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2023 DRAGON 5 SYMPOSIUM
3rd YEAR RESULTS REPORTING
11-15 SEPTEMBER 2023

[PROJECT ID. 59257]

**[MAPPING FOREST PARAMETERS AND FOREST
DAMAGE FOR SUSTAINABLE FOREST MANAGEMENT
FROM DATA FUSION OF SATELLITE DATA]**

<14/SEPT/2023, 9:00AM - 10:30AM CEST>

ID. 59257

PROJECT TITLE: MAPPING FOREST PARAMETERS AND FOREST DAMAGE FOR SUSTAINABLE FOREST MANAGEMENT FROM DATA FUSION OF SATELLITE DATA

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CO-AUTHORS: Ning Zhang, Henrik Persson, Yueting Wang, Eva Lindberg, Niwen Li, Ivan Huuva, Guoqi Chai, Lingting Lei, Long Chen, Xiang Jia, Zongqi Yao

PRESENTED BY: Langning Huo

Background:

- This project concerns the topic Ecosystems and spans the subtopics Collaborative estimation of forest quality parameters and Forest and grassland disaster monitoring.

Objective:

- Study and explore remote sensing techniques in forest applications, especially on data fusion of satellite images, laser scanning, and hyperspectral drone images.

The research contents:

- **Tree species classification**
- **Forest parameter estimation**
- **Forest insect damage detection**

ESA Third Party Missions	No. Scenes
1. Sentinel-1	173
2. Sentinel-2	380
3. SPOT	2
4. Radarsat-2	1
5. WorldView-3 SWIR	1
6.	
Total:	555
Study areas: <ul style="list-style-type: none"> • Gaofeng, Weihai, Fushun, Lu'an, Wangyedian, Genhe and Pu'er in China • Remningstorp in Sweden 	

Chinese EO data	No. Scenes
1. Gaofen-1	55
2. Gaofen-2	110
3. Gaofen-6	150
4.	
5.	
6.	
Total:	315
Study areas: <ul style="list-style-type: none"> • Gaofeng, Weihai, Fushun, Lu'an, Wangyedian, Genhe and Pu'er in China 	

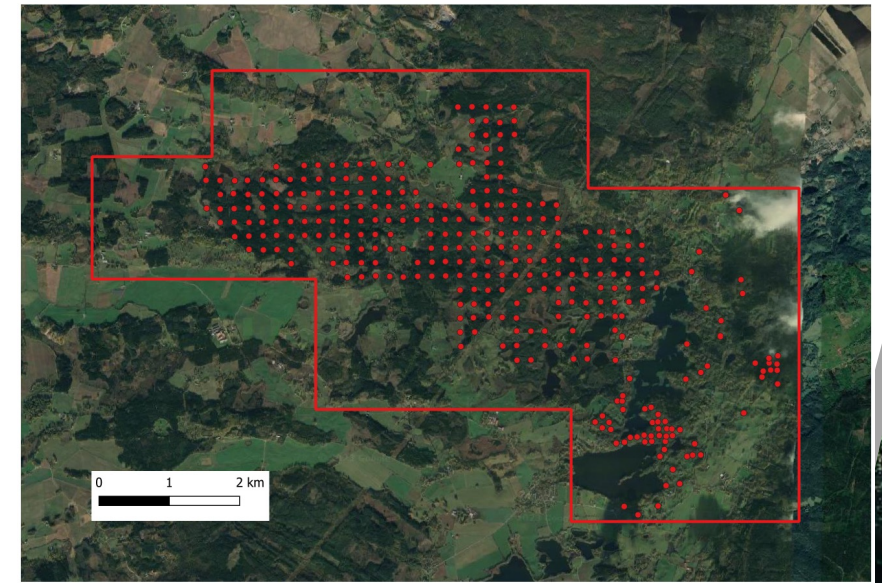
Study area in China

- Field investigation of forest parameters was conducted in **Gaofeng and Genhe**. The inventory recorded diameter at breast height, tree height, under branch height, and the coordinates of the plots.
- Spectral information was collected from healthy and pine nematode-infested forests at different stages in the **Fushun and Lu'an** study areas.
- The information of tree species, forest changes and disturbance in **Pu'er** was collected. And the occurrence status and geographical distribution information of Simao pine bark beetle diseases were recorded.



Study area in Sweden

- Southern Sweden
- 1,200 ha productive forest
- Active forest management
- Reference data for RS
- Bark beetle outbreaks in 2018

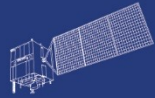




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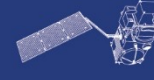
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Sentinel-2



Sentinel-3



Sentinel-5p



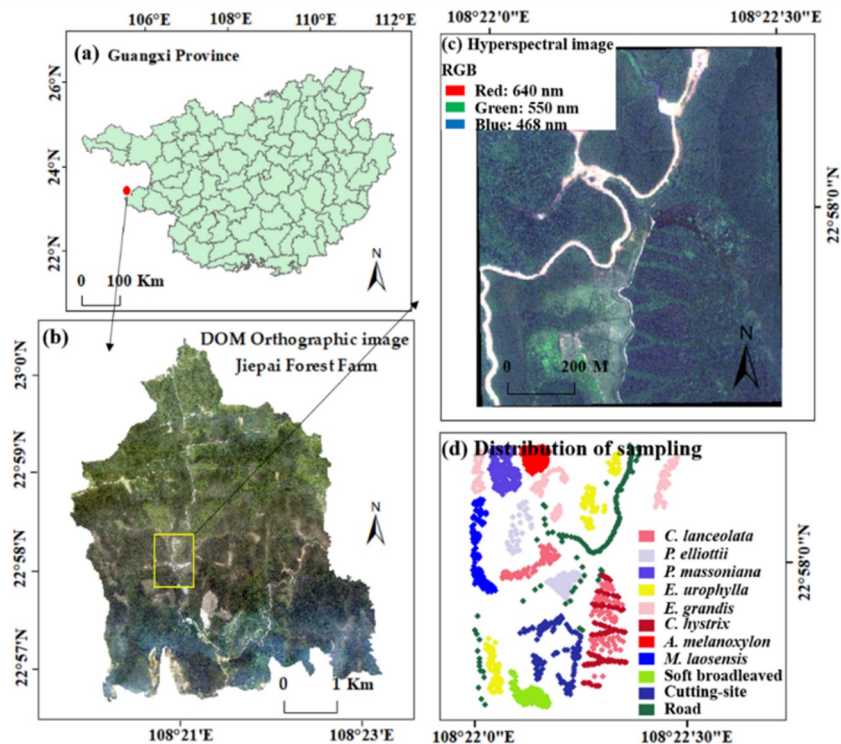
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Tree Species Classification

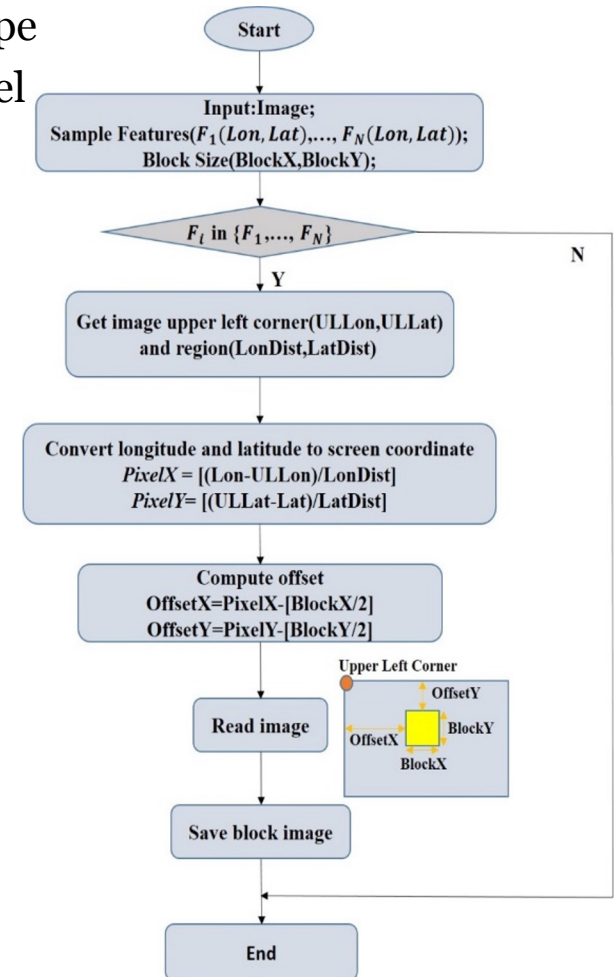
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Tree Species Classification by few-shot learning (Stand scale)

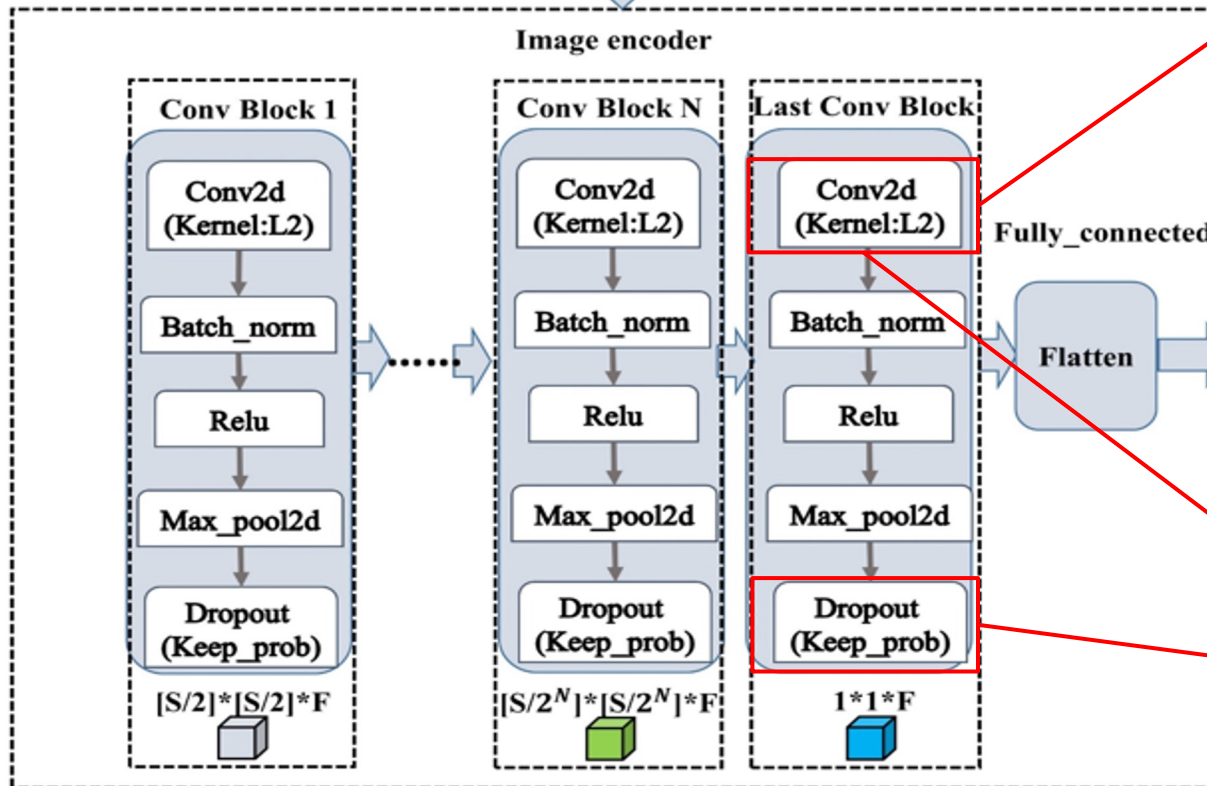
- Propose an improved prototypical networks (IPrNet), a CBAM-P-Net model of the prototype network combined with an attention mechanism, and a Proto-MaxUp+CBAM-P-Net model of the CBAM-P-Net combined with a data enhancement strategy
- Use UAVs hyperspectral data
- Obtain good classification results for **8 major tree species** in southern China



Categories	Samples	
	Train	Test
<i>Cunninghamia lanceolata</i>	96	24
<i>Pinus massoniana</i>	96	24
<i>Pinus elliotii</i>	96	24
<i>Eucalyptus grandis</i>	96	24
<i>Eucalyptus urophylla</i>	96	24
<i>Castanopsis hystrix</i>	96	24
<i>Mytilaria laosensis</i>	96	24
<i>Acacia melanoxylon</i>	96	24
Other broadleaf forest	96	24
Road	96	24
Cutting-site	96	24
Total	1056	264

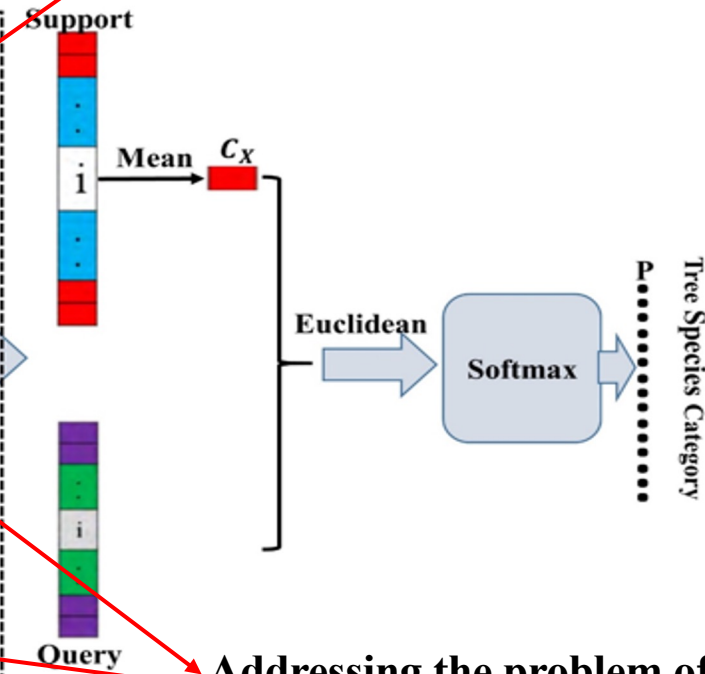


IPrNet Classification Framework



Loss function:

$$J(\phi) = -\log p_{\phi}(y = k|x) + \alpha_2 \sum_w w^2$$



Addressing the problem of overfitting in this study.

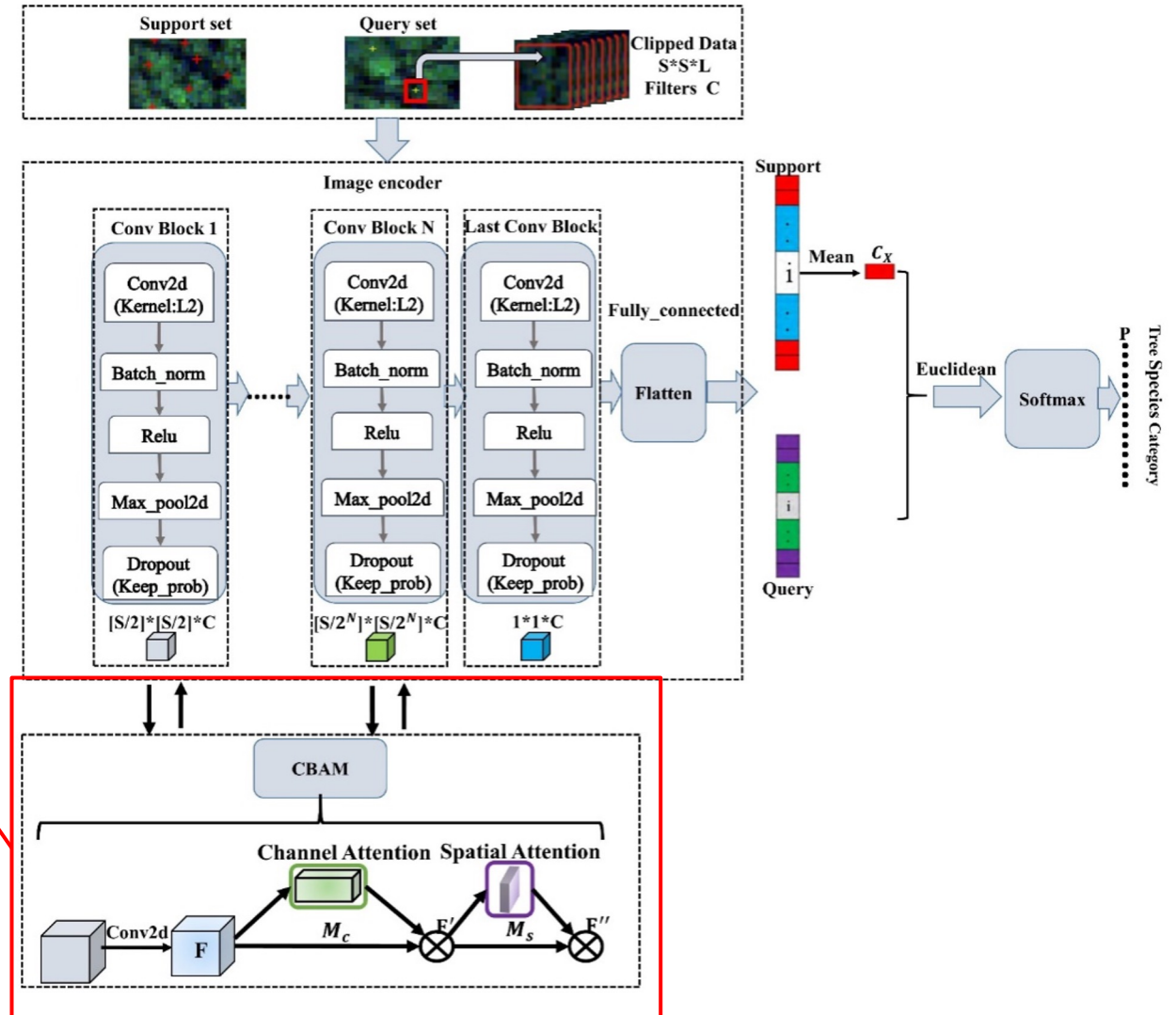
CBAM-P-Net Classification Framework

Target:

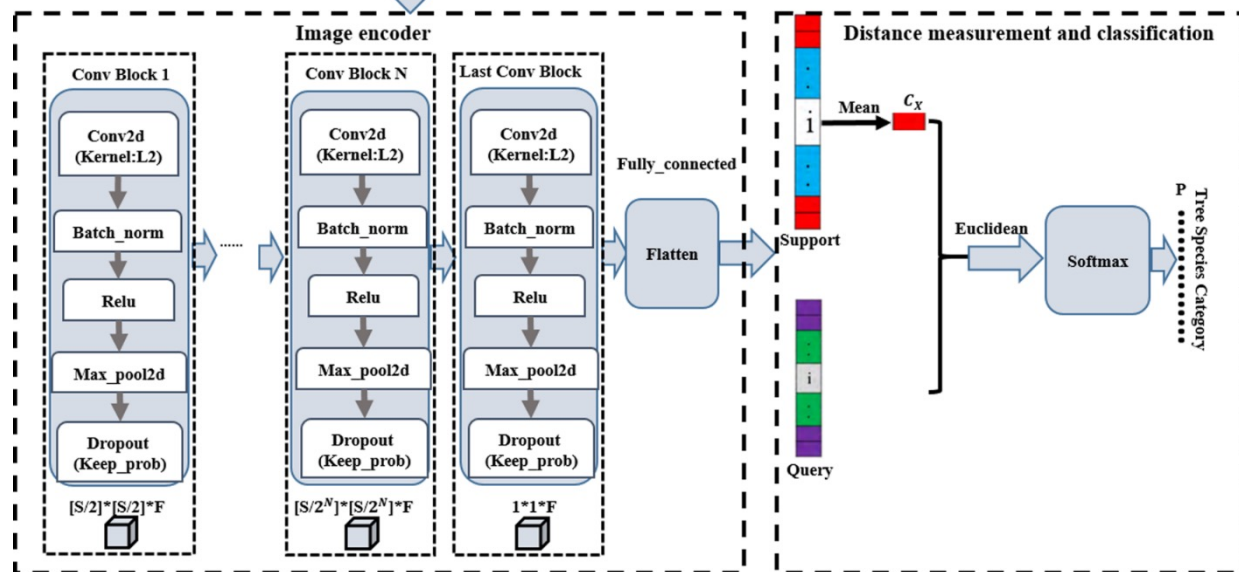
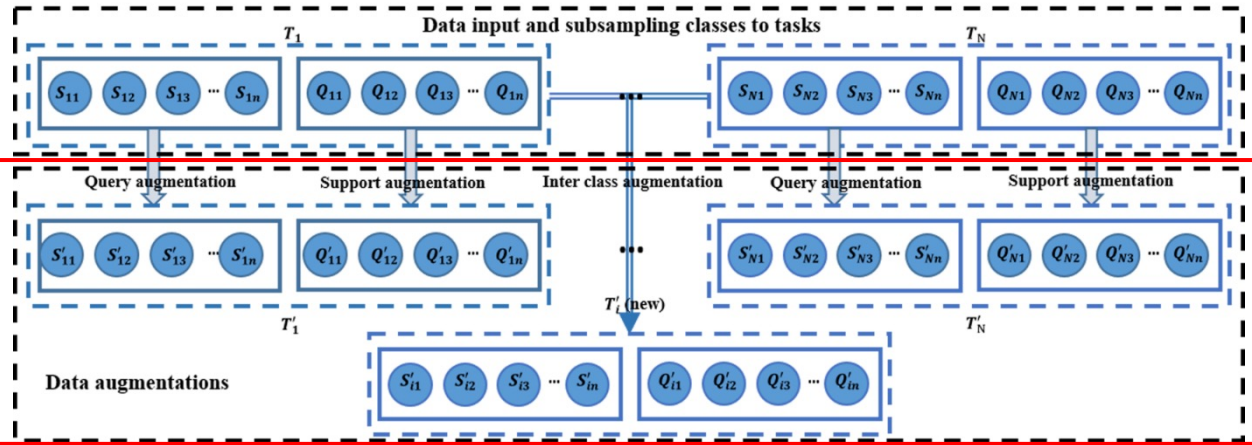
Improving the feature extraction efficiency
Overcoming the dimensional dilemma

CBAM Combination Strategy:

- Channel attention is applied globally
- Spatial attention is applied locally
- Channel First \longrightarrow Global first and then local



Proto-MaxUp Classification Framework

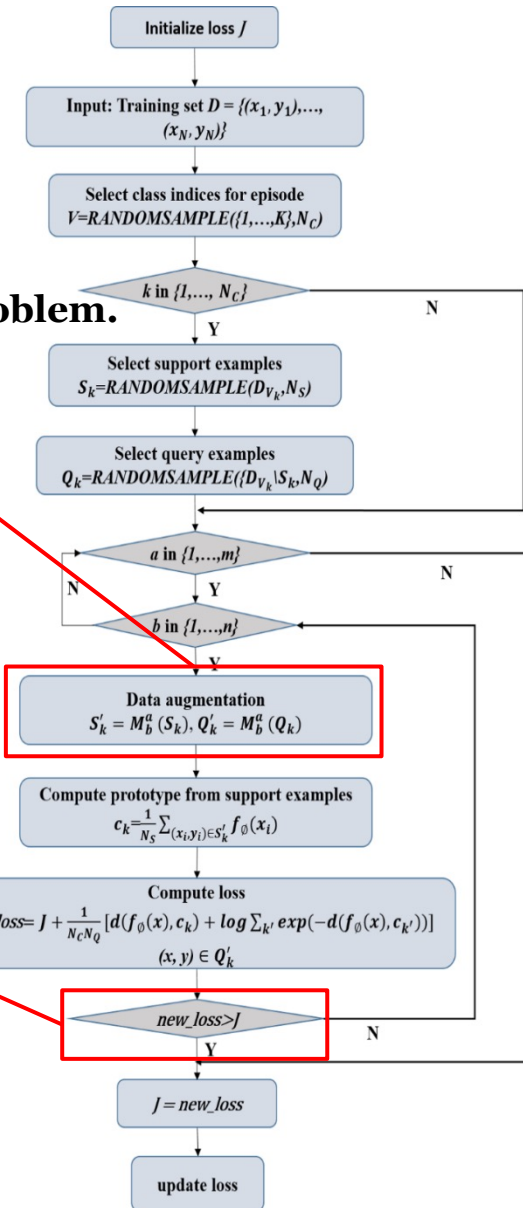


Data augmentation:

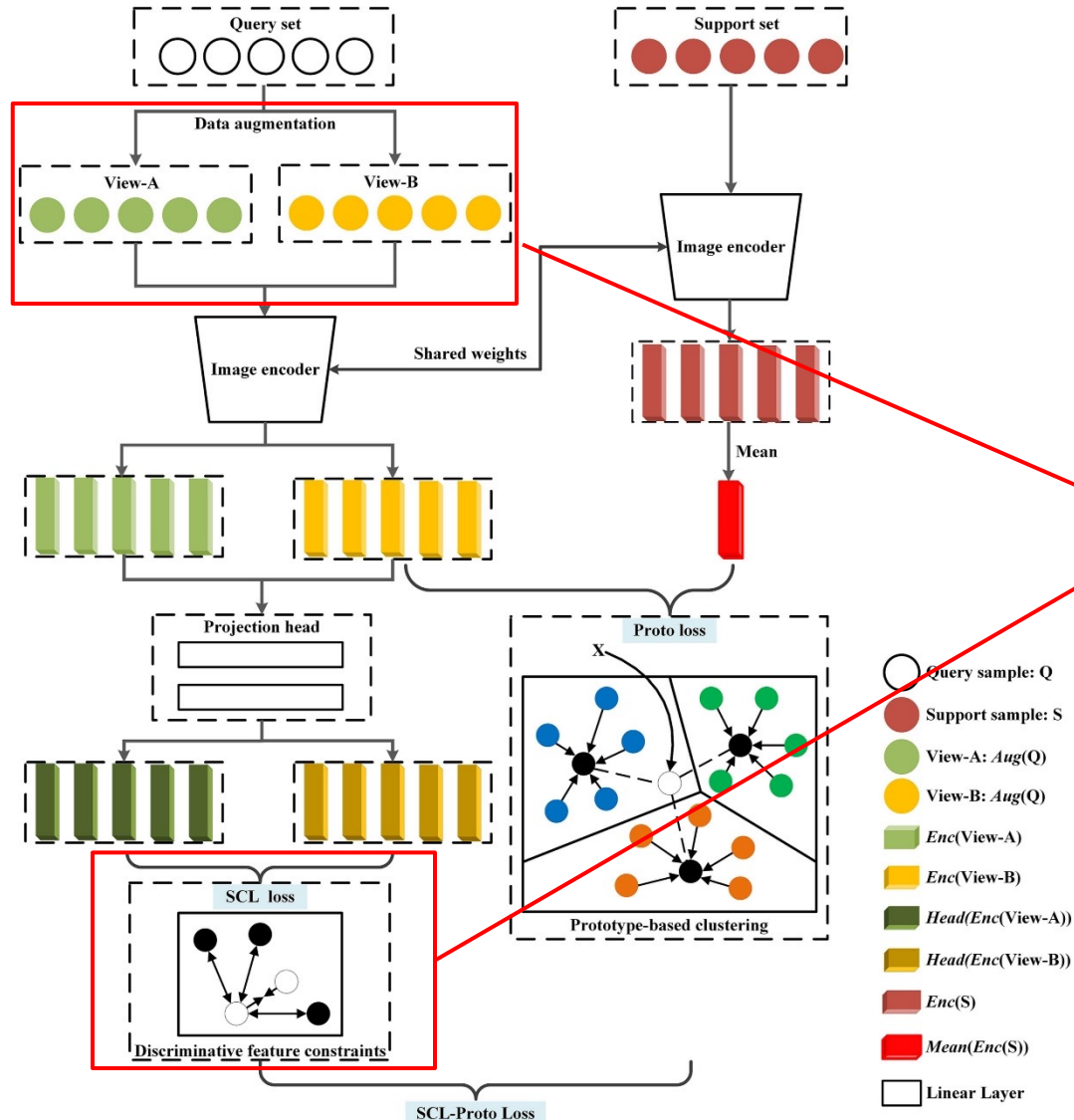
- Improving sample diversity.
- Minimizing the overfitting problem.

Proto-MaxUp:

- Adversarial training: minimize the maximum loss
- Solving the issue of saddle-point



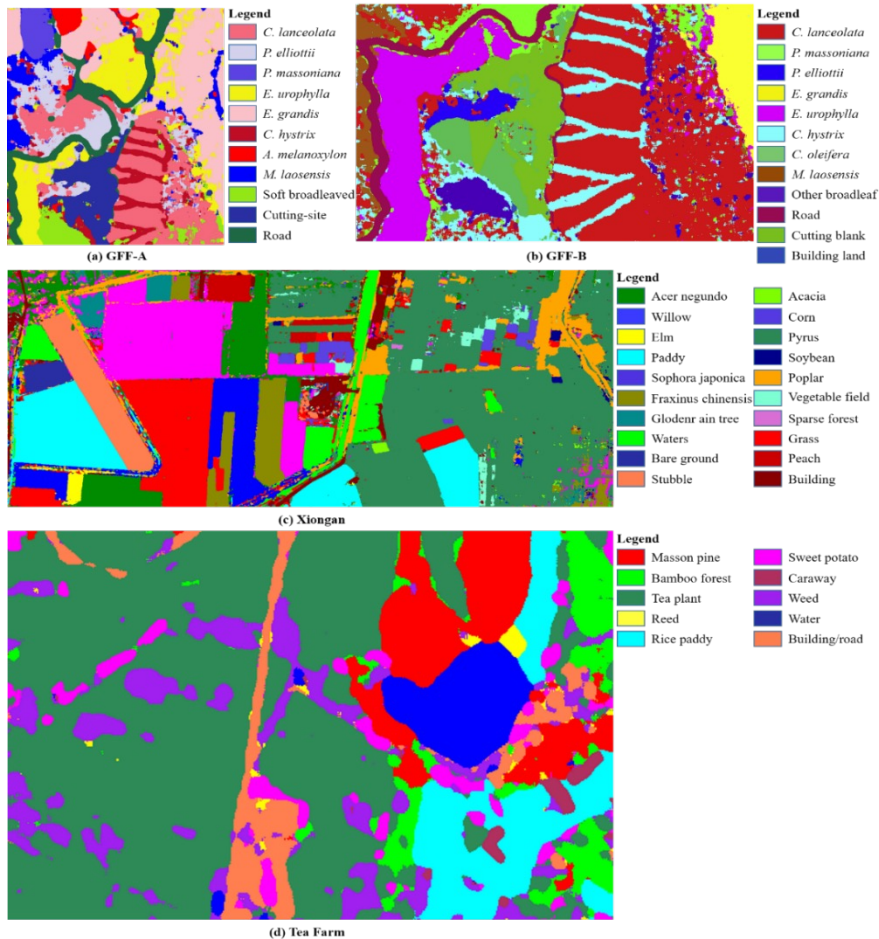
SCL-P-Net Classification Framework



Supervised Contrastive Learning for combination of data augmentation and feature enhancement Algorithms:

- Enriching sample diversity.
- In the feature space, positive (same class) samples are clustered and negative (different class) samples are separated.

SCL-P-Net Classification Map



Classification maps of SCL-P-Net with different datasets

Dataset	GFF-A	GFF-B	Xiongan	Tea Farm
OA (%)	99.23	98.39	99.30	99.54
WOA (%)	99.23	98.41	99.26	99.87
AA (%)	99.24	98.78	97.54	99.32
Class A (%)	96.91	97.93	99.18	99.72
Class B (%)	98.95	98.14	99.70	97.86
Class C (%)	100.00	97.36	97.99	99.50
Class D (%)	100.00	99.95	99.93	98.60
Class E (%)	100.00	99.70	99.60	99.88
Class F (%)	96.88	95.44	99.89	99.60
Class G (%)	100.00	99.35	99.96	99.30
Class H (%)	98.88	99.98	99.79	98.87
Class I (%)	100.00	99.67	99.53	100.00
Class J (%)	100.00	97.81	99.96	99.89
Class K (%)	100.00	99.99	97.29	-
Class L (%)		100.00	97.46	-
Class M (%)		-	99.36	-
Class N (%)		-	92.24	-
Class O (%)		-	94.92	-
Class P (%)		-	92.05	-
Class Q (%)		-	85.80	-
Class R (%)		-	99.46	-
Class S (%)		-	98.24	-
Class T (%)		-	98.39	-

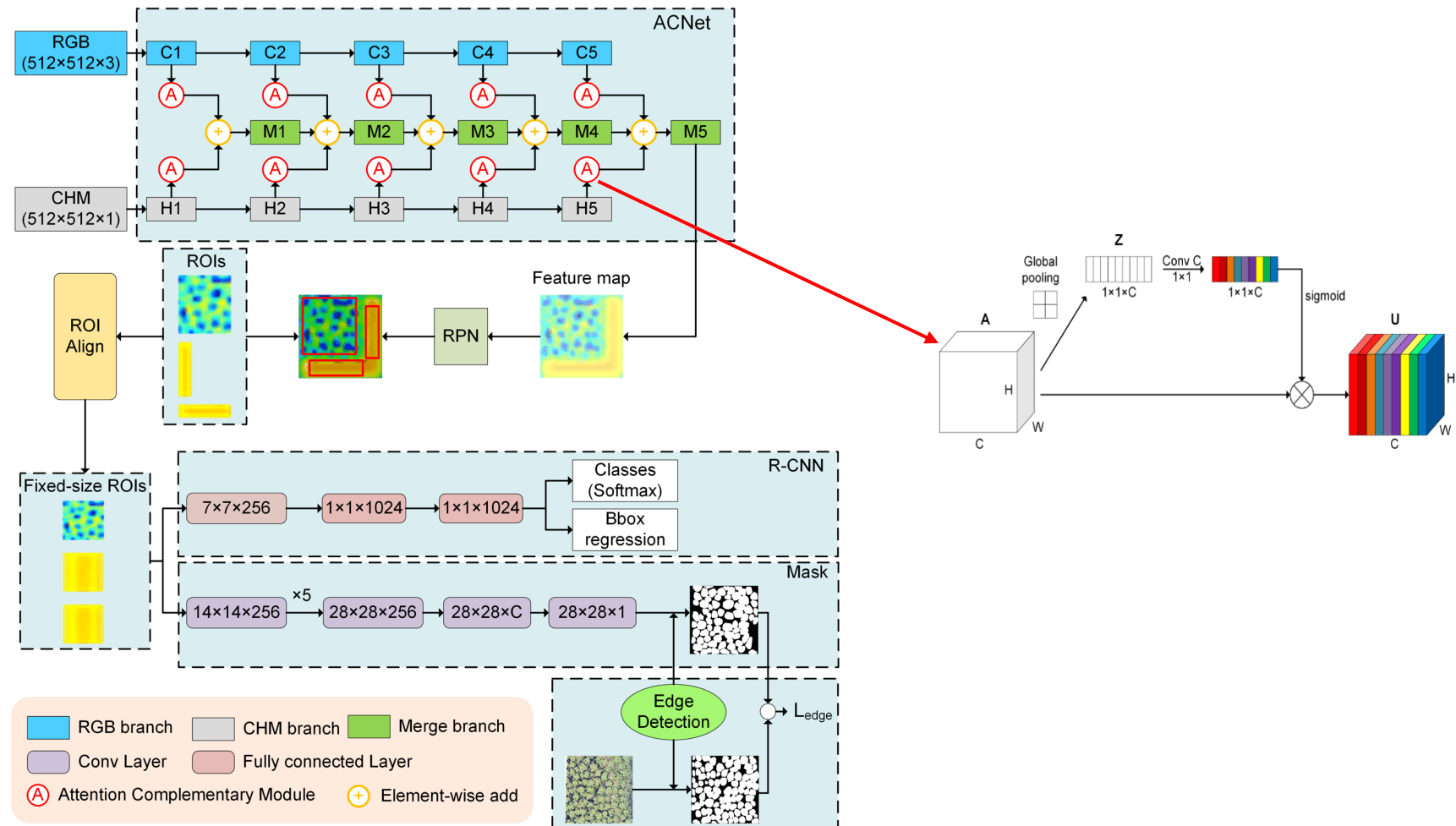
Tree Species Classification by Deep Learning

- **Improving the feature extraction efficiency**
- **Data augmentation**
- **Feature enhancement**

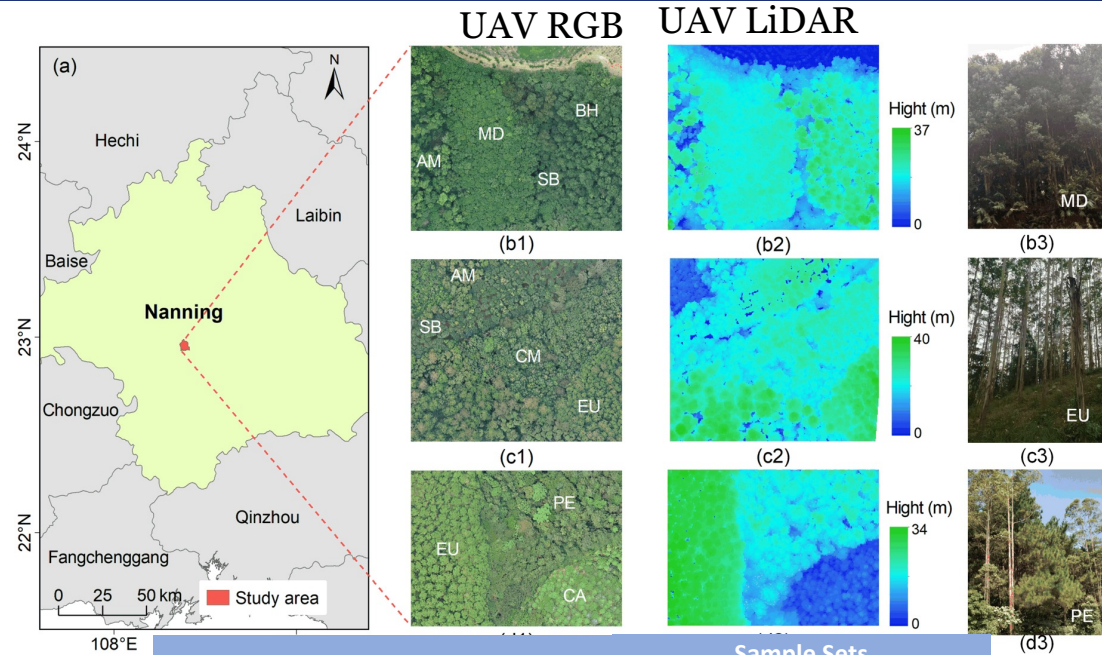
1. Chen L, Wu J, Xie Y, et al. Discriminative feature constraints via supervised contrastive learning for few-shot forest tree species classification using airborne hyperspectral images[J]. *Remote Sensing of Environment*, 2023, 295: 113710.
2. Chen L, Wei Y, Yao Z, et al. Data augmentation in prototypical networks for forest tree species classification using airborne hyperspectral images[J]. *IEEE Transactions on Geoscience and Remote Sensing*, 2022, 60: 1-16.
3. Li Y, Chai G, Wang Y, et al. Ace r-cnn: An attention complementary and edge detection-based instance segmentation algorithm for individual tree species identification using uav rgb images and lidar data[J]. *Remote Sensing*, 2022, 14(13): 3035.
4. Chen L, Tian X, et al. A New CBAM-P-Net Model for Few-Shot Forest Species Classification Using Airborne Hyperspectral Images[J]. *Remote Sensing*, 2021, 13, 1269.

Individual-Tree Species Identification by ACE R-CNN

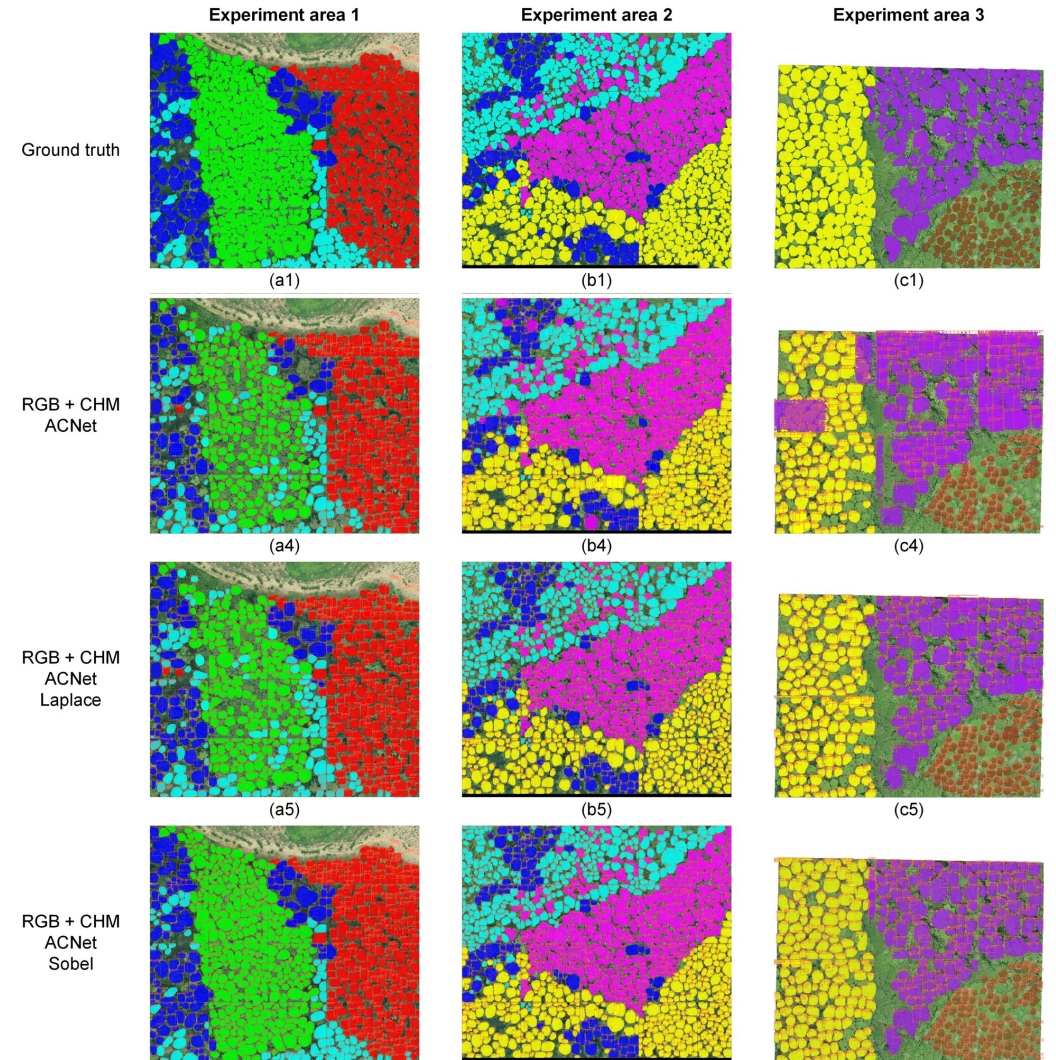
- Propose an attention mechanism, **edge detection** and region-based instance segmentation algorithm (ACE R-CNN)
- Use **UAV LiDAR and RGB** images.
- Obtain good classification results for **6 major tree species** in southern China.



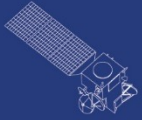
ACE R-CNN Framework



Individual-Tree Species Identification Map



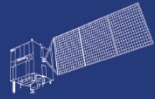
Sample Sets	Tree species	Sample Sets	
		Training Set	Test Set
Experiment area 1	BH	240	172
	MD	291	209
	AM	141	106
	SB	99	80
	Total	771	567
Experiment area 2	AM	146	114
	EU	288	212
	CM	271	192
	SB	235	174
Total	940	692	
Experiment area 3	EU	181	135
	PE	160	116
	CA	147	117
	Total	488	368



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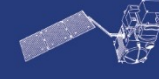
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Sentinel-2



Sentinel-3



Sentinel-5p



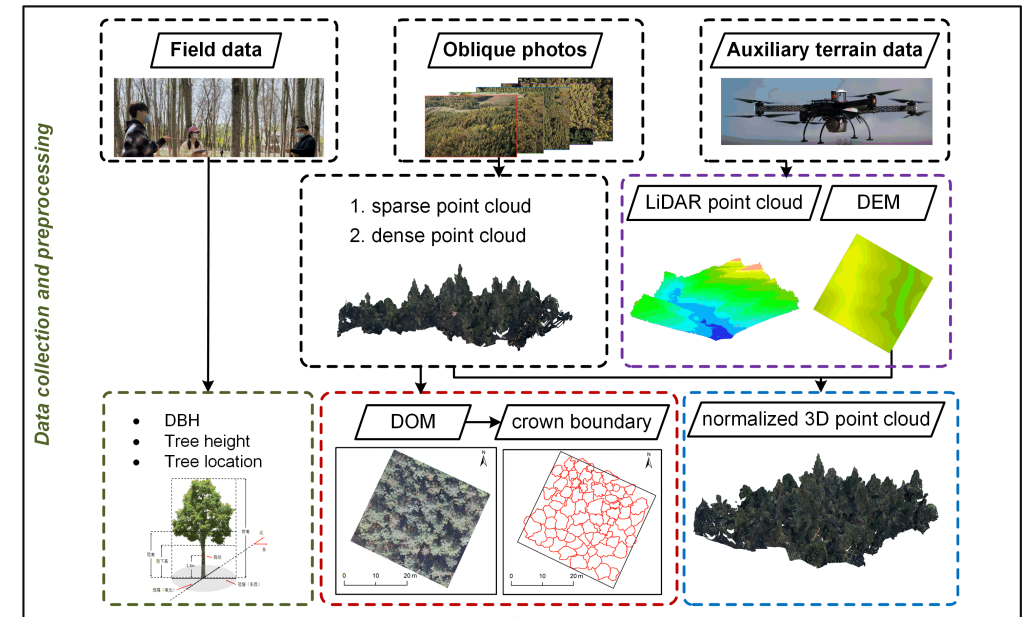
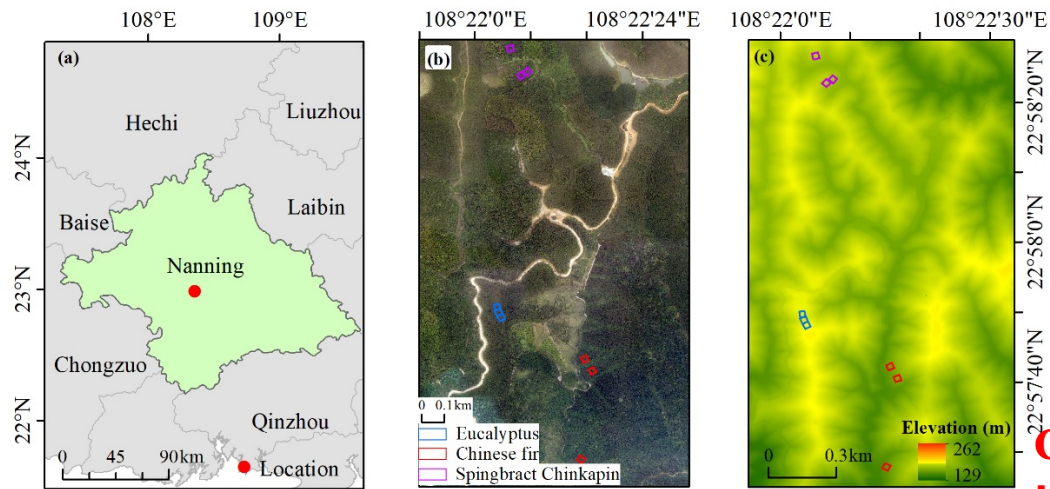
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Forest Parameter Estimation

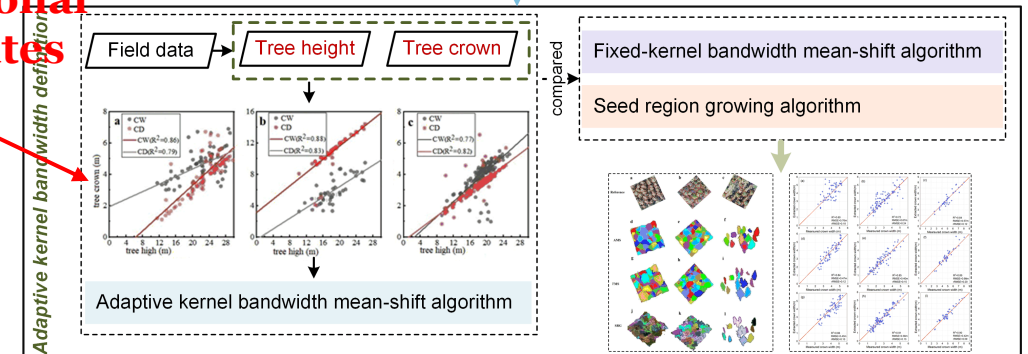
Beijing Forestry University

Individual tree crowns segmentation using UAV oblique photos

- Field data
- UAV oblique photos
- LiDAR data



Considering three-dimensional canopy attributes



Individual tree crowns segmentation using UAV oblique photos

$$M_{h^s, h^c}(X_B) = \frac{\sum_{i=1}^n X_i g^s(\|\frac{X_B^s - X_i^s}{h^s}\|^2) g^c(\|\frac{X_B^c - X_i^c}{h^c}\|^2)}{\sum_{i=1}^n g^s(\|\frac{X_B^s - X_i^s}{h^s}\|^2) g^c(\|\frac{X_B^c - X_i^c}{h^c}\|^2)} - X_B$$

Vector of mean shift at any point
Move towards the maximum of height and density

Kernel function: characterising the contribution of the offset to the mean shift vector

$$g^s(\|\frac{X_B^s - X_i^s}{h^s}\|^2) = \begin{cases} \exp\left(-\frac{1}{2}\left(\|\frac{X_B^s - X_i^s}{h^s}\|^2\right)\right) & \text{if } \left(\|\frac{X_B^s - X_i^s}{h^s}\|^2\right) \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

horizontal kernel function
Move towards the maximum of density

Horizontal kernel bandwidth

$$g^c(\|\frac{X_B^c - X_i^c}{h^c}\|^2) = \begin{cases} 1 - \|\frac{1 - \text{dist}(X_B^c, X_i^c)}{h^c}\|^2 & \text{if } \text{mask}(X_B^c, X_i^c) = 1 \\ 0 & \text{otherwise} \end{cases}$$

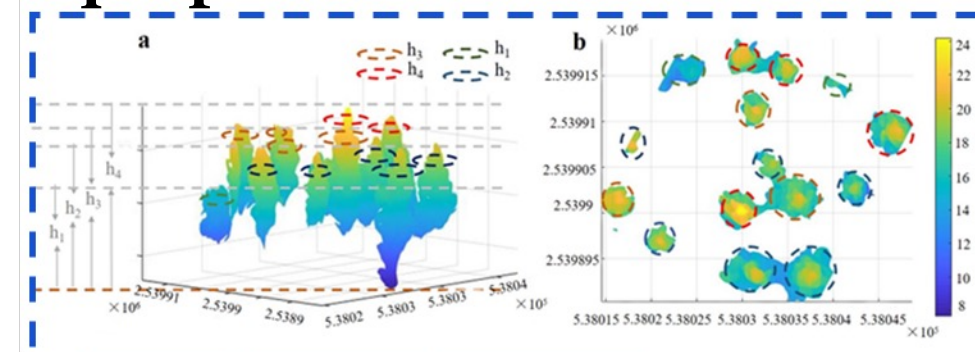
vertical kernel function
Move towards the maximum of height

vertical kernel bandwidth

$$\text{mask}(X_B^c, X_i^c) = \begin{cases} 1 & \text{if } X_B^c - \frac{h^c}{4} \leq X_i^c \leq X_B^c + \frac{h^c}{2} \\ 0 & \text{otherwise} \end{cases}$$

Fixed kernel bandwidth

$$\text{dist}(X_B^c, X_i^c) = \begin{cases} \min\left\{\left\|\frac{(X_B^c - \frac{h^c}{4}) - X_i^c}{\frac{3h^c}{8}}\right\|, \left\|\frac{(X_B^c + \frac{h^c}{2}) - X_i^c}{\frac{3h^c}{8}}\right\|\right\} & \text{if } \text{mask}(X_B^c, X_i^c) = 1 \\ 0 & \text{otherwise} \end{cases}$$

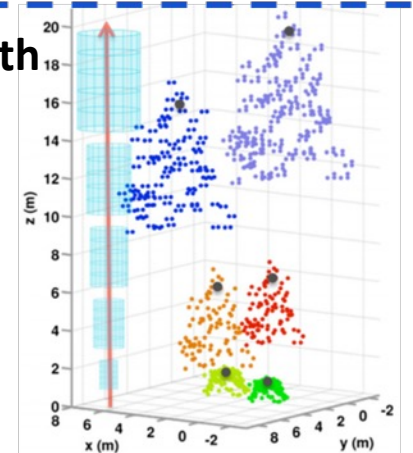


Species	Horizontal	Vertical
Eucalyptus	$h^s(X_i) = 0.16 \times z_i$	$h^c(X_i) = 0.26 \times z_i$
Spingbract Chinkapin	$h^s(X_i) = 0.2 \times z_i$	$h^c(X_i) = 0.25 \times z_i$
Chinese fir	$h^s(X_i) = 0.3 \times z_i$	$h^c(X_i) = 0.4 \times z_i$

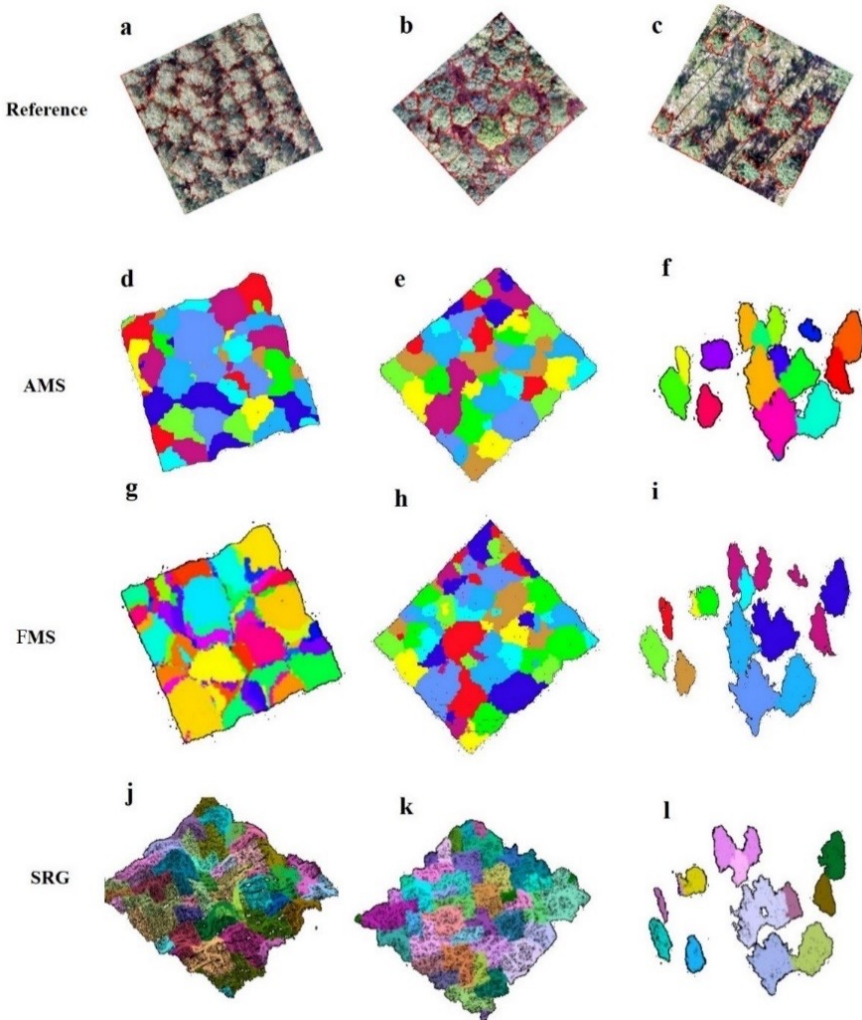
tree height

crown length and crown width

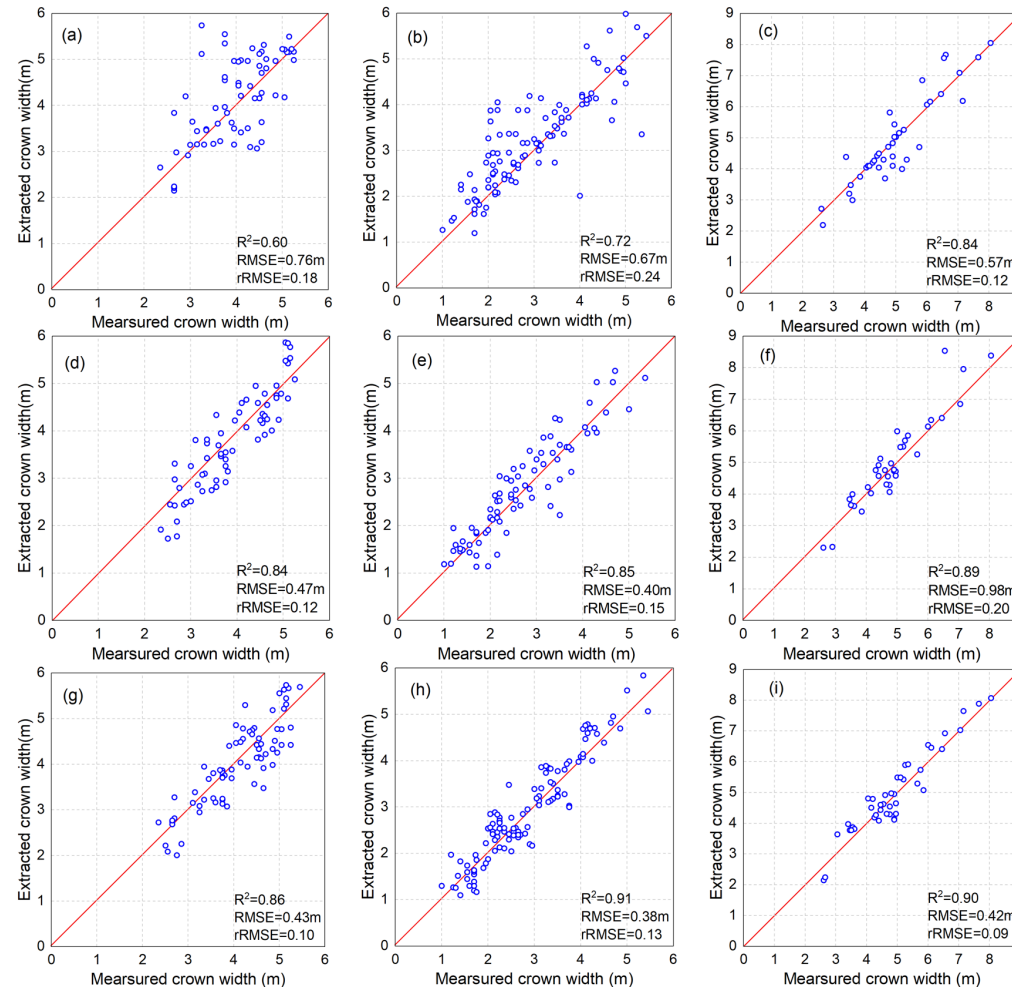
Adaptive kernel bandwidth



Individual tree crowns segmentation using UAV oblique photos



The results of ITCs segmentation (a, d, g, j are Eucalypts, b, e, h, k are Spingbract Chinkapin and c, f, i, l are Chinese fir.)



The scatter plots of measured crown width and extracted crown width obtained by the three different methods

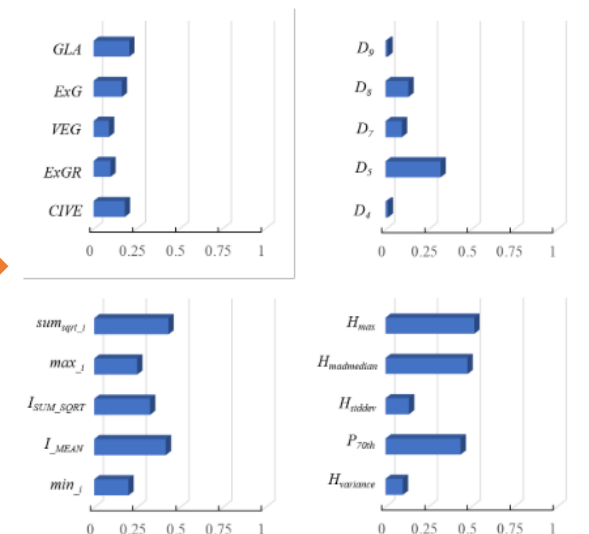
- Flexible setting of kernel bandwidth to segment ITC for each tree based on tree height.
- High accuracy can be achieved in both tree top detection and canopy width extraction.
- Appropriate reduction of point cloud density can balance efficiency and accuracy.
- The application of AMS algorithm in LiDAR data is still possible.

Individual Tree above-ground biomass estimation using UAV oblique photos

Type	Variable	Formula	Describe
RGB space	Max_i	—	Maximum intensity
	Min_i	—	Minimum intensity
	$Mean_i$	—	Mean intensity
RGB space	sum_i	$\sum_{i=1}^n (0.2 \times R_i + 0.72 \times G_i + 0.07 \times B_i)$	Total intensity
	$sum_{sqr,j}$	$sum_{sqr,j} = \sqrt{sum_i}$	Square root of intensity value
HSI space	I_{MAX}	—	Maximum intensity
	I_{MIN}	—	Minimum intensity
	I_{MEAN}	—	—
	I_{SUM}	—	—
	I_{SUM_SQRT}	—	—
Height variables	H_{std}	—	—
	H_{AIQ}	—	—
	$H_{kurtosis}$	—	—
	H_{cv}	—	—
	H_{ratio}	—	—
	H_{stddev}	$H_{stddev} = \sqrt{\frac{\sum_{i=1}^n (Z_i - Z)^2}{n}}$	Variance of Z values of all points in a statistical unit
	$H_{variance}$	$H_{variance} = \frac{\sum_{i=1}^n (Z_i - Z)^2}{n}$	Height skewness
	$H_{skewness}$	$H_{skewness} = \frac{\frac{1}{n} \sum_{i=1}^n (Z_i - Z)^3}{(\frac{1}{n} \sum_{i=1}^n (Z_i - Z)^2)^{1.5}}$	1... 99% cumulative height percentile
	$H_{1...99th}$	—	The maximum, minimum, average and median of the point cloud after normalization
	$H_{max, min, mean, median}$	—	75%, 95% high percentile
density variables	$P_{1st...99th}$	—	The proportion of height points greater than 30%, 50%, 70%, and 90% to all points
	$D_{0...9}$	—	Color index of vegetation [53]
Vegetation index	$CIVE$	$CIVE = 0.44R - 0.88G + 0.398 + 18.79$	Excess green index [54]
	ExG	$ExG = 2G - R - B$	Excess green minus excess red index [55]
	$ExGR$	$ExGR = ExG - 1.4R - G$	Green leaf algorithm [56]
	GLA	$GLA = \frac{2 \times G - R}{2 \times G + R + B}$	Normalized green-red difference index [56]
	$NGRDI$	$NGRDI = \frac{G - R}{G + R}$	Vegetation index [57]
	VEG	$VEG = \frac{G}{80 + 0.1 \times G}, a = 0.67$	Combination index [58]
	COM	$COM = 0.25ExG + 0.3ExGR + 0.33CIVE + 0.12VEG$	—

Feature variables

- RGB space
- HSI space
- Height variables
- density variables
- Vegetation index



Ranking of correlation of feature variables

Experiment A

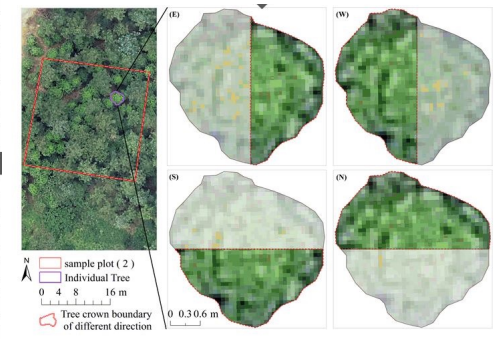
- ✓ Point cloud variables
- ✓ Vegetation index

Experiment B

- ✓ Point cloud variables
- ✓ Vegetation index
- ✓ HIS intensity variables

Experiment C

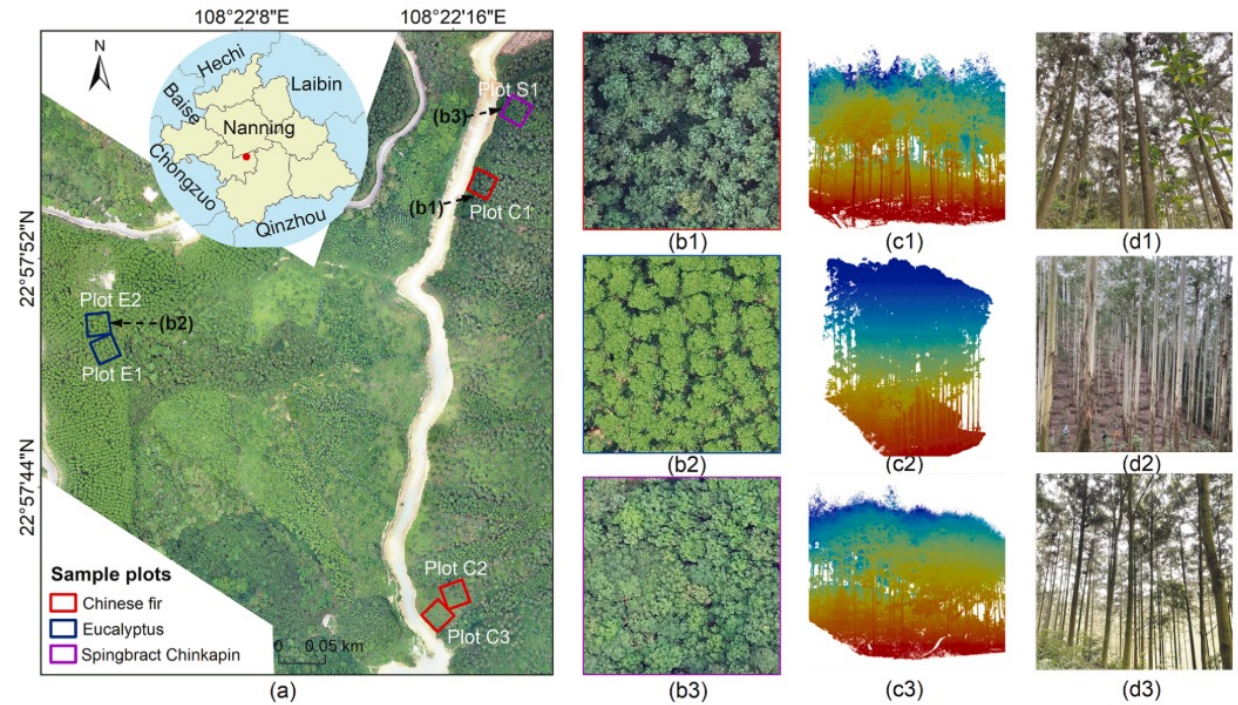
- ✓ Point cloud variables
- ✓ Vegetation index
- ✓ RGB intensity variables



- Point cloud features were the dominant features. Both density and height variable correlations are high;
- Better intensity features, significantly better than spectral features;

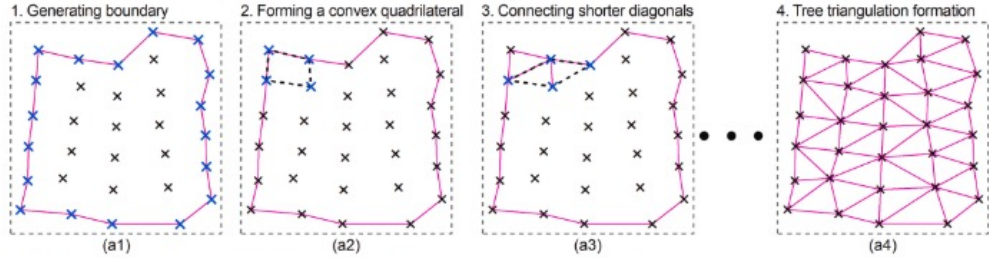
Individual tree crown parameters extraction using terrestrial close-range scanning and photogrammetry technology

- Terrestrial laser scanning
- Close-range photogrammetry sequence images

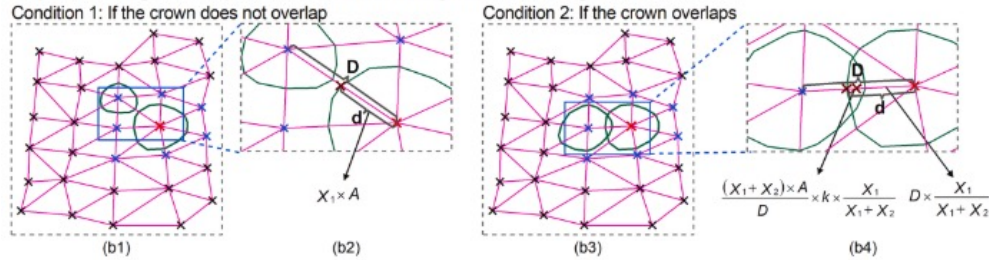


- ◆ Eucalyptus
- ◆ Chinese fir
- ◆ Spingbract Chinkapin

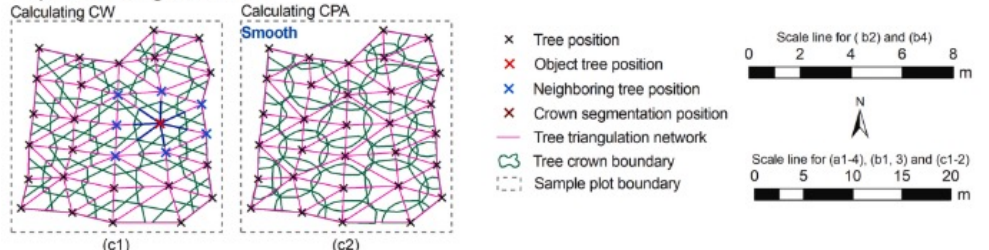
Step 1: building tree triangulation network



Step 2: obtaining division position of crown boundary in the tree triangulation



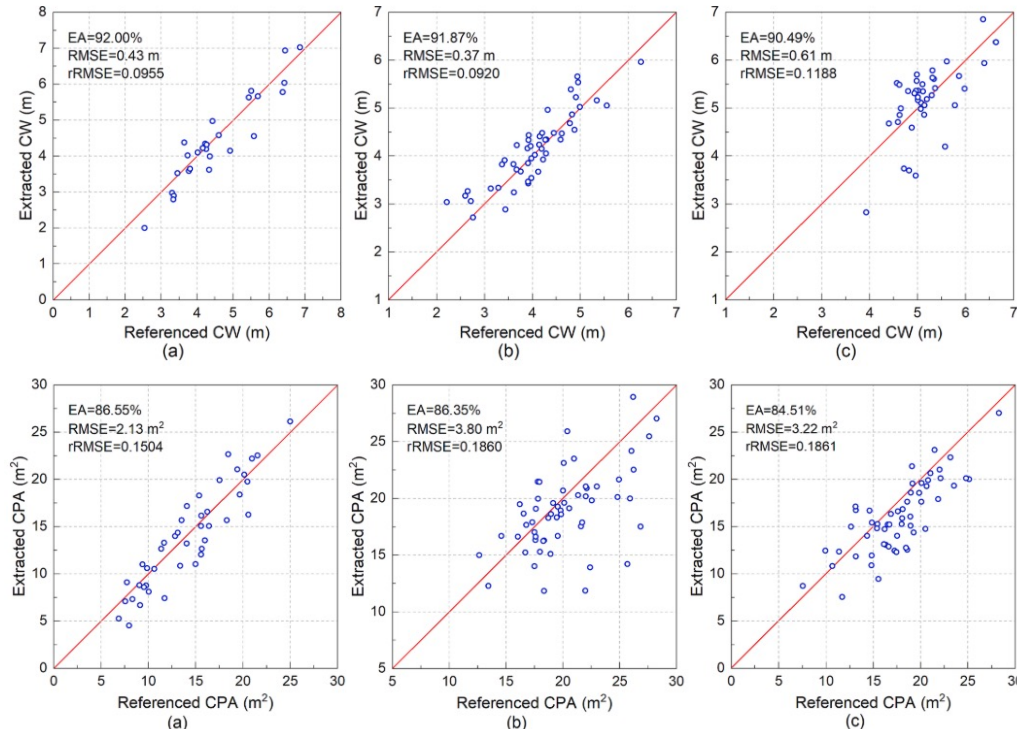
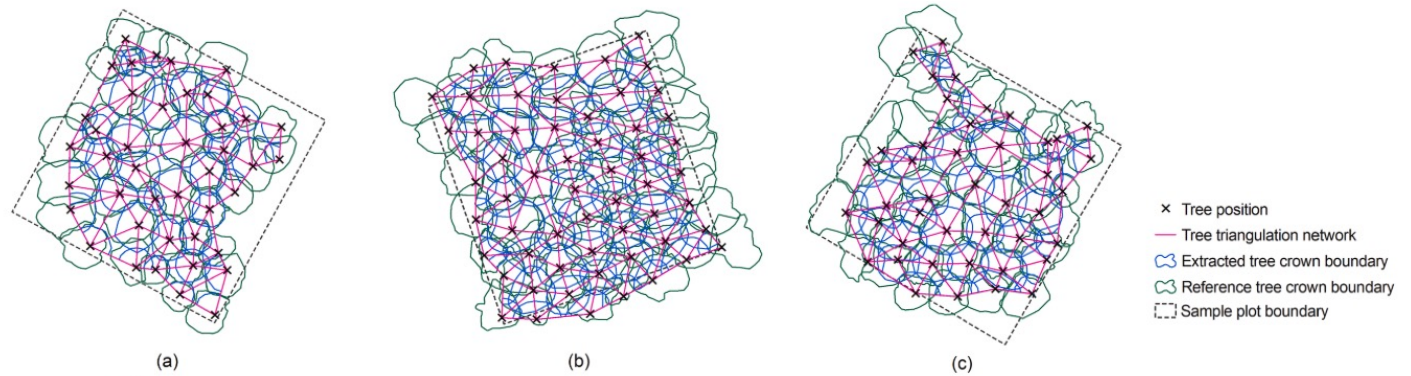
Step 3: calculating CW and CPA



$$d = \begin{cases} D \times \frac{X_1}{X_1 + X_2} + \frac{X_1 \times A}{D} \times k \times \frac{D}{X_1 + X_2} < A \\ X_1 \times A, \frac{D}{X_1 + X_2} \geq A \end{cases}$$

$$CW = \frac{1}{n} \sum_{i=1}^n d_i \times 2$$

$$CPA = CPA_{out} \times \frac{360}{A_{out}}$$

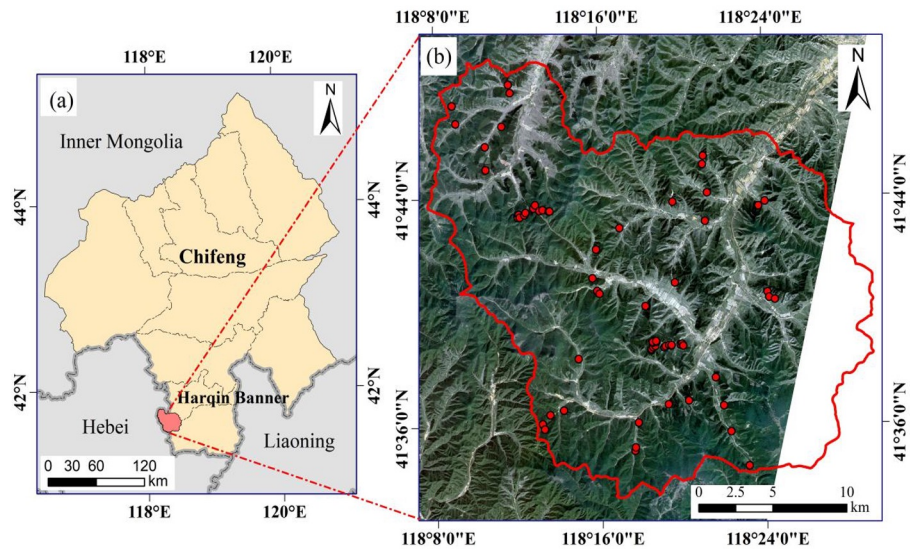


- High accuracy can be achieved in both crown width and crown projection area extraction.
- Generalizability of the model to subtropical high-density forests in subtropical China

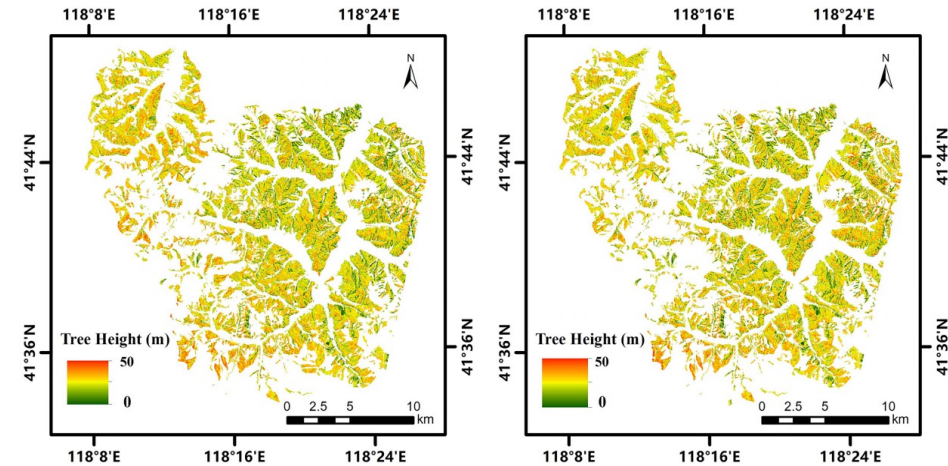
- Considering spatial distribution characteristics of trees in actual forest scenes and the inter-tree growth competitive relationships.
- Considering accessibility of competition factors and their matching with TCRO data.

Forest tree height and biomass estimation using multi-source data

- ZY-3 stereo images
- Sentinel-2 multispectral image
- ALOS DEM dataset



Location of the study area (a) and the distribution of the sample plots (b).

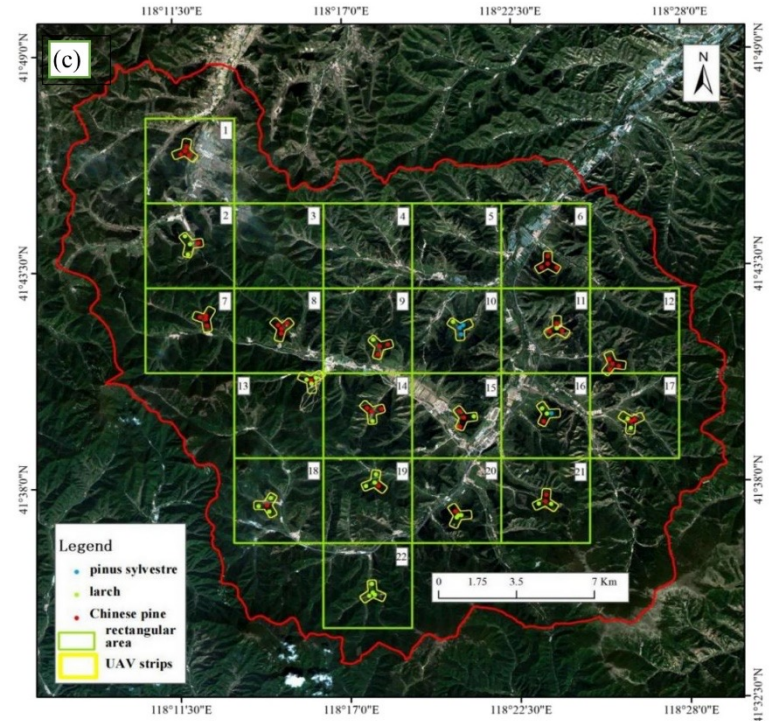
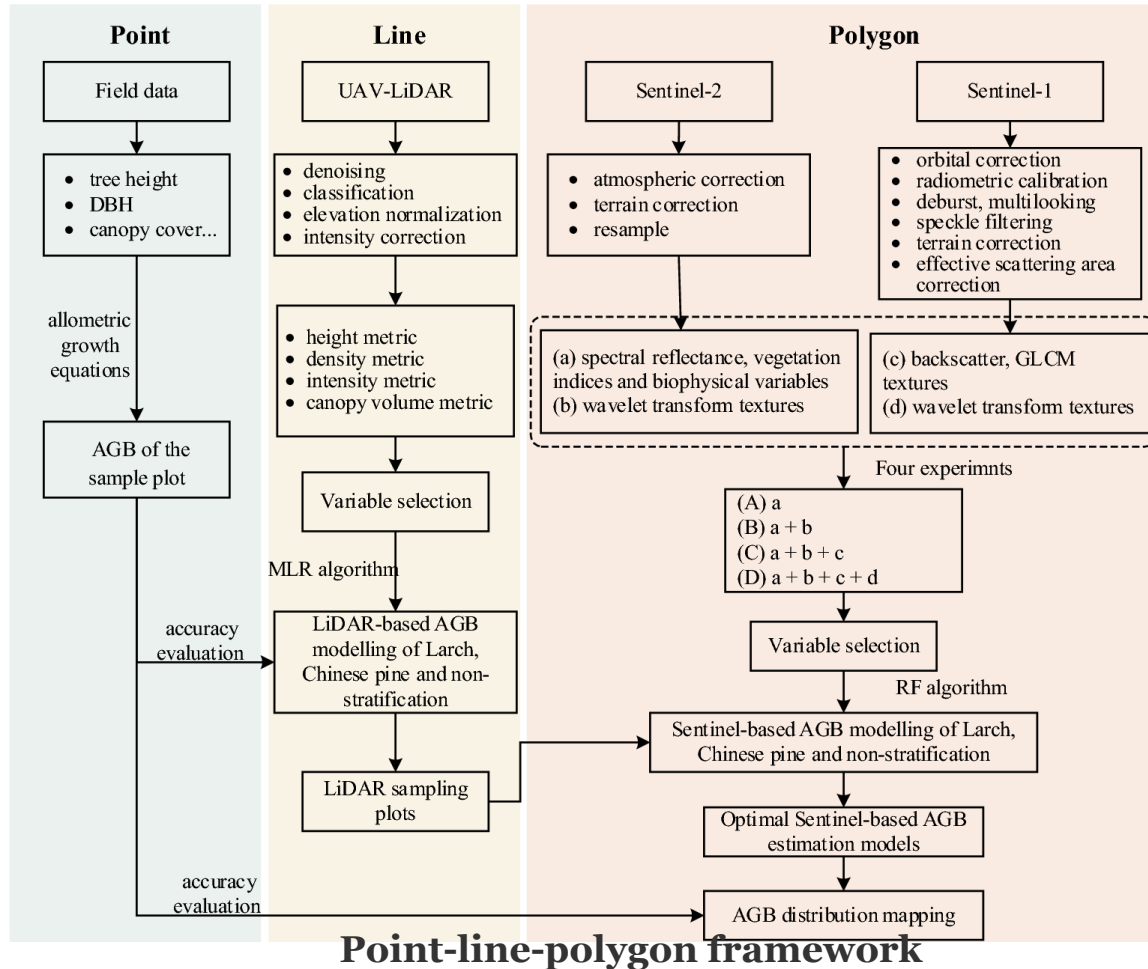


the nadir and forward views

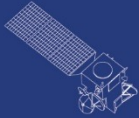
the nadir and backward views

- The nadir and forward views provide better results than the nadir and backward views.
- **A high-resolution wall-to-wall forest height map.**
- By incorporating the tree height information, the AGB estimation can be significantly improved.
- **The data saturation problem can be alleviated.**

A joint active-passive remote sensing point-line-polygon framework for regional forest aboveground biomass estimation



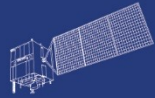
- The Point-line-polygon framework fully utilizes the respective strengths of UAV LiDAR, satellite-borne optics, and SAR data
- High-density LiDAR strip data can be used as a sample plot sampling tool to enable augmentation of sample plot data; a bridge for scale conversion
- Introducing the frequency domain and deep features of satellite-borne imagery to effectively mitigates the problem of spectral signal saturation in AGB estimation
- The point-line-polygon framework can achieve high-precision estimation and mapping of forest AGB on a large scale and can be used to assess regional forest carbon stocks.



HY



HJ-1AB



CBERS



Gaofen



Beijing-2



Sentinel-1



Sentinel-2



Sentinel-3



Sentinel-5p



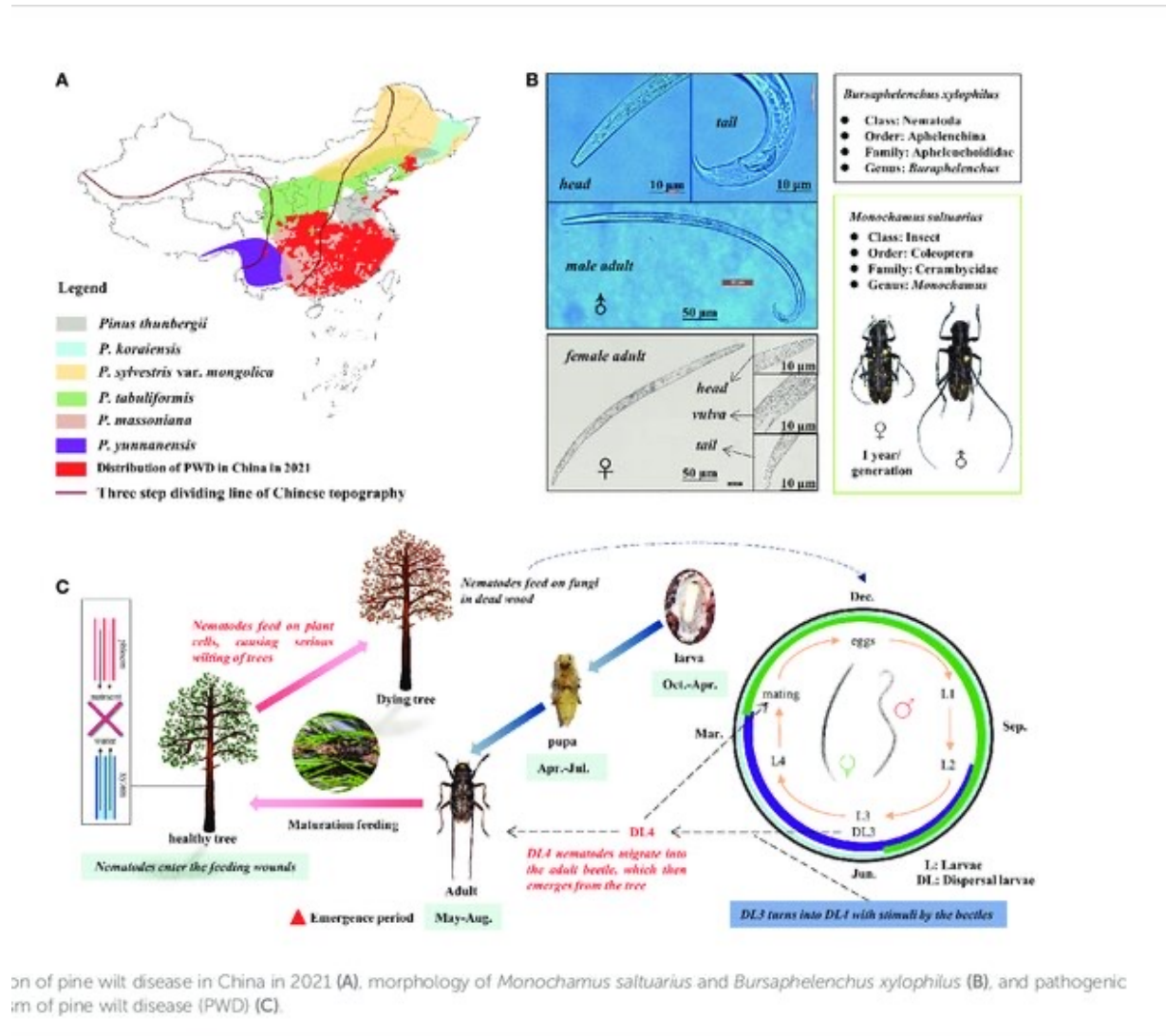
Aeolus

Forest Damage Detection

Beijing Forestry University

Swedish University of Agricultural Sciences

Monitoring of Pine Wilt Disease caused by pinewood nematode



Yu R. et, al., 2022, Early detection of pine wilt disease tree candidates using time-series of spectral signatures, *Front. Plant Sci.*, 13 October 2022, Volume 13 - 2022 | <https://doi.org/10.3389/fpls.2022.1000093>

European spruce bark beetle (*Ips typographus* [L.]

- Most destructive forest insects in Sweden and Europe





Marek Matecki/CILP

photo: Marek Matecki/CILP



Bark-beetle damaged forest in Germany.

Photo: BMEL.de



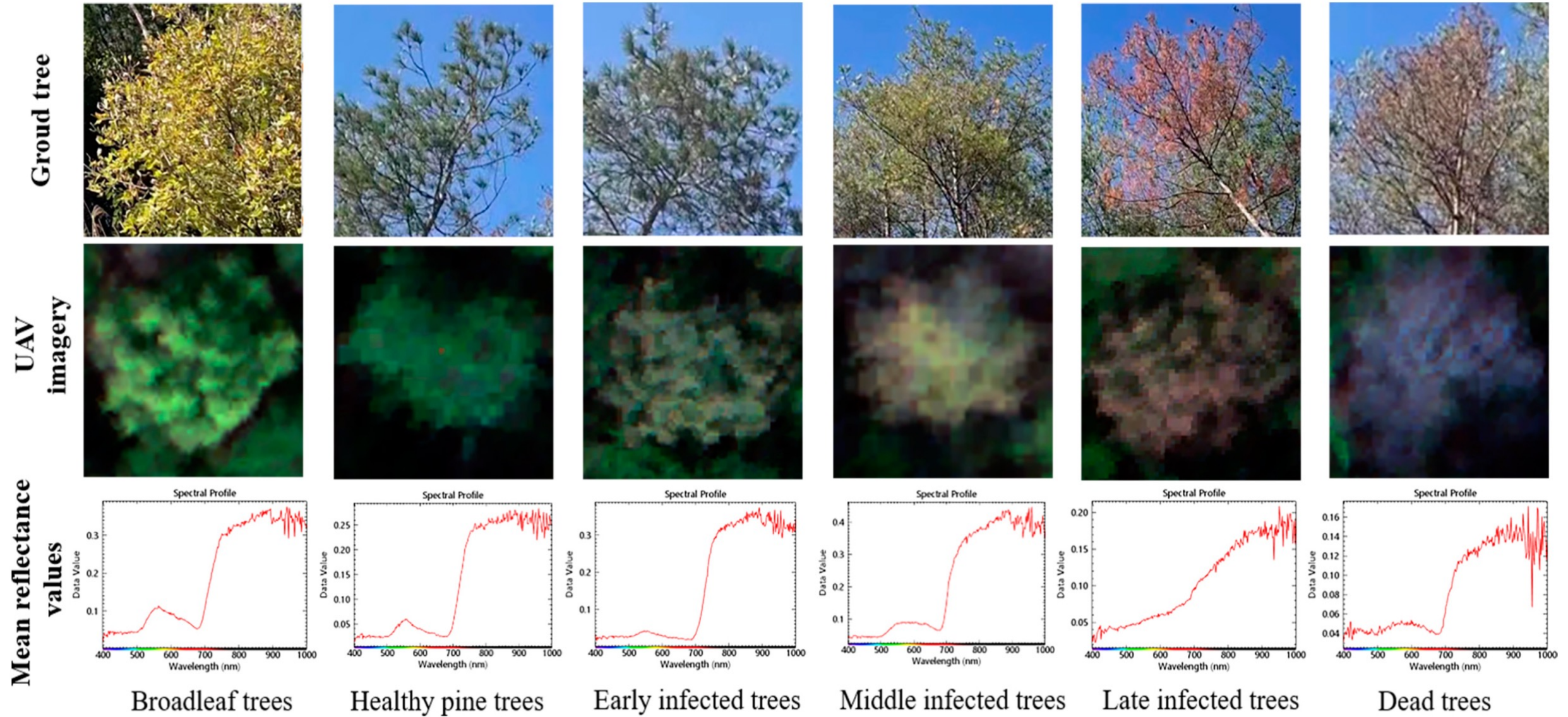
Figure

Caption

Figure 2. Norway spruce trees killed by the spruce bark beetle, Austria, Northern Front Range of the Alps. Photo: Rupert Seidl.

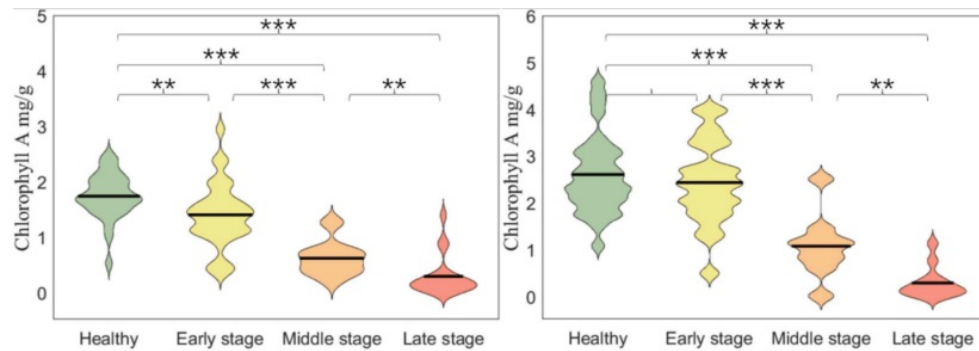
This figure was uploaded by [Paal Krokene](#)

Content may be subject to copyright.



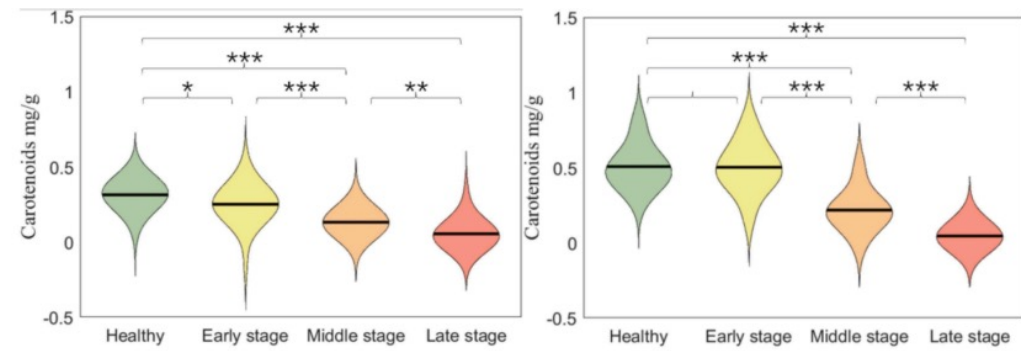
Monitoring of Pine Wilt Disease

At the needle level



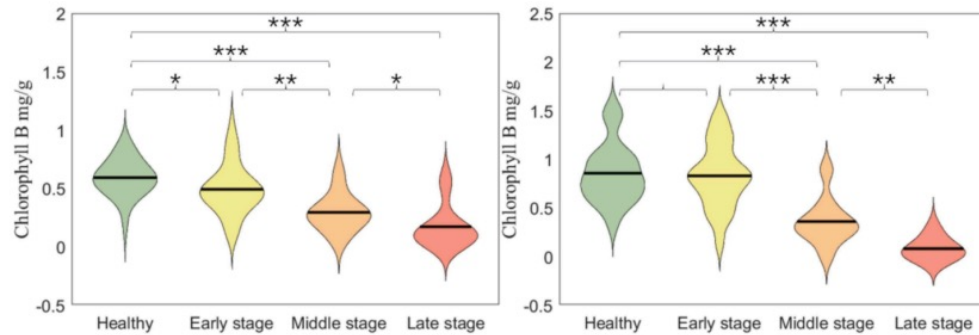
(1a)

(2a)



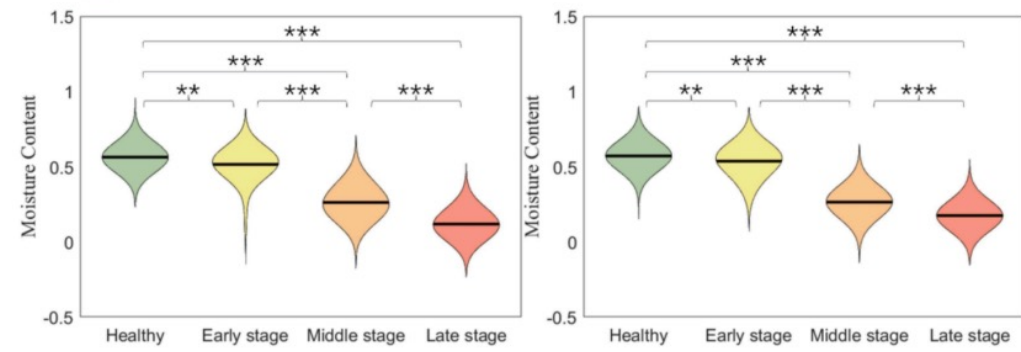
(1c)

(2c)



(1b)

(2b)



(1d)

(2d)

Monitoring of Pine Wilt Disease

At the needle level

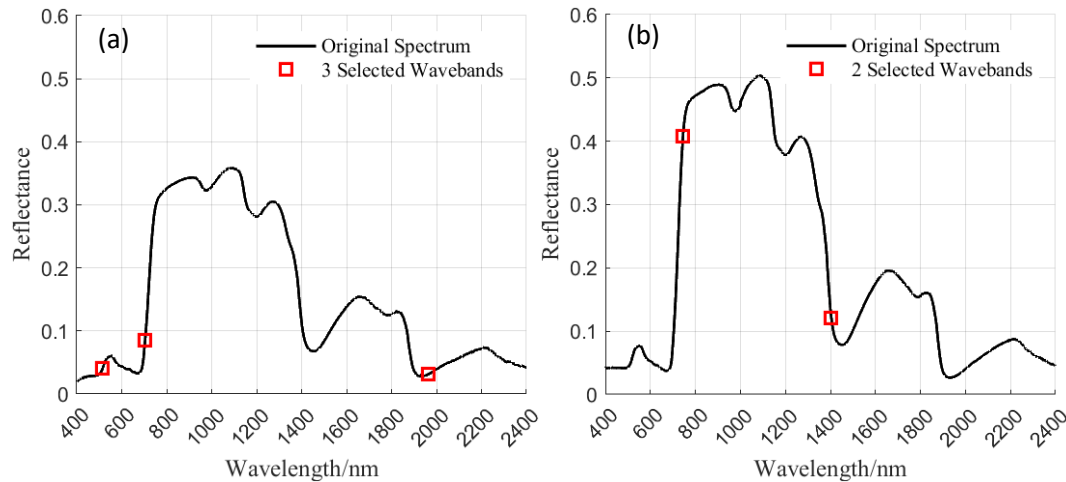


Figure. The sensitive bands of Japanese pine (a), Korean pine (b) selected by CARS-SPA.

Modeling method	Band select Algorithm	Modeling algorithm	Number of bands selected	Validation set				
				H	E	M	L	Total
Japanese pine	All bands	SVM-Linear	2001	0.82	0.58	1.00	0.89	0.78
		SVM-Polynomial	2001	0.73	0.83	1.00	0.56	0.75
		SVM-RBF	2001	0.27	0.42	1.00	0.78	0.53
	SPA	LDA	6	0.73	0.63	0.85	0.83	0.75
	CARS	LDA	15	0.70	0.63	0.79	0.79	0.72
CARS-SPA	LDA	3	0.85	0.58	0.83	0.90	0.77	
Korean pine	All bands	SVM-Linear	2001	0.91	0.75	0.40	1.00	0.79
		SVM-Polynomial	2001	0.27	0.88	0.40	1.00	0.57
		SVM-RBF	2001	0.82	0.63	0.00	1.00	0.64
	SPA	LDA	12	0.85	0.60	0.73	0.71	0.74
	CARS	LDA	14	0.75	0.67	0.76	0.88	0.74
CARS-SPA	LDA	2	0.86	0.65	0.82	0.87	0.78	

Table. Classification accuracy of Japanese pine and Korean pine samples using different selected bands and all bands. H, E, M, L represent the classes of healthy, early-, middle-, and late-stage infected samples.

Monitoring of Pine Wilt Disease

Individual tree level using hyperspectral drone images

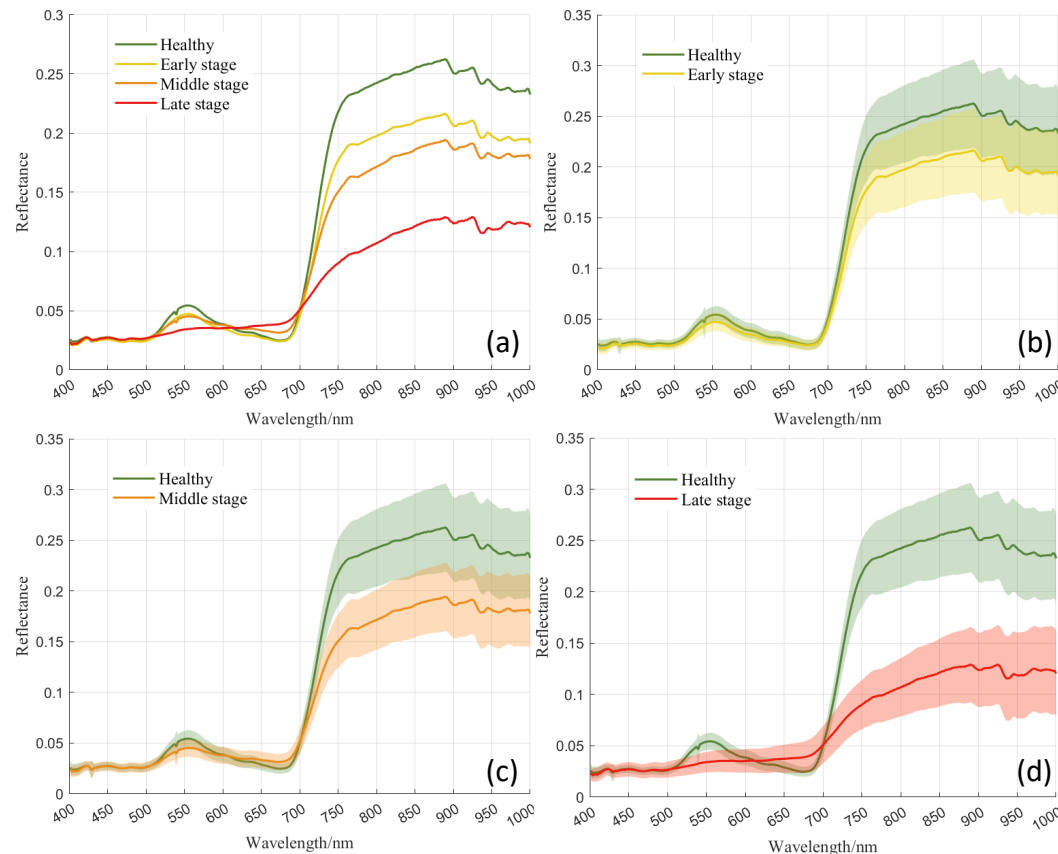


Figure. Mean spectral signature of tree crowns indifferent health status (a) and comparison between healthy and infected trees on the mean and standard deviation (std) of spectral signatures (b - d).

Monitoring of Pine Wilt Disease

- ❑ Individual tree level using hyperspectral drone images
 - ❑ Band selection
 - ❑ Bands with higher separability among healthy and early infected trees
 - ❑ Bands as Sentinel-2 images
 - ❑ Derivative reflectance
 - ❑ Vegetation indices
- ❑ Results and conclusions
 - ❑ Using first derivatives at 712 nm obtained 78.4% accuracy
 - ❑ Using red and blue edge inflection points obtained 73.8% accuracy
 - ❑ Using vegetation indices obtained up to 75% classification accuracy

Monitoring of Pine Wilt Disease

- Intelligent recognition of PWD-infected individual trees Using UAV-Based Hyperspectral Imagery
- Combining a prototypical network classification model with an individual tree segmentation algorithm

Categories	Mask R-CNN			Prototypical Network		Prototypical Network + Segmentation	
	RGB	Hyperspectral Full Bands	Feature Preferred Bands	Hyperspectral Full Bands	Feature Preferred Bands	Hyperspectral Full Bands	Feature Preferred Bands
OA (%)	64.60	68	71	92.17	92.79	82.95	83.51
AA (%)	64.58	68	70.98	91.33	93.46	82.20	84.11
Kappa	0.574	0.582	0.596	0.889	0.898	0.800	0.808
E	54.30	62.90	63.50	82.17	83.21	73.95	74.89
M	73.10	72.70	77.50	93.87	92.54	84.48	83.29
L	62	64.50	68.40	95.82	97.61	86.24	87.85
D	68.90	71.90	74.50	93.71	97.6	84.34	87.84

Figure . PWD infection stage diagnosis.

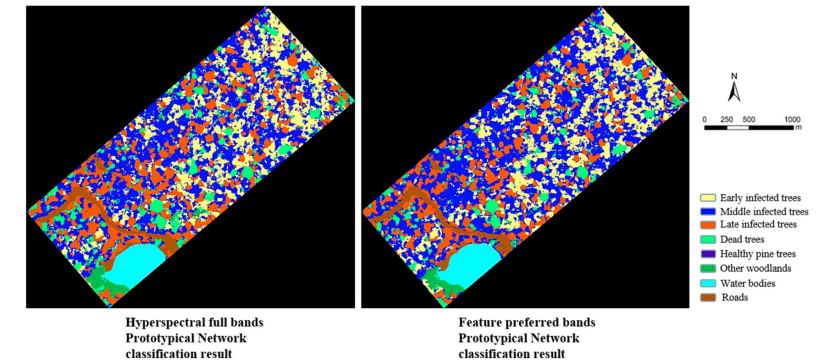


Figure . Prototypical network classification result map.

Monitoring of Pine Wilt Disease

- ❑ NDFI: A new vegetation index for mapping coniferous forest.
- ❑ A new monitoring model of the PWD infection stage was built using Machine learning algorithm.

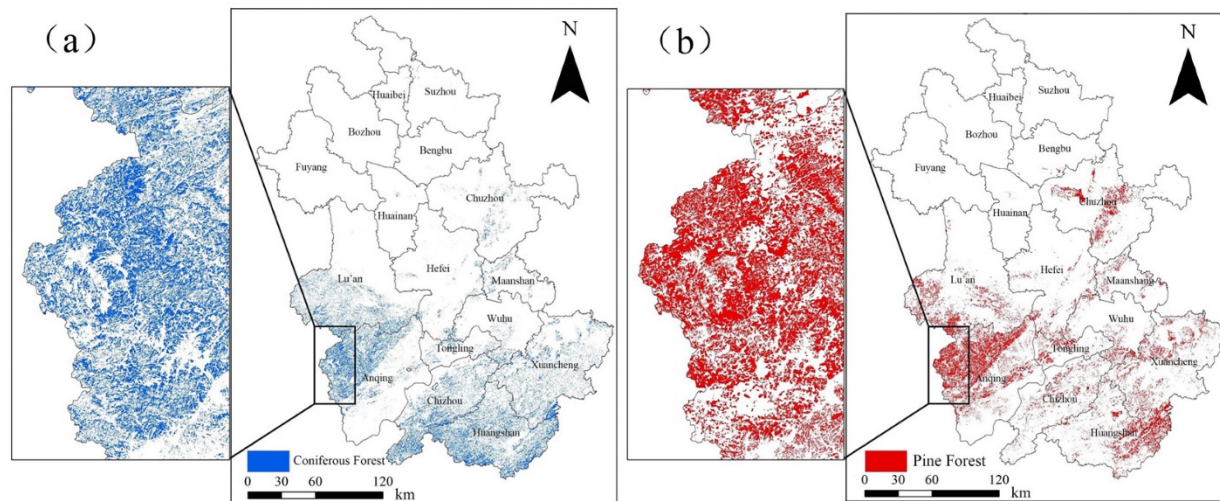


Figure. Comparison of the extracted coniferous forest area and the distribution area of pine forest sub-compartments.(a) Area of coniferous forest extracted in this paper. (b) Area of coniferous forest in Forest Management Inventory.

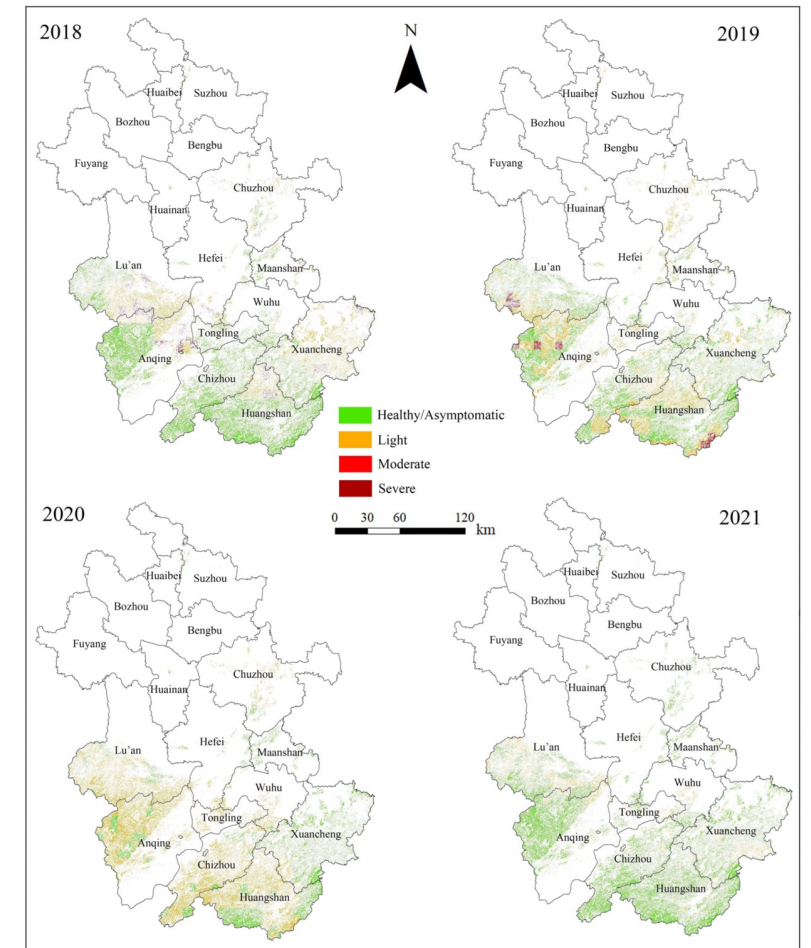


Figure. Grading map of PWD degree from 2018 to 2021.



Monitoring of European Spruce Bark Beetles

- Early detection and large area mapping using Sentinel-2 images
- A new vegetation index (NDRS) was proposed to map the bark beetle damages.
- Spectral differences were observed before attacks

$$DRS = \sqrt{(Red)^2 + (SWIR)^2}$$

$$NDRS = \frac{DRS - DRS'_{min}}{DRS'_{max} - DRS'_{min}}$$

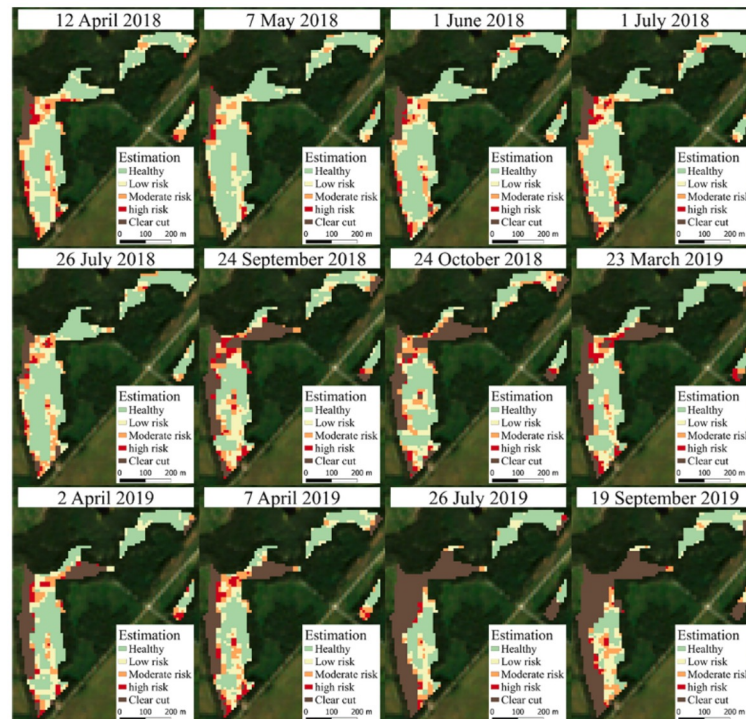
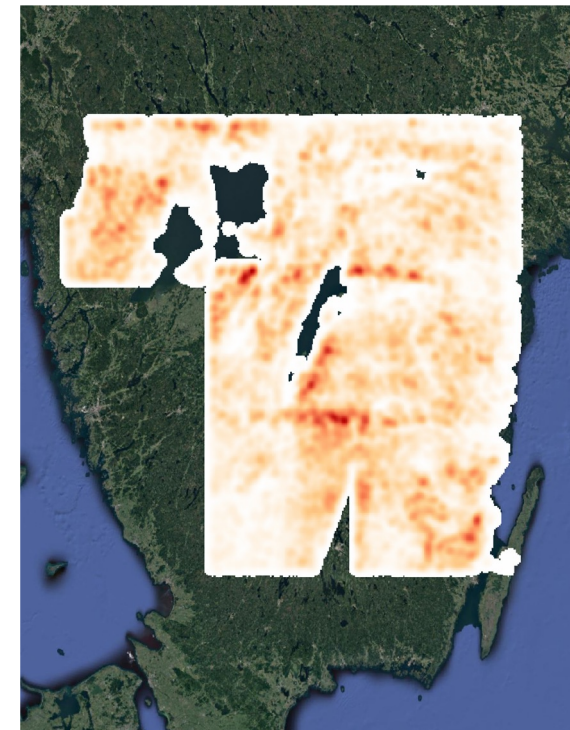
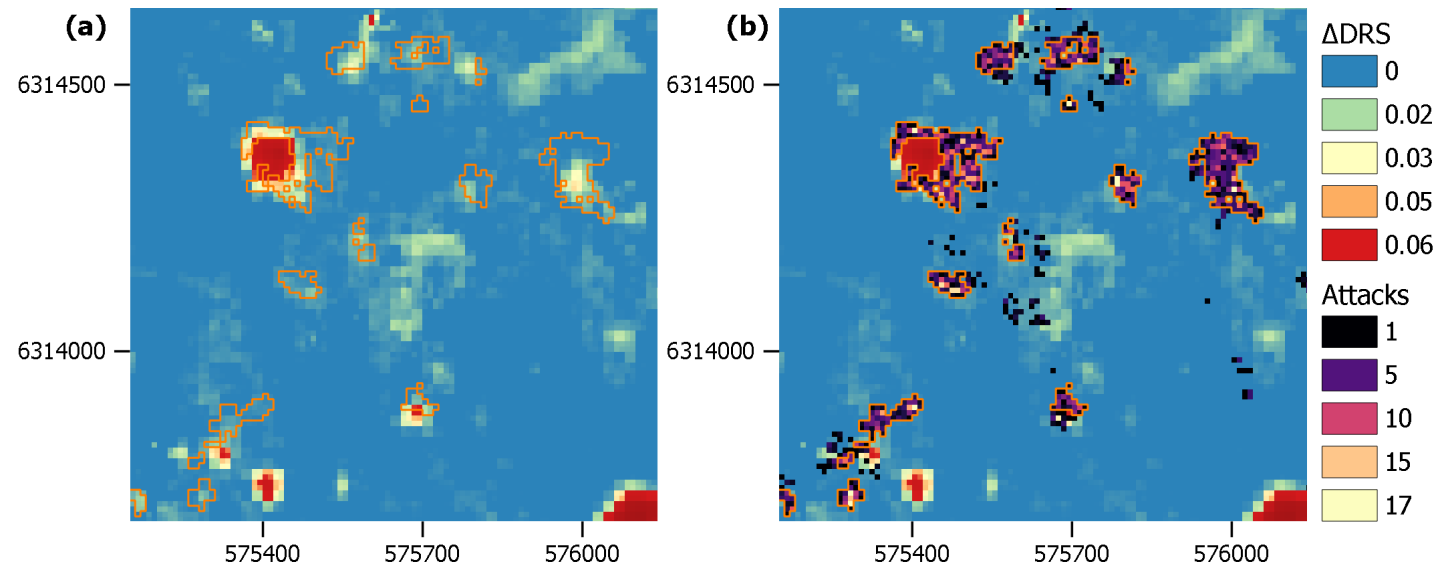
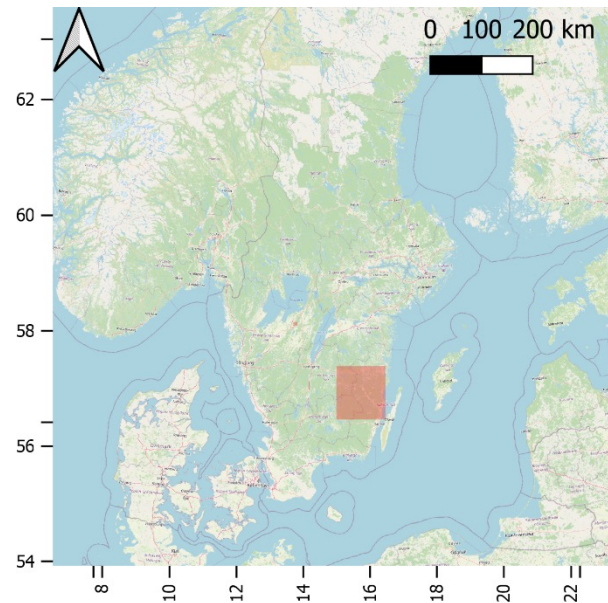


Fig. A5. A case study showing estimated attacks in a time-series and the spatial spread pattern of bark beetle infestations.



Monitoring of European Spruce Bark Beetles

- ☐ Operational large-area bark beetle mapping
- The Distance Red & SWIR index was tested to map the bark beetle damages in one Sentinel-2 tile (110×110 km²).
- Validation using harvester data, covering 11,786 pixels (10×10 m²), 842 attacked and 137 healthy tree clusters.
- An overall accuracy of 78% on classifying attacked and healthy clusters using the change of DRS.



Something interesting.....

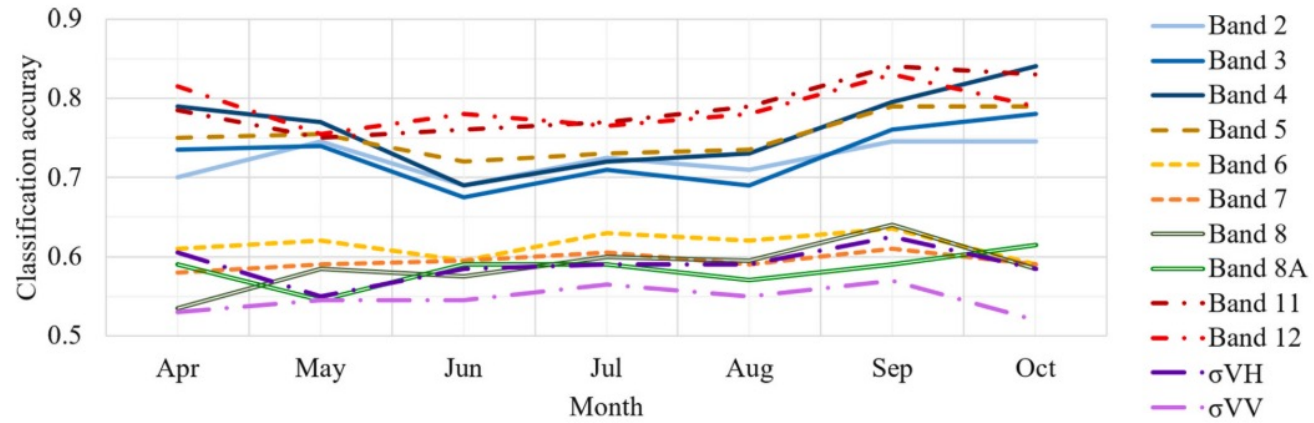


Fig. 8. Separability of individual bands shown by using CA from LDA and leave-one-out cross-validation.

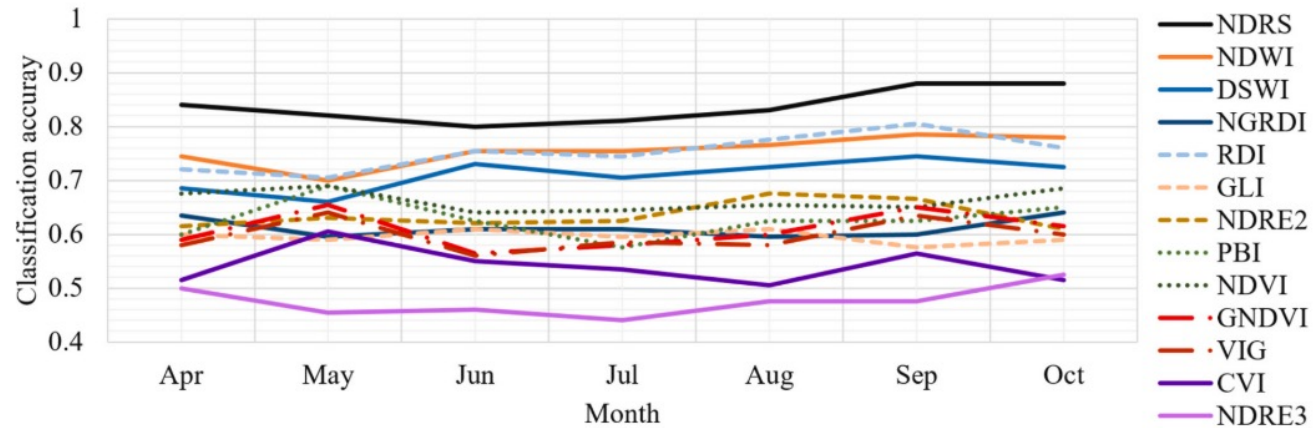


Fig. 9. Separability of vegetation indices for stress detection shown by CA from LDA and leave-one-out cross-validation.

Monitoring of European Spruce Bark Beetles

❓ Is green-attacks detectable using satellite images?

- Sentinel-2

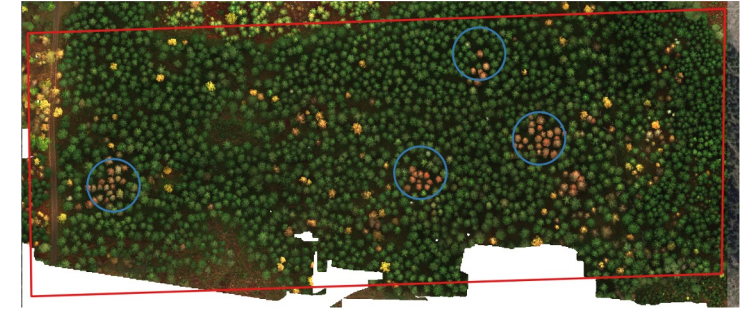
The number of attacked trees limited the time of detection

- ◆ Attacks with >20 trees showed abnormal spectral before attacks.
- ◆ Attacks with >10 trees can be identified in August.
- ◆ Attacks with 5-10 trees can be identified in September.
- ◆ Attacks with <5 trees cannot be identified.

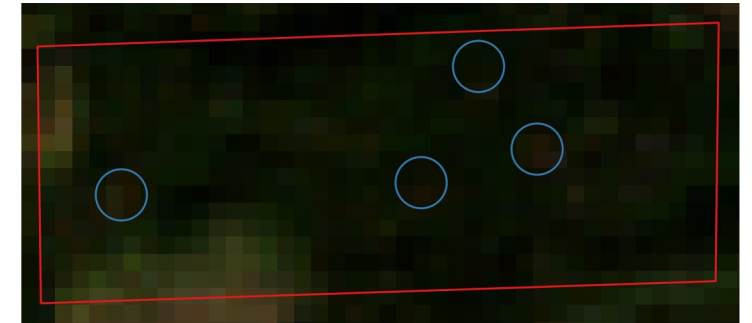
- WorldView-3 SWIR

No significant differences in June

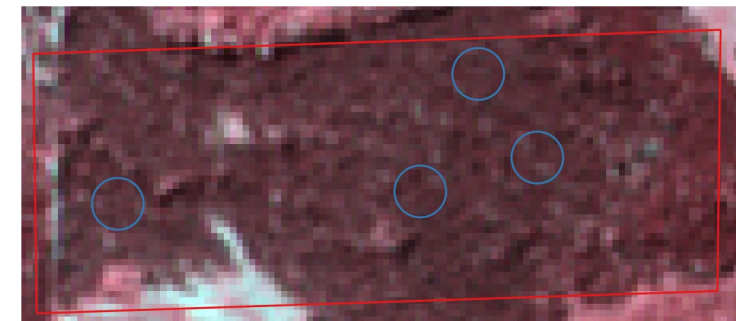
- ◆ Too early in the infestation stage
- ◆ Shadow effects



A drone image



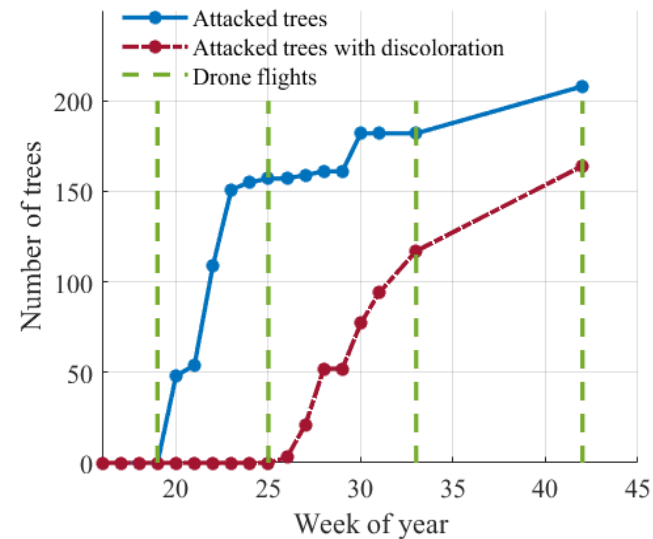
A Sentinel-2 image



A WorldView-3 SWIR image

A controlled experiment

- 977 spruces were monitored
- 208 spruces were attacked
- The first swarm started in week 20 (May 17), with 155 trees attacked.
- The second swarm started in week 30 (July 26), with 53 trees attacked.
- Drone flights in May, June, August, and October.



Drone image acquisition

- Multispectral drone images, 0.04 m pixels, 9 bands
- 80 m above the ground

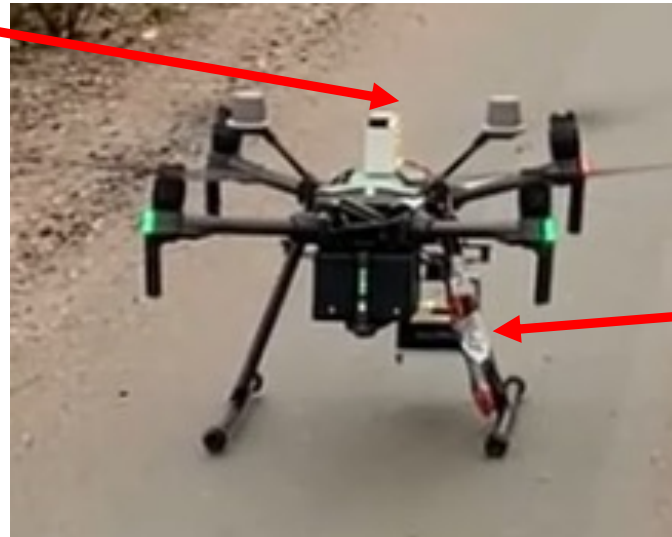
Band no.	Color	Center wavelength (nm)	Bandwidth (nm)
1	Violet	443	20
2	Blue	490	65
3	Green	560	35
4	Red	665	30
5	Red-edge	705	15
6	Red-edge	740	15
7	NIR	783	20
8	NIR	842	115
9	NIR	865	20



Incident Light Sensor (ILS)



radiometric reference targets



DJI Matrice 210 RTK

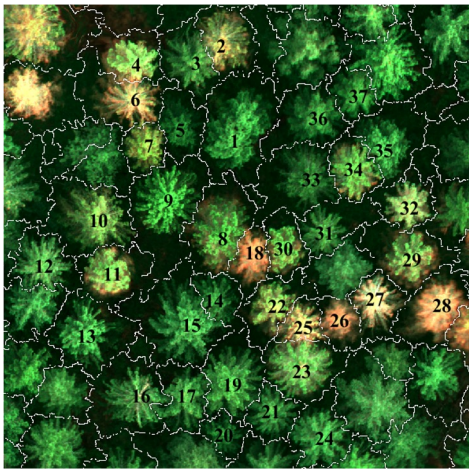


MAIA S2 multispectral camera

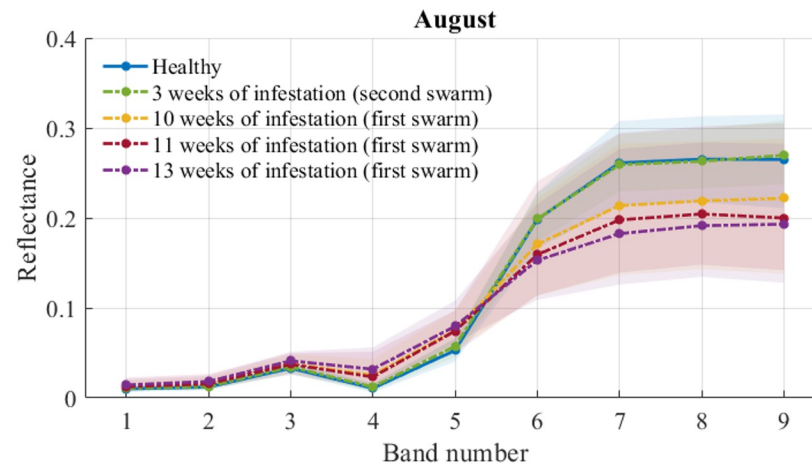


Early detection of European Spruce Bark Beetle attacks at the individual tree level

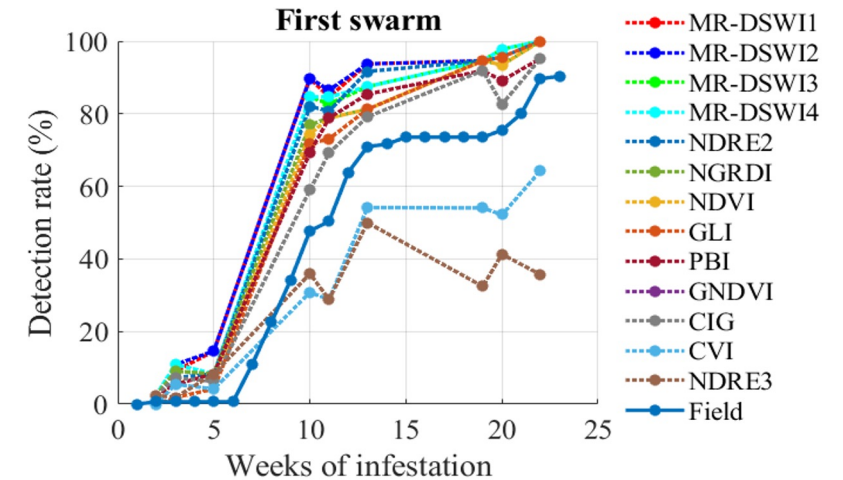
- Early detection using drone images
- Multispectral drone images were used with the same wavelengths of Sentinel-2.
- How early did the infested trees show abnormal spectra was investigated.
- The continuous changes of the detectability during green-attacks was quantified.



Segmentation of individual tree crowns in a drone image



Spectral signatures of tree groups infested for different duration

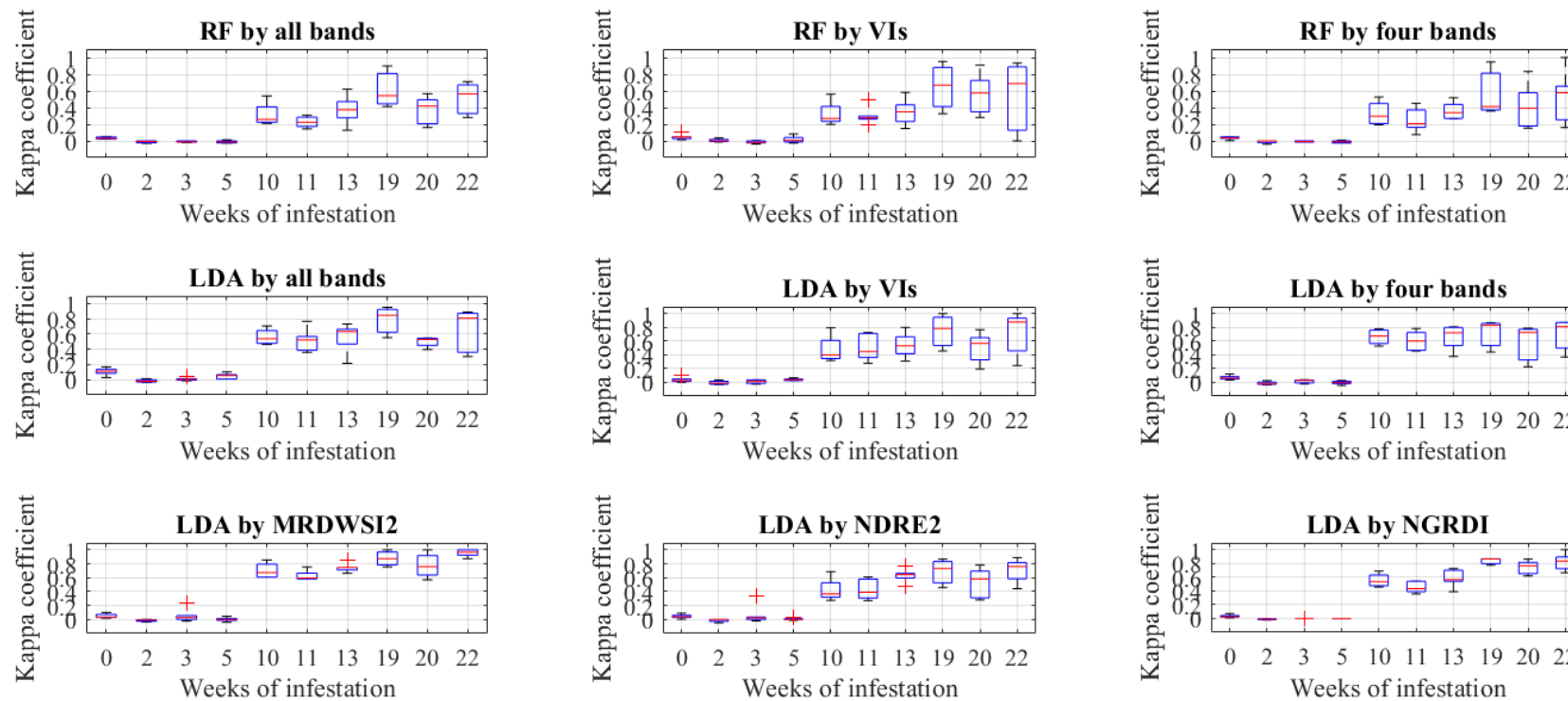


Detectability increased rapidly during 5 – 10 weeks of infestation

Monitoring of European Spruce Bark Beetles

Machine learning & vegetation indices

- RF and LDA with multiple variables showed overfitting and low transferability on untrained area.
- Using single VIs showed higher accuracy and robustness.
- Testing on untrained area is crucial to show the transferability of a model.





A drone with a hyperspectral camera



A drone flight mission for hyperspectral image acquisition



Stations monitoring sap flow changes during bark beetle attacks



Inventory of tree attributes



Recording the damages



Trees damaged by bark beetles shown on drone videos

Further research plan

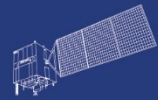
- Explore the potential of **hyperspectral drone images** on the early detection of infestations.
- Implement and improve the method of **large-area forest damage mapping** using satellite images.
- Explore the spatial and temporal distribution patterns of forest disturbance in China using improved CCDC algorithm, and to study the characteristics of different disturbance factors and vegetation restoration mechanisms.



HY



HJ-1AB



CBERS



Gaofen



Beijing-2



Sentinel-1



Sentinel-2



Sentinel-3



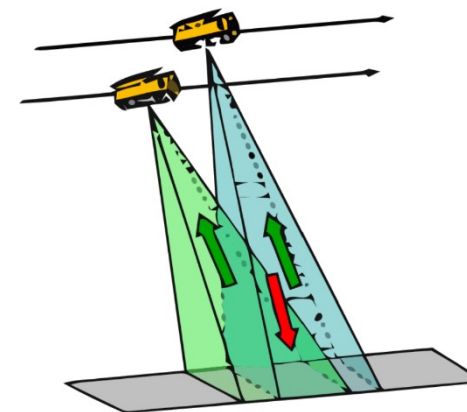
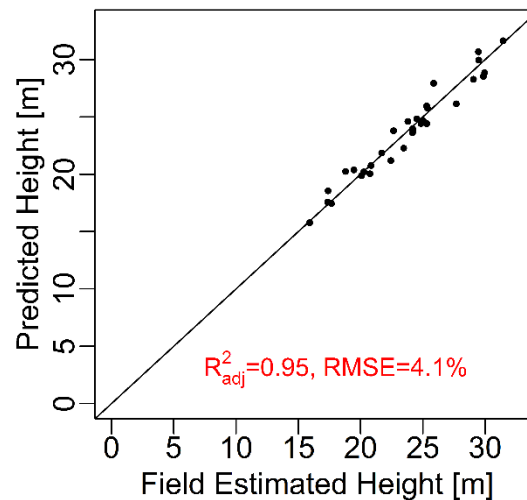
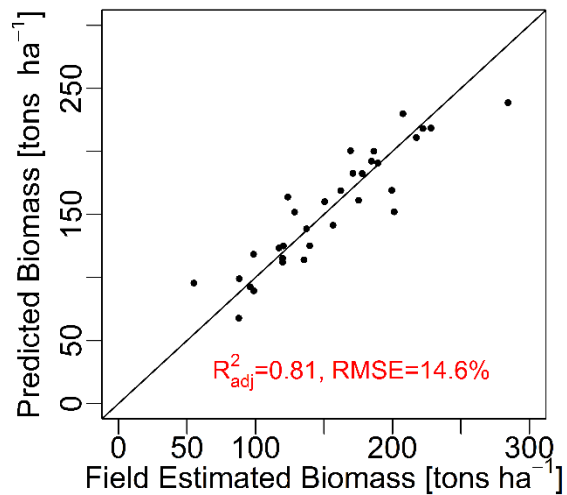
Sentinel-5p



Aeolus

Mapping forest changes and tree species

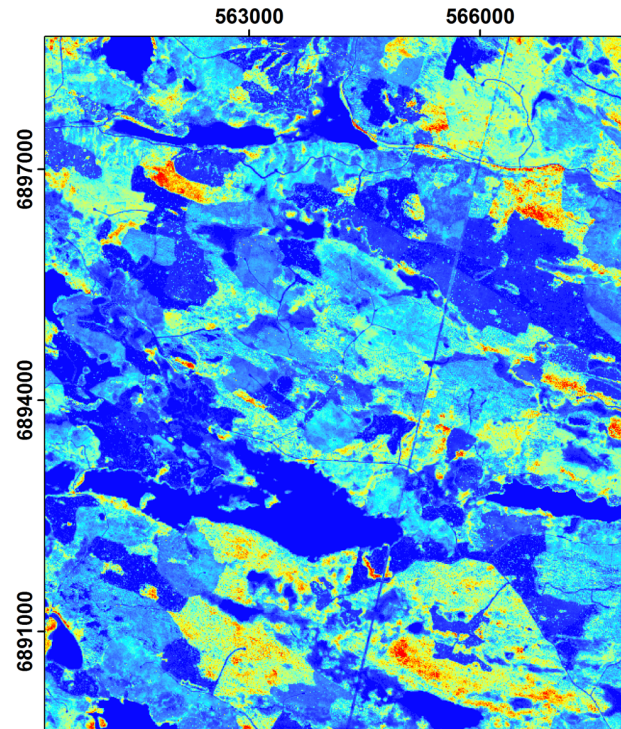
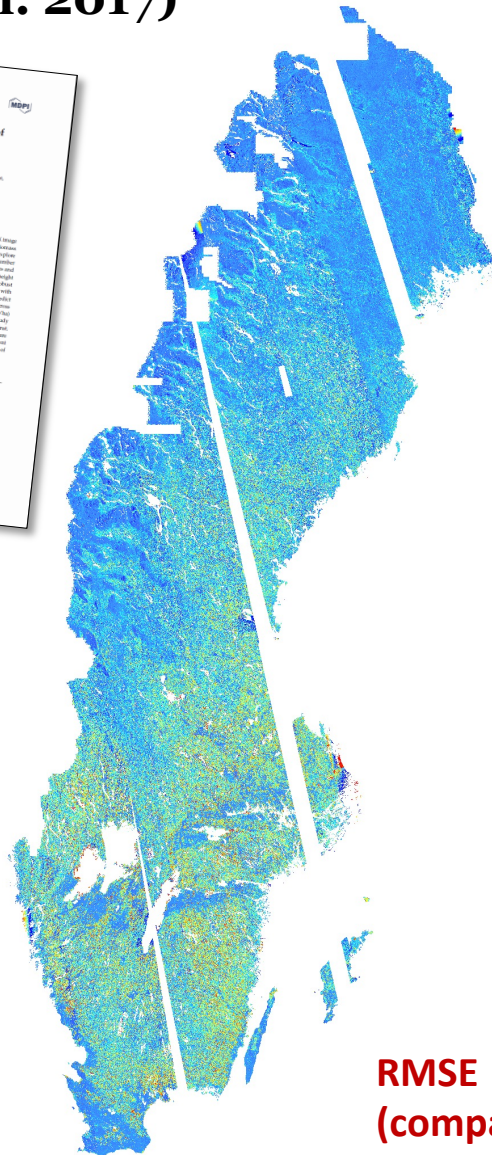
Swedish University of Agricultural Sciences



Estimations for thirty-two 0.5 ha plots in Remningstorp.

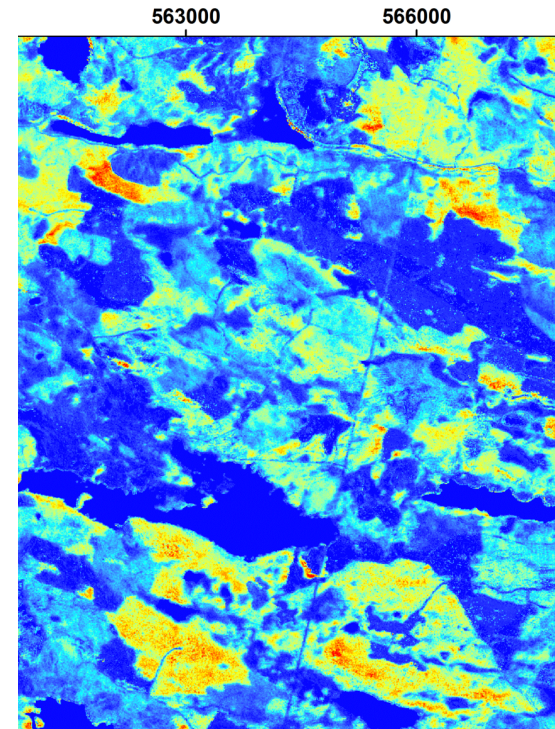
Test site	Variable	Date	R^2_{adj}	RMSE	n
Remningstorp	AGB	2011-06-04	0.81	1.1 tons/ha (14.6%)	32
Remningstorp	Height	2011-06-04	0.95	1.0 m (4.1%)	32

(Persson et al. 2017)



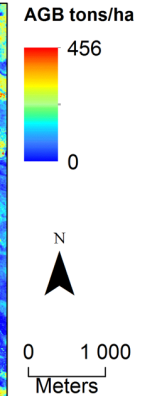
Airborne laser

RMSE ~19-22%
(compared to field inventory at stand-level)

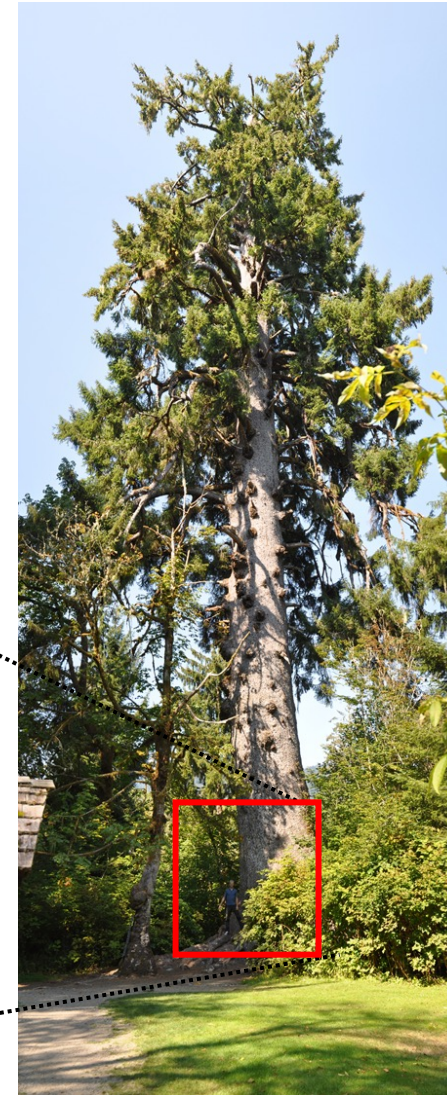


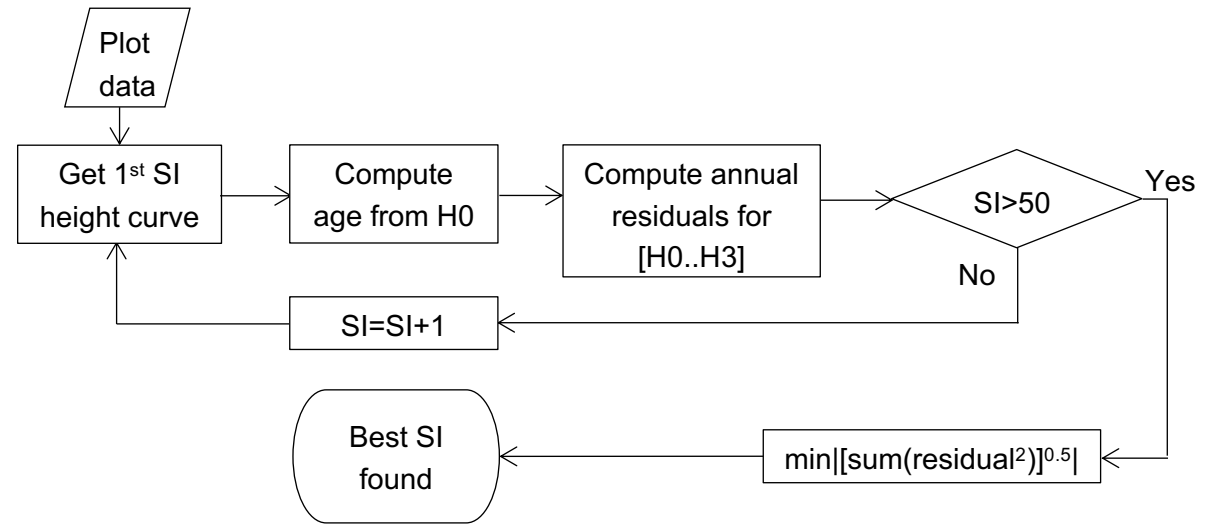
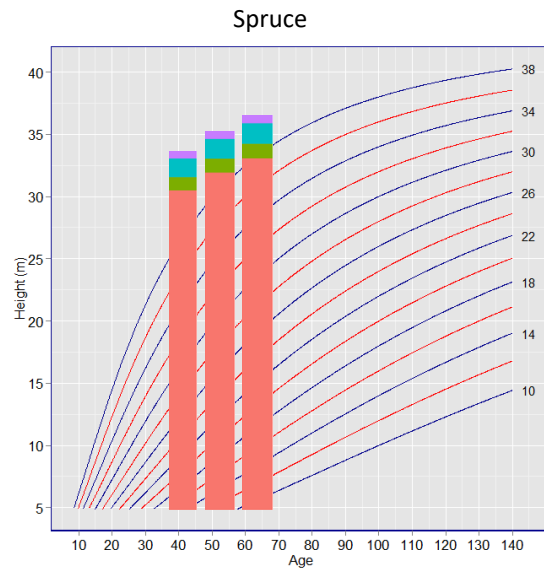
TanDEM-X radar

~21-25%



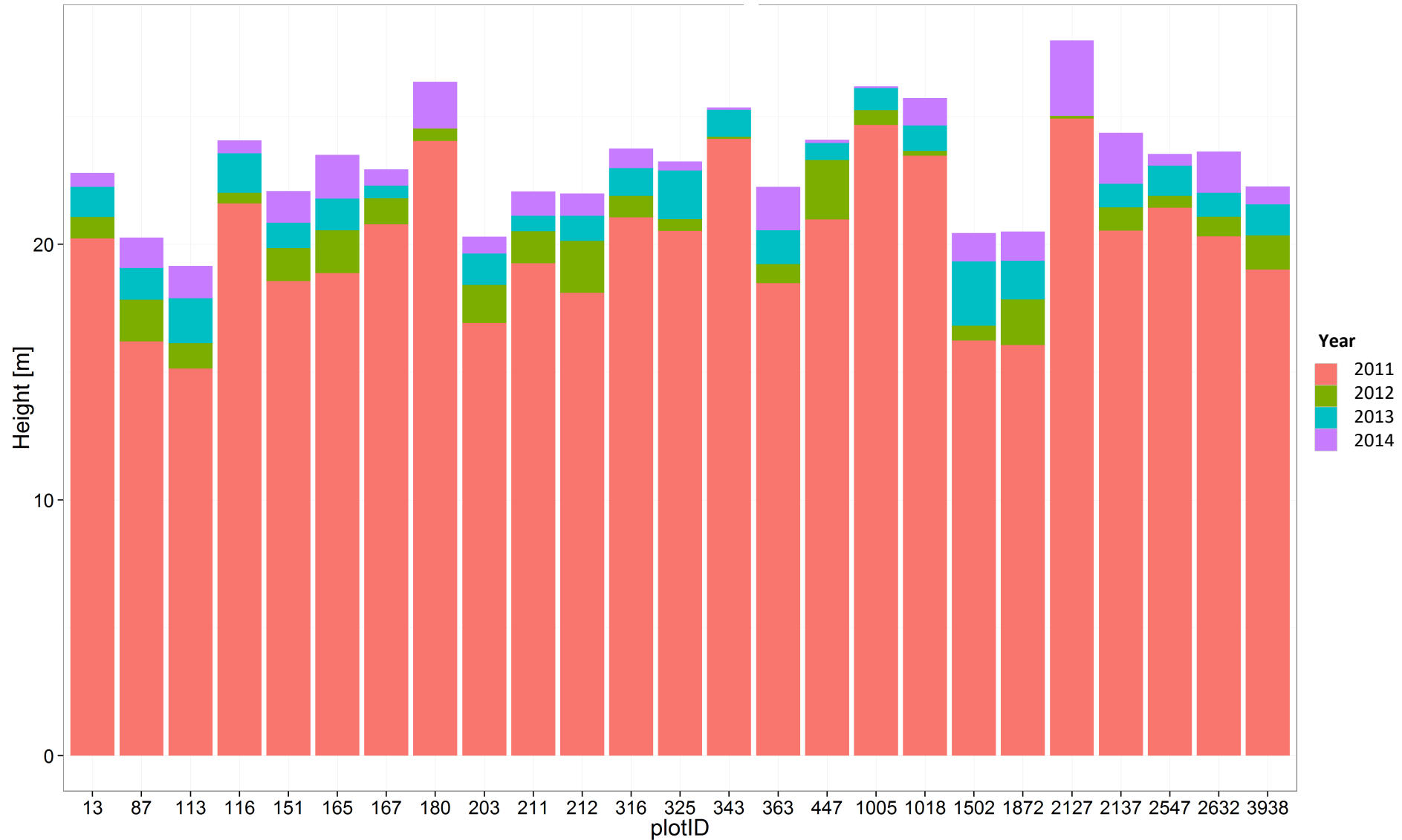
- The soil's inherent capacity to produce wood volume
- Indirect measure of forest site productivity
- Determined from habitat elements, or tree height and age





Estimating Site Index From Short-Term TanDEM-X Canopy Height Models

Henrik J. Persson and Johan E. S. Fransson, *Senior Member, IEEE* **2016**



Treatment Detection Using InSAR Time Series



TanDEM-X (German Aerospace Center (DLR))

RS data

Time series of 24 VV polarization scenes.
Aug 2011 - June 2014

Processed to obtain interferometric height using 2 m x 2 m DTM, final phase height products 10 m x 10 m in ground resolution.

Pixel level penetration depth correction: (h_a : height of ambiguity, γ : coherence)

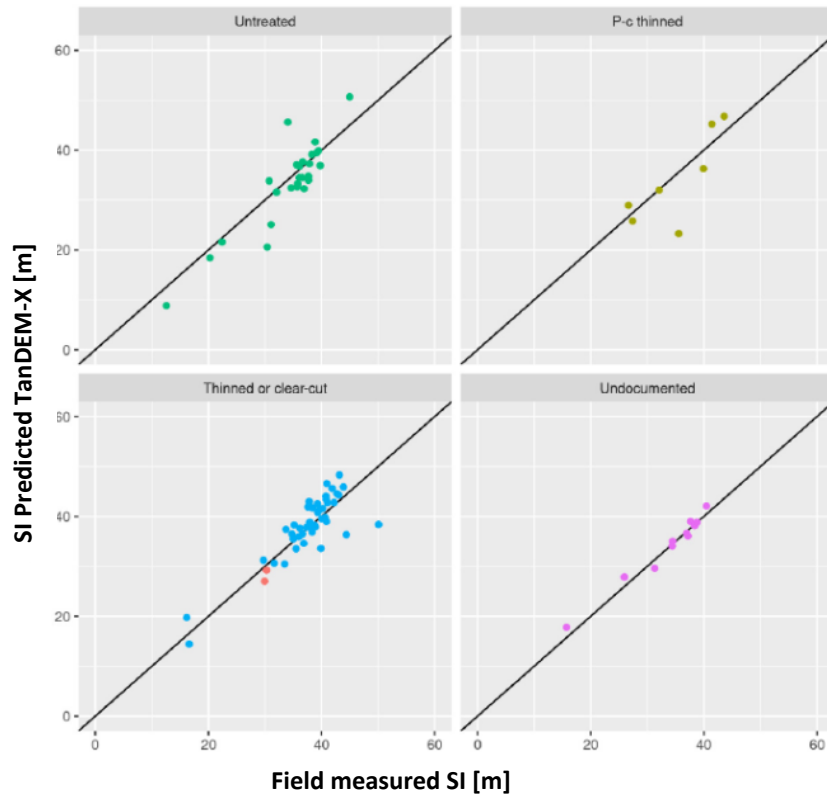
$$\Delta h = -\frac{|h_a|}{2\pi} \arctan(\sqrt{|\gamma|^{-2} - 1}), \quad (1)$$

Field data

34 plots, 40m in radius.
located inside homogenous stands.

Treatment records in forest management plan used to classify plots into 25 untreated, 5 thinned, and 4 clear-cut.

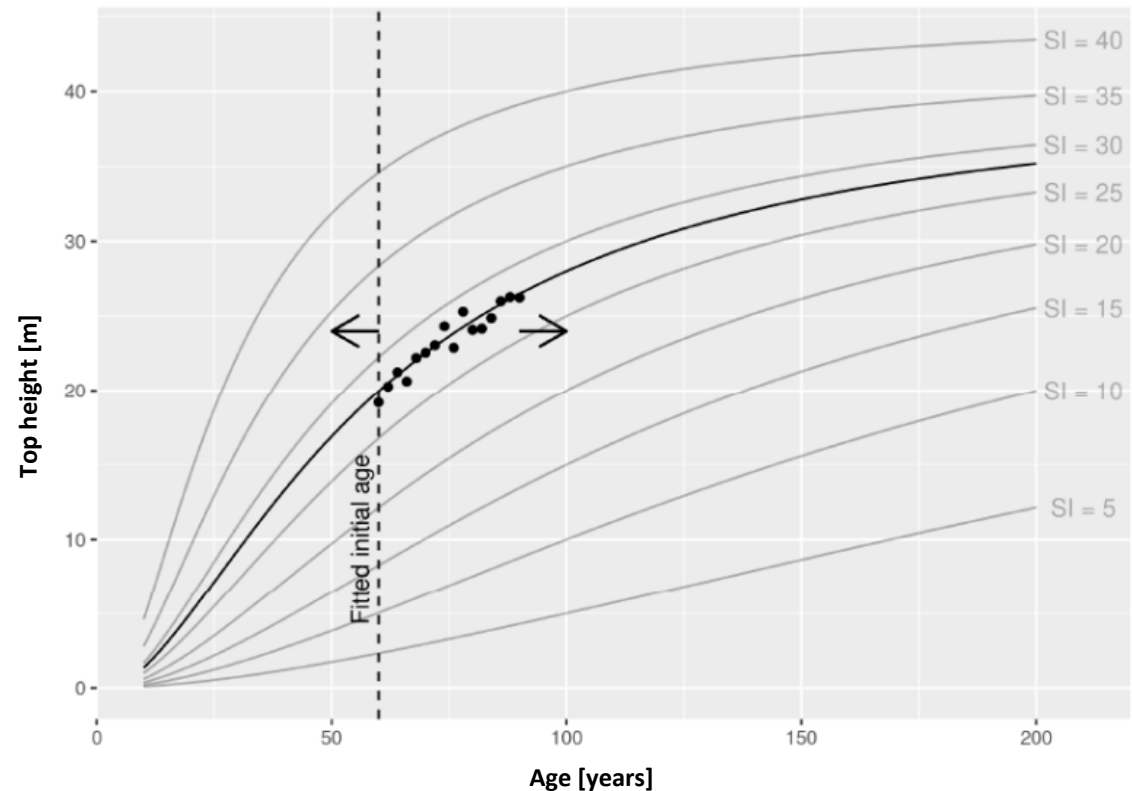
- 30 TanDEM-X images
- 91 plots á 10 m radius
- RMSE 4.4 m (12.1%)



Article

Prediction of Site Index and Age Using Time Series of TanDEM-X Phase Heights

Ivan Huuva ^{1,*}, Jörgen Wallerman ¹, Johan E. S. Fransson ² and Henrik J. Persson ¹



Forestry activities – 4 classes

- Untouched (no changes)
- Pre-commercial thinning (lower vegetation cut)
- Commercial thinning (~35% of basal area removed)
- Clear-cut (almost all trees removed)

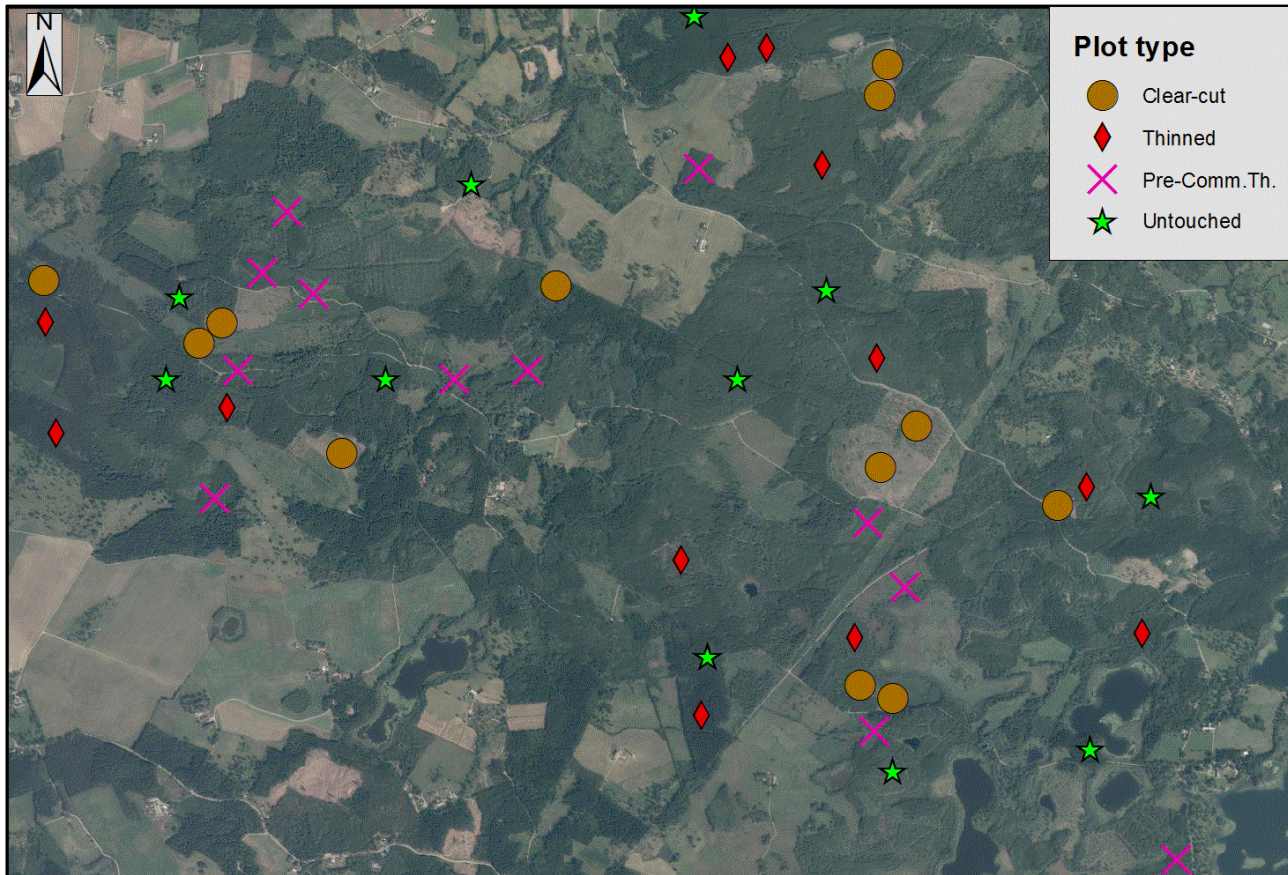


Illustration: Nils Forshed

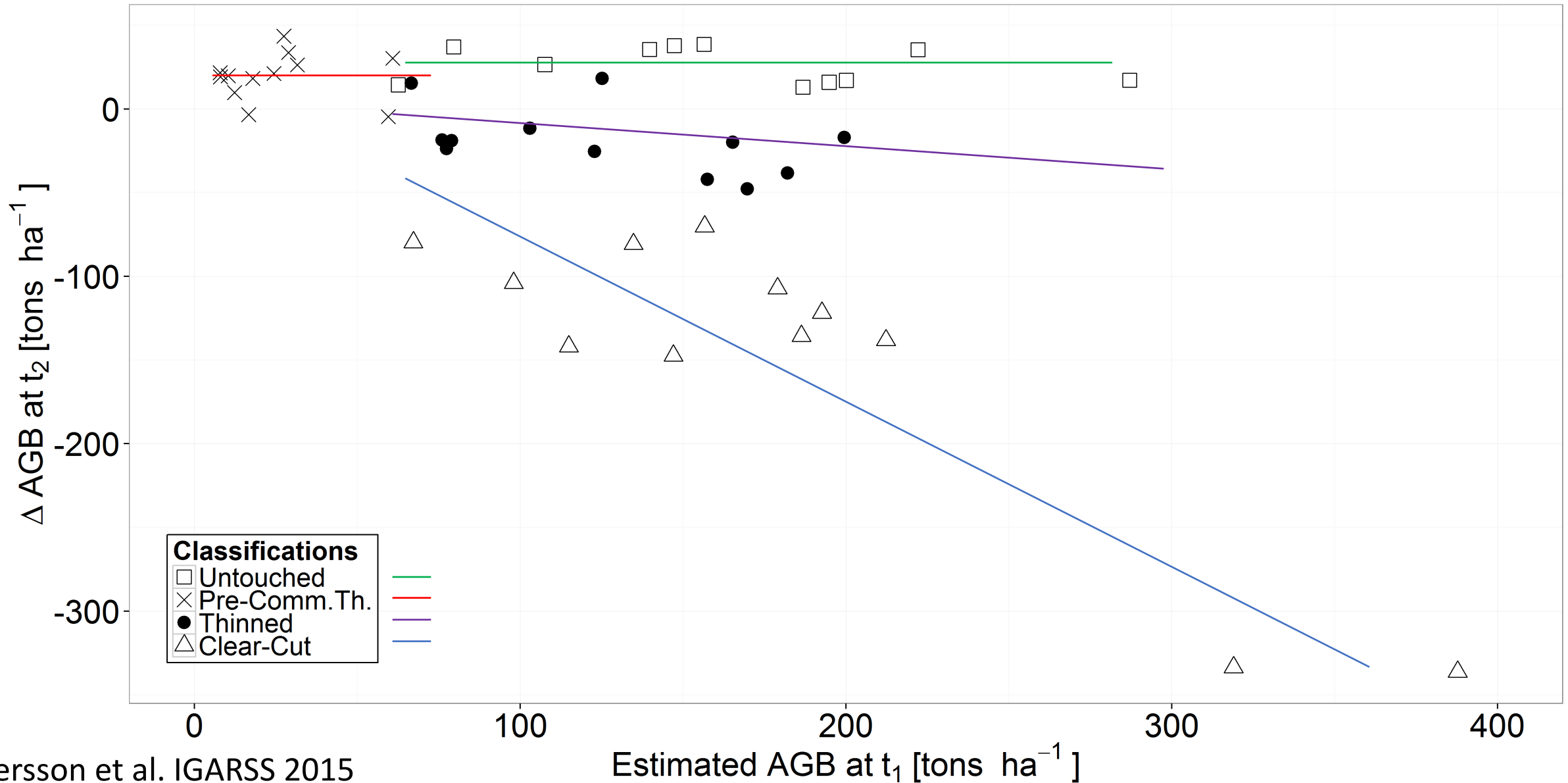


© Skogforsk · LRF Skogsägarna · Skogsstyrelsen

Forestry activities

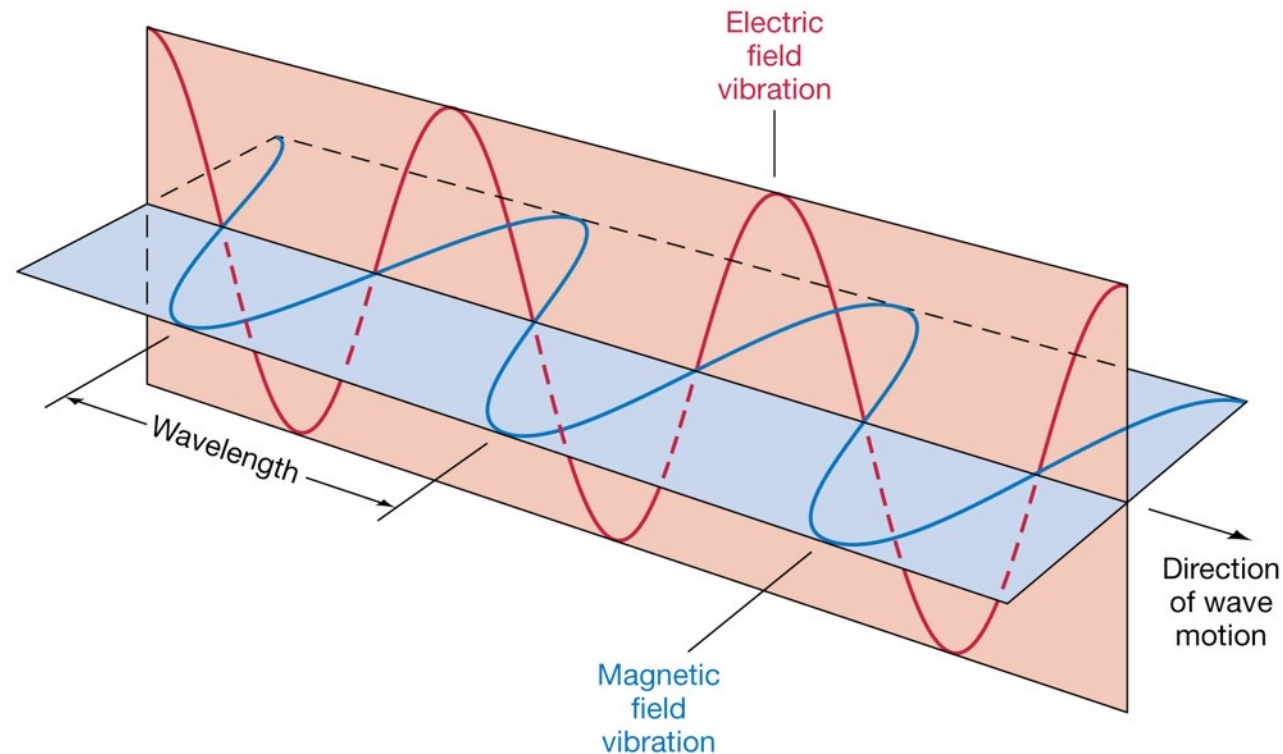


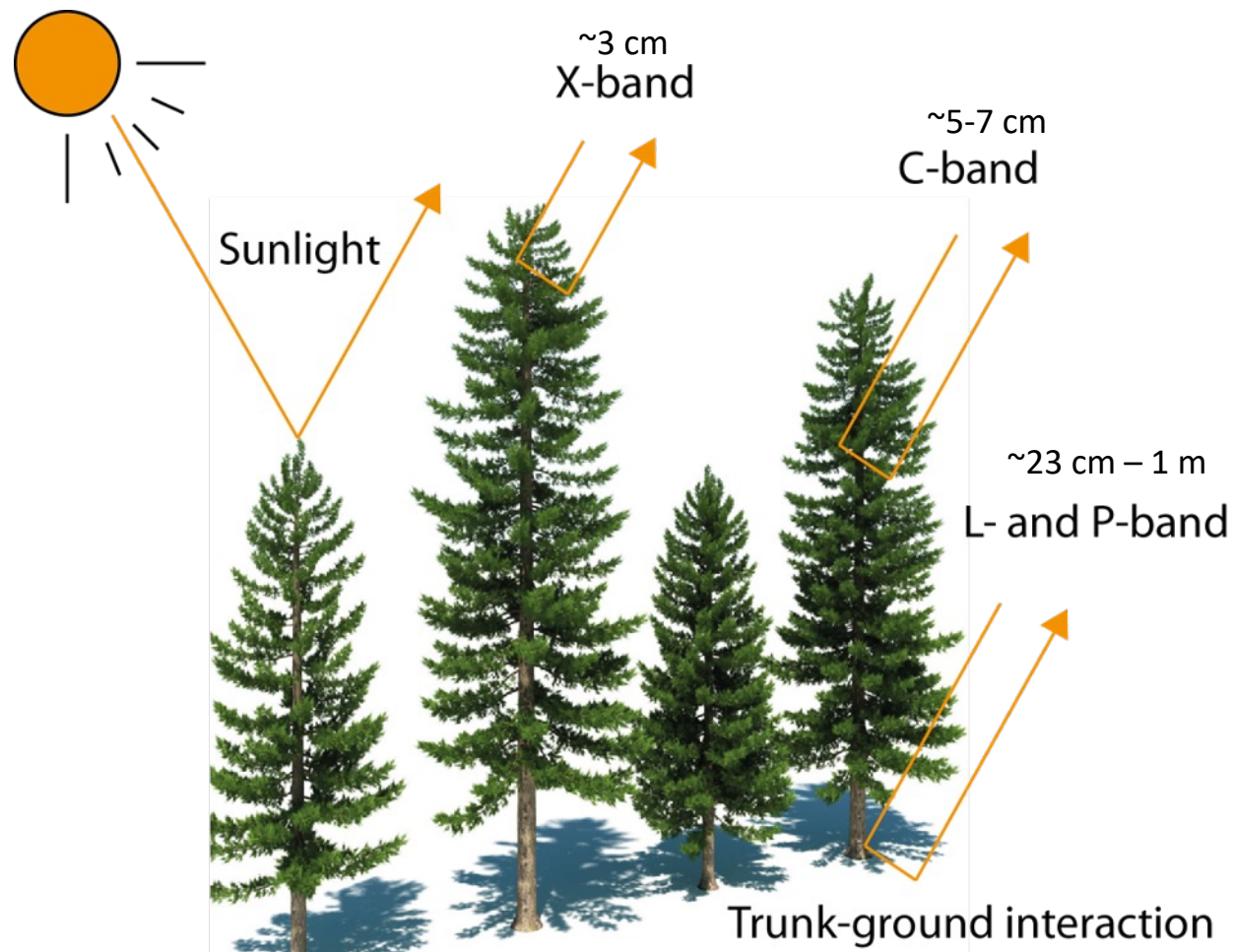
- 4 classes:
 - pre-commercial thinning
 - thinning
 - clear-cutting
 - unchanged
- 12 plots each, 40 m radius



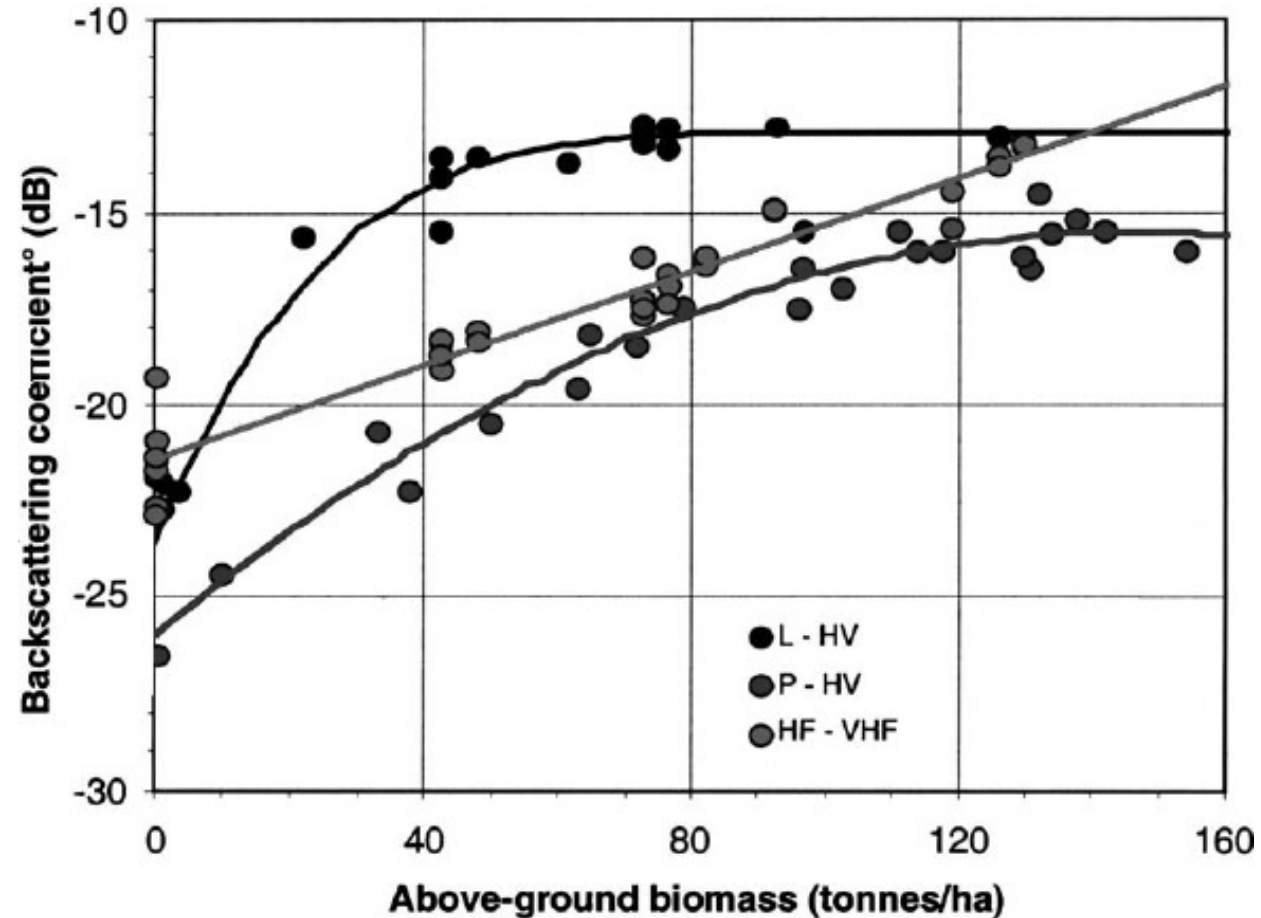
Use of Polarization

- Linear (HH, HV, VH, VV), circular or elliptical polarizations
- Sending vs. receiving polarization



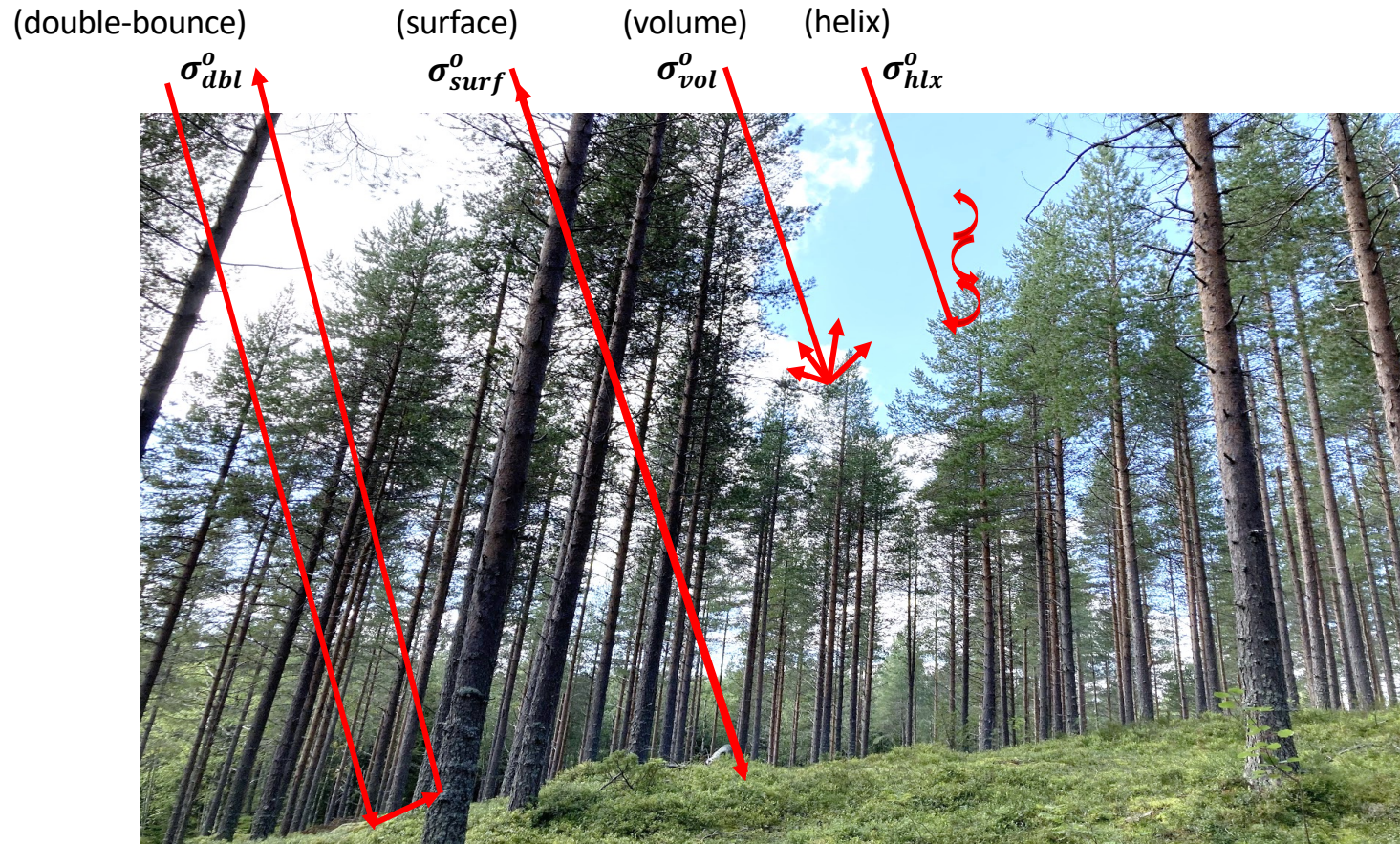


Band name	Frequency range	Wavelength range	Description
VHF	30-300 MHz	1-10 m	Very High Frequency
P	250-500 MHz	0.6-1.2 m	P for "previous"
L	1-2 GHz	15-30 cm	L for "long" wave
S	2-4 GHz	7.5-15 cm	S for "short" wave
C	4-8 GHz	3.75-7.5 cm	C for "compromise"
X	8-12 GHz	2.5-3.75 cm	X for crosshair
Ku	12-18 GHz	1.7-2.5 cm	Ku for "kurz- unten"
K	18-27 GHz	1.1-1.7 cm	German "kurz" (short)
Ka	27-40 GHz	0.75-1.1 cm	Ka for "kurz- above"



Note: This graph shows the saturation of SAR backscatter from the L-band (dark top line), P-band (gray bottom), and VHF-band (light gray, middle) over a forest in Landes, France. In this study, L- and P-band sensitivity to increasing biomass is limited after 100 tons/ha; other studies have achieved higher sensitivity by combining polarizations.

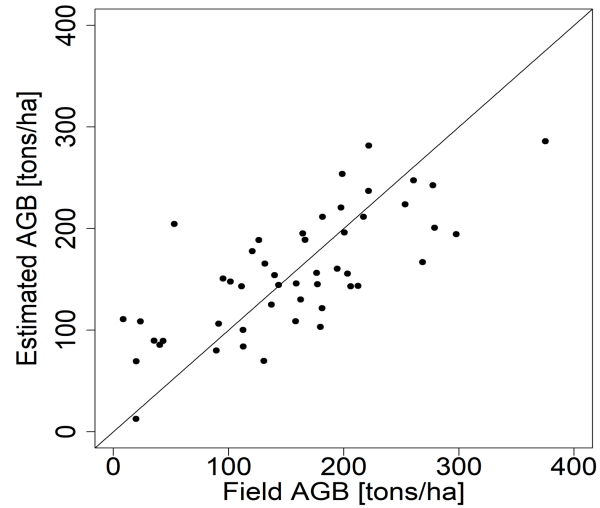
Source: Le Toan et al. 2004



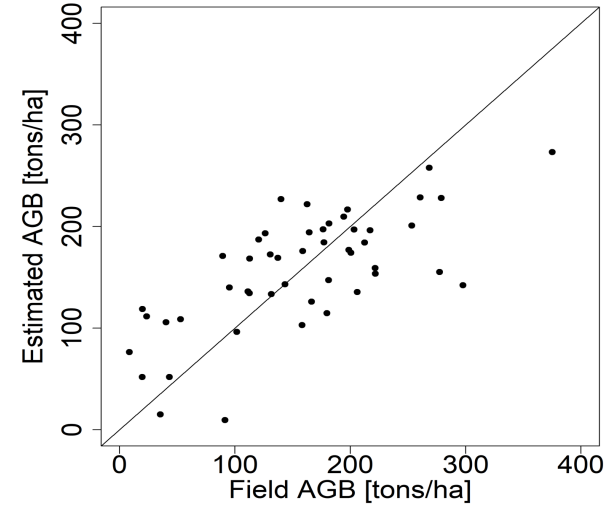
Applied Yamaguchi Four-component Decompositions in linear regression model:

$$AGB = a + b\sigma_{dbl}^0 + c\sigma_{vol}^0 + d\sigma_{surf}^0 + f\sigma_{hlx}^0 + \varepsilon$$

RadarSat-2 (C-band)



TerraSAR-X (X-band)



Sensor	Model	R_{adj}^2	RMSE [tons/ha]	n
RadarSat-2	Estimated	0.52	54.2 (34.6%)	48
TerraSAR-X	Estimated	0.47	56.8 (36.3%)	48
RadarSat-2	LOOCV	-	58.1 (37.1%)	48
TerraSAR-X	LOOCV	-	60.6 (38.6%)	48



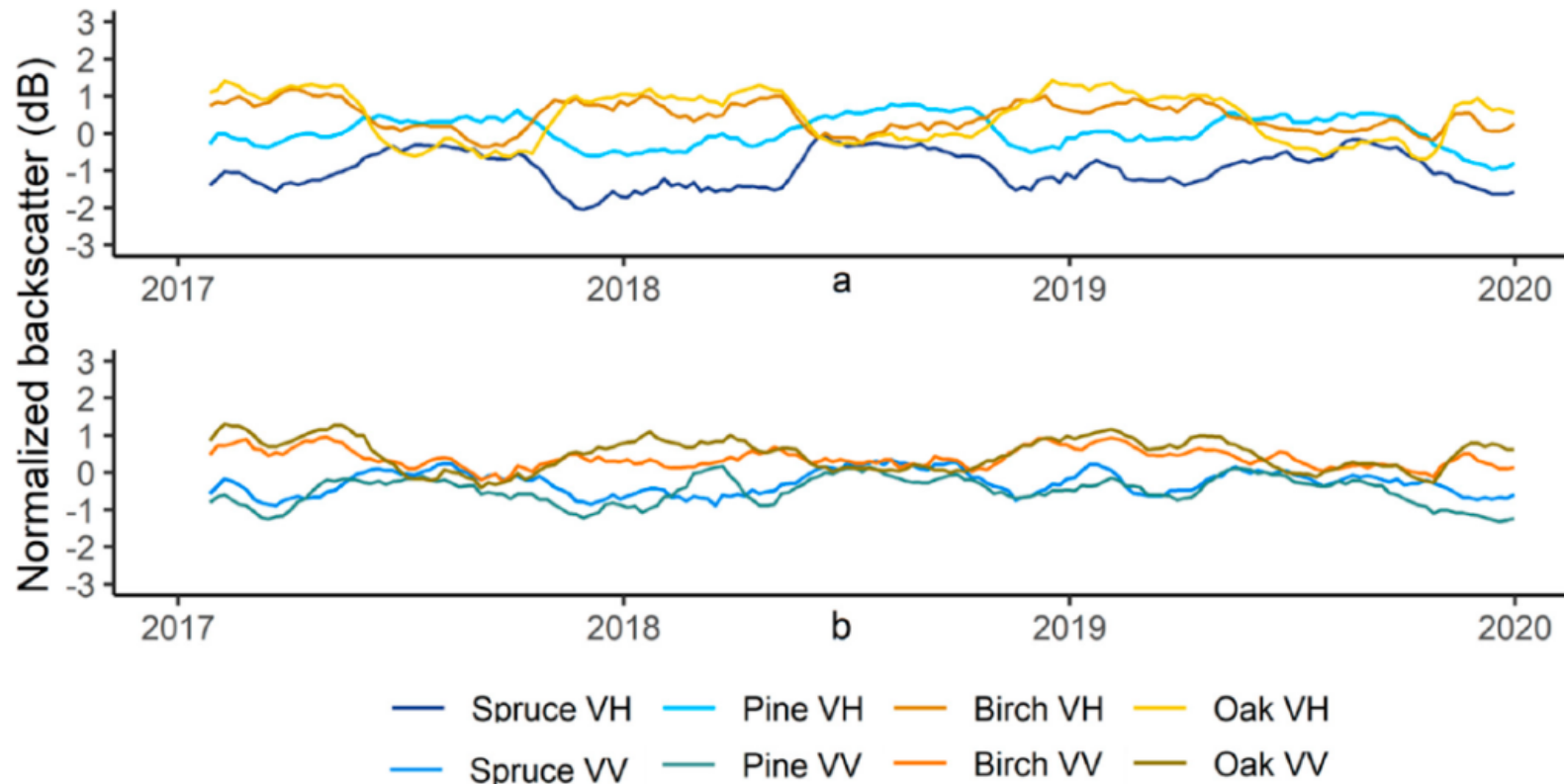
2021

Article

Assessing Forest Type and Tree Species Classification Using Sentinel-1 C-Band SAR Data in Southern Sweden

Alberto Udali ^{1,*}, Emanuele Lingua ¹ and Henrik J. Persson ²

- OA=0.94 for two forest types
- OA=0.66 for four tree species





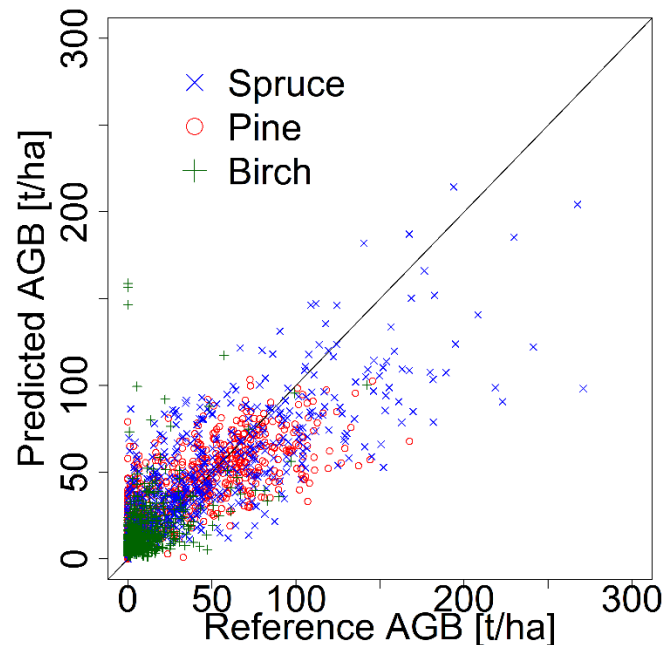
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Combining TanDEM-X and Sentinel-2 for large-area species-wise prediction of forest biomass and volume

Henrik J. Persson^{*}, Jonas Jonzén, Mats Nilsson



- kNN method – k=5 neighbors
- Spectral data Sentinel-2 and height from TanDEM-X
- OA=0.77 for majority tree species – three tree species

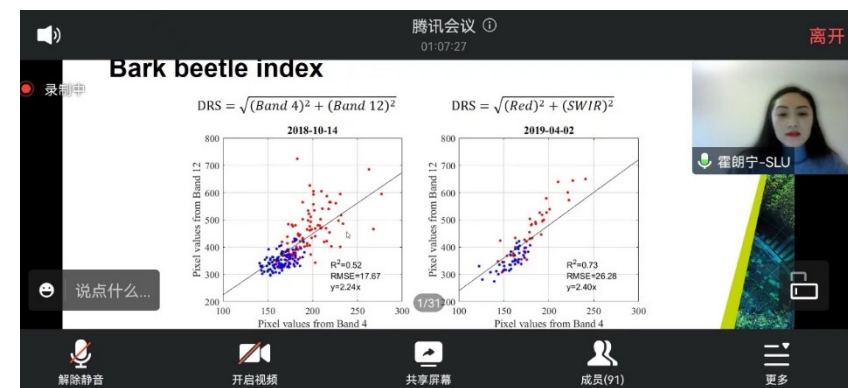
Results and conclusions

-  Biomass was estimated accurately using TanDEM-X InSAR
-  Biomass change could be estimated successfully for 3 different actions
-  Biomass was estimated relatively accurately using quad-pol Radarsat-2 and TerraSAR-X
-  Biomass was not estimated sufficiently accurate using dual-pol Radarsat-2
-  Biomass change was not possible to estimate using dual-pol Radarsat-2
-  SAR can be used to map tree species, but short wavelengths provide better information about volume than tree species

Further research plan

- Analyze impact of weather on radar measurements
 - Developing correction algorithms by including e.g., precipitation and temperature data at a tower experiment.
 - Upscale methods to satellite based SAR images.
- Detection and mapping of storm damaged forest using spaceborne synthetic aperture SAR
 - Developing methodology and algorithms
 - Perform a scientific evaluation of SAR data from satellite sensors for detecting and mapping changes in boreal forests.
- Exploring the method of tree crown extraction by combining satellite image and LiDAR data for multi-scale regional biomass dynamic monitoring with Sentinel-1 SAR data.

- Co-supervising one visiting PhD student from BFU to SLU from 2022 to 2023.
- Joint research on the early detection of pine wilt disease using hyperspectral data, publishing one research paper, two conference papers, and one manuscript under review.
- Research seminars and discussions.
- Teaching in doctoral courses.



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Thank You!



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The satellite images acquired for the study areas in China are:

- Sentinel-1, time-series images from 2019 to 2022, covering Gaofeng and Wangyedian.
- Sentinel-2, time-series cloud-free images from 2019 to 2022, covering Gaofeng, Lu'an, Wangyedian, Genhe, and Pu'er.
- Gaofen-1/2/6, 315 images from 2021 to 2022, covering Gaofen, Genhe and Pu'er.
- Radarsat-2, one image covering Fushun and one image covering Qingyuan.

The satellite images acquired in Remningstorp, Sweden are:

- Sentinel-2, time-series cloud-free images from 2018 to 2021.
- WorldView-3, one SWIR image (June 2021).
- Radarsat-2, one image each in 2020 and 2021.
- Pleiades, one image (29 Apr 2021).