# Exploring the Potential of Multi-Temporal Crop Canopy Models and Vegetation Indices from Pleiades Imagery for Yield Estimation

**Dimo Dimov, Patrick Noack**

**Symposium AI4Life 2023**

# Collaboration research

- Geocledian GmbH, Landshut, Crop Monitoring IT Company
- HSWT, Triesdorf, Prof. Dr. Patrick Noack
- What should we do???

# Collaboration research

- Let's do something with very high resolution data, but not UAV
- What are the tradeoffs between VHR satellite and UAV imagery
- Is the vertical information of crops a gain for yield estimation models
- Can we combine horizontal-spectral and vertical-structural features?

→ Variable rate application/irrigation maps

→ Yield potential zoning

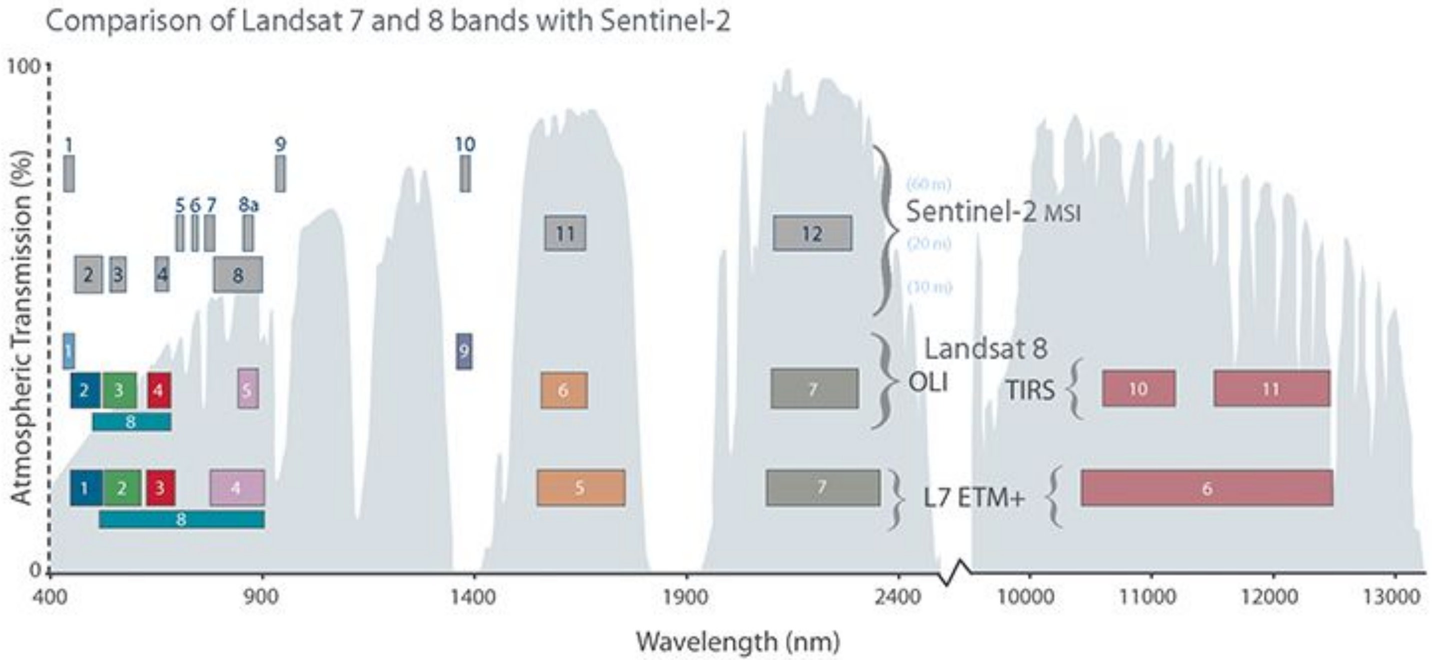
→ Crop variety evaluation

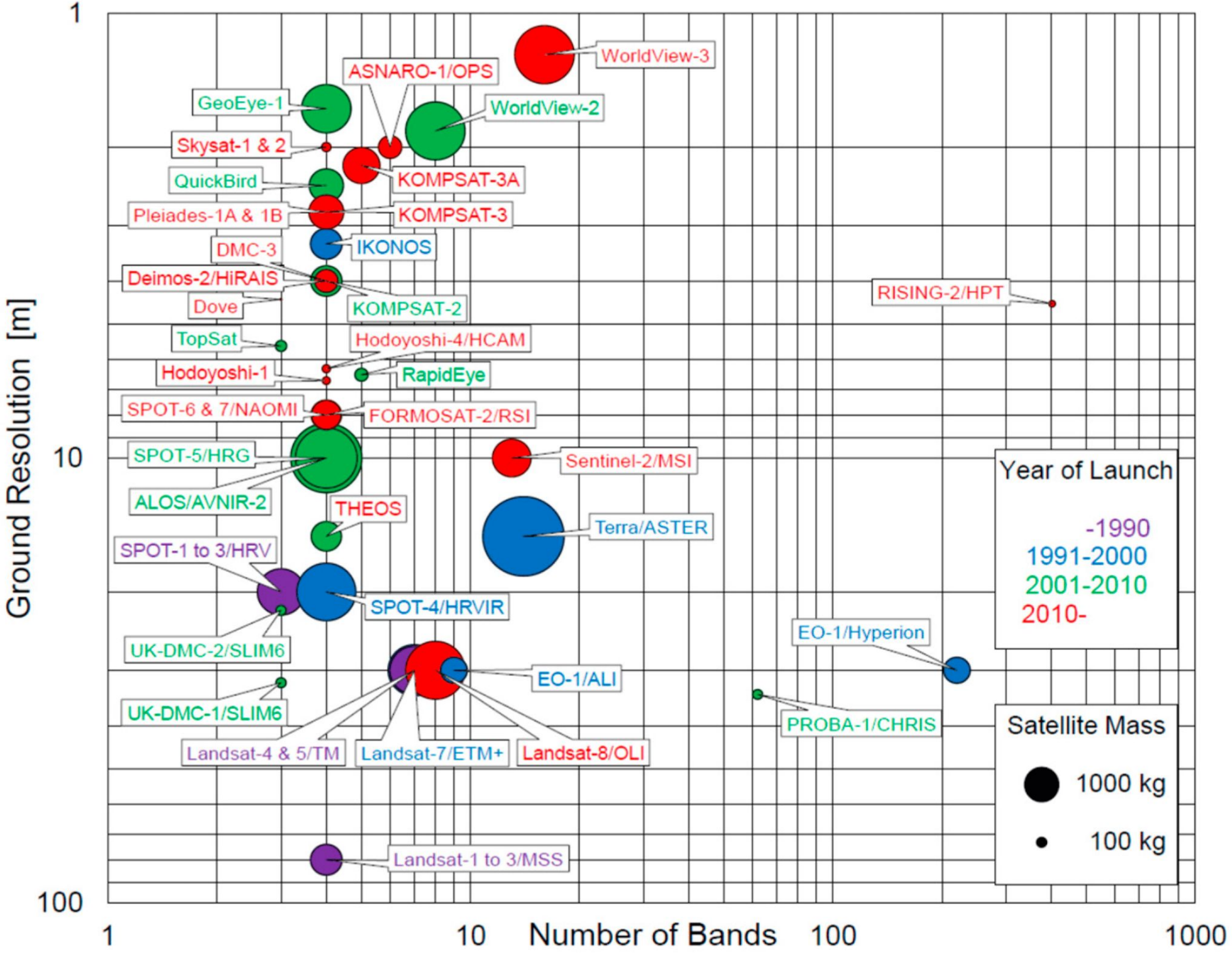
→ Hazard detection & segmentation (e.g. hail damage)

# Yield estimation via Remote Sensing

- Biophysical modelling (e.g. Light Use Efficiency model, ORYZA2000)
- Derivation of yield potential zones (e.g. from UAV)
- Crop productivity mapping based on vegetation index time series
- Deficiency mapping (e.g. irrigation failures, crop damage)
- **Yield estimation through supervised regression of RS data**

# Remote Sensing




1
10
100
1
10
100
1000
Ground Resolution [m]
Number of Bands
WorldView-3
ASNARO-1/OPS
GeoEye-1
WorldView-2
Skysat-1 & 2
KOMPSAT-3A
QuickBird
Pleiades-1A & 1B
KOMPSAT-3
DMC-3
IKONOS
Deimos-2/HiRAIS
Dove
KOMPSAT-2
RISING-2/HPT
TopSat
Hodoyoshi-4/HCAM
Hodoyoshi-1
RapidEye
SPOT-6 & 7/NAOMI
FORMOSAT-2/RSI
SPOT-5/HRG
Sentinel-2/MSI
ALOS/AVNIR-2
THEOS
Terra/ASTER
SPOT-1 to 3/HRV
SPOT-4/HRVIR
UK-DMC-2/SLIM6
EO-1/Hyperion
EO-1/ALI
UK-DMC-1/SLIM6
PROBA-1/CHRIS
Landsat-4 & 5/TM
Landsat-7/ETM+
Landsat-8/OLI
Landsat-1 to 3/MSS
Year of Launch
-1990
1991-2000
2001-2010
2010-
Satellite Mass
1000 kg
100 kg

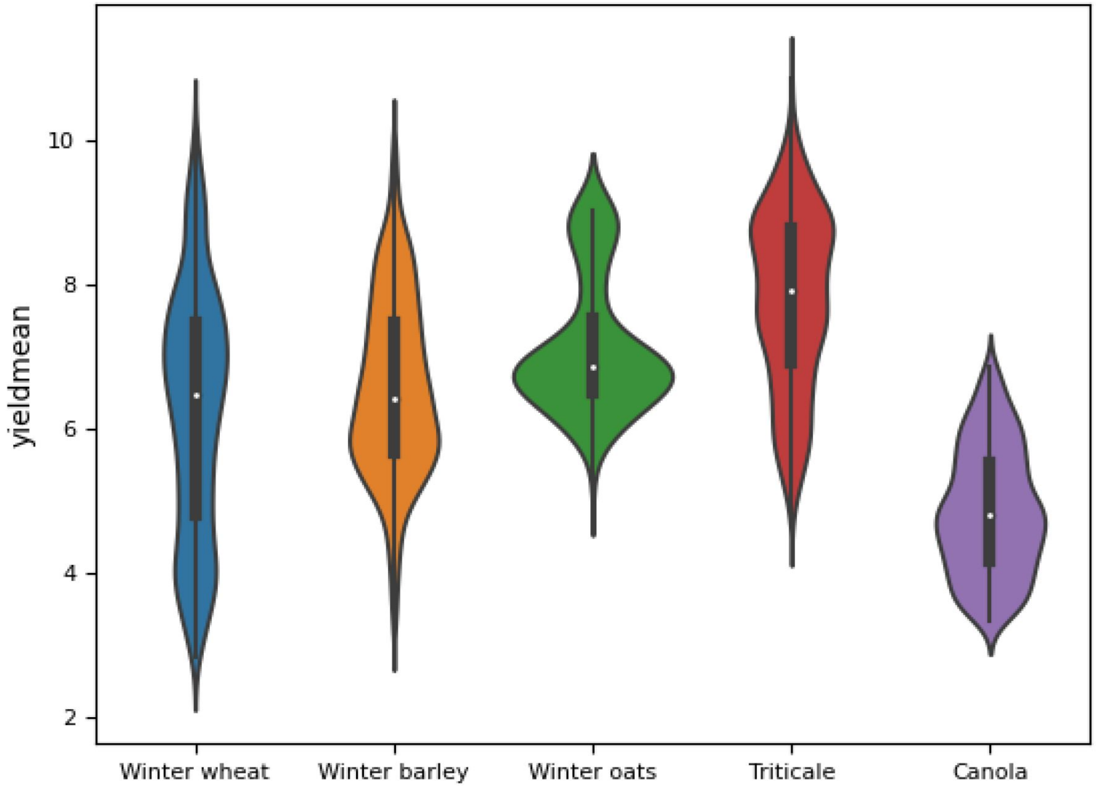
# Challenges

- Irregular satellite observations
- Atmospheric disturbances and cloud contamination
- Harmonizaton of multisensor and multisresolution data
- Domain adaptation and transfer learning still not optimal
- in ML/DL, retraining very often required

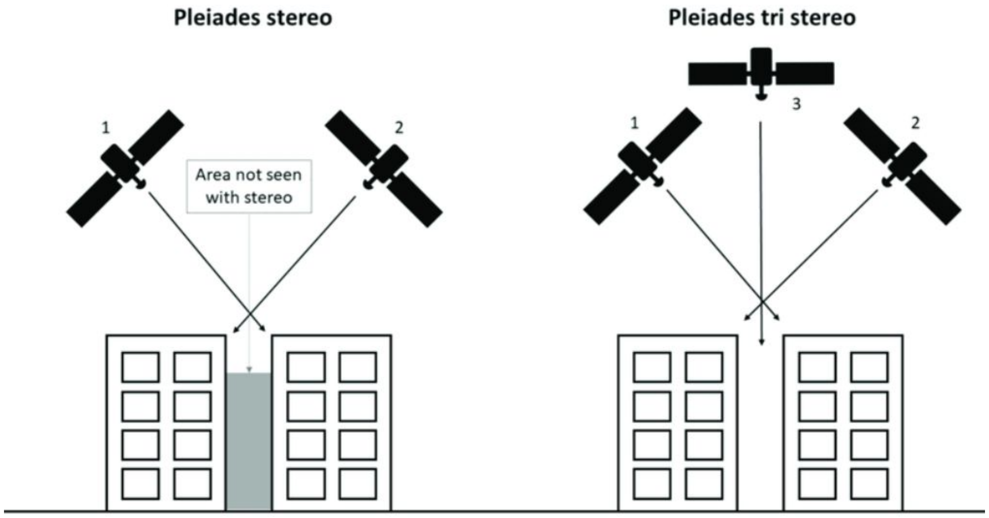
# Yield Data

- Claas Tucano combine harvester
- 8 fields with size 1 - 4.5ha
- in-situ: 2020-07-23 - 2020-08-11
- yield range: 2 t/ha -15 t/ha
- location: around Triesdorf, GER

# Yield Data

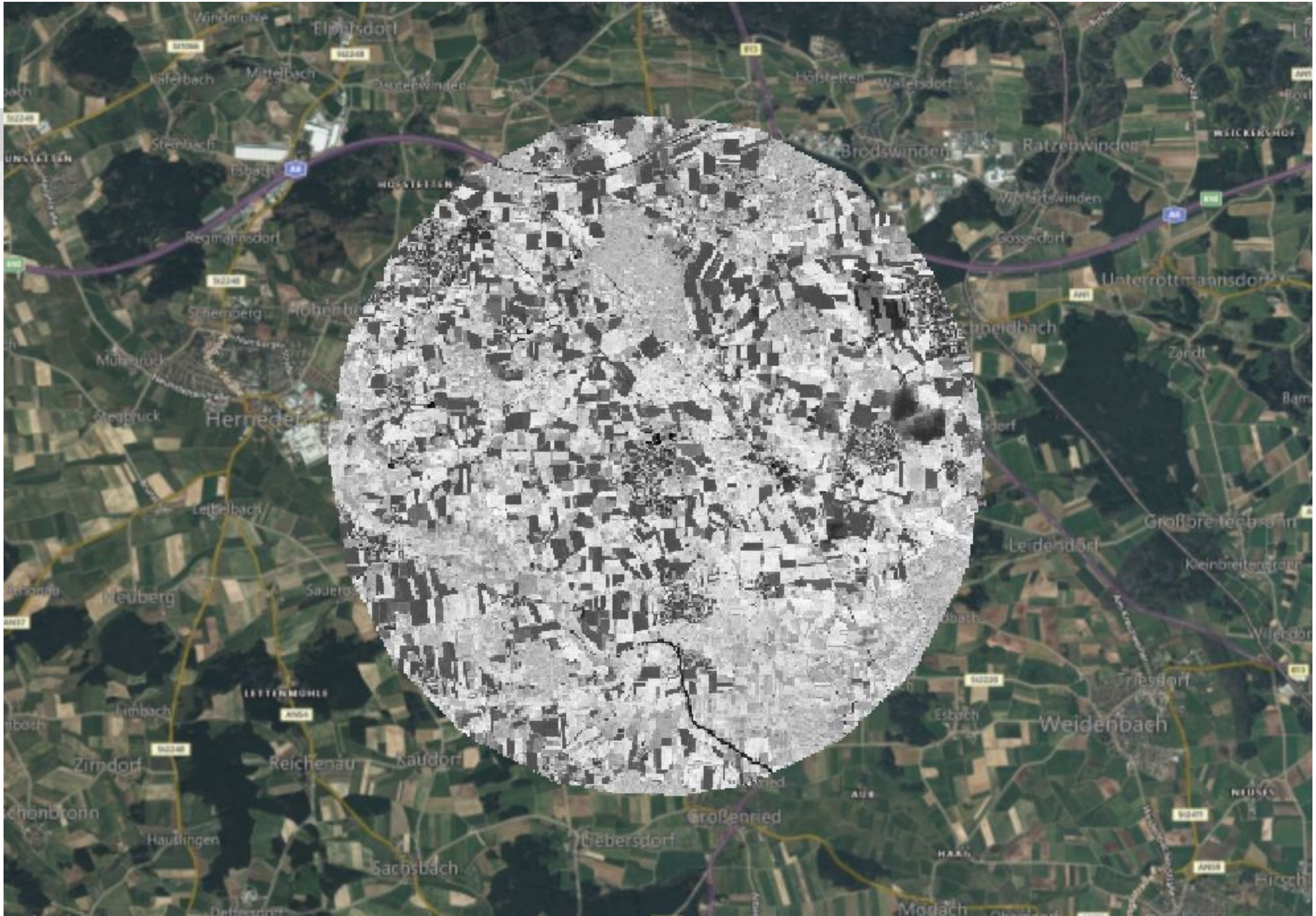

yieldmean
10
8
6
4
2
Winter wheat
Winter barley
Winter oats
Triticale
Canola

# Sat Data




from: Airbus Imaging

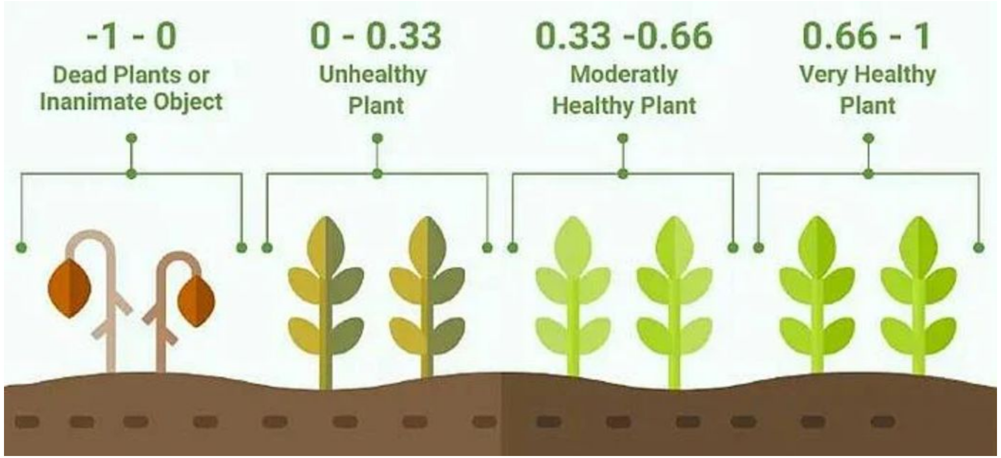
- Pleiades 1A (free for research)
- ONE Tasking → One Series - Routine (Airbus)
- 5 Stereo acquisitions in defined timeframe June-Sep 2020
- Requested area: 25km² around HWST Triesdorf Campus
- Achievable mode with minimum cloud cover
- Agile Stereo mode: same area from different angles
- 4x 2m multispectral and 1x 0.5m panchromatic bands


Kaferbach
Mittelbach
Hofstetten
Brodswinden
Ratzenwinden
Steinbach
Regmannsdorf
Herrieden
Stegbruck
Leidendorf
Weidenbach
Limbach
Zirndorf
Reichenau
Großenried
Sachsbach
Haundorf

# NDVI

- Normalized Difference Vegetation Index
- (NIR - RED) / (NIR + RED)

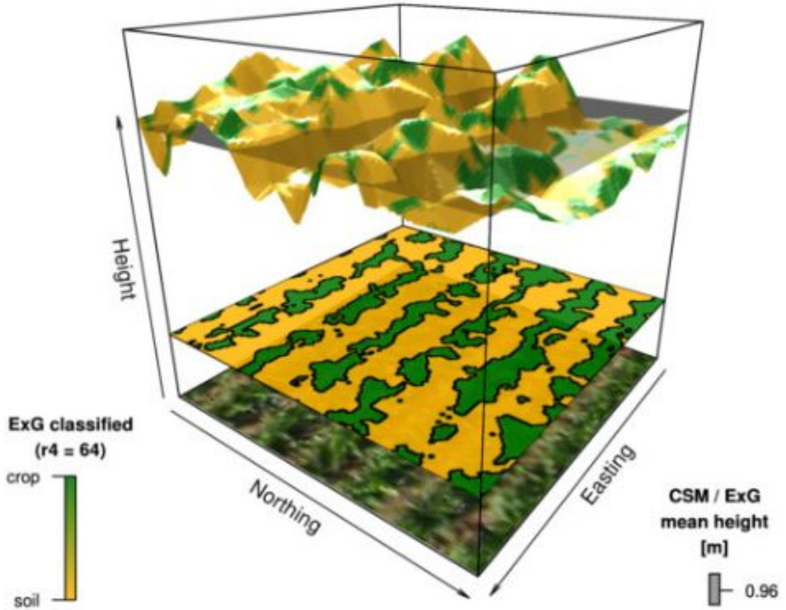
- Captures horizontal “greenness”
  - biomass
  - canopy/tillering density
  - chlorophyll content
- Captures growth dynamics
  - phenology
  - growth stages
  - crop-specific temporal signatures




from: cropin.com

# CCM

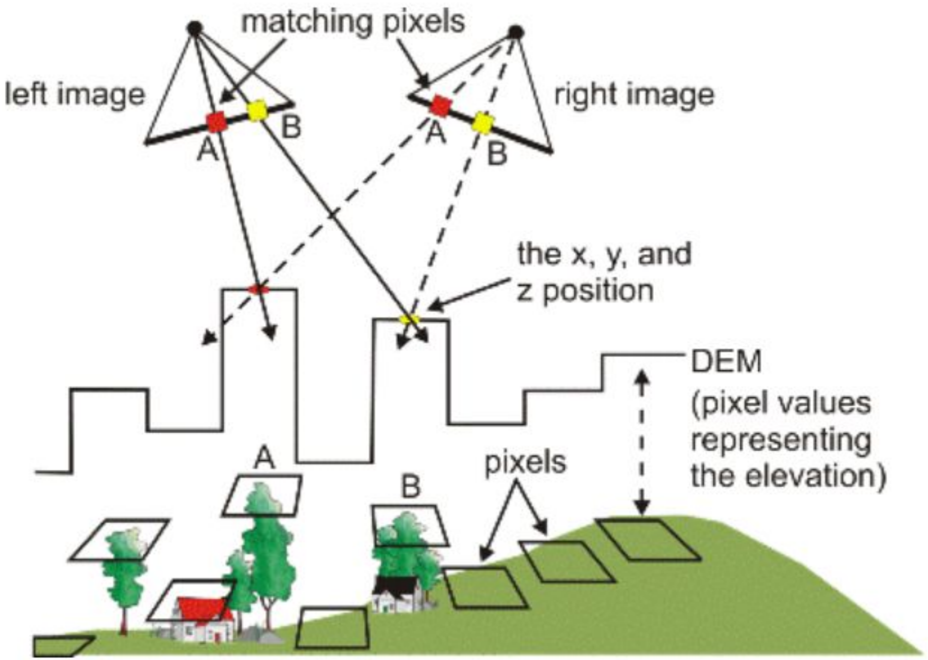
- Crop Canopy/Surface Models
- Captures vertical structures
  - biomass
  - crop height
  - canopy/tillering density
  - chlorophyll content
- Captures growth dynamics
  - phenology
  - growth stages
  - vertical-temporal signatures




from: https://doi.org/10.3390/rs61110335

# Stereo imaging

- Tie point extraction
- Creation of epipolar images
- Smoothing filter (5x5)
- Gap & spike interpolation
- Automated DTM generation
- DSM normalization




from: Catalyst.Earth

# Stereo imaging

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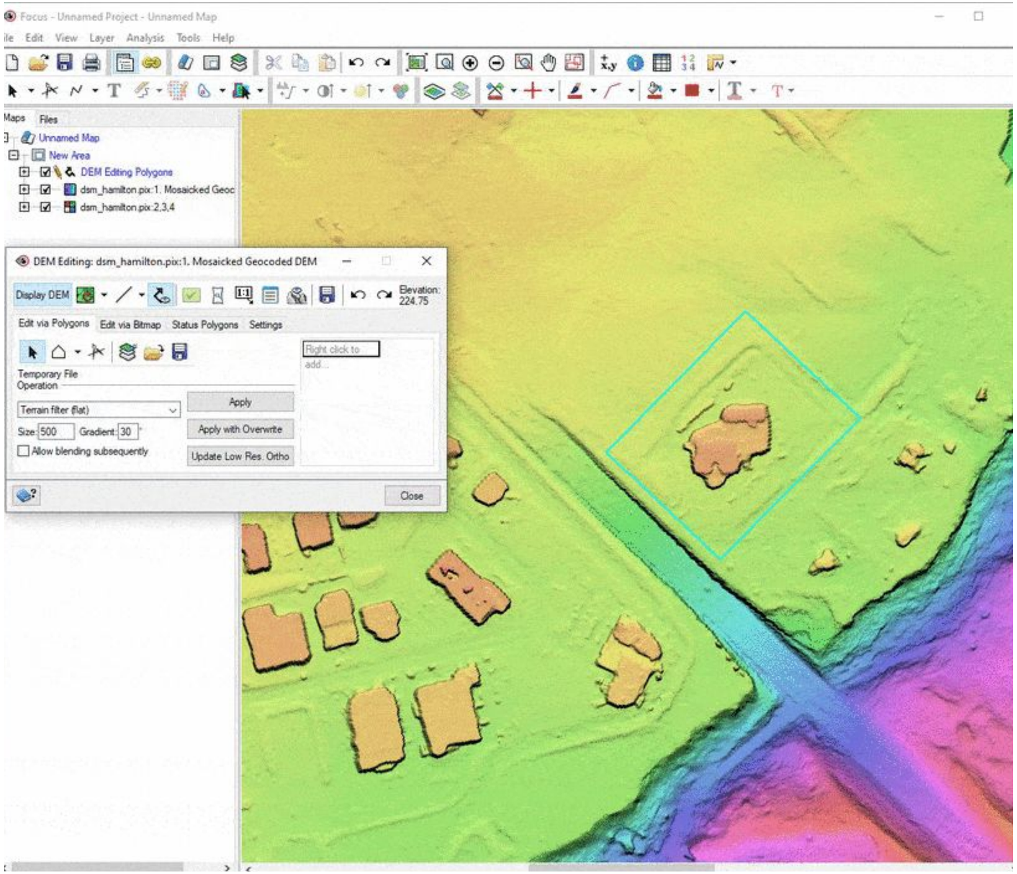



from: Catalyst.Earth

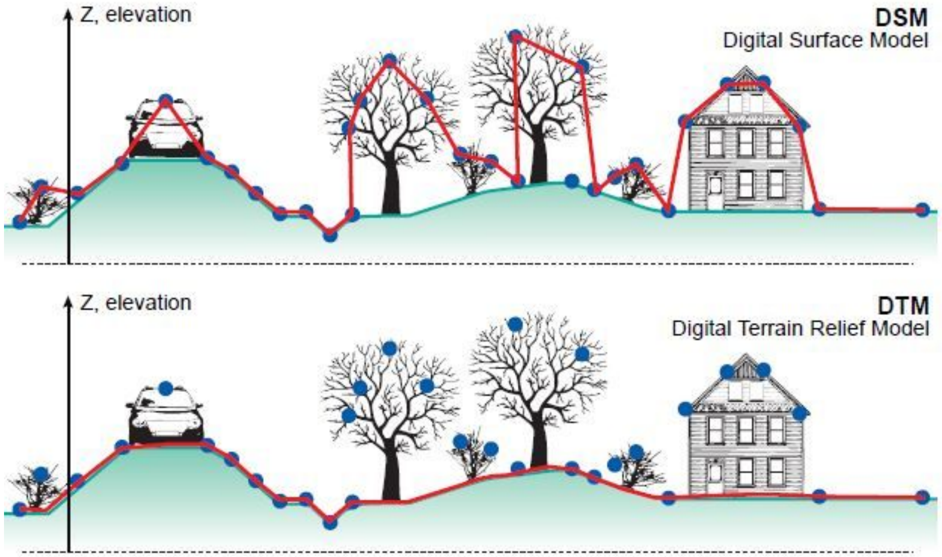
# DSM Normalization

**nDSM = DSM - DTM**

a) SRTM 30m - very bad results

b) per-pixel Minima from the 5 DSMs

c) automatic DTM creation for each DSM




from: Catalyst.Earth

# Experimental setup

a) Extraction of NDVI

b) Extraction of CCMs

c) Convolutional filtering, resampling and aggregation to Yield grids

d) PCA Transformation (for the fusion of NDVI and CCMs)

e) Training of Linear Regression & Ext. Randomized Trees

f) Validation on unseen data (retain 5%)

# Experimental setup

a) Regression tests for different crop types

b) Regression tests for different productivity levels

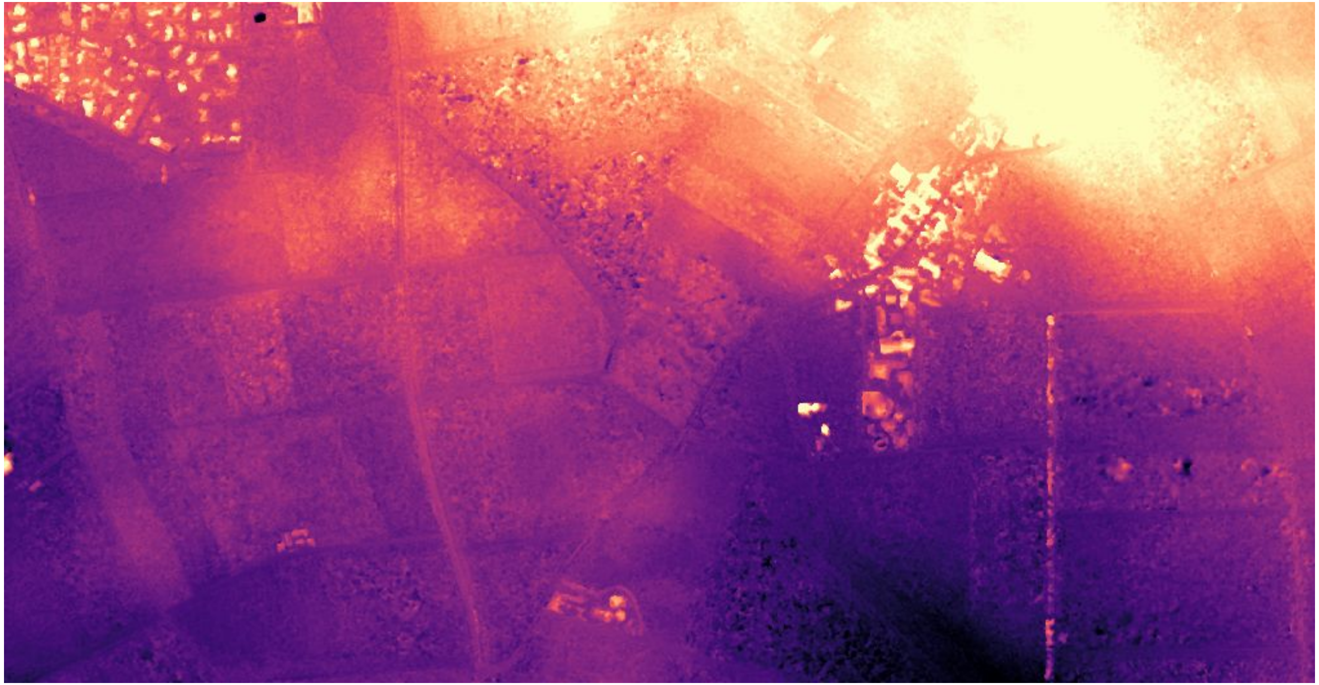
c) Regression tests for all data (generic model)

d) Cross-regression test on one field and inference on all other fields (crop-agnostic transfer)

e) Multi-temporal vs. single observations

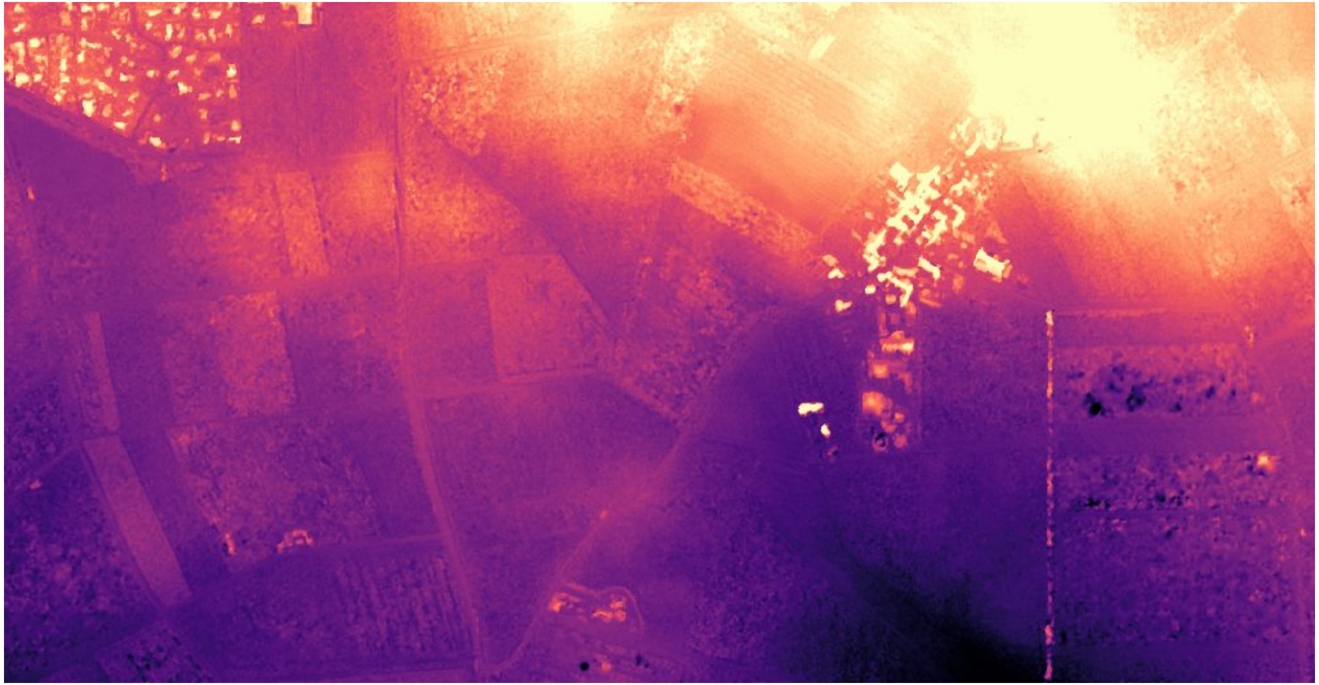
# DSM derivation

2020-06-12



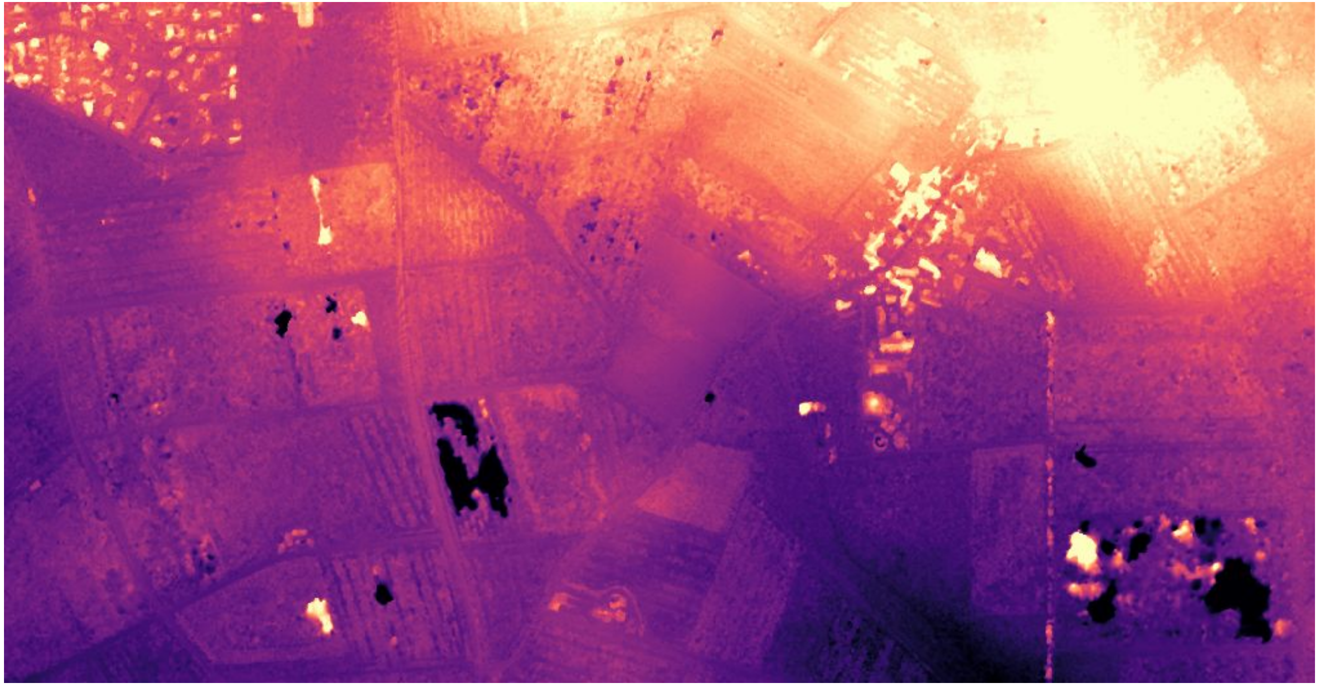
# DSM derivation

2020-06-26



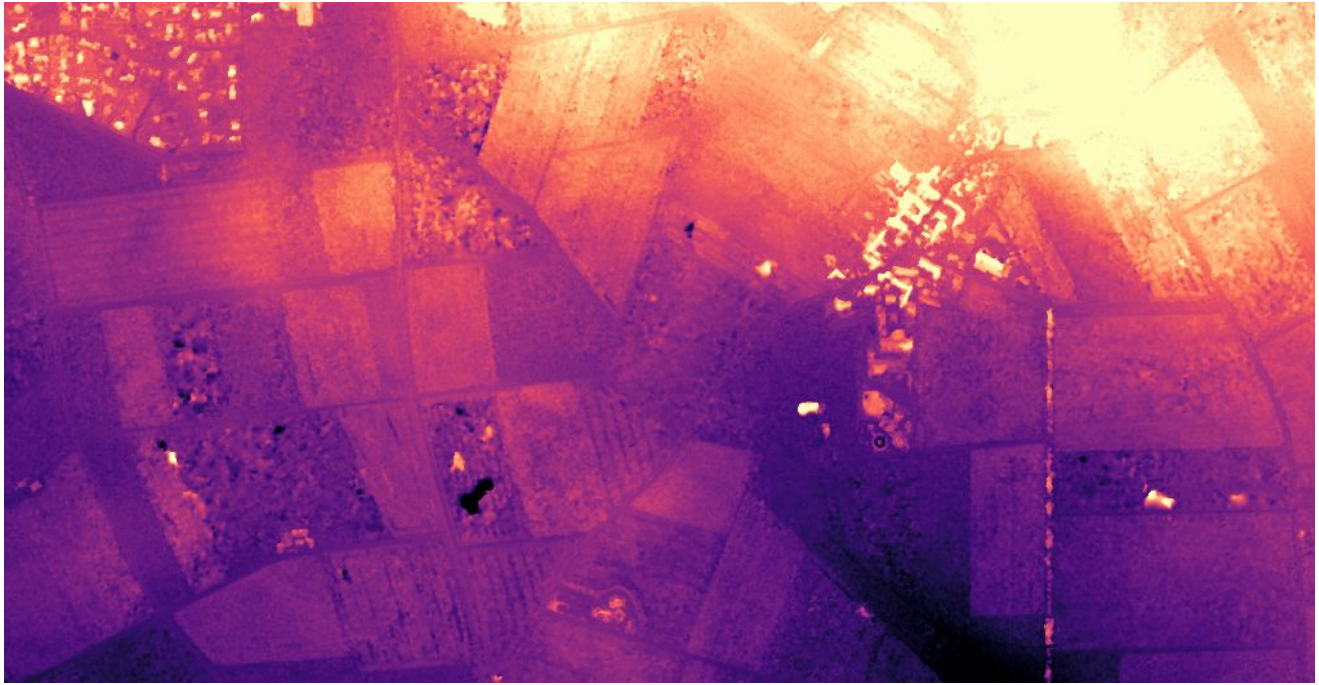
# DSM derivation

2020-07-22



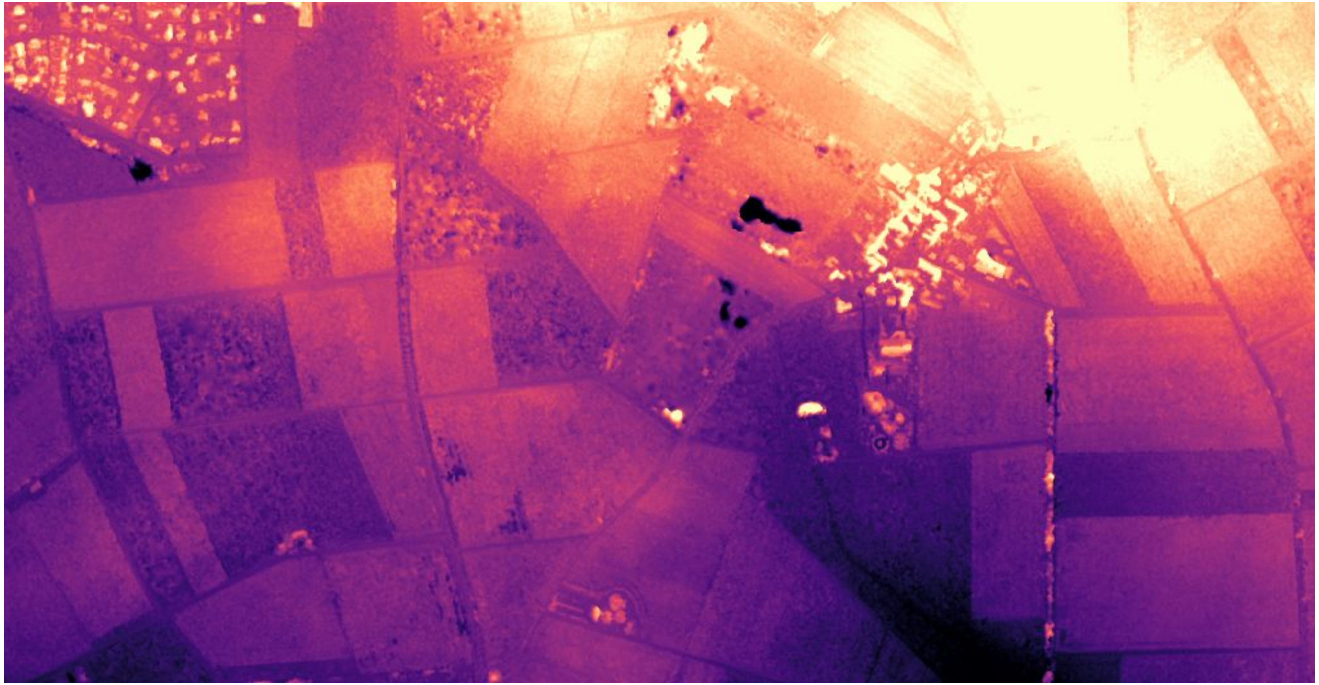
# DSM derivation

2020-08-10

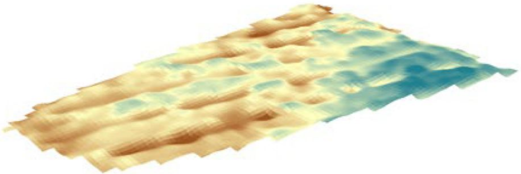


# DSM derivation

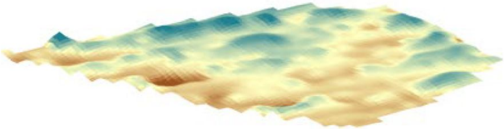
2020-09-07



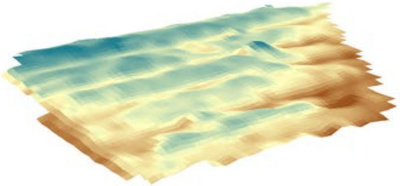
# nDSM derivation



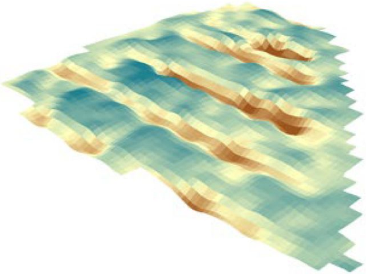
Rotunderacker, winter barley



Spessartacker, winter wheat



Steinbruch, winter barley



Weihenacker, winter barley

# NDVI

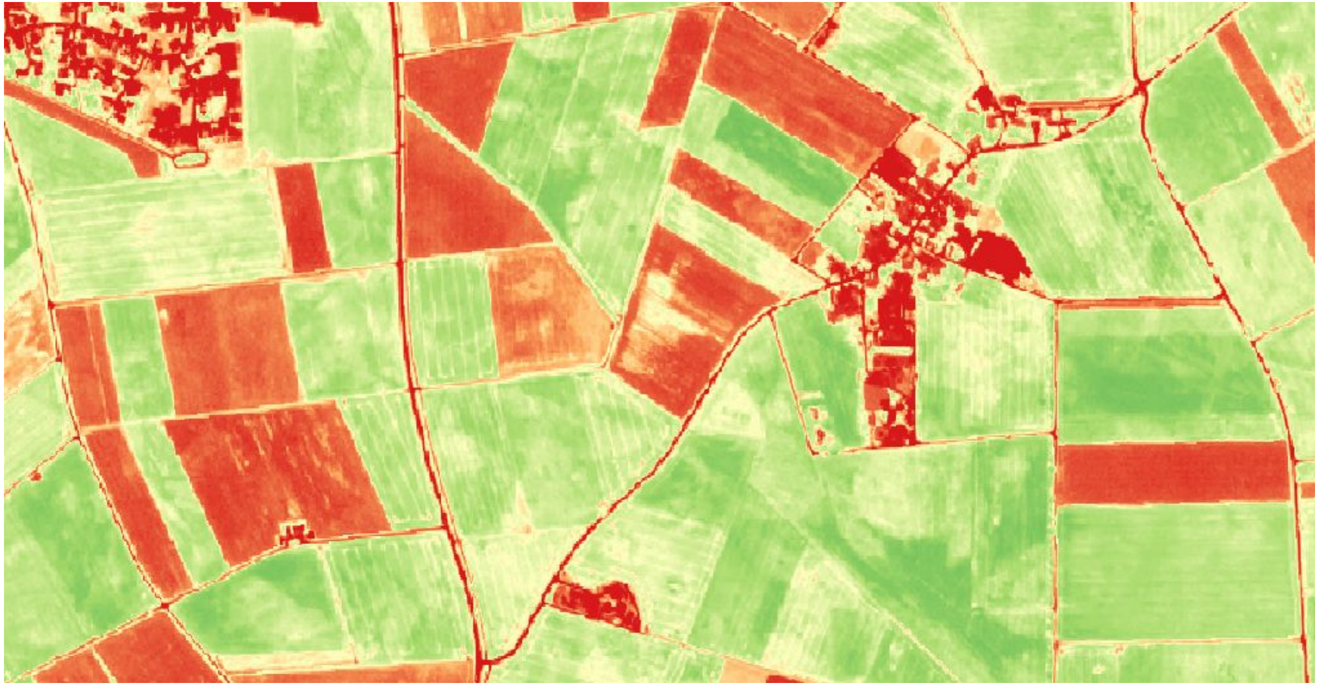
2020-06-12

# NDVI

2020-06-26

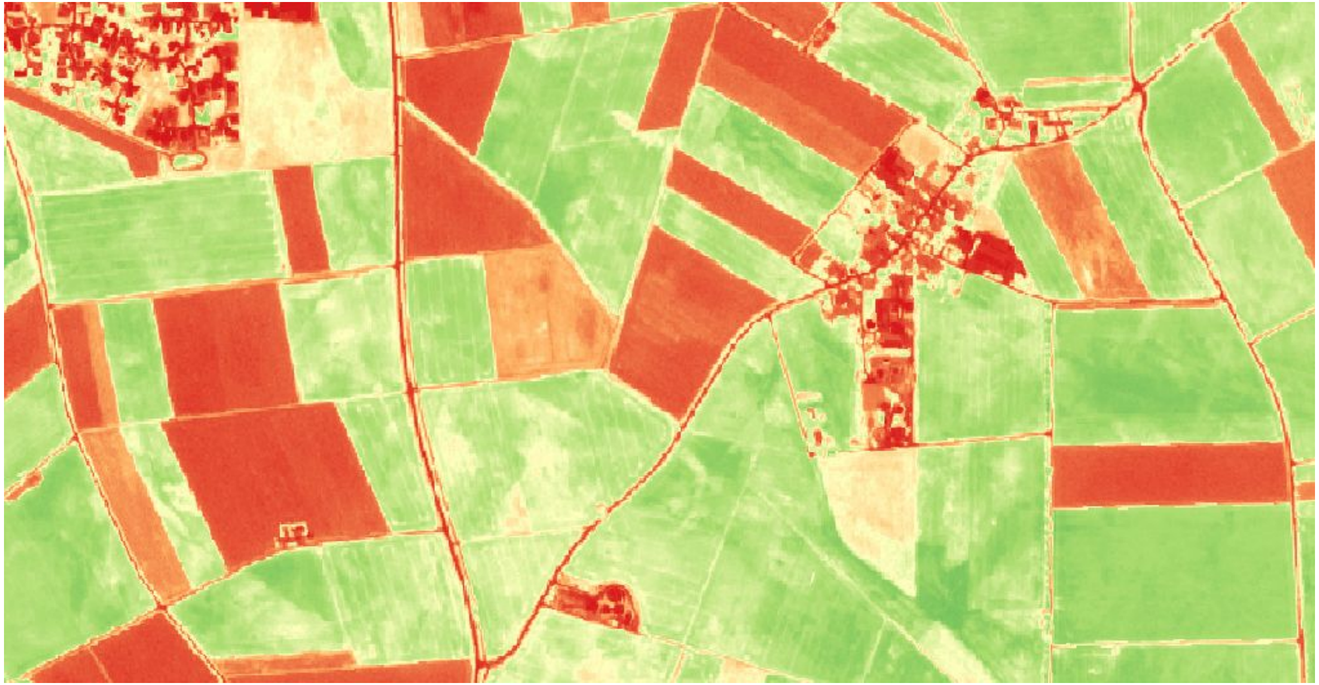
# NDVI

2020-07-22



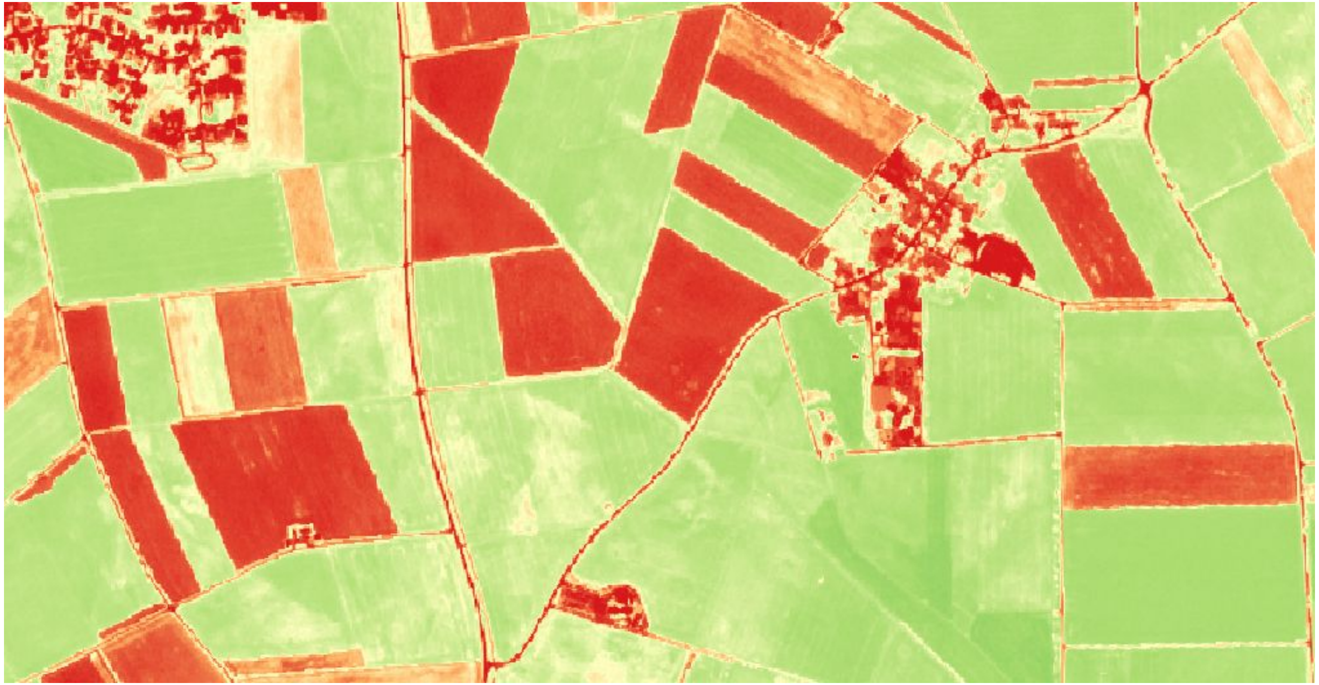
# NDVI

2020-08-10

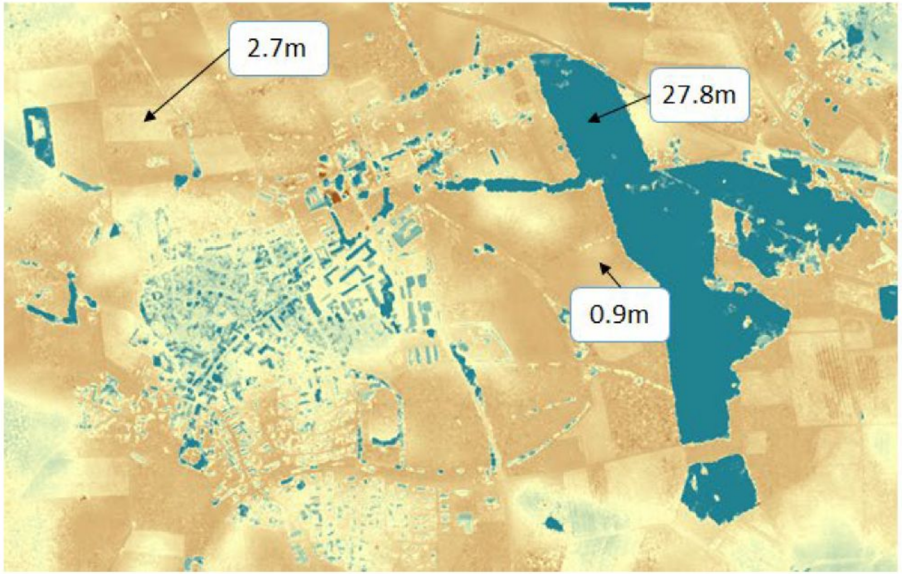


# NDVI

2020-09-07



# CCM + NDVI




# Why machine learning

- high-dimensional data
- non-linear relationships between variables → non-linear regressors
- such as: Extremely Randomized Trees, Neural Networks, XgBoost)
- automated feature selection of most responsive independent variables
- data fusion through dimensionality reduction techniques

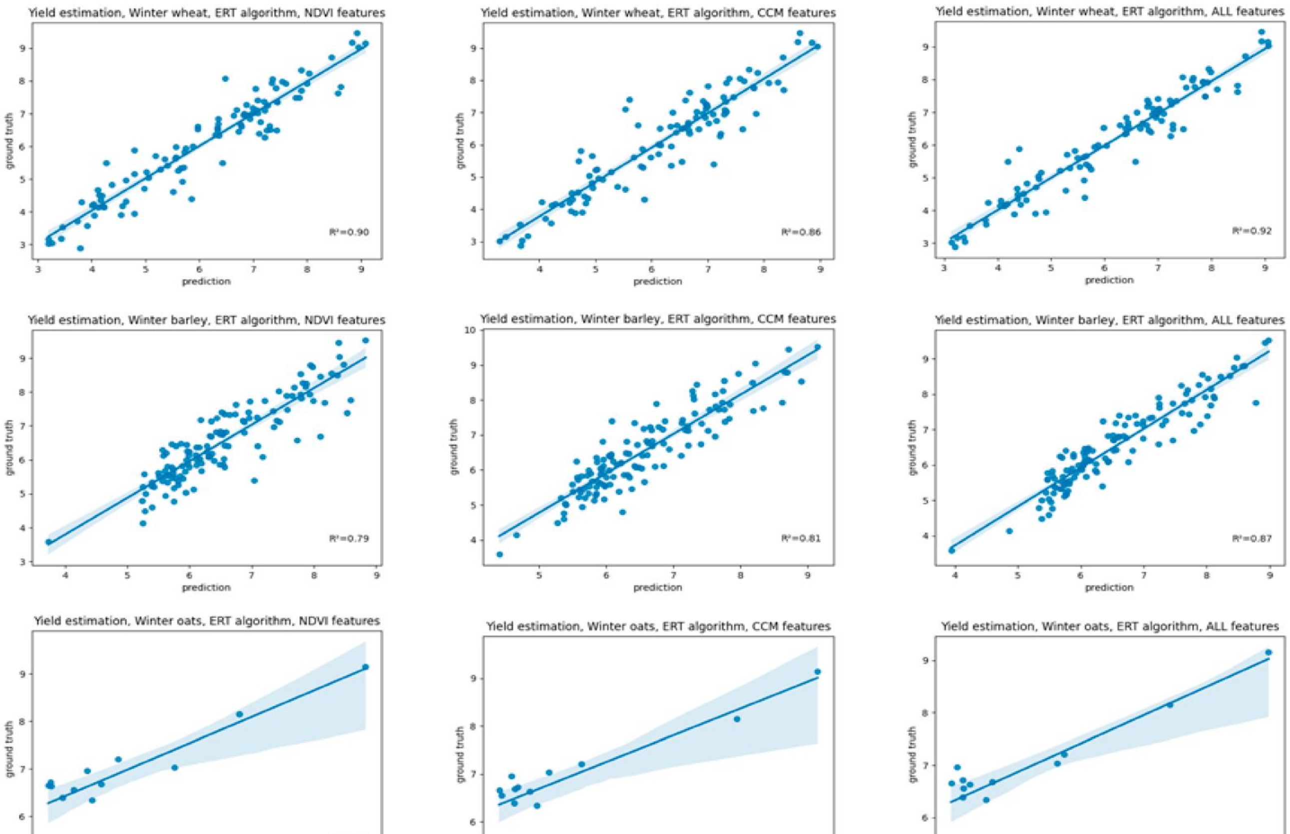
# Results - Summary

- winter wheat, highest accuracy ($R^2$ = 0.92, RMSE = 0.41, MAE = 0.31)
- winter oats, lowest accuracy ($R^2$ = 0.74, RMSE = 0.47, MAE = 0.30)

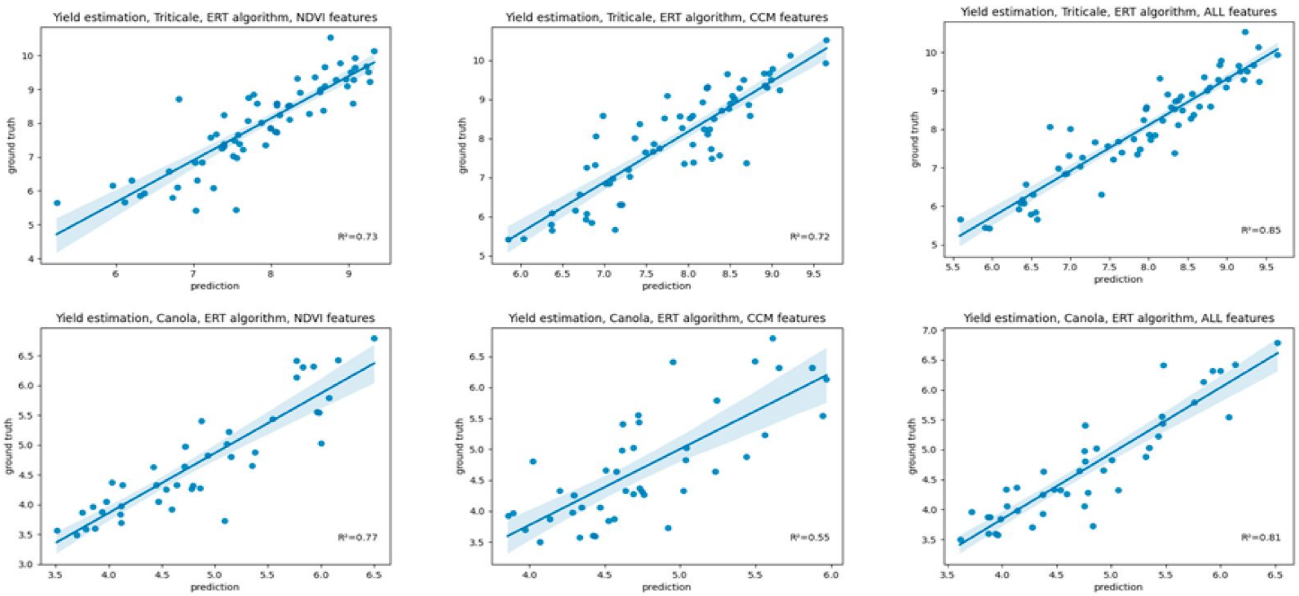
- lower productivity levels ($R^2$ = 0.62, RMSE = 0.35, MAE = 0.29)
- higher productivity levels ($R^2$ = 0.39, RMSE = 0.52, MAE = 0.45)

- NDVI features only: $R^2$ = 0.88
- CCM features only: $R^2$ = 0.84
- combined (with PCA): $R^2$ = 0.92

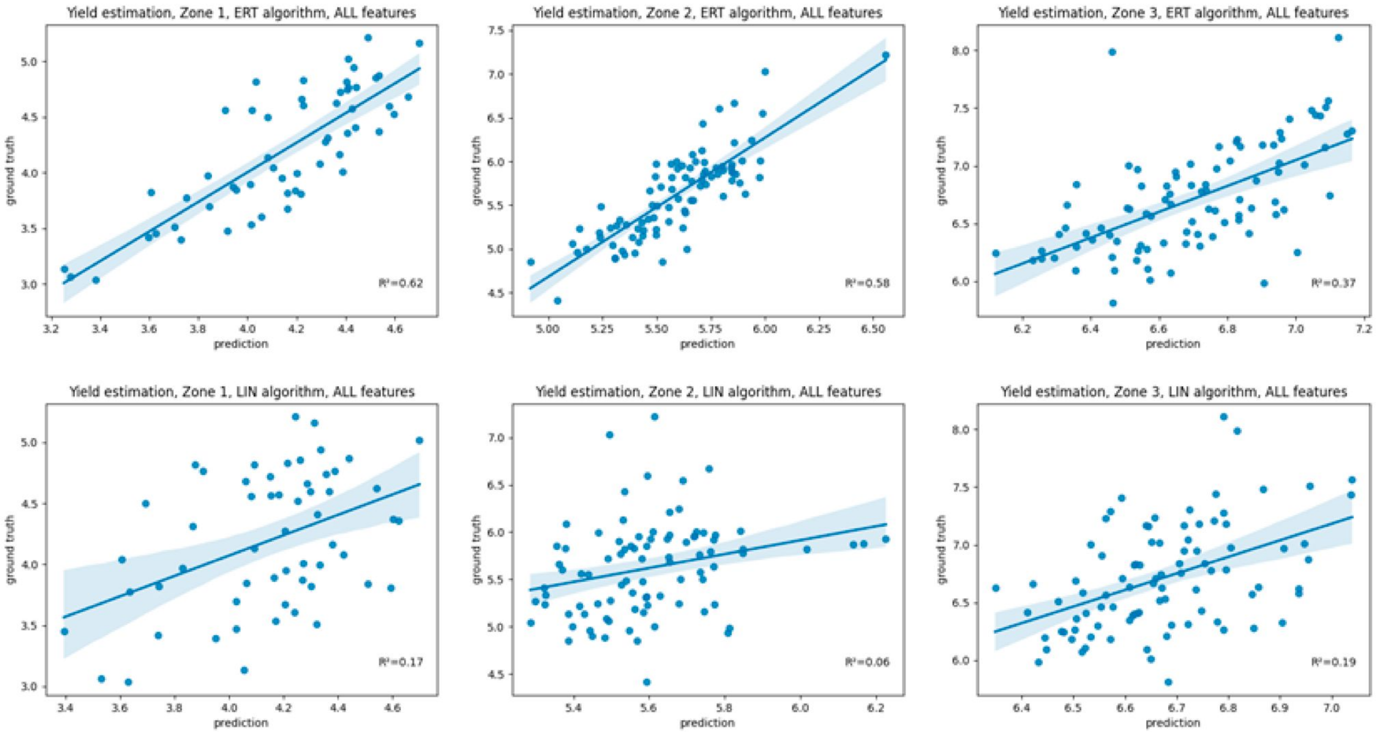
# Results – per crop type



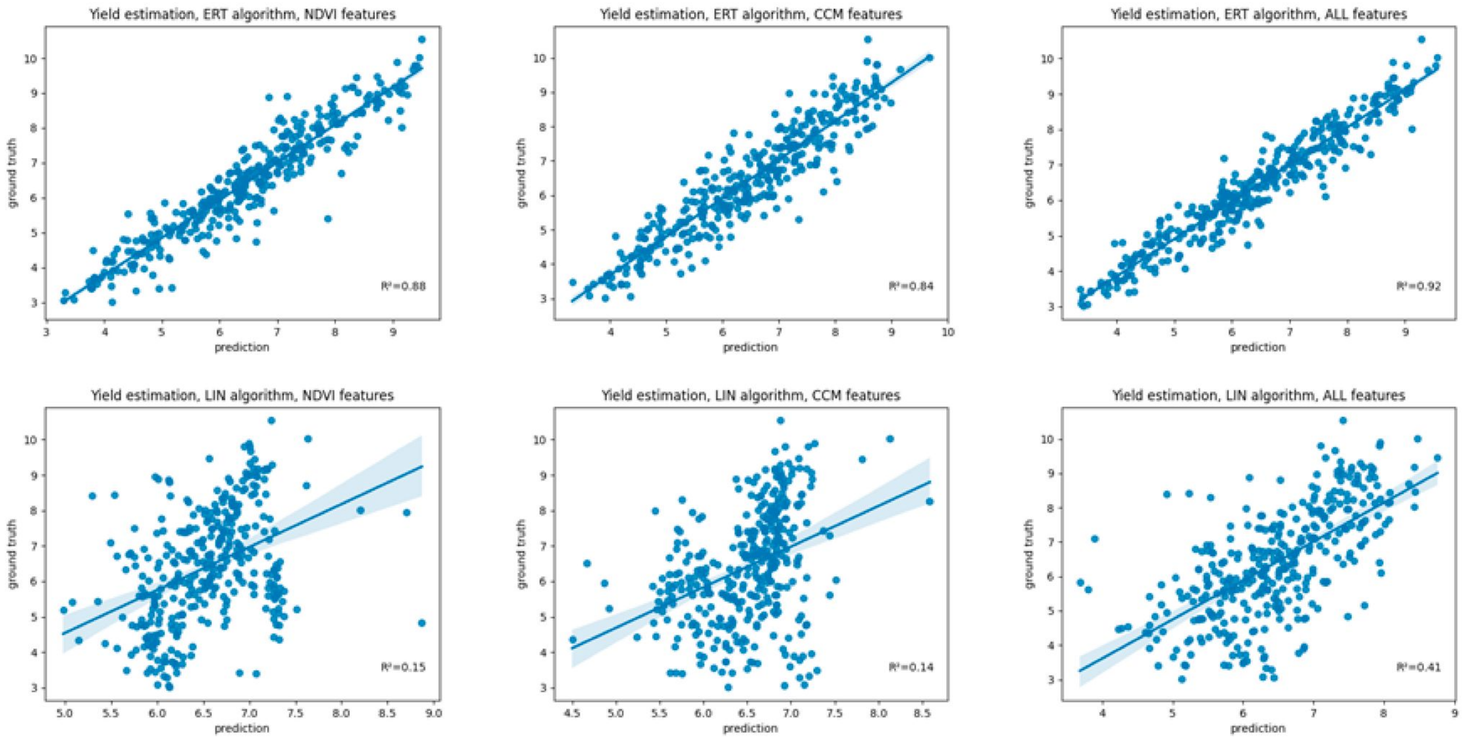
# Results - per crop type



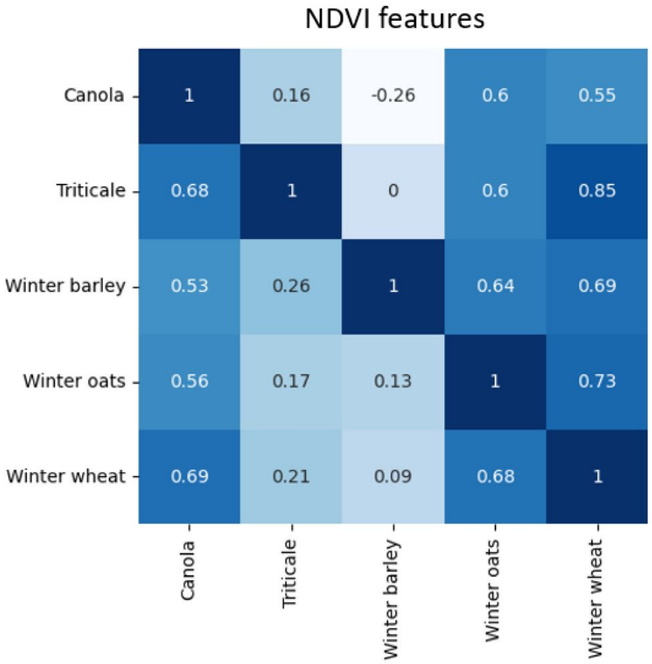
# Results – per productivity

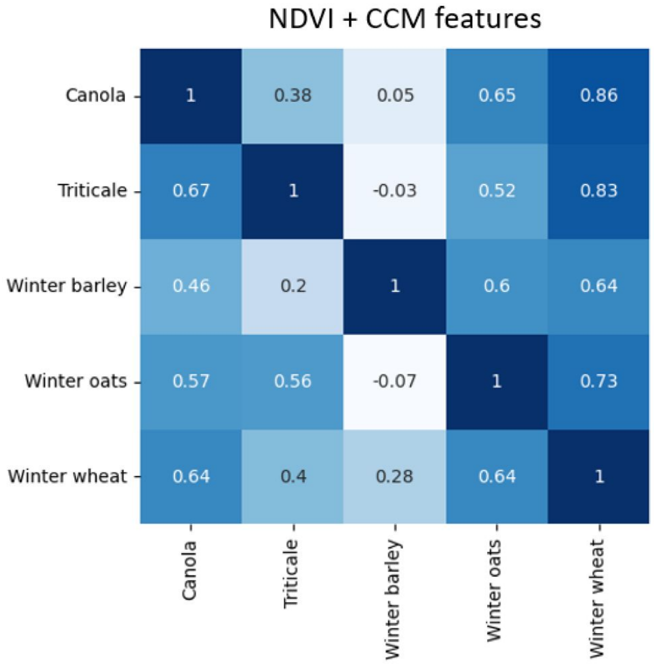


# Results – generic model

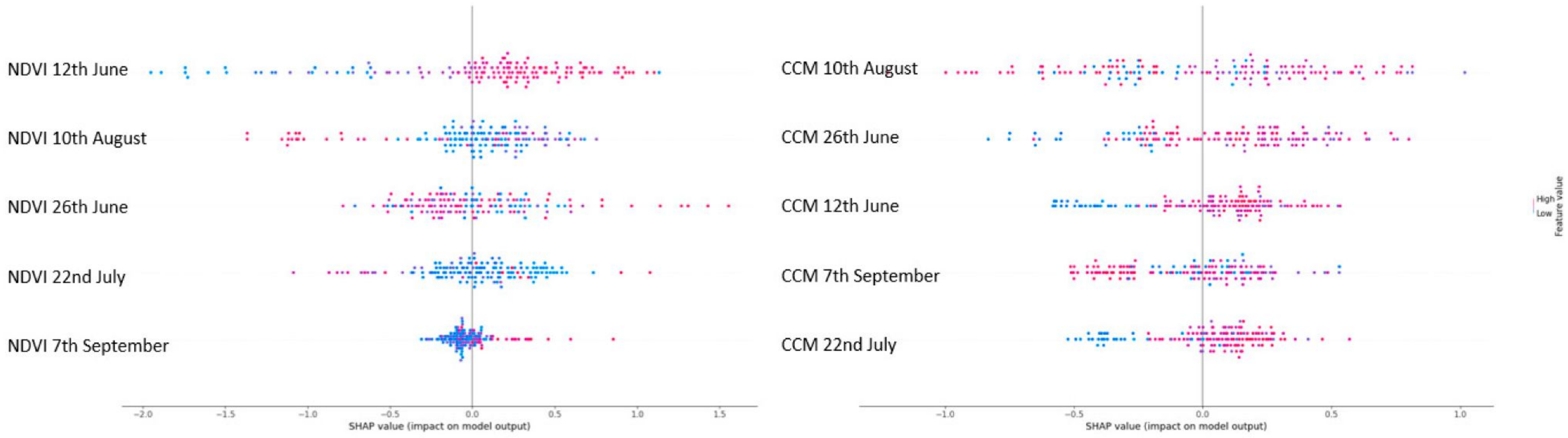


# Results - stratified cross-validation

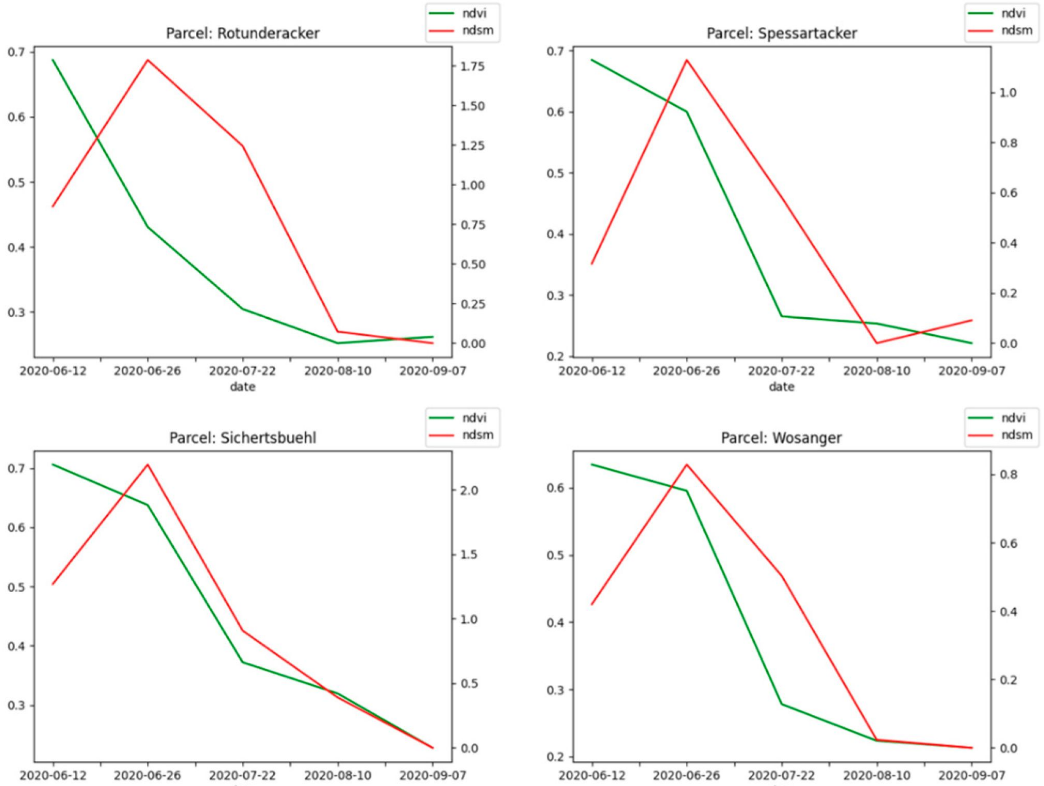


# SHapley Additive exPlanations (SHAP)



# NDVI & CCM Time Series



# Conclusion

- combinatorial use of NDVI and CCM increases accuracy
- model benefit questionable given the high costs
- transfer modelling for some crops beneficial
- Linear Regression fails between CCM and yield values
- Pleiades is suitable for high-resolution yield estimation

# Conclusion

https://www.mdpi.com/2072-4292/15/16/3990

Dimov, D.; Noack, P. Exploring the Potential of Multi-Temporal Crop Canopy Models and Vegetation Indices from Pleiades Imagery for Yield Estimation. *Remote Sens.* **2023**, *15*, 3990. https://doi.org/10.3390/rs15163990



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remote sensing



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## Exploring the Potential of Multi-Temporal Crop Canopy Models and Vegetation Indices from Pleiades Imagery for Yield Estimation

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# Thank you!

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