Using UAS Imagery to Relate Landscape and Microhabitat Conditions Across a Thawing Permafrost Peatland

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Introduction

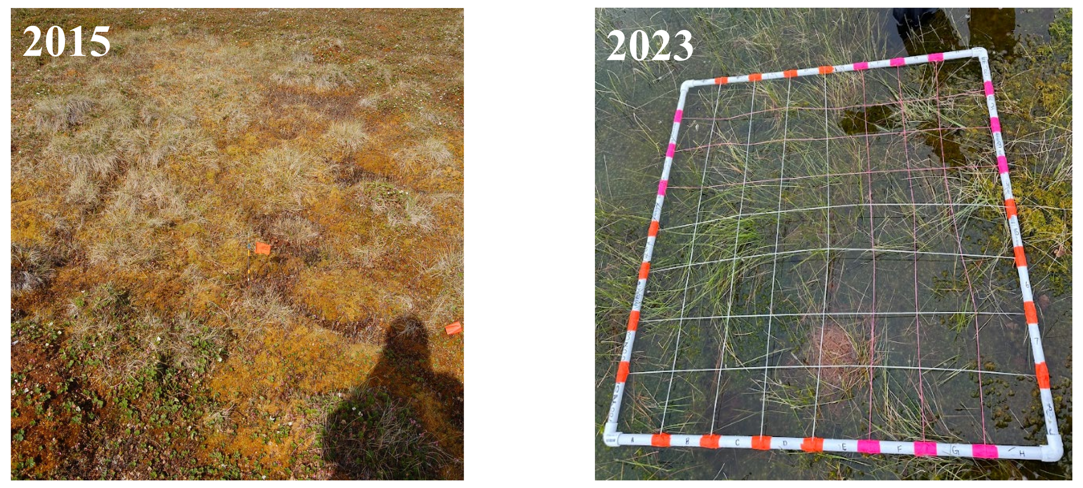

Fig. 1. Site 19 showing distinct shift from early-stage to late-stage thaw.

- Permafrost thaw generates heterogeneity in terrain, temperature, and microhabitat conditions (Fig. 4).
- Terrain features and temperature can be measured at a cm scale by UAS.

Can we use remotely sensed terrain features to predict subsurface conditions?

UAS Survey

- LiDAR and Thermal collected over entire study site

Terrain Features:

- DSM and DTM generated
- Slope, roughness, ruggedness derived from DSM and DTM

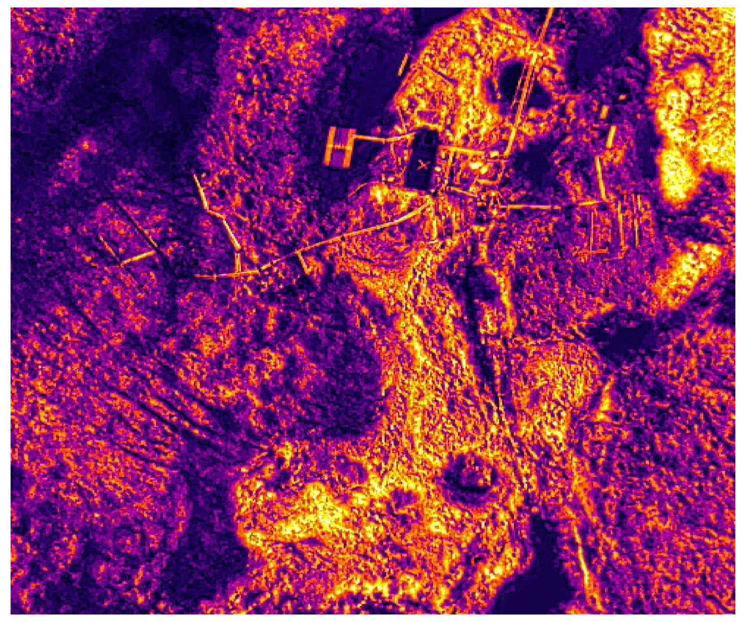

Fig. 2. Snapshot of 2023 thermal imagery

Ground Survey

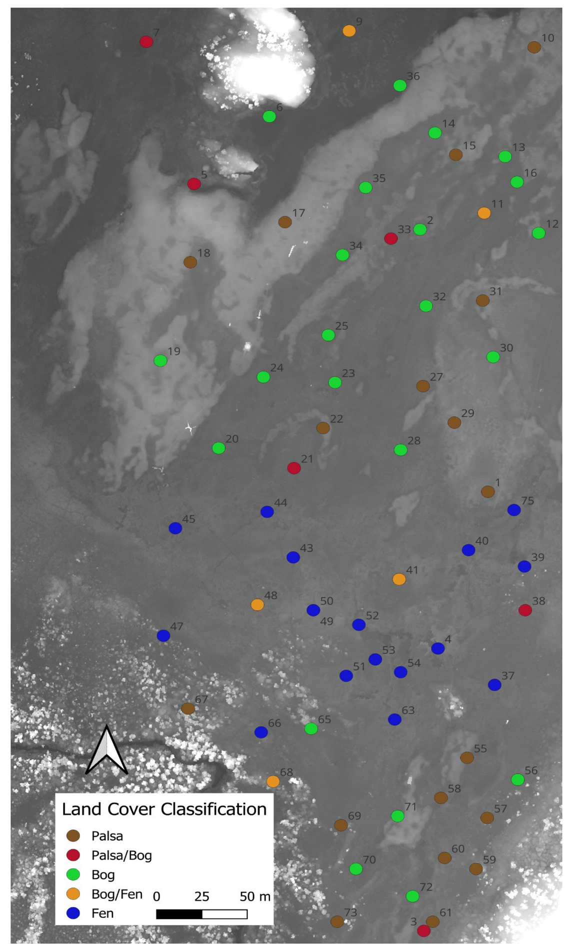

Fig. 3. DTM of Stordalen Mire and survey sites by land cover class.

- Quadrats (1m sq.) used at each site
- Land cover class, including transitions, assessed

Microhabitat Conditions:

- Vegetation composition
- Methane concentration and pH measured from porewater
- Mercury concentration measured in peat and vegetation samples

Can Terrain Predict Permafrost Thaw?

Yes, remotely sensed terrain features can predict land cover classification, which represent various stages of permafrost thaw.

- Palsas (minimal collapse) best predicted
- Collapsing permafrost well predicted on the margins of large palsas, slightly over predicted elsewhere
- Bogs and fens more variable in accuracy
- Fen predictions may not always be hydrologically representative due to sampling methods

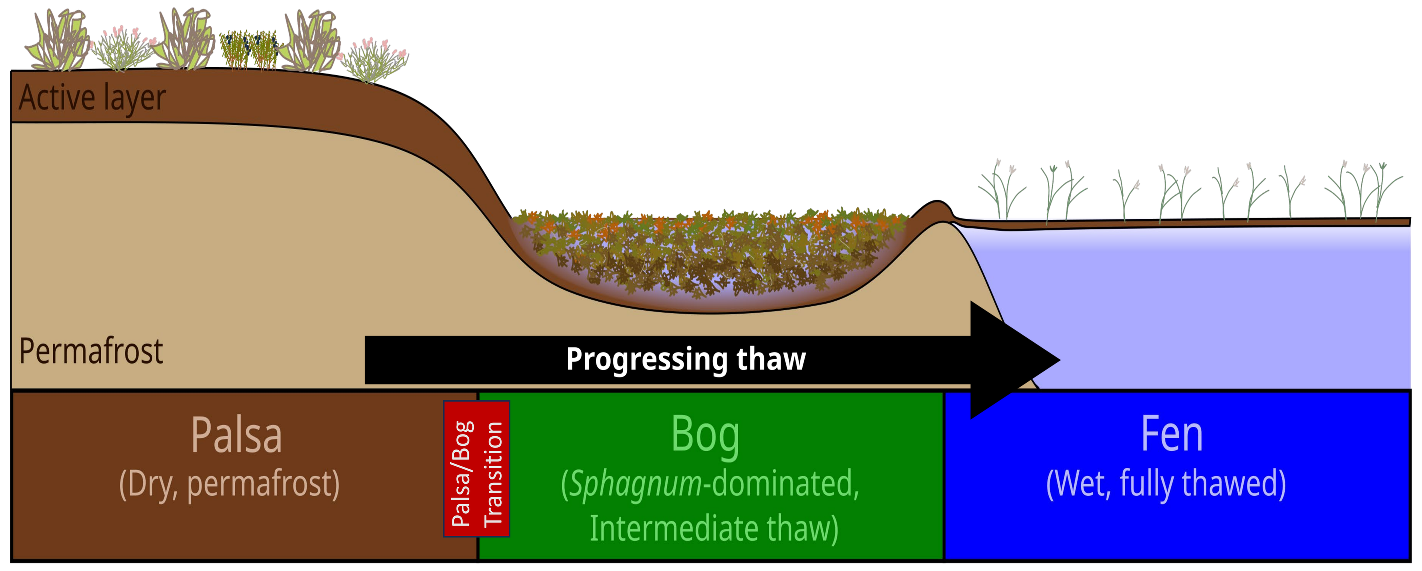

Fig. 4. Changes in land cover class and terrain over the thaw gradient. Figure credit to Dr. Hannah Holland-Moritz

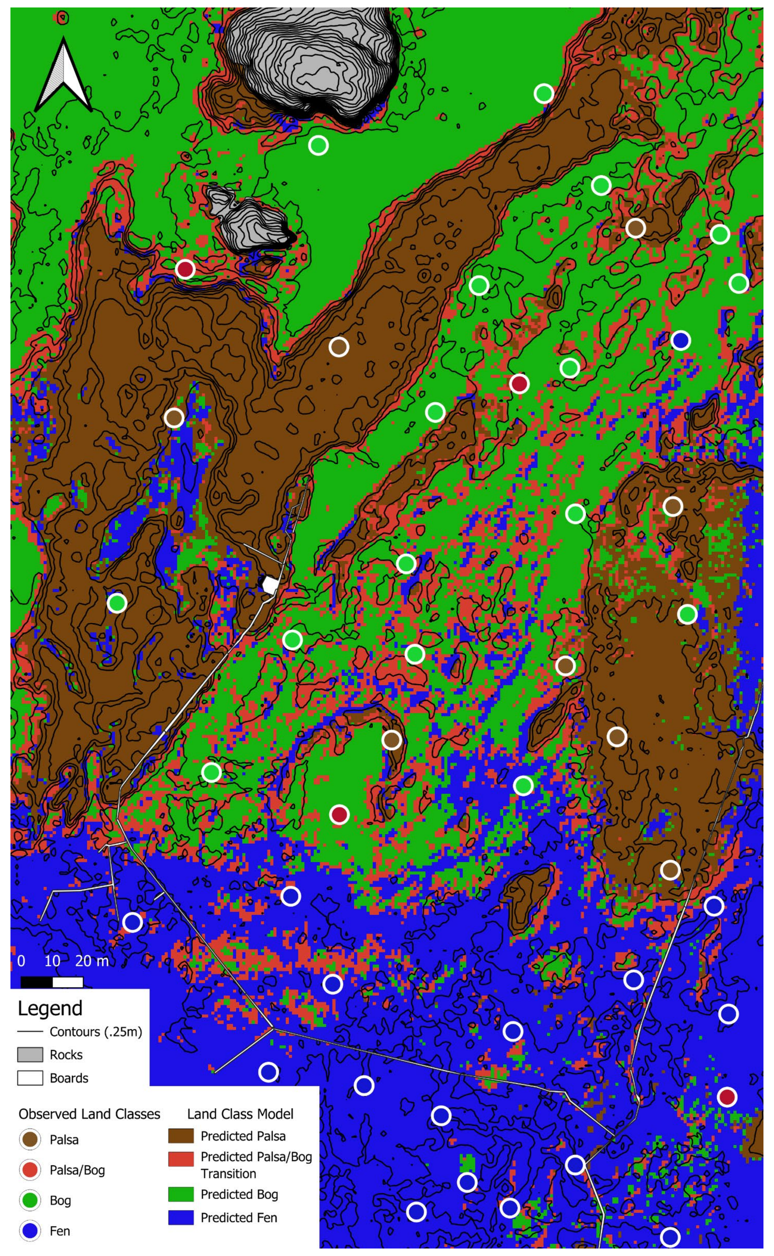

Fig. 5. Predicted land classes/thaw stage mapped over study area. R^2 Training = .84; R^2 Validation = .91

Can Terrain Predict Microhabitat Conditions?

pH is well predicted at variable depths.

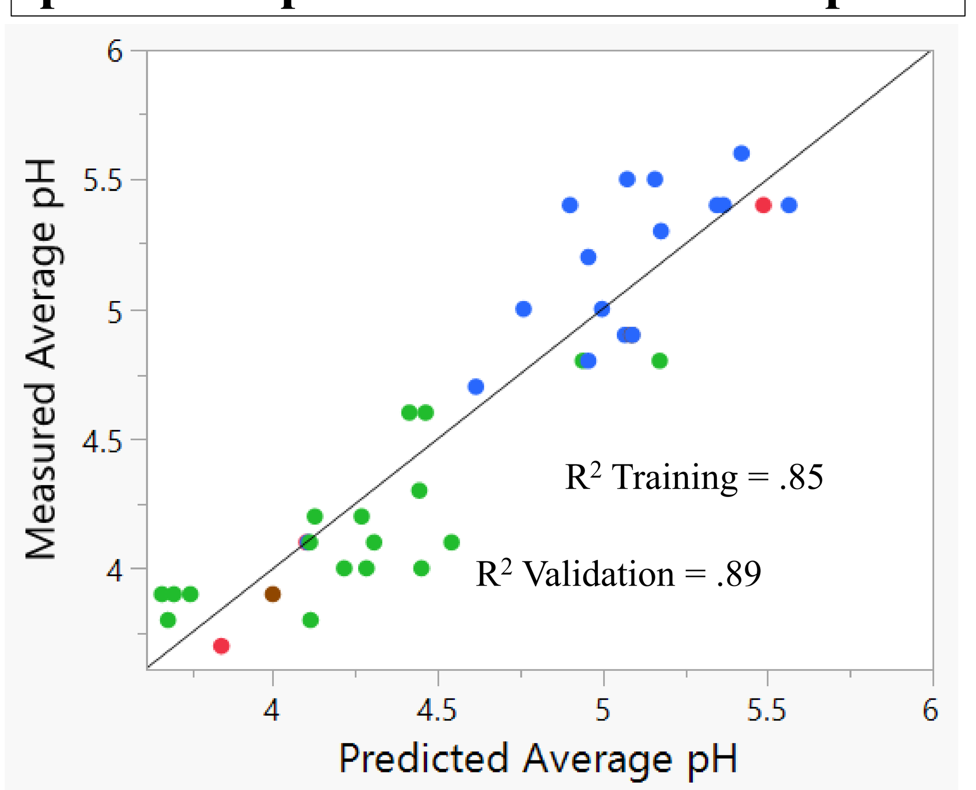

Fig. 6. Average pH model accuracy.

- 2.5 cm, 10cm, and 20cm pH all well predicted by terrain features
- Palsas underrepresented in sampling

Mercury is marginally well predicted at 2.5cm.

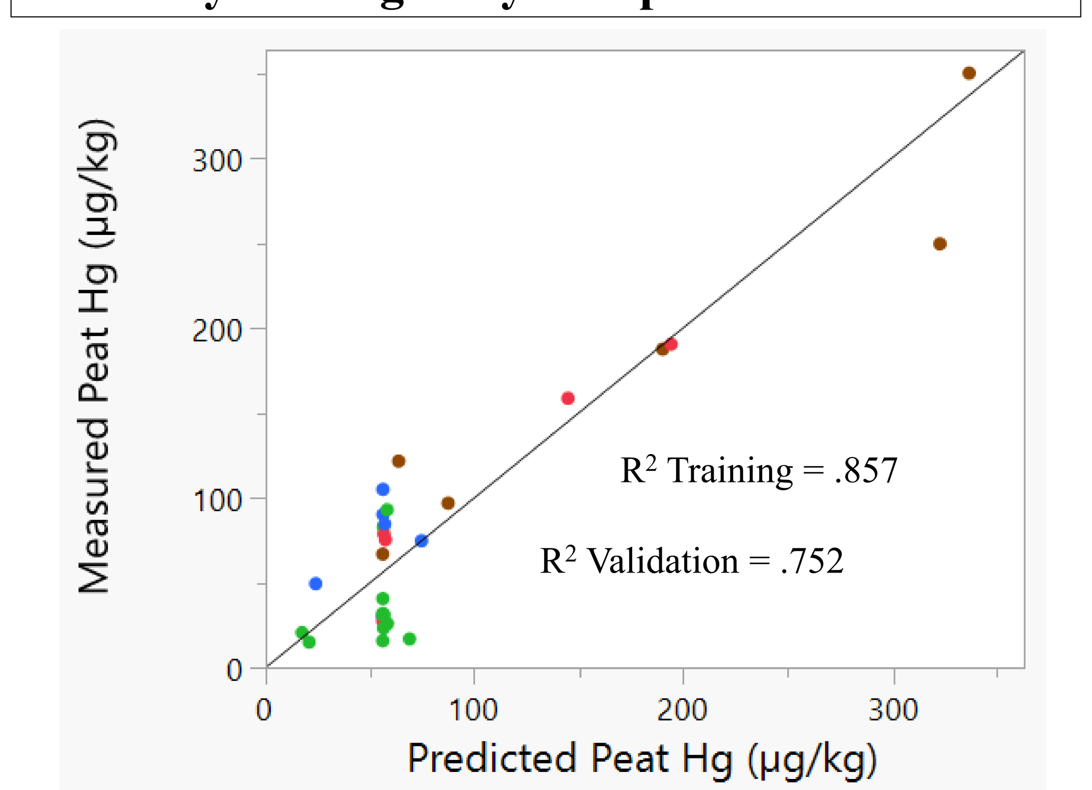

Fig. 7. Shallow peat Mercury model accuracy.

- Poorly predicted at both other depths
- Success of model could be a result of low sample size.

The estimation of Methane will require more training data.

- Methane poorly predicted at every measured depth
- Measured using porewater samples collected during a drought, resulting in an uneven representation of terrain features in the data
- Further training data needed to evaluate predictive potential

Neural Networks

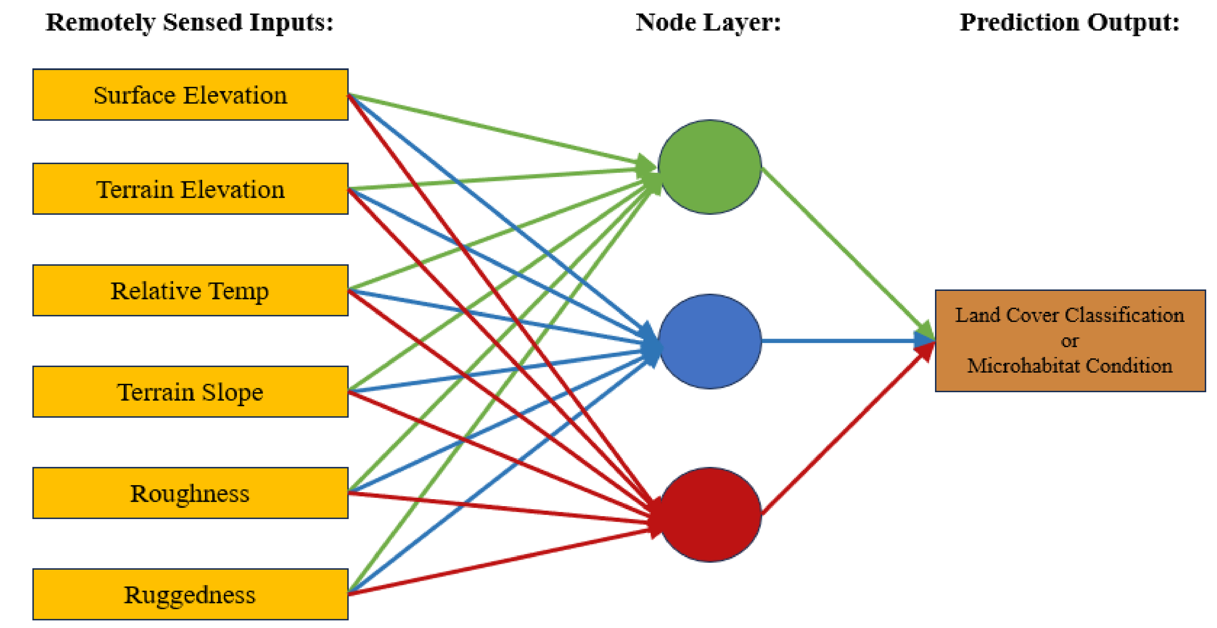

Fig. 8. Example of model construction. Ruggedness and roughness were not used in final models. All models used K-fold validation, a single node layer, and a maximum of three nodes. Models were trained using JMP Pro 17.

- Neural networks trained on ground sampled microhabitat conditions (outputs) and remotely sensed terrain features (inputs)
- Each model replicated using randomized terrain values to verify model success was not a result of the small sample size

Conclusion

With the collection of further training data, permafrost peatland subsurface and microhabitat conditions could be modeled by remotely sensed terrain features, allowing for:

- Remote predictions not reliant on light (see fig. 9)
- Comprehensive tracking of mire conditions using continuous mapping (such as fig. 5)
- Better understanding of climate change impacts on these unique ecosystems
- Reduced need for frequent, potentially destructive mire-wide surveys (fig. 9)
- Development of models of other microhabitat and subsurface conditions, such as microbial communities

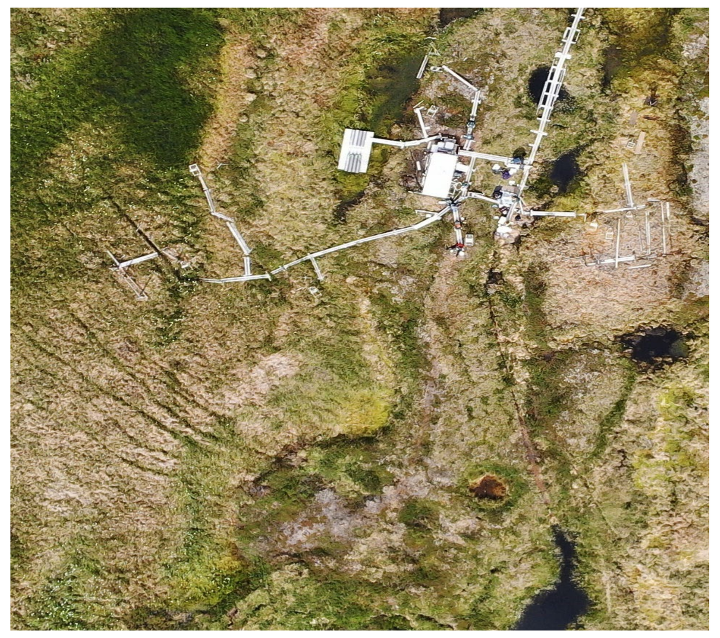

Fig. 9. Snapshot of RGB optical imagery collected over Stordalen Mire. Walking paths of surveyors visible to the left. While the addition of optical may improve these models, it is reliant on light, cloud cover, and time of day. LiDAR and thermal are not.

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Contact Me