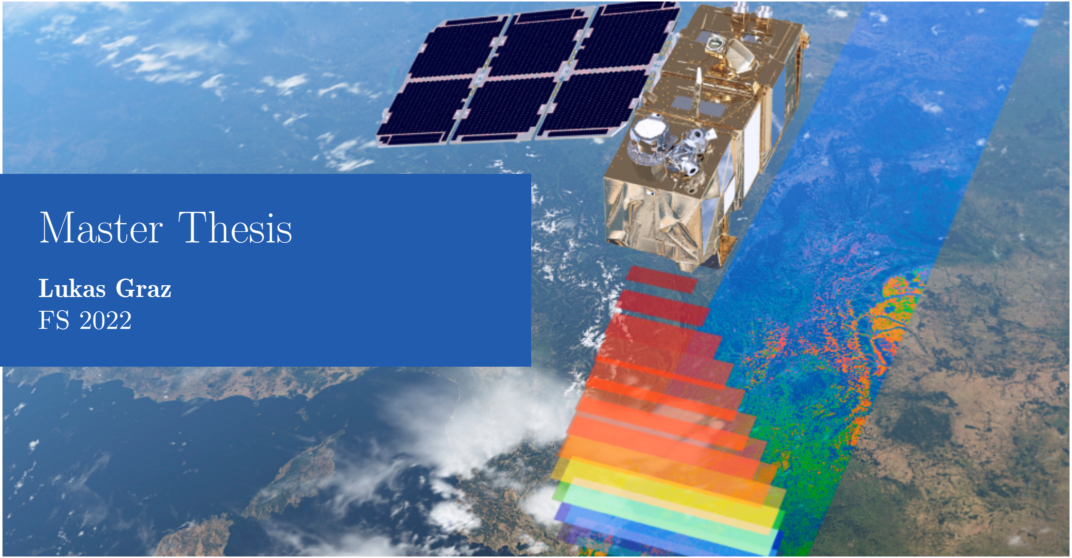
ETH zürich

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



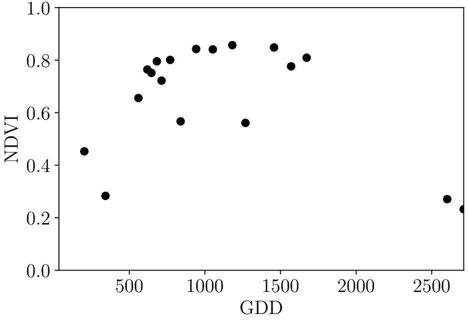
Master Thesis

Lukas Graz

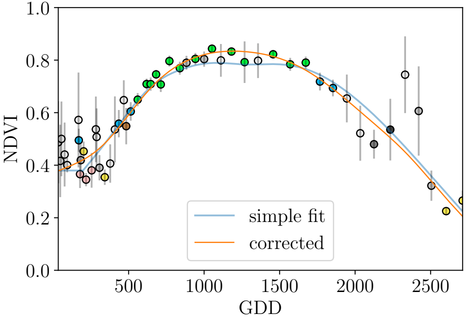
FS 2022

How to get ...

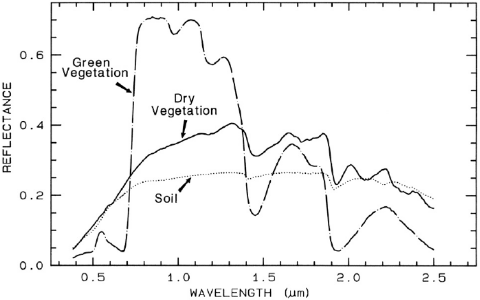
from ...



to ...



NDVI From S2 Images



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

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

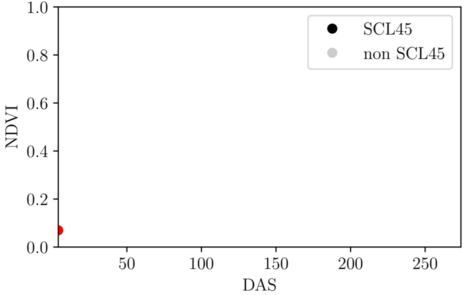
Scene Classification Layer (SCL)

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

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

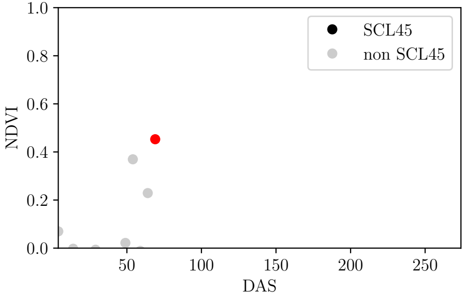
Sentinel 2 Image + NDVI Time Series

→ Cloud high probability



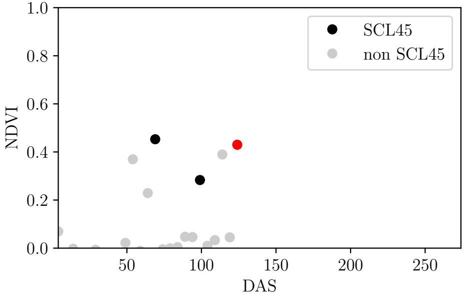
Sentinel 2 Image + NDVI Time Series

→ Bare soils



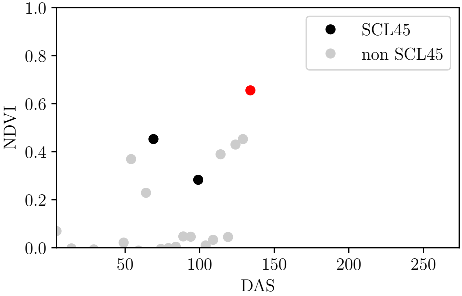
Sentinel 2 Image + NDVI Time Series

→ Cloud shadows



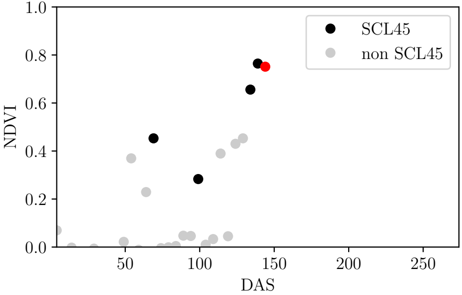
Sentinel 2 Image + NDVI Time Series

→ Vegetation



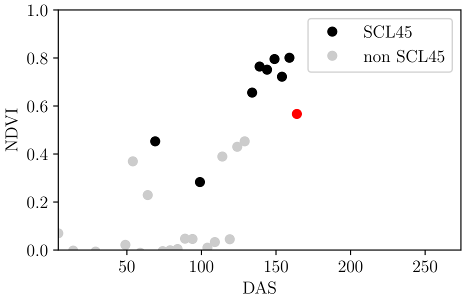
Sentinel 2 Image + NDVI Time Series

→ Vegetation



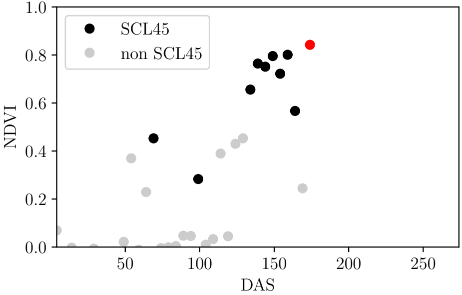
Sentinel 2 Image + NDVI Time Series

→ Vegetation

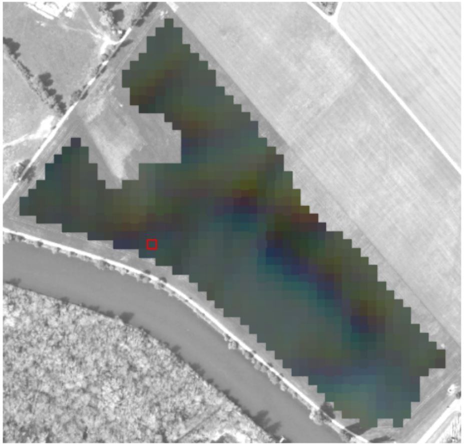


Sentinel 2 Image + NDVI Time Series

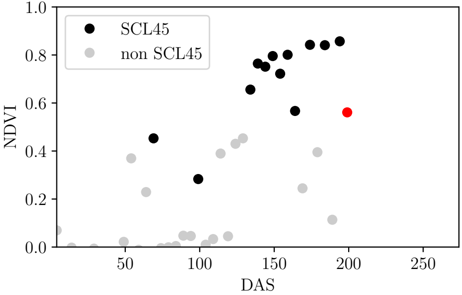
→ Vegetation



Sentinel 2 Image + NDVI Time Series

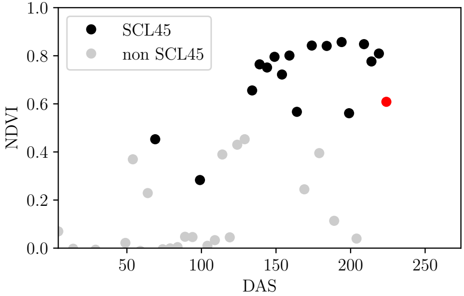


→ Vegetation



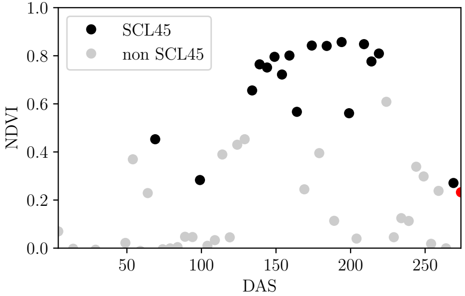
Sentinel 2 Image + NDVI Time Series

→ Thin cirrus cloud



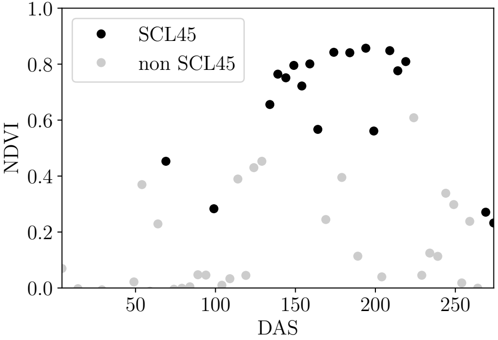
Sentinel 2 Image + NDVI Time Series

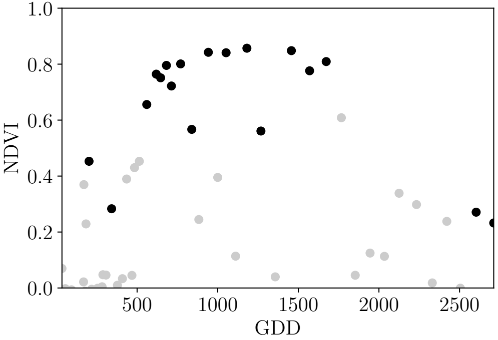
→ Bare soils

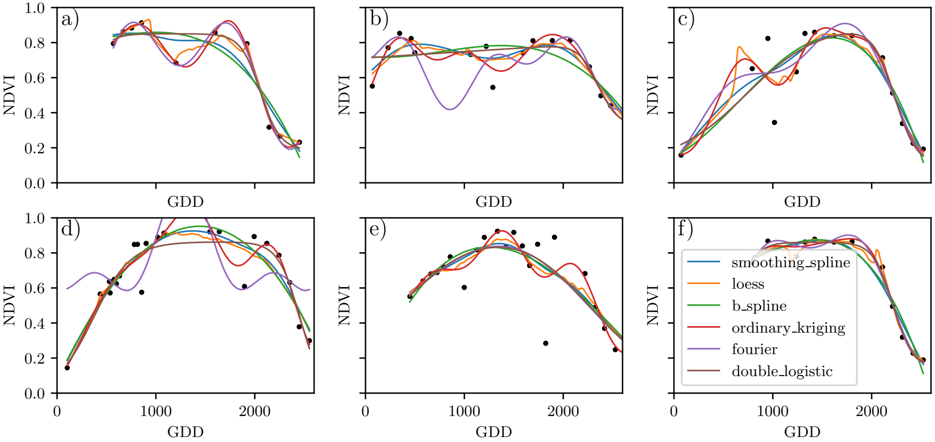


Timescale Transformation: DAS vs GDD

$$GDD_n := \sum_{i=0}^{n} \max(T_i - T_{base}, 0). \tag{1}$$



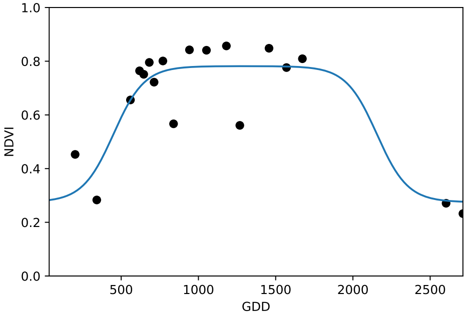



a)
b)
c)
d)
e)
f)
NDVI
GDD
1.0
0.8
0.6
0.4
0.2
0.0
0
1000
2000
smoothing_spline
loess
b_spline
ordinary_kriging
fourier
double_logistic

Double Logistic Approximation

Curve fully determined by parameters (no data)

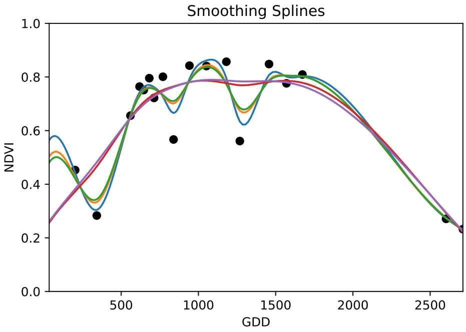
$$NDVI(t) = f(a, b, c, d, e)$$



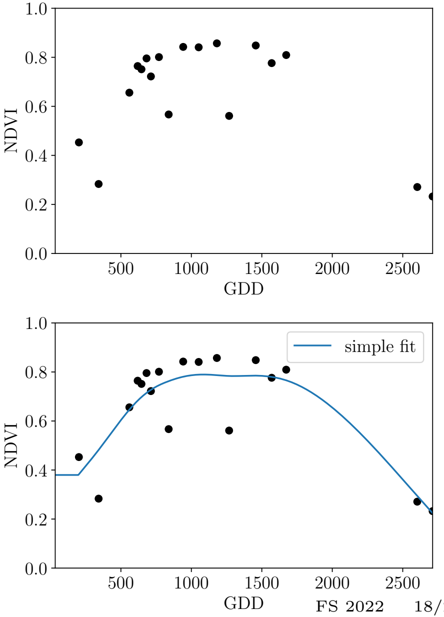
Smoothing Splines

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

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
	6:	Water
	7:	Cloud low probability
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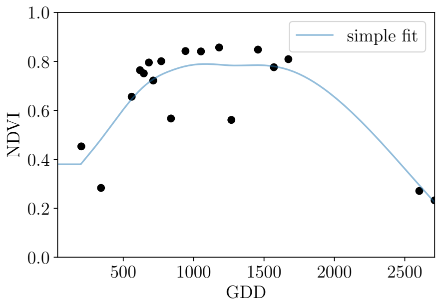
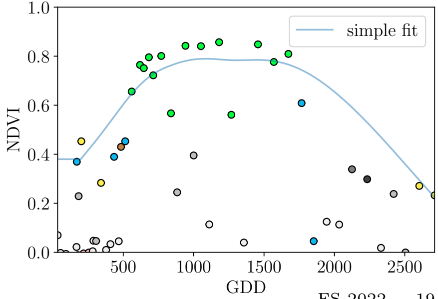
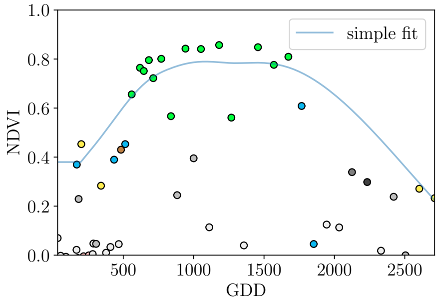


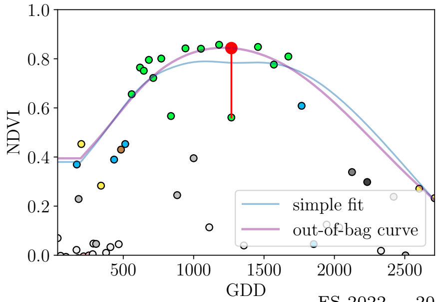


3. Correction

- get "true" NDVI
- get table:

"truth"	observed	scl-class	B2-B10	weather
"truth"	observed	scl-class	B2-B10	weather
...	...	...	...	...



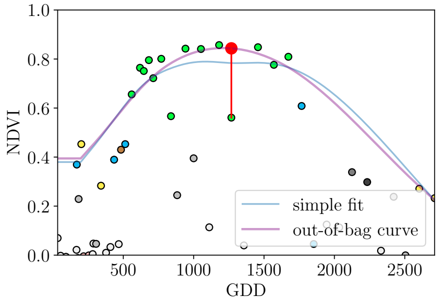


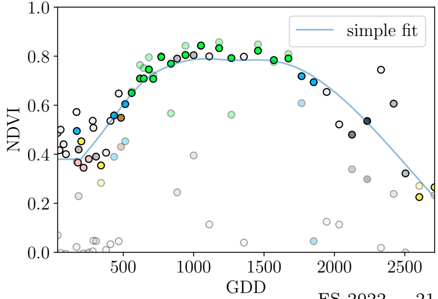
3. Correction

- get “true” NDVI
- get table:

“truth”	observed	scl-class	B2-B10	weather
“truth”	observed	scl-class	B2-B10	weather
...	...	...	...	...

- Statistical model
- predict/correct NDVI
- weather – yes or no?



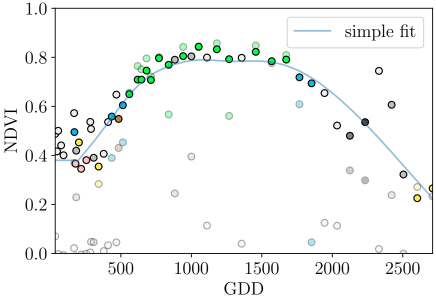


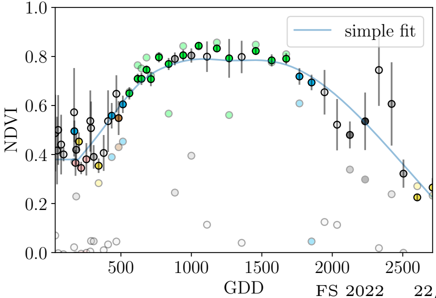
4. Uncertainty Estimation

- Table with residuals:

residuals	observed	scl-class	B2-B10	weather
residuals	observed	scl-class	B2-B10	weather
⋮	⋮	⋮	⋮	⋮

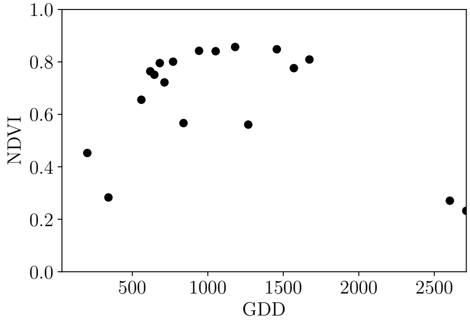
- Statistical model
- predict residuals
- $weights = \frac{1}{|residual|}$

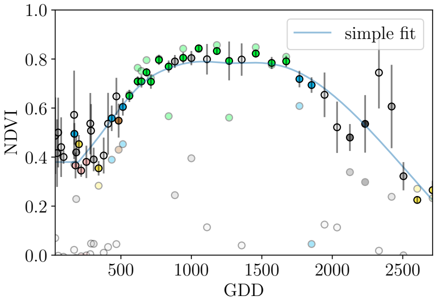


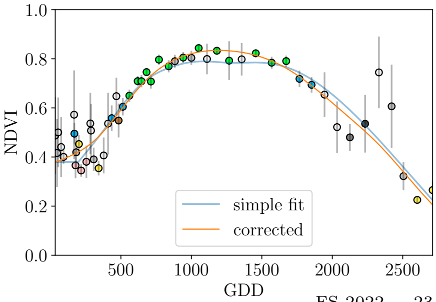


5. Robust Fit to Corrected NDVI

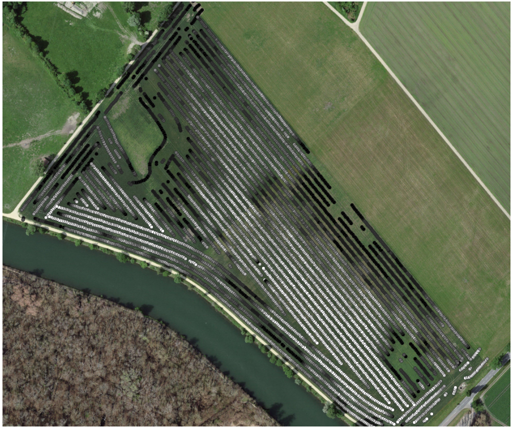
Reminder: Original Situation

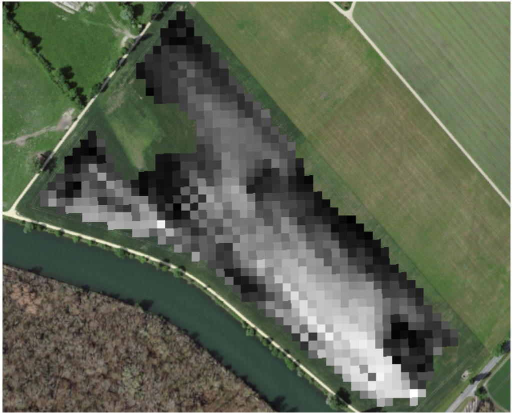




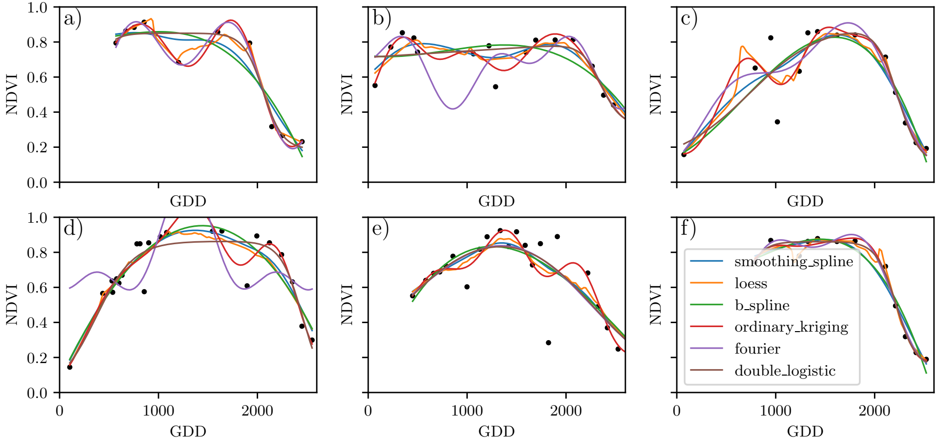


Yield Mapping Data





Robustifying



Results

	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

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})
```

Thank You !

APPENDIX: OLS^{SCL}

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

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