A New Approach for Feeding Multispectral Imagery into Convolutional Neural Networks Improved Classification of Seedlings

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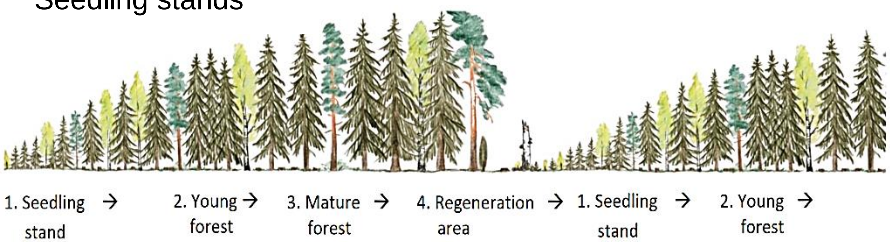
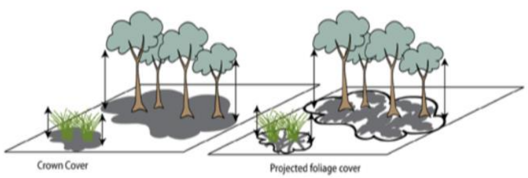
Seedling stands and related RS challenges

Seedling stands

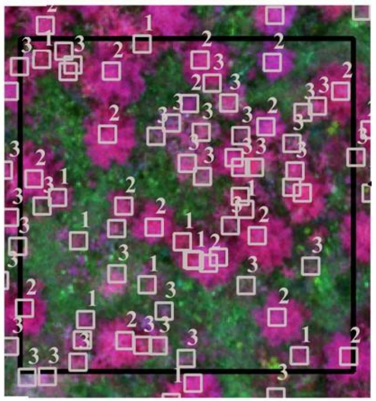


Modified from the Finnish Forest Association (URL: https://frantic.s3.amazonaws.com/smy/2015/03/The-commercial-forest-cycle.pdf)

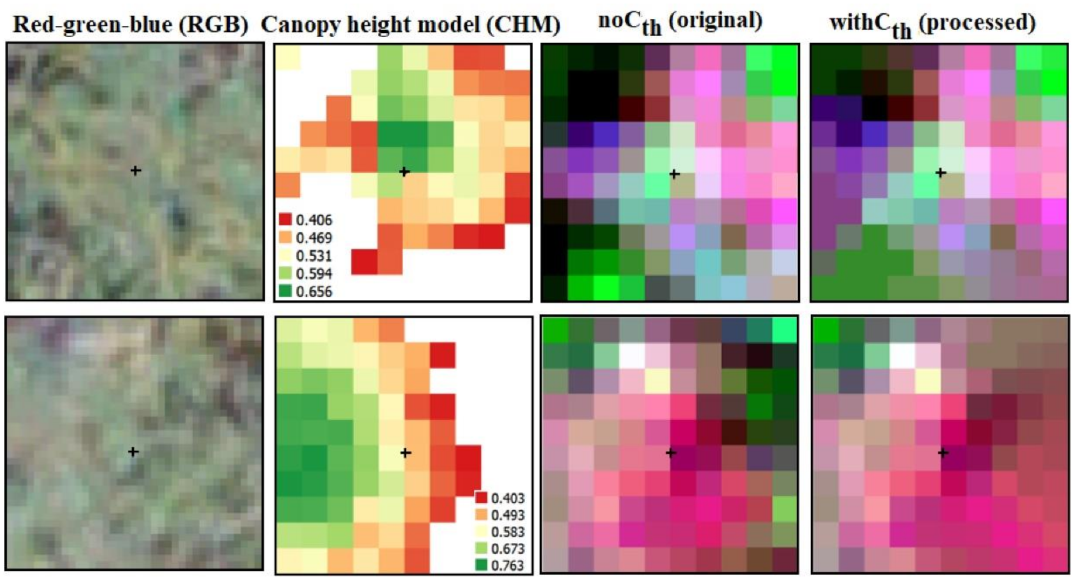
Less foliaged sparse or dense mixed canopies



Forest plot (10 × 10 m) with tensors of field-located trees



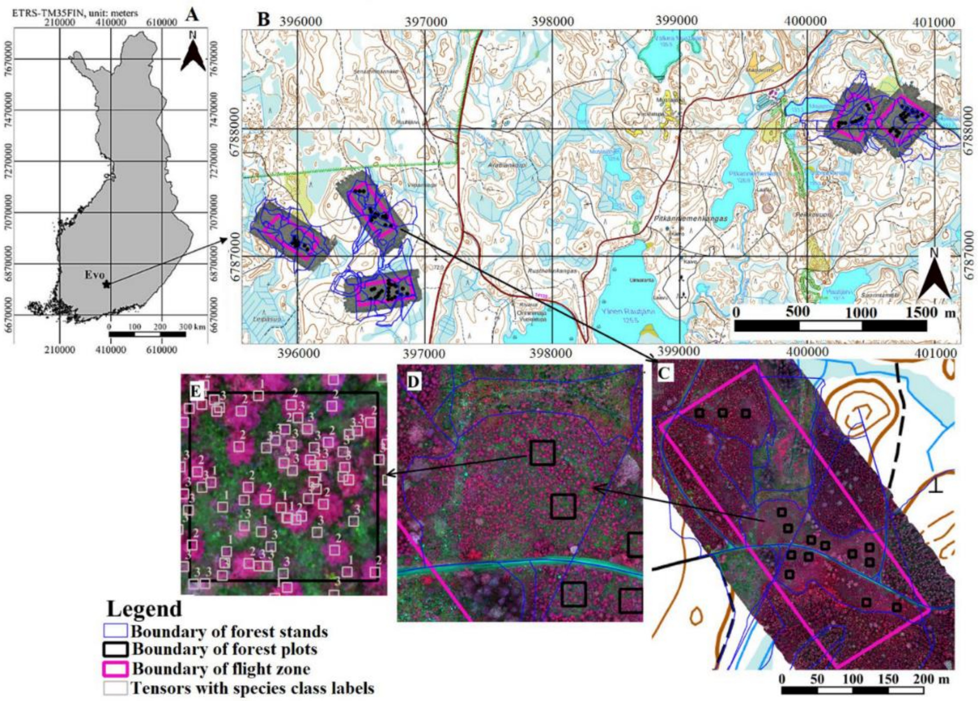
A solution we found



Visualizing the effect of applying the canopy threshold (C_{th})-based image pre-processing method introduced in this research on two sample pine trees with height 1.4 m (upper row) and 1.3 m (lower row).

The white pixels in CHM denote nullified (C_{th}-affected) pixels after image pre-processing due to a height of ≤0.4. The + symbol in the middle of the images shows the location of a field-measured treetop.

Study area

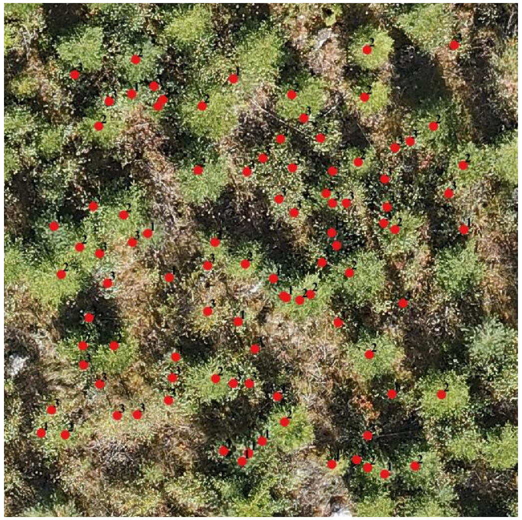


Remote sensing data:

- UAV-PPC, RGB (1.3 cm)
- MicaSense multispectral 5 cm (5 bands)

Field data:

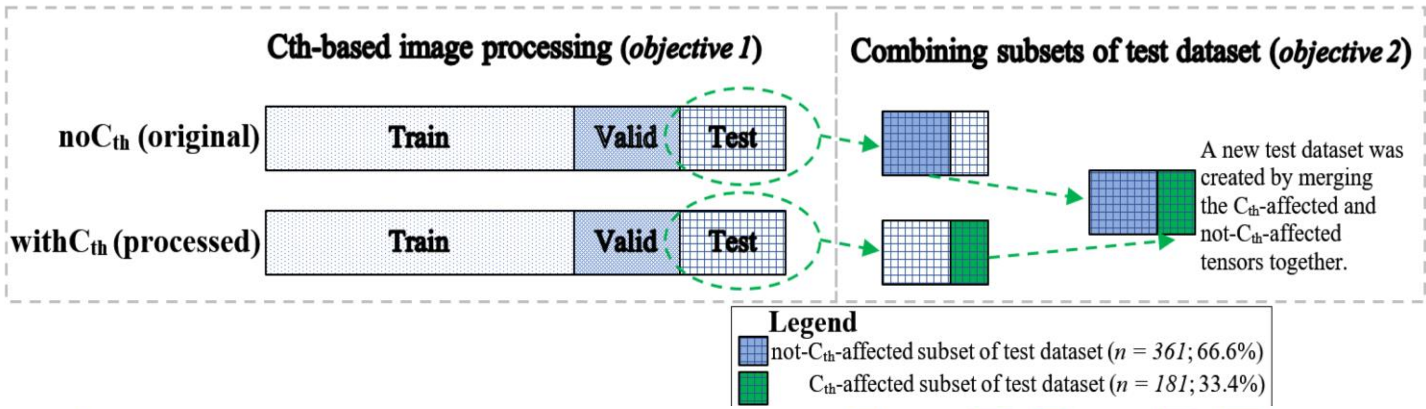
- 5 417 trees mapped with RTK
- 75 plots (10 x 10 m), 5 flight zones.
- 14 seedling stands
- Tree density (3 000 – 15 000 TPH)
  - Considering underlying trees 3 500 – 54 000 TPH)
- Height (1 – 12 m)
- Species (pine 13.6%, spruce 28.7%, birch 48.4%, other 9.3%)

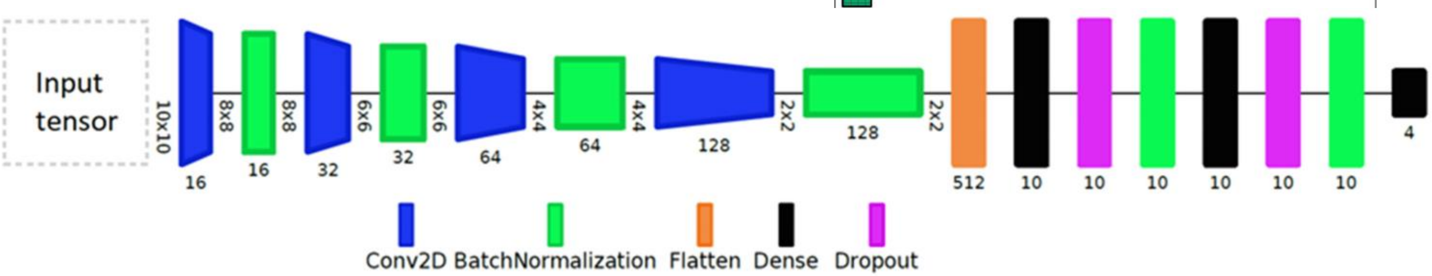


Method

We created different dataset by applying the Cth idea (noCth and withCth) and adding 8 vegetation indexes (withVI and noVIs).

A schematic graph of the methodological principles behind introducing canopy threshold (C_{th})-based image pre-processing and combining two subsets of the test dataset based on whether or not it was affected by C_{th} processing.





The model architecture used in this research.

Method

Hypertuning CNN and RF

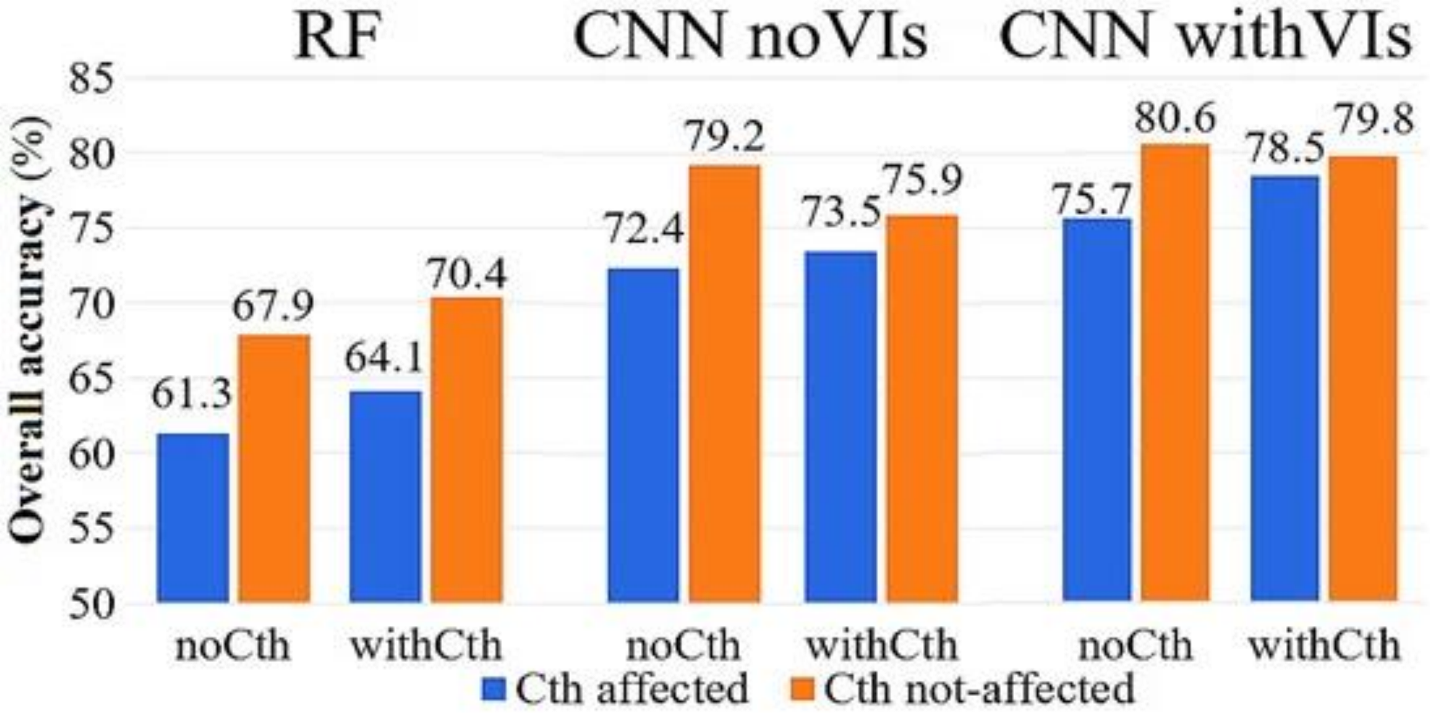
CNN hypertune
Dropout rate 1 = [0.0, 0.2, 0.4, 0.6, 0.8];
Dropout rate 2 = [0.0, 0.2, 0.4, 0.6, 0.8];
Dense unit 1 = [10, 50, 100, 150, 200, 250, 300];
Dense unit 2 = [10, 50, 100, 150, 200, 250, 300];
Batch_size = [32, 64, 128, 256, 1024, 1500].

RF hypertune

Parameter Name	Description (Pedregosa et al. [24])	Given Values for Grid	Default Value
max_depth	The maximum depth of the tree.	[None, 2, 10, 50, 80, 100]	None
min_samples_split	The minimum number of samples required to split an internal node.	[2, 3, 5, 8, 10, 12]	2 *
min_samples_leaf	The minimum number of samples required to be at a leaf node.	[1, 2, 3, 5, 20, 100]	1
max_features	The number of features to consider when looking for the best split **	[0, 2, 'auto', 'log2', 'sqrt', None]	sqrt
n_estimators	The number of trees in the forest. Usually, the bigger the better, but a larger number slows down the computation.	[75, 100, 125, 200, 500, 1000]	100

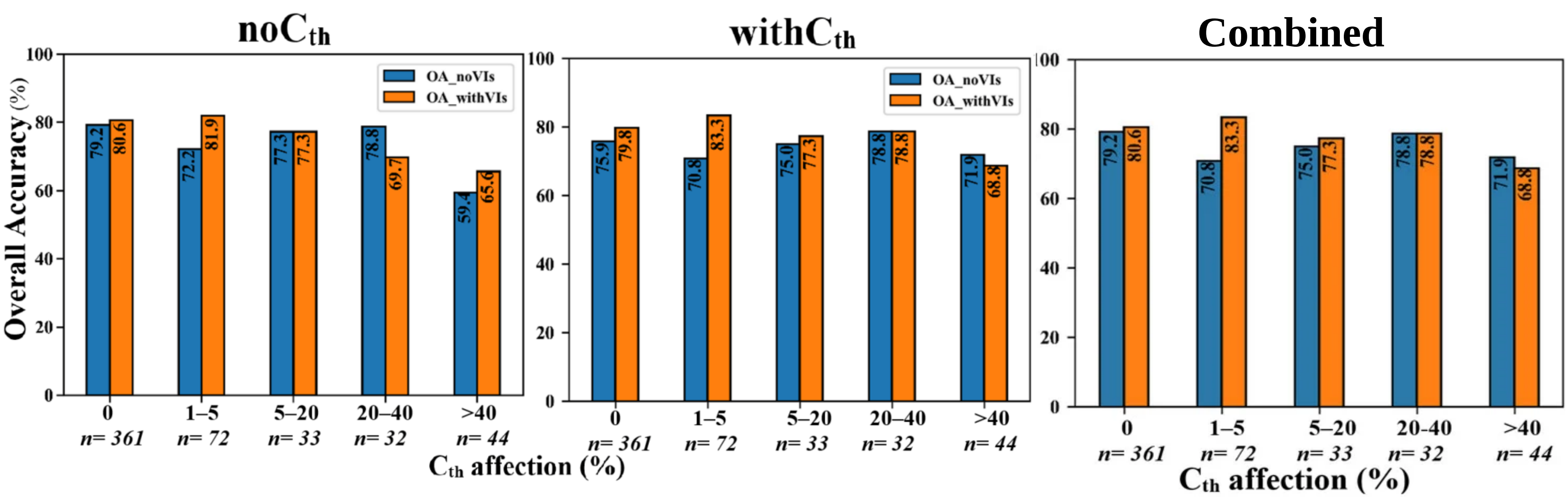
Results

Overall accuracy within the canopy threshold (C_{th})-affected (n = 161, 33.4%) and not-affected (n = 361, 66.6%) subsets of the test set (n = 542) in RF, CNN noVIs (without vegetation indices, five bands), and CNN withVIs (after fusing 8 VIs to tensors pixels, 13 bands) in the original (noC_{th}) and C_{th}-applied (withC_{th}) datasets.



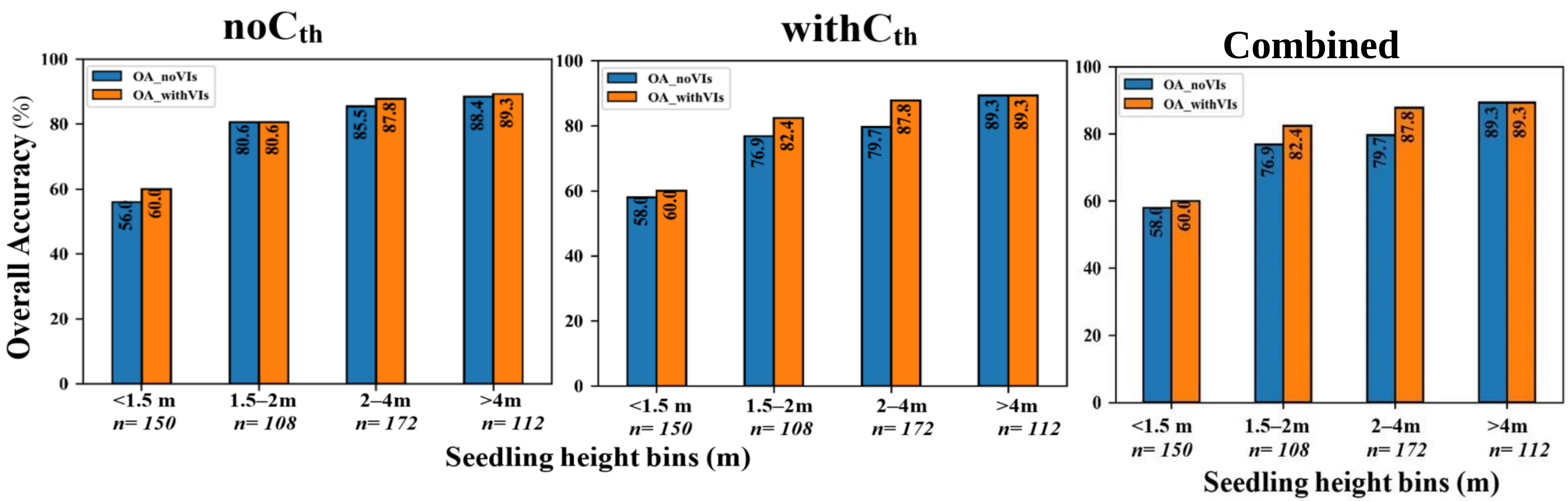
Results

Overall accuracy of species classification within different C_{th}-affection rates (%)



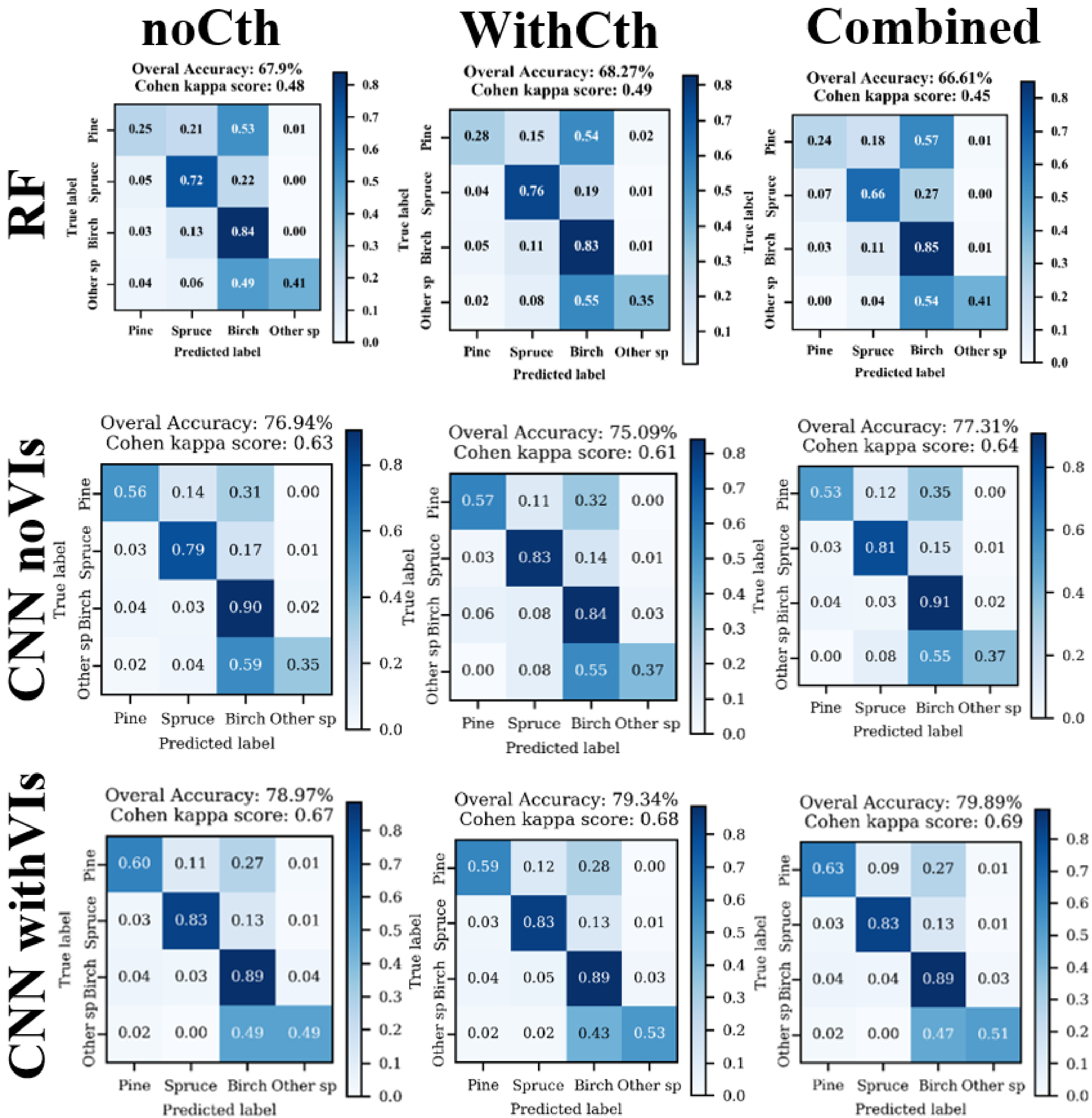
Results

Overall accuracy of species classification considering seedlings height (m)



Overall accuracy

The summary of species classification accuracies in the normalized confusion matrix together with overall accuracy and kappa values



Results

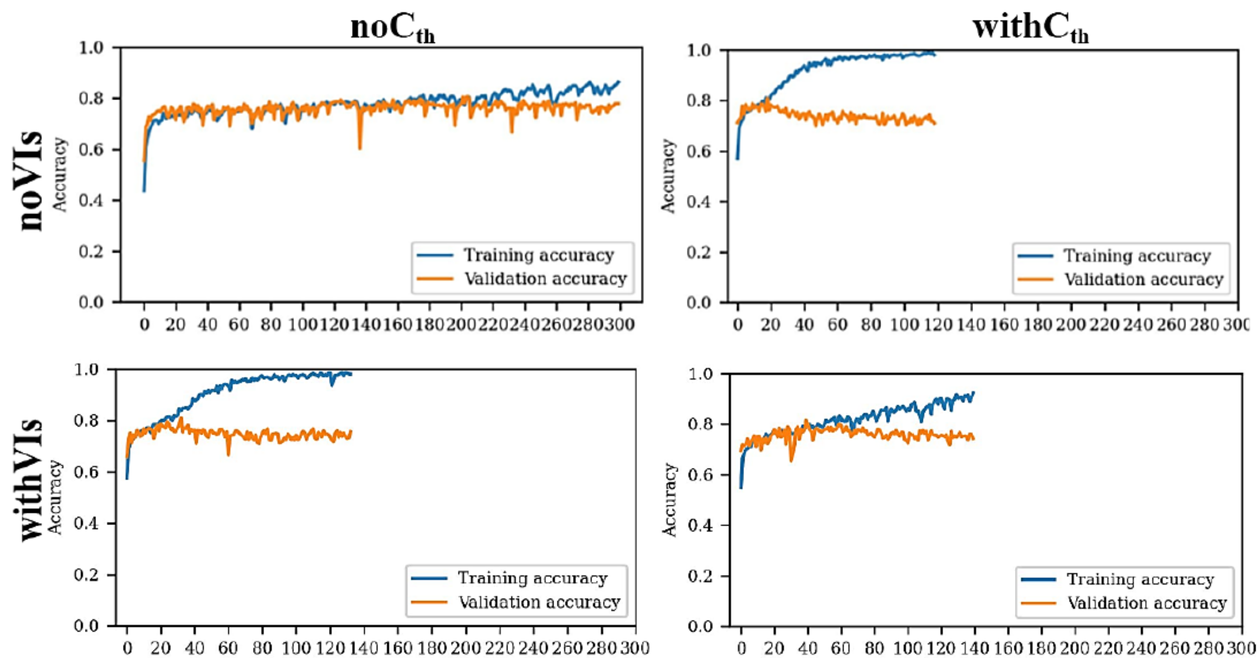
Evaluation of classification accuracy for each dataset and classifier

Dataset	Classifier	OA (%)	Kappa	Overall Precision (Per Species) *	Overall Recall (Per Species) *	Overall F1 Macro (Per Species) *	Overall F1 Micro
NoC_{th}	RF	67.9	0.5	0.7 (0.5, 0. 7, 0.7, 1.0)	0.6 (0.3, 0.7, 0.8, 0.4)	0.6 (0.3, 0.7, 0.8, 0.6)	0.7
	CNN noVIs	76.9	0.6	0.8 (0.7, 0.8, 0.8, 0.8)	0.7 (0.6, 0.8, 0.9, 0.4)	0.7 (0.6, 0.8, 0.8, 0.5)	0.8
	CNN withVIs	79.0	0.7	0.8 (0.7, 0.9, 0. 8, 0.7)	0.7 (0.6, 0.8, 0.9, 0.5)	0.7 (0.7, 0.9, 0.8, 0.6)	0.8
$WithC_{th}$	RF	68.3	0.5	0.7 (0.6, 0.7, 0.7, 0.8)	0.7 (0.3, 0.8, 0.8, 0.4)	0.6 (0.4, 0.7, 0.8, 0.5)	0.7
	CNN noVIs	75.1	0.6	0.7 (0.7, 0.8, 0.7, 0.7)	0.7 (0.6, 0.8, 0.8, 0.4)	0.7 (0.6, 0.8, 0.8, 0.5)	0.8
	CNN withVIs	79.3	0.7	0.8 (0.8, 0.8, 0.8, 0.8)	0.7 (0.6, 0.8, 0.9, 0.5)	0.7 (0.7, 0.8, 0.8, 0.6)	0.8
Combined dataset	RF	66.6	0.5	0.7 (0.6, 0.6, 0.7, 0.9)	0.5 (0.2, 0.7, 0.9, 0.4)	0.6 (0.3, 0.7, 0.8, 0.6)	0.7
	CNN noVIs	77.3	0.6	0.8 (0.7, 0.8, 0.8, 0.8)	0.7 (0.5, 0.8, 0.9, 0.4)	0.7 (0.6, 0.8, 0.8, 0.5)	0.8
	CNN withVIs	79.9	0.7	0.8 (0.8, 0.9, 0. 8, 0.7)	0.7 (0.6, 0.8, 0.9, 0.5)	0.7 (0.7, 0.9, 0.8, 0.6)	0.8

* The four numbers inside the parentheses show the accuracy metrics for each species of pine, spruce, birch, and other-species classes, respectively.

Results

Visualization of the training and validation accuracy in every epoch for the CNN models on the noC_{th} and $withC_{th}$ datasets.



Results

Model configurations selected for each classifier, together with other information regarding training and validation accuracies, as well as run time measurements. The model configuration and other information for the combined two methods were the combination of the configuration and other information of the two other methods.

Dataset	Classifier	Model Best Param (Out of GridSearch) [a]	Tunable Param	Total Param	Max Train Accuracy in the Best Model	Max Validation Accuracy in the Best Model	Number of Epochs Ran before Early Stop in the Best Model	Mean Train Time per Epoch in Best Model	St.dev of Train Time per Epoch in Best Model	Total Training Time (GridSearch Time)	Prediction Time
noC_{th}	RF	None, 0, 2, 2, 1000	7776 [b]	NA	0.99	0.7754	NA	36.03 [e]	1.94 [e]	3 h 32 min	9 ms
	CNN noVIs	32, 0.8, 0.4, 150, 100	165,762	166,742	0.86	0.80627	300	0.63	0.07	106.8 h (15.25 h) [f]	0.3 ms/step
	CNN withVIs	32, 0.6, 0, 100, 50 [c]	130,814	131,594	0.99	0.80812	133	0.75	0.19		0.3 ms/step
$withC_{th}$	RF	None, 0, 1, 2, 1000	7776 [b]	NA	1.00	0.7641	NA	8.25 [e]	0.38 [e]		9 ms
	CNN noVIs	32, 0.6, 0.2, 200, 150 [d]	206,862	208,042	0.99	0. 80812	119	0.64	0.11	102.8 h (14.68 h) [f]	0.3 ms/step
	CNN withVIs	32, 0.8, 0.2, 150, 250	266,664	267,944	0.92	0.81550	140	0.68	0.18		0.3 ms/step

Link to full paper

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Abstract

Tree species information is important for forest management, especially in seedling stands. To mitigate the spectral admixture of understory reflectance with small and lesser foliaged seedling canopies, we proposed an image pre-processing step based on the canopy threshold (C_{th}) applied on drone-based multispectral images prior to feeding classifiers. This study focused on (1) improving the classification of seedlings by applying the introduced technique; (2) comparing the classification accuracies of the convolutional neural network (CNN) and random forest (RF) methods; and (3) improving classification accuracy by fusing vegetation indices to multispectral data. A classification of 5417 field-located seedlings from 75 sample plots showed that applying the C_{th} technique improved the overall accuracy (OA) of species classification from 75.7% to 78.5% on the C_{th}-affected subset of the test dataset in CNN method (1). The OA was more accurate in CNN (79.9%) compared to RF (68.3%) (2). Moreover, fusing vegetation indices with multispectral data improved the OA from 75.1% to 79.3% in CNN (3). Further analysis revealed that shorter seedlings and tensors with a higher proportion of C_{th}-affected pixels have negative impacts on the OA in seedling forests. Based on the obtained results, the proposed method could be used to improve species classification of single-tree detected seedlings in operational forest inventory.

Keywords: seedling forest; species classification; canopy height threshold (C_{th}); image pre-processing; UAV; random forest; artificial intelligence

Thanks for your attention.

I welcome your question and comments