Usage of visual and near-infrared spectroscopy to predict soil properties in forest stands

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Motivation

- high demand for up-to-date information about humus conditions is important for site-adapted management
- continuous impact through element input, management measures and changing climate
- need for inexpensive and fast methods

Image: Thomas Frey/dpa

Background

- Vis-NIR spectroscopy as known method to estimate physical and chemical soil properties (see Kooistra et. al. (2001), Gubler (2011), Riedel et. al. (2018))
- Application so far mainly on agricultural sites and mineral soils
- First examples for analysis of forest soils (Ludwig et. Ak. 2017)
- Usage of organic layers (Cardelli et. al. 2017)

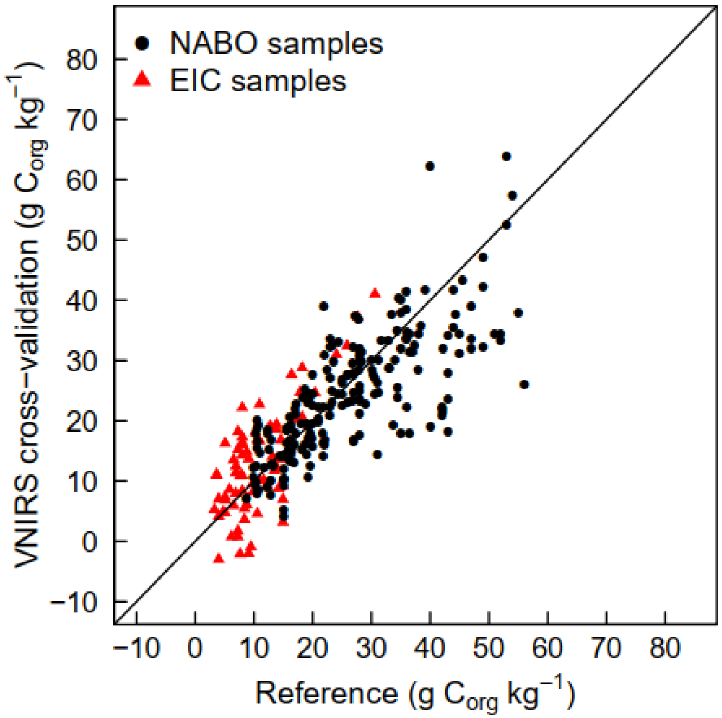


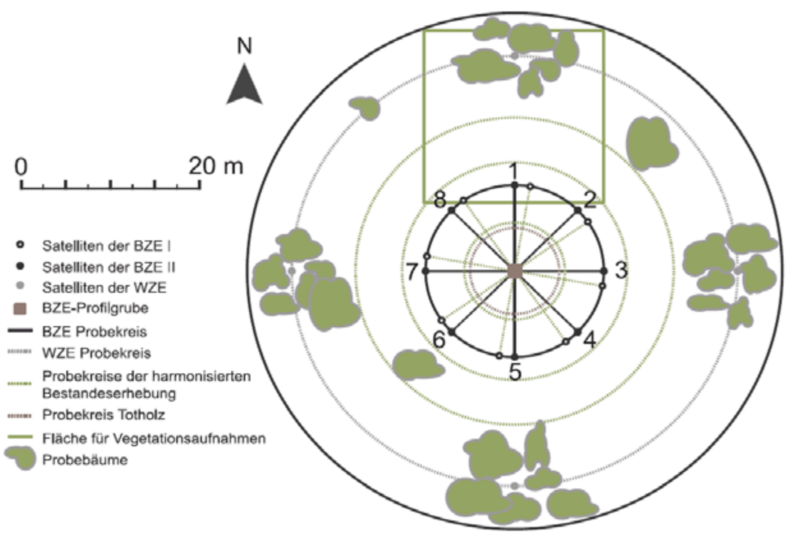
Image:Andreas Gubler

Aim

- Proximal soil sensing as support for forest monitoring
- Cooperation: Public Enterprise Sachsenforst and UFZ
- Analysis of forest soil samples with vis-NIR spectroscopy and setup of a spectral library
- Modelling of soil parameters
- Development of a fast, cost-efficient and applicable procedure for periodic forest soil mapping as supplement for current methods

Data Collection

- 378 retained samples (National Forest Soil Inventory and samples from test sites) from Saxony
- 109 additional samples from field campaign 2019
- Satellite sampling scheme (8 satellites per point, Ah/Oh horizon)



Images: Staatsbetrieb Sachsenforst

Data Collection

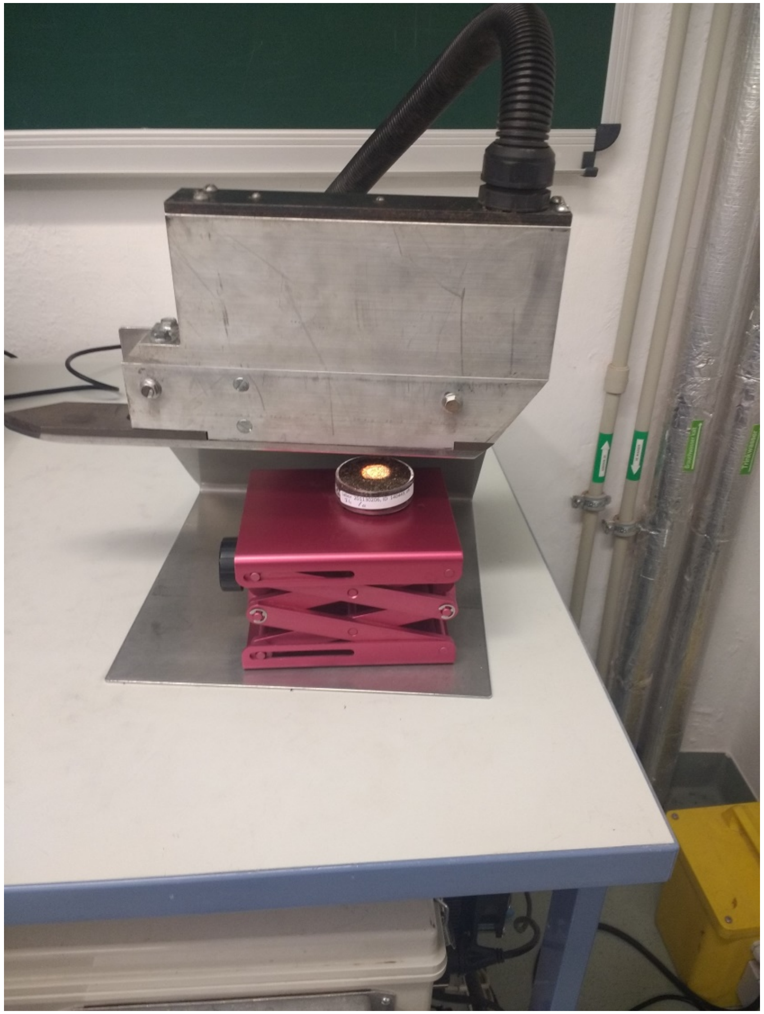
Spectral data

Protocol: Capture variability of ech sample

- Veris VIS-NIR Spectrophotometer
- Per samples five measurements from two petri dishes (ten in total)
- turn/shift der sample after each run
- Taking external references before each sample

Preprocessing

- Removing Wavelengths
- Savitzky-Golay Filter
- Standard Normal Variate
- Outlier detection



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Regression Analysis

Algorithms

- Partial Least Square Regression (PLSR)
- Suport Vector Machine (SVM)

Target Variables

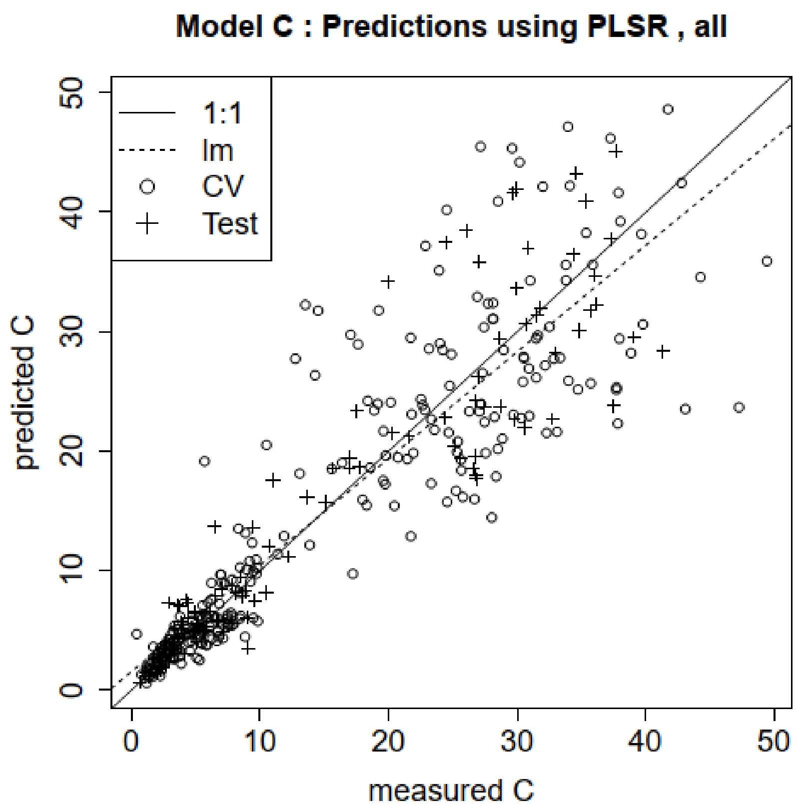
- C, N, pH-value, base saturation
- Usage of logarithmic values
- Separation of the data according to soil horizons and forest stand

Validation

- Independent test set (train/test split 70/30)
- 10-fold cross validation (cv)
- Plots (predicted/observed), RMSE, R^2
- New data from 2019 as independet test data set

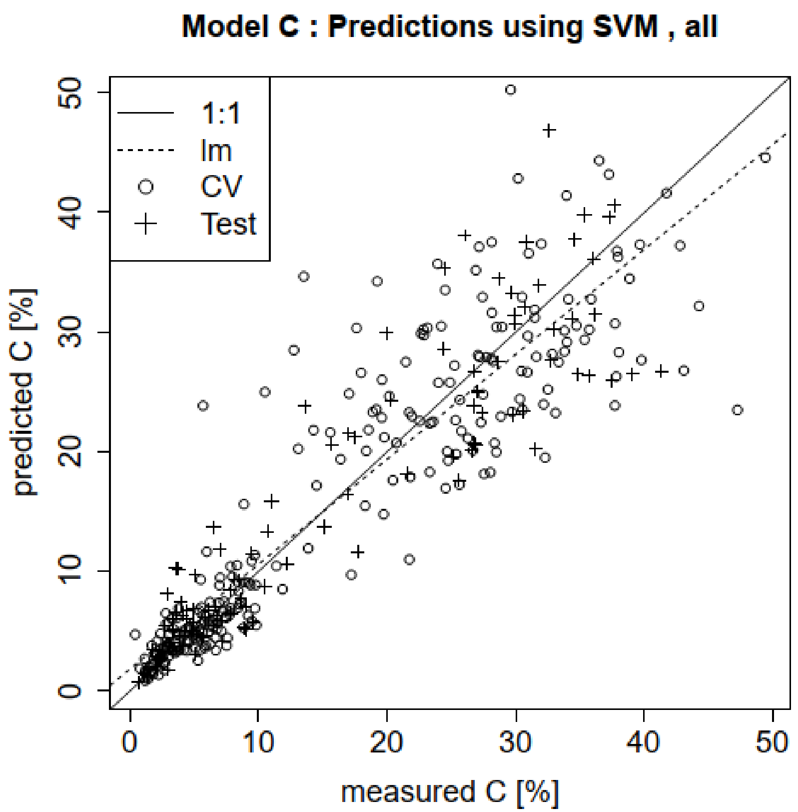
Selected Results: Carbon

Prediction results for carbon content based on retained samples for both algorithms



R^2: 0.8 (cv), 0.8 (test)

RMSE: 5.8 (cv), 5.9 (test)

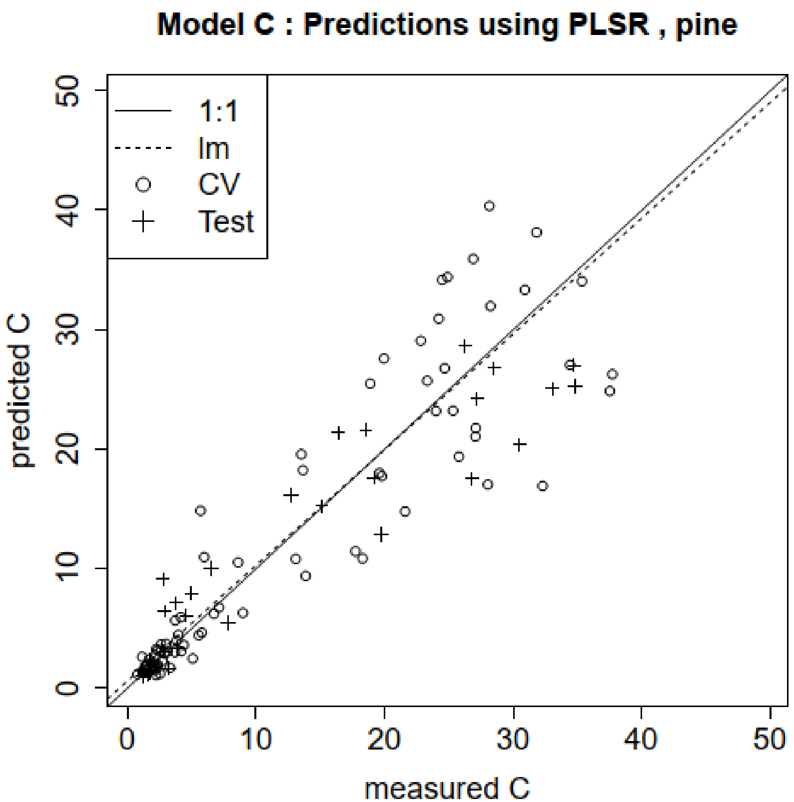


R^2: 0.82 (cv), 0.85 (test)

RMSE: 5.4 (cv), 4.9 (test)

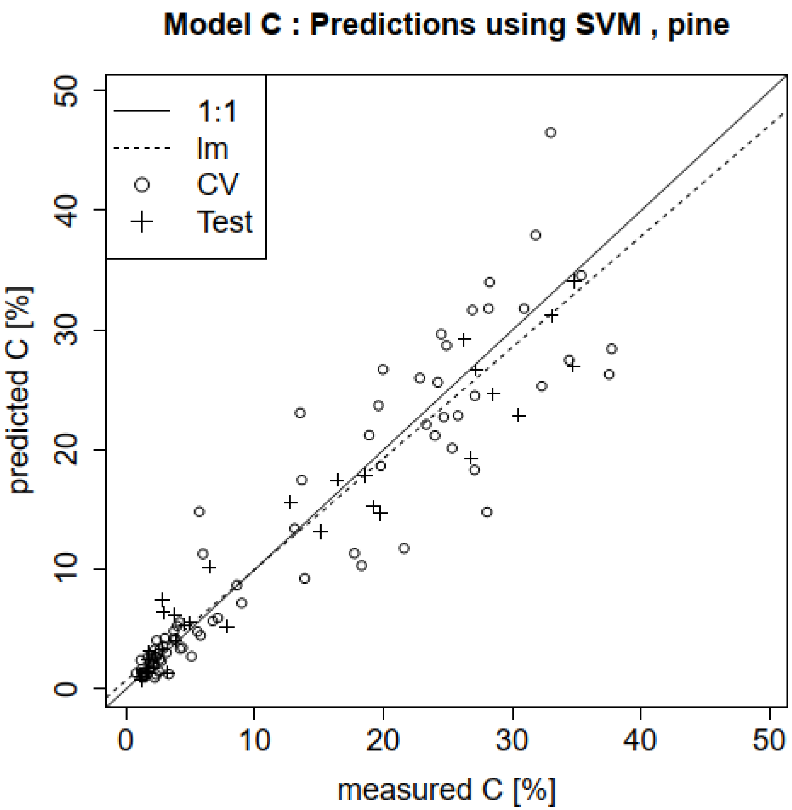
Selected Results: Carbon

Prediction results for carbon content based on retained samples for both algorithms in **pine stands**



R^2: 0.84 (cv), 0.87 (test)

RMSE: 4.9 (cv), 4.4 (test)

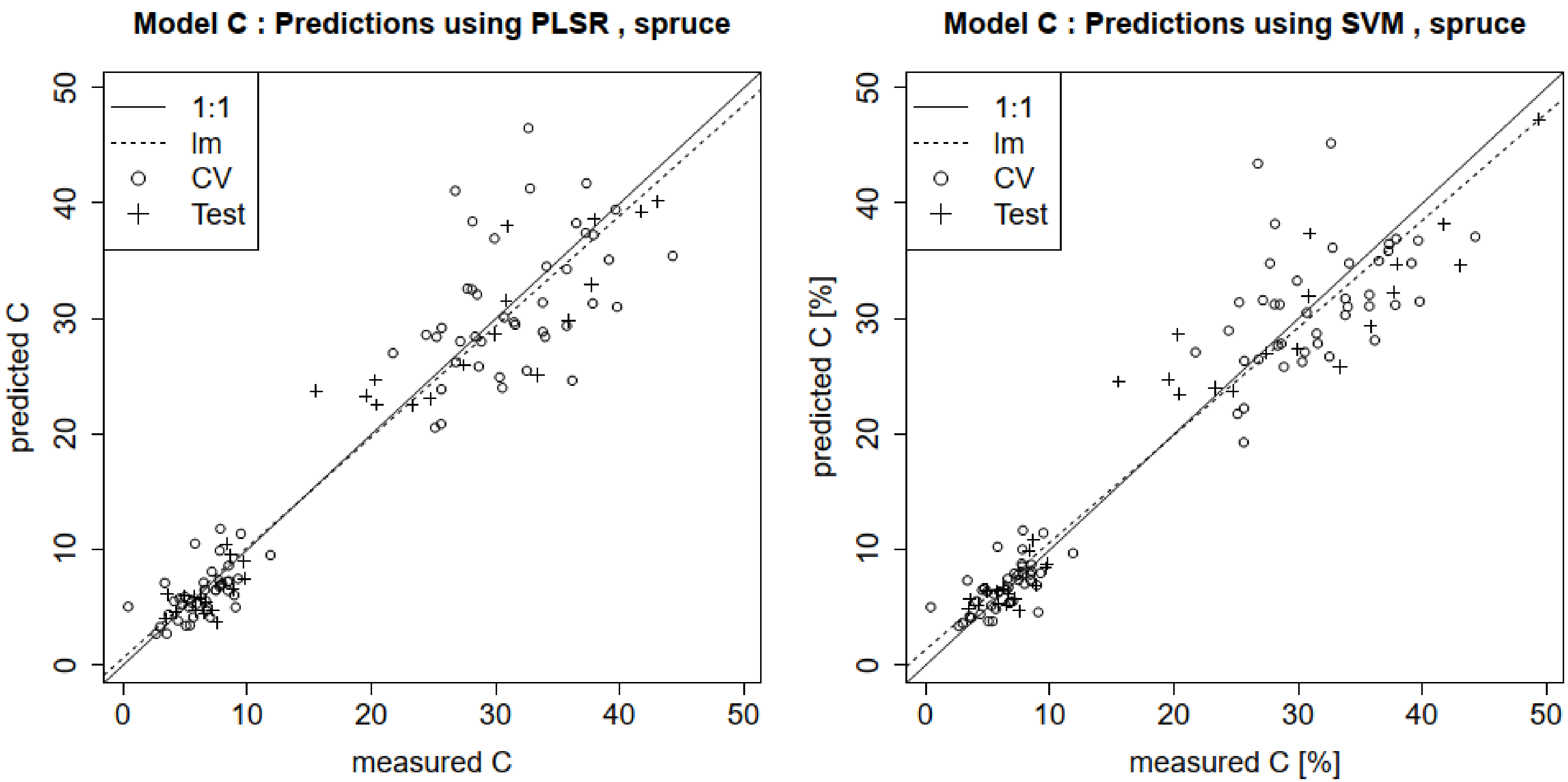


R^2: 0.86 (cv), 0.94 (test)

RMSE: 4.4 (cv), 3.2 (test)

Selected Results: Carbon

Prediction results for carbon content based on retained samples for both algorithms in **spruce stands**

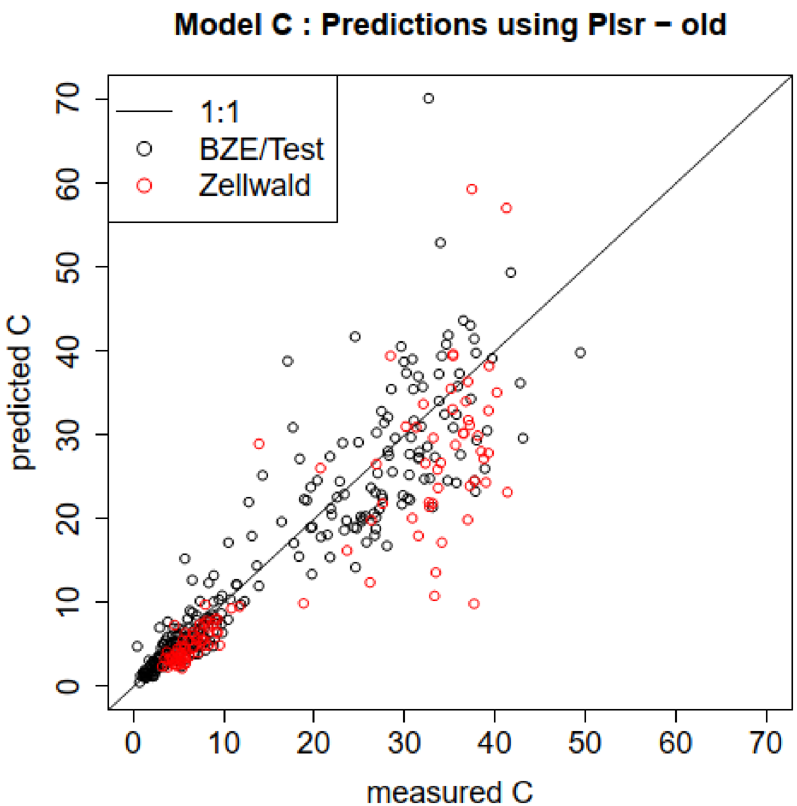


R^2: 0.91 (cv), 0.9 (test)
RMSE: 3.8 (cv), 4.8 (test)

R^2: 0.91 (cv), 0.92 (test)
RMSE: 4 (cv), 3.9 (test)

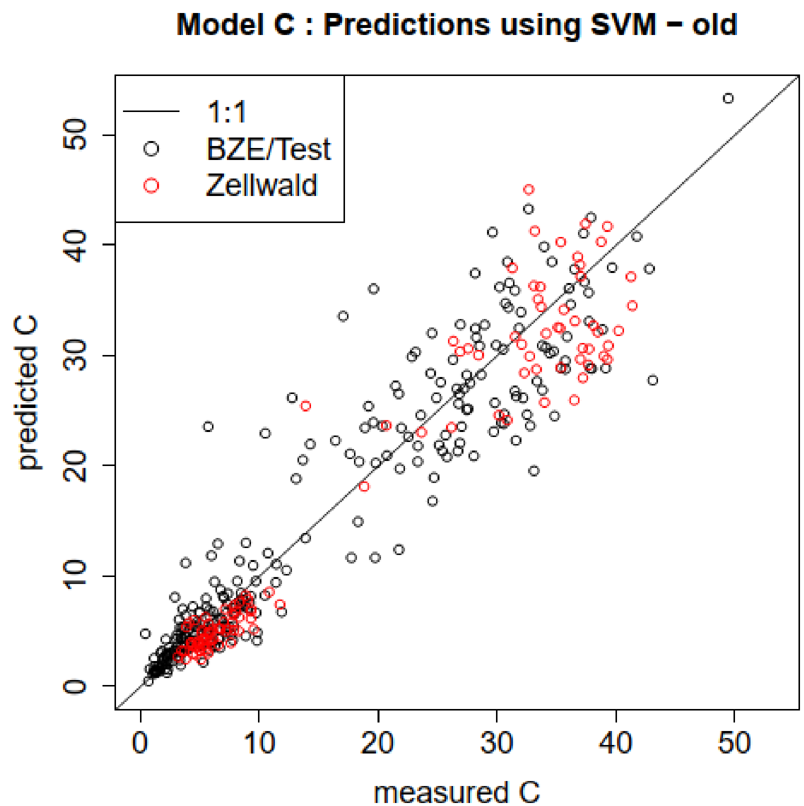
Selected Results: Carbon

Prediction results for carbon content based on retained samples with independent predictions for new data (red), for both algorithms



R²: 0.77

RMSE: 7.7

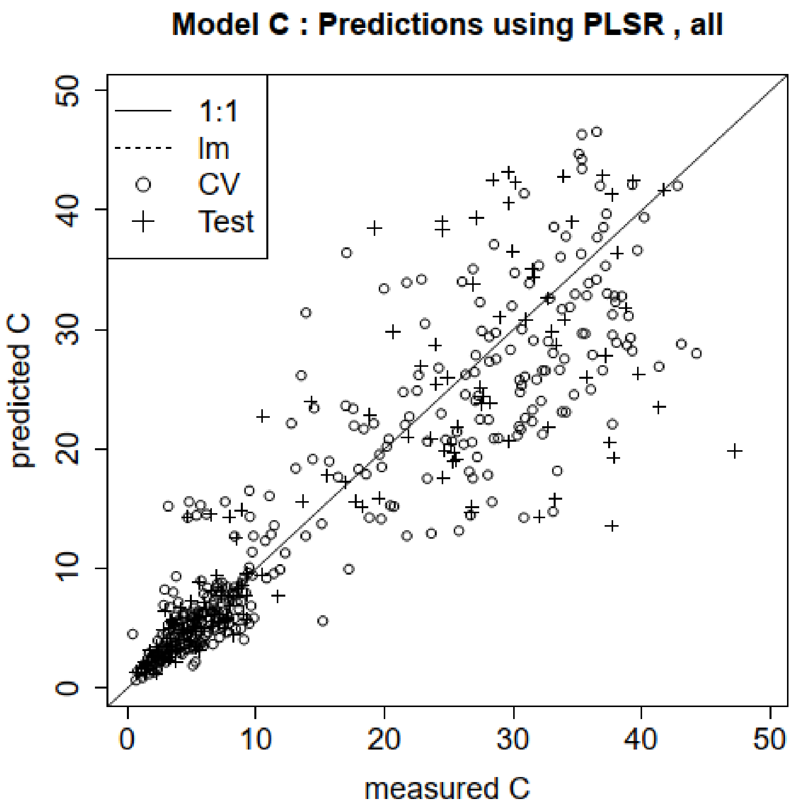


R²: 0.92

RMSE: 4.1

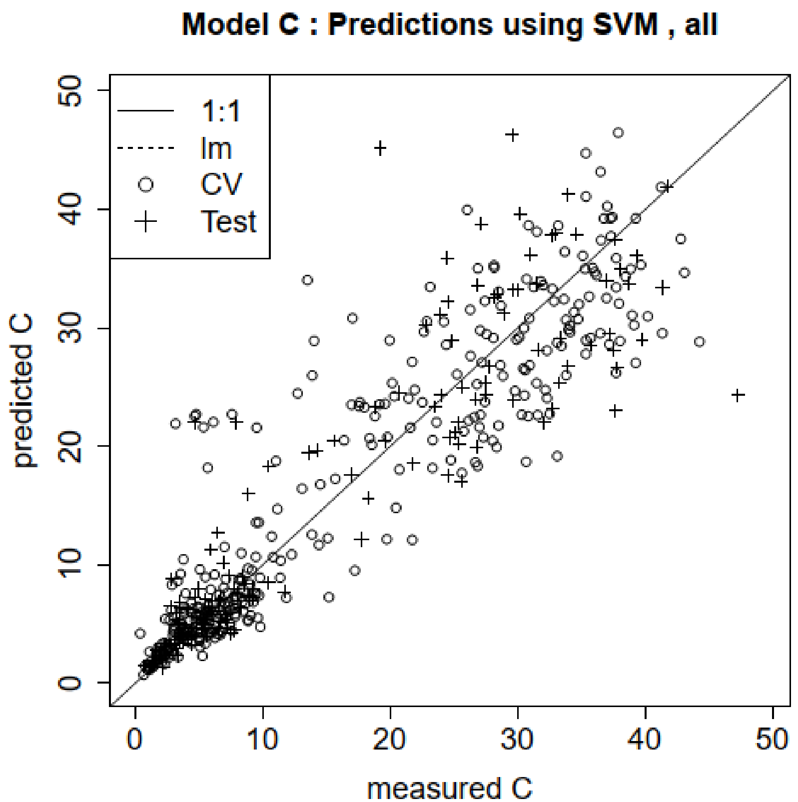
Selected Results: Carbon

Prediction results for carbon content based on retained and new samples for both algorithms



R²: 0.78

RMSE: 6.25



R²: 0.84

RMSE: 5.23

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Selected Results: Carbon

- R^2 values range from 0.25 to 0.94
- RMSE ranges from 1.78 to 7.69
- SVM produces more accurate predictions
- Separating horizons results in lower performance
- Increase in prediction accuracy for spruce and pine stands
- Models calibrated on retained samples are able to predict on new data from 2019
- Combining retained samples and new data produces results comparable to modelling based on retained samples only
- Model are robust to expansion of data basis

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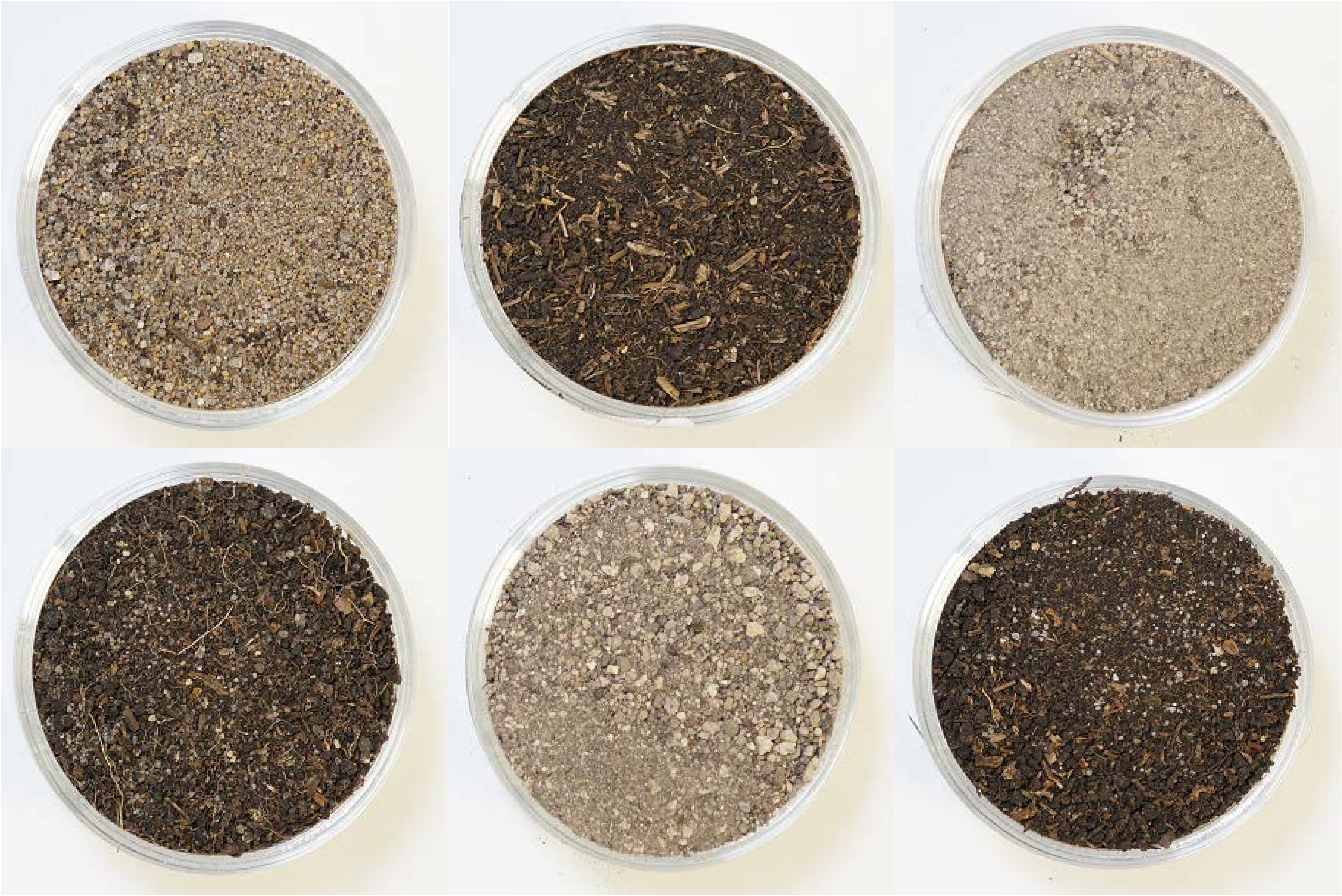
Thank you for your attention!



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" O'Reilly Media, Inc.", 2016

Appendix

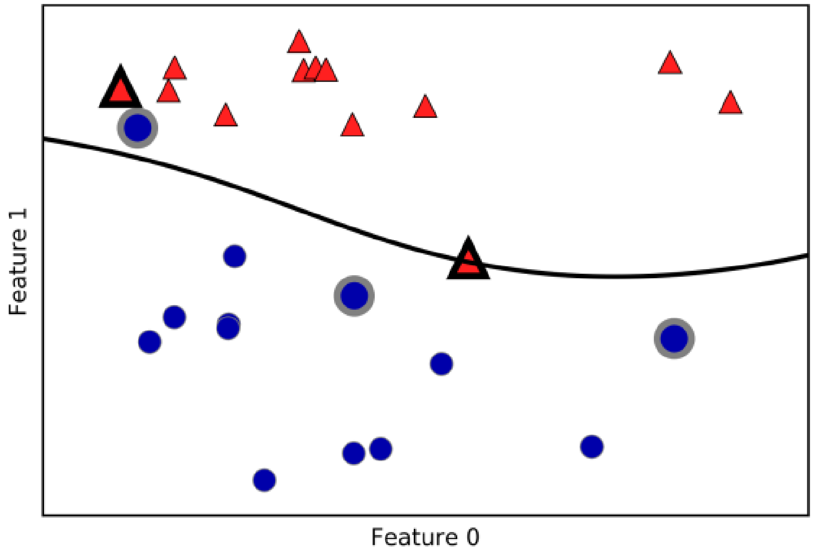
Partial Least Sqaure Regression

- Introduced by Wold et. Al. to solve multivariate calibration problems
- Extraction of components that describe the greates correlation between predictors and response variables
- Implementation of regressions based on these components instead of original data
- Highly reduces amount of data
- Is used when many collinear predictors are in use
- Reliable method to predict soil parameters

Appendix

Support Vector Machines (SVM)

- Representation of every object of the training data as a vector
- SVM creates a hyperplane that sepearates the training objects in two classes while maximising the distance to the adjacent vectors
- For the creation of the plane, only the adjacent vectors are required (support vectors, see picture)



Müller, et. al. (2016)

Appendix

Value Distribution for retained (red) and new samples (blue)