

# Comparison of uncertainty quantification methods on the example of soil organic carbon (SOC) stock mapping in Hungary



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# Research Highlights

- The applied digital soil mapping (DSM) techniques provided different uncertainty models with different performances.
- In point of uncertainty quantification, sequential Gaussian simulation and quantile regression forest outperformed the others.
- We have demonstrated that uncertainty models must be validated.
- Special attention should be paid to the assumptions made in uncertainty modelling.

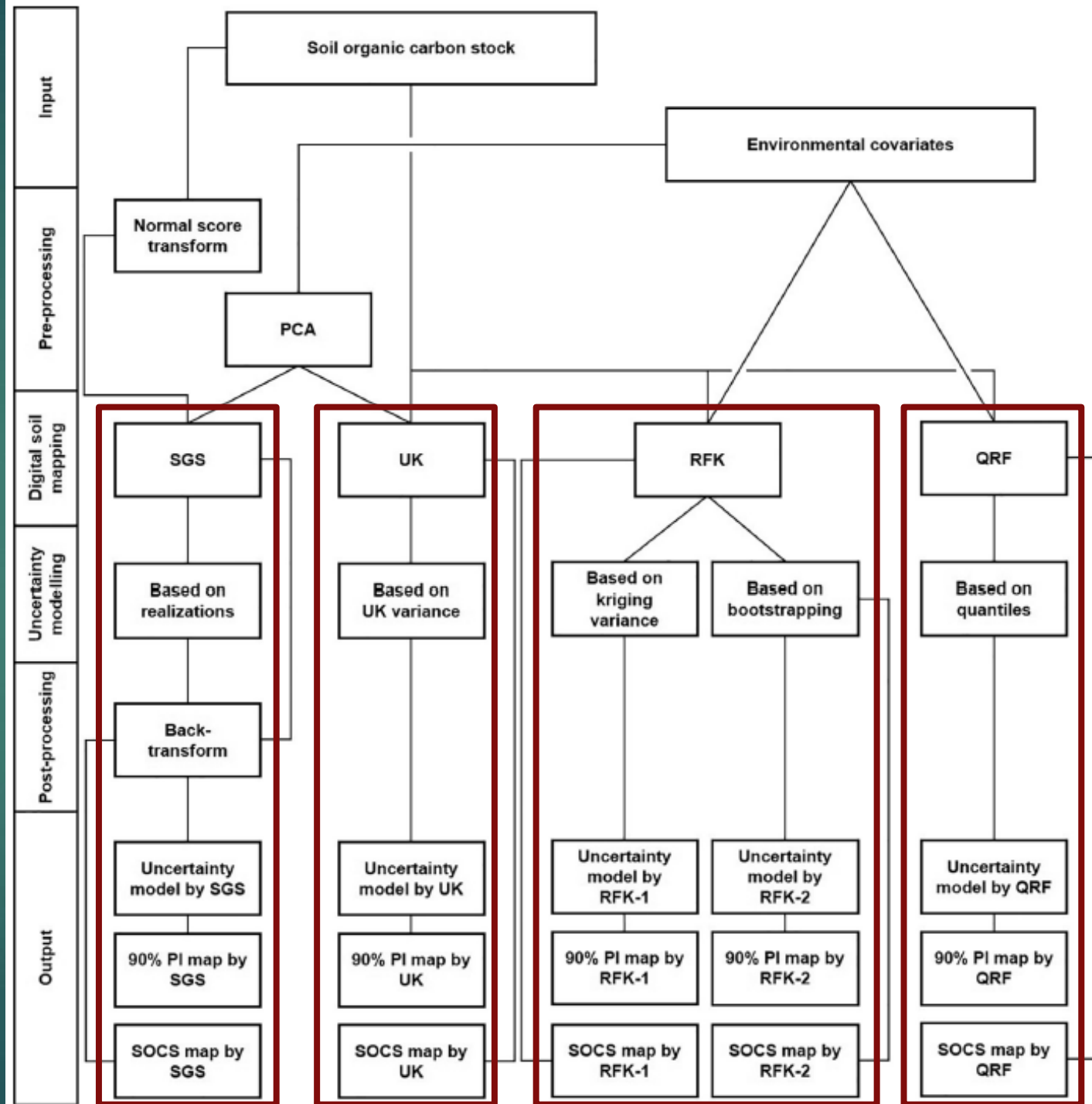
# Flowchart

## Applied DSM techniques:

1. Sequential Gaussian simulation (SGS)
2. Universal kriging (UK)
3. Random forest + kriging (RFK)
  - 3.1. Based on kriging variance (RFK-1)
  - 3.2. Based on bootstrapping (RFK-2)
4. Quantile regression forest (QRF)

### Abbreviations:

SOCS: soil organic carbon stock,  
PCA: principal component analysis,  
PI: prediction interval



Source: Szatmári & Pásztor (2019)

<https://doi.org/10.1016/j.geoderma.2018.09.008>

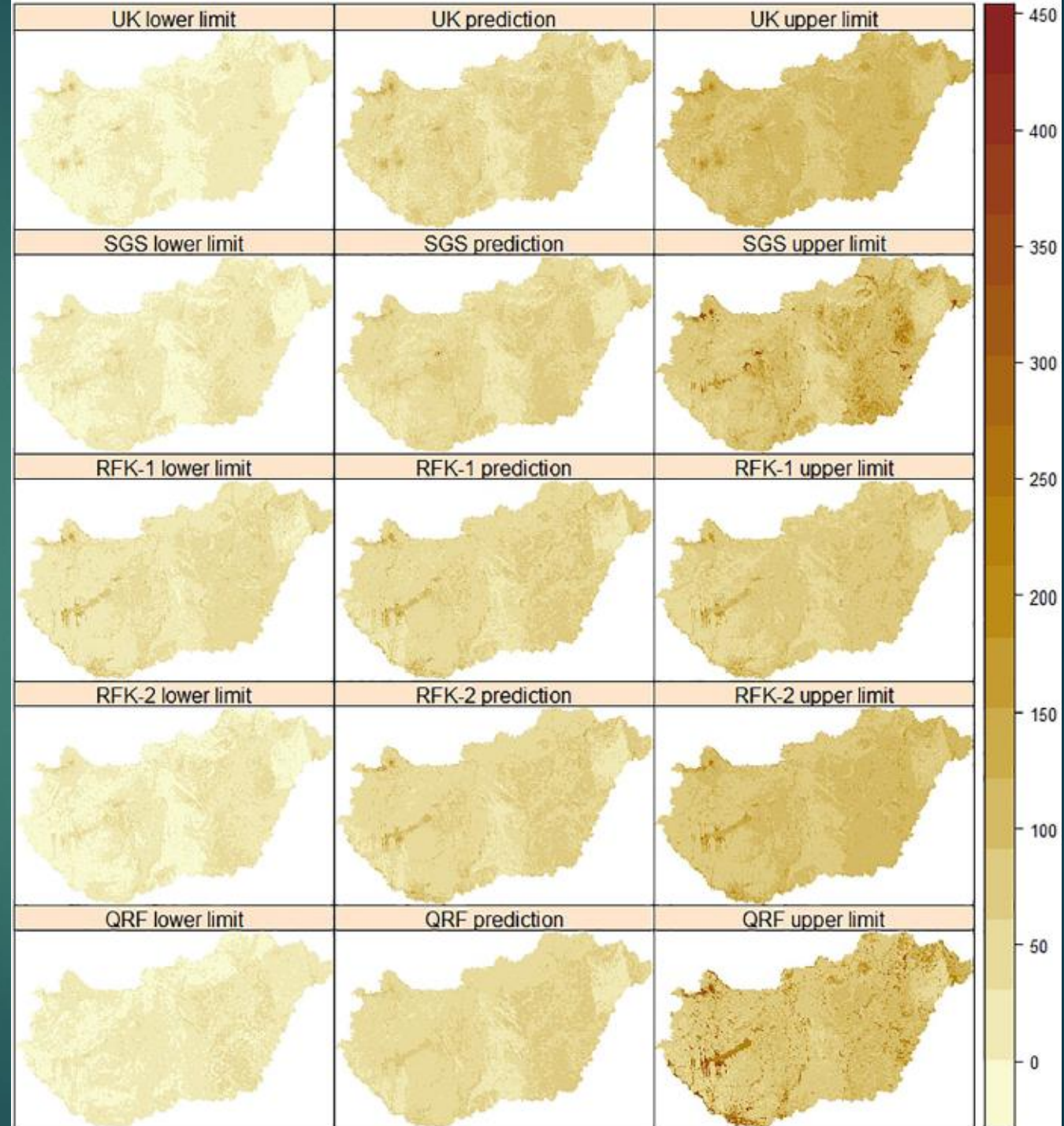
# SOC stock maps & their uncertainties

## Visualization of uncertainty:

The upper and lower limit of the 90% prediction interval are presented. This prediction interval reports the range of values within which the true value is expected to occur 9 times out of 10.

The unit of the maps is **tons · ha<sup>-1</sup>**

The geometric resolution of the maps is **500 m**



# Validation of uncertainty quantifications

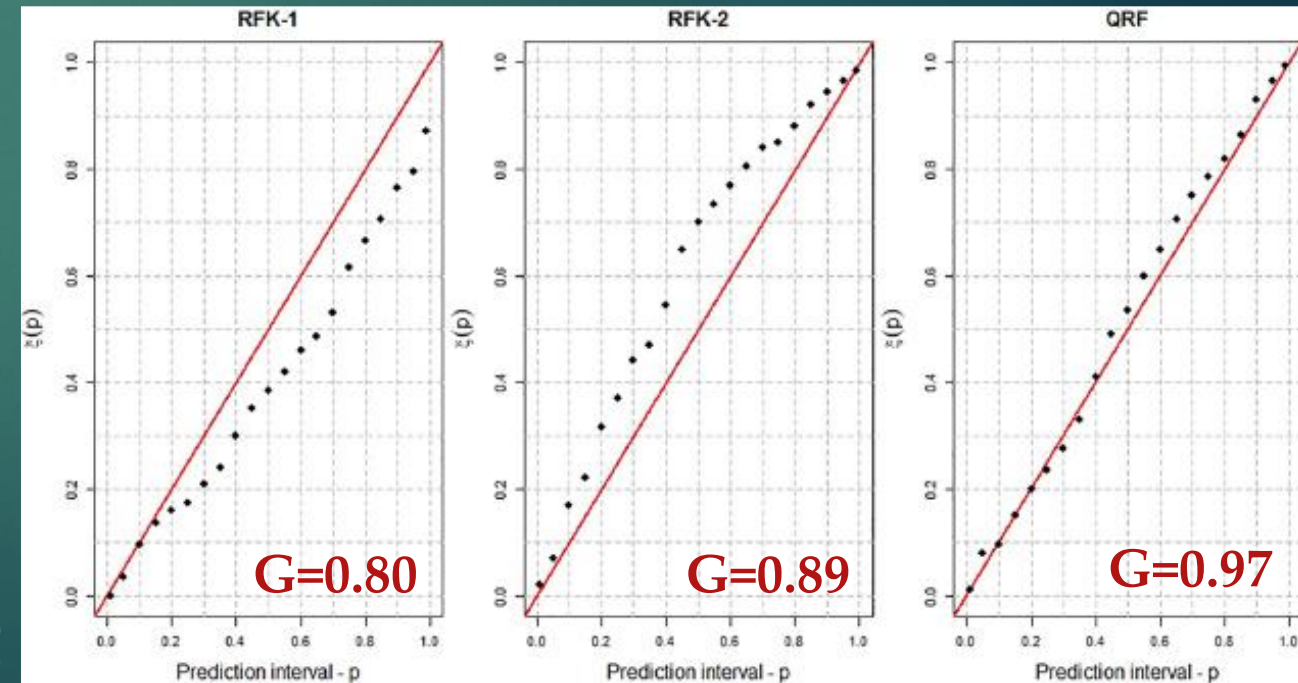
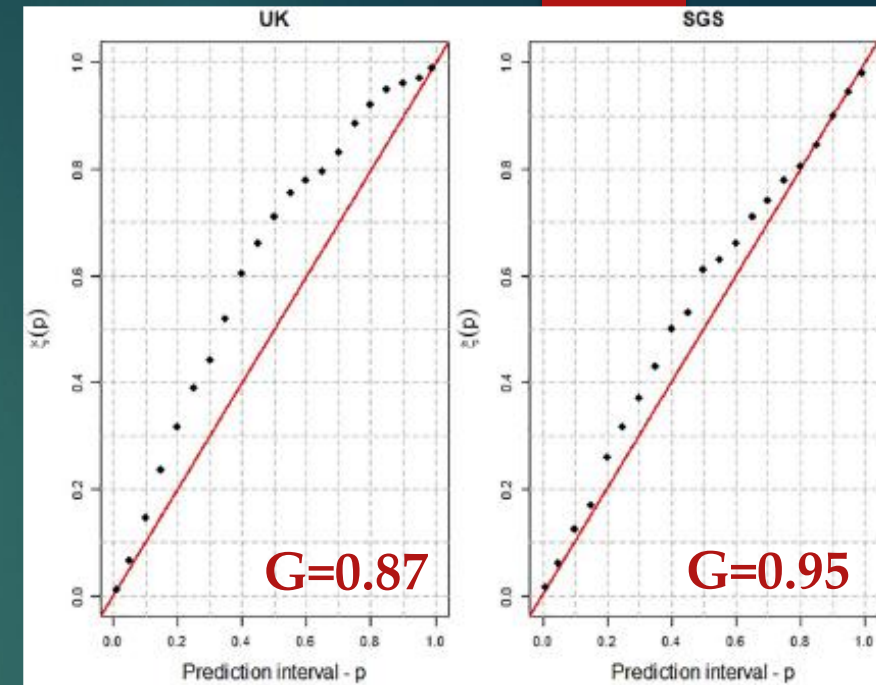
Validation was carried out by using 200 independent SOC stock observations

Rank of the applied DSM techniques (from best to worst):

**QRF, SGS, RFK-2, UK, RFK-1**

*Accuracy plot graphically shows the actual fraction of true values falling within symmetric prediction intervals of varying width.*

*The value of  $G$  shows the closeness of the actual and expected fractions. Ideally,  $G$  is equal to 1.*



# If you want to know more...


...You can take a look at the paper below

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## Comparison of various uncertainty modelling approaches based on geostatistics and machine learning algorithms

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**ABSTRACT**

We compared the suitability of several commonly applied digital soil mapping (DSM) techniques to quantify uncertainty with regards to a survey of soil organic carbon stocks. To ensure a fair comparison, a wide range of DSM techniques were simulated using a geostatistical simulation (SGS), random forest combined with kriging (RFK) and quantile regression (QR) based on different uncertainty quantification approaches were adopted based on the results of the simulation (RFK-1, RFK-2). The selection of the potential environmental covariates was based on the results of the soil formation. The spatial predictions of SOCS and their uncertainty were validated using a control dataset. For this purpose, we applied the most common metrics (RMSE, MAE, mean square error), furthermore, accuracy plot and G statistic. According to our results, QR produced the best uncertainty models. UK and RFK-2 overestimated the uncertainty whereas RFK-1 produced the worst uncertainty quantification according to the accuracy plots and G statistics. We could draw the general conclusion that there is a need to validate the uncertainty models. Furthermore, great attention should be paid to the assumptions made in uncertainty modelling.

