Remote sensing and GIS-based project activities in Finland

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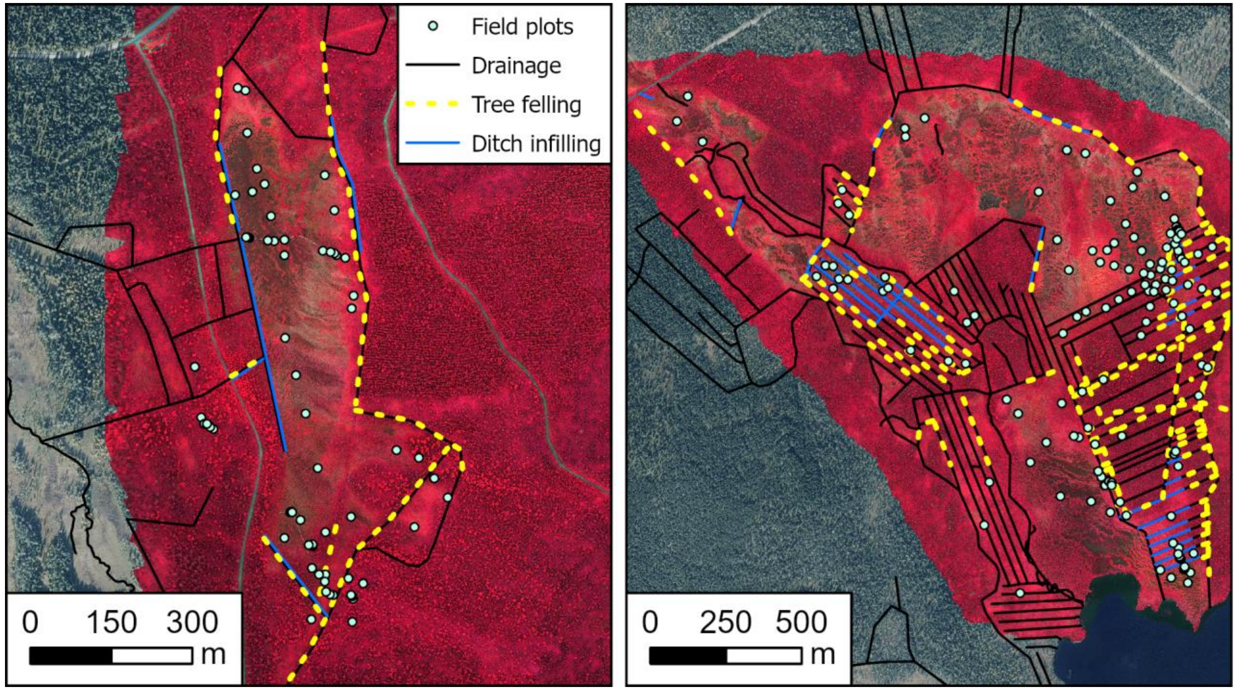
Content

1. Finnish study sites and revision on their high-resolution classifications
2. Nationwide peatland typing for nationwide GHG-modelling
3. Other analyses

Finnish study sites and field data

- 206 plots across two sites
- Vegetation inventories from all plots
  →153 with species-level coverages
  →53 with plant functional type -level coverages
- Floristic clustering system created with vegetation data
  →Each cluster represent microhabitat with different kind of vegetation community
- Training data of previous classification included only species-level plots



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Revision on high-resolution classifications

- Some updates to previous versions
- All PFT-field plots have been assigned to clustering system which was created from species-level vegetation data

→More field plots for training the classifier

→For each field plot, 3 extra plots created with visual interpretation close to the original plot to increase data sample size

- In summer 2025 some corrections to GEST-typing was conducted by Latvian colleagues
- Now separate classifiers for Välisuo and Matorovansuo (previously combined classifier)

Classifications

- As training data is not truly independent (extra plots), validation strategy need to take this into account
- Modelling conducted using random forest
  - XGBoost and deep neural networks were also tested but they did not improve the classification performance
- Validation takes spatial autocorrelation of extra plots into account
  - Certain type of leave-one-out-cross validation is used

Cluster classification results

- Välisuo OA 61%, Matorovansuo 54%
- While the accuracies are relatively poor, they still reveal real-life attributes from the area
- Cluster classifications look quite similar to old one
  - →Some changes in drier, treed clusters
  - →Should not have large impact into GHG estimations

Välisuo

	Class	Precision	Recall	F1	Support
...1	(1) Flark	1.0000000	0.8750000	0.9333333	32
...2	(2) Trichophorum lawn	0.4000000	0.3571429	0.3773585	28
...3	(3) Rich carex lawn	0.5531915	0.6500000	0.5977011	40
...4	(4) Pleurozium hummock	0.6250000	0.4166667	0.5000000	36
...5	(5) S. fuscum hummock	0.3142857	0.2750000	0.2933333	40
...6	(6) Wet forest	0.6774194	0.8289474	0.7455621	76
Accuracy	Accuracy	NA	NA	0.6071429	252
...8	Macro Avg	0.5949828	0.5671261	0.5745481	252
...9	Weighted Avg	0.6027102	0.6071429	0.5981619	252

Matorovansuo

Class	Precision	Recall	F1	Support
(1) Flark	0.7179487	0.7000000	0.7088608	80
(2) Trichophorum lawn	0.4081633	0.3571429	0.3809524	56
(3) Rich carex lawn	0.3818182	0.2763158	0.3206107	76
(4) Pleurozium hummock	0.5824176	0.6625000	0.6198830	160
(5) S. fuscum hummock	0.4444444	0.5000000	0.4705882	88
(6) Wet forest	0.5643564	0.5480769	0.5560976	104
Accuracy	NA	NA	0.5390071	564
Macro Avg	0.5165248	0.5073393	0.5094988	564
Weighted Avg	0.5324507	0.5390071	0.5333968	564

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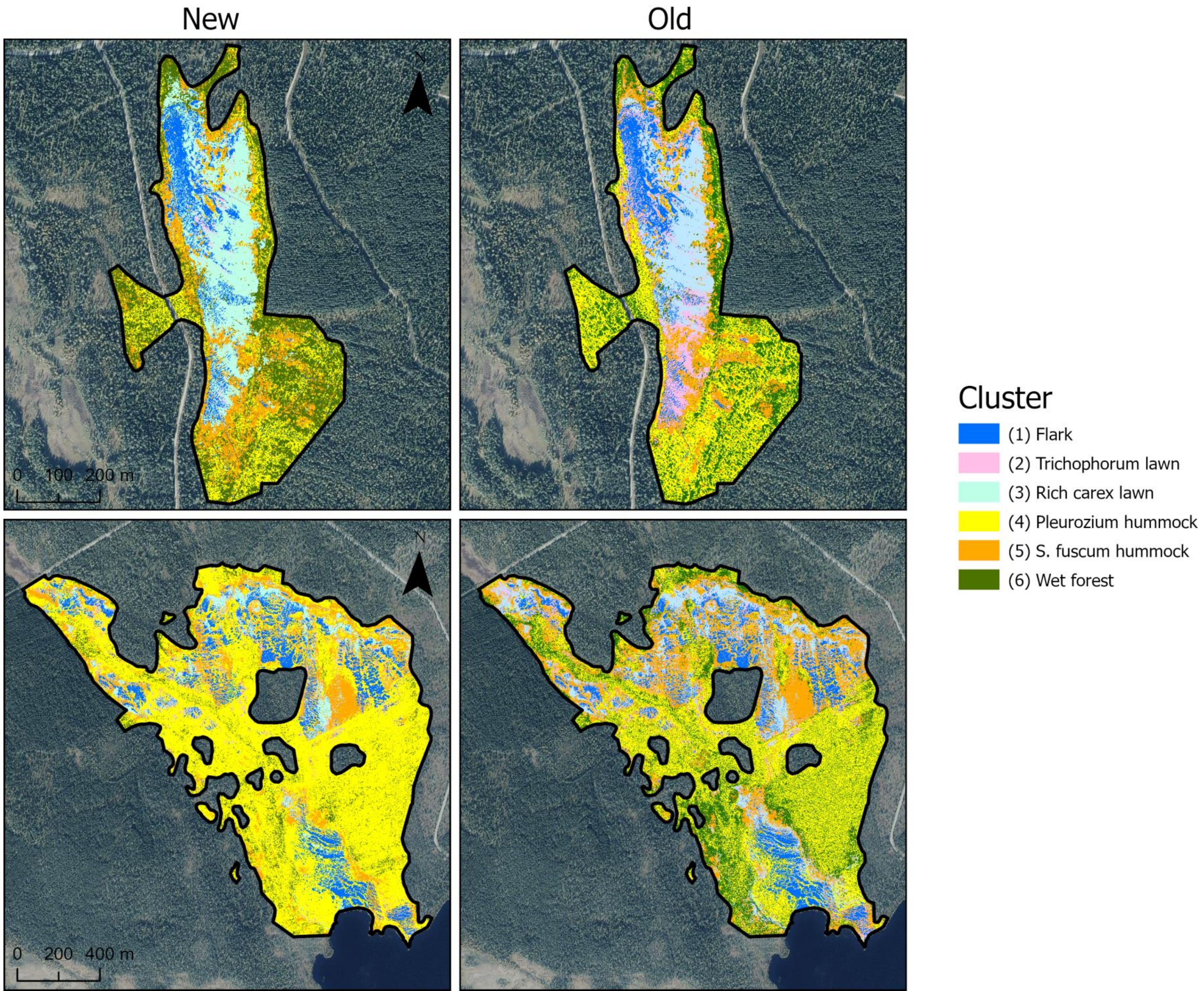

New
Old
0 100 200 m
0 200 400 m
N
Cluster
(1) Flark
(2) Trichophorum lawn
(3) Rich carex lawn
(4) Pleurozium hummock
(5) S. fuscum hummock
(6) Wet forest

GEST classification results

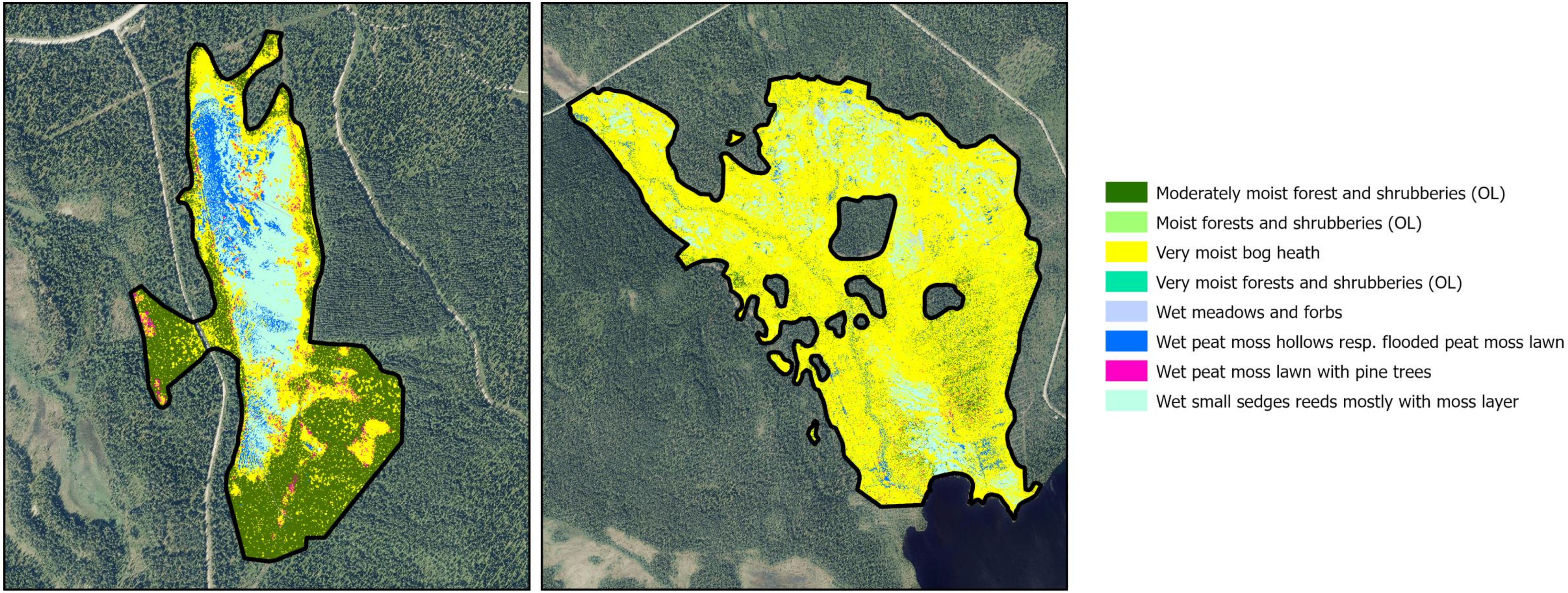
- Välisuo OA 73%, Matorovansuo 47%
- Välisuo classification looks good and quite similar to cluster-based classification
- Matorovansuo accuracy is quite bad and most classes have very bad F-score
- Matorovansuon output does not look meaningful

Välisuo

	Class	Precision	Recall	F1	Support
...1	Moderately moist forest and shrubberies (OL)	0.8555556	0.9166667	0.8850575	84
...2	Very moist bog heath	0.4750000	0.3958333	0.4318182	48
...3	Wet peat moss hollows resp. flooded peat moss lawn	0.9655172	0.7777778	0.8615385	36
...4	Wet peat moss lawn with pine trees	0.4000000	0.3000000	0.3428571	20
...5	Wet small sedges reeds mostly with moss layer	0.6756757	0.8333333	0.7462687	60
Accuracy	Accuracy	NA	NA	0.7258065	248
...7	Macro Avg	0.6743497	0.6447222	0.6535080	248
...8	Weighted Avg	0.7176041	0.7258065	0.7166159	248

Matorovansuo

	Class	Precision	Recall	F1	Support
...1	Moderately moist forest and shrubberies (OL)	0.3650794	0.3382353	0.3511450	68
...2	Moist forests and shrubberies (OL)	NA	0.0000000	NA	20
...3	Very moist bog heath	0.4488889	0.7214286	0.5534247	140
...4	Very moist forests and shrubberies (OL)	0.0000000	0.0000000	NaN	20
...5	Wet meadows and forbs	0.0000000	0.0000000	NaN	12
...6	Wet peat moss hollows resp. flooded peat moss lawn	0.2500000	0.1136364	0.1562500	44
...7	Wet peat moss lawn with pine trees	0.4166667	0.2777778	0.3333333	36
...8	Wet small sedges reeds mostly with moss layer	0.6451613	0.6818182	0.6629834	88
Accuracy	Accuracy	NA	NA	0.4649533	428
...10	Macro Avg	0.3036852	0.2666120	0.4114273	428
...11	Weighted Avg	0.3982337	0.4649533	0.4172310	428


Moderately moist forest and shrubberies (OL)
Moist forests and shrubberies (OL)
Very moist bog heath
Very moist forests and shrubberies (OL)
Wet meadows and forbs
Wet peat moss hollows resp. flooded peat moss lawn
Wet peat moss lawn with pine trees
Wet small sedges reeds mostly with moss layer

Problem with GEST-types

- First problem is that some types occur in the training dataset only once or maximum of few times
  - →Classifiers needs more balanced class distribution to properly function
    - →These classes are removed or converted into similar GEST-type in training data
  - →Classes very difficult to be labelled from UAV image alone
    - →Difficult to produce new training data
- Second and larger problem:
  - In the training data, similar areas have been labelled differently
  - In Välisuo all plots within wet flarks have been labelled as "Wet peat moss hollow resp. flooded peat moss lawn"
  - In Matorovansuo only 6/17 of flark plots have been labelled to this GEST type
  - Rest of the flark plots in Matosuo have been labelled as "Wet small sedges reeds mostly with moss layer"

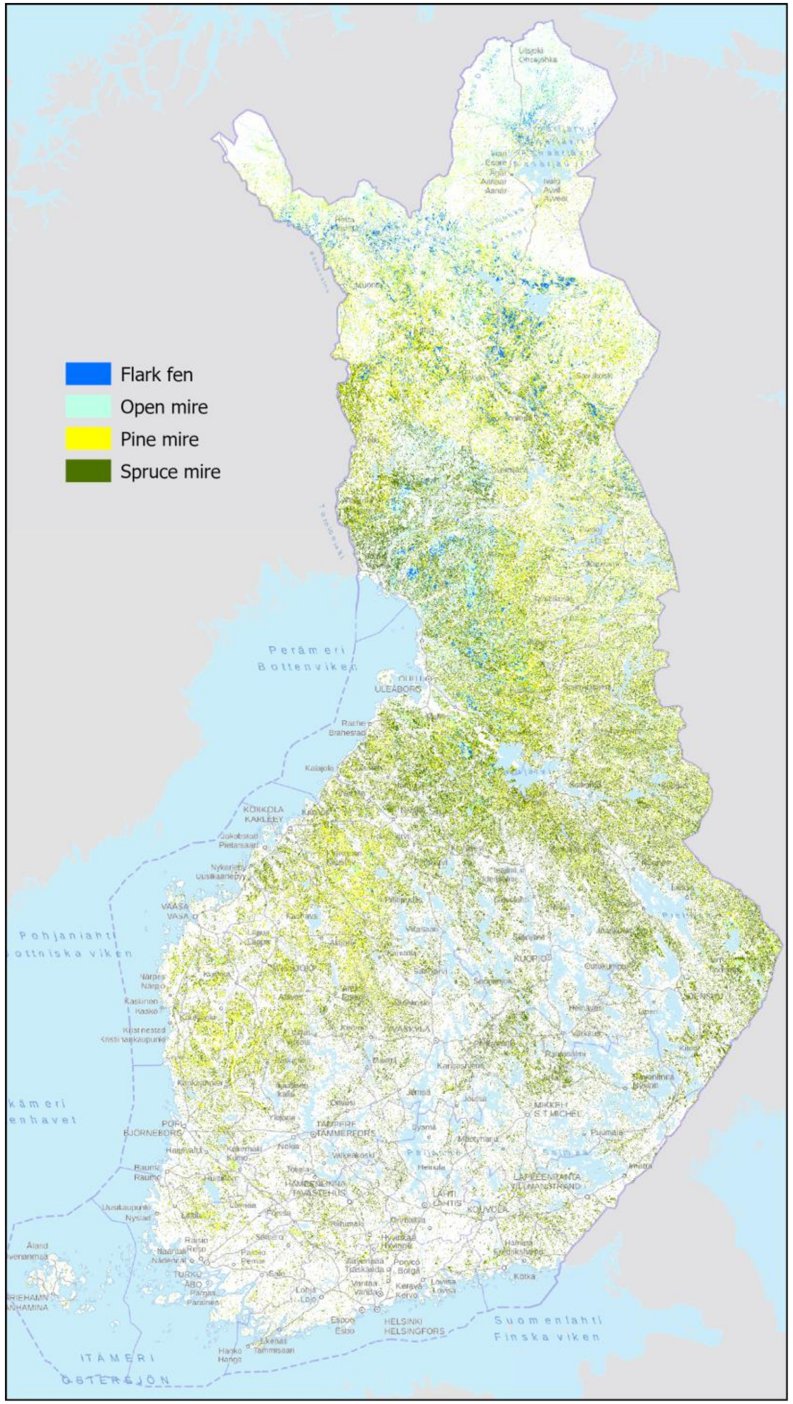
Nationwide peatland typing

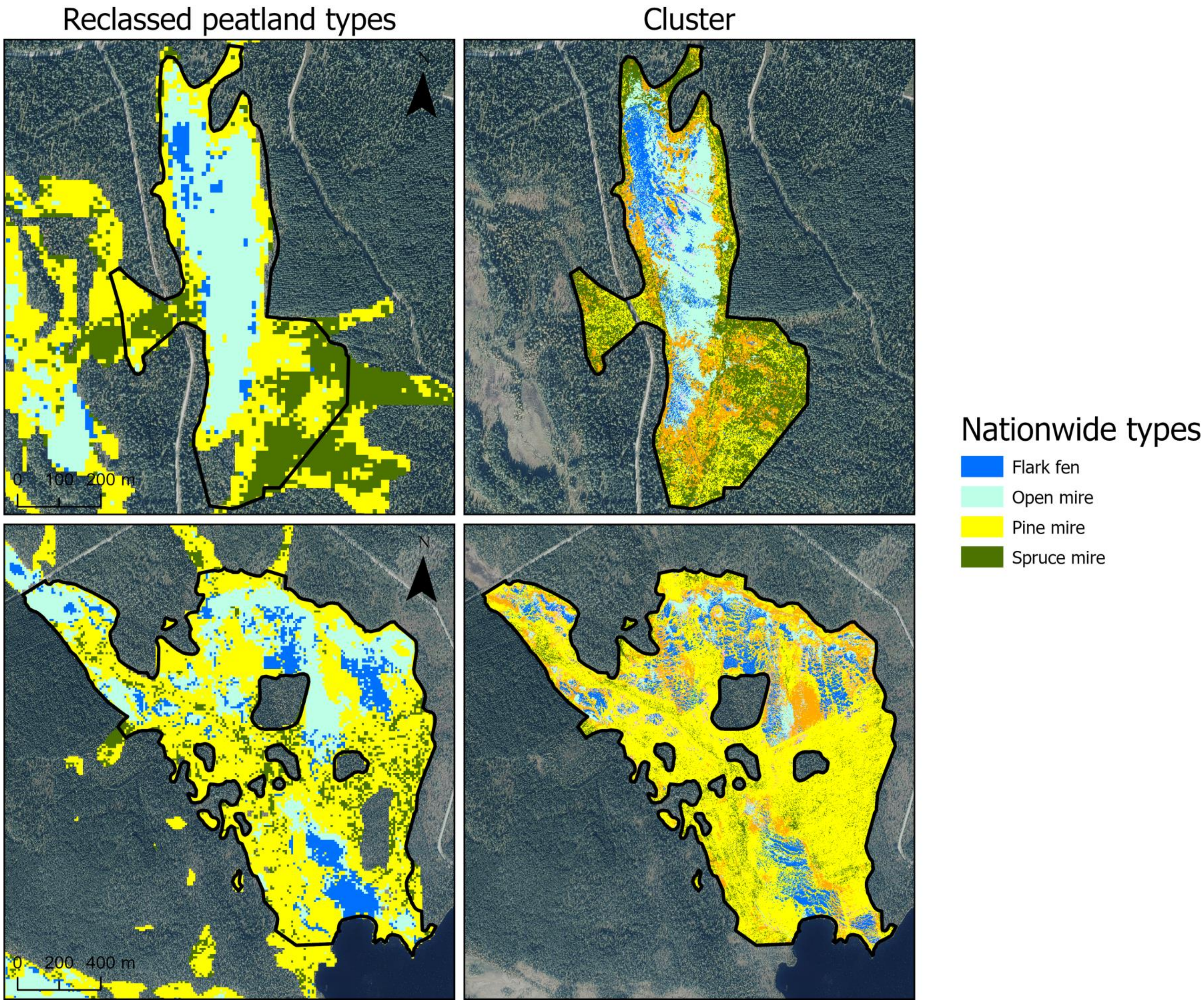
- We used thematic classification created by Geological Survey of Finland (GTK) as our base data
- Includes 42 classes and separate datasets for undrained and drained areas
- Aim was to produce general and distinct classification suitable for nationwide GHG-modelling purposes

1. Spruce mires (peatland forest/swamp)
2. Pine mires (pine bogs)
3. Open mires (treeless fens and bogs)
4. Flark fens (highly wet open mires)

	Drained	Undrained
Spruce mires	30106 km^2	4851 km^2
Pine mires	13811 km^2	15796 km^2
Open mires	4464 km^2	12152 km^2
Flark fens	724 km^2	4906 km^2

- 57% of all Finnish peatlands are considered here as drained
- From drained peatlands, spruce mires most common
- From undrained peatlands, pine mires most common





Reclassed peatland types
Cluster
N
0 100 200 m
0 200 400 m
Nationwide types
Flark fen
Open mire
Pine mire
Spruce mire

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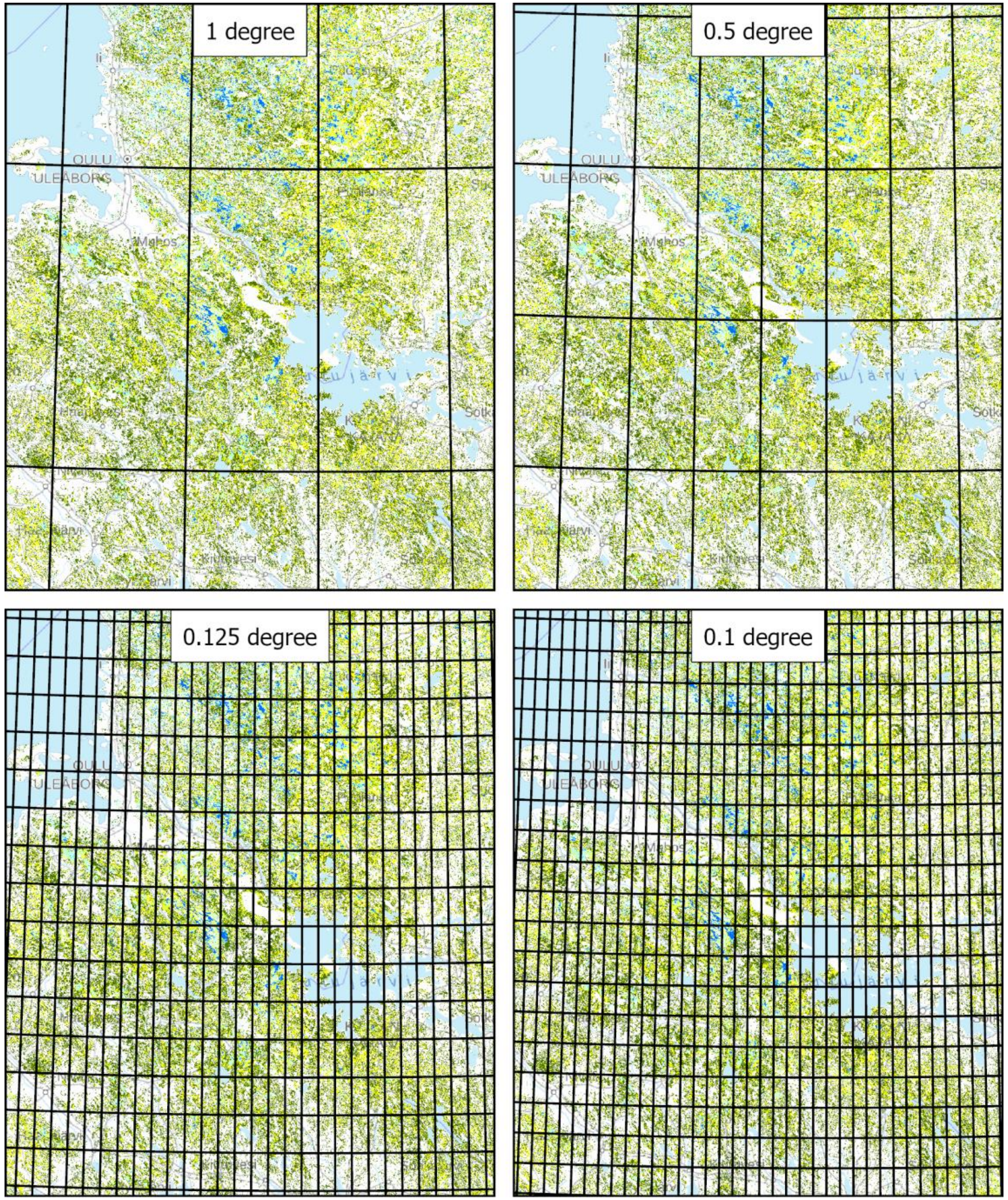
Nationwide peatland typing

- Nationwide GHG modelling is conducted using climatic grids
- Currently we are using grids sized 1, 0.5, 0.125, and 0.1 degree (WGS84)
- Proportion of each type within the grid is extracted



Other analyses

- Manual water table data from Pallas sites used in two case studies
  - Was gathered when establishing vegetation monitoring plots during July 2023
- We tested whether
  1. Multisource remote sensing data enables more reliable continuous water table models
  2. Downscaling techniques could be utilised for wetness monitoring
- Both caste studies lay the foundations for assessing restoration success and its spatial variability
- Conducted in collaboration with projects EkoSuo, AlfaWetlands, and Priodiversity LIFE.

Modelling water table using multisource data

- We used multispectral and LiDAR data gathered with drones to model field measured water table
- Modelling was conducted using random forest regression
- Using only multispectral data produced relatively weak models
- LiDAR-based predictors improved the models

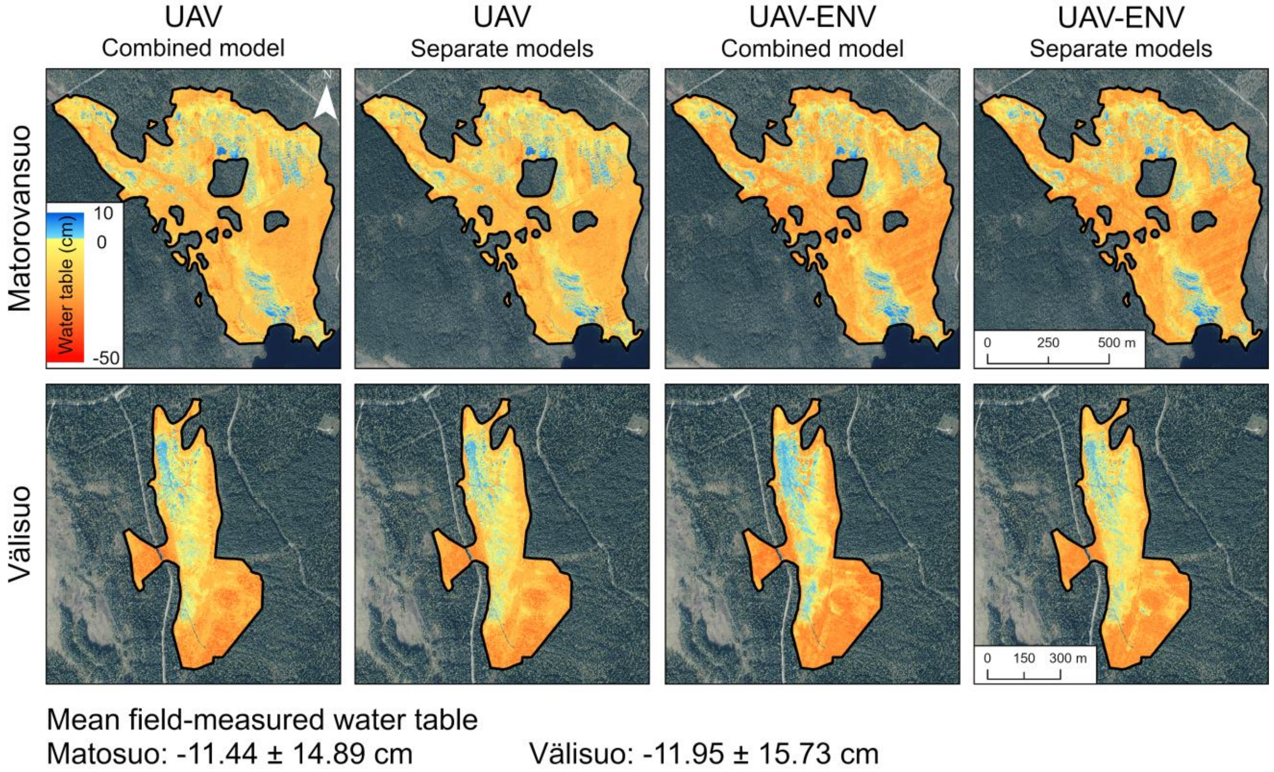


Figure: Christiani, P., Räsänen, A., Kuzmin, A., Ojanen, P., Minkkinen, K., Korpelainen, P., Rana, P., Kumpula., T. & Isoaho, A. (2025). Environmental Variables improve remote sensing-based water monitoring in peatlands. Manuscript submitted for publication.

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Downscaling Sentinel-2 –based OPTRAM

- We tested whether downscaled OPTRAM could be used as spatial wetness proxy
- Downscaling strengthened the connection between WT and OPTRAM but the correlation remained weak
- UAV-derived variables had stronger correlations with water table

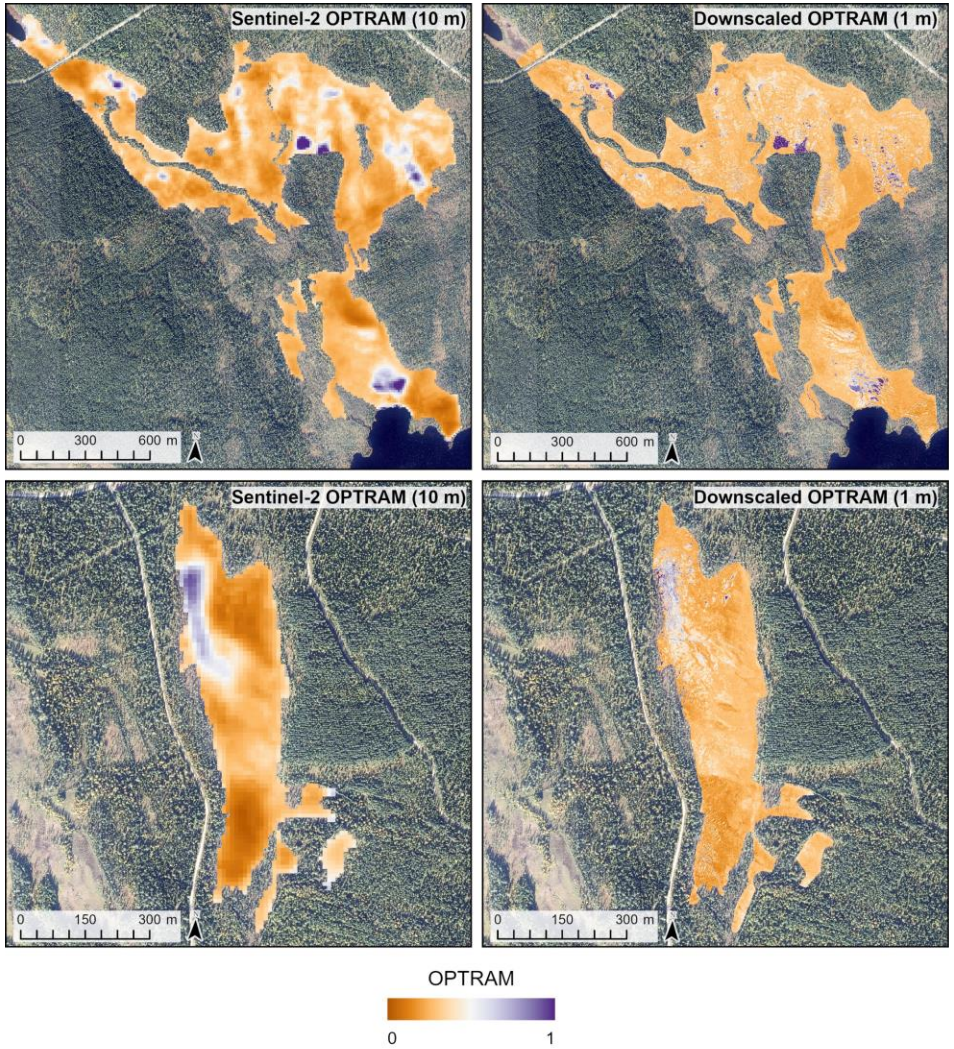

Figure: Heikkinen, S., Räsänen, A., Kumpula, T., Korpelainen, P., Kuzmin, A & Isoaho, A. (2025). Downscaling satellite-derived optical trapezoid model with uncrewed aerial vehicle data in peatland water table monitoring. Manuscript submitted for publication.

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Thank you!

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