Spatial distribution of soil organic carbon stocks in France

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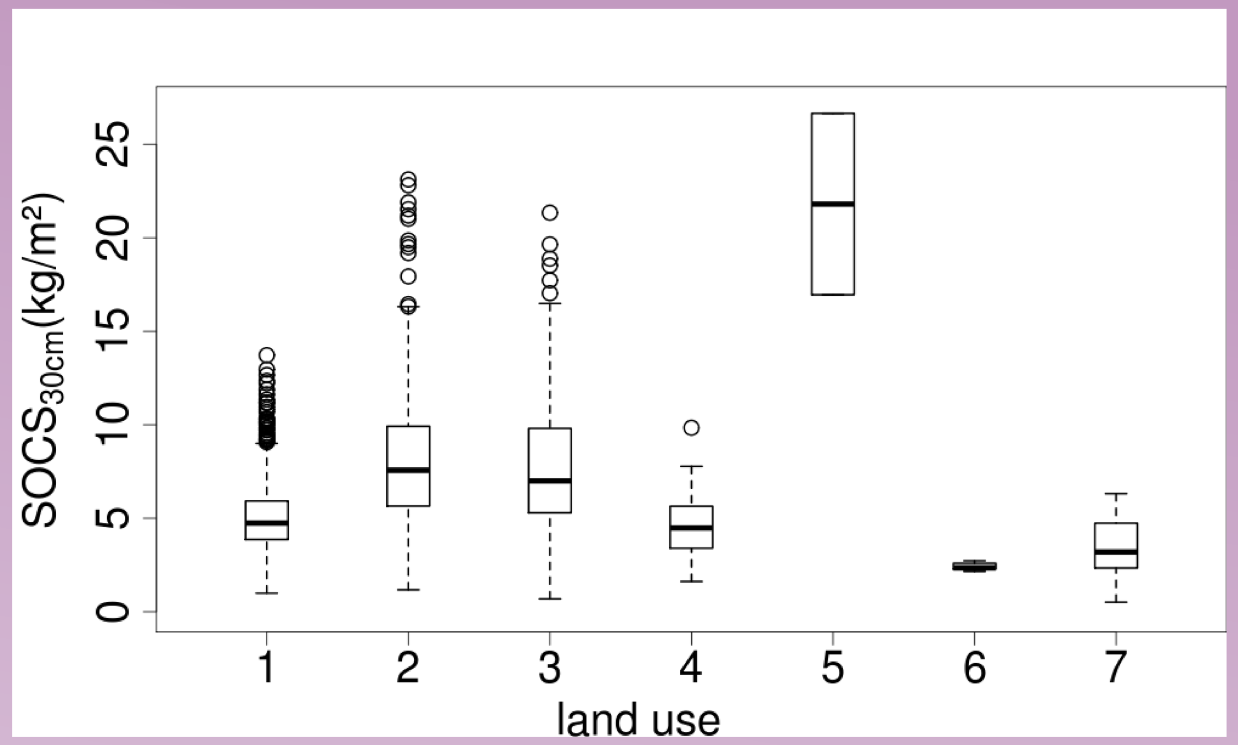
Introduction

The French soil monitoring network has been established on a 16x16km grid and the first sampling campaign has recently been completed, providing around 2200 measurements of stocks of soil organic carbon, obtained through an in situ composite sampling, uniformly distributed over the French territory. We calibrated a boosted regression tree model on the observed stocks, modelling SOC stocks as a function of other variables such as climatic parameters, vegetation net primary productivity, soil properties and land use. The calibrated model was evaluated through cross-validation and eventually used for estimating SOC stocks for mainland France.

Distribution of the 1974 sites within the French monitoring network which were used in the present study.



SOC stocks for the first 30cm as a function of land cover type according to the adapted IPCC land use classification (various crops (1, n=817), permanent grasslands (2, n=463), woodlands (3, n=468) orchards and shrubby perennial crops (4, n=18), wetlands (5, n=2), others(6, n=5), vineyards (7, n=32)).

Material and methods

Data associated with the point SOC estimates:

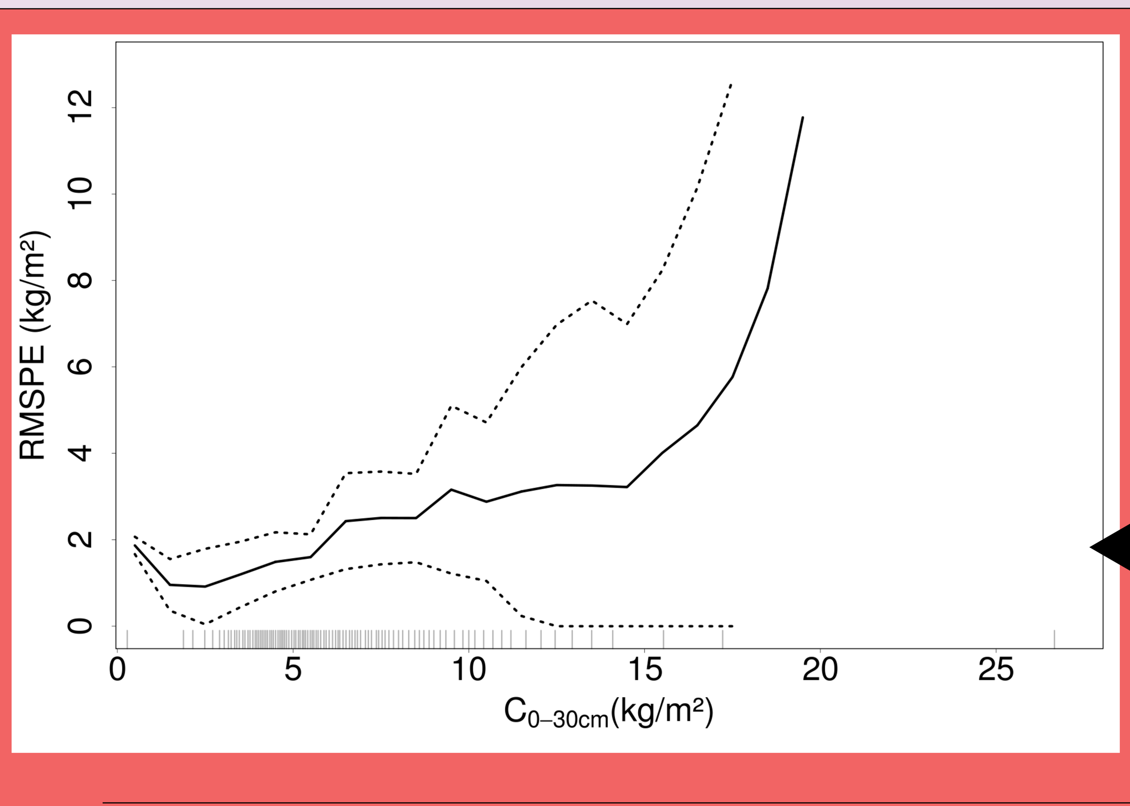
-In situ observed land use and soil properties; Climate and net primary productivity (NPP) values at each location (x_i,y_i) of the RMQS sites, estimated from the maps used for continuous spatial prediction; Mineralization coefficients as estimated by the RothC model.

Data used for continuous spatial prediction:

NPP : Modis data, 1km resolution, averaged over the 2000-2007 period; Land use : Teruti, departmental (infra-regional) resolution, for the year 2004; Clay content : 1/1 000 000 European soil map; climatic data : interpollated climatic data, averaged for the 1992-2004 period, on a 12x12km² grid; mineralization modifiers : estimated from pedo-climatic and land cover data

Three Boosted Regression Trees models were fitted using the R gbm package

- the Cult model: lu1, lu2 and lu3 (land use coded according to, respectively, the L1, L2 and L3 RMQS land cover classifications), clay (%), silt (%), rf (rock fragments, mass percentage), potential evapotranspiration (pet, mm/month) monthly precipitation (rain, mm/month), temperature (temp, °C), pH, wregime (water-regime), wlogging (water-logging), the two RothC mineralization modifiers, a and b and the net primary productivity (npp, gC/m²/yr).
- the F model : it shared the same predictors without the lu1 predictor.
- the Extra model: lu_ipcc (land use classification adapted from the IPCC guidelines, 2006), clay, pet, rain, temp, a, b and npp.



Validation of the models

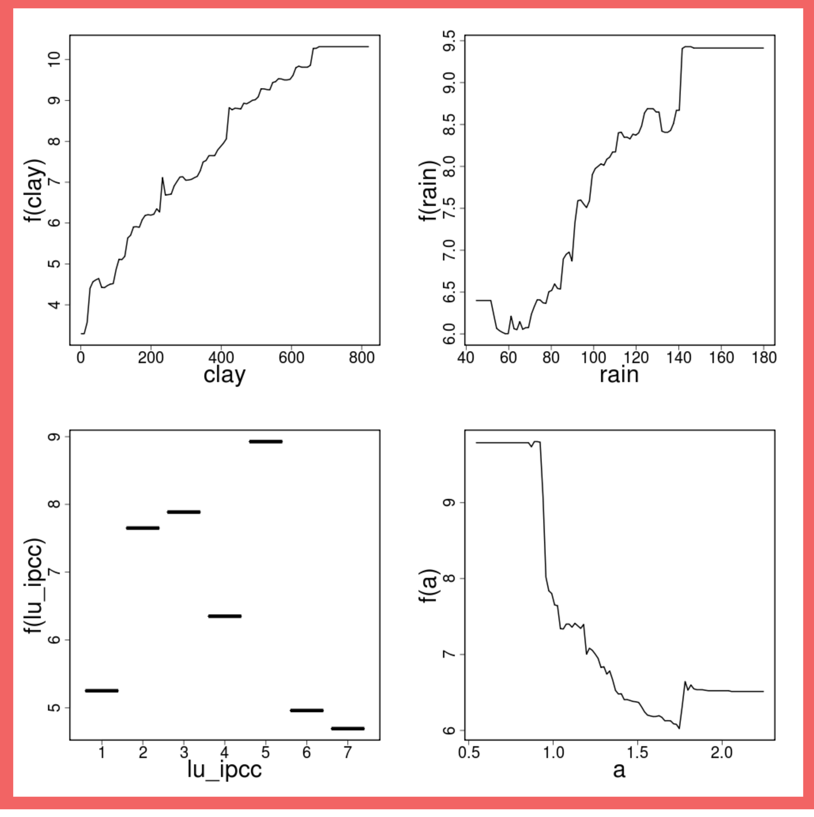
Fit and cross validation results for a ratio of 0.9/0.1 training vs. validation datasets. Quality of the fit on the full data set is expressed using R², mean prediction error (MPE, kg/m²), standard deviation of the prediction error (SDPE, kg/m²), and root mean square prediction error (RMSPE, kg/m²).

The cross-validation results are expressed using R^2_{ext}, MPE_{ext} (kg/m²), $SDPE_{ext}$ (kg/m²) and $RMSPE_{ext}$ (kg/m²) estimated using the validation datasets. The 95% confidence intervals obtained for the corresponding normal distributions using the standard percentile method are given in brackets.

Model	R^2	MPE	SDPE	RMSPE	$\langle R^2_{ext} \rangle$		$\langle MPE_{ext} \rangle$		$\langle SDPE_{ext} \rangle$		$\langle RMSPE_{ext} \rangle$	
Cult	0.91	−0.001	0.935	0.934	0.58	[0.445, 0.723]	−0.041	[−0.379, 0.297]	1.94	[1.481, 2.397]	1.94	[1.486, 2.395]
F	0.74	2e-04	1.912	1.910	0.36	[0.141, 0.57]	−0.009	[−0.845, 0.827]	2.75	[2.036, 3.467]	2.76	[2.053, 3.459]
Extra	0.73	−0.001	1.727	1.727	0.5	[0.386, 0.613]	−0.002	[−0.348, 0.344]	2.27	[1.86, 2.68]	2.27	[1.862, 2.68]

Results

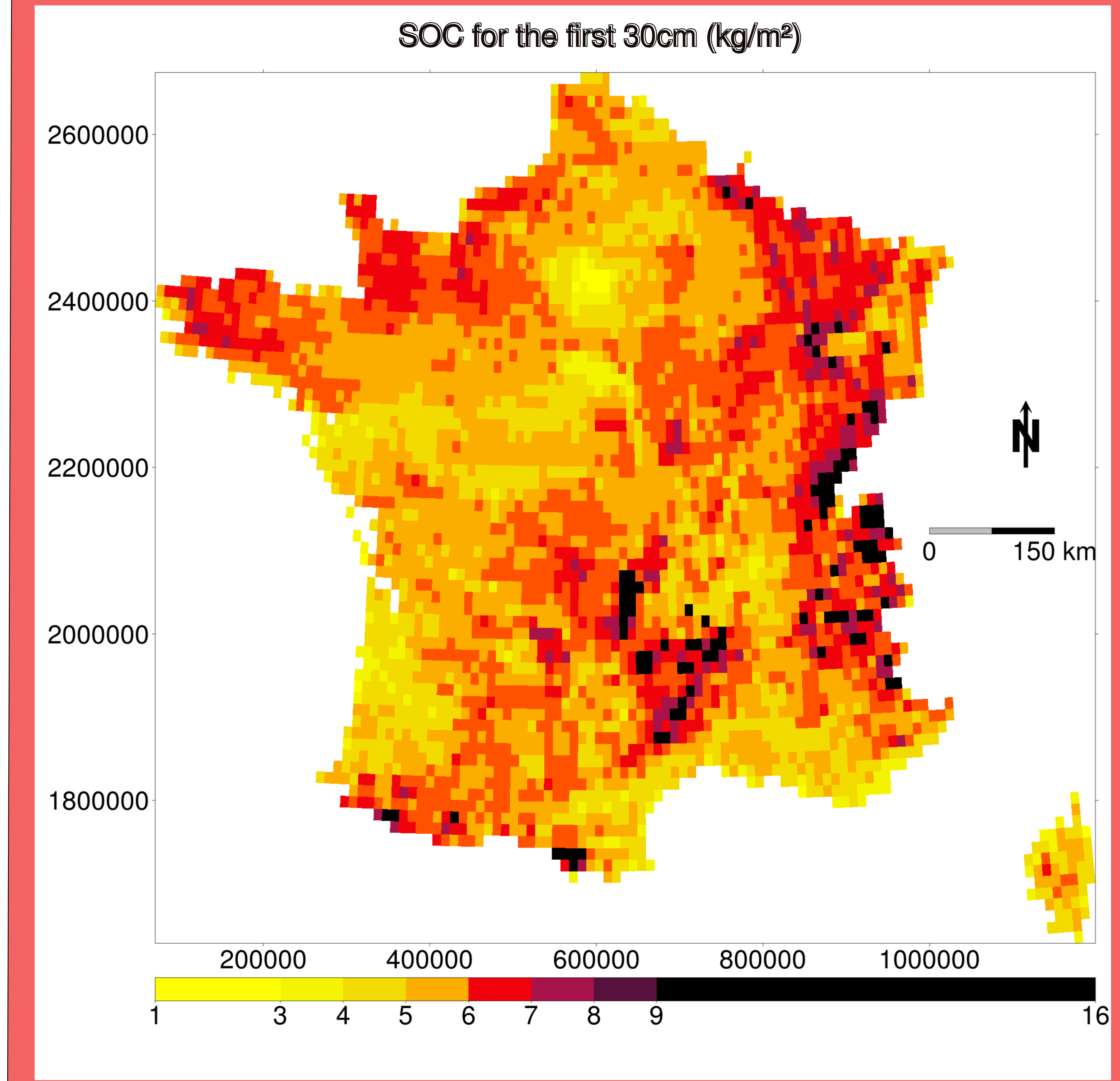
Effect of the different variables



The nature of the dependence between the predictors and the response variable can be assessed by using average or partial dependence plots. Put it briefly, they represent the effect of a set of selected predictors (usually 1 to 3)on the modelled response variable after accounting for the effects or the remaining (not selected) predictors.

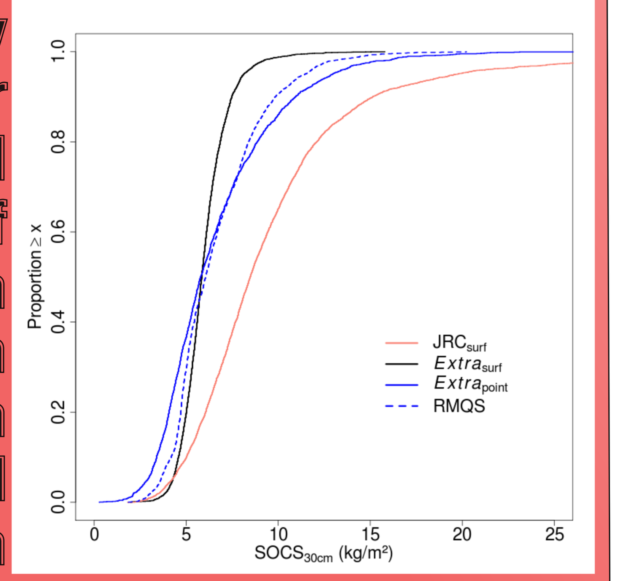
	Cult model		F model		Extra model	
redictor	VIM	rank	VIM	rank	VIM	rank
lu3	33.66	1	0.77	11	–	–
lu2	1.26	13	0.00	14	–	–
lu1	0.11	15	–	–	–	–
lu_ipcc	0	16	–	–	26.83	2
a	7.1	3	1.47	10	8.76	4
b	3.72	7	4.83	7	6.53	6
rain	6.6	4	13.27	3	10.66	3
pet	3.3	8	4.4	8	5.73	7
temp	3.03	9	1.83	9	6.77	5
npp	2.89	10	6.54	5	5.33	8
wlogging	1.34	12	0.06	12	–	–
wregime	1.14	14	0.03	13	–	–
rf	6.08	5	8	4	–	–
clay	22.55	2	29.55	1	29.4	1
silt	1.96	11	5.91	6	–	–
ph	5.26	6	23.35	2	–	–

Relative influences of the predictors for each model, expressed as variable importance indexes (VIM), and rank according to the VIM values.The predictors are grouped, starting with the variables related to land use, then related to the climatic or pedo-climatic factors,then to plant productivity and finally related to the soil properties only.



- The modelled relationships between SOC strongly depended on the land use, and more specifically differed between forest soils and cultivated soils.

- A new estimate for the spatial distributon of SOC stocks in the top 30cm of soils in France, based on the French monitoring network (RMQS) : 3.260±0.872 PgC



- To be compared to another estimate based on the previously published European octop maps : 5.303 PgC.

Conclusion/Perspectives

- The RMQS datasets are provided by a sampling scheme which ensures an efficient treatment of the spatial variability of SOC, both locally (through composite sampling) and of over a larger extent (through the use of a regular 16x6km² grid) and it provides bulk densities.
- BRTs have been confirmed here as being robust tools for predicting SOC stocks.

Future work :
- refinement of spatial data layers of soil and land use will be a critical step for improving SOC stocks assessments at the country level.
- inclusion of topography, pH as SOC predictors.