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VTT

UNet+ models using multi-source EO data in forest inventory

ESA RepreSent user workshop
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Multi-source EO data and regression task

Typical plot level-accuracies[1] using traditional modelling approaches (e.g., RF, SVM, MLR)

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

Deep learning models

→ 25-35 %

→ 20-30 %

→ 20-25 %

→ 17-19 %

- 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 and weakly supervised learning scenarios are suitable

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esa Forest Carbon Monitoring

1. Antropov et al. “Intercomparison of EO data and methods for forest mapping in the context of forest carbon monitoring”, IGARSS 2022
2. Ge et al. Improved semisupervised unet deep learning model for forest height mapping with satellite sar and optical data, IEEE JSTARS, 2022
3. Ge et al. Improved LSTM model for boreal Forest Height Mapping Using Sentinel-1 Time Series, Remote Sensing, 2022

How to train DL models using small amount of reference data?

UNet model as an good example

- Popular deep learning model in computer vision
- Accurate, efficient, flexible with reduced data requirements
- Well suitable for satellite image analysis thanks to symmetric structure
- Good performance in prior exercises with fully segmented labels for semantic segmentation and regression tasks

Ways to use “weak” reference data

- Use model pretraining over areas where fully segmented labels are available to develop a forest-specific model
- Perform model transfer for fine-tuning using a small set of reference labels in the target site

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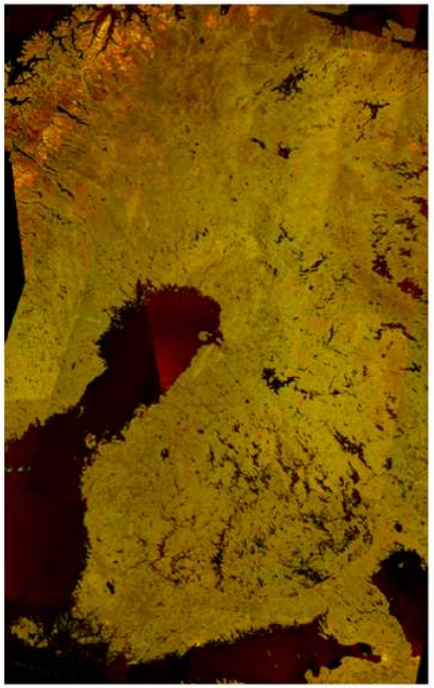
Prior experience in DL semantic segmentation



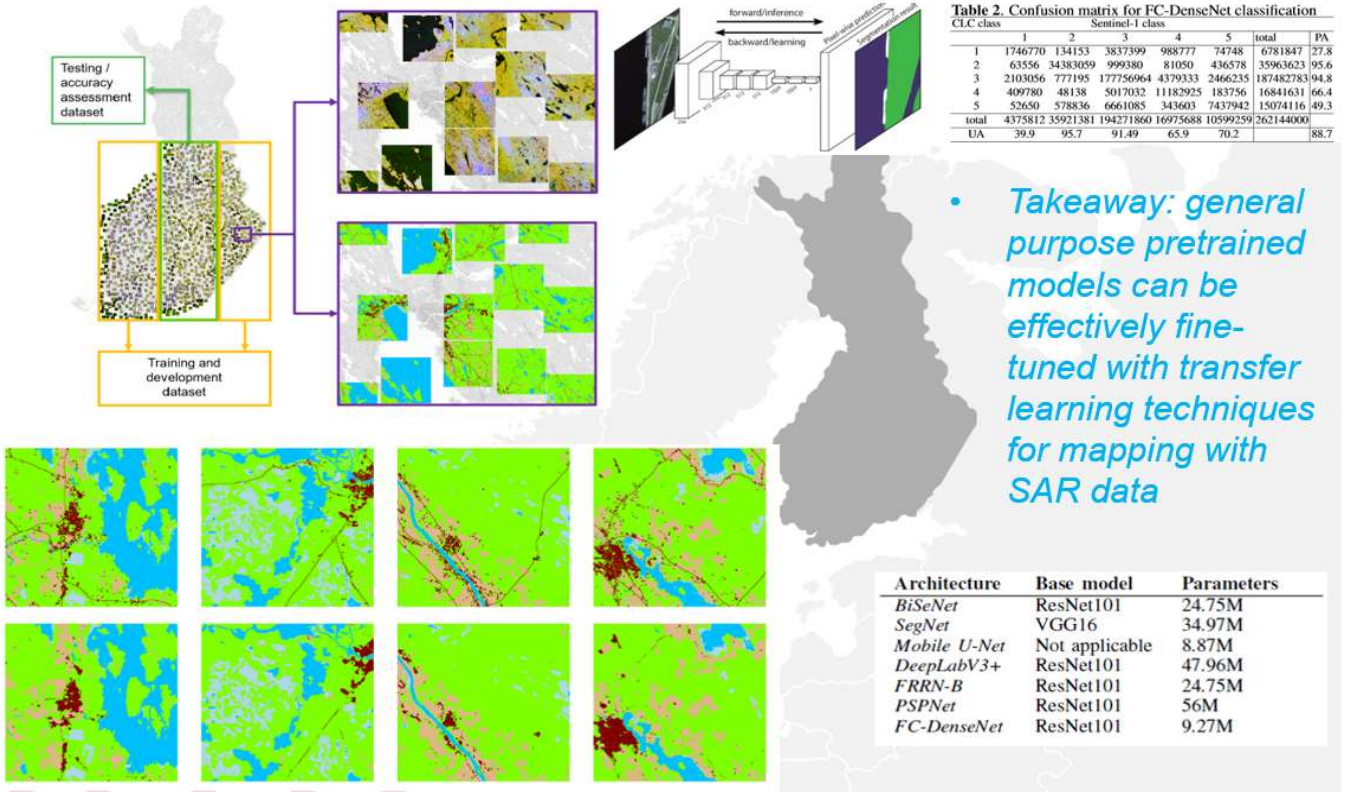


Table 2. Confusion matrix for FC-DenseNet classification

CLC class	Sentinel-1 class						
	1	2	3	4	5	total	PA
1	1746770	134153	3837399	988777	74748	6781847	27.8
2	63556	34383059	999380	81050	436578	35963623	95.6
3	2103056	777195	17775964	4379333	2466235	187482783	94.8
4	409780	48138	5017032	11182925	183756	16841631	66.4
5	52650	578836	6661085	343603	7437942	15074116	49.3
total	4375812	35921381	194271860	16975688	10599259	262144000	
UA	39.9	95.7	91.49	65.9	70.2		88.7

- *Takeaway: general purpose pretrained models can be effectively fine-tuned with transfer learning techniques for mapping with SAR data*

Architecture	Base model	Parameters
BiSeNet	ResNet101	24.75M
SegNet	VGG16	34.97M
Mobile U-Net	Not applicable	8.87M
DeepLabV3+	ResNet101	47.96M
FRRN-B	ResNet101	24.75M
PSPNet	ResNet101	56M
FC-DenseNet	ResNet101	9.27M

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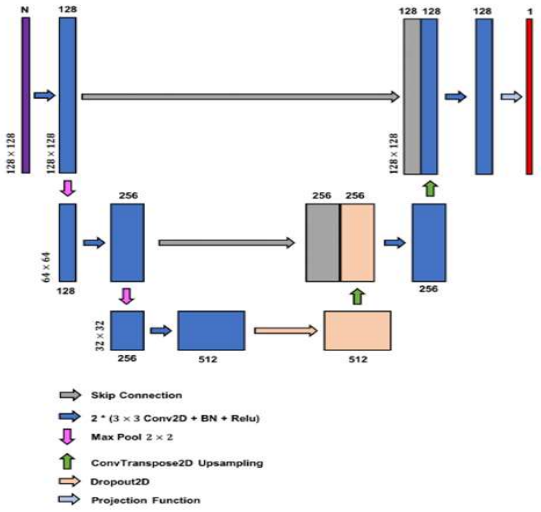
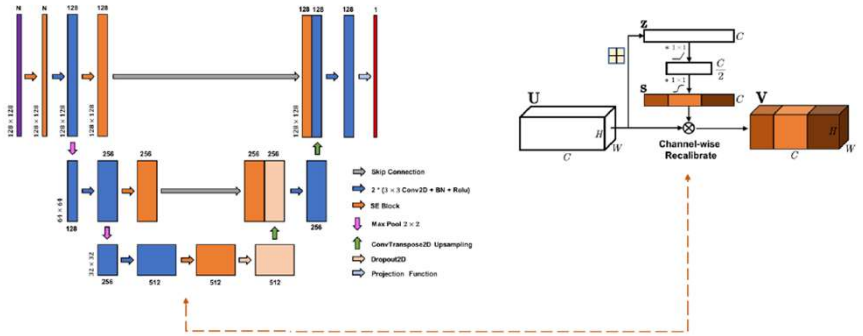
Šćepanović, Antropov, et al. Wide-area land cover mapping with Sentinel-1 imagery using deep learning semantic segmentation models. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2021.

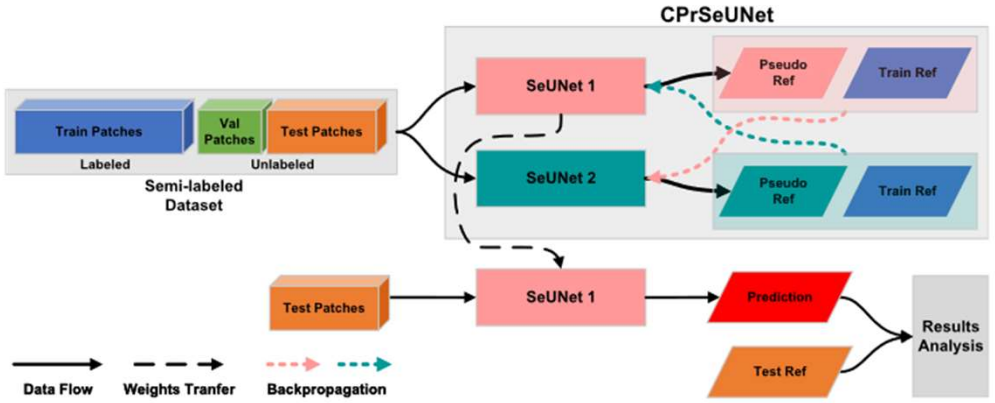
UNet based models



UNet model



SeUNet model (embedded squeeze-excitation blocks)



advanced UNet models*

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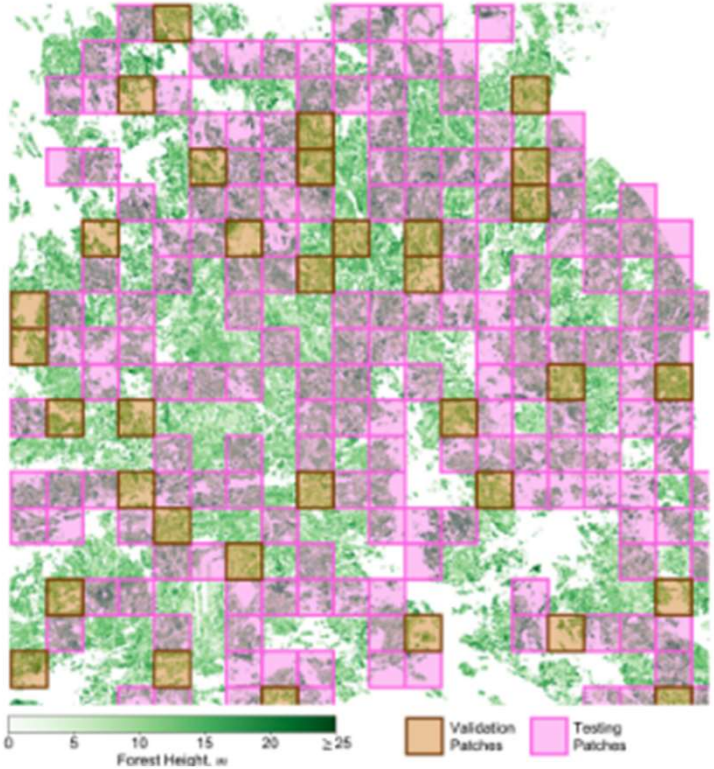
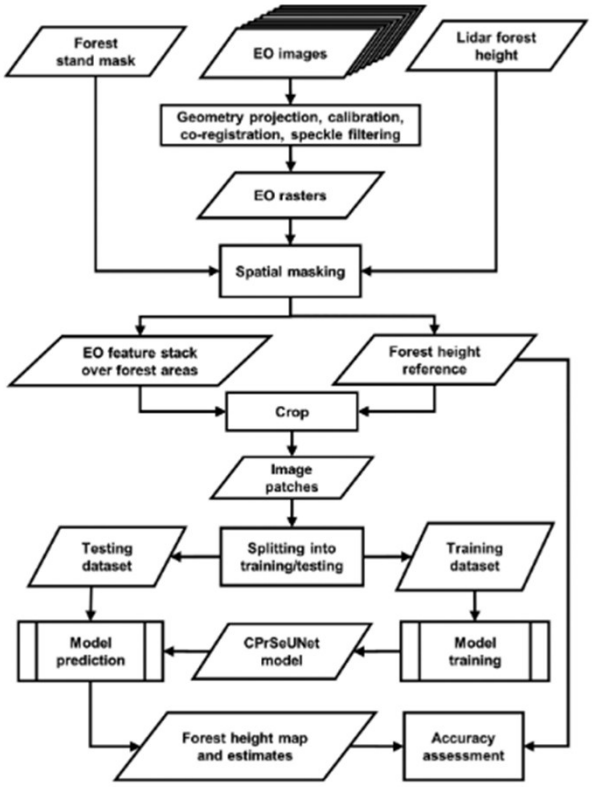
*Ge, Gu, Su, Praks, Antropov, Improved semi-supervised UNet deep learning model for forest height mapping with satellite SAR and optical data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2022.

UNet based models





Key points:

- Target variable – forest tree height, reference data – airborne laser measurements, predictor variables – features from several sets of satellite EO datasets (radar channels, optical bands)
- Comparison with popular machine learning approaches: MLR, SVR, random forests
- Testing separately Sentinel-1 images (frozen/nonfrozen), Sentinel-1 time series (27 datatakes), “good” Sentinel-2 image

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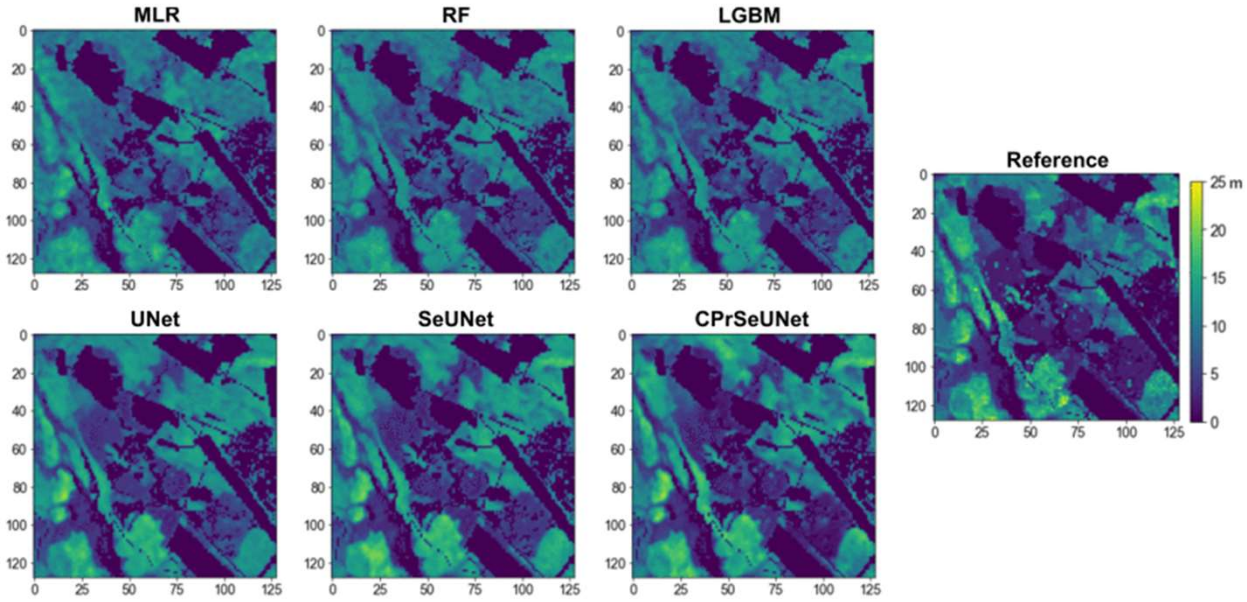
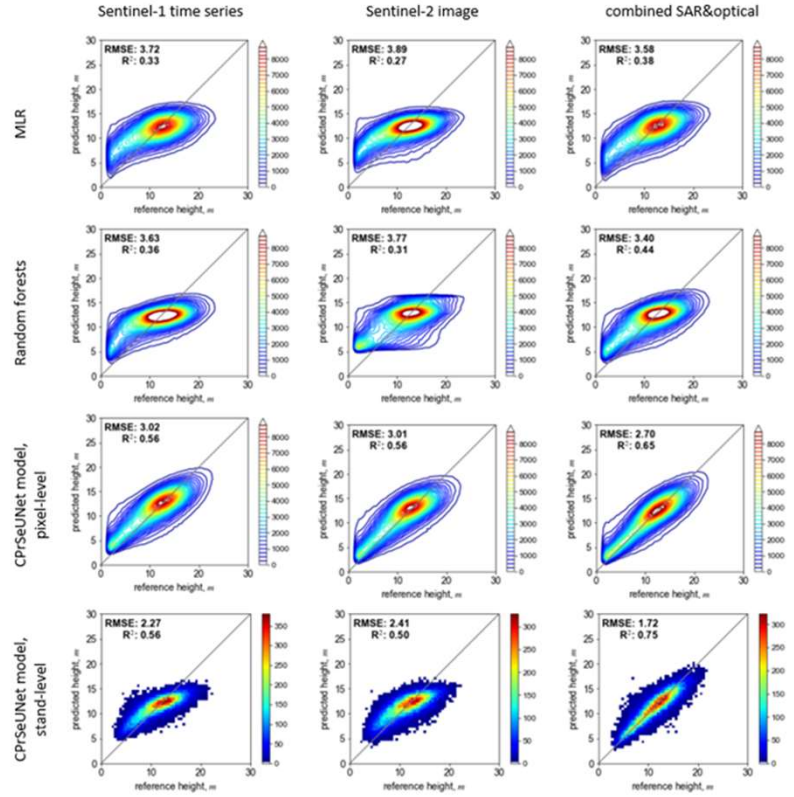
Ge, Gu, Su, Praks, Antropov, Improved semi-supervised UNet deep learning model for forest height mapping with satellite SAR and optical data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2022.

Results using fully segmented data



Examples of predicted forest height maps vs reference



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

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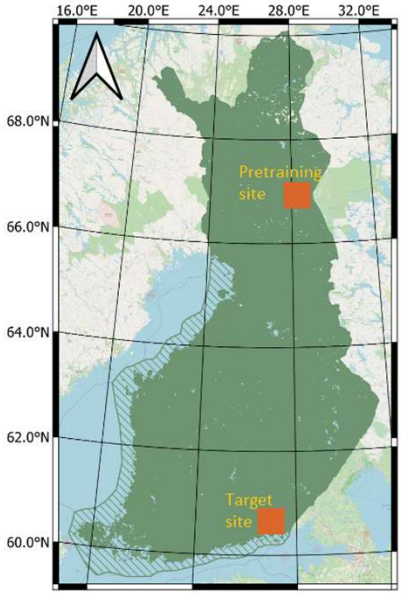
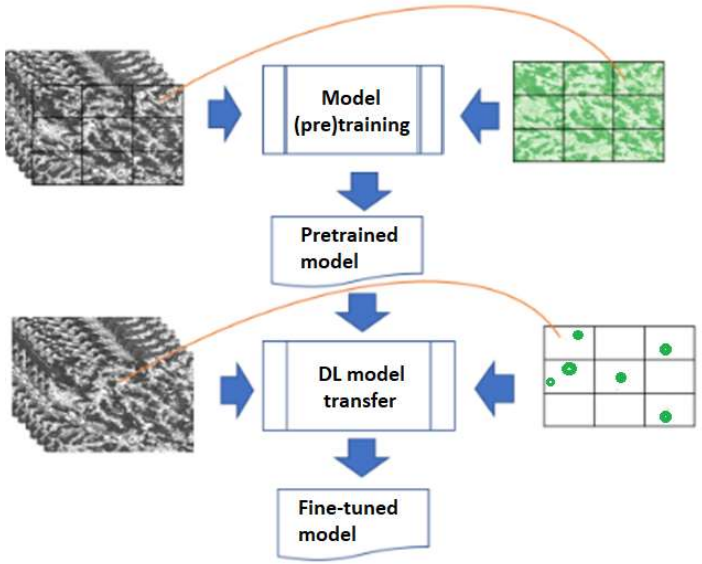
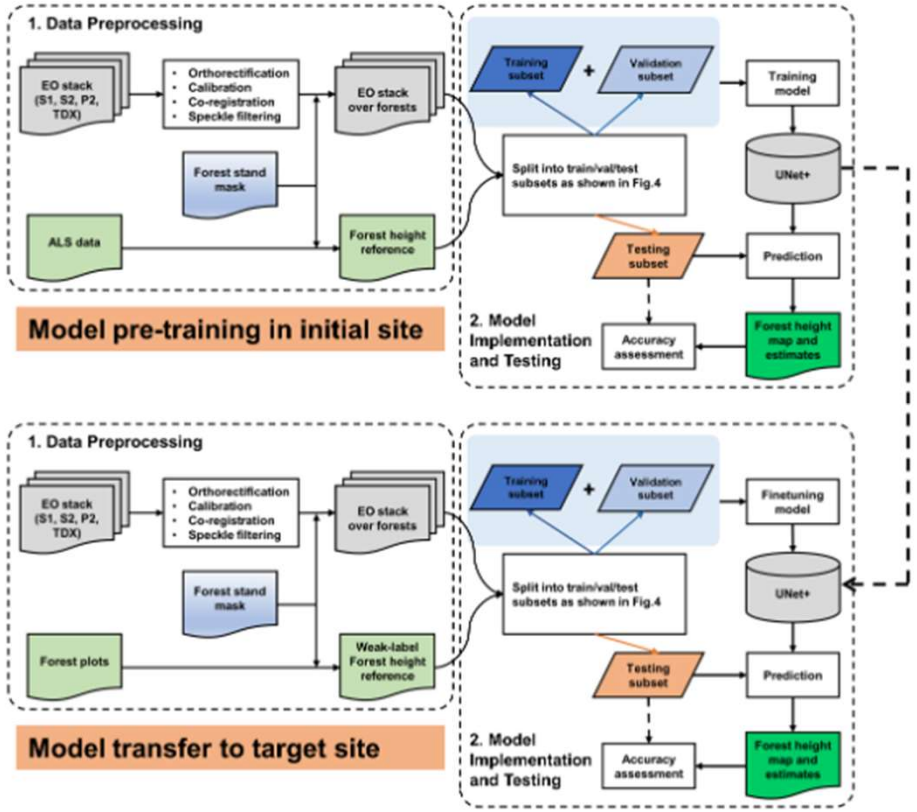
Ge, Gu, Su, Praks, Antropov, Improved semi-supervised UNet deep learning model for forest height mapping with satellite SAR and optical data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2022.

DL model transfer







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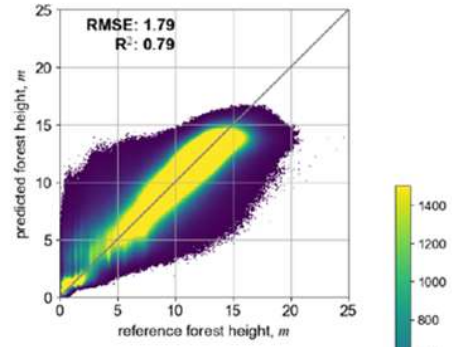
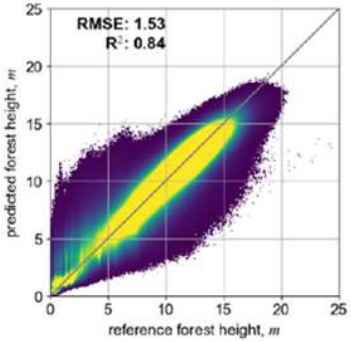
*Ge, Antropov, Häme, Miettinen et al. Deep learning models with transfer learning in boreal forest mapping using multi-source satellite SAR/InSAR and optical images, *submitted, 2023.*

DL model transfer

MS-EO: Sentinel-2 & Sentinel-1 & ALOS-2 PALSAR-2 &TanDEM-X

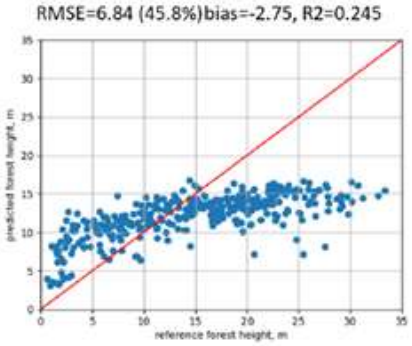


Sentinel-2

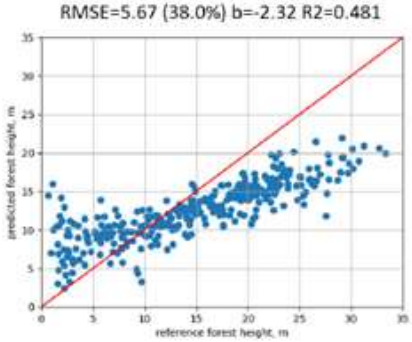


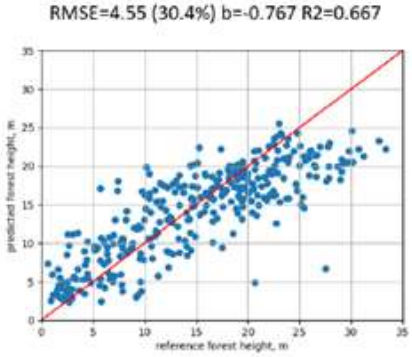
MS-EO

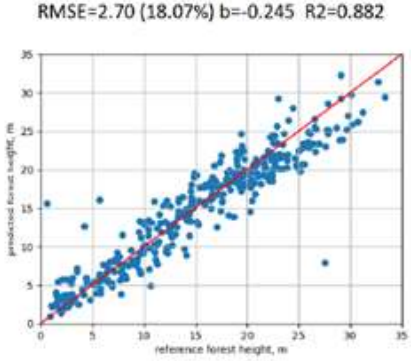
Sentinel-2

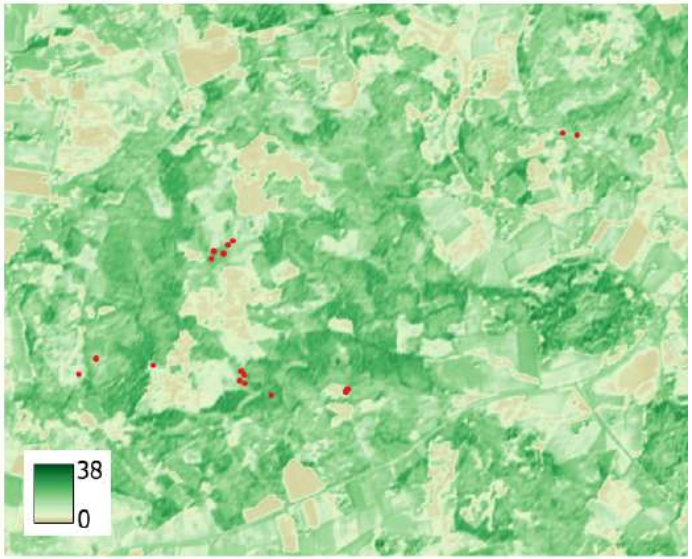


MS-EO









forest height map

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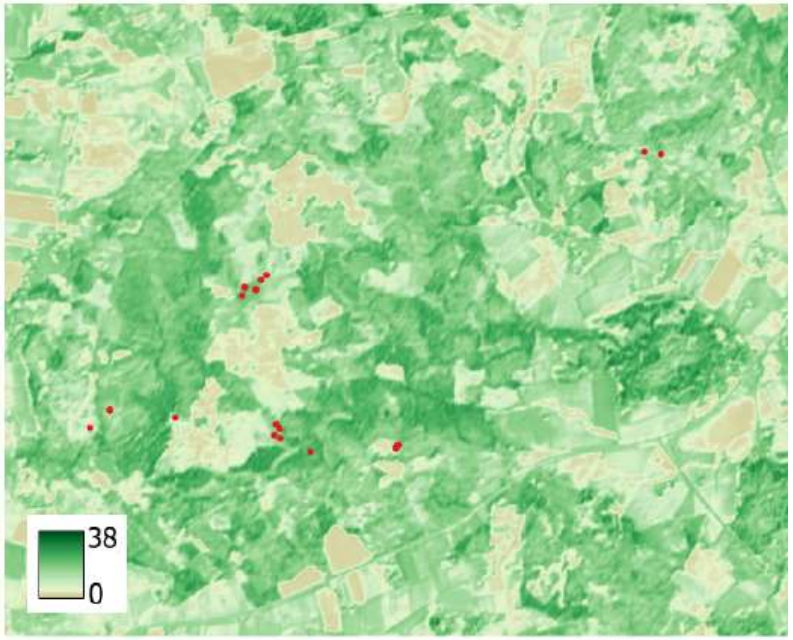
Conclusions

- Forest specific model pretraining works well
- Prediction accuracies are only slightly worse compared to model trained using fully-segmented labels
- Prediction accuracy considerably better compared to classical methodologies, including kNN, random forests, SVR.
- Method is “robust” in no-data or scarce data scenario (e.g., when number of plots is reduced to dozens instead of hundreds, or certain heigh/biomass classes are underrepresented or completely missing)
- The approach is applicable to other forest variables (e.g., growing stock volume or forest biomass)
- Several pretrained models are available via F-TEP



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Thank you!