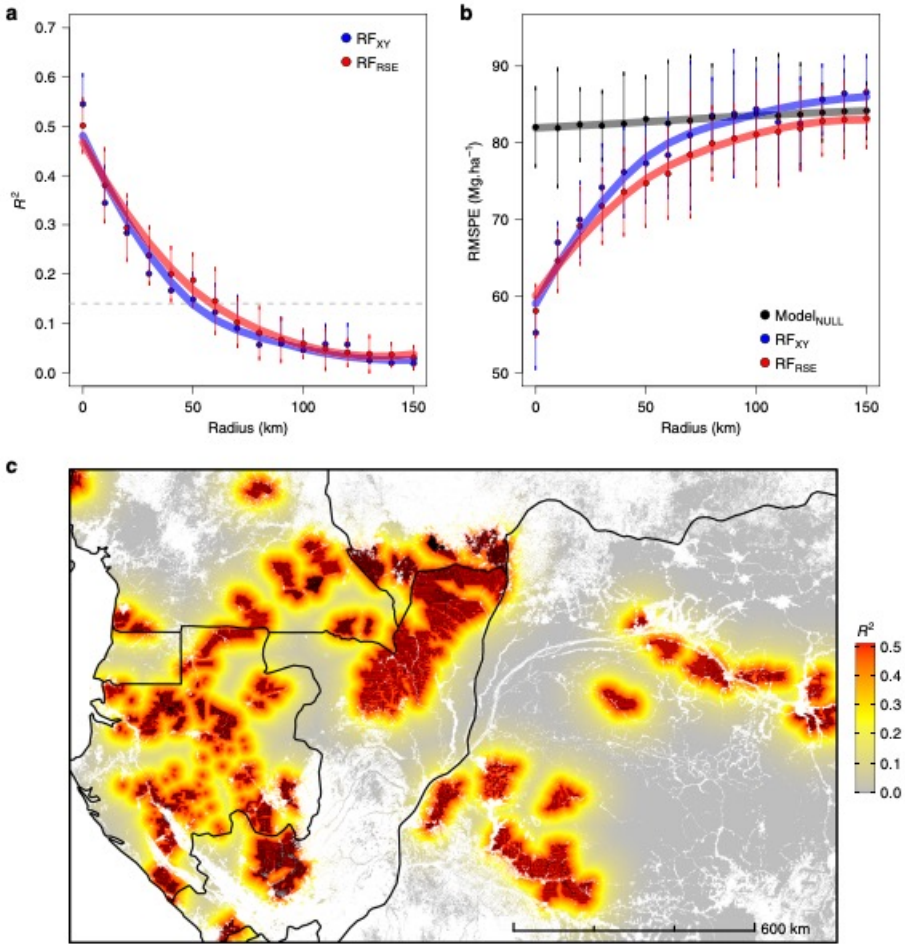


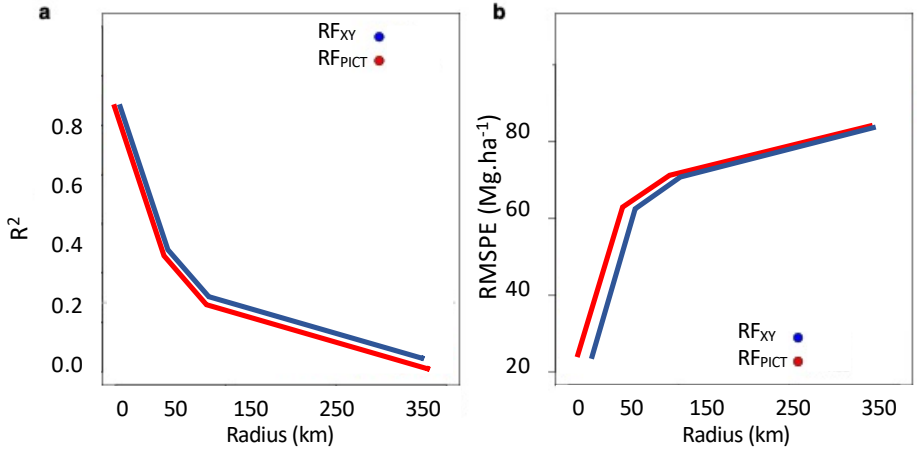


Buffer-Leave-One-Out cross-validation (B-LOO)

100 randomly selected test pixels + buffer (radius 10 to 150 kms)






a
RF$_{XY}$
RF$_{PICT}$
R^2
0.0
0.2
0.4
0.6
0.8
0
50
150
250
350
Radius (km)
b
RMSPE (Mg.ha^{-1})
20
40
60
80
RF$_{XY}$
RF$_{PICT}$
0
50
150
250
350
Radius (km)

Conclusion

• Biological processes are spatially autocorrelated for reasons independent from the environment (biotic interactions, dispersal, etc.)

• By multiplying spatial combinations of predictors, RF (ML?) creates local overfitting, i.e. predict well local spatial configurations not determined by the environmental predictors

• Spatial cross-validation is mandatory to asses the predictive performance of spatial models

• We still miss the main drivers of tropical forest above-ground biomass 😟

http://3dformod.free.fr/