2025 DRAGON 6 SYMPOSIUM

14-18 JULY 2025

[PROJECT ID. 95470]

[CHINA ESA FOREST OBSERVATION (CEFO-2)]







Outline



1. Project consortium
2. In-situ Data and Remote Sensing Datasets
3. Overview of Research Proceeding
4. Summary and Outlook

CEFO-2 Year 1 Results, Presenters

PROJECT TITLE: CHINA-ESA FOREST OBSERVATION 2 (CEFO-2)

PRINCIPAL INVESTIGATORS: Pang Yong, Juan Suárez, Li Zengyuan, Jacqueline Rosette

CO-AUTHORS: Jia Wen, Tian Xin, Wang Cangjiao, Cai Shangshu, Li Ningna, Costanza Cagnina, Miguel Ibañez, Reuben Lynch, Stan Clark and Ben Arthur

PRESENTED BY: Pang Yong, Juan Suárez

Training of Young Scientists

Name	Institution	Poster title	Contribution including period of research
Jia Wen	IFRIT/CAF	/	Tree Species Classification
Wang Cangjiao	IFRIT/CAF	/	Spaceborne LiDAR for Forest Application
Cai Shangshu	IFRIT/CAF	/	TLS/ALS for Forest Application
Li Linna	IFRIT/CAF	/	Multi-platform Data Fusion for Forest Application
Costanza Cagnina	Swansea Univ	/	Forest Health
Miguel Ibanez	Forest Research	/	Time-series Satellite Imagery
Reuben Lynch	Univ Edinburgh, Undergrad	/	Modelling
Ben Arthur	Univ Edinburg, Undergrad		Visualisation
Stan Clark	Univ Edinburgh, Undergrad	/	Modelling

Project consortium



SCIENTIFIC QUESTIONS

1. Model to complement/validate direct observations. Effective integration of RS observations to forecast future carbon stocks. Can they be combined using data assimilation techniques.
2. Accuracy of proximal and remote sensing derived cartographic products. Methods to upscale local estimates over larger areas without losing detail or quality.
3. Use of ground sensors for training and validating methods and as a benchmark for upscaling regional/national estimates.
4. Use of combined earth observation to quantify other ecosystem services and how to balance them with carbon sequestration goals. How to integrate stakeholders and government policies into a common framework

PROJECT OBJECTIVES

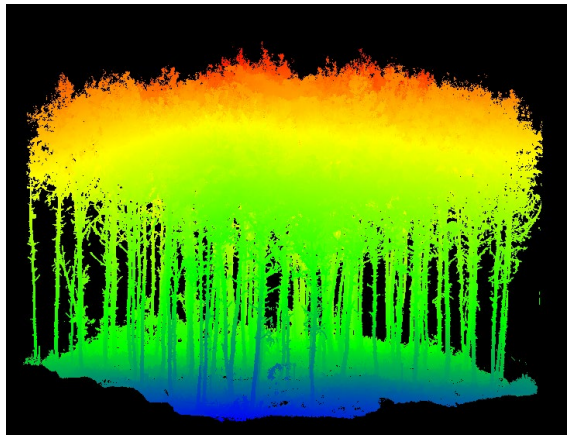
- Develop accurate **inventories of carbon and biomass in forests**.
- Detect **forest ecosystem dynamic processes by data-driven models** developed by time-series of RS data.
- Quantify **effects on other forest ecosystem services** across biomass conservation stages.
- Create a DT framework to integrate cartographic products, models, monitoring capabilities, reporting and management scenarios.

Year 1- Work Plan Summary

WORK PLAN - YEAR 1

- **Field data collection campaigns** (mensuration, MLS/TLS, drones, ALS, spectral data, wood density).
- **Use of traditional mensuration methods**, MLS, drones, and ALS.
- **Analysis of time-creation of 3D tree models and comparison to existing models.**
- **Time-series medium-resolution satellite imagery** (Sentinel-1/2, Gaofen,Landsat)
- Monitoring phenological cycles and **detecting disturbances**.
- Correlation of satellite-based models with field measurements.

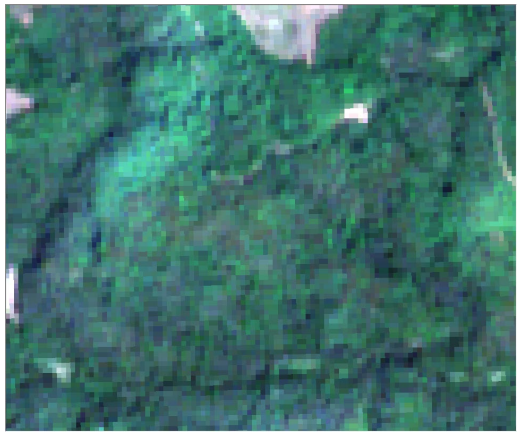
LiDAR



GF-2



Sentinel-2/Landsat



Study sites in UK and China

China sites

- Inner Mongolia Genhe (GH), Heilongjiang Mengjiagang (MJG), Hebei Saihanba (SHB), Chongqing Beibei (BB), Yunnan Pu'er (PUER), and Hainan provience (HN).



UK sites

Aberfoyle Forest District, Kielder Forest,

Thetford Forest, Forest of Dean



In-situ Data and Remote Sensing Datasets

ESA/ Copernicus Missions	No. Scenes
1. Sentinel-2	20
Total:	20
Issues:	

ESA Third Party Missions	No. Scenes
1. Landsat (2000-2024)	380
Total:	380
Issues:	

ESA Third Party Missions	No. Scenes
1.TECIS Multi-Angle optimal images	16
2. TECIS Waveform LiDAR data	108
Total:	124
Issues:	

In-situ Data and Remote Sensing Datasets

CAF-LiTHy:
Chinese Academy of Forestry's Lidar-Thermal-Hyperspectral Airborne Observation System



LiDAR scanner: Riegl VQ580-II			
Wavelength	1064 nm	Laser beam divergence	0.25 mrad
Laser pulse length	3 ns	Scan angle range	±35°
Maximum laser	2000 kHz	Maximun scanning speed Point density@1000 m	300 lines/s 30 pts/m^2
Echo intensity	15 / beam-forming	Vertical accuracy	0.02 m

Medium wave infrared (MWIR) camera : InfraTec ImageIR		Long wave thermal infrared (LWIR)camera: InfraTec VarioCam HD	
Wavelength	2.0-5.7μm	Wavelength	7.5-14μm
Spatial pixels	640 x 512	Spatial pixels	1024 x 768
Frame rate	106 Hz	Frame rate	30 Hz
Focal length	28.6mm	Focal length	11.1mm
FOV	33.8°	FOV	46.6°
Temperature resolution	0.02 k	Temperature resolution	0.02 k
Temperature range	-40-1500°C	Temperature range	-40-2000°C

Hyperspectral sensor: Specim Aisa FENIX1K			
Wavelength	380-2500 nm	Spatial pixels	1024
Focal length	18.1mm	Spectral resolution	4.5/12 nm
FOV	40°	Maximum bands	87-348/256
Frame rate	100 lines/s	Output	12/16 bits

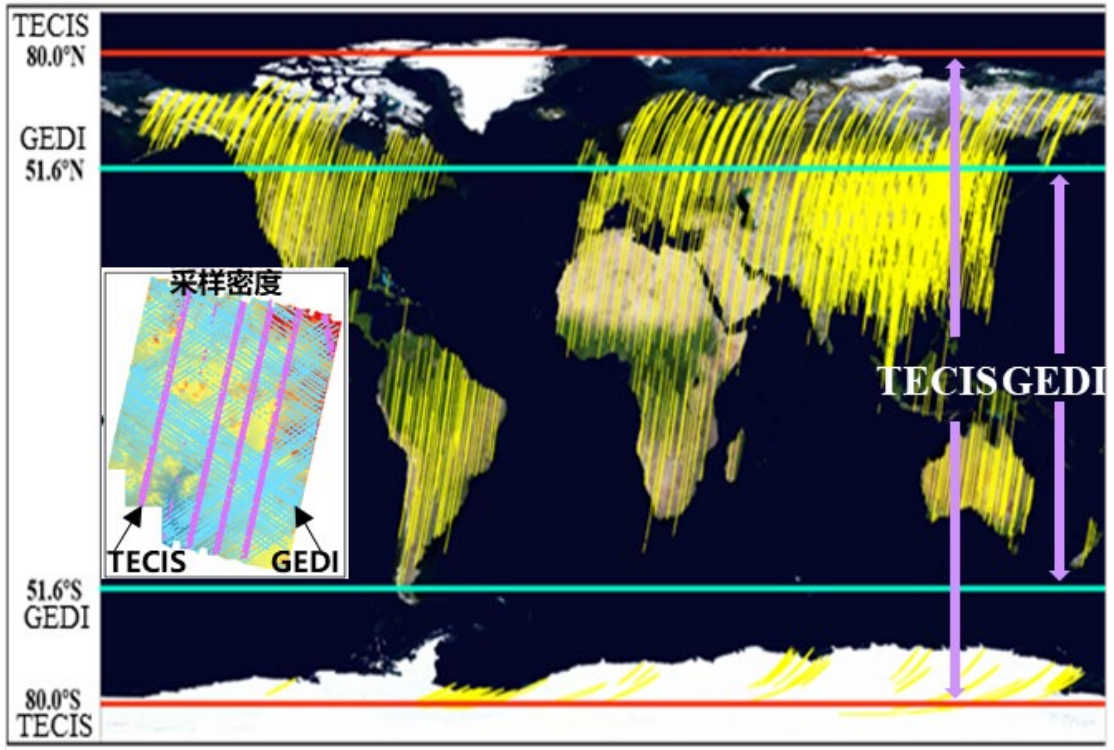
In-situ Data and Remote Sensing Datasets

TECIS:

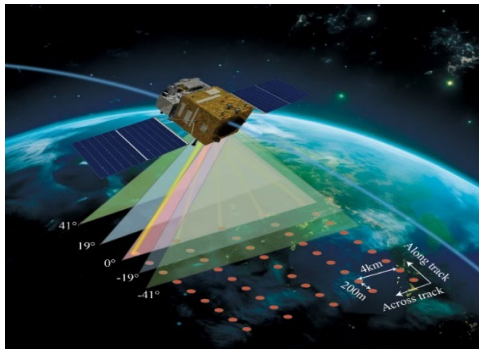
Chinese Terrestrial Ecosystem Carbon Inventory Satellite

GEDI:

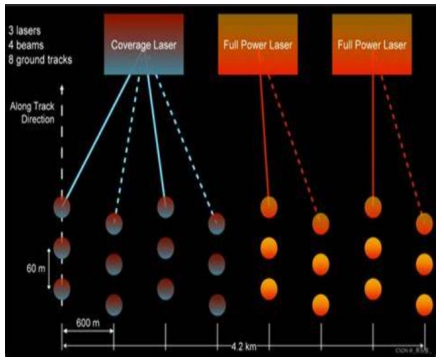
Global Ecosystem Dynamics Investigation



Distribution of GEDI and TECIS observations



Configuration of TECIS



Configuration of GEDI

Parameters of GEDI and TECIS

Parameter (unit)	TECIS	GEDI
Wavelength (nm)	1064	1064
Number of beams	5	8
Number of lasers	5	3
Laser energy (mJ)	70	10/5
Divergence angle (urad)	50	56
Repetition frequency (Hz)	40	242
Laser pulse width (ns)	5	14
Footprint size (m)	25	25
Vertical resolution (m)	0.125	0.15
Digitization frequency (GHz)	1.2	1
Quantization bits (bit)	12	12
Dynamic range (dB)	40	-
Cross track beam interval	~4 km	600 m
Along track beam interval	200 m	60 m

Overview of Research Proceeding (Digital Twin showcase – UK)

DT Components:

1. Baseline cartography (Digital Model):

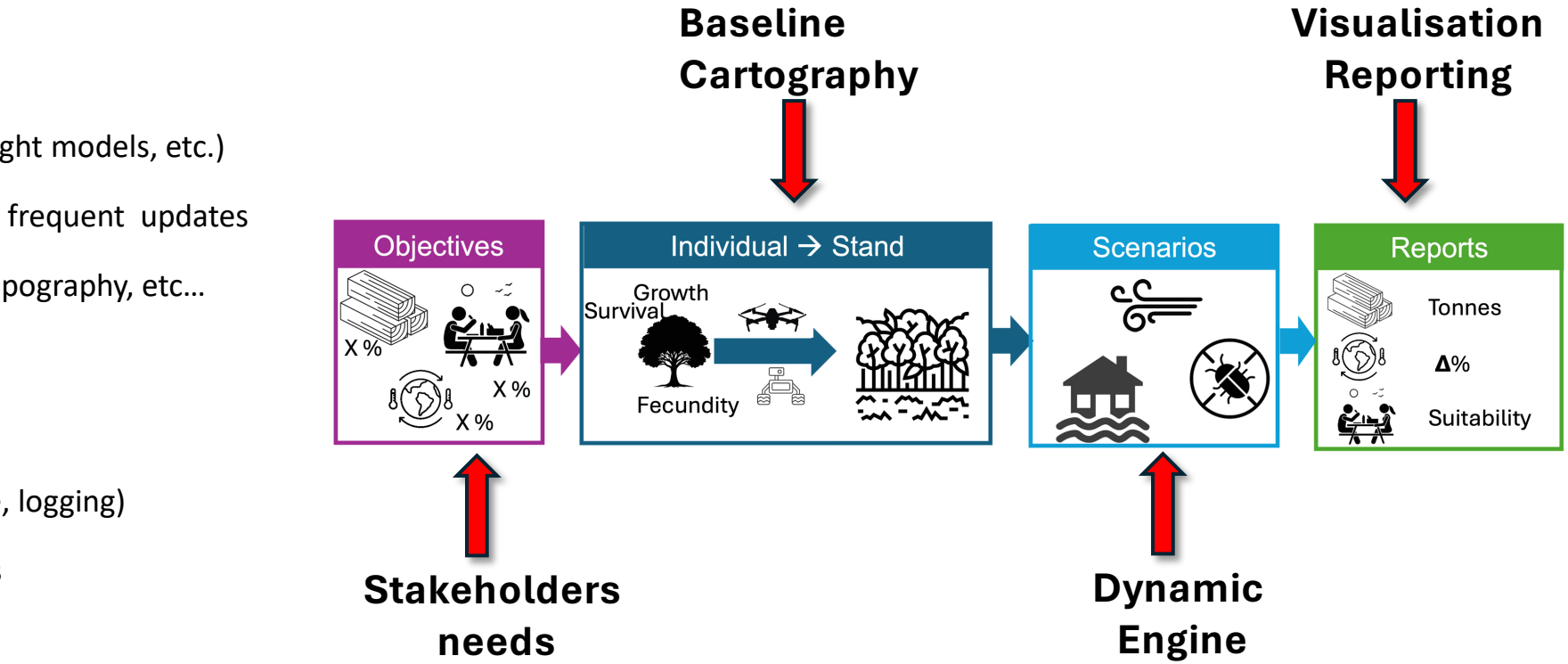
- Historical **LiDAR** data (point clouds, canopy height models, etc.)
- Ongoing **satellite** and **drone** imagery providing frequent updates
- Ancillary datasets: climate, soil, biodiversity, topography, etc…

2. Dynamic Models:

- Tree/stand-level growth prediction
- Change detection (e.g., storm damage, disease, logging)
- Simulation of different **management scenarios**

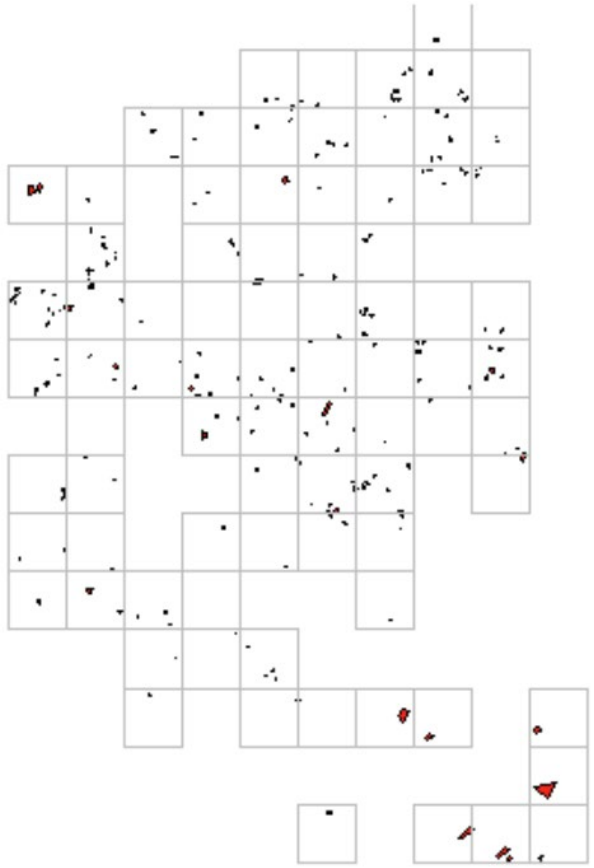
3. Functional Interface:

- A **dashboard or app** for forest managers to interact with the twin, simulate outcomes, and update plans

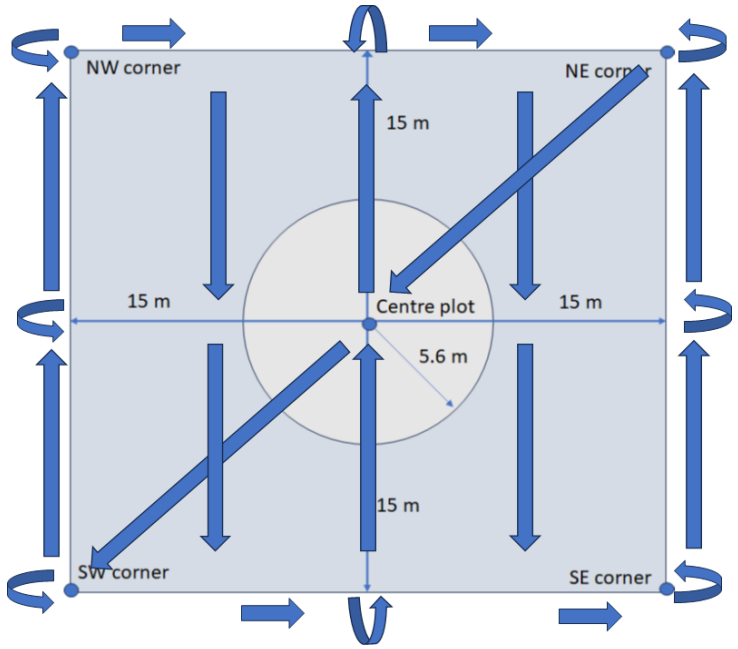


Overview of Research Proceeding (Field Data Collection Campaigns – UK)

Field data campaign in Forest of Dean



Species were identified manually using field plots and sub-compartment database. Quadrants were used to ensure that training and validation did not occur in the vicinity.



30x30 m sample plots where all trees were measured by TLS and traditional methods. Position of individual trees located with GNSS and Total Station.

Oak, Beech, Corsican pine, Norway spruce and Douglas fir 9 plots each were surveyed based on a combination of species and age groups. Three plots were surveyed in each combination.

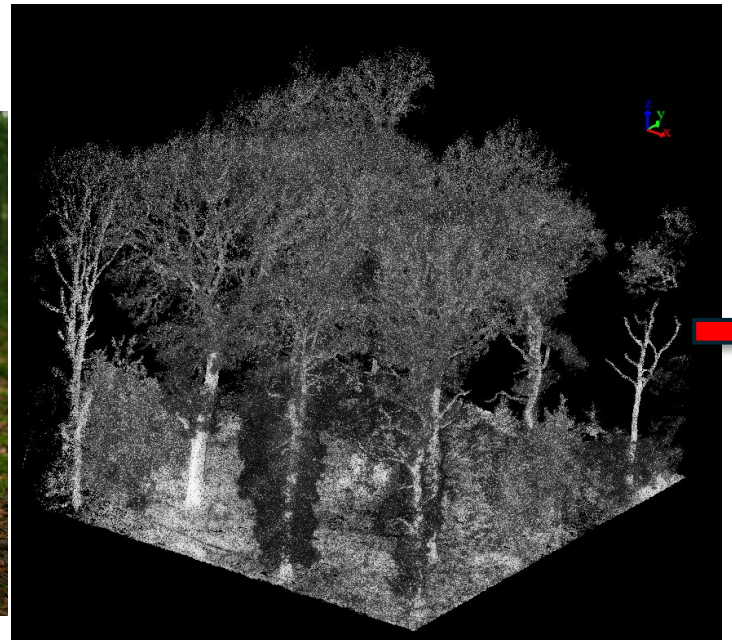
Age group	Plot no	Eastings	Northings	Elevation
Before 1936	1	362000.80	212471.55	211.00
Before 1936	2	362457.39	213506.31	201.30
Before 1936	3	360240.34	211746.43	228.41
Intermediate (1937-1966)	1	362696.17	213820.52	202.73
Intermediate (1937-1966)	2	359776.63	213853.13	256.56
Intermediate (1937-1966)	3	361495.01	206937.96	111.78
Young (after 1966)	1	361490.29	208841.09	152.12
Young (after 1966)	2	363304.58	212377.97	243.47
Young (after 1966)	3	359258.24	212660.50	276.49

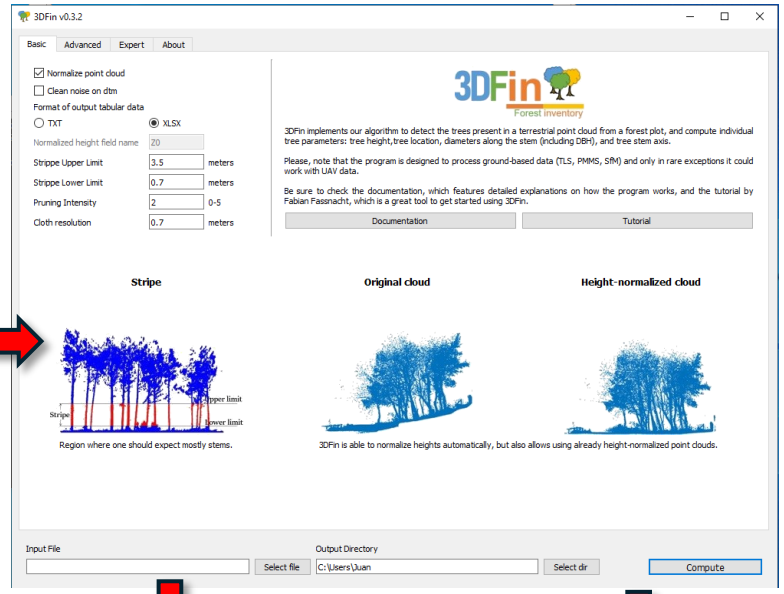
Example of plots surveyed in the Oak group

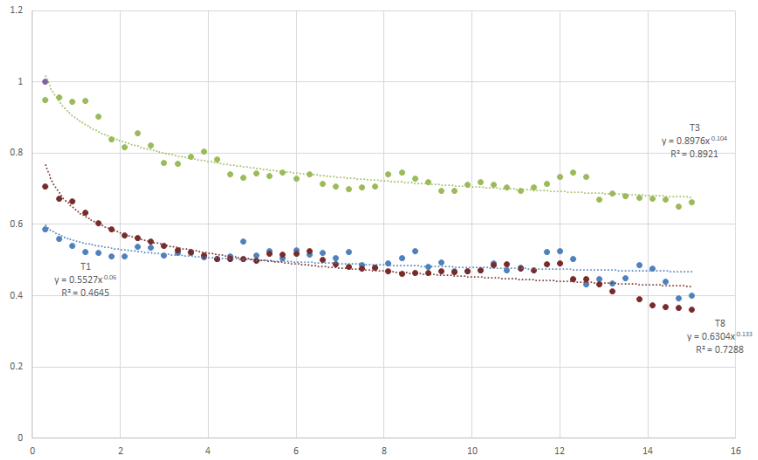
Overview of Research Proceeding (Field Data Collection Campaigns - UK)

MLS in Aberfoyle and FoDean

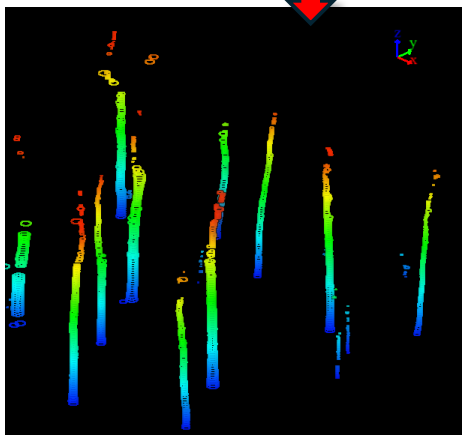






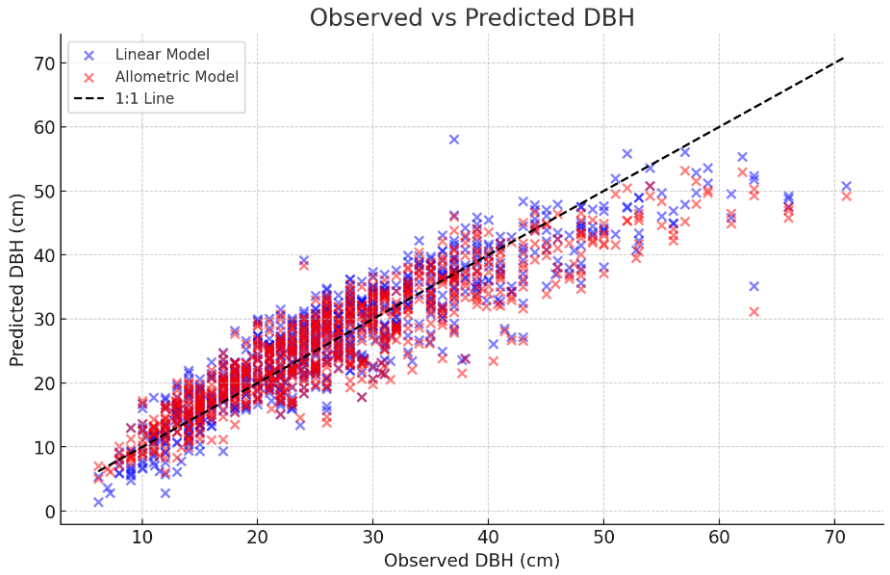


	TH	DBH		Y
T1	22.9646	0.510116	362011.3	212451.4
T2	29.43983	1.020254	361988.5	212455.2
T3	28.36474	0.838962	362007.8	212458.1
T4	29.47755	0.844054	361992.2	212464.7
T5	24.58476	0.582598	362007.2	212472.5
T6	25.24821	0.470719	361996.1	212475.5
T7	23.98332	0.675895	361980.6	212475.5
T8	27.5584	0.586332	361988.5	212478.4
T9	21.19804	0	362006.2	212482.4
T10	21.93979	0.219096	362013.7	212466.6
T11	24.43982	0.157622	362010.9	212470.6
T12	23.65886	0.382152	362013.1	212476.7
T13	25.45292	0	361980.1	212476.9
T14	26.16224	0.64566	362001.5	212448.3
T15	29.51323	0.594577	361995.6	212457.7
T16	24.94654	0	361998.8	212480.5
T17	28.97589	0	361982.2	212448.6
T18	24.4775	0.079065	361993.7	212471.1
T19	30.02678	0.079979	361986.6	212456
T20	29.86918	0	361984.5	212454.3



Overview of Research Proceeding (Field Data Collection Campaigns - UK)

Allometric models for selected species in Forest of Dean



1. Linear Model (Blue)

DBH=−6.87+0.88*Height+5.41*CrownRadius

- **R²:** 0.826
- **RMSE:** ±4.83 cm,.

2. Allometric Model (Red)

DBH=1.62*Height$^{0.77}$*CrownRadius$^{0.40}$

- **R²:** 0.819
- **RMSE:** ±4.92 cm

Species	Observations	Linear R²	Linear RMSE	Allometric R²	Allometric RMSE	Linear Equation	Allometric Equation
Beech	865	0.682	±10.35	0.653	±10.8	DBH = -3.75 + 0.47*Height + 7.97*CrownRadius	DBH = 4.77 * Height^0.34 * CrownRadius^0.75
Norway spruce	834	0.826	±4.83	0.819	±4.92	DBH = -6.87 + 0.88*Height + 5.41*CrownRadius	DBH = 1.62 * Height^0.77 * CrownRadius^0.40
Corsican pine	5304	0.803	±4.62	0.794	±4.73	DBH = -2.56 + 0.85*Height + 8.28*CrownRadius	DBH = 5.46 * Height^0.40 * CrownRadius^0.71
Oak	236	0.765	±6.33	0.754	±6.47	DBH = -8.08 + 0.88*Height + 4.70*CrownRadius	DBH = 1.08 * Height^0.87 * CrownRadius^0.40
Douglas fir	3164	0.856	±2.7	0.866	±2.6	DBH = -5.56 + 1.20*Height + 3.50*CrownRadius	DBH = 0.93 * Height^1.02 * CrownRadius^0.36
Japanese larch	124	0.819	±2.86	0.82	±2.85	DBH = -1.74 + 0.83*Height + 3.62*CrownRadius	DBH = 2.64 * Height^0.60 * CrownRadius^0.43
Scots pine	2861	0.898	±3.91	0.888	±4.11	DBH = -3.11 + 0.84*Height + 5.27*CrownRadius	DBH = 1.71 * Height^0.78 * CrownRadius^0.44
Western hemlock	57	0.884	±6.65	0.87	±7.05	DBH = -5.68 + 0.91*Height + 7.11*CrownRadius	DBH = 1.70 * Height^0.72 * CrownRadius^0.73
Beech	865	0.682	±10.35	0.653	±10.8	DBH = -3.75 + 0.47*Height + 7.97*CrownRadius	DBH = 4.77 * Height^0.34 * CrownRadius^0.75
Birch	312	0.879	±4.43	0.873	±4.54	DBH = -5.05 + 0.81*Height + 4.01*CrownRadius	DBH = 1.29 * Height^0.81 * CrownRadius^0.41
Sweet Chestnut	1672	0.542	±19.48	0.549	±19.34	DBH = -9.55 + 0.13*Height + 13.56*CrownRadius	DBH = 7.21 * Height^0.04 * CrownRadius^1.25

Overview of Research Proceeding (Field Data Collection Campaigns-UK)

Volume estimates for selected species

$$V = \alpha + \beta_1 \times DBH^{\beta_2} \times H^{\beta_3}$$

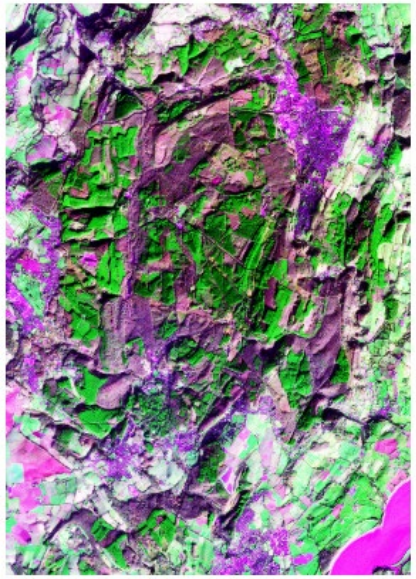
- **V** is the merchantable stem volume (m^3)
- **DBH** is the diameter at breast height (cm)
- **H** is the total height (m)
- **α, β_1, β_2,** and **β_3** are species-specific model parameters. These parameters are general values selected when no prior data is available. Otherwise, the **β_1** is site specific, and can be calibrated by the user.

Beech	Norway spruce	Corsican pine	Oak
α = -0.01499241	α = -0.01422840	α = -0.01293224	α = -0.01586186
β_1 = 0.00005584	β_1 = 0.00007827	β_1 = 0.00004852	β_1 = 0.00007772
β_2 = 1.863140	β_2 = 1.779849	β_2 = 2.000000	β_2 = 1.880742
β_3 = 1.000000	β_3 = 1.000000	β_3 = 0.939523	β_3 = 0.890227
Douglas fir	**Japanese larch**	**Scots pine**	**Western hemlock**
α = -0.01338343	α = -0.01083665	α = -0.01555046	α = -0.01444532
β_1 = 0.00007669	β_1 = 0.00005096	β_1 = 0.00008029	β_1 = 0.00006641
β_2 = 1.885578	β_2 = 2.000000	β_2 = 1.925729	β_2 = 1.839099
β_3 = 0.925127	β_3 = 0.909984	β_3 = 0.818042	β_3 = 1.000000
Birch	**Sweet Chestnut**		
α = -0.01263069	α = -0.02691119		
β_1 = 0.00008328	β_1 = 0.00014472		
β_2 = 2.000000	β_2 = 2.000000		
β_3 = 0.683508	β_3 = 0.566741		

Overview of Research Proceeding (Baseline cartography-UK)

Species Classification using phenological cycles captured by time-series of satellite imagery

Winter- 26th January 2024



Spring- 19th May 2024

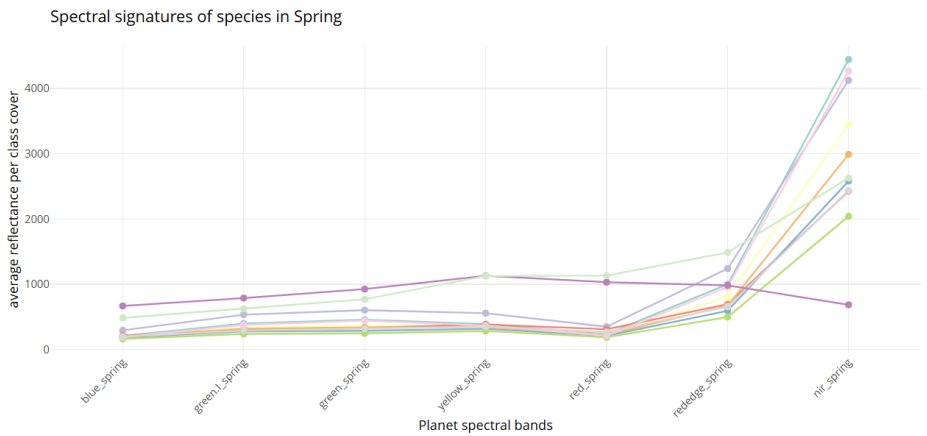


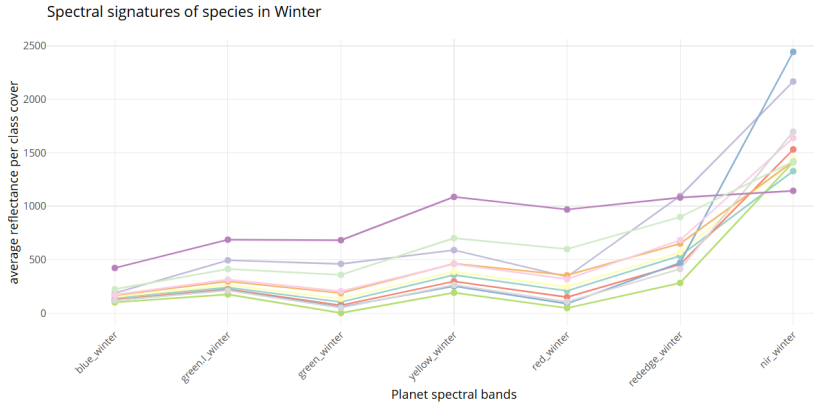
Summer- 14th August 2022



Autumn- 10th October 2022

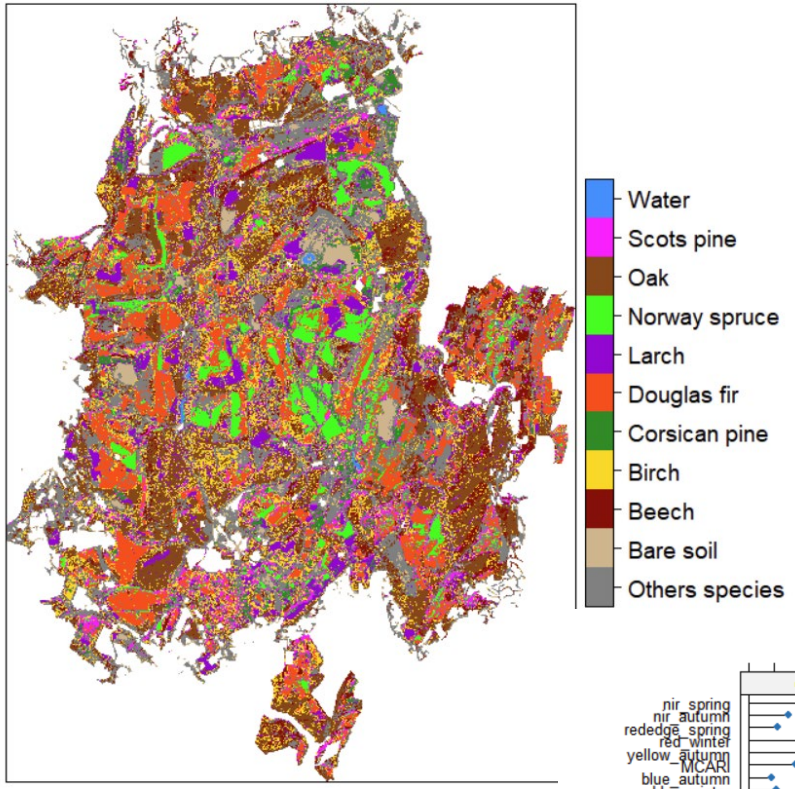


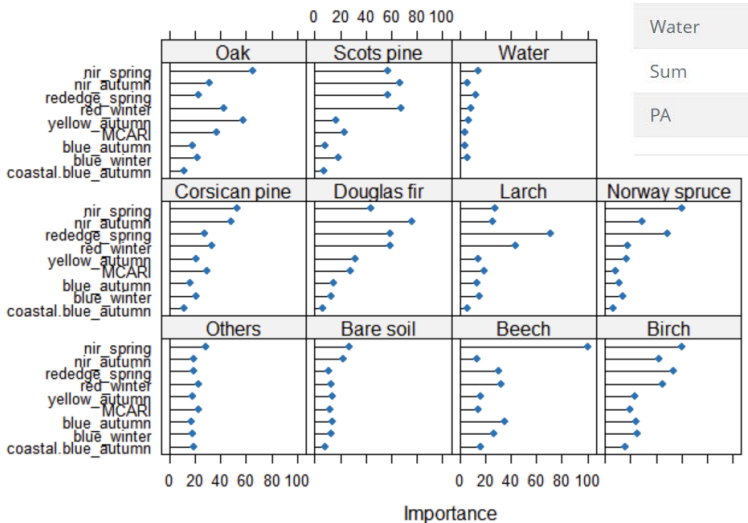




Overview of Research Proceeding (Baseline Cartography-UK)

The selection of key variables is achieved after several cross-validations, then Random Forest is applied for species classification

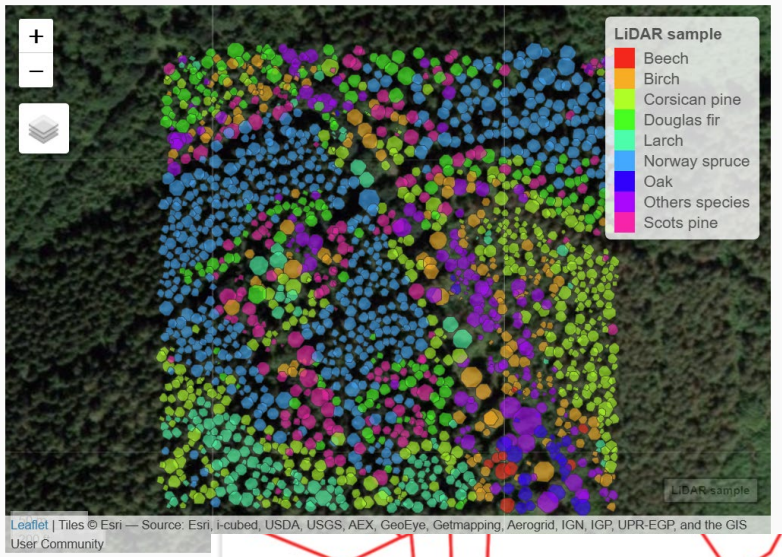


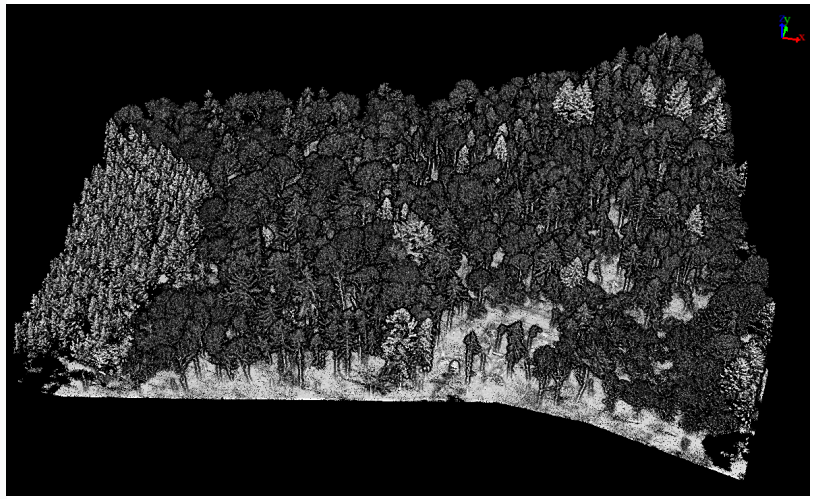


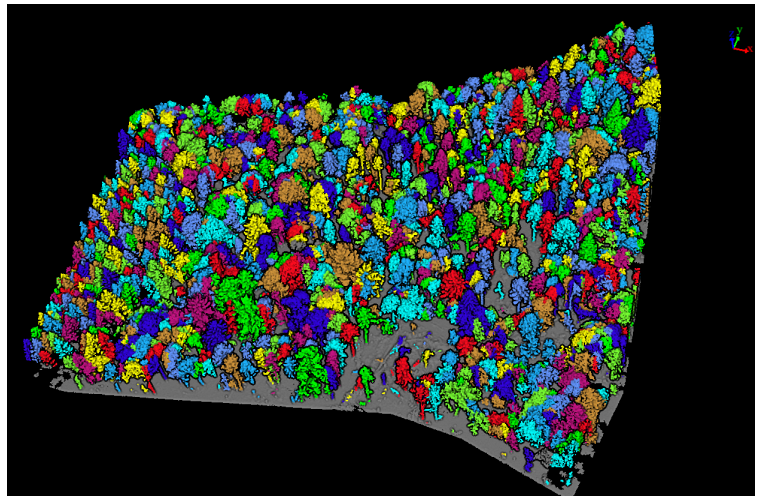
	Others	Bare soil	Beech	Birch	Corsican pine	Douglas fir	Larch	Norway spruce	Oak	Scots pine	Water	Sum	UA
Others	6608.0	0	12.0	27.0	7	152.0	0.0	37.0	59.0	1.0	0	6903	95.7
Bare soil	0.0	1705	0.0	0.0	0	0.0	0.0	0.0	0.0	0.0	0	1705	100.0
Beech	11.0	0	1585.0	51.0	0	0.0	2.0	0.0	84.0	0.0	0	1733	91.5
Birch	40.0	0	21.0	894.0	3	12.0	31.0	0.0	103.0	21.0	0	1125	79.5
Corsican pine	0.0	0	0.0	4.0	1154	8.0	6.0	2.0	0.0	43.0	0	1217	94.8
Douglas fir	83.0	0	0.0	3.0	3	1970.0	2.0	38.0	0.0	25.0	0	2124	92.7
Larch	10.0	0	0.0	4.0	15	6.0	2500.0	0.0	0.0	7.0	0	2542	98.3
Norway spruce	16.0	0	0.0	0.0	11	41.0	0.0	2036.0	0.0	20.0	0	2124	95.9
Oak	3.0	0	74.0	38.0	0	5.0	0.0	0.0	2253.0	0.0	0	2373	94.9
Scots pine	1.0	0	0.0	9.0	119	36.0	6.0	16.0	0.0	627.0	0	814	77.0
Water	0.0	0	0.0	0.0	0	0.0	0.0	0.0	0.0	0.0	6591	6591	100.0
Sum	6772.0	1705	1692.0	1030.0	1312	2230.0	2547.0	2129.0	2499.0	744.0	6591	29251	NA
PA	97.6	100	93.7	86.8	88	88.3	98.2	95.6	90.2	84.3	100	NA	95.5

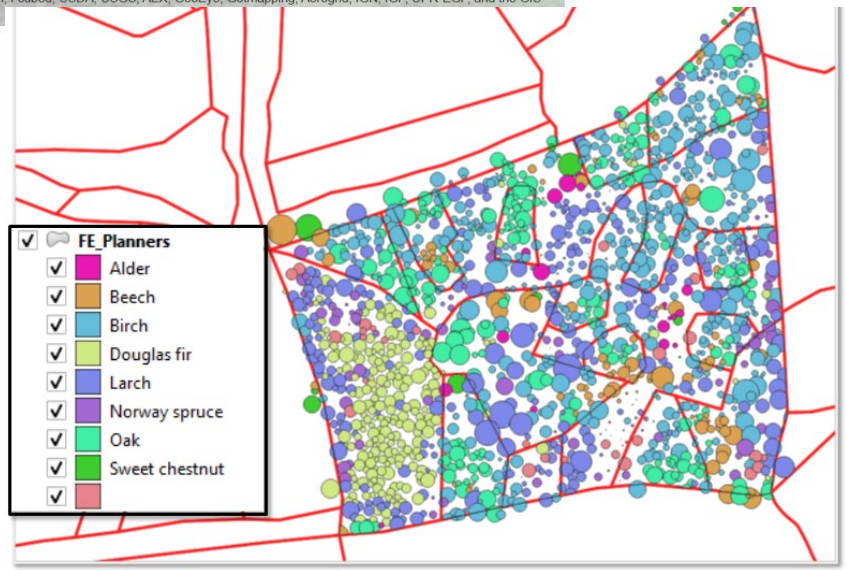
Overview of Research Proceeding (Baseline cartography-UK)

Tree lists combining canopy detection from LiDAR and species classification with satellite imagery









Total number of trees in forest of Dean = 1,248,413

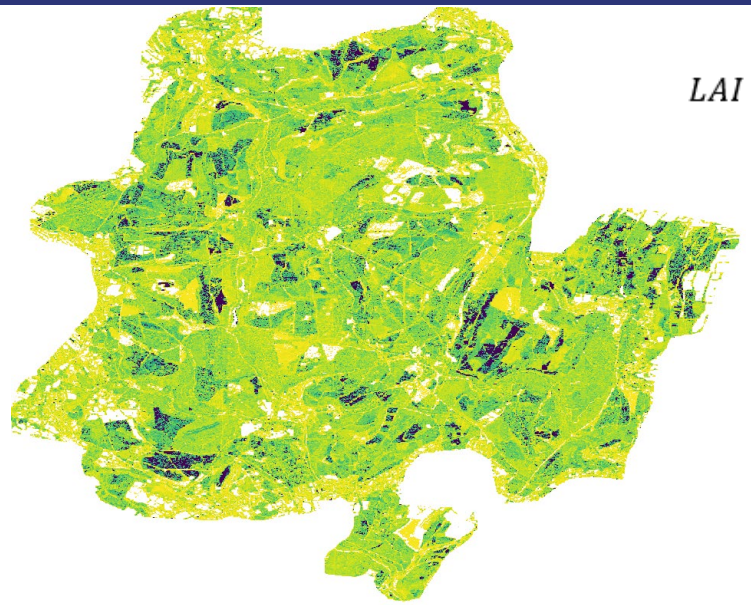
85% accuracy

	A	B	C	D	E	F	G	H	I	J	K
1	TreeID	TreePosX	TreePosY	TreePosZ	TreeHeight(metre)	DBH(metre)	CrownDiameter(metre)	CrownDiameter(S-N)(metre)	CrownDiameter(E-W)(metre)	CrownArea(square metre)	CrownVolume(cubic metre)
2	1	361923.619	212568.559	15.496	15.5	0	6.4	5.9	11.6	31.9	74.6
3	2	361914.142	212557.119	15.366	15.4	0	0.6	0.9	0.5	0.2	0.2
4	3	361908.556	212556.252	23.222	23.2	0	10.2	13.3	11.5	81.5	501.1
5	4	361908.213	212554.706	23.535	23.5	0	5.5	5.8	6.3	24.2	140.1
6	5	361903.726	212551.838	19.145	19.1	0	4.1	5.8	5.1	13.3	35.9
7	6	361925.485	212550.121	26.361	26.4	0	21	18.4	27.9	346.5	4264.4
8	7	361914.199	212547.012	26.309	26.3	0	11.2	9.6	15	98.9	895
9	8	361901.753	212547.399	18.484	18.5	0	3.5	4.2	3.3	9.8	21.4
10	9	361911.833	212547.535	24.459	24.5	0	2.8	3.3	2.6	6.1	16.7
11	10	361908.845	212545.544	25.843	25.8	0	8	8.2	8.8	50.6	199.7
12	11	361903.164	212541.638	19.836	19.8	0	9.8	13.5	7.3	75.2	173.8
13	12	361895.656	212540.176	21.397	21.4	0	9.9	9.6	11.7	76.5	541
14	13	361919.05	212539.501	13.875	13.9	0	5.8	5.9	6.1	26.6	64.5
15	14	361897.1	212537.946	21.681	21.7	0	5.2	3.9	7.4	21	98.5
16	15	361918.956	212537.088	13.434	13.4	0	5.3	5.6	6.4	22.2	86.6
17	16	361930.789	212536.714	18.475	18.5	0	6.2	10.4	4.8	30.4	117.2
18	17	361889.38	212536.509	17.307	17.3	0	4.2	4.6	5.5	14.1	40
19	18	361902.259	212535.204	16.326	16.3	0	5	6	4.8	19.3	62.1

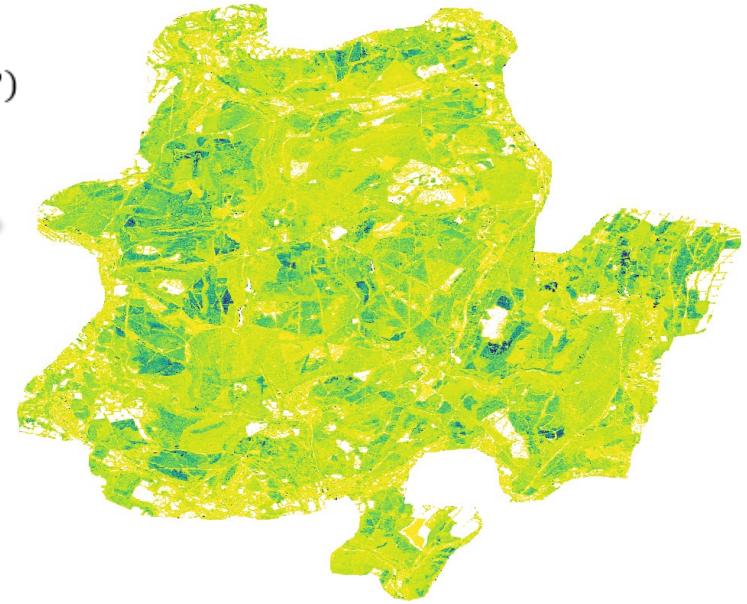
e.g. Forest of Dean Compartment 4358

Overview of Research Proceeding (Dynamic Models-UK)

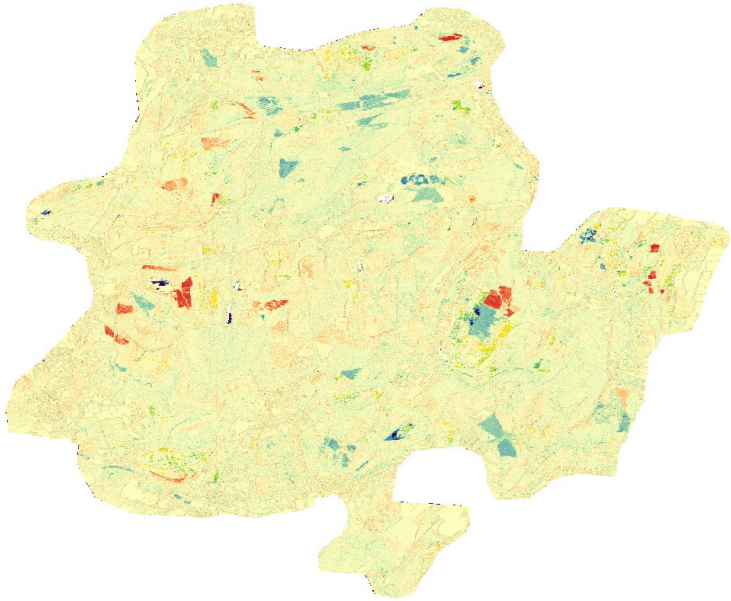
$$LAI = -\frac{1}{k}\ln(P)$$



Leaf Area Index in 2018, in m^2.
Values range from 0 (Yellow) to 23 (Dark blue).

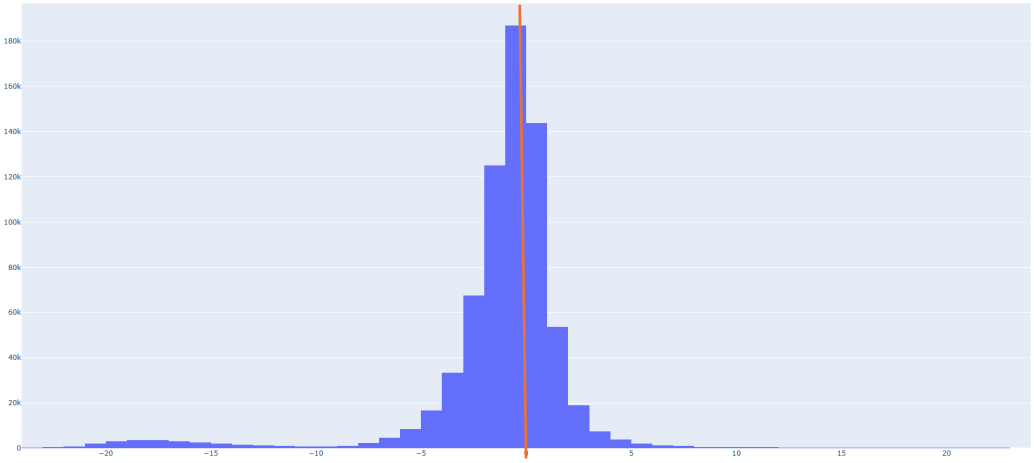


Leaf Area Index in 2022



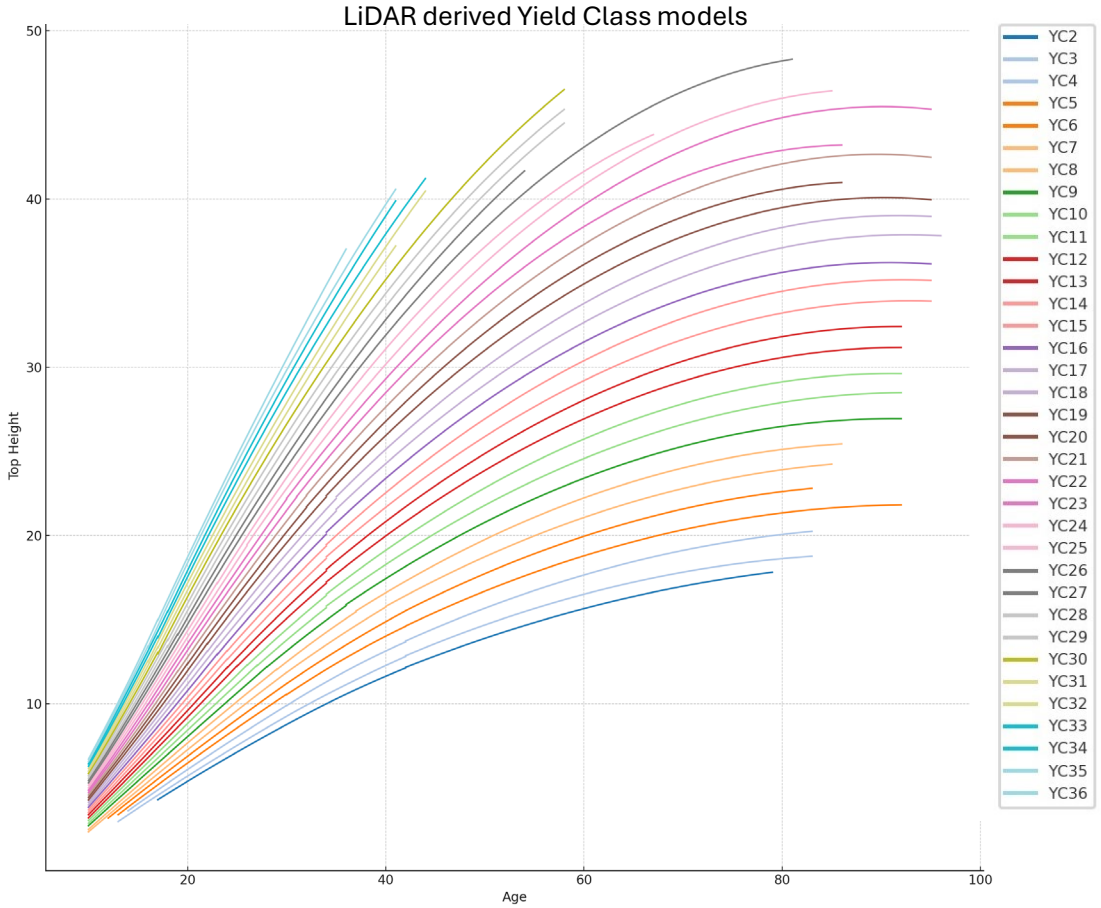
Gap fraction differences in between LiDAR surveys. Values range from -1 (Red), 0 (Yellow) to 1 (Dark blue).

LAI differences between 2018 and 2022



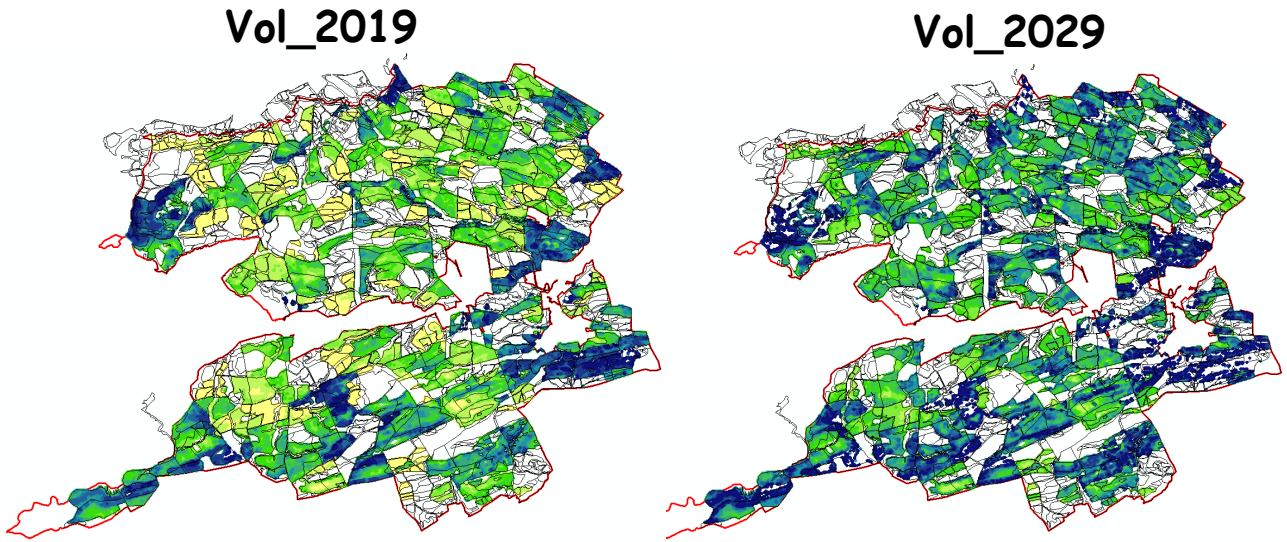
Overview of Research Proceeding (Dynamic Models-UK)

Chronosequences of LiDAR data (ABA) to forecast volume increments



New **Yield Class/Site Index** models being generated by grouping LiDAR observations into a chronosequences.

Growth modulated by fractional cover and disturbances



Overview of Research Proceeding (Dynamic Models-UK)

Physics-Informed Neural Network (PINN) to model height

$$Loss_{\text{PINN}} = \underbrace{\frac{1}{N}\sum_{i=1}^{N}(f(x_i|\theta) - y_i)^2}_{\text{Data loss}} + \underbrace{\lambda_{\text{ph}}\frac{1}{N}\sum_{i=1}^{N}(p(x_i, f(x_i,|\theta)))^2}_{\text{Physics loss}} + \lambda_1\|\theta\|_1$$

PINNs leverage the capabilities of PDEs in supervised learning tasks to ensure compliance with physical laws (Chapman-Richards, CR)

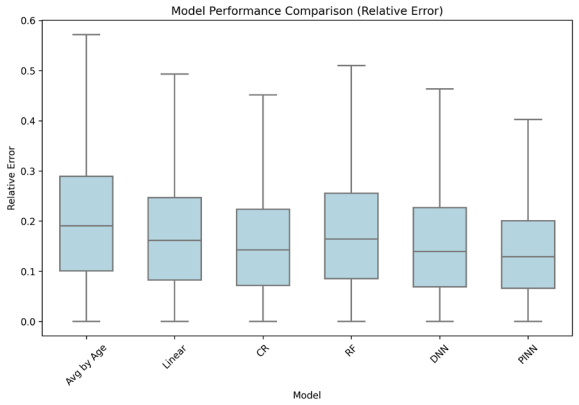
Such non-linear Partial Derivative Equations (PDEs) can model complex systems, including ecological growth patterns, making them particularly suited for simulating instances such as forest growth.

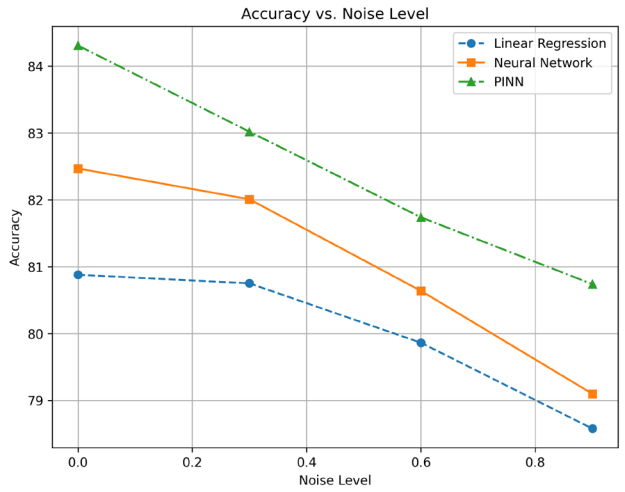
$$\mathcal{L}_{\text{total}} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 + \lambda_{\text{ph}} \cdot \frac{1}{N}\sum_{i=1}^{N}\left(\frac{d\hat{y}_i}{dt} - \frac{d\hat{y}_{\text{cr},i}}{dt}\right)^2 + \lambda_1\|\theta\|_1$$

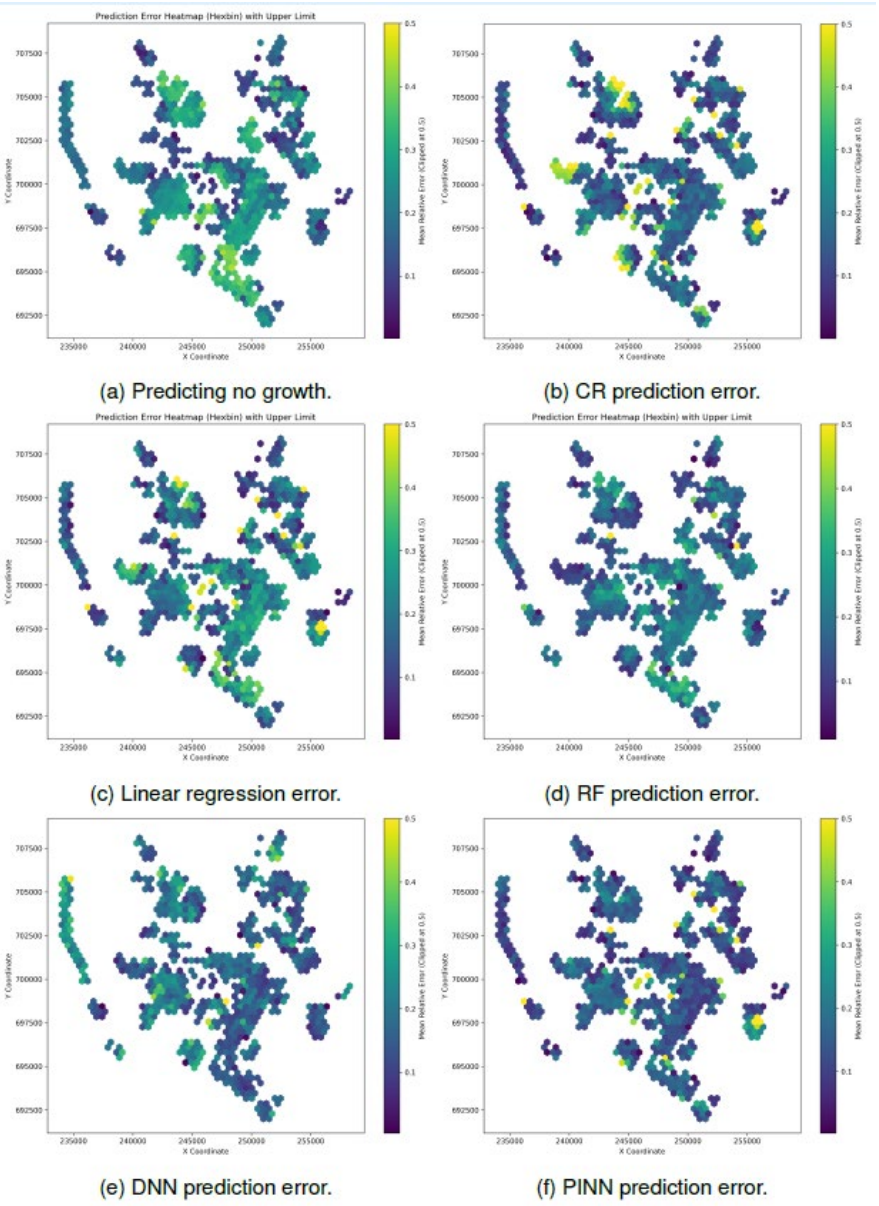
$$\frac{d\hat{y}_{\text{cr}}}{dt} = y_{\max} \cdot p \cdot \left(1 - e^{-k\cdot t}\right)^{p-1} \cdot k \cdot e^{-k\cdot t}$$

where:

- $\hat{y}$ is the predicted height computed from the neural network architecture.
- $\hat{y}_{\text{cr}}$ is the predicted height given by the CR equation.
- y is the true height value.



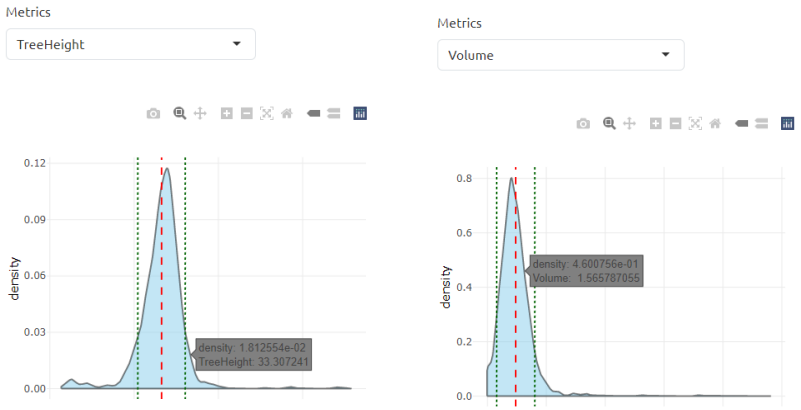




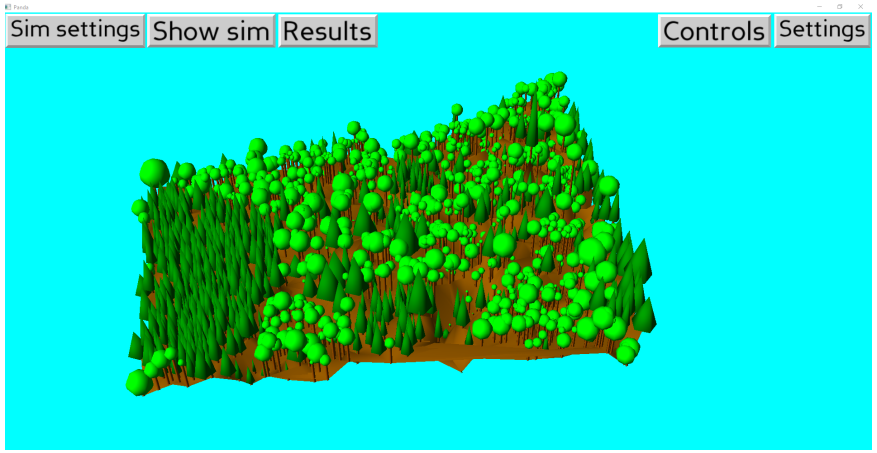
Overview of Research Proceeding (Interface to results-UK)



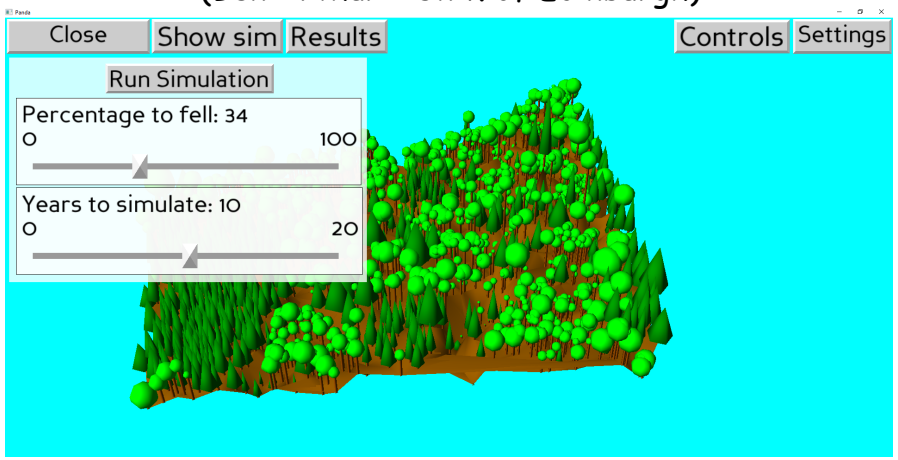
(Miguel Ibañez, FR)



Simulation tools



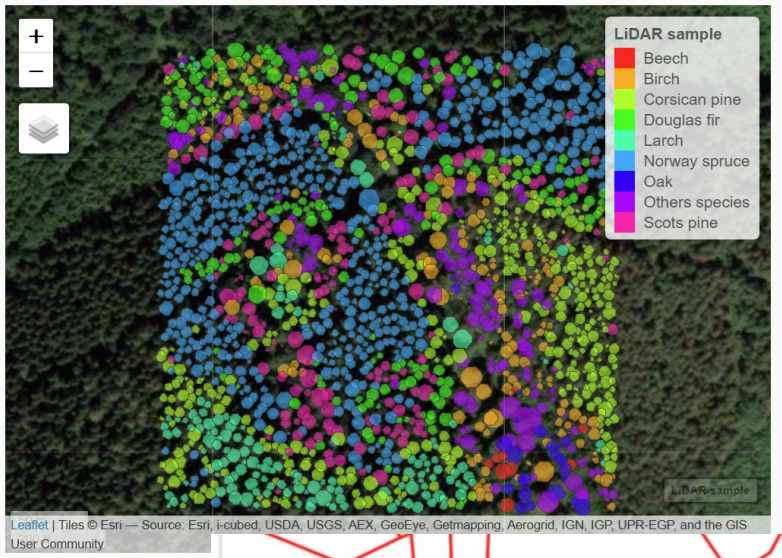
(Ben Arthur - Univ. of Edinburgh)

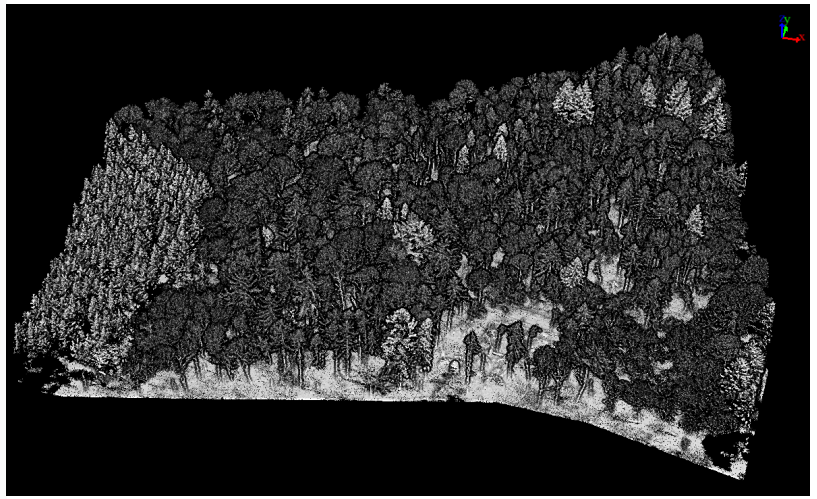


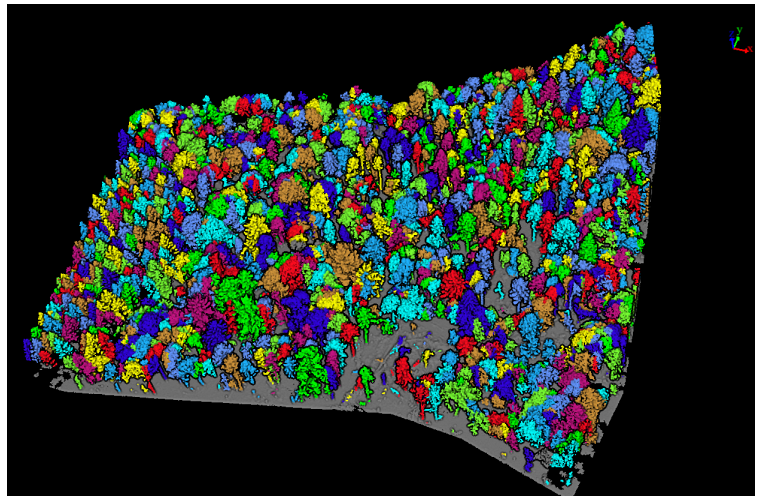
Compartment 4358, felling simulation (34%) removal and 10 years growth

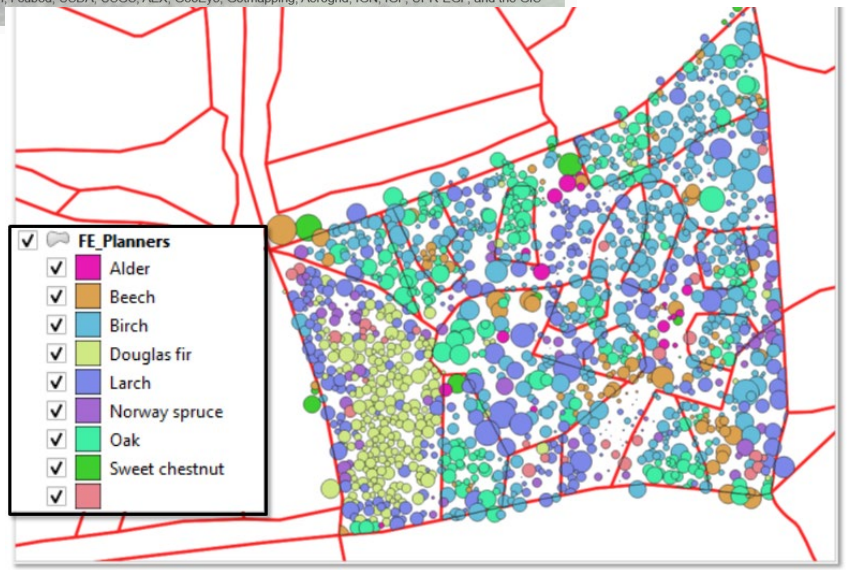
Overview of Research Proceeding (Baseline cartography-UK)

Tree lists combining canopy detection from LiDAR and species classification with satellite imagery





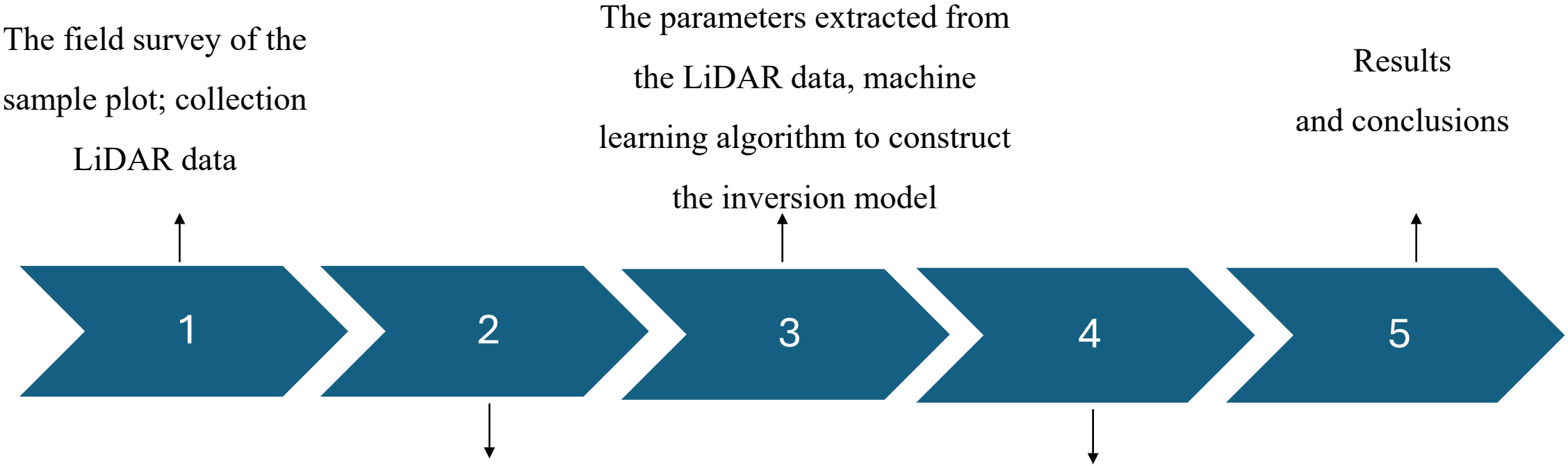




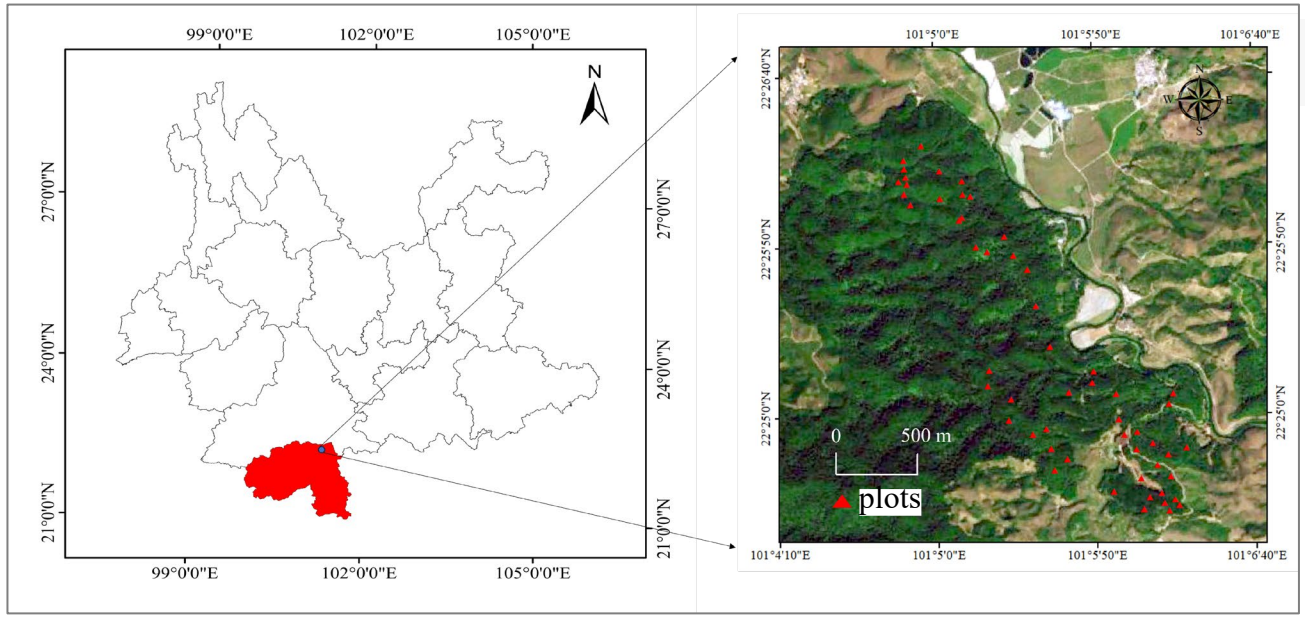
	A	B	C	D	E	F	G	H	I	J	K
1	TreeID	TreePosX	TreePosY	TreePosZ	TreeHeight(metre)	DBH(metre)	CrownDiameter(metre)	CrownDiameter(S-N)(metre)	CrownDiameter(E-W)(metre)	CrownArea(square metre)	CrownVolume(cubic metre)
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3	2	361914.142	212557.119	15.366	15.4	0	0.6	0.9	0.5	0.2	0.2
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9	8	361901.753	212547.399	18.484	18.5	0	3.5	4.2	3.3	9.8	21.4
10	9	361911.833	212547.535	24.459	24.5	0	2.8	3.3	2.6	6.1	16.7
11	10	361908.845	212545.544	25.843	25.8	0	8	8.2	8.8	50.6	199.7
12	11	361903.164	212541.638	19.836	19.8	0	9.8	13.5	7.3	75.2	173.8
13	12	361895.656	212540.176	21.397	21.4	0	9.9	9.6	11.7	76.5	541
14	13	361919.05	212539.501	13.875	13.9	0	5.8	5.9	6.1	26.6	64.5
15	14	361897.1	212537.946	21.681	21.7	0	5.2	3.9	7.4	21	98.5
16	15	361918.956	212537.088	13.434	13.4	0	5.3	5.6	6.4	22.2	86.6
17	16	361930.789	212536.714	18.475	18.5	0	6.2	10.4	4.8	30.4	117.2
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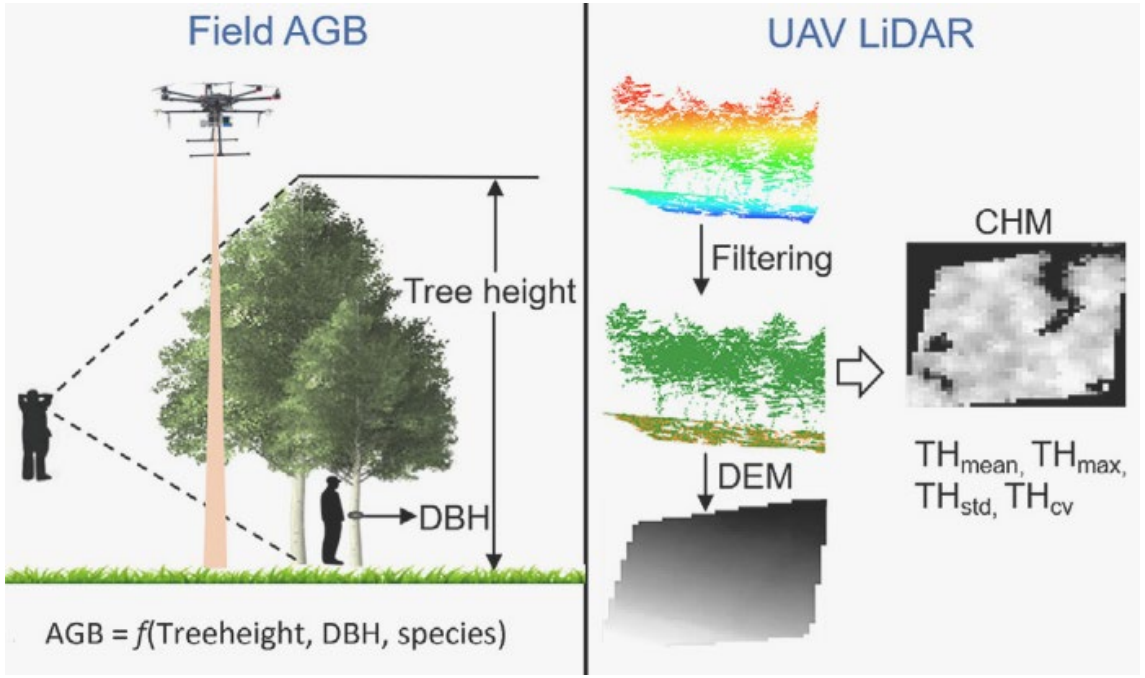
e.g. Forest of Dean Compartment 4358

Overview of Research Proceeding (Inversion of AGB in Broadleaf Forests Using LiDAR and Ensemble Algorithms- A Case Study of Puwen Forest Farm-China)



Overview of Research Proceeding (Inversion of AGB in Broadleaf Forests Using LiDAR and Ensemble Algorithms- A Case Study of Puwen Forest Farm-China)





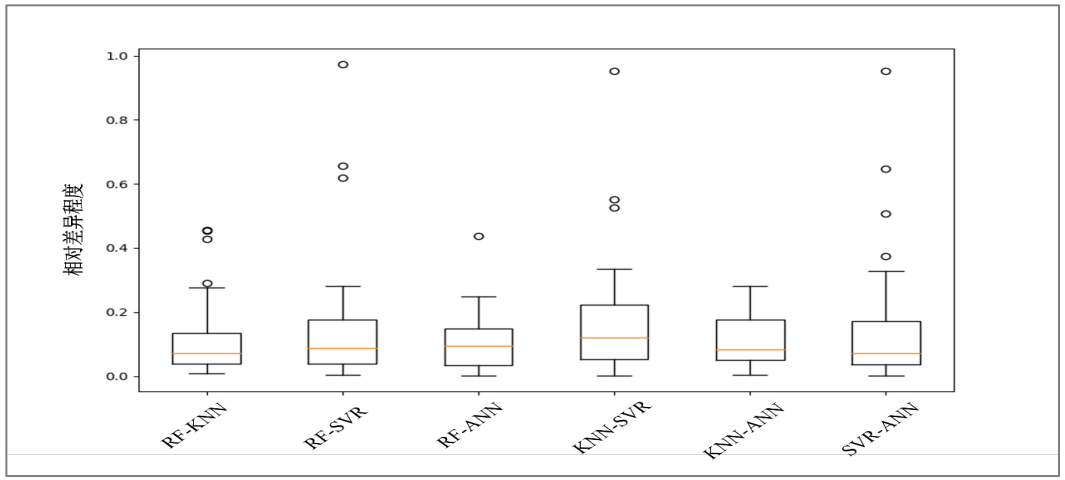
Field AGB survey:

record the tree height and DBH,
calculate AGB with allometric equation
(55 sample plots)

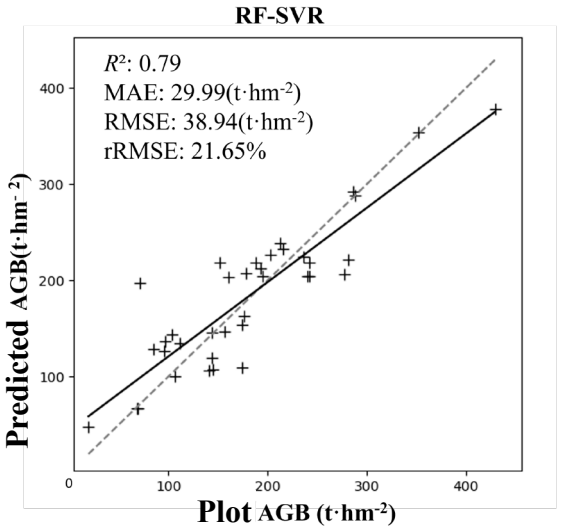
LiDAR data:

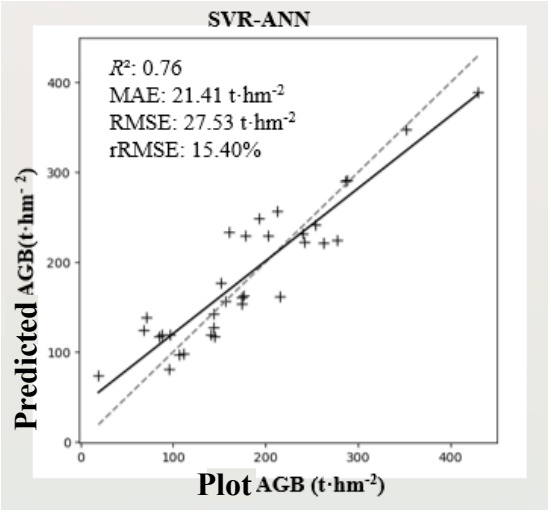
LiDAR data use extract LiDAR metrics

Overview of Research Proceeding (Inversion of AGB in Broadleaf Forests Using LiDAR and Ensemble Algorithms- A Case Study of Puwen Forest Farm-China)

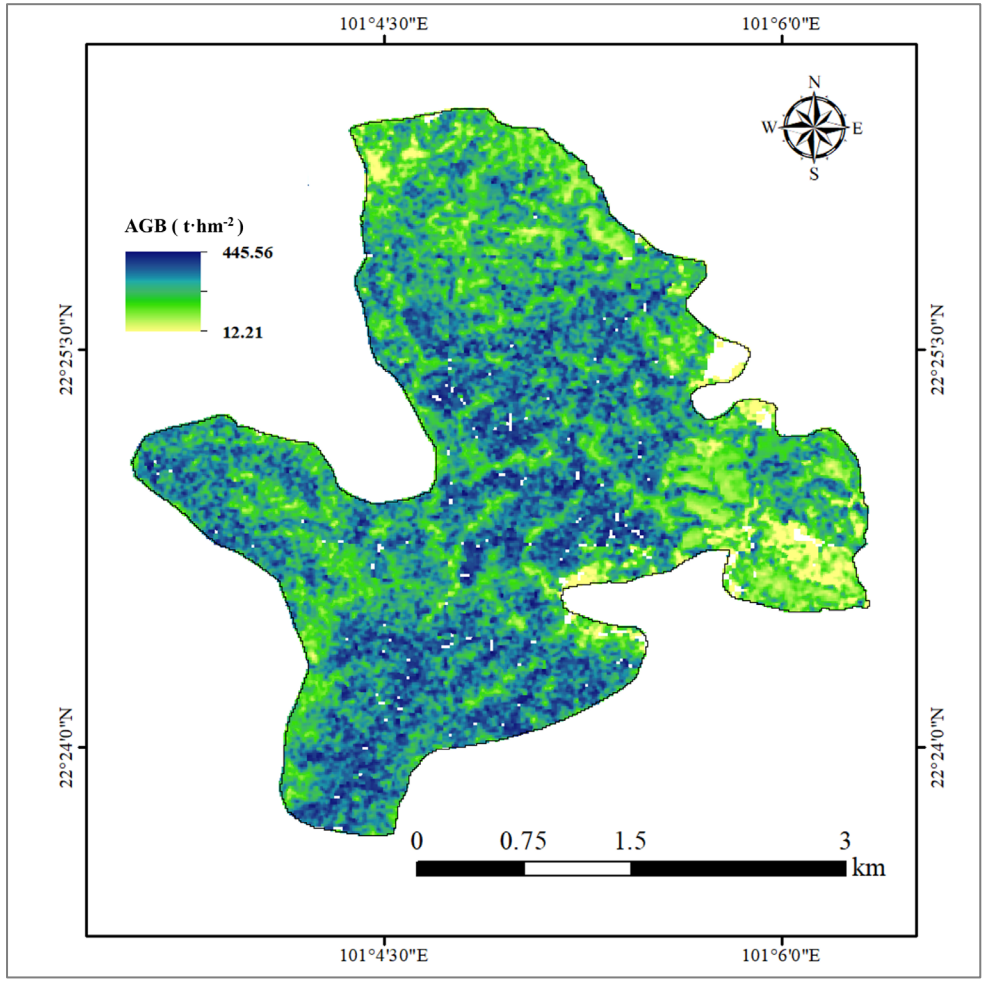


Comparison of differences in base learners





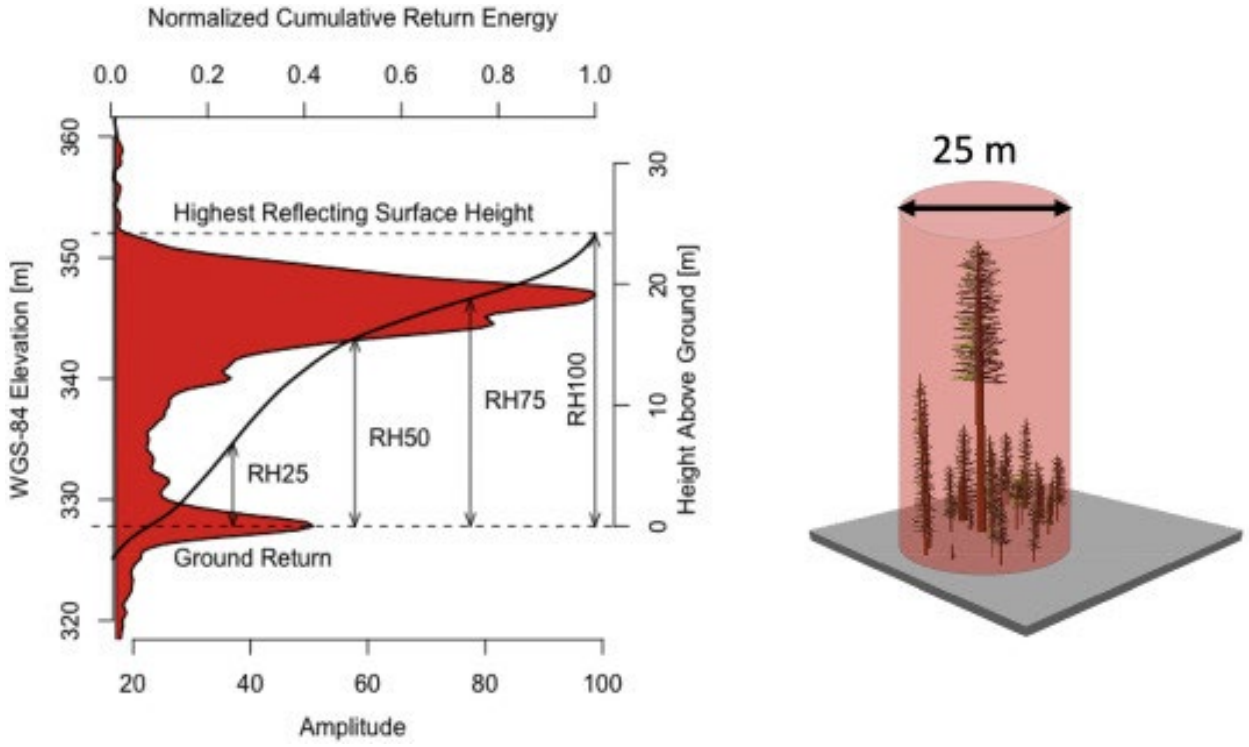
The best combination of two types of data



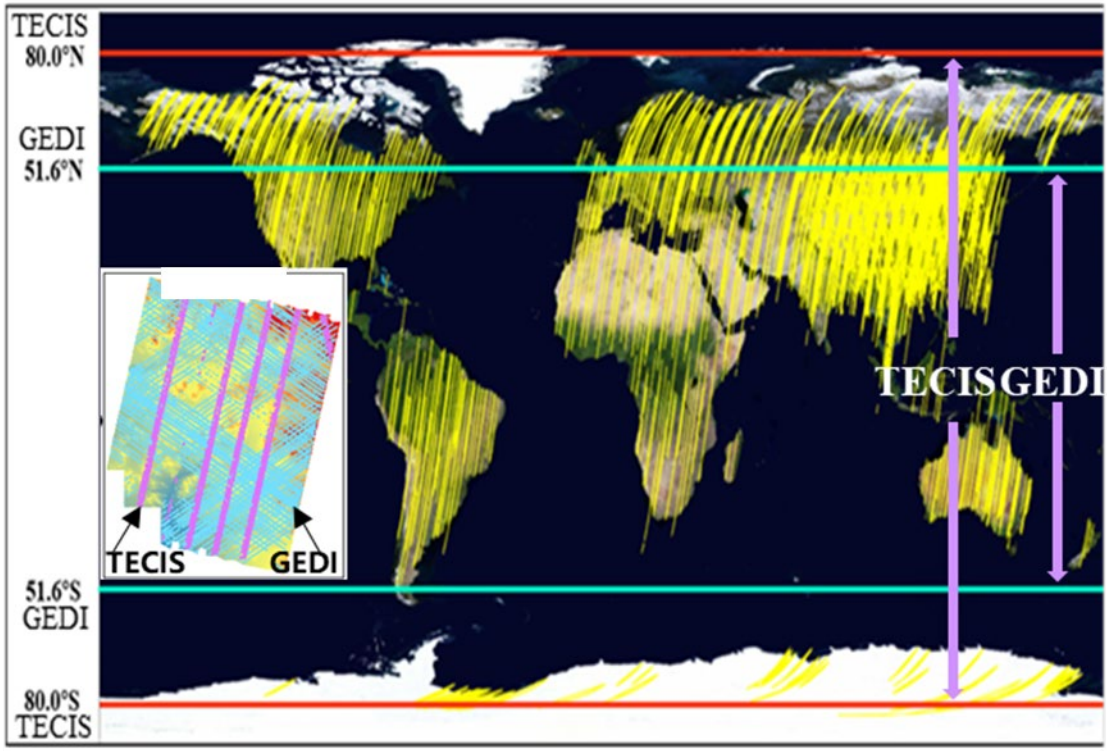
AGB mapping

Overview of Research Proceeding (Spaceborne LiDAR for Forest Application-China)

The Terrestrial Ecosystem Carbon Inventory Satellite (TECIS) is the first satellite integrating waveform LiDAR and multi-angle imaging for forest carbon mapping; How is data quality difference between GEDI and TECIS waveform for forest parameter estimation?



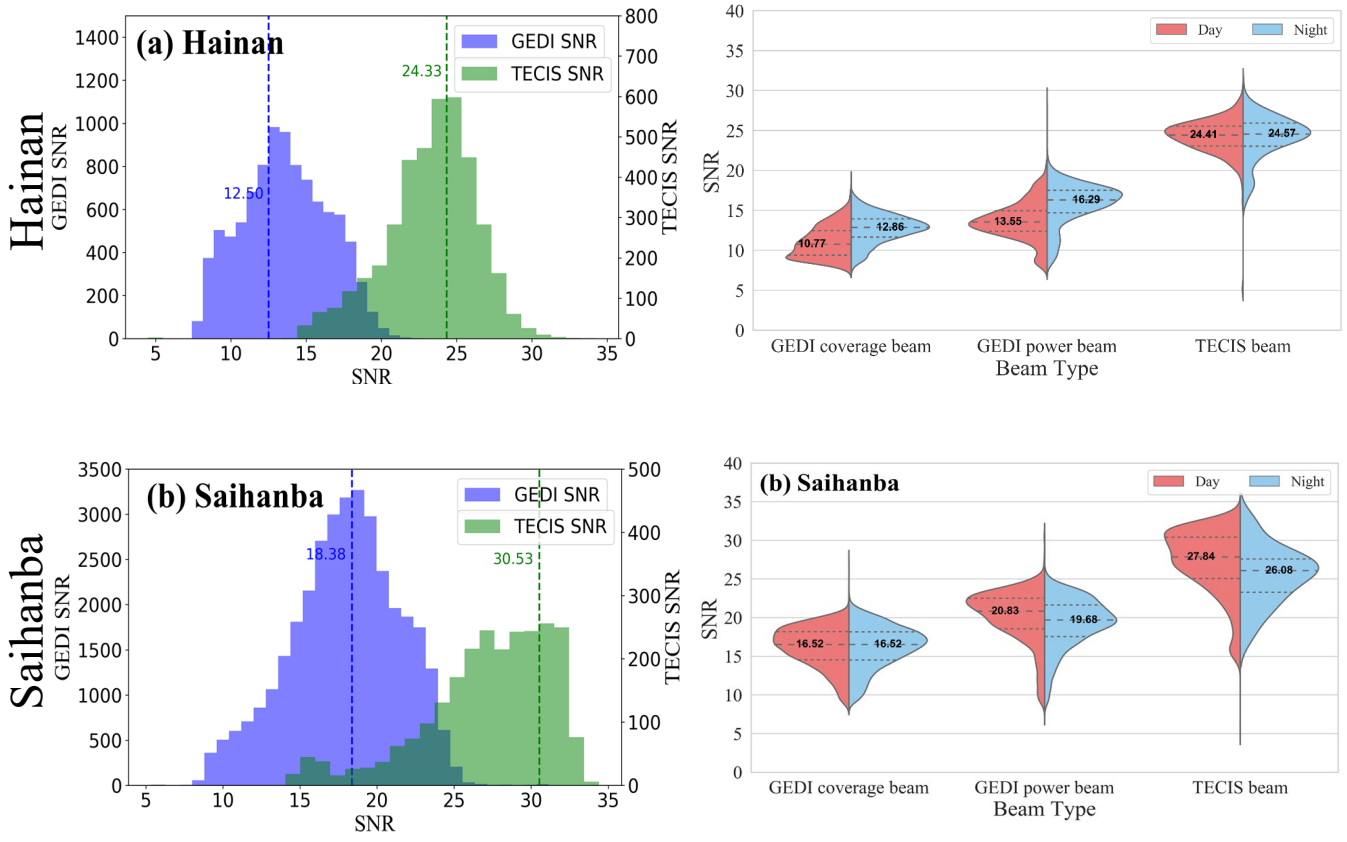
Large Footprint Full Waveform
(Dubayah et al., 2020)



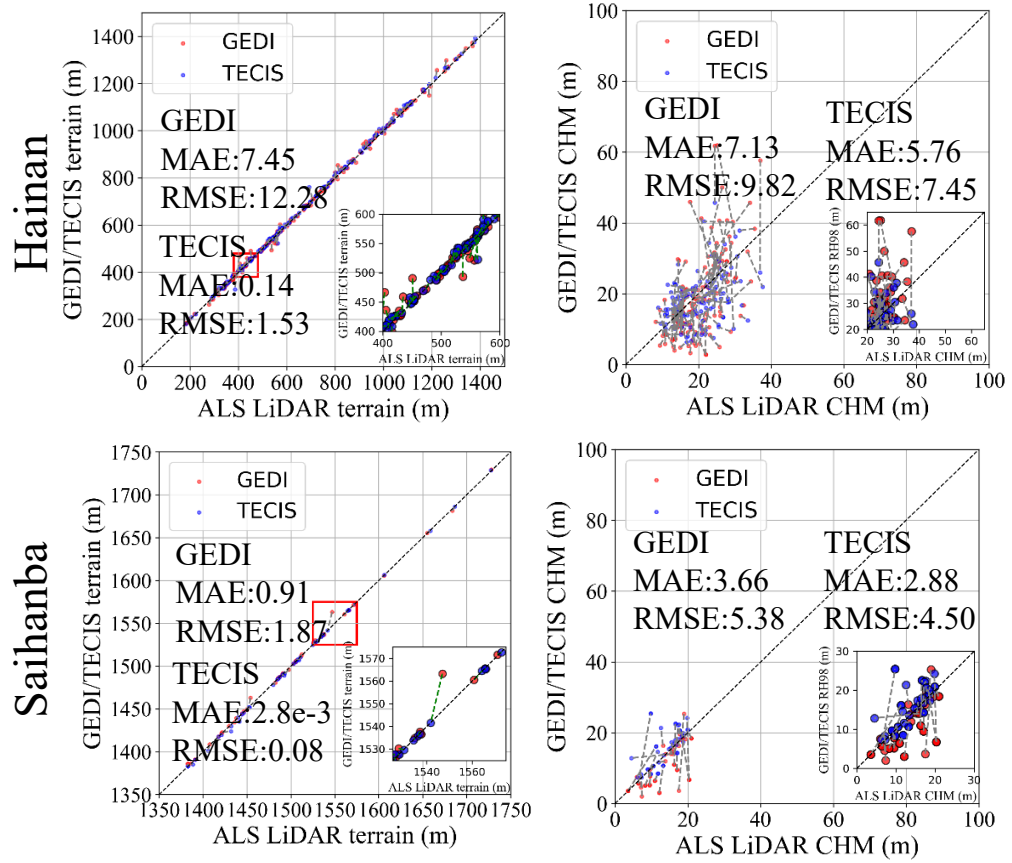
Distribution of GEDI and TECIS observations

Overview of Research Proceeding (Spaceborne LiDAR for Forest Application-China)

- **There are significant difference of data quality and accuracy between TECIS and GEDI.**



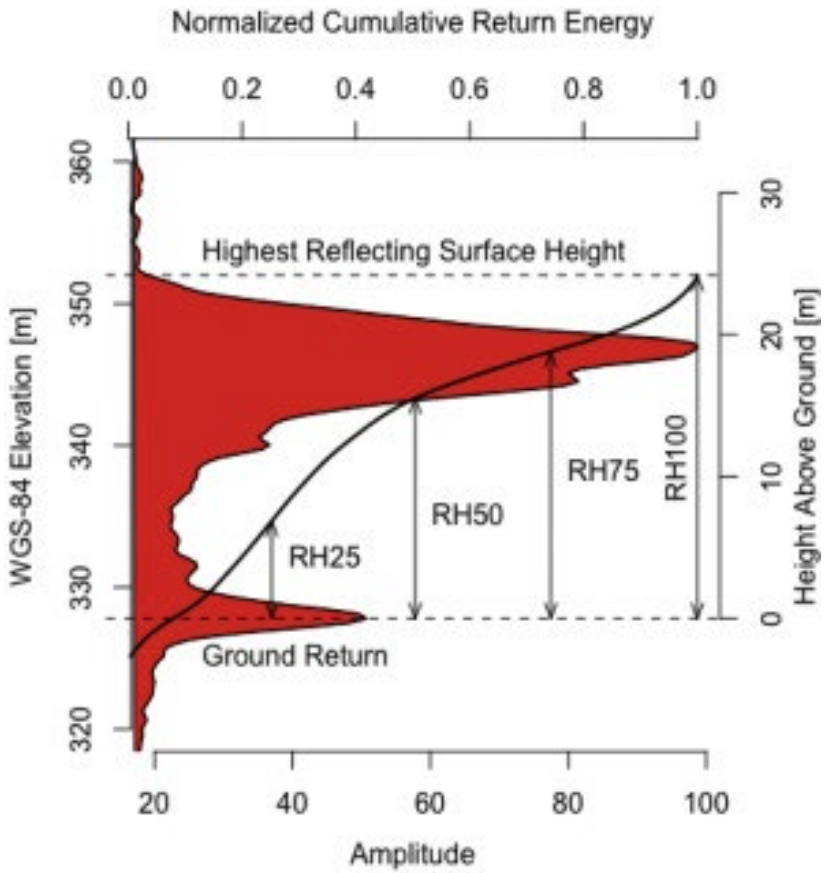
Comparison of data quality between GEDI and TECIS



Comparison of forest parameter accuracy of GEDI and TECIS

Overview of Research Proceeding (Spaceborne LiDAR for Forest Application-China)

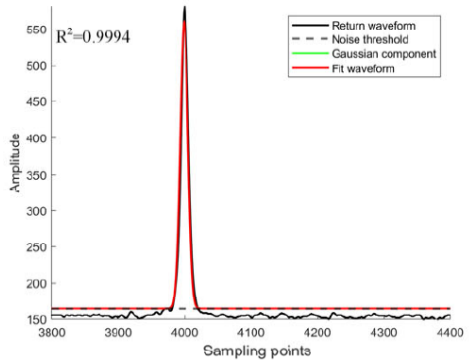
- **There is still a lack of automated method for effective signal recognition for spaceborne large footprint full waveform LiDAR**



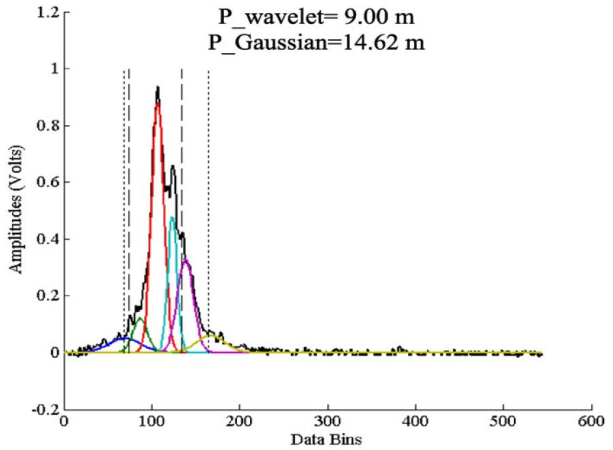
Spaceborne LiDAR for canopy height estimation

Empirical threshold(Zhang et al., 2025)

$$T_k = mean_{noise} + k \times \sigma_{noise}$$



Gaussian decomposition method(Wang et al., 2016)



GLAS: k values of 3~5□ (Qi Chen, 2010)

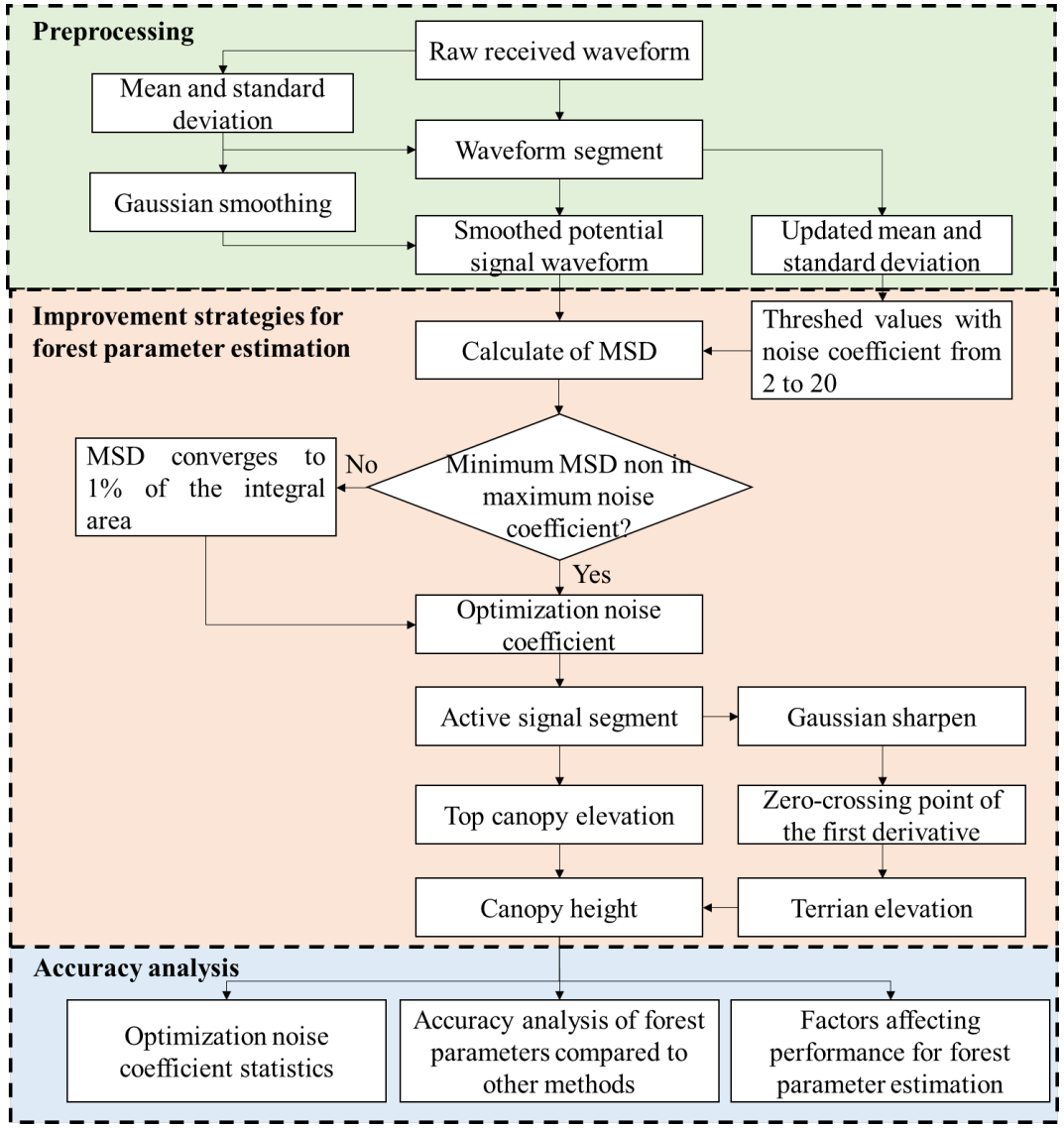
GEDI: k values of 2~6□ (Dubayah et al., 2022)

TECIS: k values of 2~12□ (Liang et al., 2025)

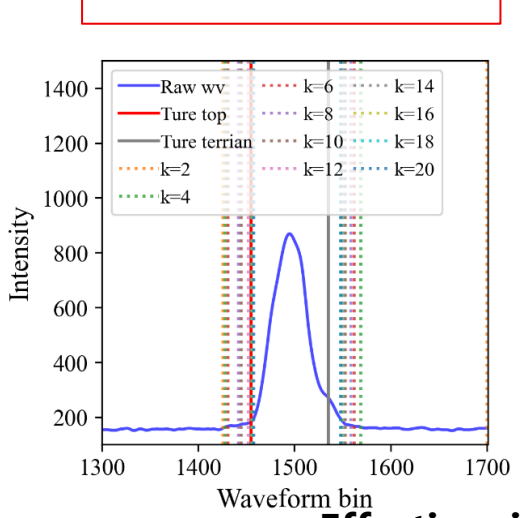
GF-7:k values of 3□ (Du et al., 2024)

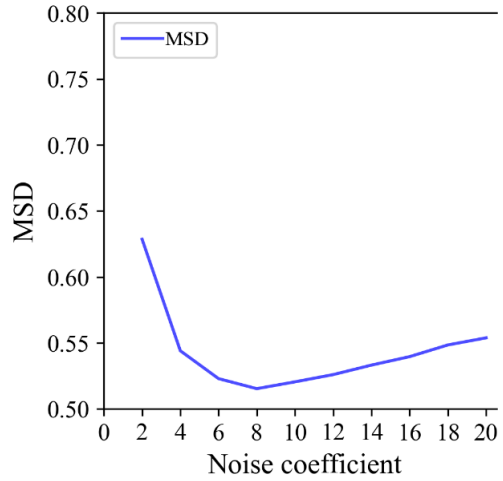
k values for different spaceborne LiDAR

Overview of Research Proceeding (Spaceborne LiDAR for Forest Application-China)



$$T_k = mean_{\text{noise}} + k \times \sigma_{noise}$$

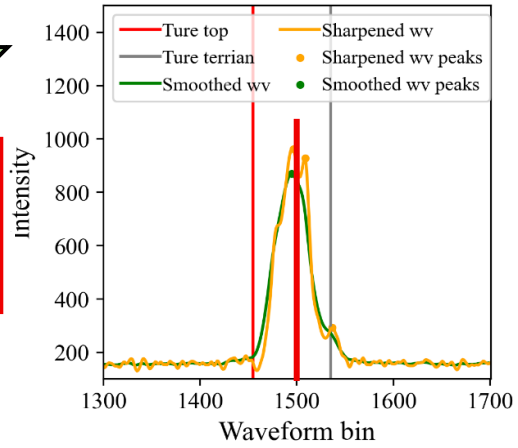




Effective signal recognition

$$F^{(n)}(x) = f(x)g^{(n)}(x)$$

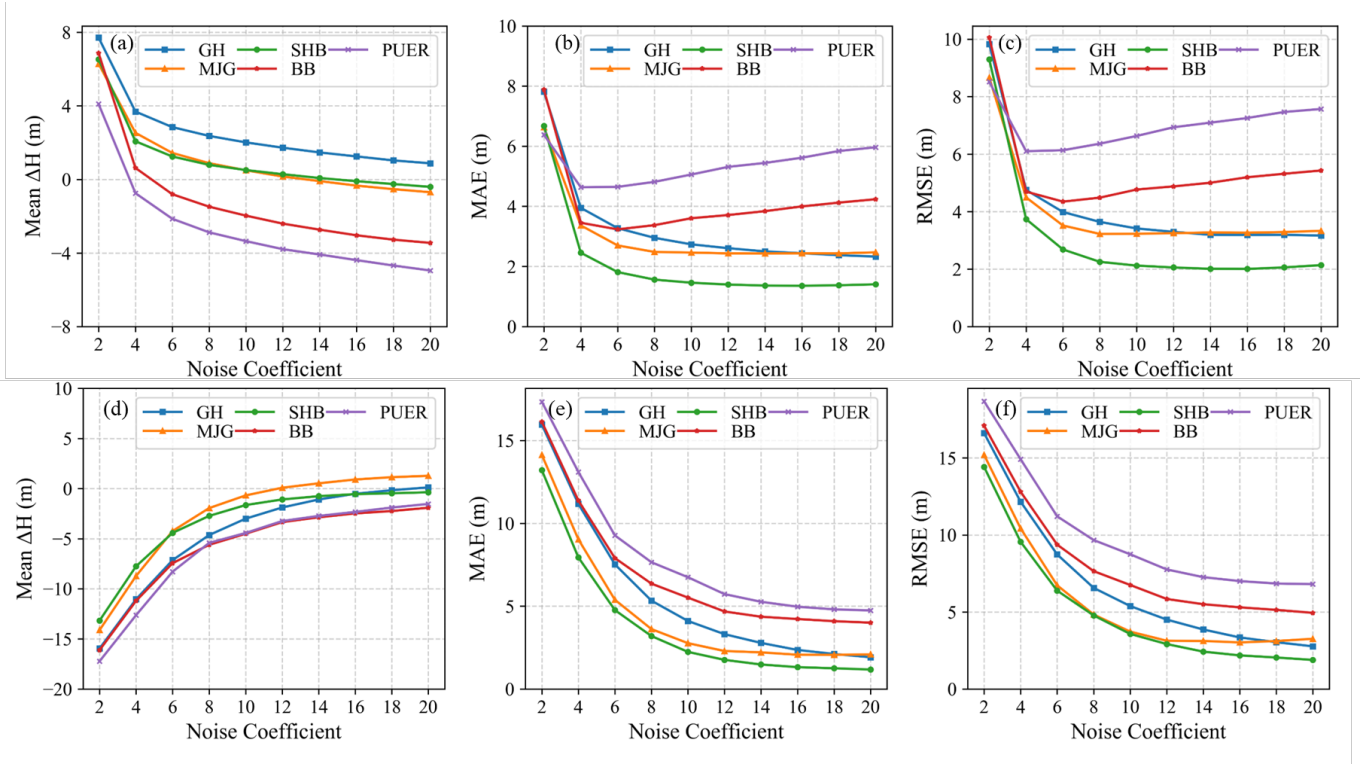
$$g^{(n)}(x) = Gaussian(x) - \mathrm{r}\ Gaussian^{(n)}(x)$$

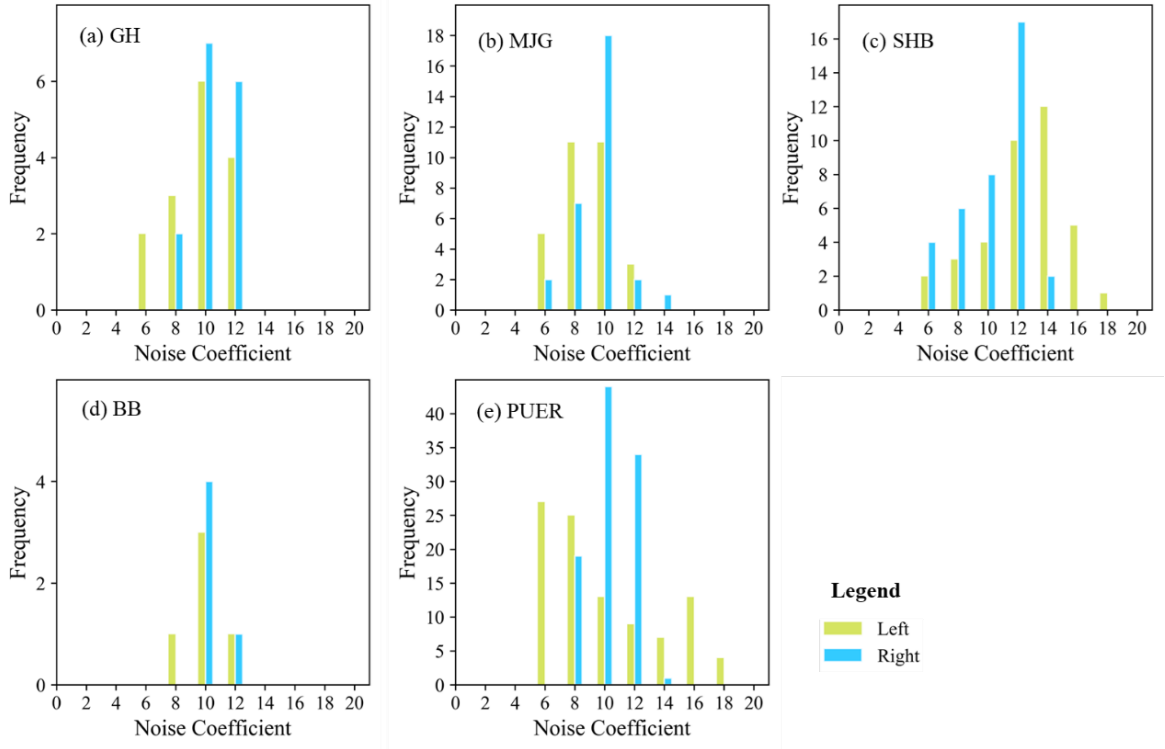


Ground location recognition

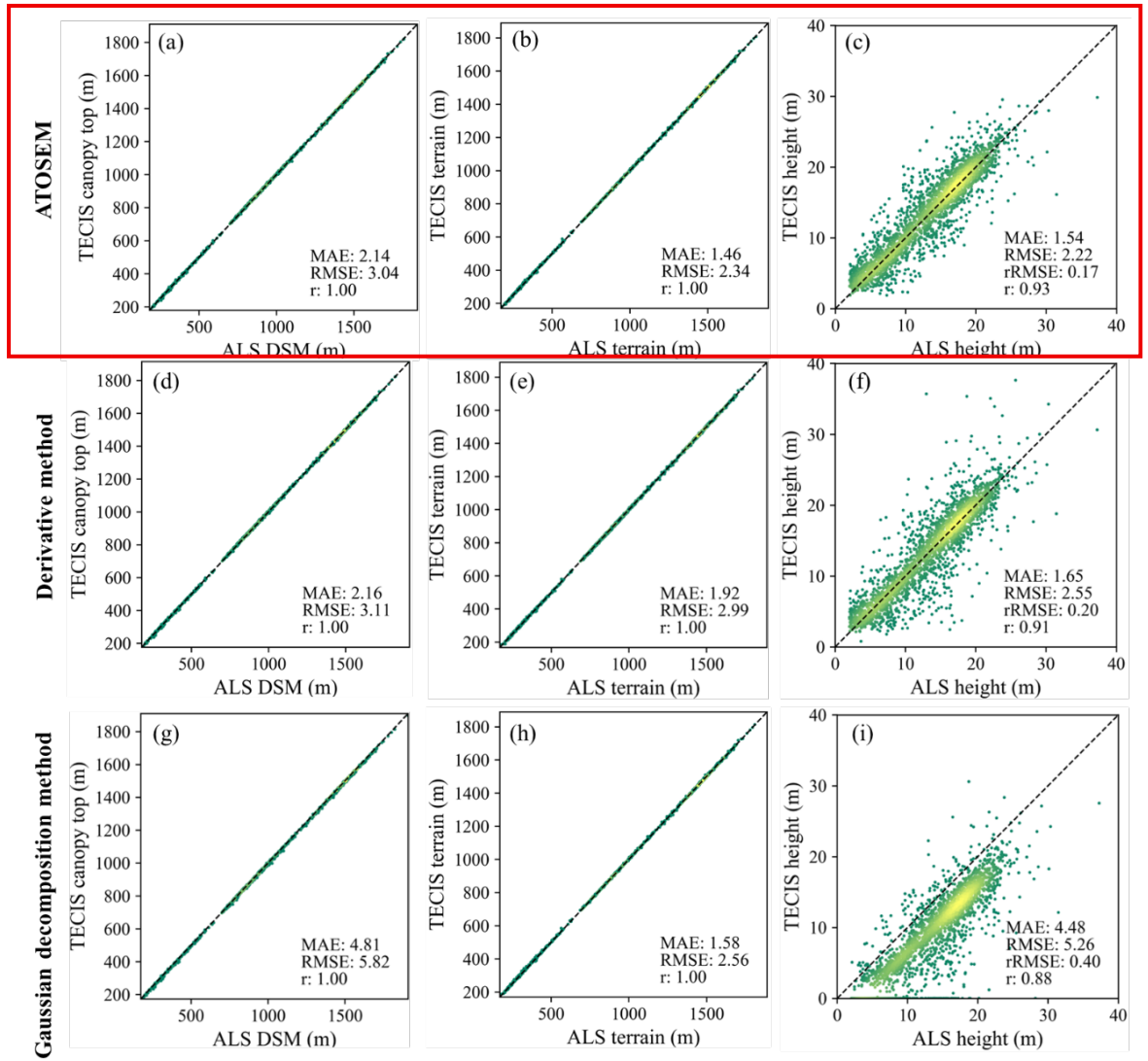
Overview of Research Proceeding (Spaceborne LiDAR for Forest Application-China)

- Noise coefficient can cause a 2–8 m on the canopy top estimation while 12–13 m for terrain.
- There is 0–4 for forward while 2–10 for backward noise coefficients compared to the empirically optimal noise coefficients.





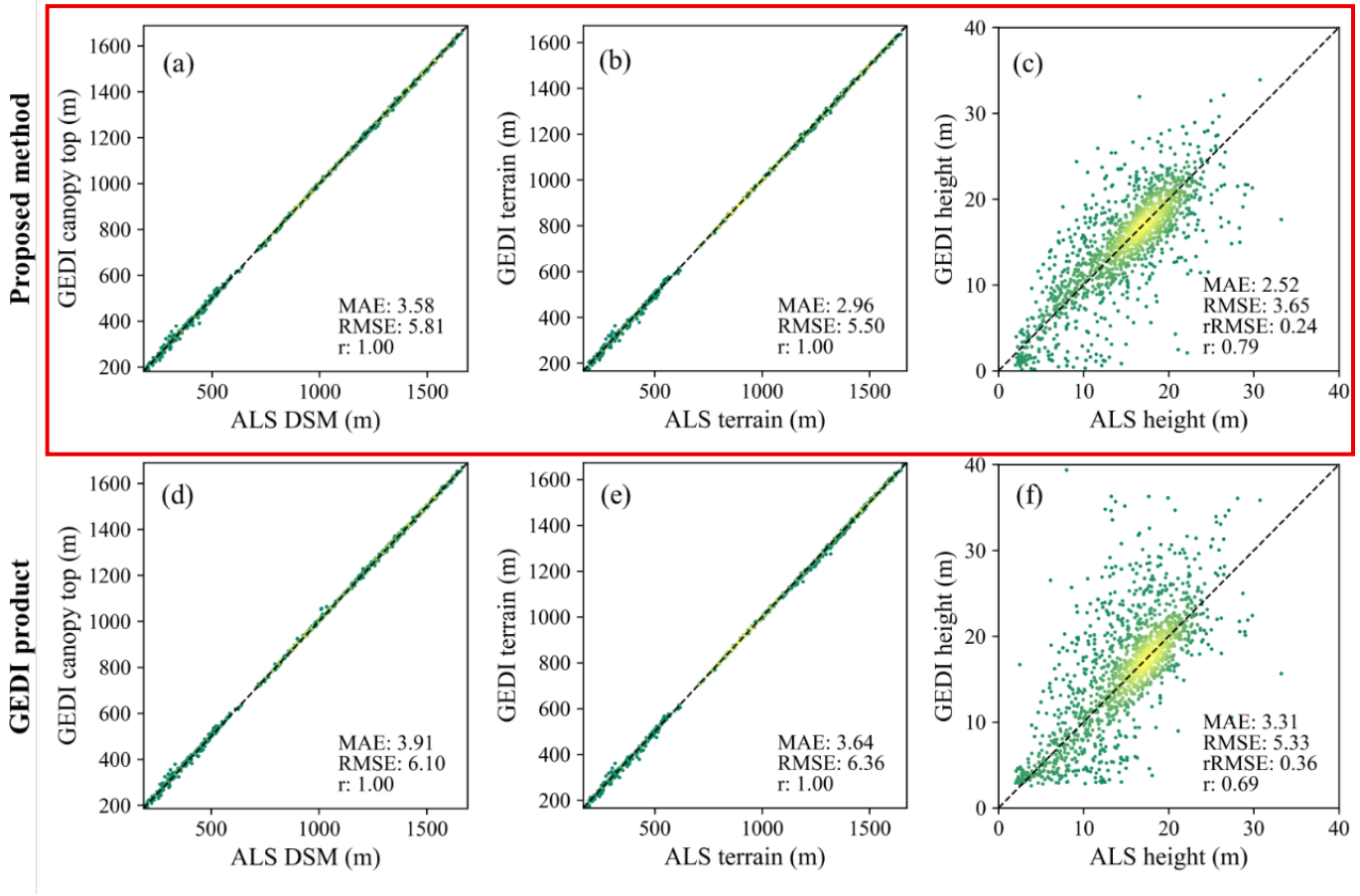
Overview of Research Proceeding (Spaceborne LiDAR for Forest Application-China)



Sites	Method	Metrics	Canopy top (m)	Terrian (m)	Height (m)
GH	Proposed method	MAE	2.68	**1.4**	1.69
		RMSE	3.38	**1.94**	2.34
	Derivative method	MAE	**2.5**	2.12	**1.47**
		RMSE	3.19	3.04	**2.14**
	Gaussian decomposition method	MAE	4.02	1.46	4.04
		RMSE	4.99	2.02	4.66
MJG	Proposed method	MAE	**2.45**	**2.05**	**1.66**
		RMSE	3.27	**3.02**	**2.03**
	Derivative method	MAE	**2.45**	2.31	2
		RMSE	**3.26**	3.15	2.89
	Gaussian decomposition method	MAE	5.04	2.38	5.08
		RMSE	6.07	3.68	5.82
SHB	Proposed method	MAE	**1.36**	**1.02**	**1.21**
		RMSE	**2.03**	**1.65**	**1.72**
	Derivative method	MAE	1.4	1.25	1.32
		RMSE	2.14	2.05	2.02
	Gaussian decomposition method	MAE	4.73	1.11	4.33
		RMSE	5.32	1.82	4.93
BB	Proposed method	MAE	**3.82**	**3.75**	3.73
		RMSE	**5.24**	**5.06**	4.64
	Derivative method	MAE	4.82	4.27	**3.15**
		RMSE	6.24	5.48	**4.16**
	Gaussian decomposition method	MAE	8.46	4.25	7.35
		RMSE	9.83	5.68	8.46
PUER	Proposed method	MAE	4.23	**3.38**	**3.41**
		RMSE	5.47	**4.85**	**4.34**
	Derivative method	MAE	**3.94**	4.15	4.7
		RMSE	**5.22**	5.77	6.03
	Gaussian decomposition method	MAE	8.7	3.82	6.49
		RMSE	10.15	5.42	7.87

Overview of Research Proceeding (Spaceborne LiDAR for Forest Application-China)

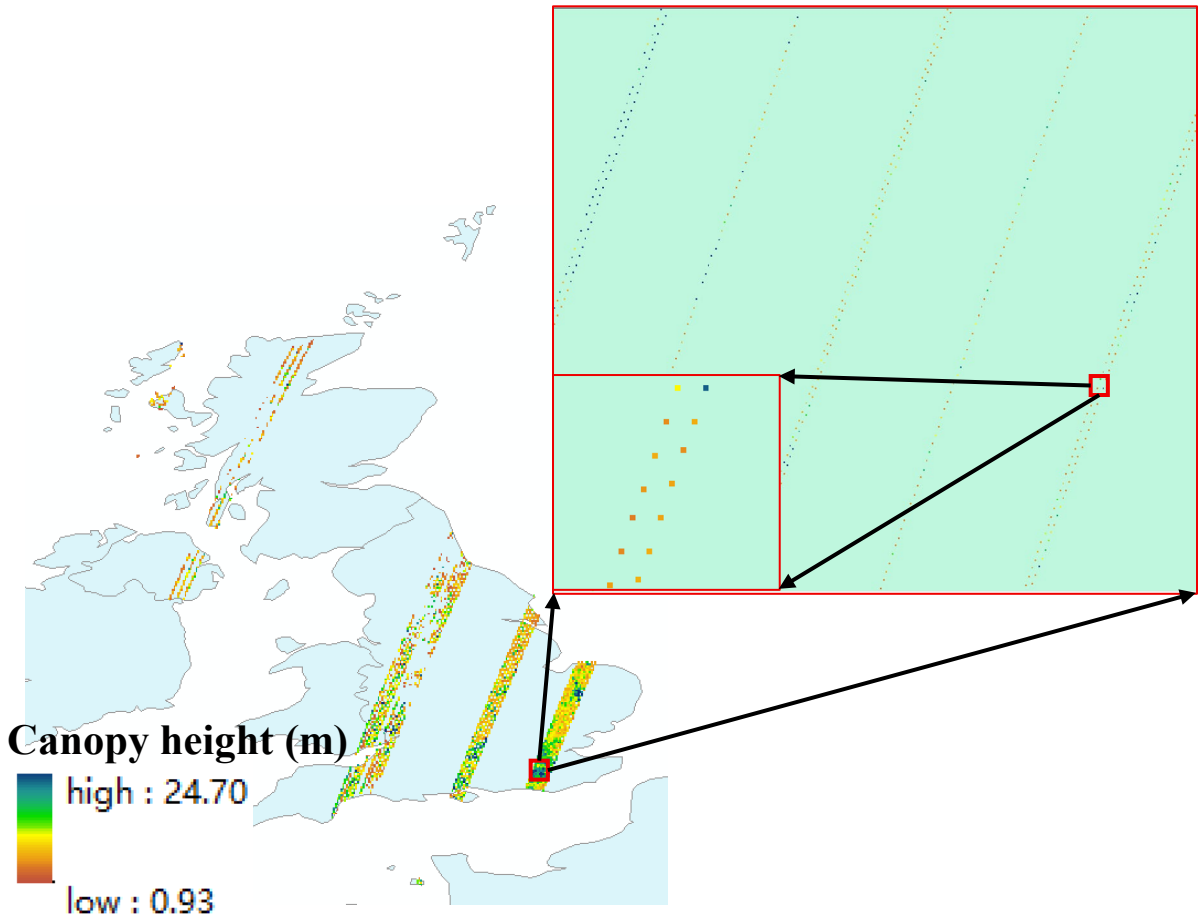
- **Compared to GEDI's optimal algorithm, the proposed method effectively reduces RMSE by 1.5 m and rRMSE by 12%.**

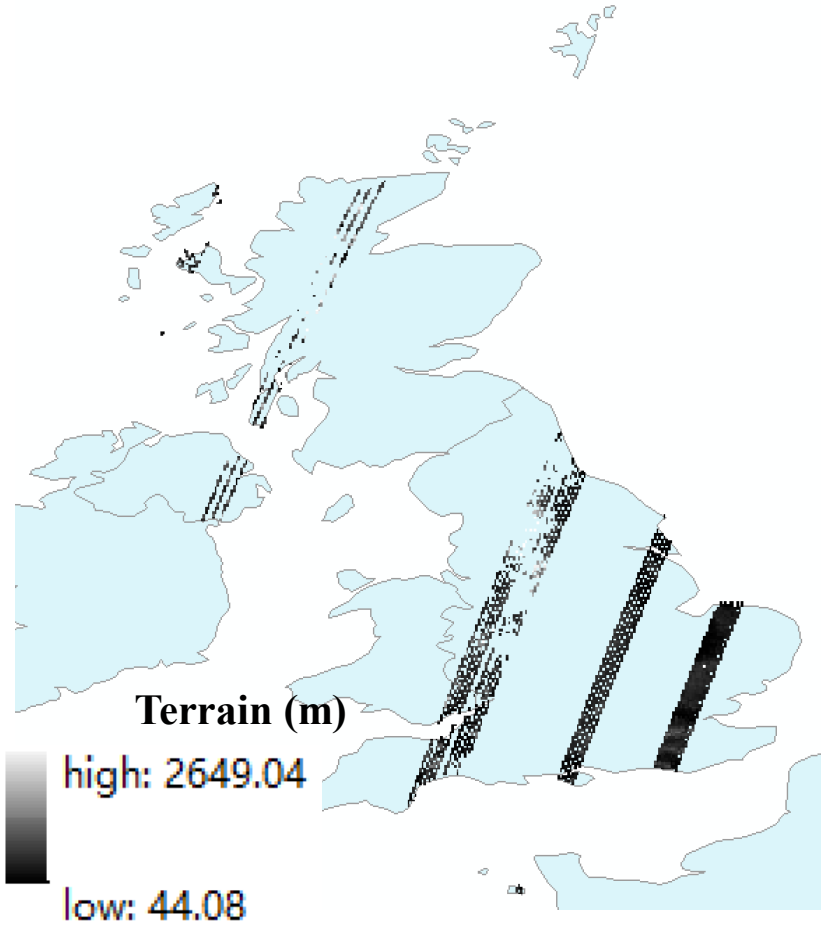


Sites	Method	Metrics	Canopy top (m)	Terrain (m)	Canopy height (m)
GH	Proposed method	MAE	**2.48**	**1.47**	**1.90**
		RMSE	**3.57**	**2.25**	**2.93**
	GEDI product	MAE	3.00	1.65	2.04
		RMSE	4.83	2.50	4.55
MJG	Proposed method	MAE	**2.01**	2.03	1.97
		RMSE	**2.73**	2.95	2.64
	GEDI product	MAE	2.16	1.95	1.91
		RMSE	3.10	2.91	2.39
SHB	Proposed method	MAE	**2.17**	**1.52**	**1.78**
		RMSE	**3.07**	**2.25**	**2.72**
	GEDI product	MAE	2.77	2.10	2.24
		RMSE	3.44	2.99	3.38
BB	Proposed method	MAE	**6.28**	**5.70**	**4.27**
		RMSE	**8.08**	**7.87**	**5.44**
	GEDI product	MAE	6.54	6.12	4.83
		RMSE	8.28	8.26	6.08
PUER	Proposed method	MAE	**3.52**	**4.08**	**4.54**
		RMSE	**4.49**	**5.51**	**5.78**
	GEDI product	MAE	6.31	6.25	4.51
		RMSE	7.99	8.05	5.83

Overview of Research Proceeding (Spaceborne LiDAR for Forest Application-China)

- **Using TECIS LiDAR to extracting forest height and terrain.**





Overview of Research Proceeding (Spaceborne LiDAR for Forest Application-China)

- **A deep neural network was established, using footprint-level aboveground carbon density (ACD) as the pivot, to map wall-to-wall forest ACD.**

ALS carbon

↓

TECIS waveform parameters

↓

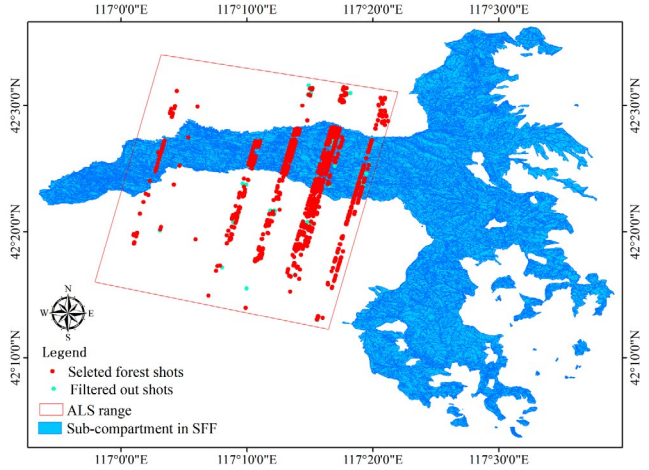
Footprint ACD values

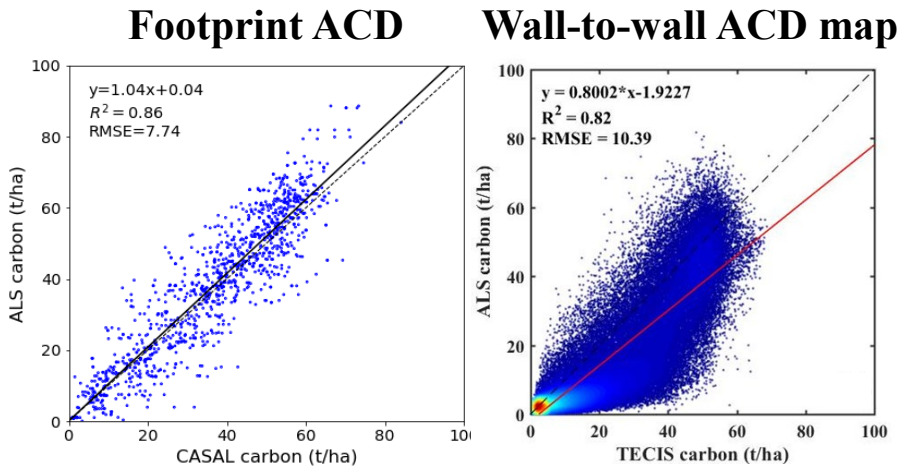
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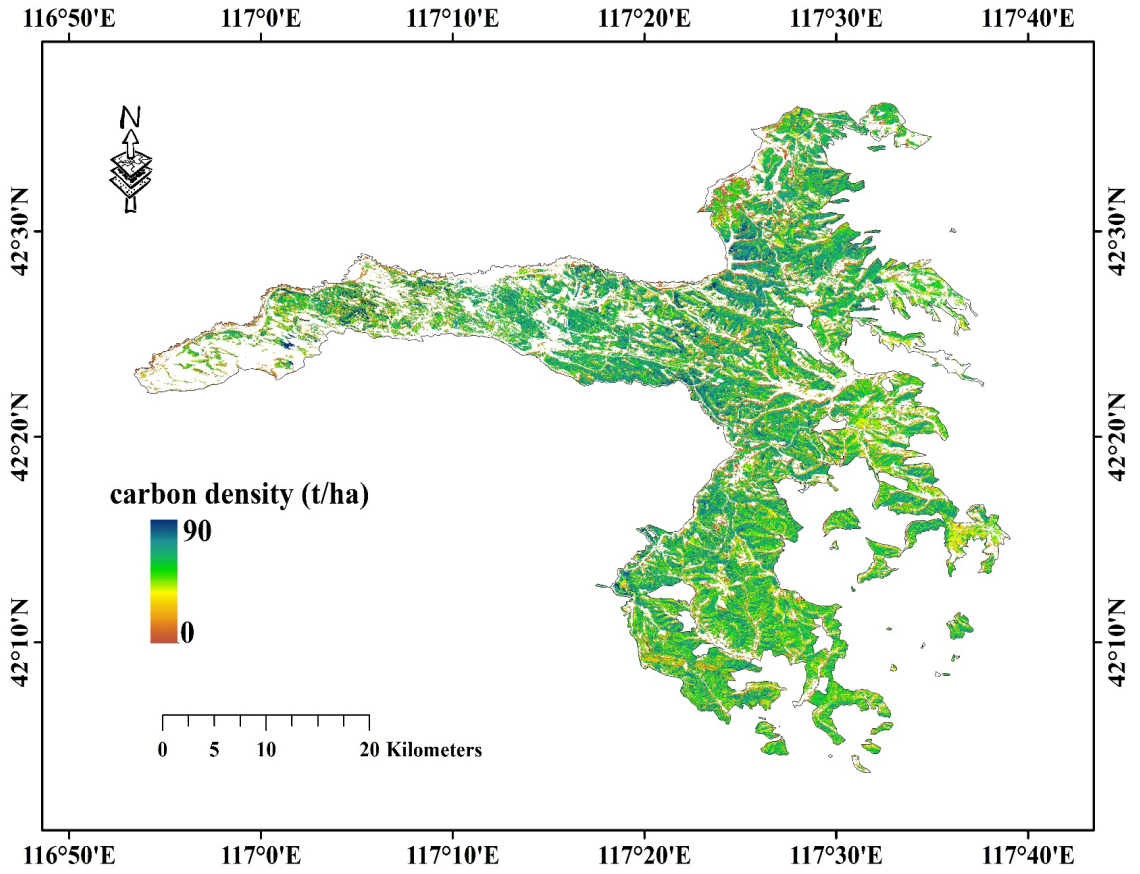
Integrating optical images and footprint ACD

↓

Wall-to-wall forest ACD







Overview of Research Proceeding (Forest Disturbance and its Classification-China)

Thinning



Selective Canopy Thinning



Clear-Cutting





Growth-Enhancing Silviculture



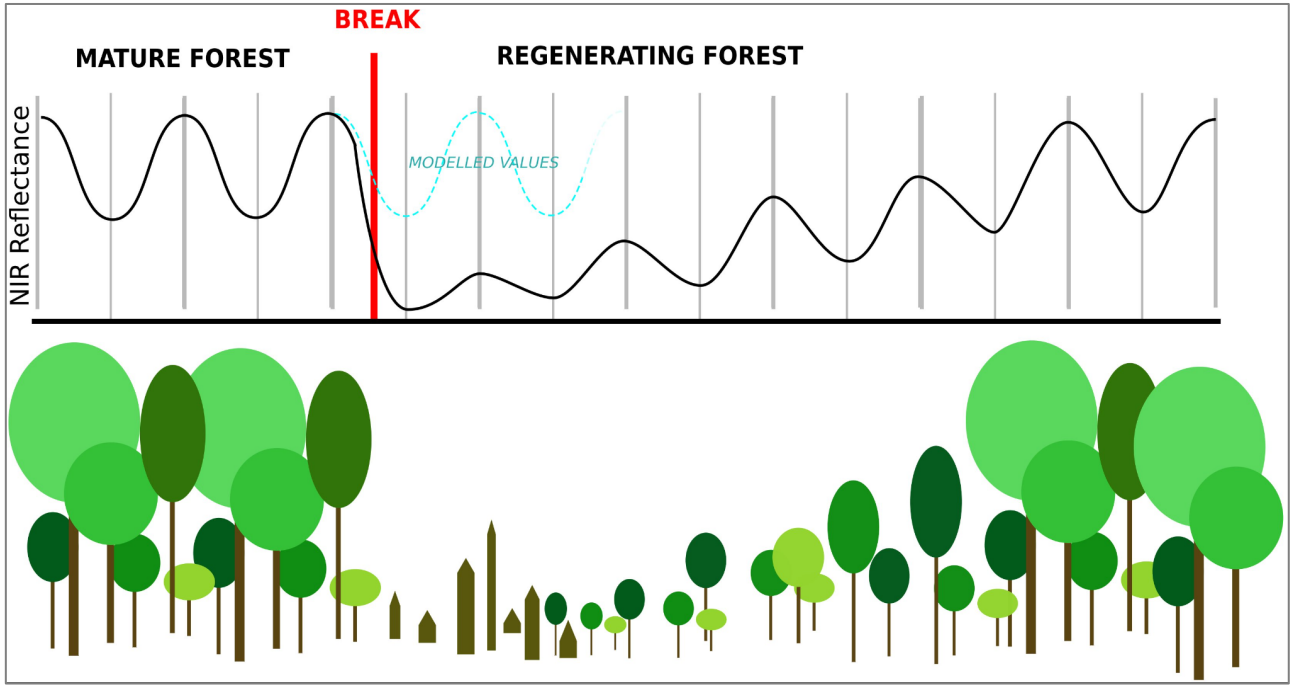
Canopy Opening



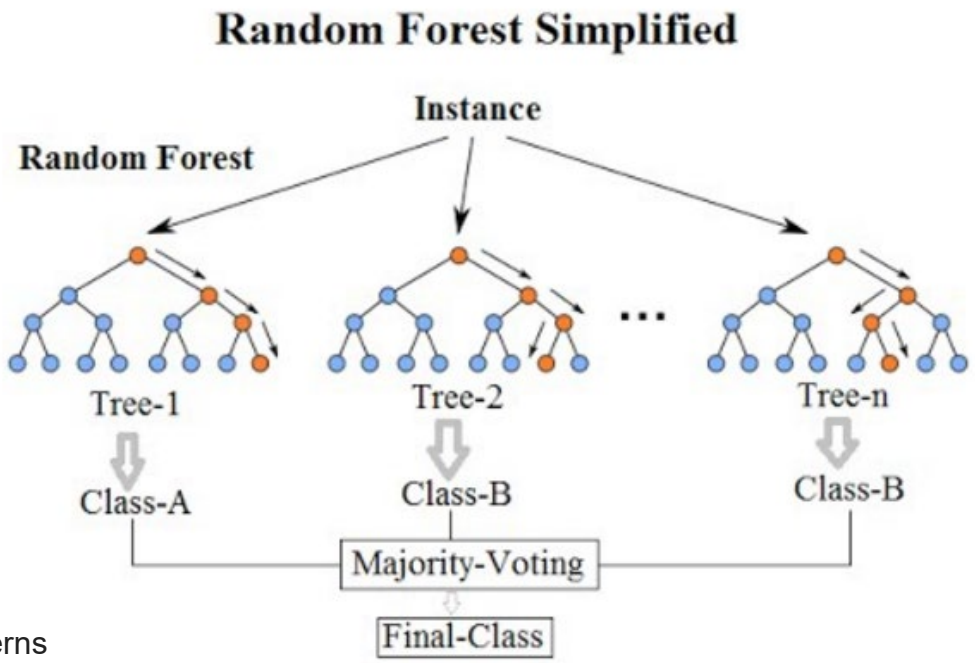
Ecological Thinning



Overview of Research Proceeding (Forest Disturbance and its Classification-China)



Near-real time disturbance detection using time series looks for breaks from modelled seasons patterns in forest reflectance. The nrt Python package implements several algorithms that rely on this concept. © European Union, 2022; Jonas Viehweger.

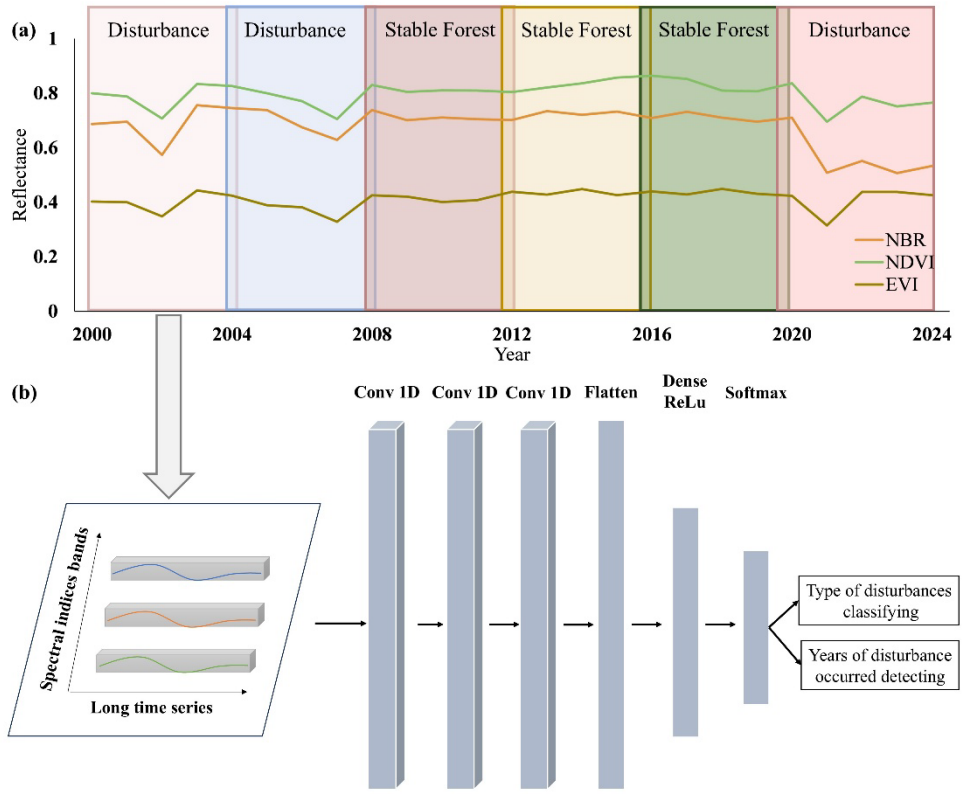


Overview of Research Proceeding (Forest Disturbance and its Classification-China)

1. **Convolutional layers (1D-CNN):** three one-dimensional convolutional layers, 64 convolution kernels.
2. **No pooling layer:** the role of the pooling layer is to reduce the resolution of the features, which will reduce the classification performance
3. **Fully convolutional layer:** further feature extraction and classification.
4. **Log-Softmax layer:** generated classification probability distribution

Hyperparameters	TempCNN
Learning rate	0.001
Batch size	32
Optimizer	Adam
Loss function	Cross Entropy
Data augmentation	No
Dropout	0.4
Num epochs	240
Kernel size	3

- The architecture of TempCNN, including three convolutional layers, followed by a fully convolutional layer and a Softmax layer.

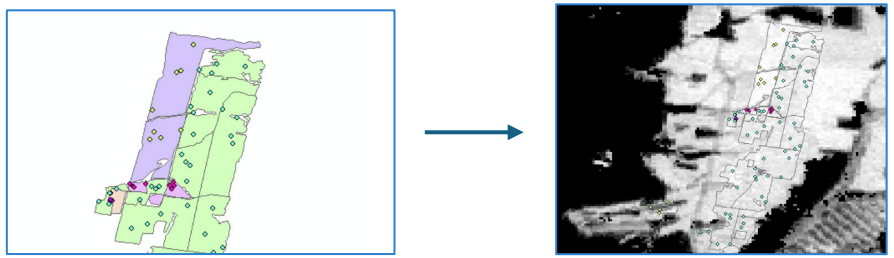


Overview of Research Proceeding (Forest Disturbance and its Classification-China)

Disturbance reference data

- Sub-compartment map
- Random points were selected within each sample plot polygon (50m)
- Calculating NBR, NDVI, EVI



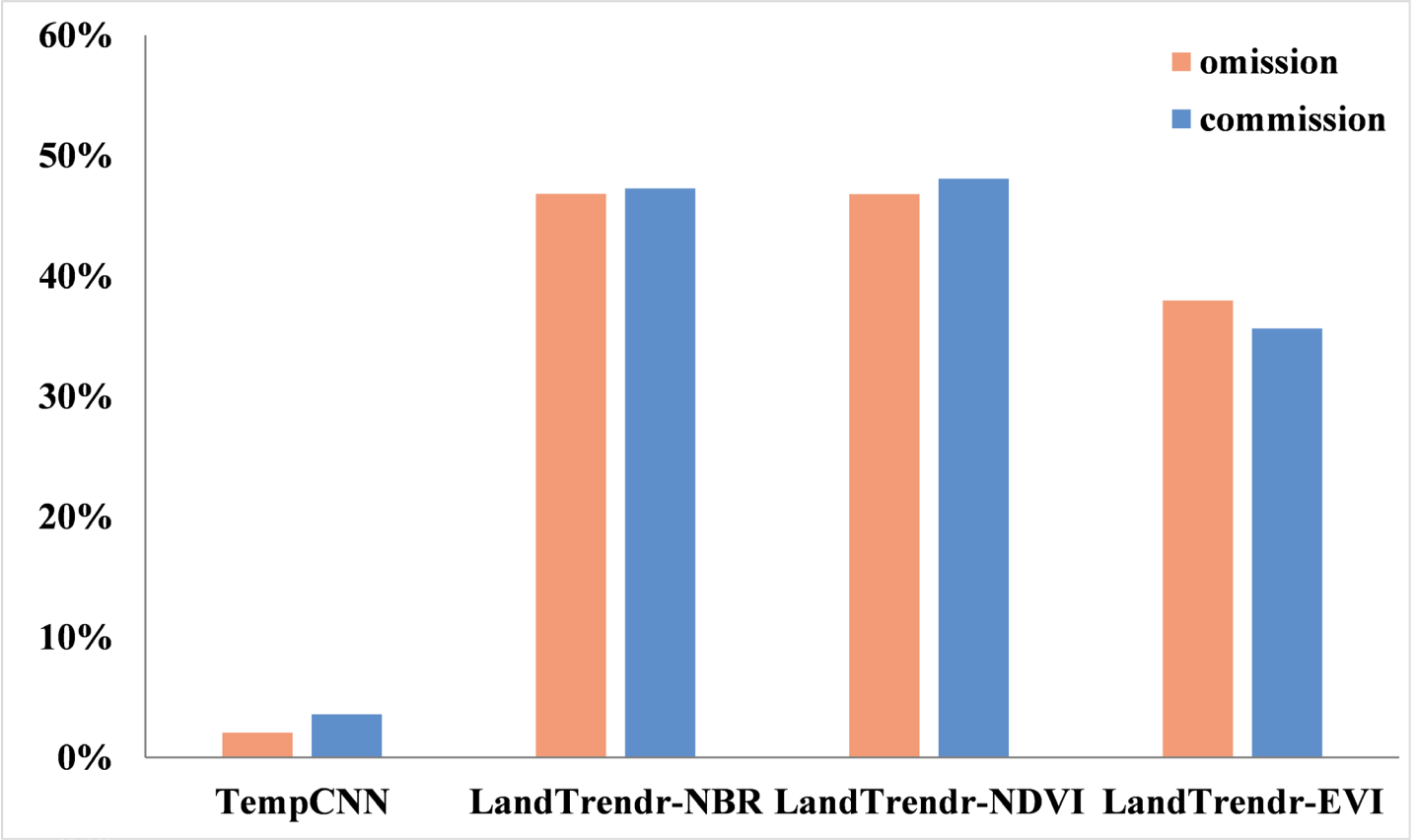


Type of disturbances	The total area/ha (forest sub-compartment map)	Count
Thinning	236.31	174
Clear-Cutting	117.65	172
Canopy Opening	95.28	103
Selective Canopy Thinning	345.02	125
Growth-Enhancing Silviculture	201.59	110
Ecological Thinning	950.51	348
Forest Closure and Natural Regeneration	546.744	118
Stable forest	\	100
Total	2493.11	1250

Overview of Research Proceeding (Forest Disturbance and its Classification-China)

Models accuracy

- TempCNN
  - Omission: 2.10%
  - Commission: 3.59%



TempCNN				LandTrendr-NBR				LandTrendr-NDVI				LandTrendr-EVI			
Kappa	MSE	RMSE	MAE	Kappa	MSE	RMSE	MAE	Kappa	MSE	RMSE	MAE	Kappa	MSE	RMSE	MAE
0.75	1.41	1.12	0.84	0.29	13.13	3.61	2.40	0.17	3.79	1.94	1.45	0.30	38.93	6.22	3.99

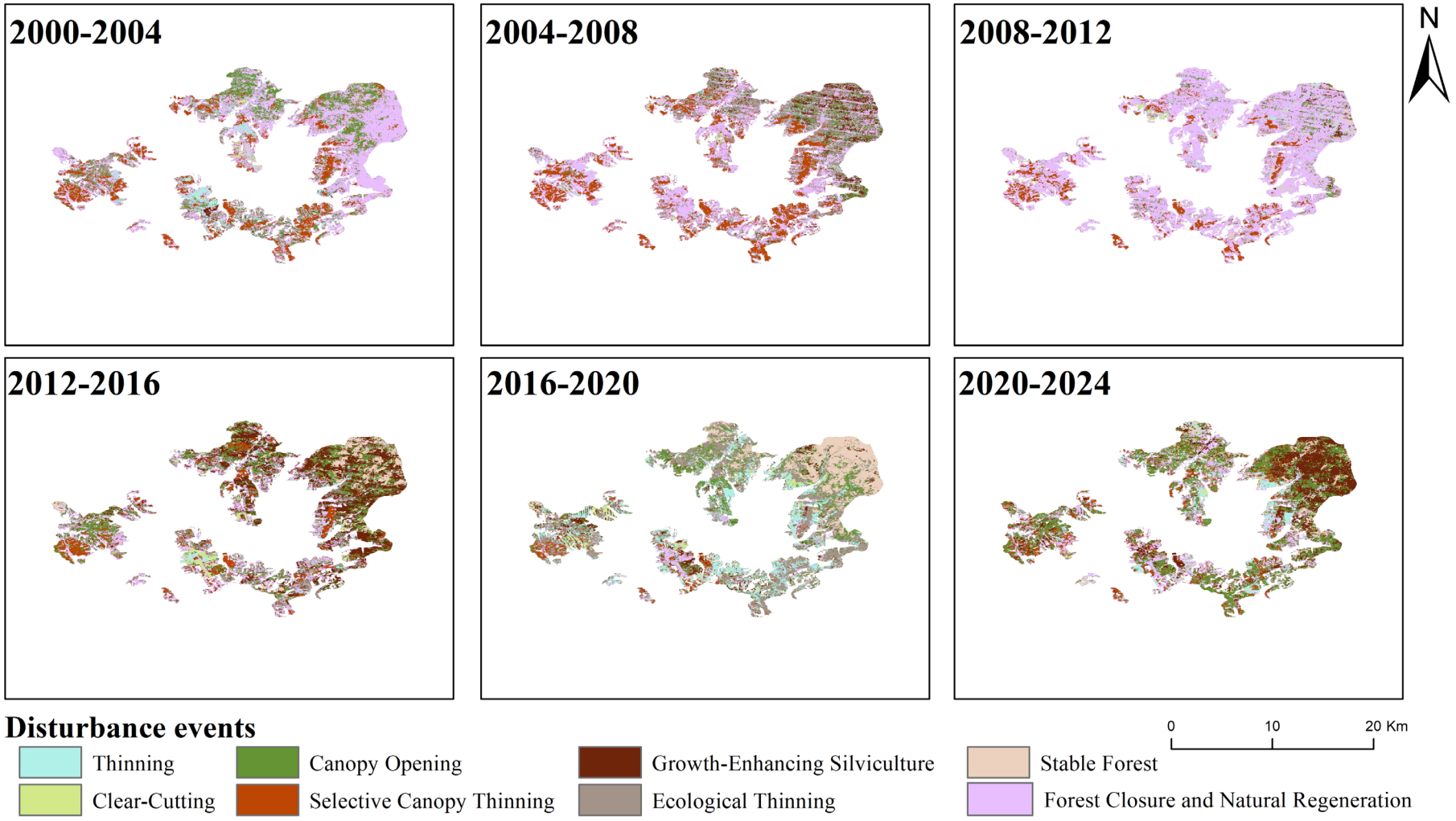
Overview of Research Proceeding (Forest Disturbance and its Classification-China)

Year of disturbance accuracy

Type	TempCNN				LandTrendr-NBR				LandTrendr-NDVI				LandTrendr-EVI			
	Kappa	MSE	RMSE	MAE	Kappa	MSE	RMSE	MAE	Kappa	MSE	RMSE	MAE	Kappa	MSE	RMSE	MAE
Thinning	0.71	0.51	0.63	0.31	0.21	1.38	1.17	0.93	0.07	1.75	1.31	1.12	0.24	1.13	1.04	0.85
Clear-Cutting	**0.95**	**0.15**	**0.27**	**0.07**	0.19	1.34	1.14	0.86	0.22	2.27	1.48	1.17	0.28	1.96	1.39	1.14
Canopy Opening	0.67	0.19	0.30	0.13	0.10	1.64	1.21	1.00	0.13	1.40	1.15	0.99	0.16	1.01	0.99	0.82
Selective Canopy Thinning	0.64	0.19	0.36	0.19	0.01	1.64	1.25	0.95	0.01	2.96	1.66	1.23	0.02	2.46	1.55	1.11
Growth-Enhancing Silviculture	0.51	1.14	1.02	0.70	0.17	1.92	1.35	1.07	0.11	2.68	1.63	1.36	0.13	1.93	1.35	1.10
Ecological Thinning	0.58	0.62	0.76	0.37	0.06	2.00	1.41	1.13	0.09	2.08	1.44	1.20	0.10	1.48	1.21	0.96
Forest Closure and Natural Regeneration	0.71	0.60	0.76	0.34	0.30	7.43	2.70	1.85	0.24	6.62	2.54	1.75	0.33	5.71	2.34	1.72

Overview of Research Proceeding (Forest Disturbance and its Classification-China)

Forest disturbance maps



Summary and Outlook

For the first year, we've developed method for:

(1) Integrating of multi-platform LiDAR and optical imageries for forest parameter extraction;

(2) Forest dynamics classification and prediction.

For the next year, we'll focus on:

(1) Strengthening the China-Europe scientific collaboration network;

(2) Developing methods for time series imagery, phenology, and national-level upscaling.



Thank you!