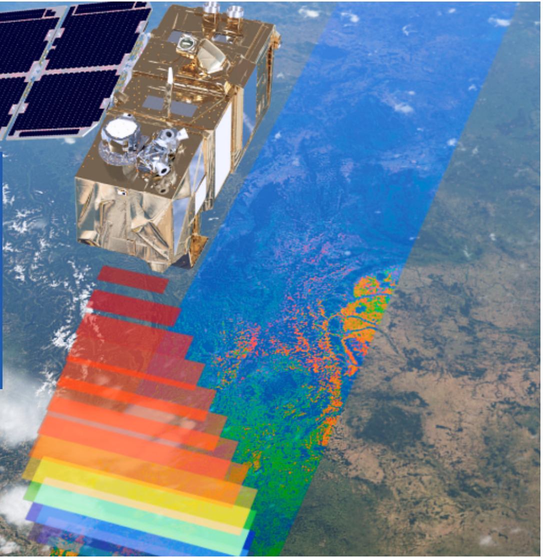
ETH zürich

D-MATH — Seminar for Statistics
D-USYS — Crop Science



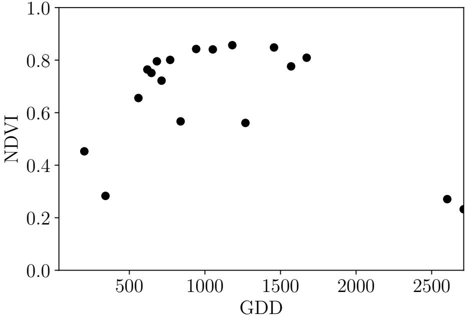
Interpolation and Correction of Satellite Image Time Series

Lukas Graz

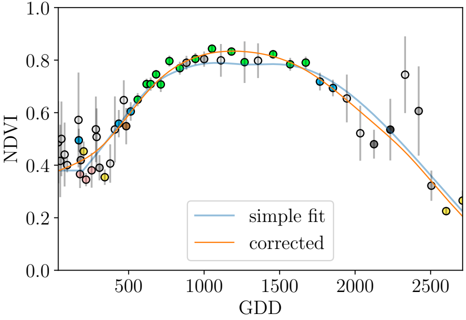
September 13th, 2022

How to get ...

from ...



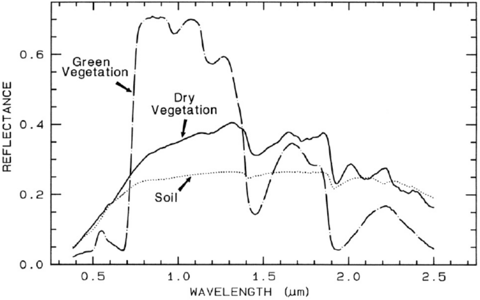
to ...



Scene Classification Layer (SCL)

Color	No.	Class
	0:	Missing Data
	1:	Saturated or defective pixel
	2:	Dark features / Shadows
	3:	Cloud shadows
	4:	Vegetation
	5:	Bare soils
	6:	Water
	7:	Cloud low probability
	8:	Cloud medium probability
	9:	Cloud high probability
	10:	Thin cirrus cloud
	11:	Snow or ice

NDVI From S2 Images



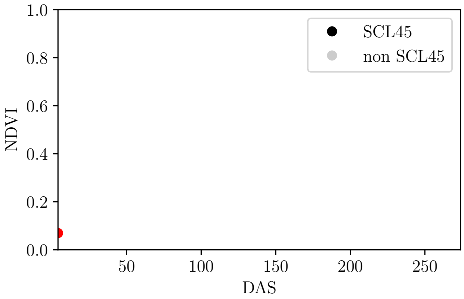
Normalized **D**ifference **V**egetation **I**ndex:

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{Red})}{(\mathrm{NIR} + \mathrm{Red})}$$

[0] Spectral Reflectances https://www.researchgate.net/figure/Reflectance-spectra-of-photosynthetic-green-vegetation-non-photosynthetic-dry_fig4_236677371

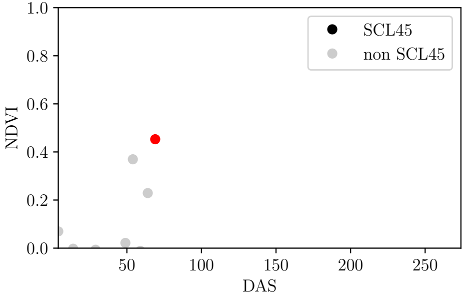
Sentinel 2 Image + NDVI Time Series

→ Cloud high probability



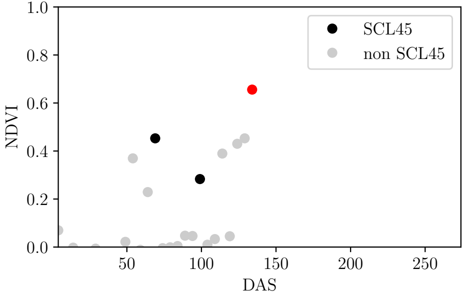
Sentinel 2 Image + NDVI Time Series

→ Bare soils



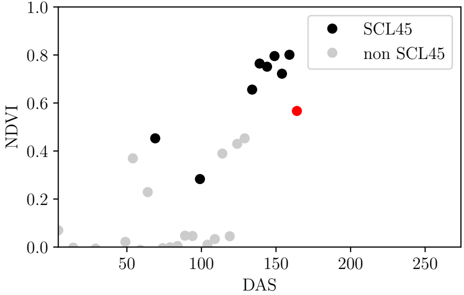
Sentinel 2 Image + NDVI Time Series

→ Vegetation



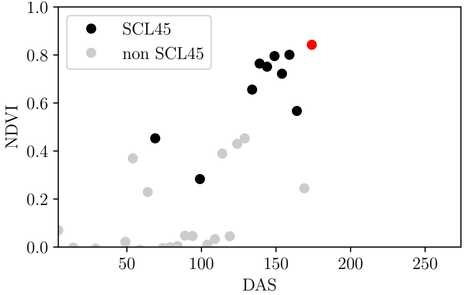
Sentinel 2 Image + NDVI Time Series

→ Vegetation

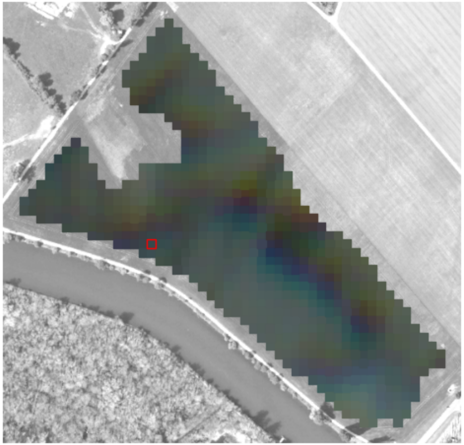


Sentinel 2 Image + NDVI Time Series

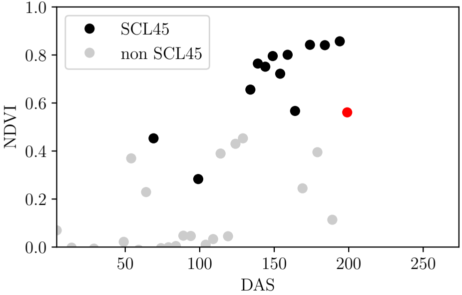
→ Vegetation



Sentinel 2 Image + NDVI Time Series

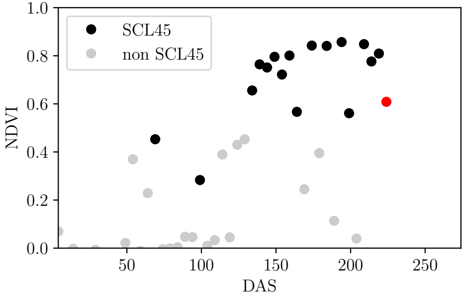


→ Vegetation



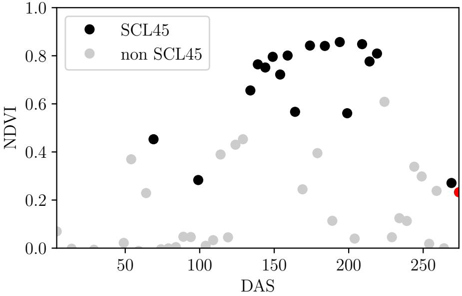
Sentinel 2 Image + NDVI Time Series

→ Thin cirrus cloud



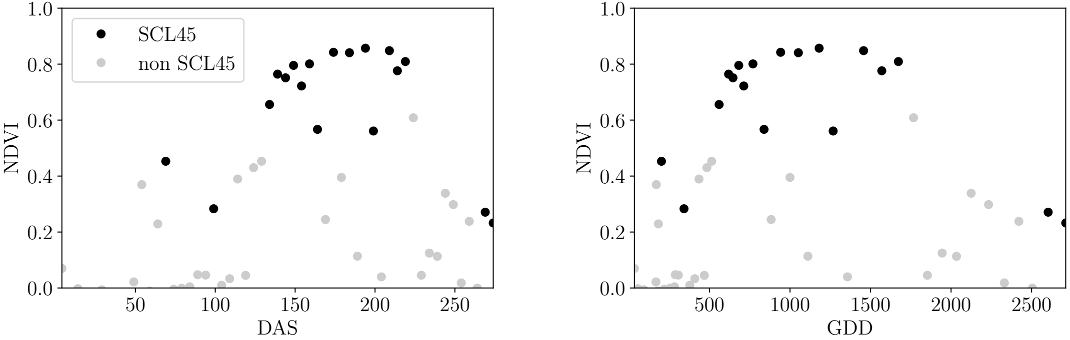
Sentinel 2 Image + NDVI Time Series

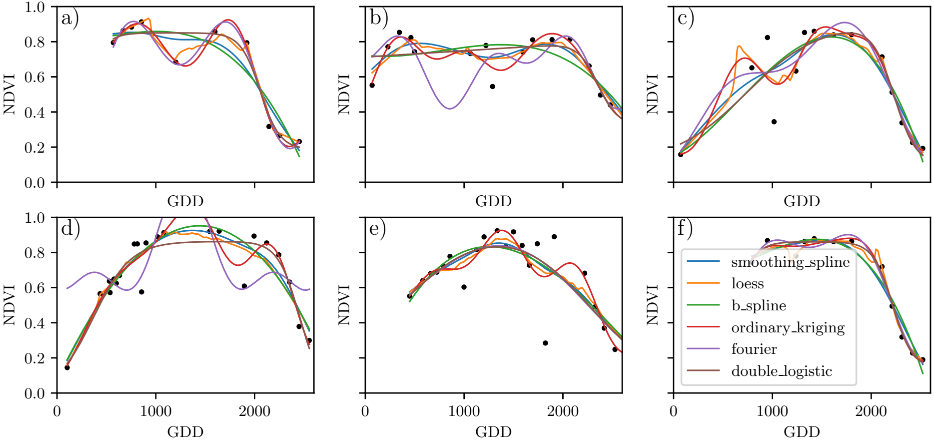
→ Bare soils



Timescale Transformation: DAS vs GDD

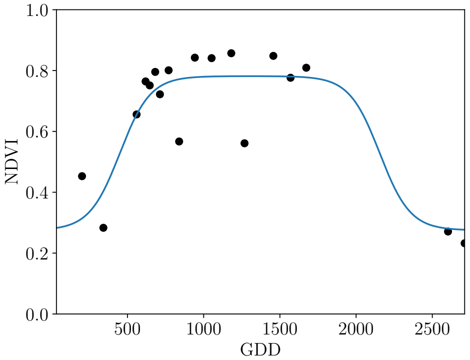
$$GDD_n := \sum_{i=0}^{n} \max(T_i - T_{base}, 0).$$




a)
b)
c)
d)
e)
f)
NDVI
GDD
1.0
0.8
0.6
0.4
0.2
0.0
0
1000
2000
smoothing_spline
loess
b_spline
ordinary_kriging
fourier
double_logistic

Double Logistic Approximation

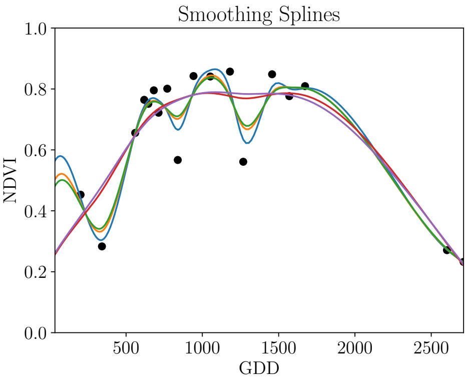
$$\mathrm{NDVI}(t) = y_{\min} + (y_{\max} - y_{\min}) \left(\frac{1}{1 + e^{-d_0 (t - t_0)}} + \frac{1}{1 + e^{-d_1 (t - t_1)}} - 1 \right)$$



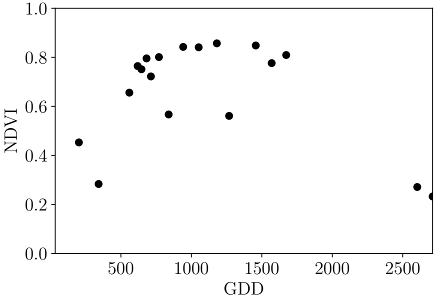
Smoothing Splines

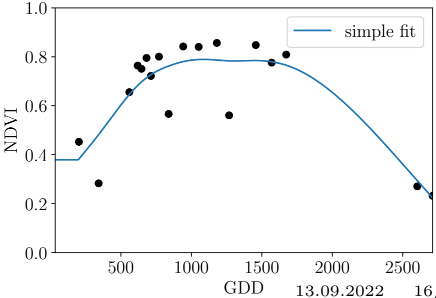
$$\widehat{NDVI} := \underset{f \in \mathcal{F}}{\operatorname{argmin}} \underbrace{\sum_{i=1}^{n} \left(Y_i - f\left(x_i\right)\right)^2}_{\text{sum of squares}} + \lambda \underbrace{\int f''(x)^2 dx}_{\text{smoothness}}$$

Similar to the Whittaker (but more general)



1. Interpolation





2. Other SCL-Classes

Color	No.	Class
	0:	Missing Data
	1:	Saturated or defective pixel
	2:	Dark features / Shadows
	3:	Cloud shadows
	4:	Vegetation
	5:	Bare soils
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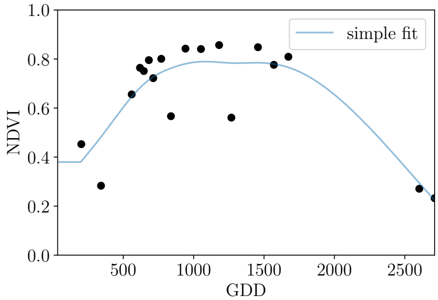
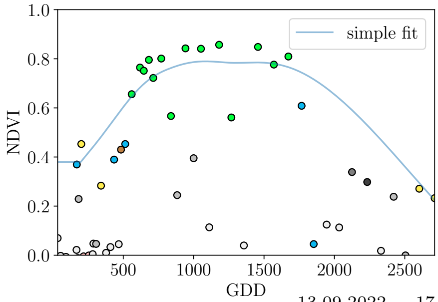
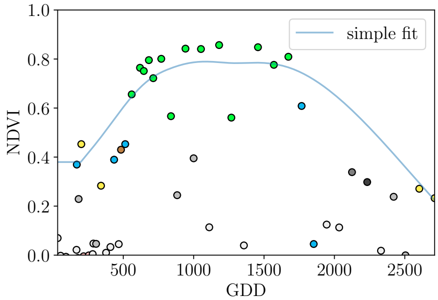


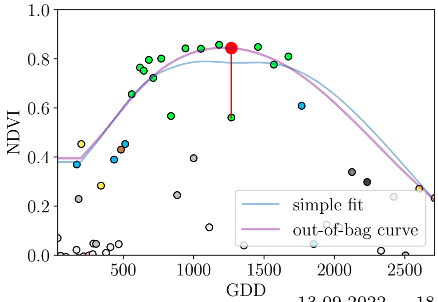


3. Correction

- get 'true' NDVI
- get table:

$\text{NDVI}^{\text{'true'}}$	$\text{NDVI}^{\text{observed}}$	SCL	B2-B10
$\text{NDVI}^{\text{'true'}}$	$\text{NDVI}^{\text{observed}}$	SCL	B2-B10
$\ldots$	$\ldots$	$\ldots$	$\ldots$



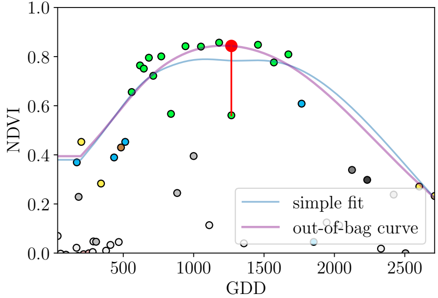


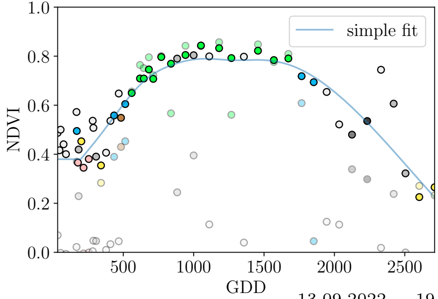
3. Correction

- get 'true' NDVI
- get table:

NDVI$^{\text{'true'}}$	NDVI$^{\text{observed}}$	SCL	B2-B10
NDVI$^{\text{'true'}}$	NDVI$^{\text{observed}}$	SCL	B2-B10
...	...	...	...

- Statistical model
- predict/correct NDVI



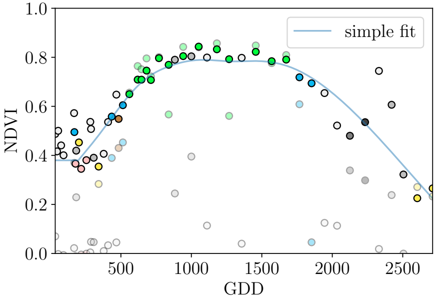


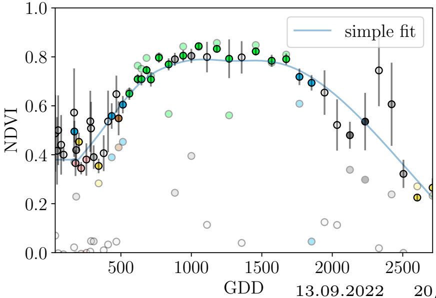
4. Uncertainty Estimation

$$|\,\text{residuals}\,| = |\,\text{NDVI}^{\text{`true'}} - \widehat{\text{NDVI}^{\text{`true'}}}\,|$$

$\lvert\text{residuals}\rvert$	$\text{NDVI}^{\text{observed}}$	SCL	B2-B10
$\lvert\text{residuals}\rvert$	$\text{NDVI}^{\text{observed}}$	SCL	B2-B10
$\vdots$	$\vdots$	$\vdots$	$\vdots$

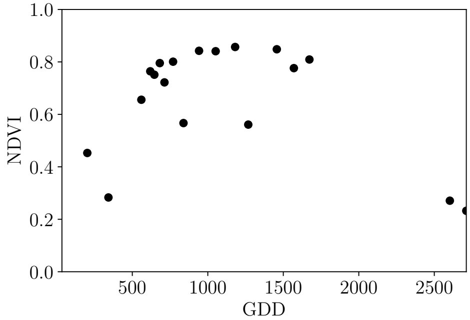
- Statistical model
- predict absolute residuals
- $\mathit{weights} = \dfrac{1}{|\widehat{\mathit{residual}}|}$

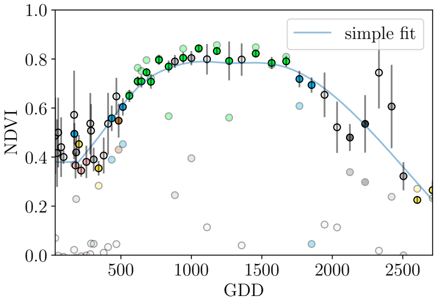


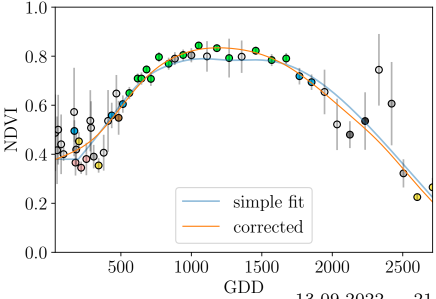


5. Robust Fit to Corrected NDVI

Reminder: Original Situation





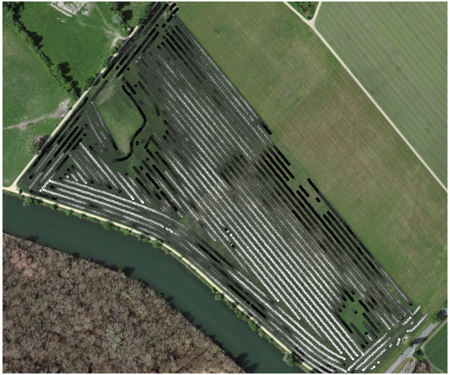


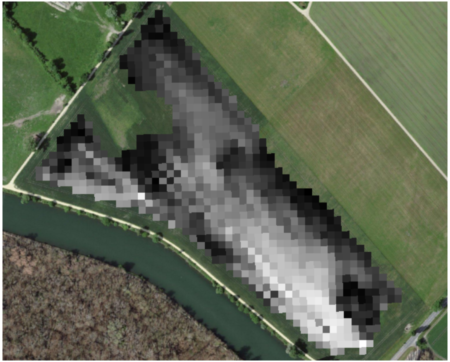
R-Package Provided

```r
library(CorrectTimeSeries)
data(timeseries_list) # load NDVI-TS data

# Train RF
  # Add "true" NDVI (or generally the response), by Out-Of-Bag estimation
    timeseries_list <- lapply(timeseries_list, function(df) {
      df$oob_ndvi <- OOB_est(df$gdd, df$ndvi_observed) # gdd is the time-axis
      df})
  # Train correction model
    formula <- "oob_ndvi ~ B02+B03+B04+B05+B06+B07+B08+B8A+B11+B12+scl_class"
    RF <- train_RF_with_fromula(formula, timeseries_list, robustify=TRUE)
# ADD CORRECTION
  timeseries_list <- lapply(timeseries_list, function(df) {
    df$corrected_ndvi <- randomForest:::predict.randomForest(RF, df)
    df})

# Get interpolation for each timeseries
  lapply(timeseries_list, function(df){
    ss <- smoothing_spline(df$gdd, df$corrected_ndvi)
    predict(ss, 1:1000)$y})
```

How to assess the quality of NDVI time series?

Yield Mapping Data



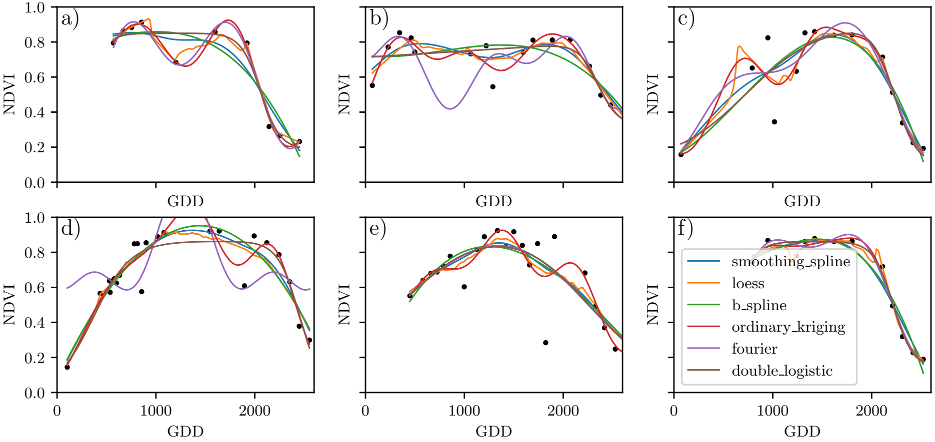


yield in [t/ha]
0.1
0.85
1.6
2.35
3.1
3.85
4.6
5.35

Unexplained variance in NDVI-based yield prediction reduced by 10.5%.

Thank You !

Robustifying



Coefficient of Determination (R^2)

	RF	OLS^{SCL}	OLS^{all}	MARS	GAM	LASSO	no correction
SS	0.676	0.736	0.726	0.731	0.729	0.731	0.703
SS^{rob}	0.676	0.724	0.709	0.704	0.715	0.716	0.705
DL	0.672	0.692	0.691	0.691	0.702	0.701	0.667
DL^{rob}	0.667	0.685	0.690	0.719	0.704	0.697	0.669

$$\frac{(1-0.705)-(1-0.736)}{1-0.705} = 10.5\%$$

$\mathrm{OLS}^{\mathrm{SCL}}$

$$
\begin{aligned}
\widehat{\mathrm{NDVI}}_{\text{‘true’}} = \quad & 0.711\,\mathrm{NDVI}_{\text{observed}} + 0.215\,\mathbb{1}_{SCL=2} + 0.237\,\mathbb{1}_{SCL=3} + 0.210\,\mathbb{1}_{SCL=4} \\
& + 0.116\,\mathbb{1}_{SCL=5} + 0.162\,\mathbb{1}_{SCL=6} + 0.327\,\mathbb{1}_{SCL=7} + 0.474\,\mathbb{1}_{SCL=8} \\
& + 0.575\,\mathbb{1}_{SCL=9} + 0.306\,\mathbb{1}_{SCL=10} + 0.512\,\mathbb{1}_{SCL=11}
\end{aligned}
$$

$$
\begin{aligned}
\widehat{\mathrm{abs}}\left(\mathrm{NDVI}_{\text{‘true’}} - \widehat{\mathrm{NDVI}}_{\text{‘true’}}\right) = \quad & -0.133\,\mathrm{NDVI}_{\text{observed}} + 0.186\,\mathbb{1}_{SCL=2} + 0.185\,\mathbb{1}_{SCL=3} \\
& + 0.146\,\mathbb{1}_{SCL=4} + 0.089\,\mathbb{1}_{SCL=5} + 0.167\,\mathbb{1}_{SCL=6} \\
& + 0.203\,\mathbb{1}_{SCL=7} + 0.181\,\mathbb{1}_{SCL=8} + 0.173\,\mathbb{1}_{SCL=9} \\
& + 0.180\,\mathbb{1}_{SCL=10} + 0.172\,\mathbb{1}_{SCL=11}
\end{aligned}
$$