KlimBA Project Workshop

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Data Basis

1) German national forest inventory 2012
2) FORCE-Datacube containing Sentinel-2 satellite images [1]
3) Forest disturbance map [2]
4) Individual tree continuity information from latest forest inventory
5) Copernicus tree cover map 2018 [3]
6) Digital orthophotos from the Federal Agency for Cartography and Geodesy

[1] Frantz, D. (2019): FORCE – Landsat + Sentinel-2 Analysis Ready Data and beyond: Remote Sensing 11, 1124
[2] Senf, C., Seidl, R. Mapping the forest disturbance regimes of Europe. Nat Sustain 4, 63–70 (2021)
[3] https://land.copernicus.eu/en/products/high-resolution-layer-tree-cover-density/tree-cover-density-2018

Data Basis: FORCE datacube

FORCE is a satellite image processing suite provided by David Frantz and others. [1]

- Bottom of atmosphere (BOA) reflectance data from Landsat and Sentinel-2 for Germany
- Sentinel-2 data
  - is resampled to 10m
  - comprises 10 bands
  - is available from 2015 – now
- Provides quality assurance information (QAI)
  - Cloud, snow, illumination, …, conditions
- Hosted on CODE-DE / EO-Lab platform

Why FORCE?

- Open source and well documented
- All data is processed in the same way
- Data is spatially aligned

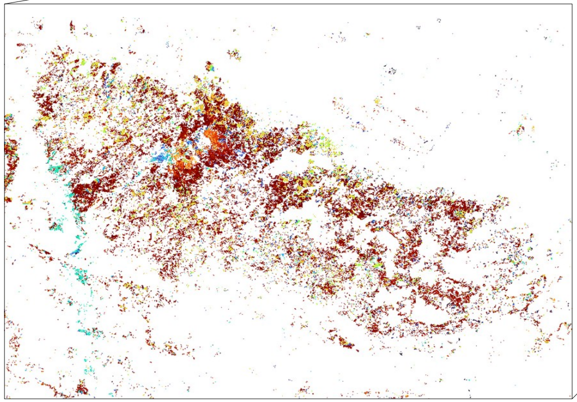
→ Coherent time series

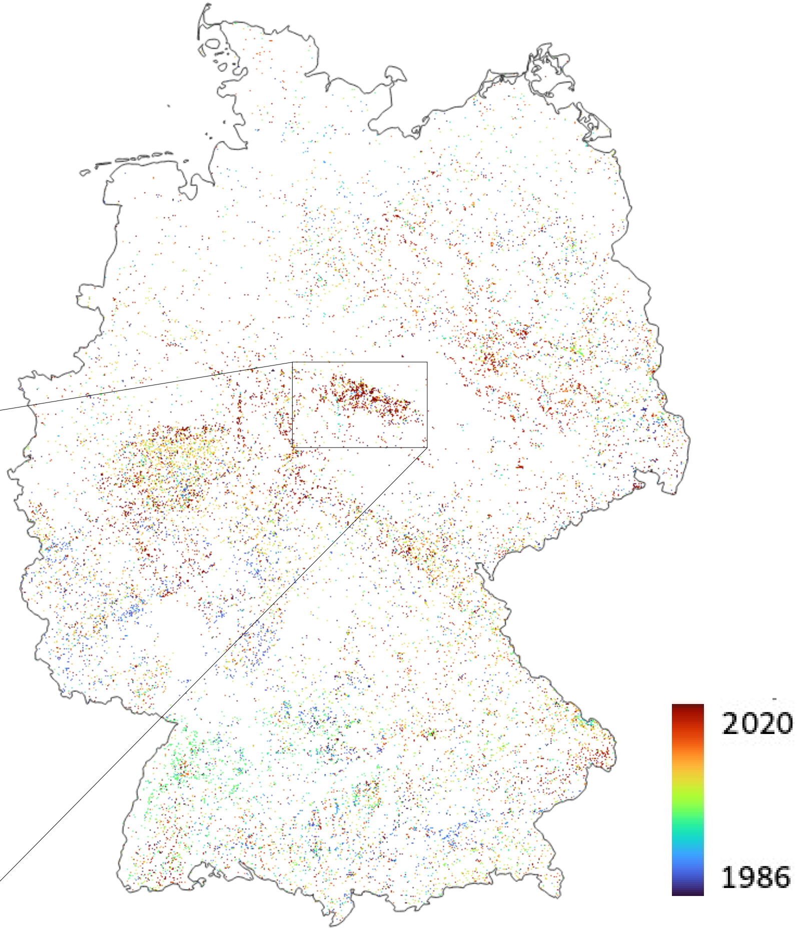
[1] Frantz, D. (2019): FORCE – Landsat + Sentinel-2 Analysis Ready Data and beyond: Remote Sensing 11, 1124

Data Basis: Forest disturbance map & tree continuity information

- Maps forest disturbances from 1986-2020
- Provides disturbance years and intensities
- Developed by C. Senf & R. Seidel [1]

- In addition:
  - From the latest NFI, we have information about which trees are still present in 2022

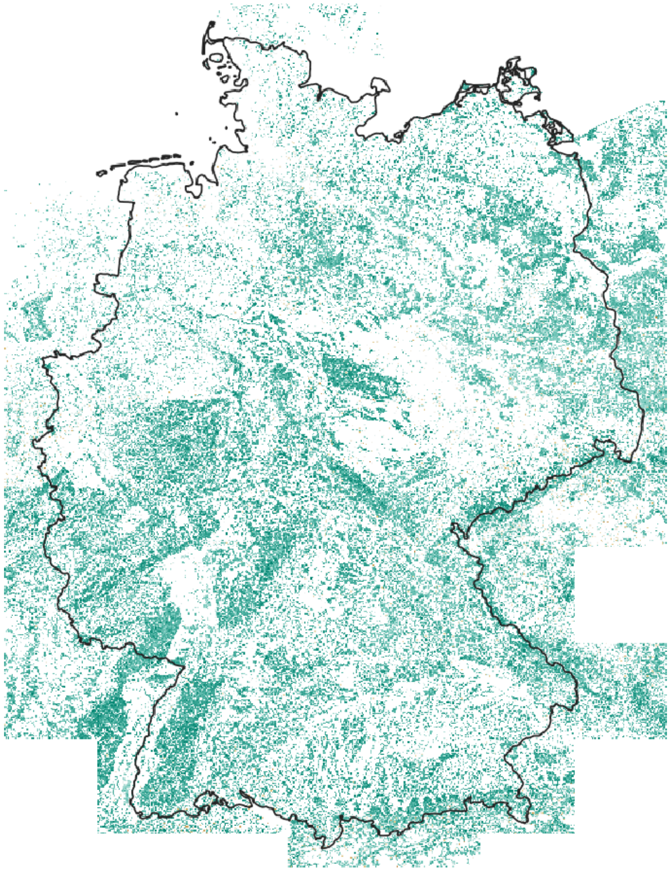




[1] Senf, C., Seidl, R. Mapping the forest disturbance regimes of Europe. Nat Sustain 4, 63–70 (2021)

Data Basis: Forest cover map

- Forest cover map for Germany in 2018
- Provided by Copernicus Land Monitoring Service [1]
- 10m spatial resolution
- Used to sample non-forest pixels
- These are needed during the training of machine learning models



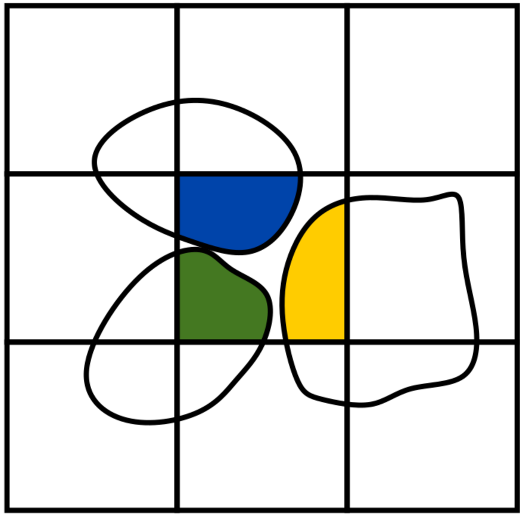
[1] https://land.copernicus.eu/en/products/high-resolution-layer-tree-cover-density/tree-cover-density-2018

Data Basis: Digital orthophotos

- Digital orthophotos of each cluster plot
- Data provided by Federal Agency of Cartography and Geodesy [1]
- Various acquisition dates between 2017 and 2022
- 20 cm spatial resolution
- 4 bands (red, green, blue, near infrared)
- All seasons
- Images cover 300m x 300m around NFI plots

[1] Geobasisdaten: © GeoBasis-DE / BKG (2022)

Pixel-centric approach



Pixel-centric approach: Methods

Initial idea: Derive species composition for each satellite image pixel in the surroundings of NFI plots (300m x 300m)

1) Delineate trees in aerial orthophotos
2) Match trees with NFI data
3) Classify every tree in the orthophotos
4) Use these as labels for satellite data

Pixel-centric approach: Methods

1) Delineate trees in aerial orthophotos
   - Method published
   - Accuracy: ~50% depending on image quality and forest structure
   - Applicable to 20cm BKG imagery

Neural Computing and Applications (2022) 34:22197–22207
https://doi.org/10.1007/s00521-022-07640-4

ORIGINAL ARTICLE

Check for updates

Individual tree crown delineation in high-resolution remote sensing images based on U-Net

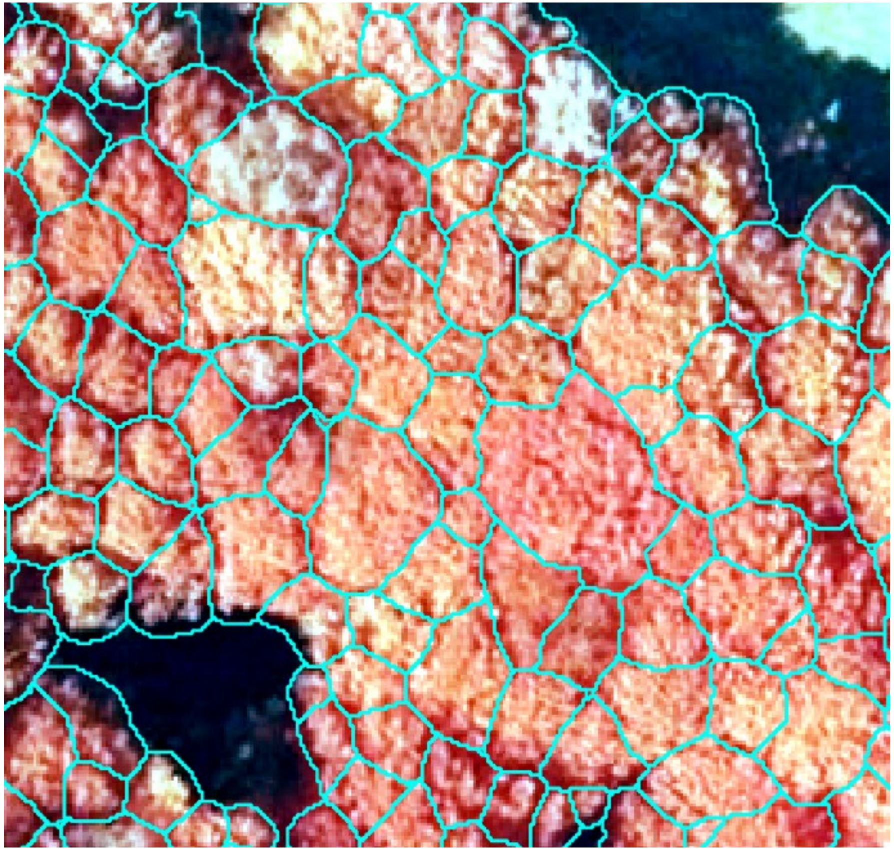
Maximilian Freudenberg[1] · Paul Magdon[2] · Nils Nölke[1]

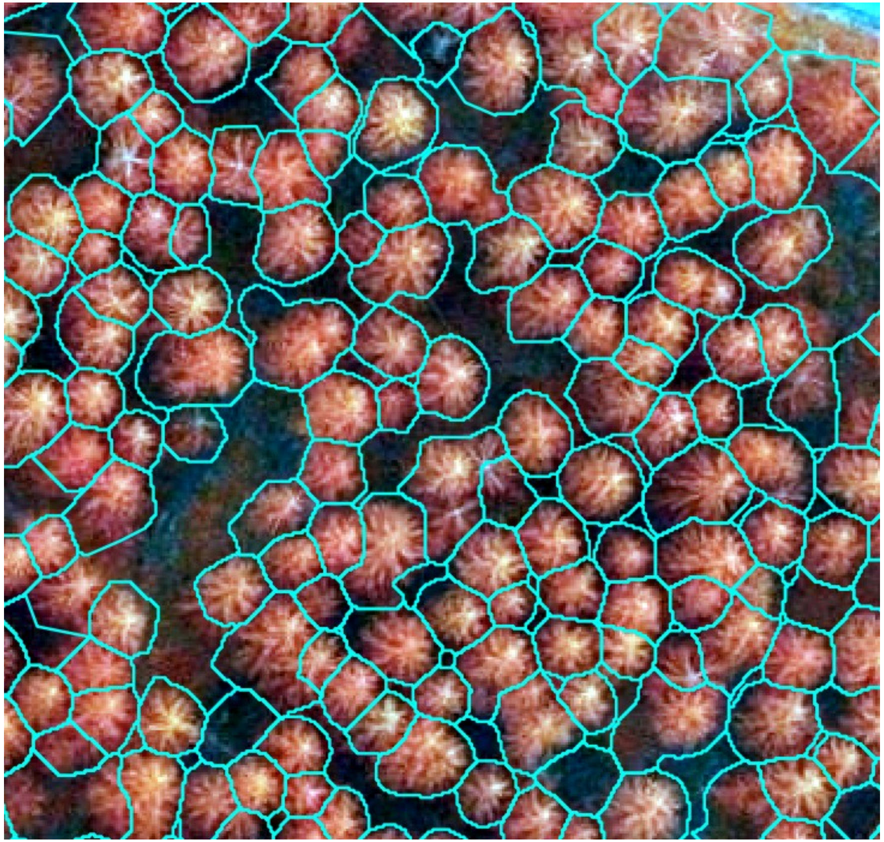
Received: 22 December 2021 / Accepted: 18 July 2022 / Published online: 16 August 2022

Abstract
We present a deep learning-based framework for individual tree crown delineation in aerial and satellite images. This is an important task, e.g., for forest yield or carbon stock estimation. In contrast to earlier work, the presented method creates irregular polygons instead of bounding boxes and also provides a tree cover mask for areas that are not separable. Furthermore, it is trainable with low amounts of training data and does not need 3D height information from, e.g., laser sensors. We tested the approach in two scenarios: (1) with 30 cm WorldView-3 satellite imagery from an urban region in Bengaluru, India, and (2) with 5 cm aerial imagery of a densely forested area near Gartow, Germany. The intersection over union between the reference and predicted tree cover mask is 71.2% for the satellite imagery and 81.9% for the aerial images. On the polygon level, the method reaches an accuracy of 46.3% and a recall of 63.7% in the satellite images and an accuracy of 52% and recall of 66.2% in the aerial images, which is comparable to previous works that only predicted bounding boxes. Depending on the image resolution, limitations to separate individual tree crowns occur in situations where trees are hardly separable even for human image interpreters (e.g., homogeneous canopies, very small trees). The results indicate that the presented approach can efficiently delineate individual tree crowns in high-resolution optical images. Given the high availability of such imagery, the framework provides a powerful tool for tree monitoring. The source code and pretrained weights are publicly available at https://github.com/AWF-GAUG/TreeCrownDelineation.

Keywords Deep learning · U-Net · Remote sensing · Tree · Delineation · Segmentation

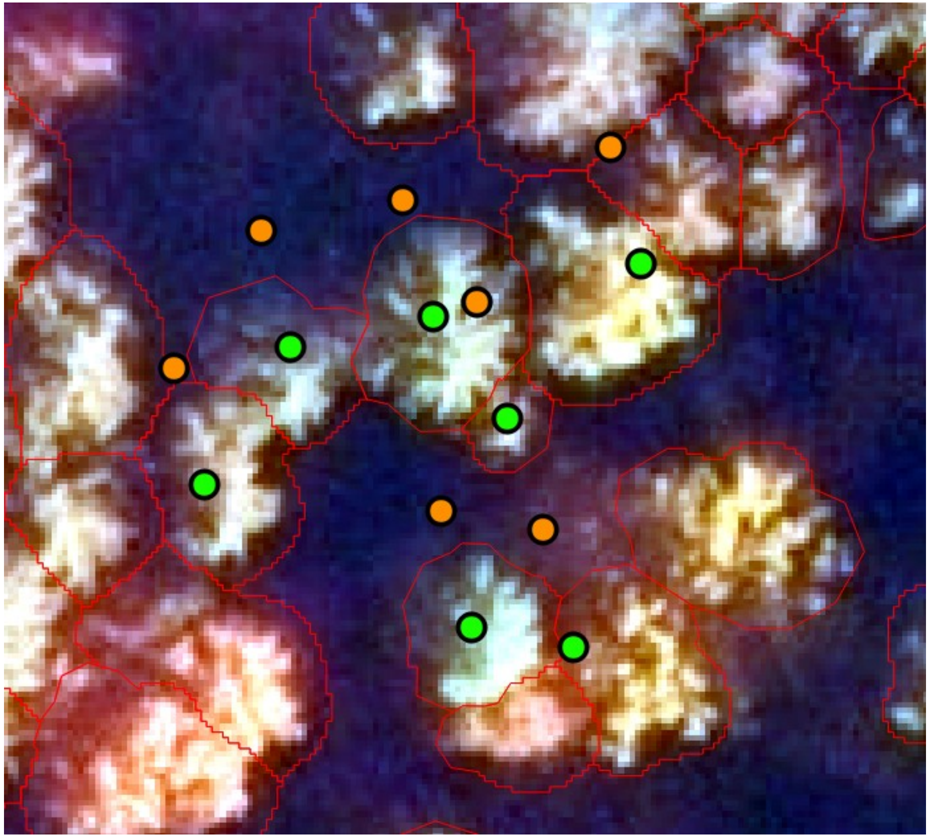
Pixel-centric approach: Methods





Pixel-centric approach: Methods

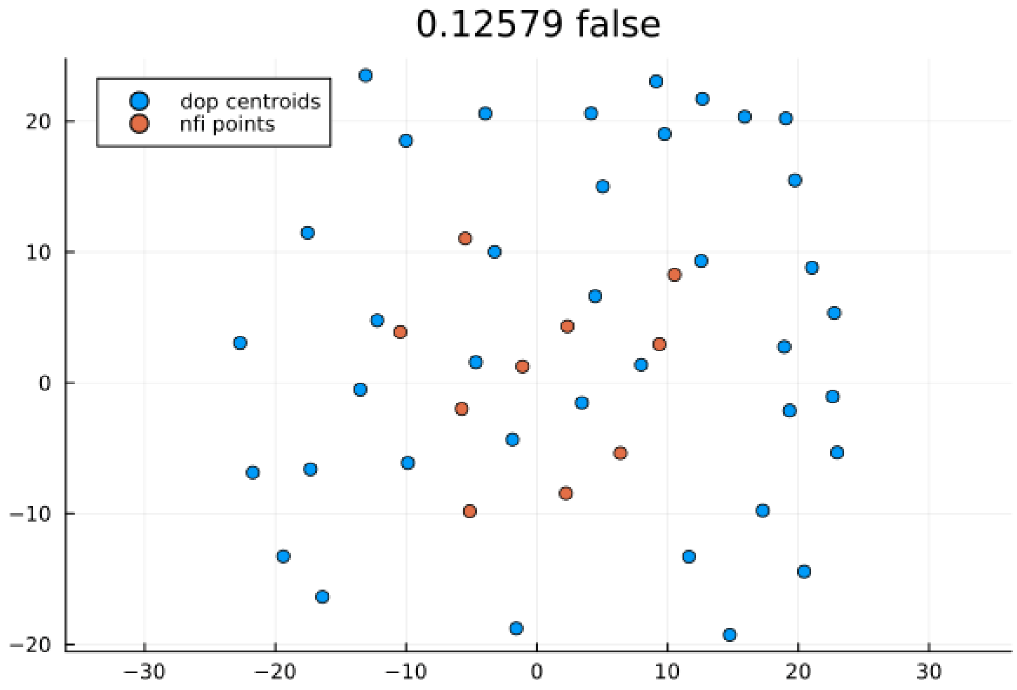
1) Delineate trees in aerial orthophotos
2) Match trees with NFI data



orange: measured positions, green: shifted

Pixel-centric approach: Methods

1) Delineate trees in aerial orthophotos
2) Match trees with NFI data
   - Method: Find matches by shifting and rotating entire NFI plot.
   - Maximizing distance-based metric using gradient ascent
   - Assign matches starting from lowest distance up to cutoff
   - Accuracy: 65% in true DOP images, 42% in pseudo DOP
   - Comparable to agreement between different humans



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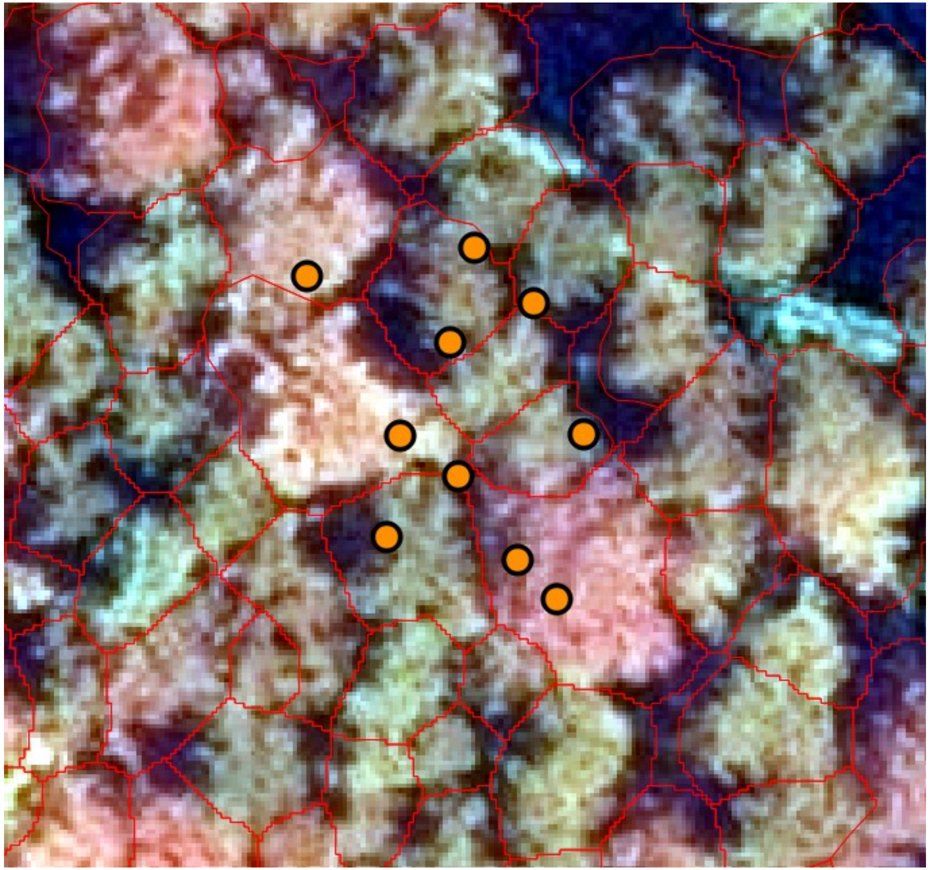

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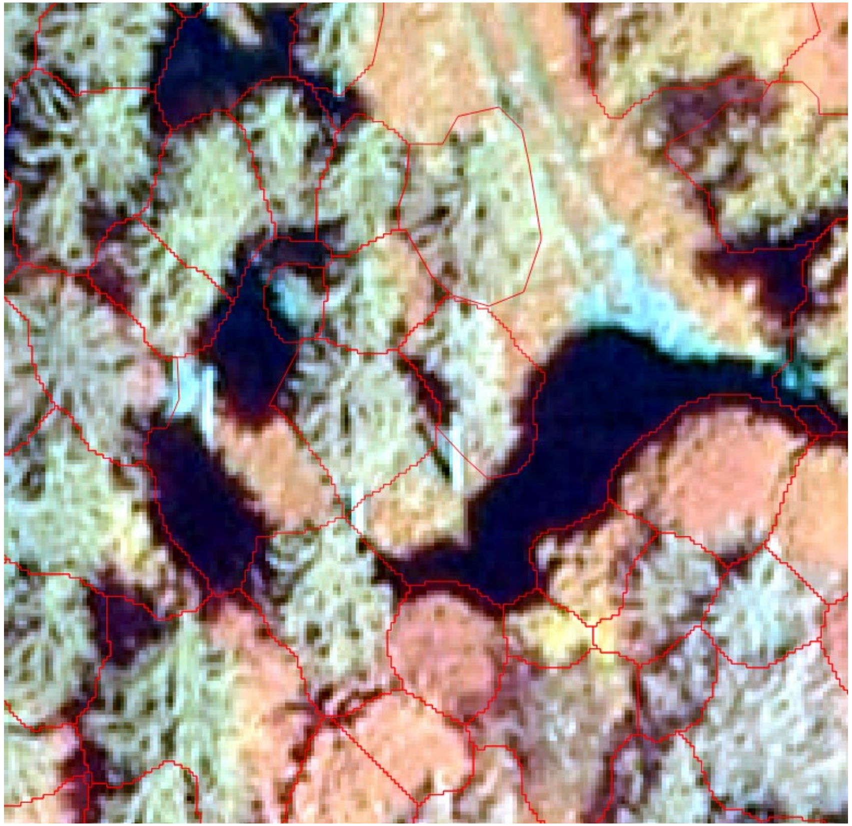

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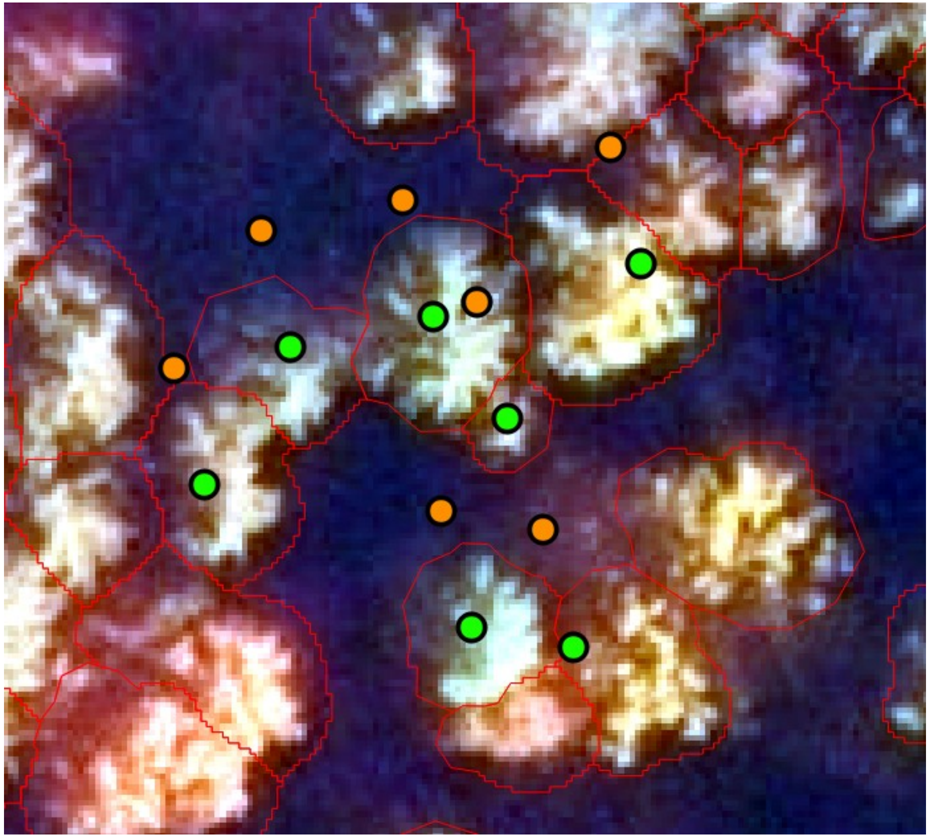
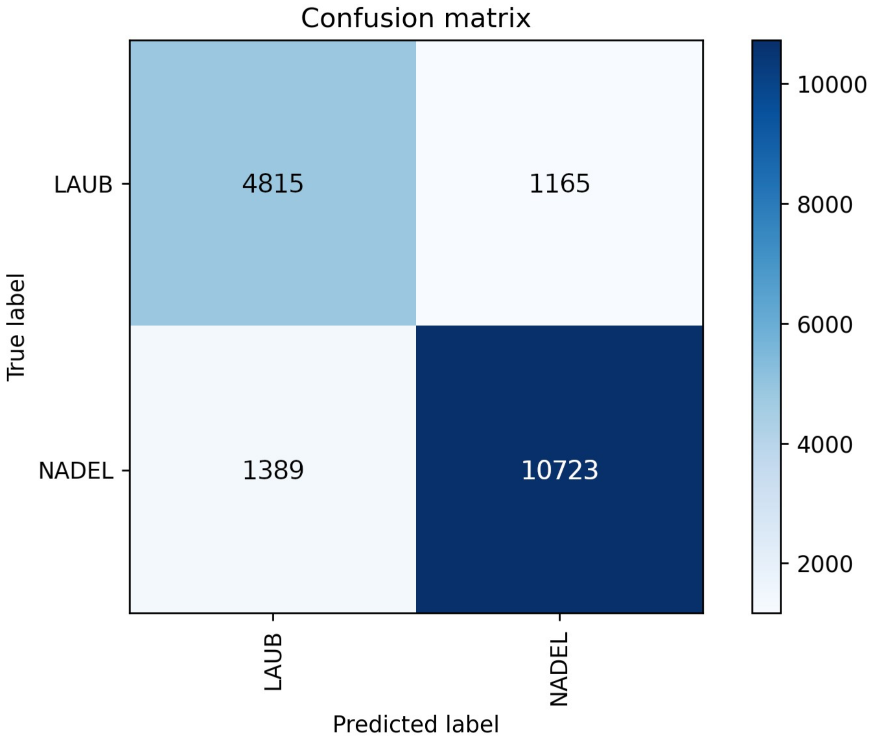


orange: measured positions, green: shifted

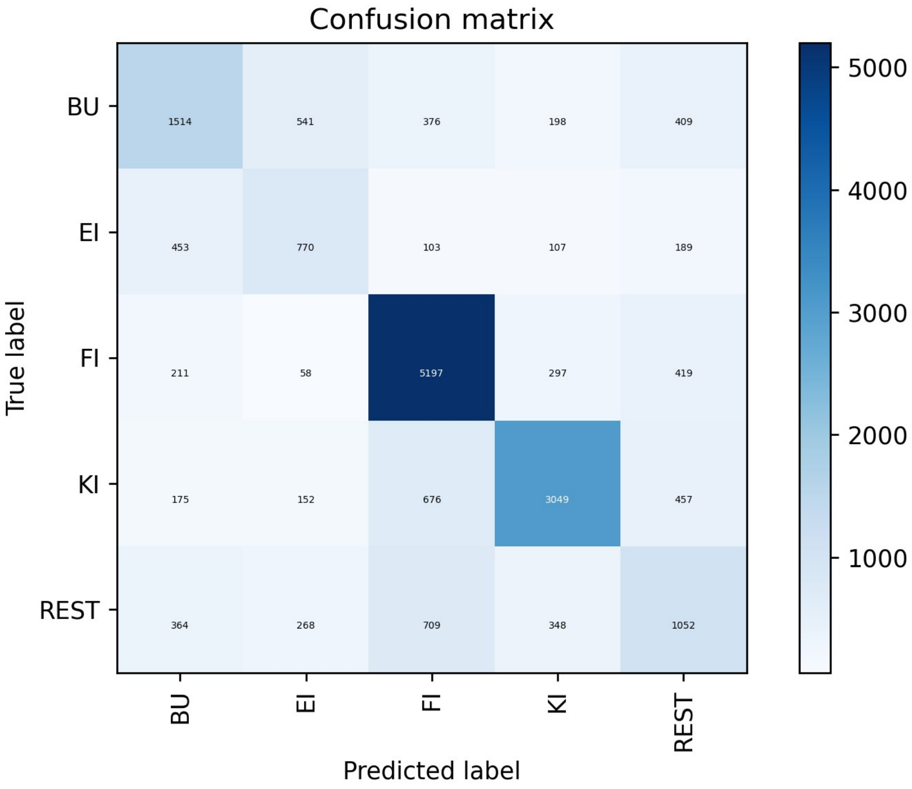
Pixel-centric approach: Results

1) Delineate trees in aerial orthophotos
2) Match trees with NFI data
3) Classify every tree in the orthophotos
   - ResNet-34 applied to tree cutouts
   - Accuracy for coniferous / deciduous: 89%



Pixel-centric approach: Results

1) Delineate trees in aerial orthophotos
2) Match trees with NFI data
3) Classify every tree in the orthophotos
    - ResNet-34 applied to tree cutouts
    - Accuracy for 5 species: 64%



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2) Match trees with NFI data
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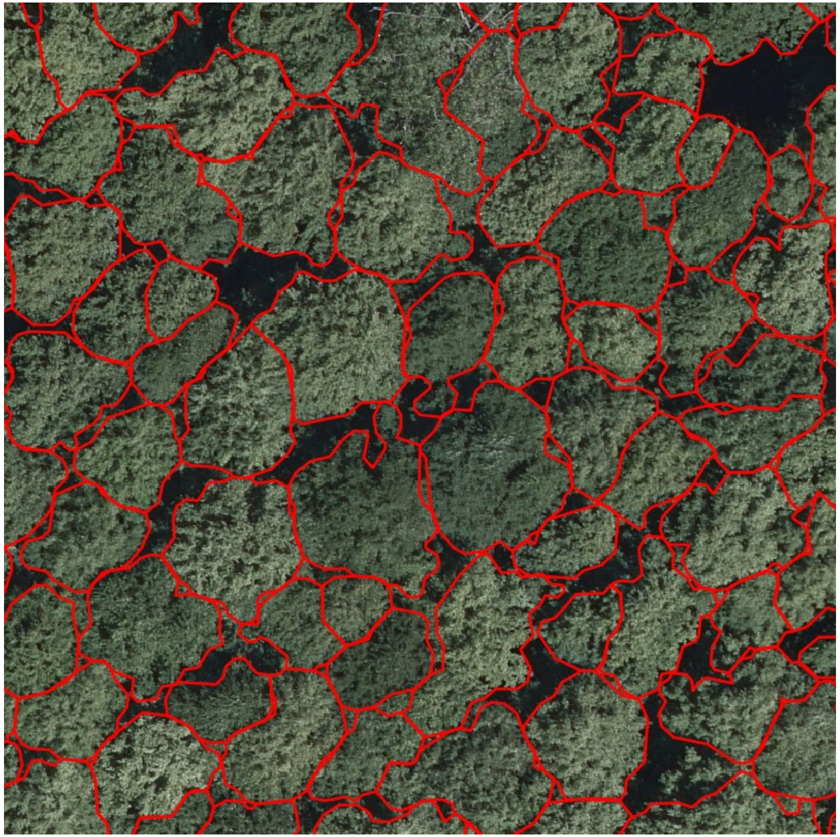
4) ~~Use these as labels for satellite data~~
    - Not feasible: Combination of previous accuracies too low
    - True ortho photos needed for matching
    - GNSS precision of NFI measurements not sufficient
    - Higher image resolution and quality needed for reliable classification

Pixel-centric approach: Methods

Aerial Orthophoto, 5cm



Referenz	Bi	Er	Bu	Ei	GE	Fi	Ki	Dg	La	Hi
Bi	93	1	1	1	0	1	1	0	2	1
Er	1	90	3	3	1	0	0	0	1	0
Bu	0	4	83	16	0	1	0	0	0	0
Ei	1	3	12	71	1	0	0	1	0	1
GE	0	1	0	1	94	0	0	0	0	0
Fi	0	0	0	0	0	91	0	2	1	2
Ki	3	1	0	5	4	3	95	9	3	12
Dg	0	0	0	2	0	3	1	80	8	3
La	1	1	0	0	0	1	1	6	83	1
Hi	1	0	0	1	0	1	1	2	1	80

(a) Precision [%]

	Bi	Er	Bu	Ei	GE	Fi	Ki	Dg	La	Hi
Bi	92	0	0	0	0	0	3	0	1	1
Er	1	95	2	1	0	0	0	0	1	0
Bu	0	6	82	11	0	1	0	0	0	0
Ei	1	8	18	65	1	0	3	1	0	2
GE	0	1	0	1	96	0	0	0	1	1
Fi	0	0	0	0	0	93	2	2	1	2
Ki	1	0	0	1	1	1	92	2	1	3
Dg	1	1	0	1	0	3	6	77	8	3
La	2	1	0	0	0	1	3	6	86	1
Hi	2	1	0	0	0	1	5	2	1	88

(a) Recall [%]

Nils Nölke, Maximilian Freudenberg, Christoph Kleinn, Hans Fuchs, Paul Magdon (2020). Neue Wege in der Forsteinrichtung (IV) - Künstliche Intelligenz (KI) im Waldmonitoring: Neue Möglichkeiten der Baumartenerkennung. AFZ Der Wald 15/2020

Pixel-centric approach: Methods

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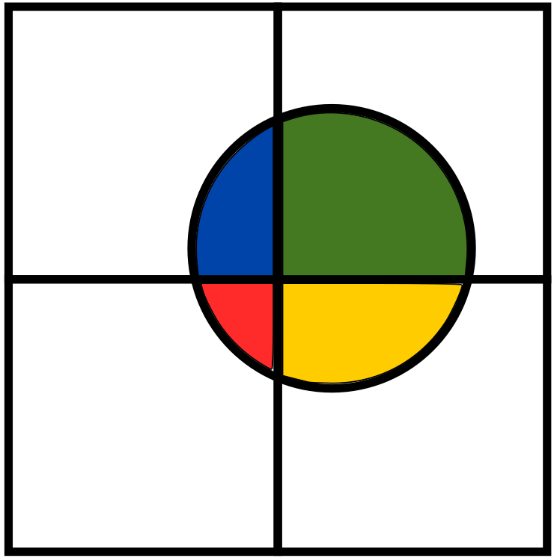
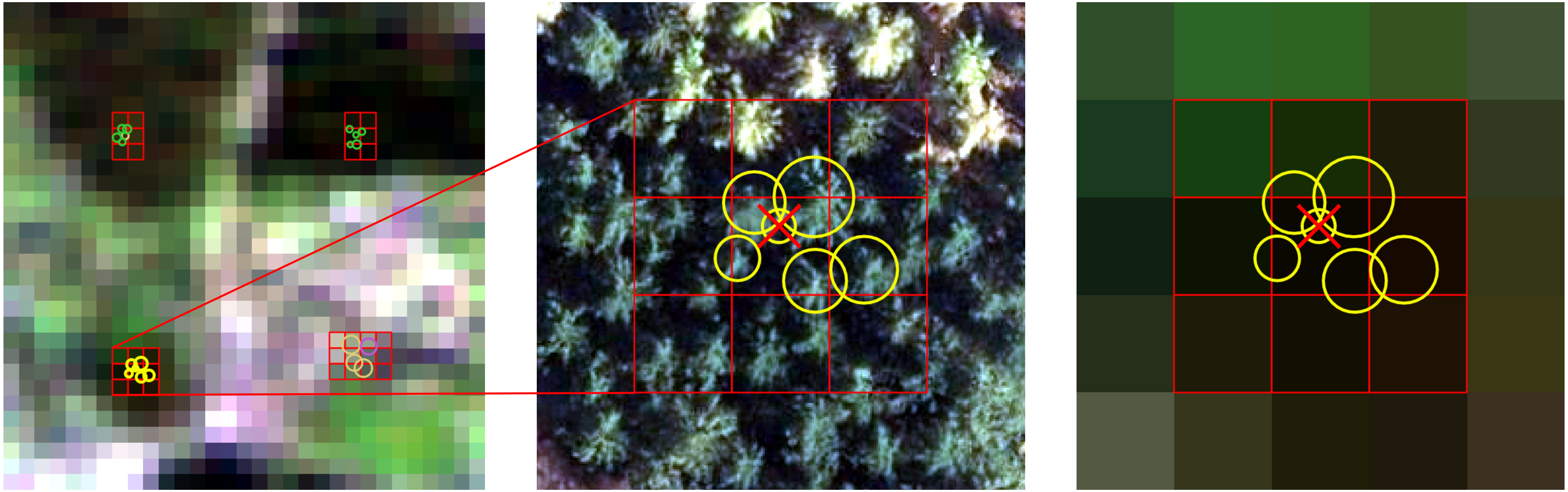
→ Shift to tree-centric approach

Tree-centric approach



Tree-centric approach: Data extraction

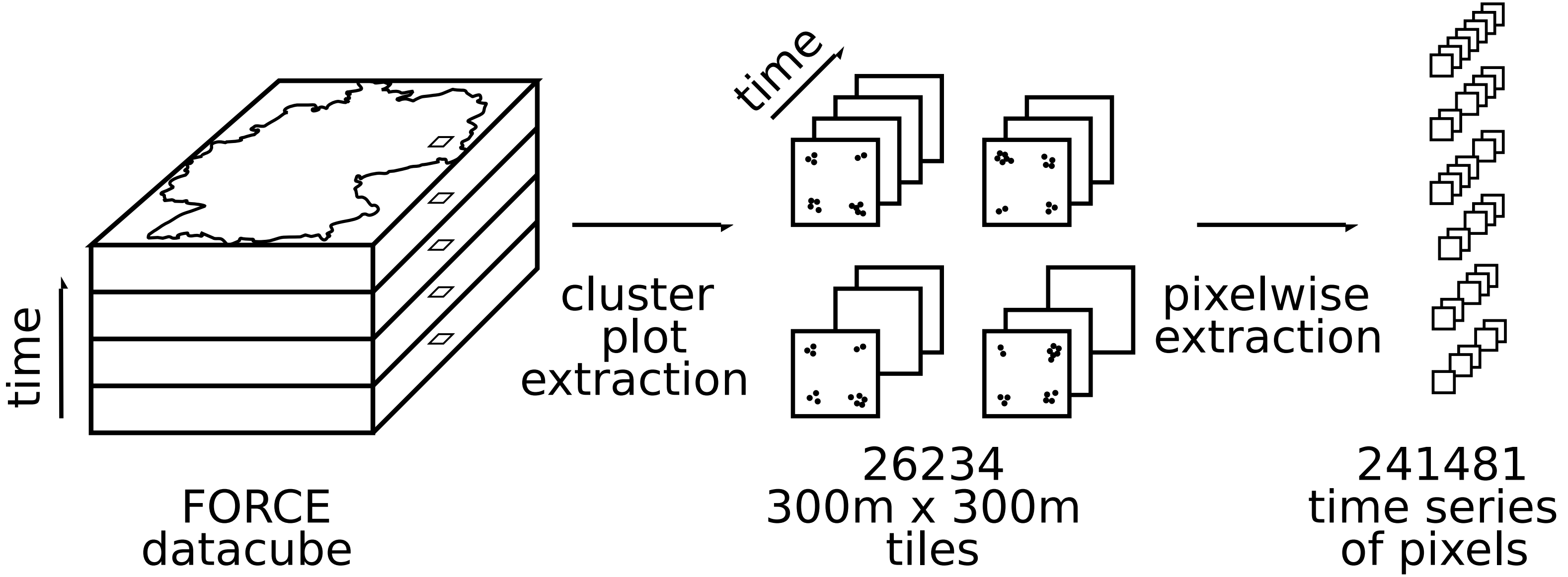
1) Filter NFI data
    1) Model tree crown diameter based on stem diameter [1]
    2) Remove trees that are not visible from above; too small or too close to others
        - Remove trees that are understory according to NFI
        - Remove small trees whose crown area is overshadowed by more than 50% by other trees



[1] Riedel et al. (2017) Die dritte Bundeswaldinventur: BWI 2012; Inventur-und Auswertungsmethoden

Tree-centric approach: Data extraction

1) Filter NFI data
2) Crop images from the satellite image data cube
3) Extract bottom of atmosphere (BOA) reflectance for each tree crown as weighted average of intersecting pixels
4) Merge with NFI data (species, DBH, height) and other variables (disturbance year)



Tree-centric approach: Data obfuscation

NFI plot positions are confidential, therefore we obfuscated the data.

- A random noise of up to 5% has been added to BOA reflectance values
- Timestamps have been randomly shifted by up to 3 days

Tree-centric approach: Data extraction

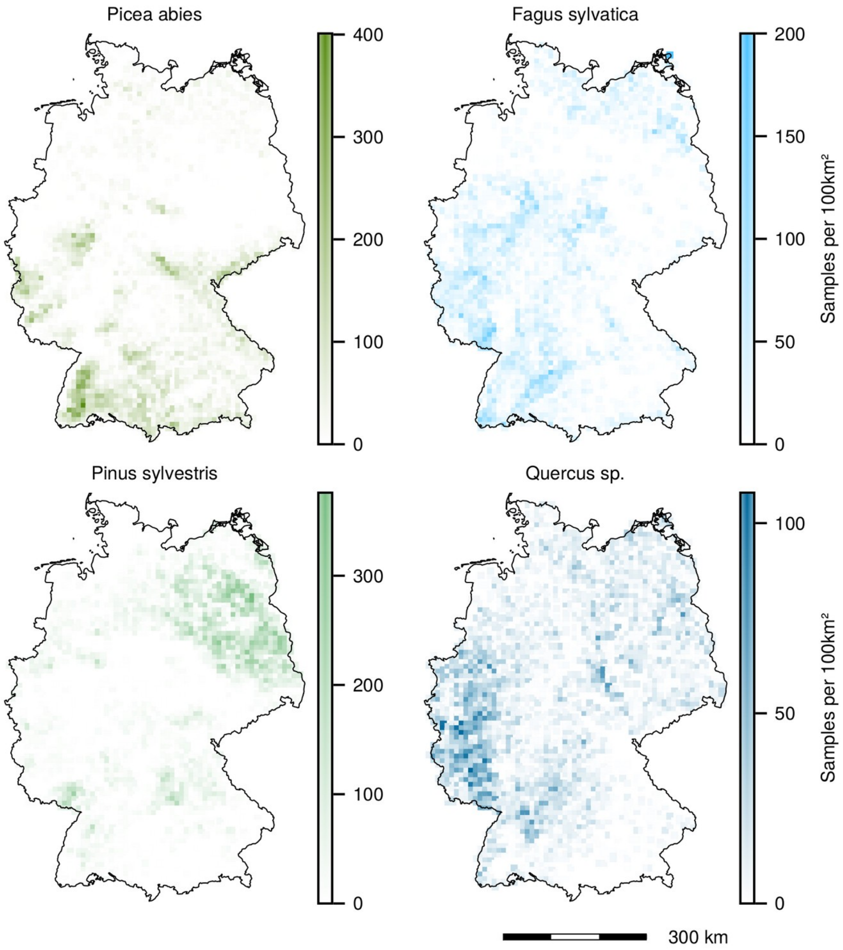
Available variables:

- Cluster plot ID
- Sub-plot ID
- Global tree ID
- Species
- Time
- BOA Reflectance
- Quality assurance information
- Stand purity information
- Random split into train and validation set
- Diameter at breast height
- Predicted tree height
- Predicted tree crown area
- Inspire grid coordinates (1km x 1km)
- Information whether GNSS was corrected
- Disturbance year
- Whether the tree is still present in 2022
- Day of the year

Results: Overview of dataset

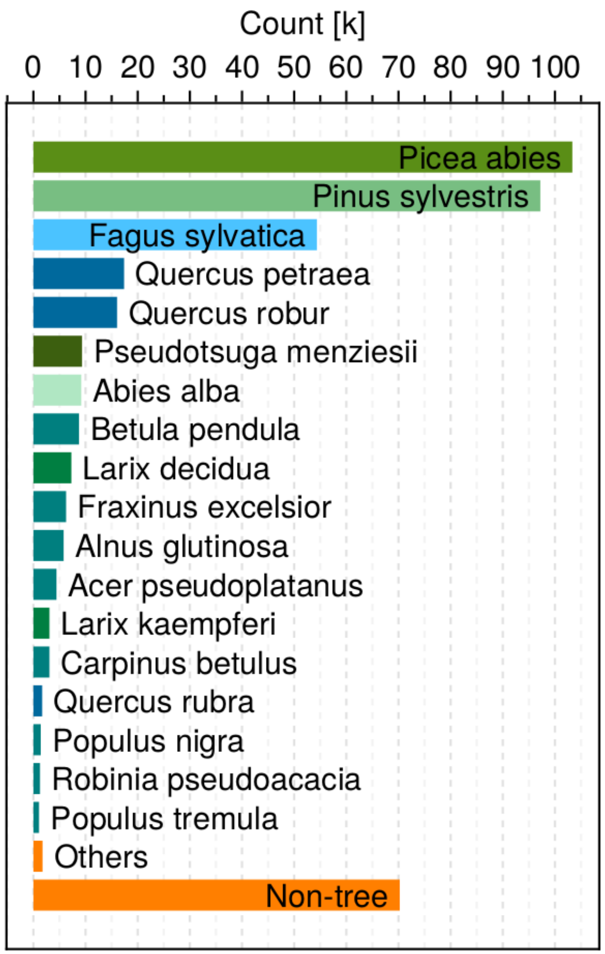
- ~360 000 trees
- Over 80 million records
- 50 species plus non-forest samples
- Whole Germany covered
- July 2015 – October 2022
- Publication of complete method in preparation
- Extraction code: https://github.com/AWF-GAUG/German-NFI-S2-Dataset
- Dataset will be published in OpenAgrar in the next days

Results: Species distribution



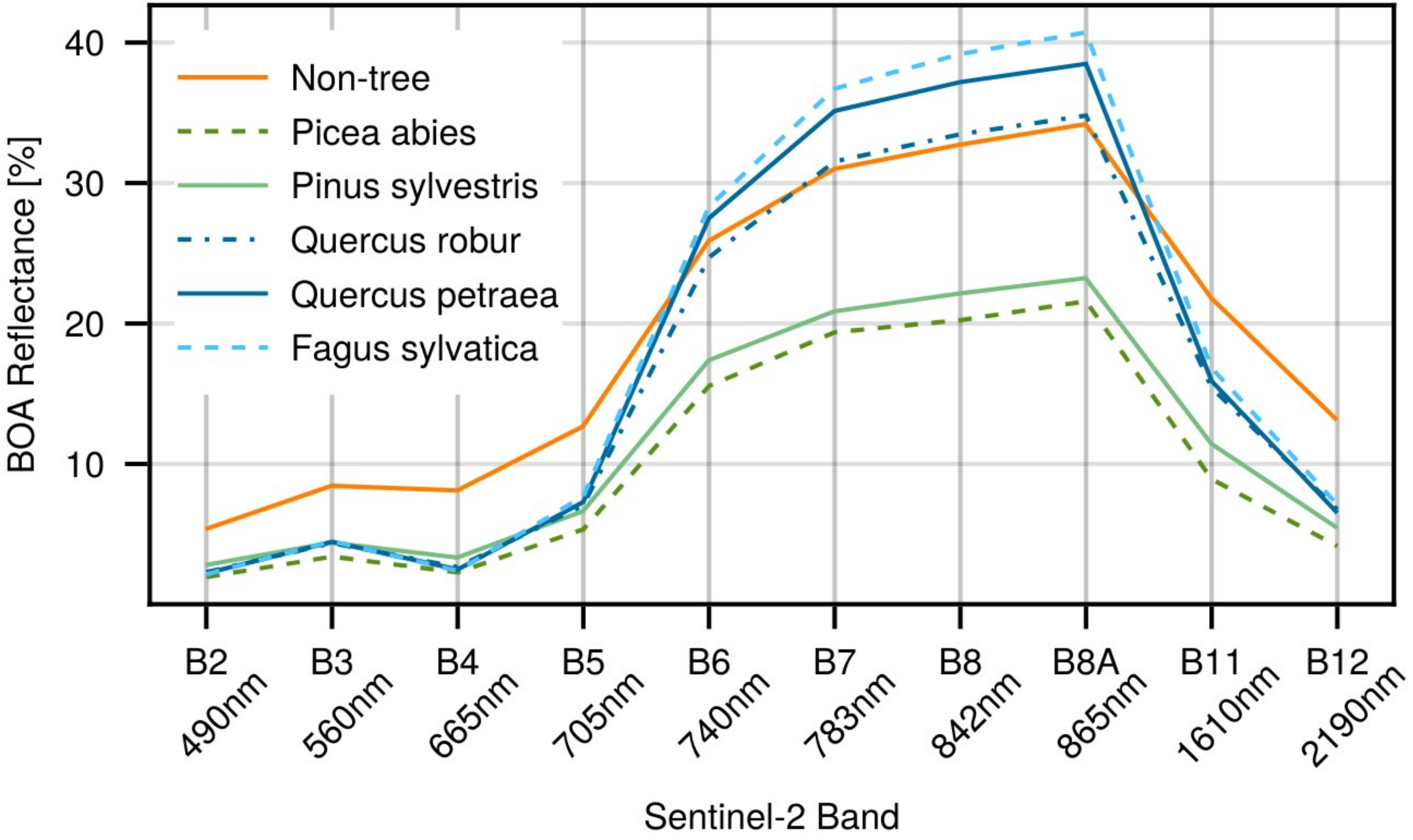
Source: Freudenberg et al. (in prep)

Results: Species histogram



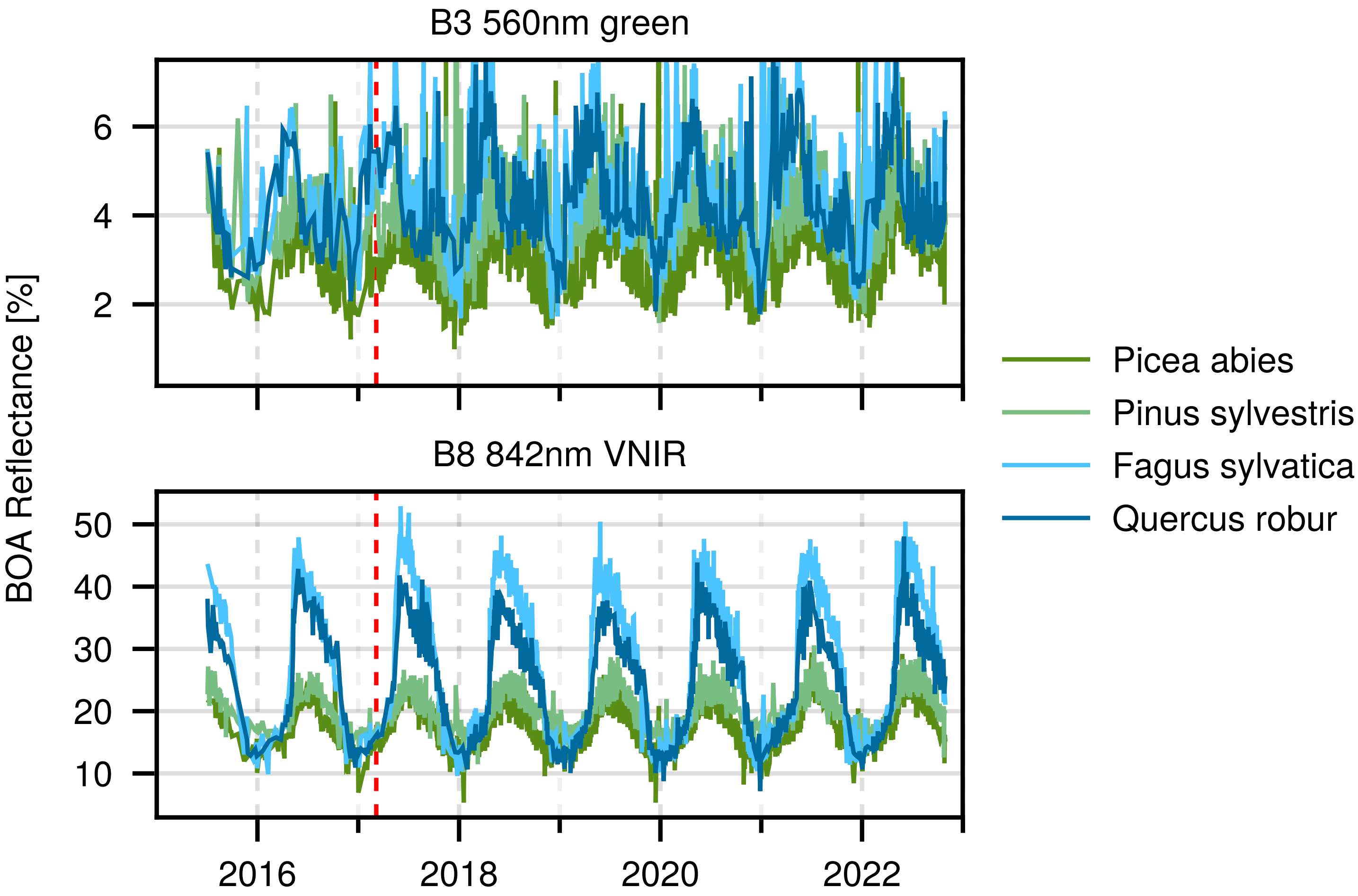
Source: Freudenberg et al. (in prep)

Results: Species spectra in pure stands between May and August



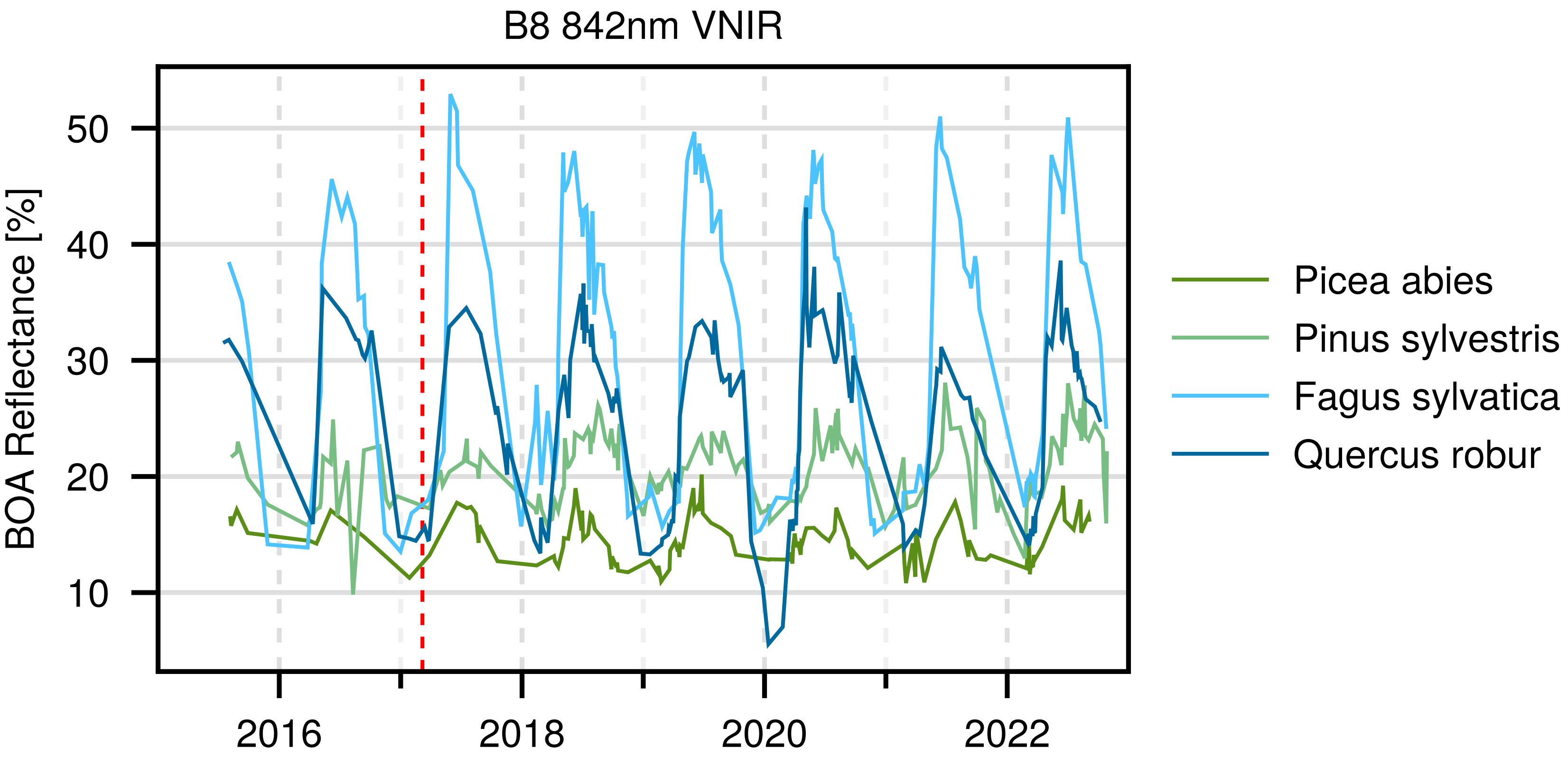
Source: Freudenberg et al. (in prep)

Results: Averaged time series



Source: Freudenberg et al. (in prep)

Results: Single tree time series



Source: Freudenberg et al. (in prep)

Results: NDVI histograms over time

Video

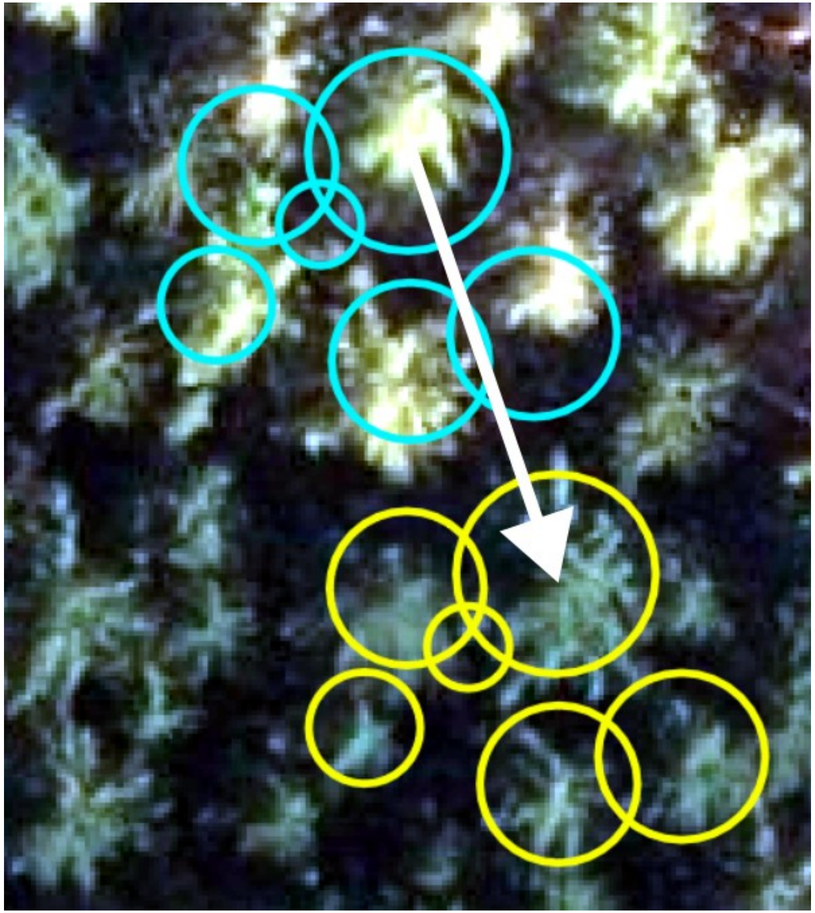
Source: Freudenberg et al. (in prep)

Discussion: Error sources

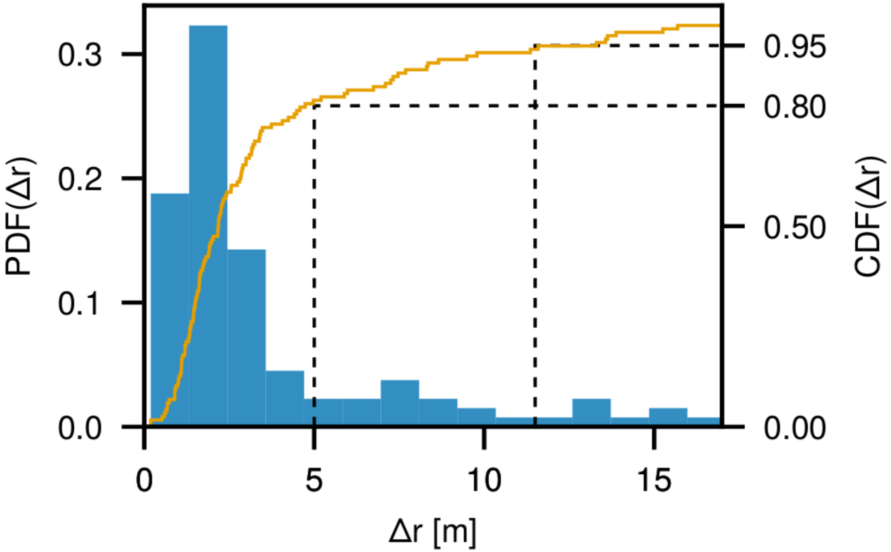
- GNSS errors in NFI data
- Satellite image geometric error
- Mixed pixels
- ...

Source: Freudenberg et al. (in prep)

Discussion: Error sources - NFI geolocation error



To quantify the NFI GNSS error we
- Shifted 200 sampling points to their “true position” in true DOP images
- Measured the required shift
- 80% of plots < 5m shift
- Shift smaller than S2 pixels



Source: Freudenberg et al. (in prep)

Discussion: Error sources - Sentinel-2 geometric error

- FORCE co-registers S2 images with averaged Landsat image
- Landsat is in turn co-registered with global Sentinel-2 reference image
- Final accuracy difficult to quantify
- Estimate: 90% of data lie within 10.2m of true location [1]

[1] USGS Landsat Quarterly Calibration and Validation Report—Quarter 3, 2022

Discussion

- **Differential GNSS** measurements should be the standard for all plots
- Satellite images should be aligned with Sentinel-2 global reference image
- Pixel based approach in combination with ortho photos still interesting
  - But: At least 10cm **true** orthophotos in vegetation period with better quality needed
  - Manual label generation needed as long as matching is not reliable enough

Conclusion and Outlook

- We present the currently largest dataset combining spatial, spectral and temporal Sentinel-2 information and NFI data
- This dataset can be used to train machine learning models

  for tree species classification
- It can be used to study tree phenology for different regions and species
- Furthermore, it provides information on long term trends of BOA reflectances and can be combined with e.g. climate data to generate further insights