Designing soil monitoring schemes for large areas based on digital soil mapping products

Alex B. Mcbratney, Jaap de Gruijter, Nicolas N. Saby, Budiman Minasny

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Designing soil monitoring schemes for large areas based on digital soil mapping products

- Alex McBratney, Nicolas Saby,
- Jaap de Gruijter, Budiman Minasny

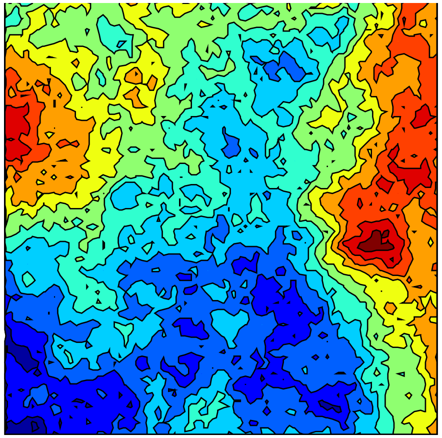
DSM & Soil Monitoring

- Digital soil maps have been produced at continental, country and regional extents.

- These maps of soil properties along with their uncertainty can be used to establish strata for soil monitoring.

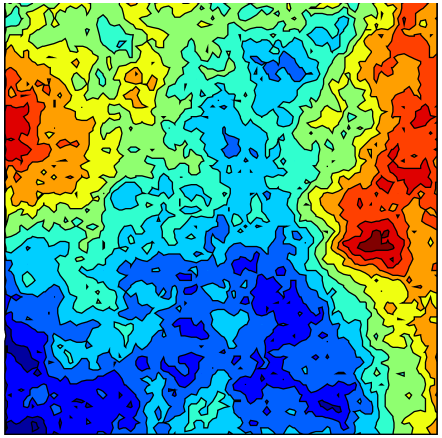
HOW?

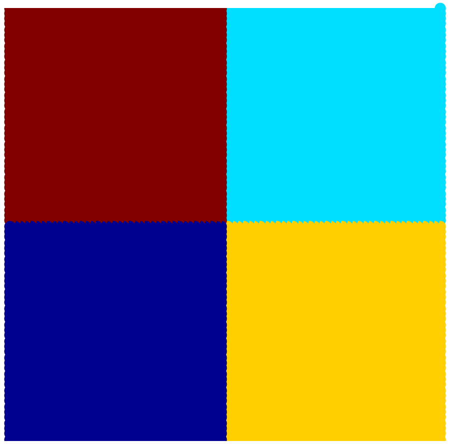
Map of prediction of target variable



How to stratify?

Map of prediction of target variable

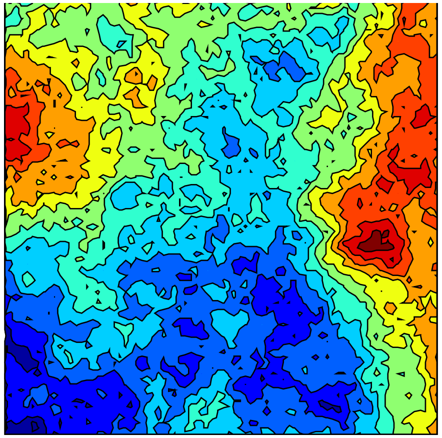


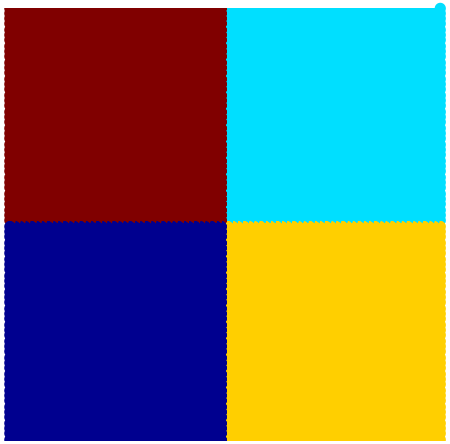


compact geographical stratification
K-means, minimise the mean of the
shortest distance

How to stratify?

Map of prediction of target variable





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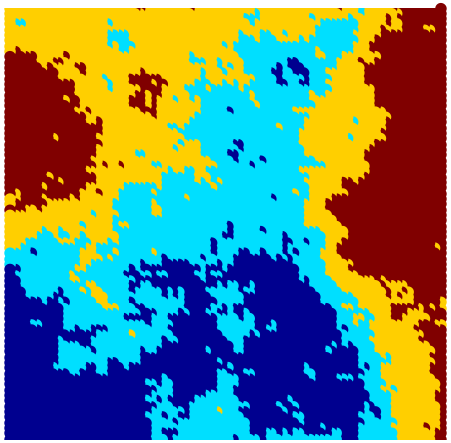


Minimise sampling variance
Cum √f method
(Dalenius and Hodges, 1959)

The two extremes

1. No prior information at all? (Brus et al. 2003)

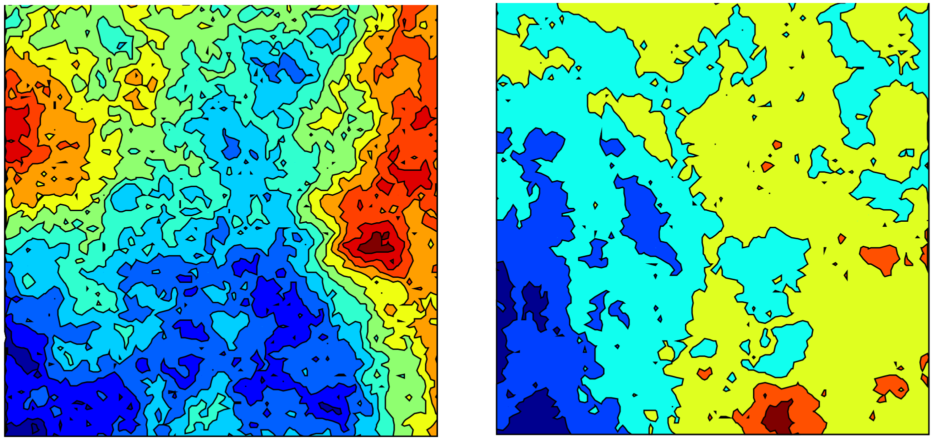
$$J_{\mathrm{MSSD}} = \frac{1}{N} \sum_{i=1}^{N} \min_{j} \left(D_{ij}^{2} \right) \ .$$

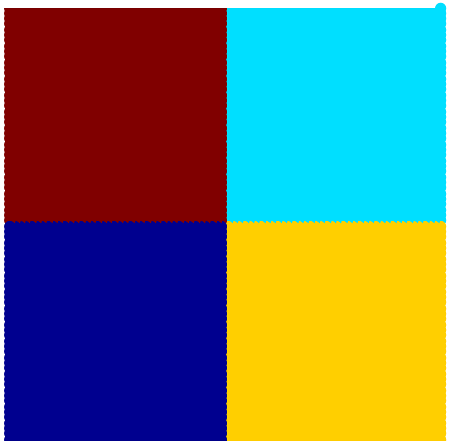
2. No spatial context, assume implicitly that th

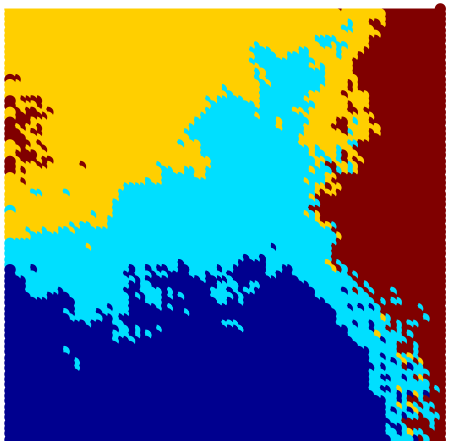
$$V(\hat{\bar{z}}) = \sum_{h=1}^{H} (N_h/N)^2 \cdot V(\hat{\bar{z}}_h) = \sum_{h=1}^{H} (N_h/N)^2 \cdot S_h/n_h$$

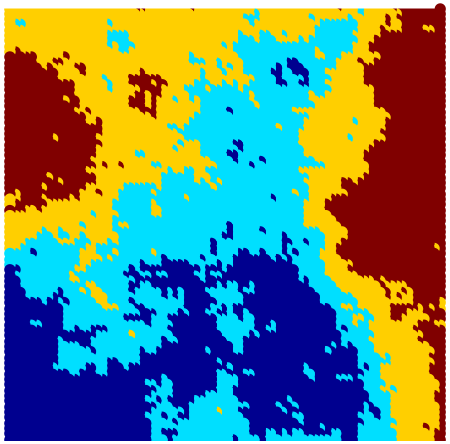
rors,

Optimal stratification (Ospats)


Map of prediction of target variable & uncertainty


compact geographical stratification


OSPATS


Minimise sampling variance

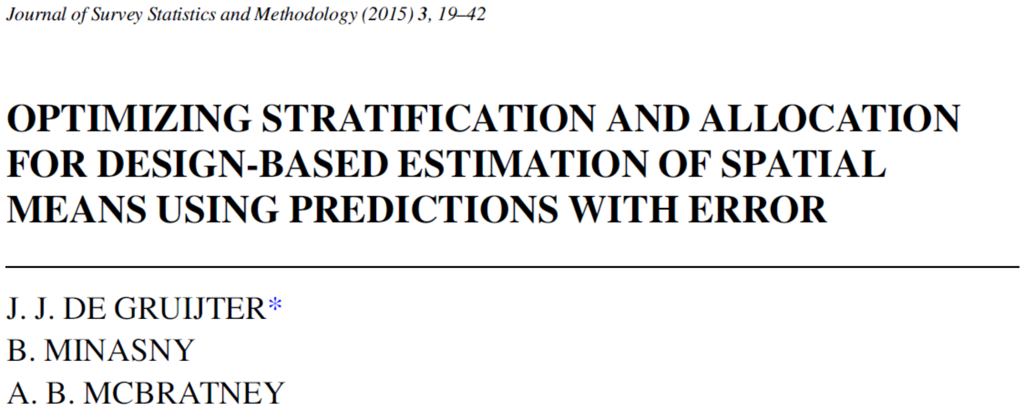
Optimal stratification (OSPATS)
de Gruijter et al. 2015

$$O = \sum_{h=1}^{H} \left\{ \sum_{i=1}^{N_h - 1} \sum_{j=i+1}^{N_h} d_{ij}^2 \right\}^{1/2}$$

$$d_{ij}^2 \text{ for } (z_i - z_j)^2$$

$$D_{ij}^2 = \mathrm{E}_\xi(\tilde{z}_i - \tilde{z}_j)^2 = (\tilde{z}_i - \tilde{z}_j)^2 + \mathrm{E}_\xi(e_i - e_j)^2$$

Predictor $$D_{ij}^2 = (\tilde{z}_i - \tilde{z}_j)^2 + V(\tilde{z}_i) + V(\tilde{z}_j) - 2\,\mathrm{Cov}(e_i, e_j)$$



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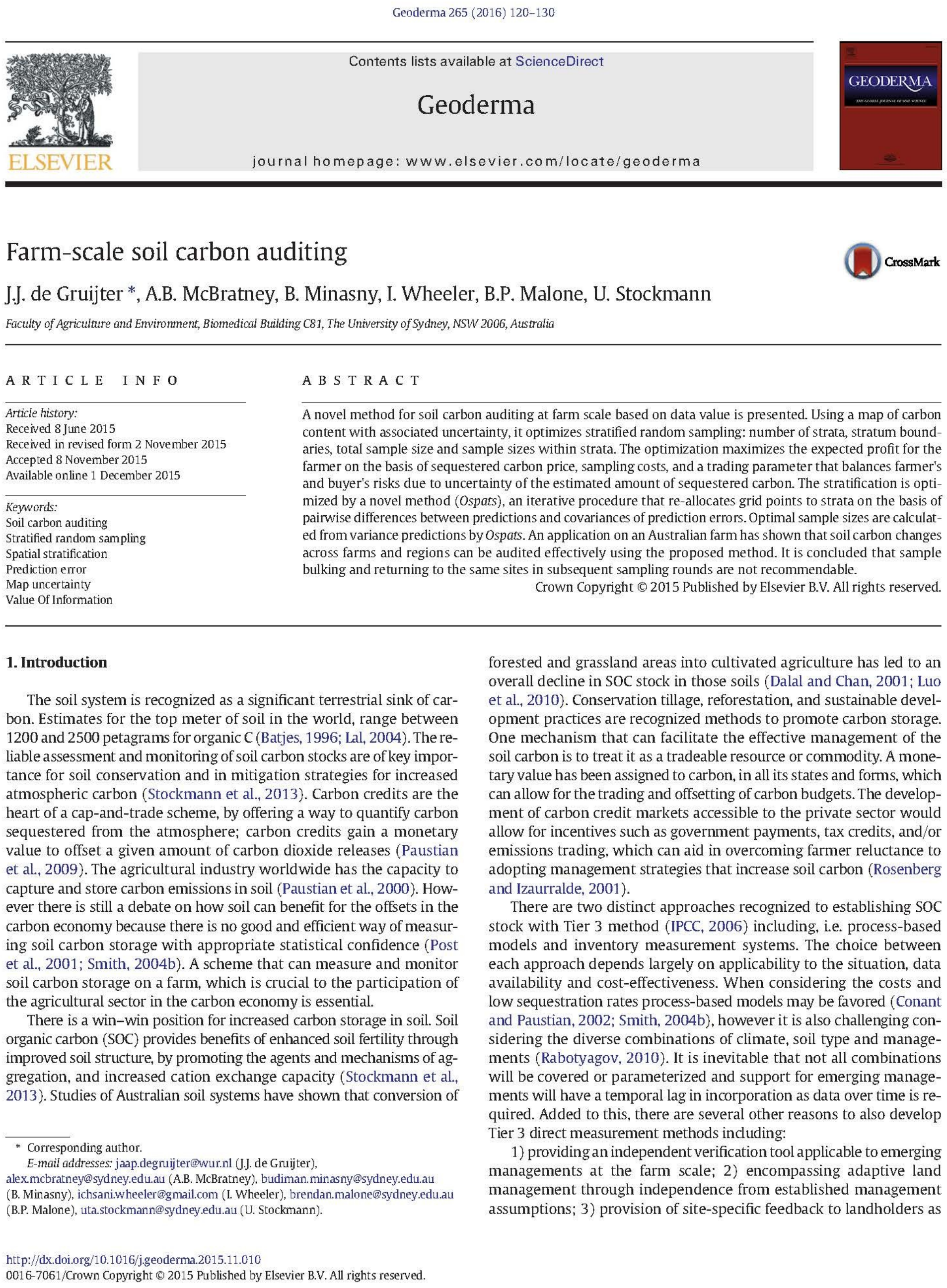
OPTIMIZING STRATIFICATION AND ALLOCATION FOR DESIGN-BASED ESTIMATION OF SPATIAL MEANS USING PREDICTIONS WITH ERROR

J. J. DE GRUIJTER*
B. MINASNY
A. B. MCBRATNEY

Designed for small extents



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Farm-scale soil carbon auditing

J.J. de Gruijter *, A.B. McBratney, B. Minasny, I. Wheeler, B.P. Malone, U. Stockmann

Faculty of Agriculture and Environment, Biomedical Building C81, The University of Sydney, NSW 2006, Australia

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ABSTRACT

A novel method for soil carbon auditing at farm scale based on data value is presented. Using a map of carbon content with associated uncertainty, it optimizes stratified random sampling: number of strata, stratum boundaries, total sample size and sample sizes within strata. The optimization maximizes the expected profit for the farmer on the basis of sequestered carbon price, sampling costs, and a trading parameter that balances farmer's and buyer's risks due to uncertainty of the estimated amount of sequestered carbon. The stratification is optimized by a novel method (*Ospats*), an iterative procedure that re-allocates grid points to strata on the basis of pairwise differences between predictions and covariances of prediction errors. Optimal sample sizes are calculated from variance predictions by *Ospats*. An application on an Australian farm has shown that soil carbon changes across farms and regions can be audited effectively using the proposed method. It is concluded that sample bulking and returning to the same sites in subsequent sampling rounds are not recommendable.

1. Introduction

The soil system is recognized as a significant terrestrial sink of carbon. Estimates for the top meter of soil in the world, range between 1200 and 2500 petagrams for organic C (Batjes, 1996; Lal, 2004). The reliable assessment and monitoring of soil carbon stocks are of key importance for soil conservation and in mitigation strategies for increased atmospheric carbon (Stockmann et al., 2013). Carbon credits are the heart of a cap-and-trade scheme, by offering a way to quantify carbon sequestered from the atmosphere; carbon credits gain a monetary value to offset a given amount of carbon dioxide releases (Paustian et al., 2009). The agricultural industry worldwide has the capacity to capture and store carbon emissions in soil (Paustian et al., 2000). However there is still a debate on how soil can benefit for the offsets in the carbon economy because there is no good and efficient way of measuring soil carbon storage with appropriate statistical confidence (Post et al., 2001; Smith, 2004b). A scheme that can measure and monitor soil carbon storage on a farm, which is crucial to the participation of the agricultural sector in the carbon economy is essential.

There is a win–win position for increased carbon storage in soil. Soil organic carbon (SOC) provides benefits of enhanced soil fertility through improved soil structure, by promoting the agents and mechanisms of aggregation, and increased cation exchange capacity (Stockmann et al., 2013). Studies of Australian soil systems have shown that conversion of forested and grassland areas into cultivated agriculture has led to an overall decline in SOC stock in those soils (Dalal and Chan, 2001; Luo et al., 2010). Conservation tillage, reforestation, and sustainable development practices are recognized methods to promote carbon storage. One mechanism that can facilitate the effective management of the soil carbon is to treat it as a tradeable resource or commodity. A monetary value has been assigned to carbon, in all its states and forms, which can allow for the trading and offsetting of carbon budgets. The development of carbon credit markets accessible to the private sector would allow for incentives such as government payments, tax credits, and/or emissions trading, which can aid in overcoming farmer reluctance to adopting management strategies that increase soil carbon (Rosenberg and Izaurralde, 2001).

There are two distinct approaches recognized to establishing SOC stock with Tier 3 method (IPCC, 2006) including, i.e. process-based models and inventory measurement systems. The choice between each approach depends largely on applicability to the situation, data availability and cost-effectiveness. When considering the costs and low sequestration rates process-based models may be favored (Conant and Paustian, 2002; Smith, 2004b), however it is also challenging considering the diverse combinations of climate, soil type and managements (Rabotyagov, 2010). It is inevitable that not all combinations will be covered or parameterized and support for emerging managements will have a temporal lag in incorporation as data over time is required. Added to this, there are several other reasons to also develop Tier 3 direct measurement methods including:

1) providing an independent verification tool applicable to emerging managements at the farm scale; 2) encompassing adaptive land management through independence from established management assumptions; 3) provision of site-specific feedback to landholders as

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* Corresponding author.
E-mail addresses: jaap.degruijter@wur.nl (J.J. de Gruijter), alex.mcbratney@sydney.edu.au (A.B. McBratney), budiman.minasny@sydney.edu.au (B. Minasny), ichsani.wheeler@gmail.com (I. Wheeler), brendan.malone@sydney.edu.au (B.P. Malone), uta.stockmann@sydney.edu.au (U. Stockmann).

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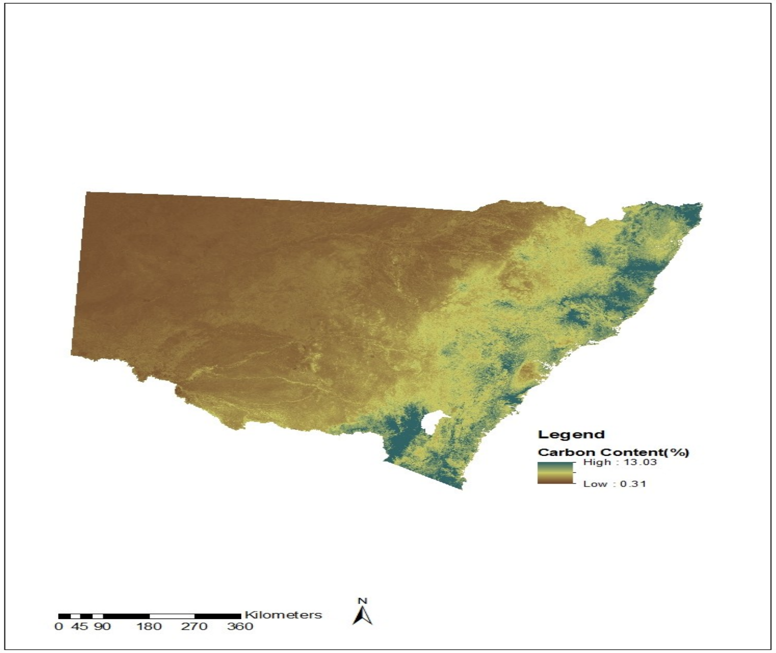
See talk by Hedley et al. for an example from New Zealand

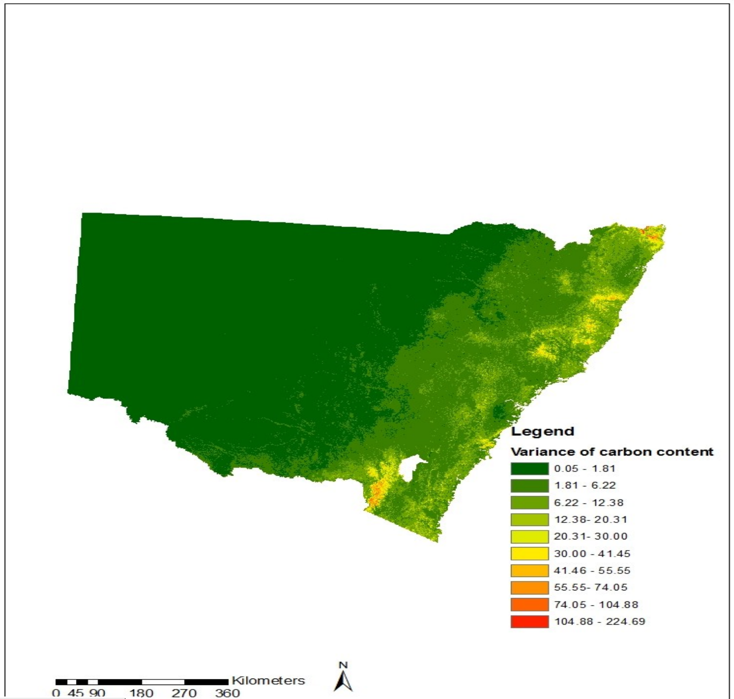
Applying it to a very large extent

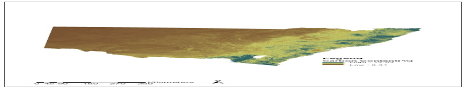
- Computationally expensive/challenging

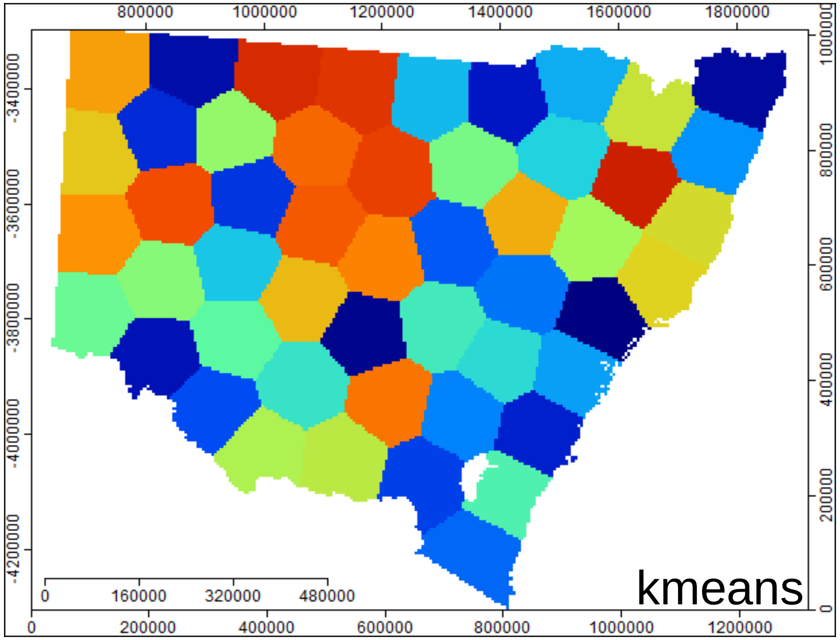
NSW, Australia

809,000 km2



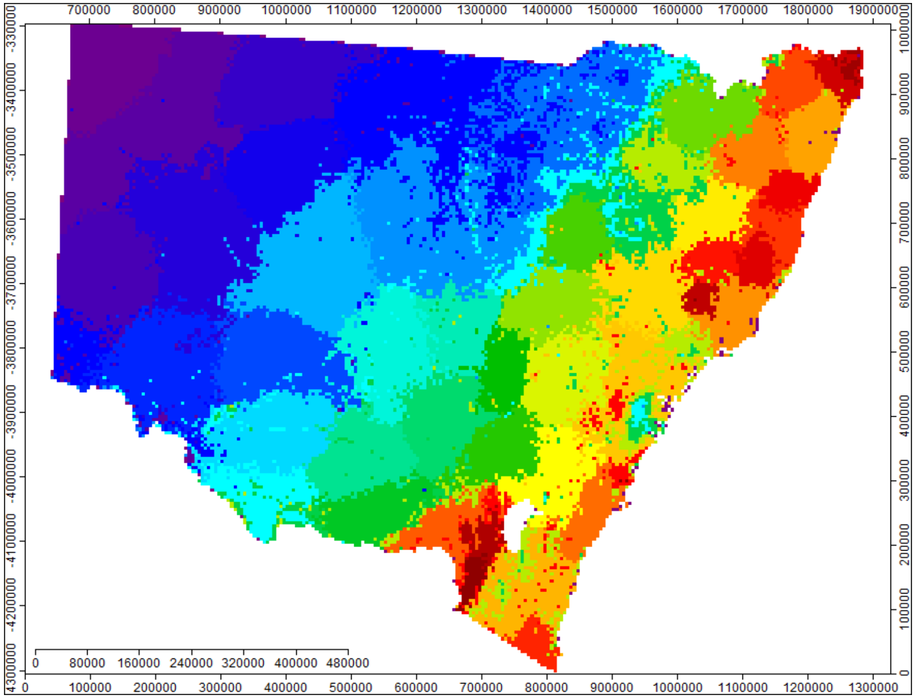


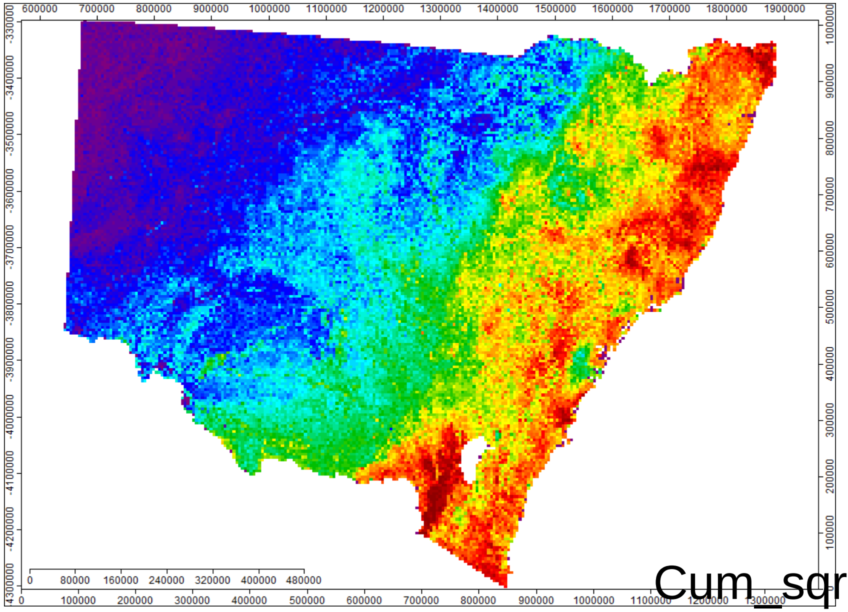




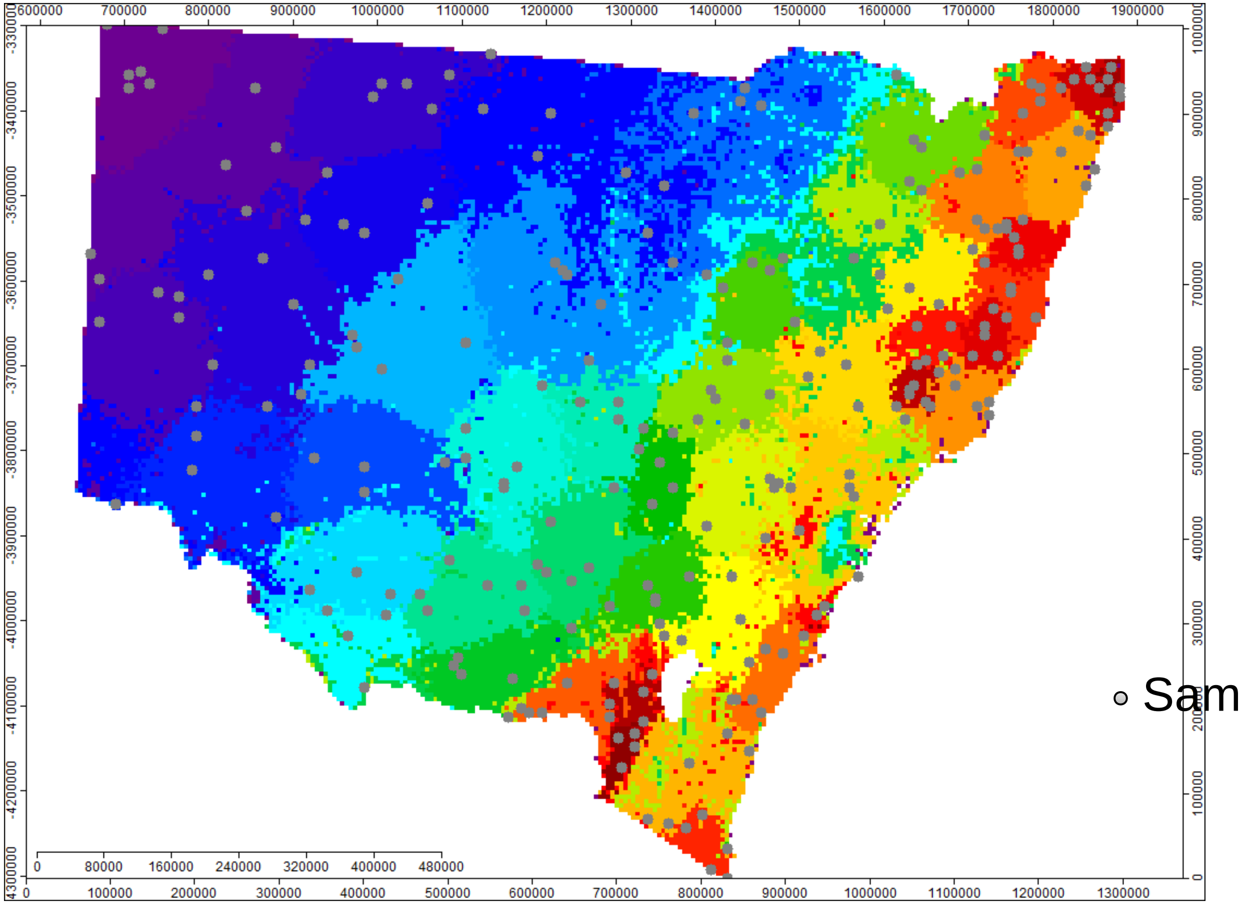
kmeans

OSPATS





Cum_sqrt_f

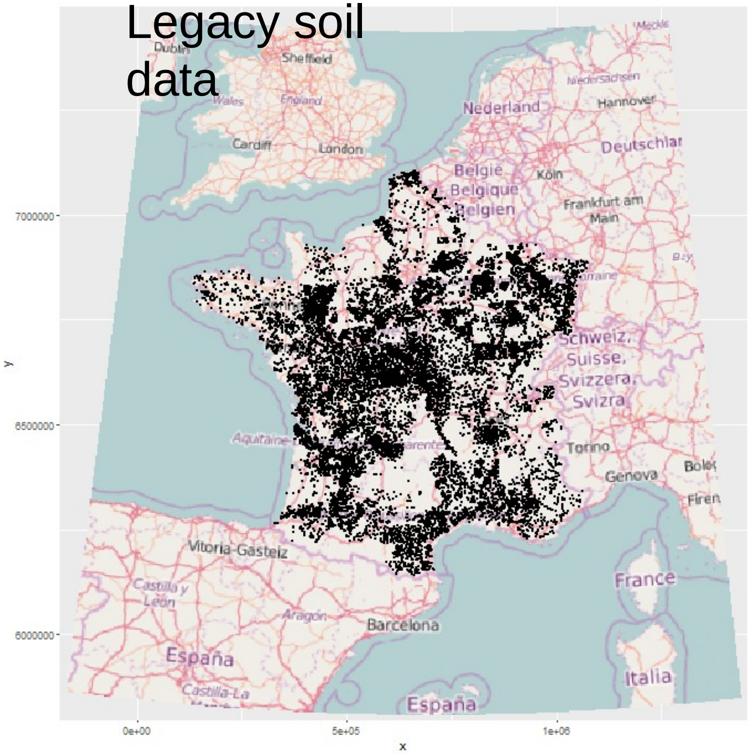


○ Sampling location

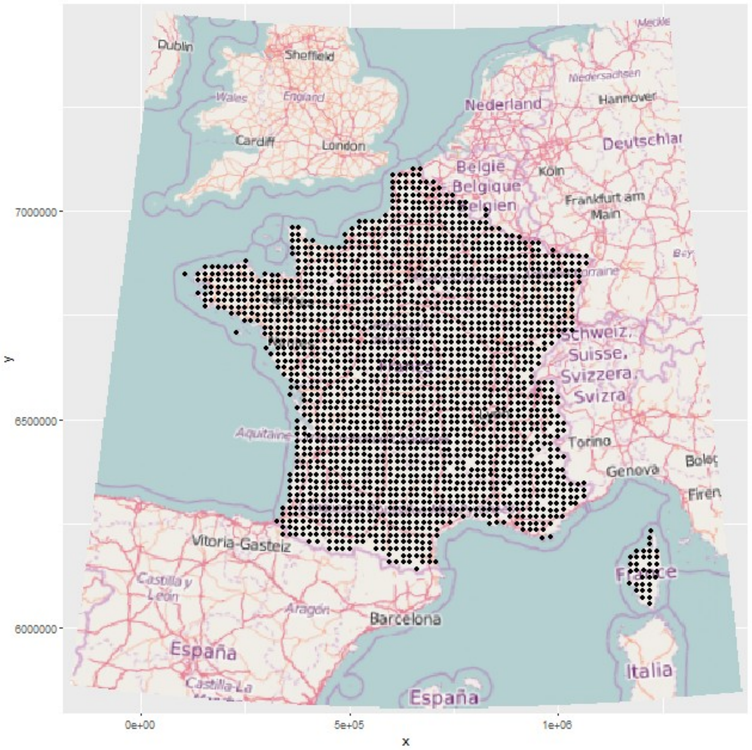
France

550,000 km2

Calibration data:
Legacy soil data

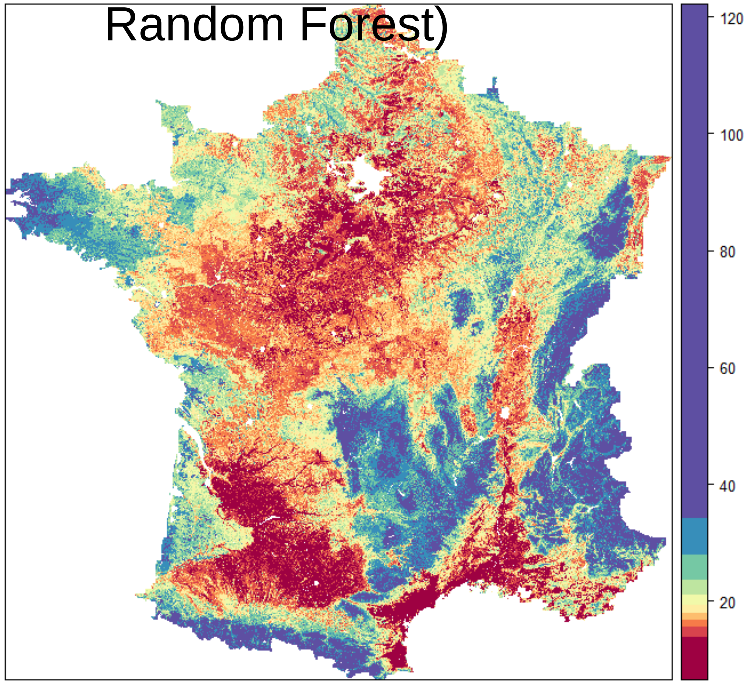


Validation data:
Soil Monitoring Network

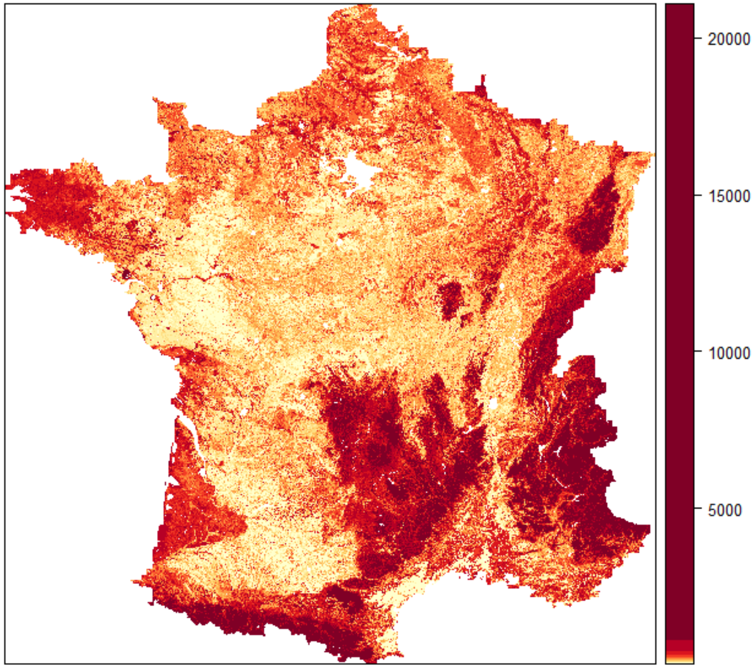


Map of topsoil (0-30 cm) C content

Prediction mean (using Quantile Random Forest)



Prediction variance



Independent Validation
R2 = 0.32 RMSE = 17.52 g/kg

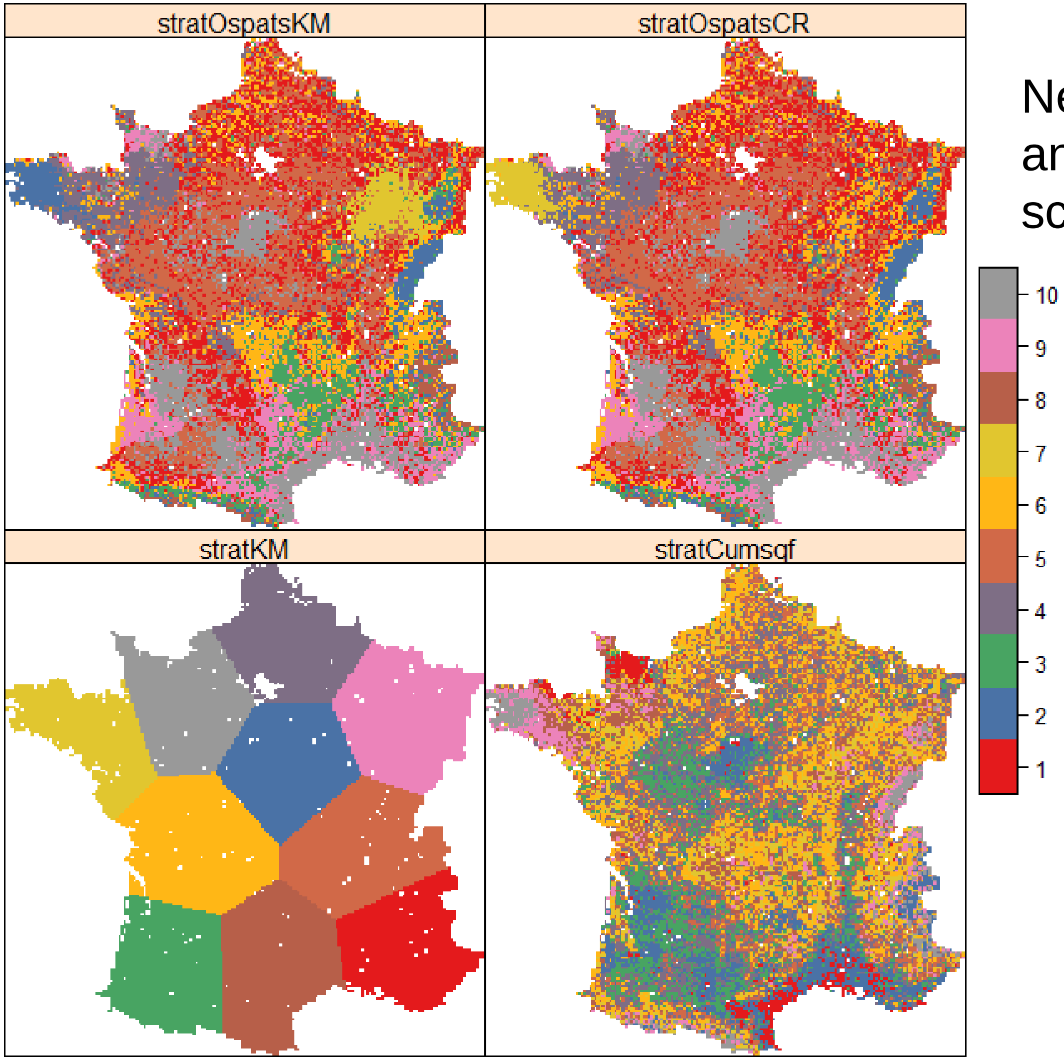
Stratifications

- 5km grid
- 10 strata

Sologne

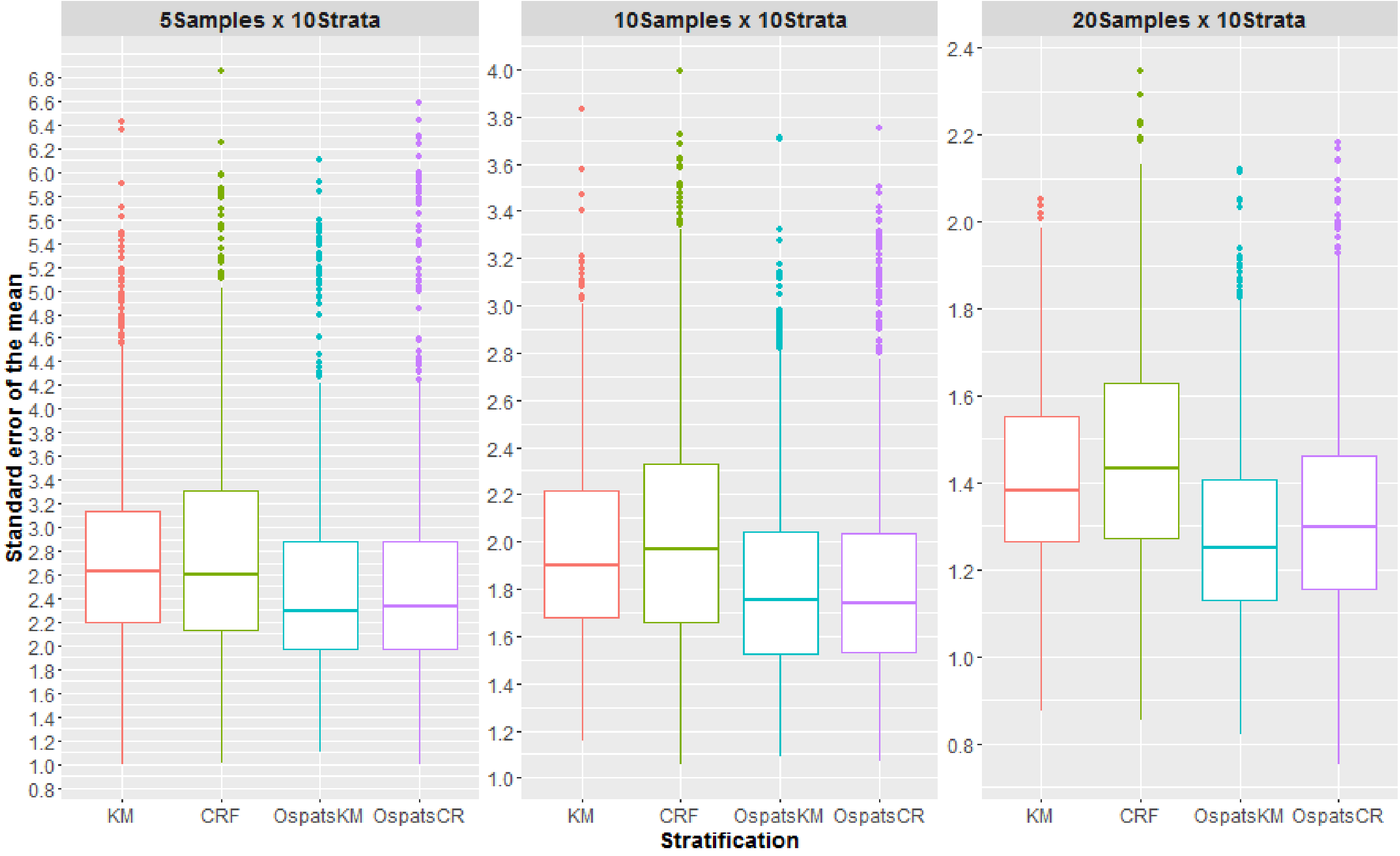
Jura

Massif Central



Needs annealing schedule

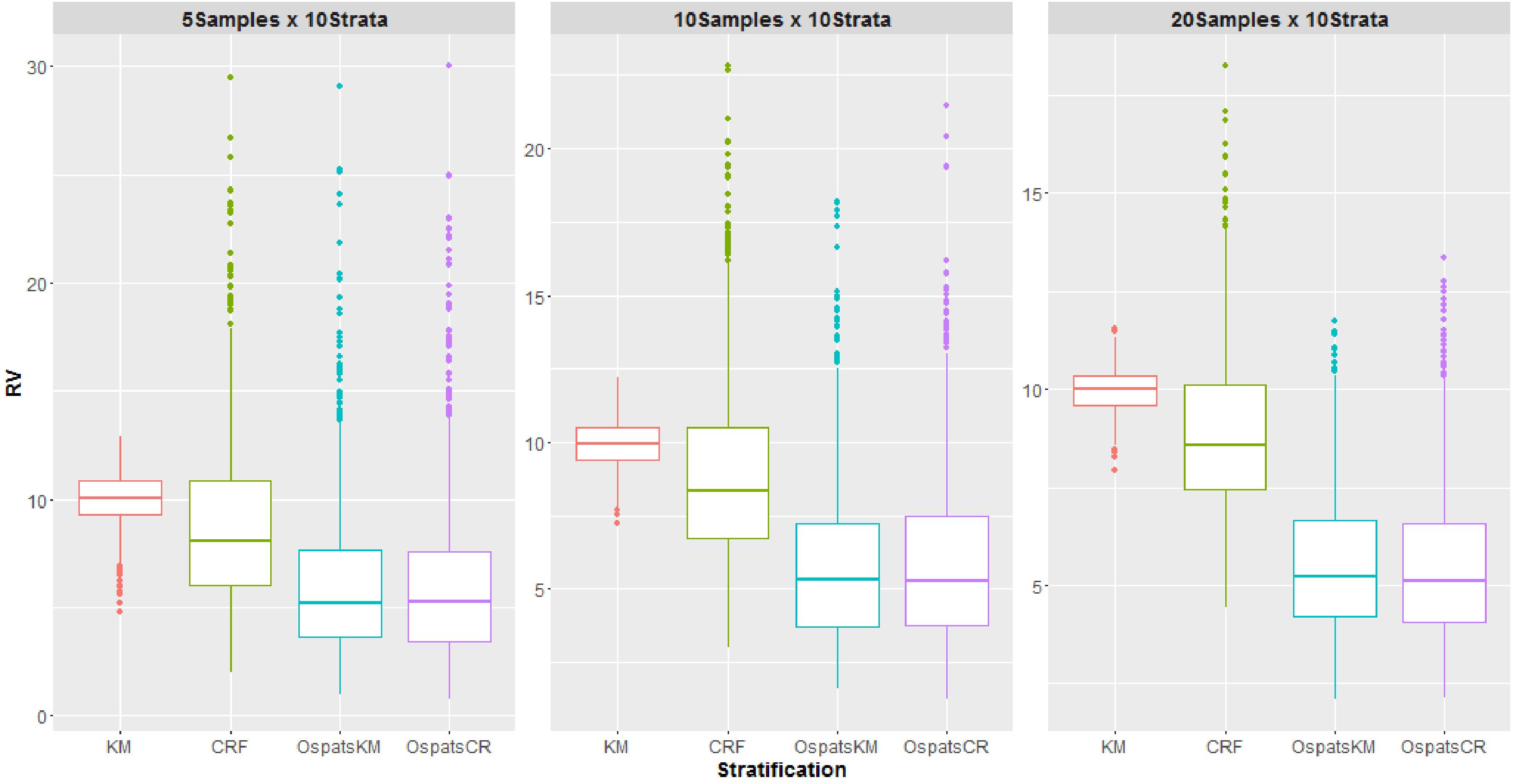
Standard error of the mean of C content in g/kg



Percentage *RVp*

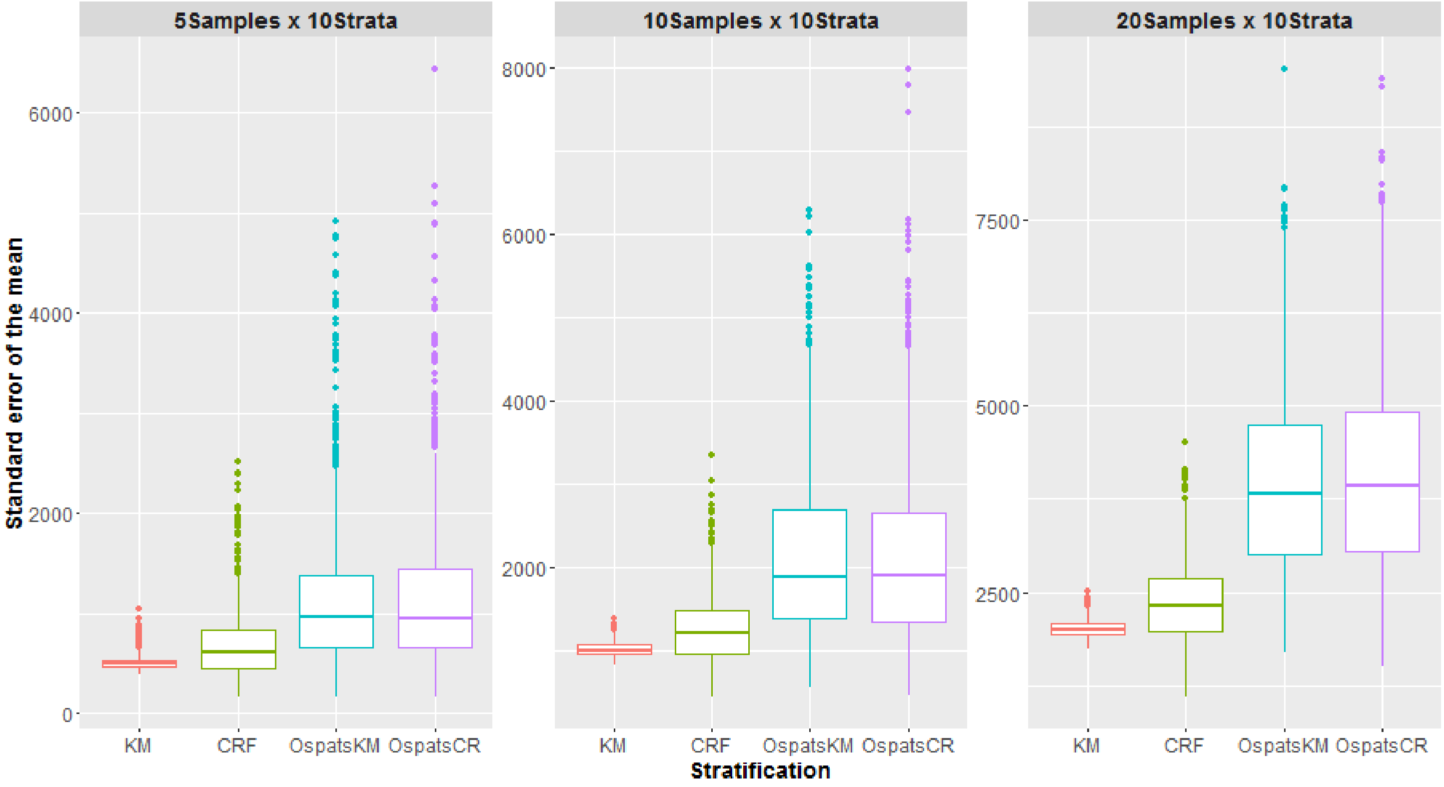
$$RV_p = 100 \times V_p(\hat{\bar{z}}) / V_{srs}(\hat{\bar{z}}),$$

- Calculated using the SMN observations



the ‘equivalent sample size’, which would yield the same precision if Simple Random Sampling were used

$$n_{\mathrm{eq}} = V_{\mathrm{r}} \cdot n \, . \qquad (7.19)$$



Conclusions

- Use of national or global DSM (e.g., GlobalSoilMap) products can be used for designing regional or national soil monitoring schemes to detect regional or national mean change.

- Conversely these monitoring schemes can be used to remove bias and/or update national or global DSM products (e.g., GlobalSoilMap).