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Forest Carbon Monitoring

Algorithm evaluation and comparison

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Forest carbon monitoring

Two primary approaches available for forest biomass and carbon monitoring*:

- *Stock-difference approach*, where mean annual carbon emissions or removals are estimated as the ratio of the difference in carbon stock estimates at two points in time and the number of intervening years (GFOI 2016, Chap. 3), (Eggleston et al.. 2006, Vol. 4, Chap. 3).
- *Gain-loss approach*, emissions are estimated as differences between additions to and removals from carbon pools. Specifically, emissions are estimated as the product of activity data defined as the areas of “human activity causing emissions and removals” and emissions factors defined as the per unit area responses of carbon stocks for those activities (GFOI 2016, pp. xvii, 22), (Eggleston et al. 2006, Vol. 1, Chap. 1, Sect. 1.2).

*McRoberts et al., 2020, Remote Sensing Support for the Gain-Loss Approach for Greenhouse Gas Inventories ' , Remote Sensing , vol. 12 , no. 11 , 1891

Forest inventory with Earth Observation data

- Forest inventories provide detailed information about the current state of the forest and its change.
- Information can reported, e.g., on sample unit level (plots), on forest compartment level, other small-area or large-area level.
- Forest variables: forest tree height, canopy closure, tree species, growing stock volume, diameter at breast height, basal area.
- Data sources “traditionally” used in connection with forest inventories: aerial images, field survey, ALS data

Use of satellite Earth Observation data as auxiliary data along with plot-level data:

- allows to increase precision of estimation compared to using only forest plots;
- enables estimation for small areas when the plot sample size does not allow direct estimation;
- allows producing estimates in remote or hardly accessible areas;
- enables producing wall-to wall maps with reference information key for model training and uncertainty quantification.

Image source: Google Earth, forest information: Metsäkeskus and National Land Survey, 2015

Three main pathways in the algorithm evaluation in the Forest Carbon Monitoring project

Field reference: Company plots, NFI plots

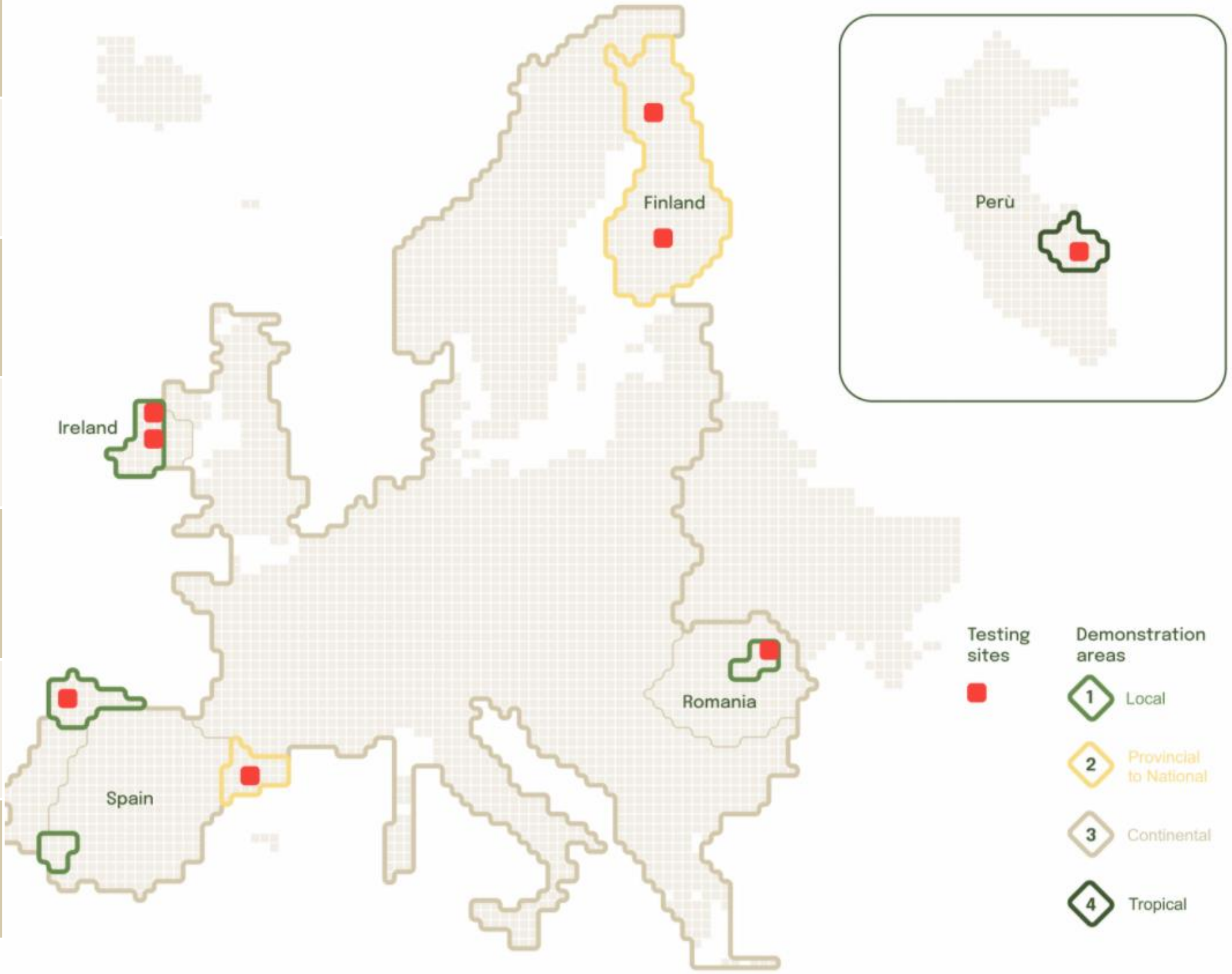
EO data: Sentinel-2, Sentinel-1, ALOS-2 PALSAR-2, TanDEM-X, LiDAR, VHR imagery

Auxiliary data: Copernicus products, climatic data etc.

	Methods	Outputs
1 Forest variable and ecosystem modelling	• PREBAS • Data assimilation	Above ground biomass, Below ground biomass, Stem volume increment
	• Probability • K-NN • Finnish MS-NFI • BIOMASAR approach • Support vector • Random forest • Multiple linear regression • SAR/InSAR inversion	Basal area, Diameter, Height Species prop., Site fertility, Growing stock volume
2 Direct volume and biomass estimation	(same methods as above)	Growing stock volume
	• Expansion factors	Above ground biomass, Below ground biomass
3 Change detection	• AutoChange • Radiometric texture • TanDEM-X InSAR height	Change type, Change intensity

Testing sites

Site	Country	Forest types	Climate zone	Topography
1	Finland	Semi-natural coniferous and broadleaf	Arctic	Hilly
2	Finland	Semi-natural coniferous and broadleaf	Boreal	Gently undulating
3	Ireland	Mainly coniferous plantations, some broadleaf	Atlantic	Gently undulating
4	Romania	Semi-natural coniferous and broadleaf	Temperate/ Continental	Hilly
5	Spain	Eucalypt plantations, some natural forests	Atlantic	Hilly
6	Spain	Semi-natural coniferous and broadleaf	Mediterranean	Hilly to Mountainous
7	Peru	Amazonian evergreen	Tropical	Gently undulating



Forest variable prediction intercomparison

Rationale: Benchmarking presently available satellite image datasets and suitable classification/prediction methodologies to identify

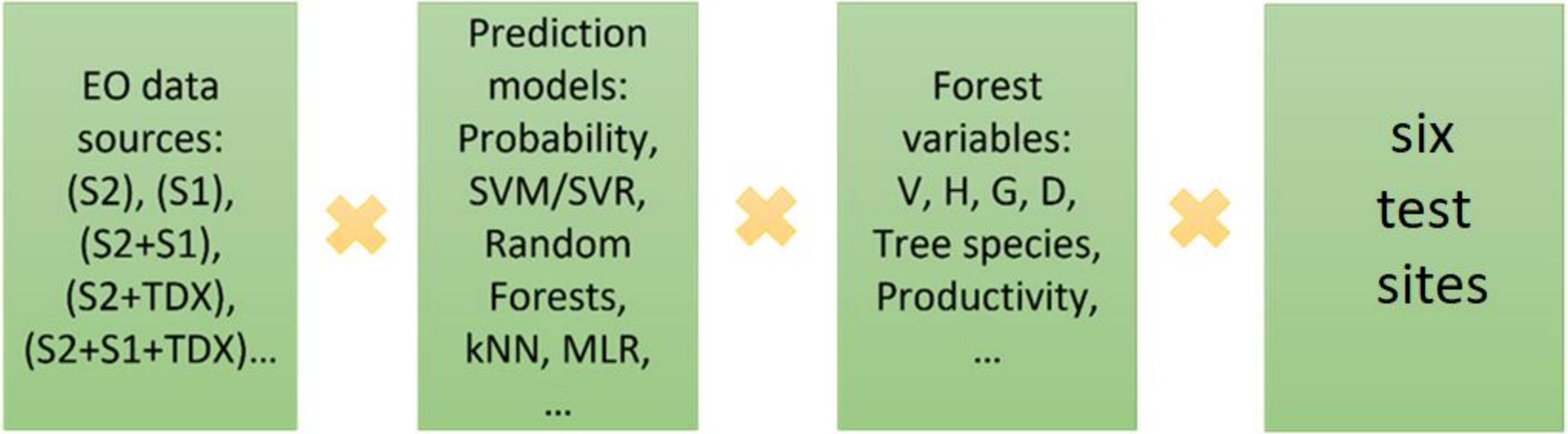


Illustration of studied combinations in the method intercomparison

Sensor image data

- Optical multispectral images
- Synthetic aperture radar images
  - Multitemporal / time-series
  - Multipolarization
  - Interferometric
- Various combinations of SAR and optical images

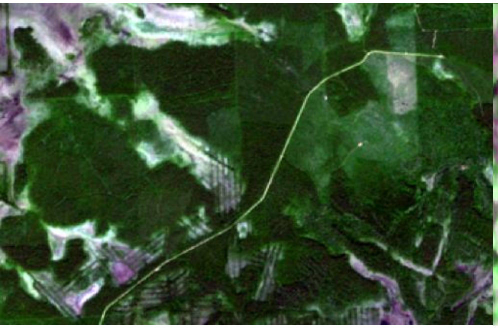
$$I\,(m,x,y) = F\,[\ldots, \{\text{ target properties }\}, \ldots]$$

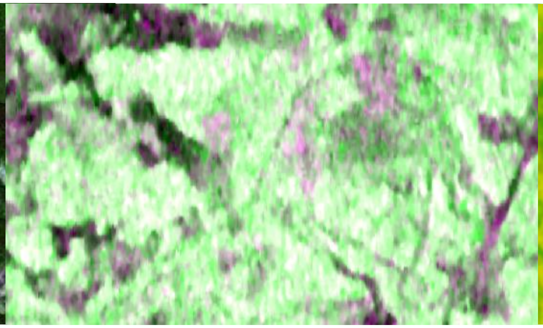
$$\{\text{ target properties }\} = F^{-1}\,[\,I\,(x,y)\,]$$

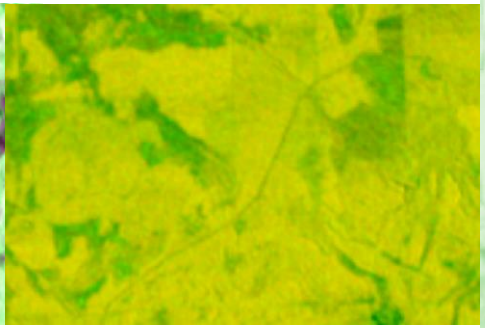
{ target properties} : {volumetric water content, roughness, orientation, vertical structure, density, spatial structure}

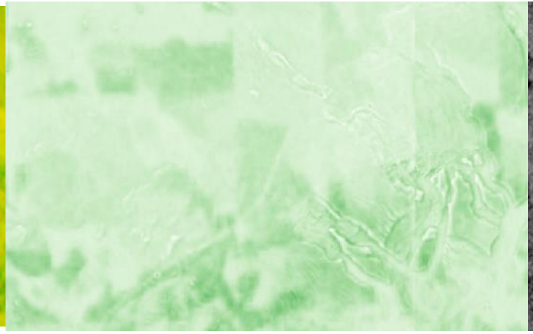
{ forest variables} : {growing stock volume, height, DBH, tree species, …}

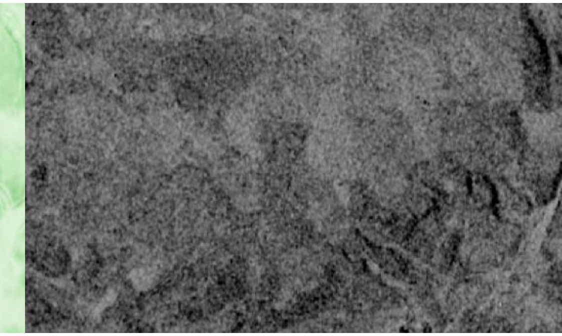
$$\{\text{ forest variables }\} = Z\,[\,I\,(m,x,y)\,]$$


Sentinel-2


ALOS-2 PALSAR-2


Sentinel-1


TanDEM-X InSAR CHM


TanDEM-X coherence

Modelling principles

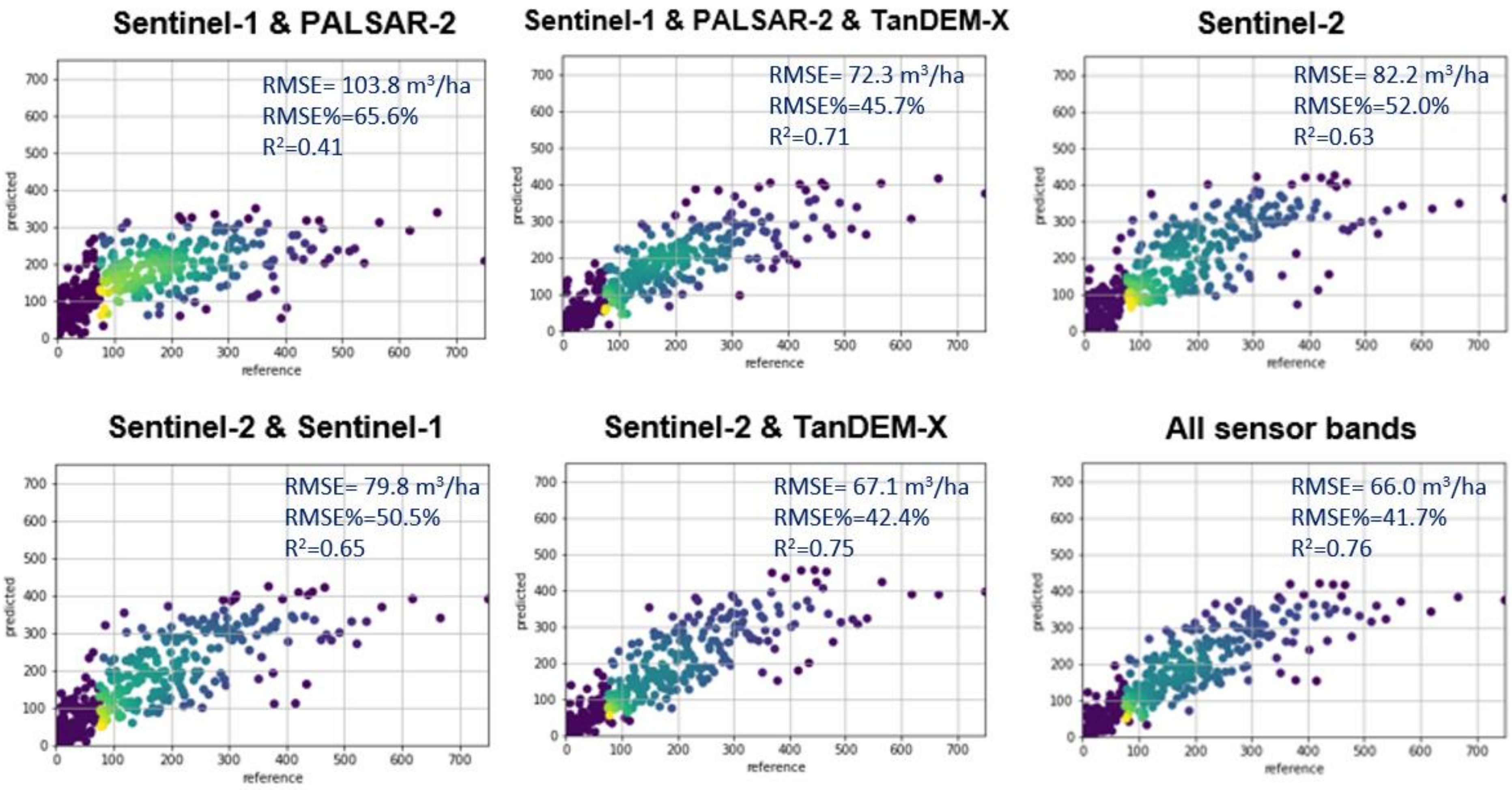
Models describing relationship between forest variables and RS observables:

- physics-based and semi-empirical (motivated by wavelength, resolution, env conditions), reference data used for “calibration”
  - normally suitable for a given sensor/wavelength
    (e.g., InSAR coherence models for vegetation, WCM vegetation)
- Statistical parametric models (partly overlaps with earlier), model fitting is used, reference data are used for teaching models
  - often don’t care about “nature” of EO data
- Non-parametric approaches - completely dependent on reference data
  - normally don’t care about “nature” of EO data
- Semi-supervised approaches - utilize EO data even when reference data are missing

Methodologies for prediction/classification

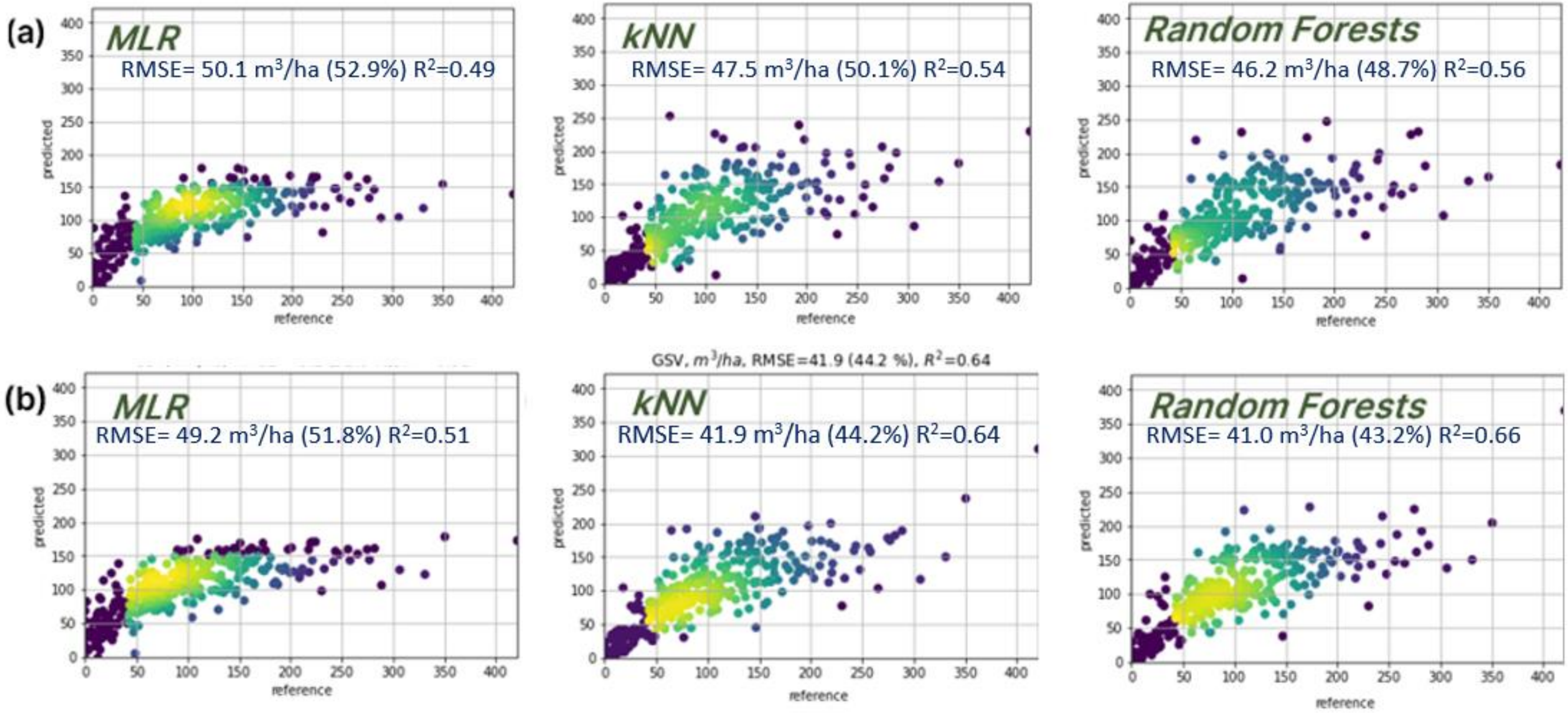
- Parametric, semi-empirical and physics-based models:
  - Water cloud model (WCM) derived
  - Random volume over ground (RVoG) derived
- Statistical parametric methodologies:
  - Multiple linear regression (MLR)
- Machine learning non-parametric methods:
  - kNN,
  - Support vector regression (SVR),
  - Random forests (RF)
- Semisupervised non-parametric methods:
  - Probability

EO data intercomparison: SAR and optical images



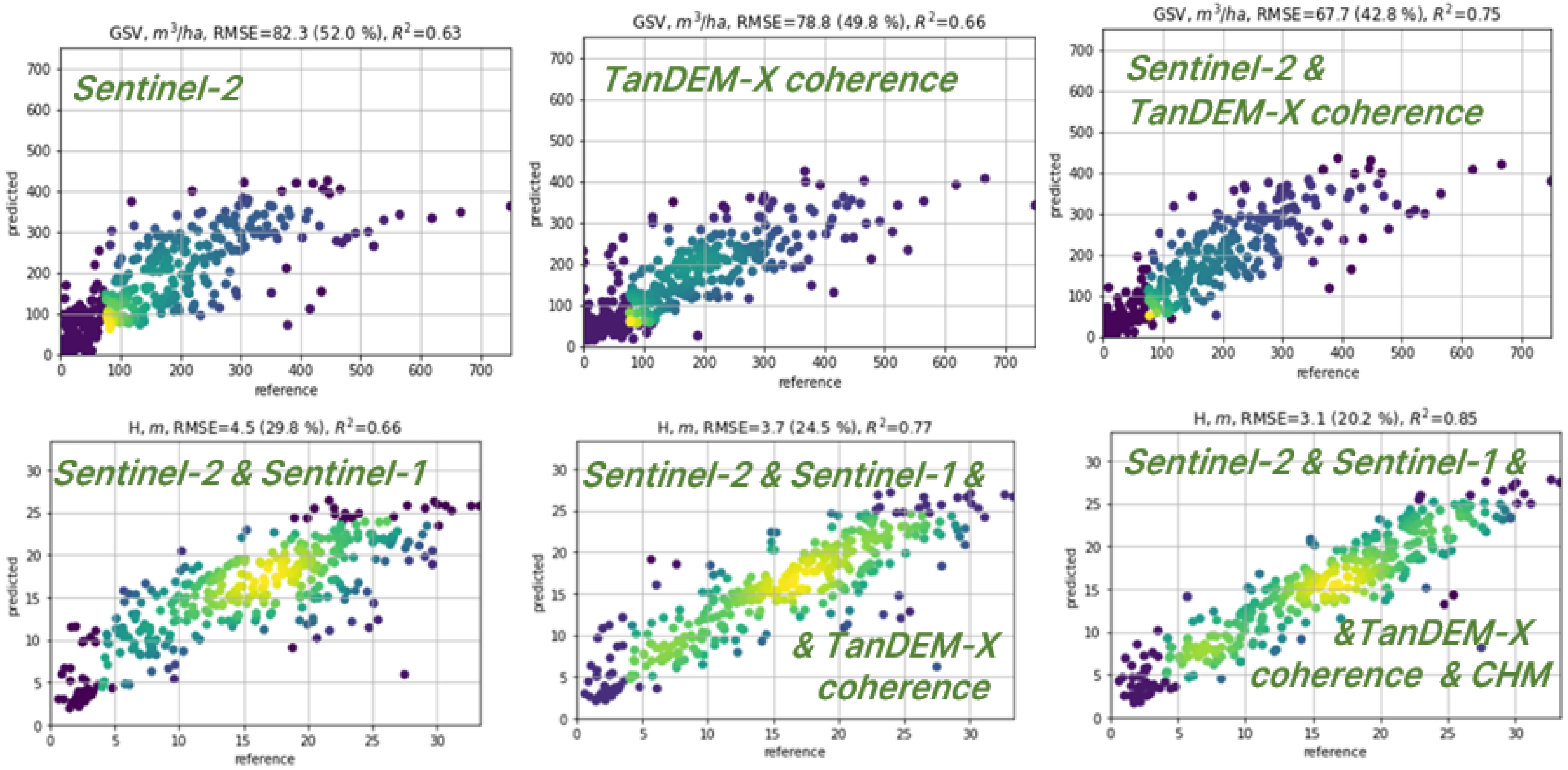
Southern Finland site GSV predictions with kNN using various combinations of EO images

Algorithm and dataset comparison



GSV prediction over Northern Finland site using various methods and EO data combinations:
(a) Sentinel-2; (b) Sentinel-2 & Sentinel-1

EO data intercomparison: role of vertical structure



Role of the TanDEM-X dataset was important with all methods and many forest variables, least with forest tree species proportions and site index.

Southern Finland site forest variable predictions using various EO imagery with the k-NN method: top row – growing stock volume, bottom row – forest tree height.

Feature selection

Rank	H	G	V	D	PINE	SPRUCE	BL
1	TDX-Coh	S2-5	TDX-CHM	TDX-Coh	S2-1	S2-6	S2-4
2	TDX-CHM	TDX-CHM	S2-6	S2-4	S2-4	S1-VH	S2-2
3	S2-5	P2-HV	TDX-Coh	TDX-CHM	TDX-CHM	S1-VV	S2-3
4	S2-7	S2-4	P2-HV	S1-VV	S1-VH	S2-5	TDX-CHM
5	S2-1	S2-1	S2-5	P2-JD	S1-VV	S2-1	S2-6
6	S2-2	S2-2	S2-4	S1-VH	S2-2	S2-2	S2-5
7	P2-HH	S2-6	P2-HH	P2-HH	TDX-Coh	S2-7	S2-7
8	S2-4	P2-HH	S1-VH	P2-HV	P2-HV	P2-HH	P2-HH
9	P2-HV	P2-JD	S2-2	S2-5	S2-5	P2-HV	P2-HV
10	S2-3	S1-VV	S2-1	S2-7	P2-HH	P2-JD	S2-1
11	P2-JD	S1-VH	S2-7	S2-1	S2-6	TDX-CHM	S1-VV
12	S1-VH	S2-3	S2-3	S2-2	S2-7	TDX-Coh	S1-VH
13	S2-6	S2-7	P2-JD	S2-3	P2-JD	S2-3	TDX-Coh
14	S1-VV	TDX-Coh	S1-VV	S2-6	S2-3	S2-4	P2-JD

S2-1	Sentinel-2 band 2 Blue
S2-2	Sentinel-2 band 3 green
S2-3	Sentinel-2 band 4 Red
S2-4	Sentinel-2 band 8 NIR
S2-5	Sentinel-2 band 5 VegRE
S2-6	Sentinel-2 band 11 SWIR
S2-7	Sentinel-2 band 12 SWIR
S1-VH	Sentinel-1 VH-pol
S2-VV	Sentinel-1 VV-pol
P2-HH	ALOS-2 PALSAR-2 HH-pol
P2-HV	ALOS-2 PALSAR-2 HV-pol
P2-JD	ALOS-2 PALSAR-2 day index
TDX-Coh	TanDEM-X coherence magnitude
TDX-CHM	TanDEM-X InSAR CHM

Sequential feature selection of EO data features over Northern Finland site

Feature selection

- Lasso feature selection, alpha=1.0:

	S2-1	S2-2	S2-3	S2-4	S2-5	S2-6	S2-7	S1-VH	S1-VV	P2-HH	P2-HV	P2-JD	TDX-CHM	TDX-Coh
H	0,0	0,0	0,0	0,3	1,9	0,0	0,0	0,0	0,0	0,0	0,0	0,0	2,2	2,4
G	0,0	0,0	0,0	0,8	3,1	1,3	0,0	0,0	0,0	0,2	1,7	0,0	2,7	0,0
V	0,0	2,5	0,0	15,1	36,2	0,0	7,0	0,0	1,1	4,1	10,8	0,0	59,9	9,5
D	0,0	0,0	0,0	2,1	1,3	0,0	0,0	0,0	0,0	0,1	0,0	0,0	2,1	2,9
PINE	1,6	16,9	0,4	20,9	0,0	0,0	0,0	26,7	25,0	0,0	1,4	0,0	5,7	0,0
SPRUCE	2,5	0,0	0,0	0,0	0,0	12,9	0,0	27,6	25,4	1,3	0,0	0,0	0,0	0,0
BL	0,0	15,5	0,0	22,0	6,4	14,6	0,0	0,6	0,0	2,4	0,0	0,0	3,0	1,9

- Random forest ranking:

	S2-1	S2-2	S2-3	S2-4	S2-5	S2-6	S2-7	S1-VH	S1-VV	P2-HH	P2-HV	P2-JD	TDX-CHM	TDX-Coh
H	0.014	0.089	0.019	0.11	0.093	0.052	0.042	0.018	0.015	0.023	0.04	0.0012	0.26	0.22
G	0.021	0.12	0.027	0.08	0.15	0.17	0.12	0.02	0.013	0.024	0.1	0.0023	0.1	0.046
V	0.018	0.078	0.02	0.13	0.15	0.13	0.096	0.011	0.011	0.022	0.06	0.0014	0.19	0.087
D	0.019	0.046	0.016	0.16	0.09	0.079	0.055	0.017	0.014	0.036	0.036	0.0012	0.23	0.2
PINE	0.084	0.074	0.15	0.22	0.059	0.067	0.039	0.058	0.11	0.033	0.032	0.0022	0.038	0.032
SPRUCE	0.051	0.079	0.086	0.11	0.098	0.14	0.13	0.07	0.095	0.038	0.022	0.0031	0.035	0.042
BL	0.051	0.073	0.068	0.27	0.053	0.11	0.064	0.029	0.041	0.084	0.052	0.0032	0.055	0.043

- Mutual information ranking:

	S2-1	S2-2	S2-3	S2-4	S2-5	S2-6	S2-7	S1-VH	S1-VV	P2-HH	P2-HV	P2-JD	TDX-CHM	TDX-Coh
H	0.2	0.5	0.3	0.5	0.6	0.4	0.4	0.3	0.1	0.2	0.3	0.0	1.0	0.7
G	0.4	0.8	0.4	0.6	0.9	1.0	0.8	0.3	0.2	0.4	0.8	0.0	0.6	0.4
V	0.5	0.8	0.4	0.7	1.0	0.9	0.7	0.1	0.2	0.5	0.6	0.0	0.9	0.6
D	0.3	0.6	0.3	0.7	0.8	0.7	0.5	0.3	0.3	0.4	0.5	0.0	1.0	0.8
PINE	0.8	0.3	0.7	1.0	0.6	0.2	0.3	0.0	0.7	0.1	0.0	0.2	0.1	0.0
SPRUCE	0.7	0.7	0.7	0.6	0.7	1.0	0.8	0.1	0.3	0.3	0.2	0.0	0.4	0.0
BL	0.0	0.1	0.2	1.0	0.3	0.6	0.4	0.0	0.0	0.6	0.4	0.0	0.2	0.0

S2-1	Sentinel-2 band 2 Blue
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TDX-CHM	TanDEM-X InSAR CHM

Findings of forest variable prediction: Methods

- Over majority of test sites, **MLR** proved to be a robust prediction method in the sense that increasing number of independent variables improved prediction accuracy.
- Basic **InSAR/SAR models** often required supervision/**fine-tuning** to achieve accuracy levels similar to other studied approaches. However, they seem robust when lacking reference data.
- **kNN** and **Probability** approach have demonstrated similar performance levels and were suitable for **multivariate prediction** of forest attributes.
- **Nonparametric methods** (e.g., kNN) often favoured smaller dimensionality of feature space and appear very **sensitive to non-representative** data.
- **RF** was somewhat superior to **SVR** (aside from site index), with both approaches yielding the **best** possible **predictions after finetuning** their hyperparameters.
- RF & SVR demonstrated the best possible predictions for several forest variables.
- **Visual assessment** of produced maps can **affect final ranking**

Findings of forest variable prediction: EO datasets

- Sentinel-2 or combined **Sentinel-2 & Sentinel-1** was the most important data combination for predicting **tree species** proportions.
- For **other structural variables**, most centrally GSV and forest height, the best predictions were provided by **combining radar and optical datasets**, with a key role of Sentinel-2 and TanDEM-X datasets.
- From “all forest variables” perspective it is worthwhile to say that Sentinel-2 was the single best dataset, followed by TanDEM-X in case it was available.
- For practically all sites, **combining Sentinel-1 with Sentinel-2** improved prediction accuracy by a small **margin of 2-4 percentage units**, indicating it is useful to combine the two Copernicus datasets.
- For several studied prediction methods and test sites, using all data bands simultaneously provided the best performance.
- With non-parametric approaches, such as kNN and Probability method, **excluding “noisy” bands improved the prediction** in several cases. Use of feature weighting in prediction can be useful to overcome the issue.

Conclusions on data and method combinations (I)

Datasets	Accuracy*	Considerations
Sentinel-1 only	50-80%	• Time series required • Limited accuracy • All weather capability
Sentinel-2 only	20-60%	• Required for species • Best single dataset • Inter-image variation
Sentinel-2 + Sentinel-1 or PALSAR2	20-60%	• Minor improvement to Sentinel-2 alone
Sentinel-2 + Sentinel-1 + TanDEM-X coherence	20-40%	• Great improvement for Height and GSV • Limited availability

* Typical plot level accuracy variation between variables and sites. RMSE percent of the mean.

Conclusions on data and method combinations (II)

- Recommended “decision tree” for selecting methods:

Field data for training available? → yes → Sufficient* number of field plots? → yes → Multiple output variables ? → yes

Field data for training available? → no:

BIOMASAR

Growing stock vol.
Above ground bio.
Below ground bio.

20-100 m res.

Sufficient* number of field plots? → no:

Probability

Basal area
Diameter
Height
Growing stock vol.
Species
Site

PREBAS

Above ground bio.
Below ground bio.
Stem volume incr.

10 m res.

Multiple output variables ? → no:

Many options

Individual interest variables (e.g., forest height) can be predicted with a method like Random Forests.

10 m res.

Multiple output variables ? → yes:

k-NN

Basal area
Diameter
Height
Growing stock vol.
Species
Site

PREBAS

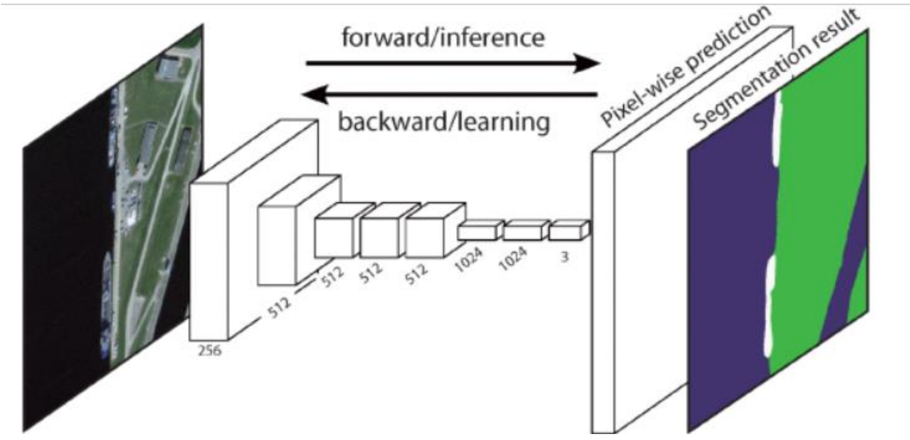
Above ground bio.
Below ground bio.
Stem volume incr.

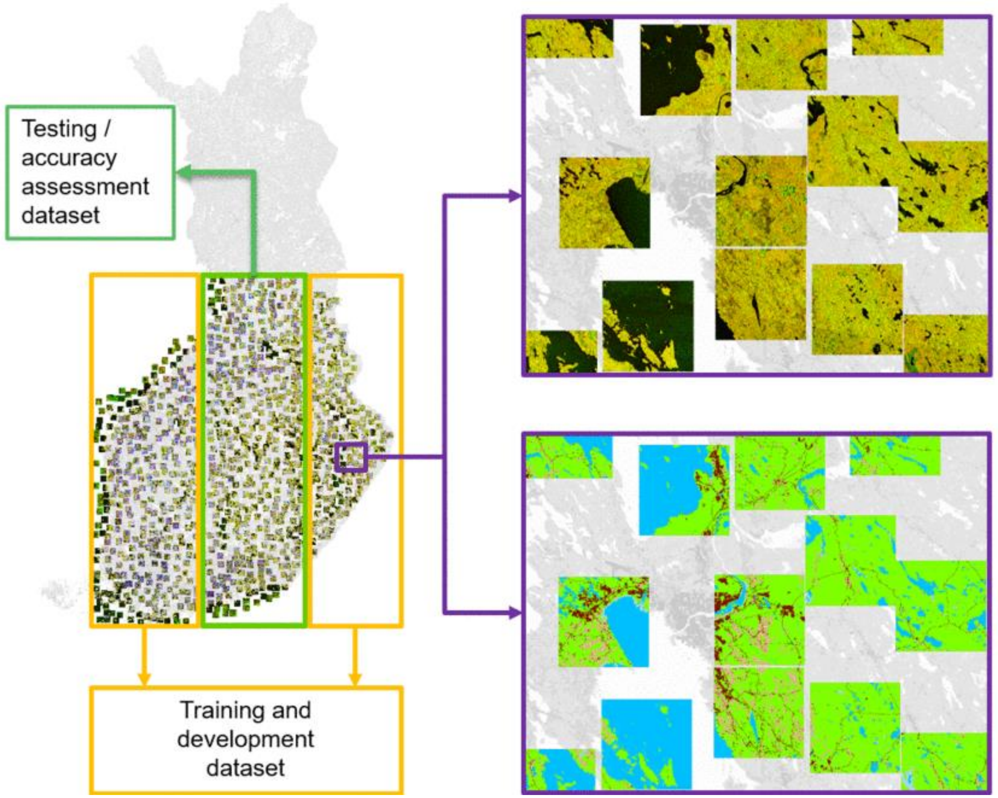
10 m res.

*Typically at least 100 plots

New Horizons: Deep Learning

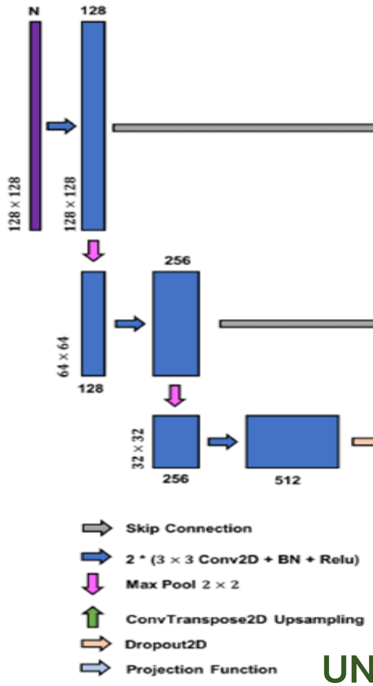
- Capable of automatically extracting spatial textural and temporal dependencies vs ”hand-engineered features”
- Require high quality and extensive reference data labels, that is fully segmented labels
- Already quite popular in semantic segmentation tasks with EO data, such as land cover mapping
- Semi-supervised learning scenarios already demonstrated
- Possible domain adaptation or model transfer
- Several ”pilot” studies in forest variable prediction using EO data



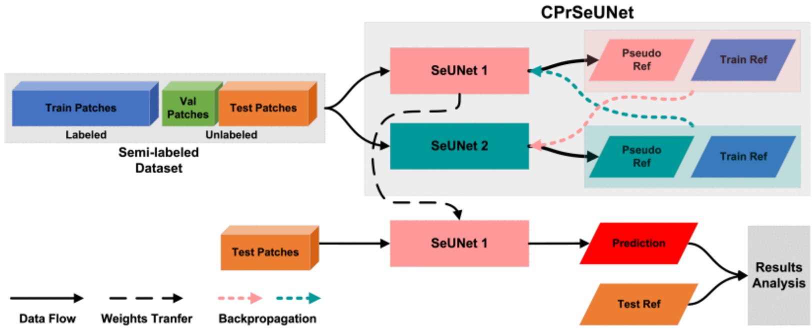


Šćepanović et al., Wide-Area Land Cover Mapping With Sentinel-1 Imagery Using Deep Learning Semantic Segmentation Models," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2021

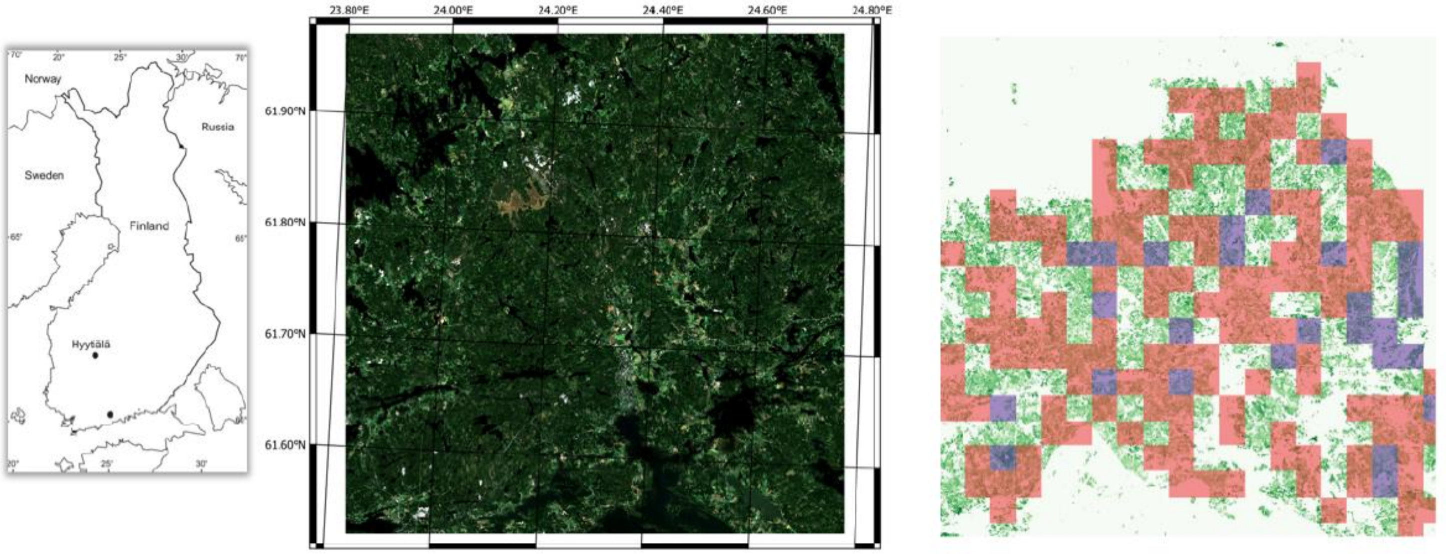
CNN-based improved models



UNet deep learning model



Improved CPrSeUNet model



Study site location and division into training(red), validation (blue) and testing sets, 50x50 km2 size

Key points:

- Target variable – forest tree height, reference data – airborne laser measurements, predictor variables – features from several EO datasets (radar channels, optical bands)
- Comparison with machine learning approaches MLR, SVR, RF
- Testing separately Sentinel-1 images (frozen/nonfrozen), Sentinel-1 time series (27 datatakes), "good" Sentinel-2 image, SAR and optical combined

Ge, Antropov et al., "Improved Semisupervised UNet Deep Learning Model for Forest Height Mapping With Satellite SAR and Optical Data," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 5776-5787, 2022.

CNN-based improved models

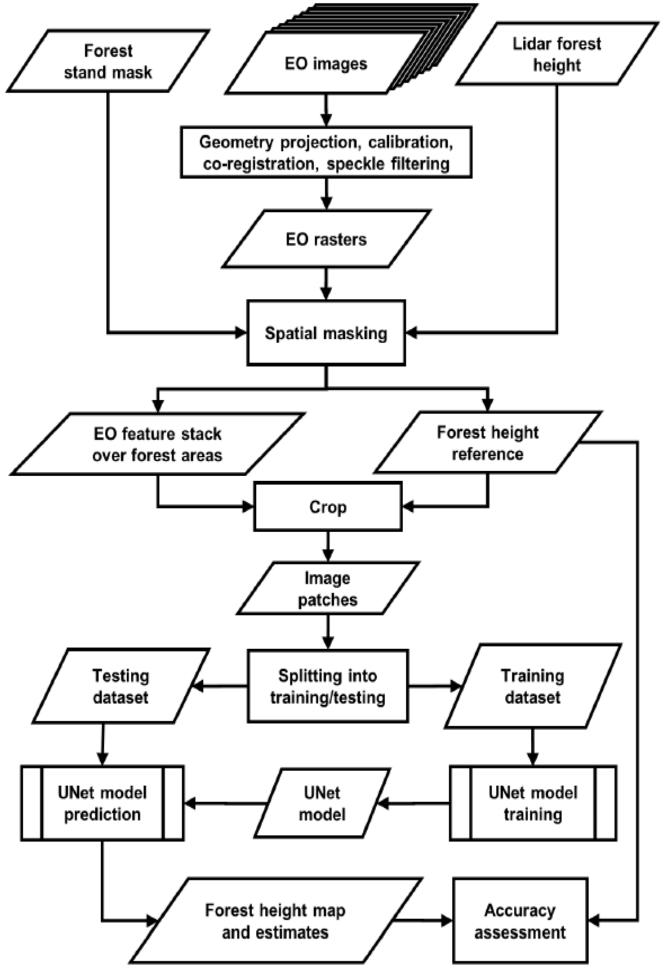
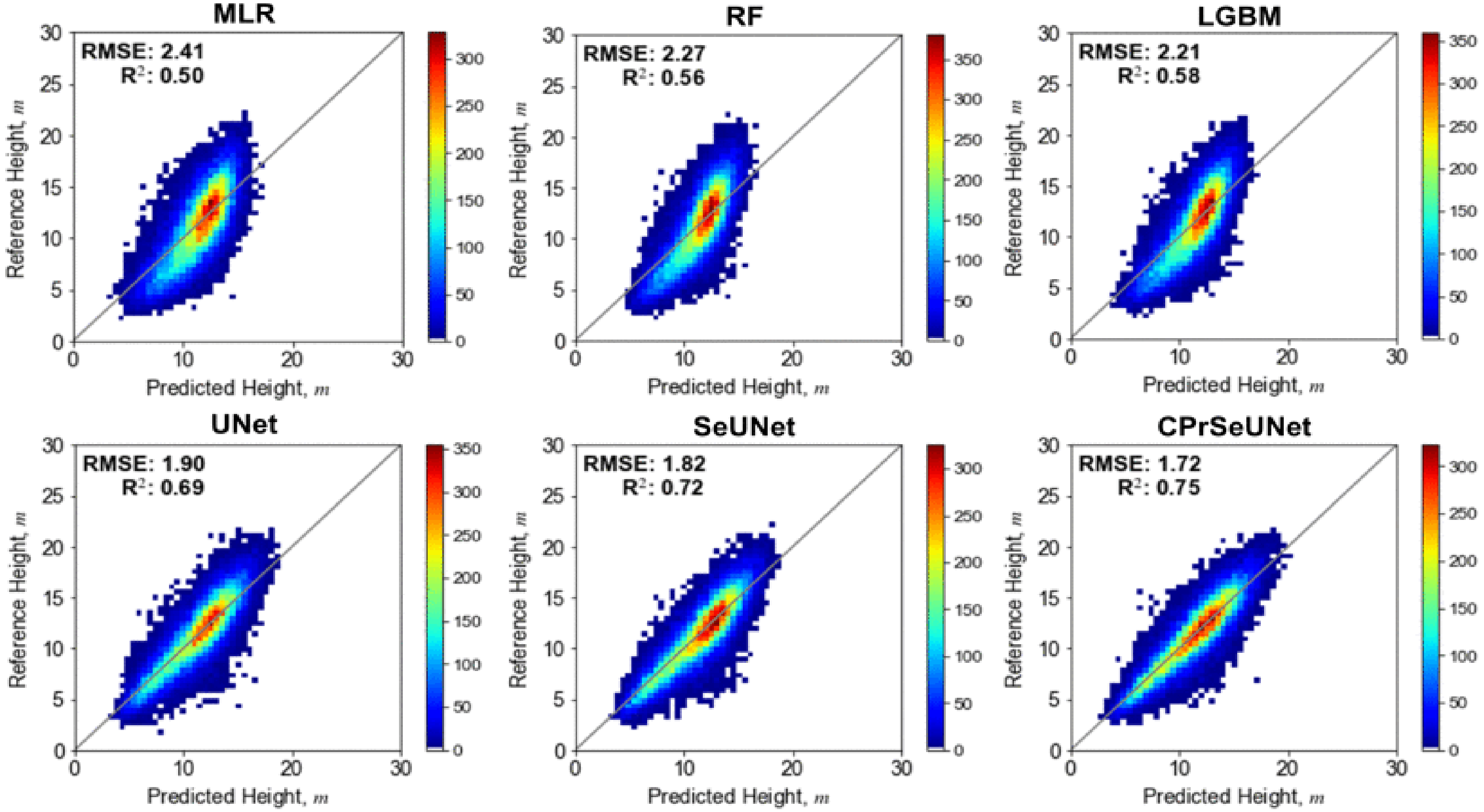


Image processing pipeline



Forest height prediction scatterplots

Ge, Antropov et al., "Improved Semisupervised UNet Deep Learning Model for Forest Height Mapping With Satellite SAR and Optical Data," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* vol. 15, pp. 5776-5787, 2022.

CNN-based improved models

TABLE I
ACCURACY ASSESSMENT USING PIXEL-LEVEL DATA

	RMSE, m	RMSE%	MAE	Bias	R^2
Sentinel-1 time series					
MLR	3.72	33.28	2.95	0.00	0.33
RF	3.63	32.50	2.89	0.01	0.36
LGBM	3.58	32.08	2.81	-0.01	0.38
UNet	3.09	27.68	2.36	0.06	0.54
SeUNet	3.03	27.14	2.29	-0.13	0.56
CPrSeUNet	3.02	27.03	2.29	0.05	0.56
Sentinel-2					
MLR	3.89	34.80	3.08	0.01	0.27
RF	3.77	33.79	2.99	0.03	0.31
LGBM	3.75	33.61	2.98	0.02	0.32
UNet	3.12	27.90	2.36	-0.05	0.53
SeUNet	3.04	27.21	2.29	-0.12	0.55
CPrSeUNet	3.01	26.98	2.26	0.11	0.56
Sentinel-1 time series and Sentinel-2					
MLR	3.58	32.04	2.79	-0.03	0.38
RF	3.40	30.44	2.66	0.01	0.44
LGBM	3.36	30.09	2.61	-0.02	0.45
UNet	2.88	25.76	2.14	-0.17	0.60
SeUNet	2.79	25.00	2.07	-0.02	0.62
CPrSeUNet	2.70	24.14	1.96	-0.07	0.65

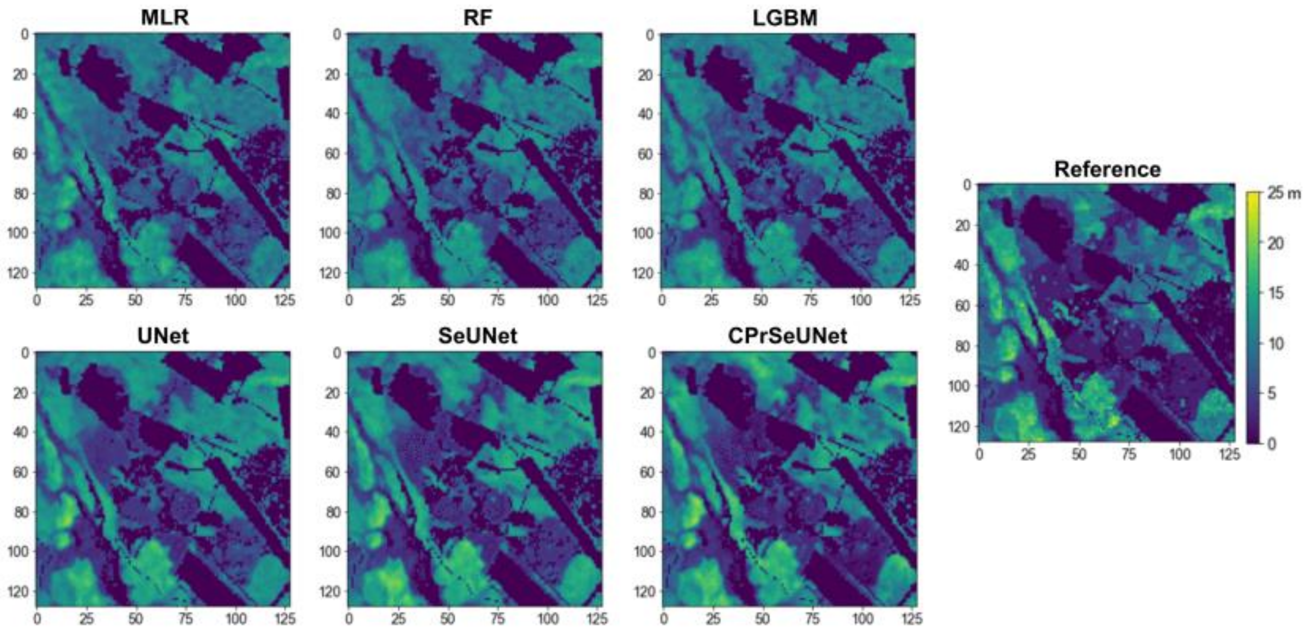
TABLE II
ACCURACY ASSESSMENT USING STAND-LEVEL DATA

	RMSE, m	RMSE%	MAE	Bias	R^2
Sentinel-1 time series					
MLR	2.53	22.66	2.01	0.06	0.45
RF	2.51	22.49	2.01	0.05	0.46
LGBM	2.40	21.49	1.90	0.04	0.51
UNet	2.09	18.76	1.60	0.07	0.62
SeUNet	2.03	18.23	1.53	-0.10	0.64
CPrSeUNet	2.02	18.10	1.53	0.03	0.65
Sentinel-2					
MLR	2.72	24.35	2.16	-0.03	0.37
RF	2.55	22.80	2.02	-0.02	0.44
LGBM	2.55	22.81	2.02	-0.03	0.44
UNet	2.13	19.09	1.62	-0.01	0.61
SeUNet	2.07	18.50	1.56	-0.09	0.63
CPrSeUNet	2.03	18.15	1.52	0.09	0.65
Sentinel-1 time series and Sentinel-2					
MLR	2.41	21.60	1.88	-0.00	0.50
RF	2.27	20.33	1.78	0.01	0.56
LGBM	2.21	19.78	1.72	-0.00	0.58
UNet	1.90	17.06	1.41	-0.13	0.69
SeUNet	1.82	16.30	1.34	0.01	0.72
CPrSeUNet	1.72	15.38	1.25	-0.03	0.75

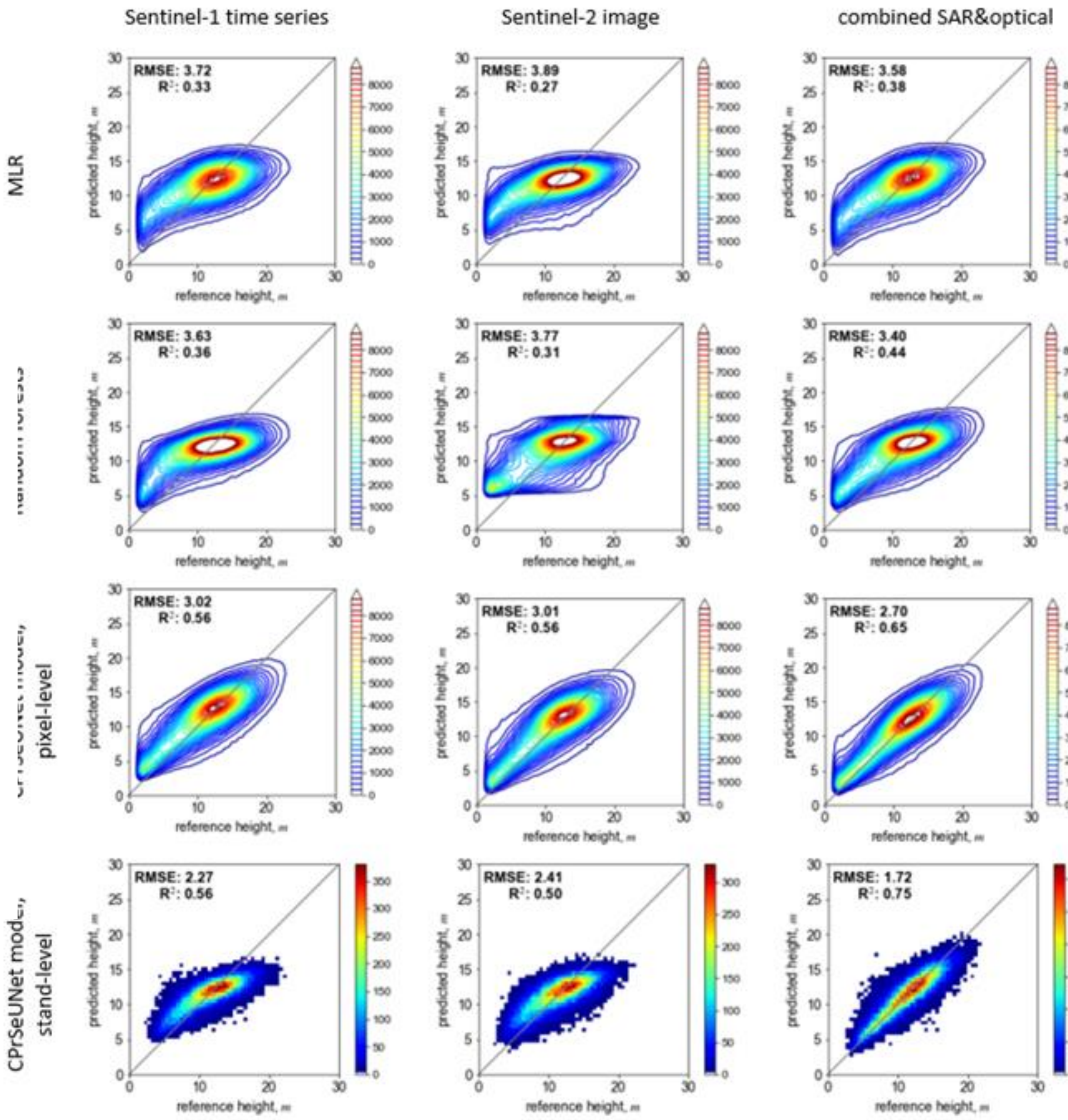
Forest prediction accuracy statistics

Ge, Antropov et al., "Improved Semisupervised UNet Deep Learning Model for Forest Height Mapping With Satellite SAR and Optical Data," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 15, pp. 5776-5787, 2022.

CNN-based improved model

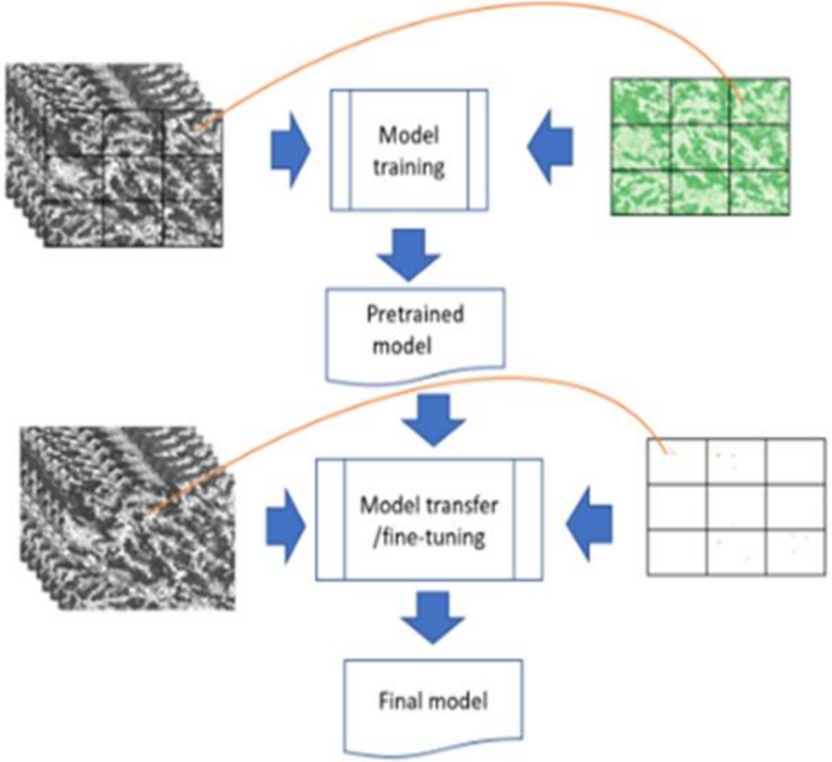


Forest height prediction: examples of predicted image patches and overall scatterplots for various data&methods

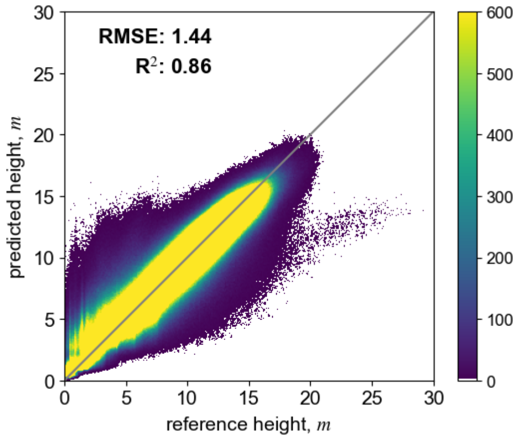


Forest height prediction performance for various EO datasets and prediction methods. (Ge et al. 2022)

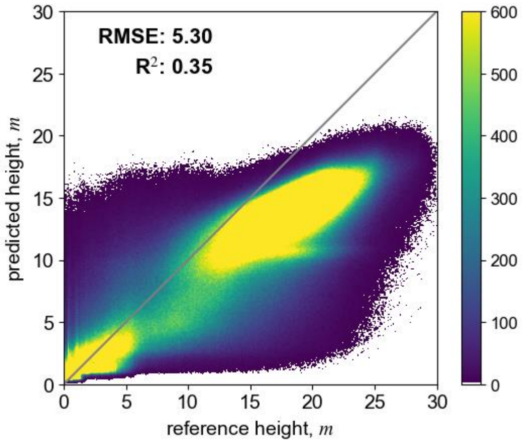
Potential of model transfer



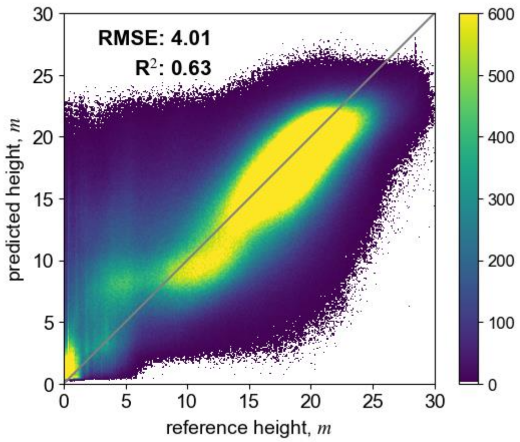
Forest height prediction over initial study area



Forest height prediction over target area



Without fine-tuning



With fine-tuning

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Conclusions

- Processing chains were developed and tested for wide area forest variable mapping using high resolution optical and radar satellite images
- Optimal pathways were suggested for currently available data
- Optimal sensor combinations identified, SAR + optical combination recommended
- Important role of TanDEM-X and vertical structure
- Potential for further development of the approaches with deep learning and Copernicus data

Forest Carbon *Monitoring*

Thank you!

More information at:
https://www.forestcarbonplatform.org