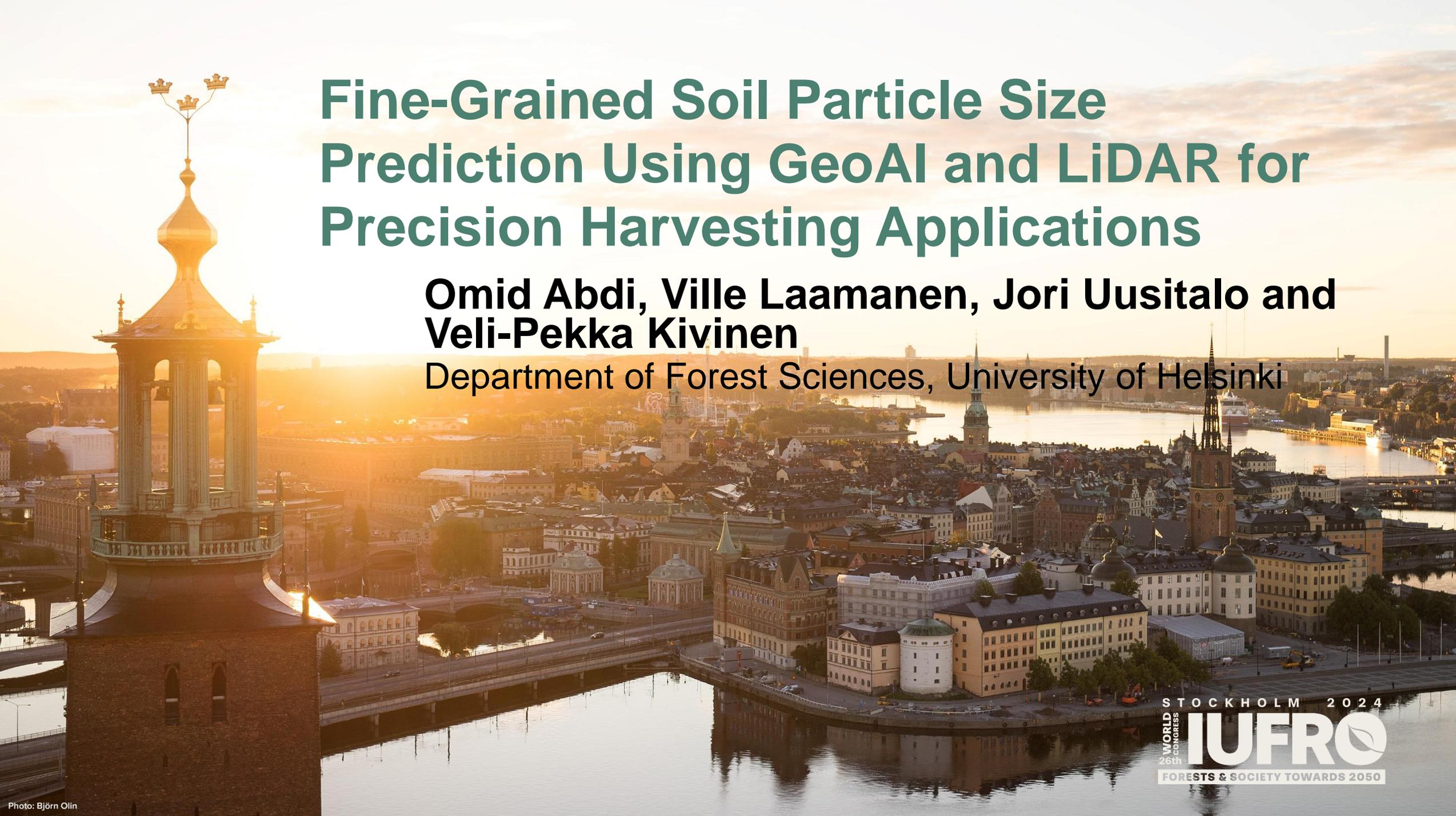# Welcome to the
# 26th IUFRO World Congress
## Stockholm, Sweden, 23–29 June 2024

STOCKHOLM 2024
WORLD CONGRESS 26th
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FORESTS & SOCIETY TOWARDS 2050

Photo: Björn Olin

# Fine-Grained Soil Particle Size Prediction Using GeoAI and LiDAR for Precision Harvesting Applications

**Omid Abdi, Ville Laamanen, Jori Uusitalo and Veli-Pekka Kivinen**

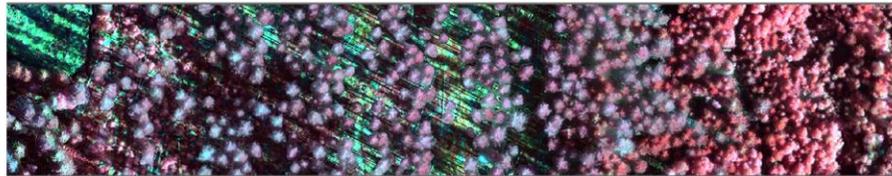Department of Forest Sciences, University of Helsinki

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# LUOMUHAKKUU

**Euroopan unionin rahoittama**

NextGenerationEU

Multi-Spectral Data

Orthomosaic Image

3D Point Clouds

Machine control handles moves camera

Forest simulation

Single tree detection

GNSS satellites

LiDAR

Correction RTK

Low-cost receiver/Rover

Base station

2024

26th WORLD CONGRESS IUFRO

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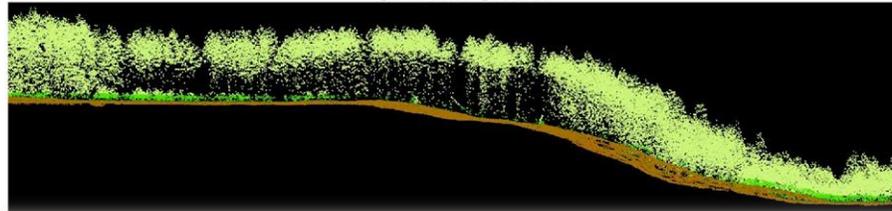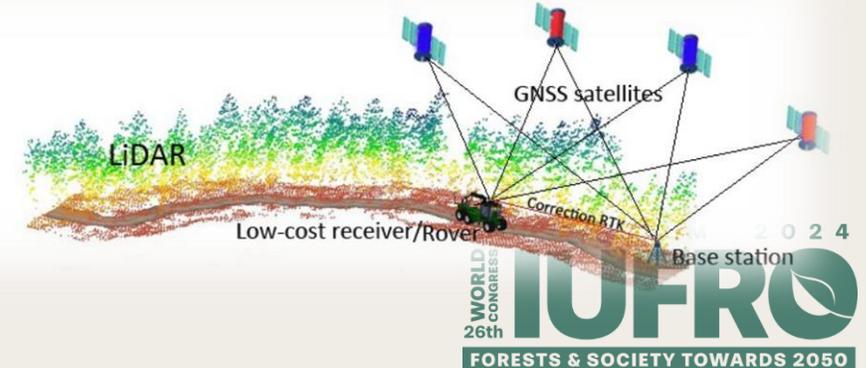
# Introduction

o  Fine-grained soil particles (clay < 2 µm and silt < 60 µm)

o  The importance of fine-grained soil particle sizes in precision harvesting (soil-bearing capacity)

o  Challenges of mapping soil particles in forest (soil properties and sampling)

o  Geospatial Artificial Intelligence (GeoAI) for digital soil mapping

# Objectives

o  To identify the top covariates for mapping fine-grained soil particle sizes

o  To develop a deep learning-based approach that utilizes high-density LiDAR data and Sentinel derivatives to estimate the values of fine-grained soils in boreal forests, Finland

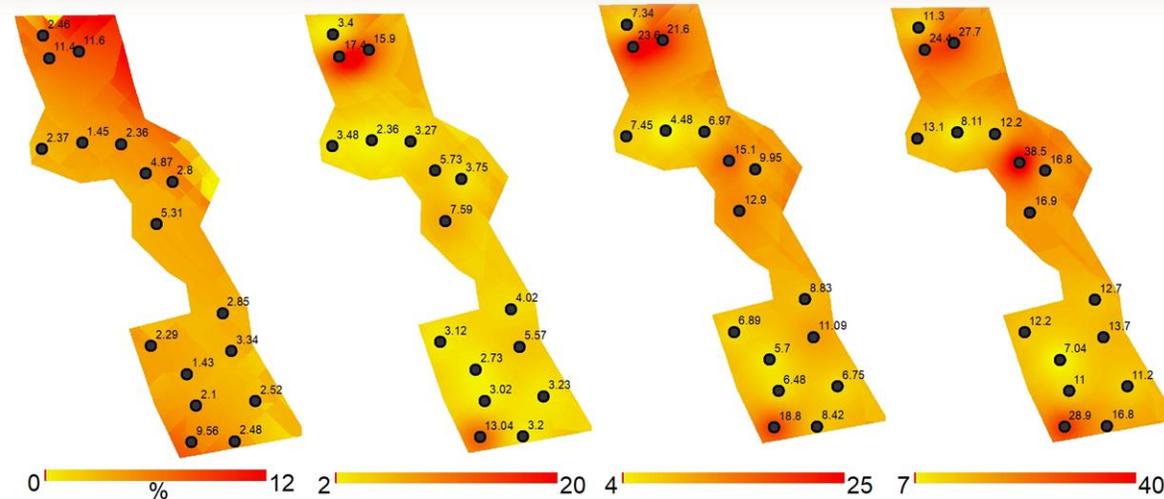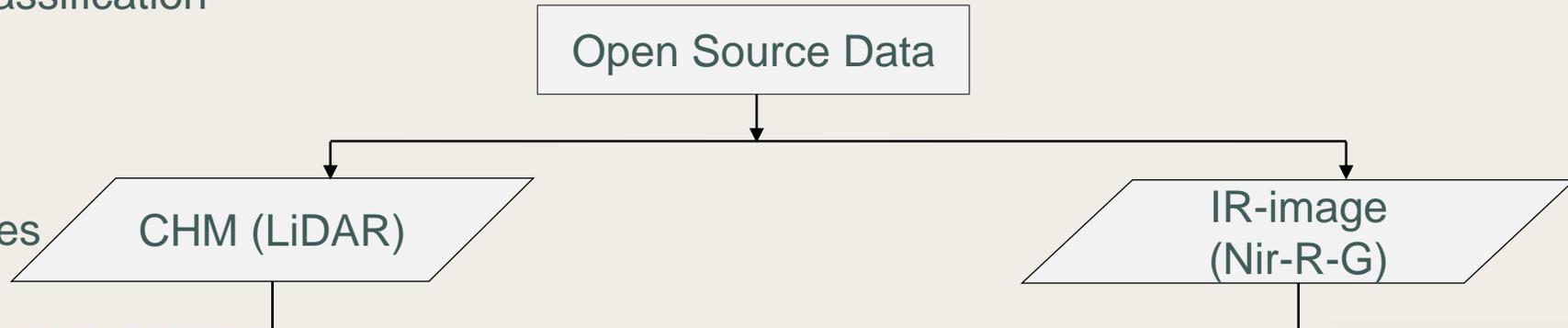# Local Prediction of Soil Particle Size
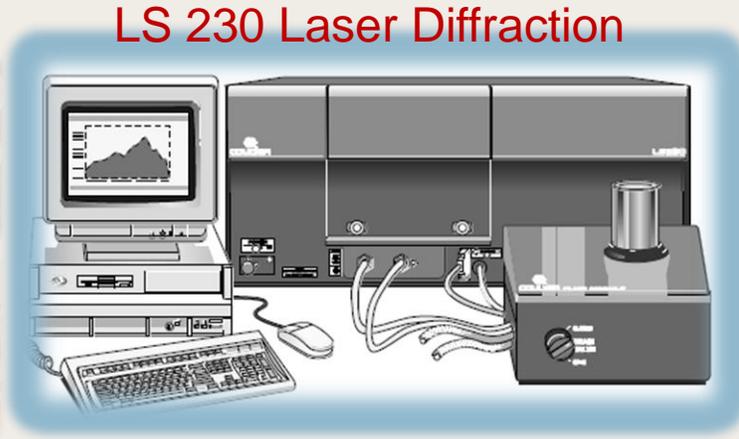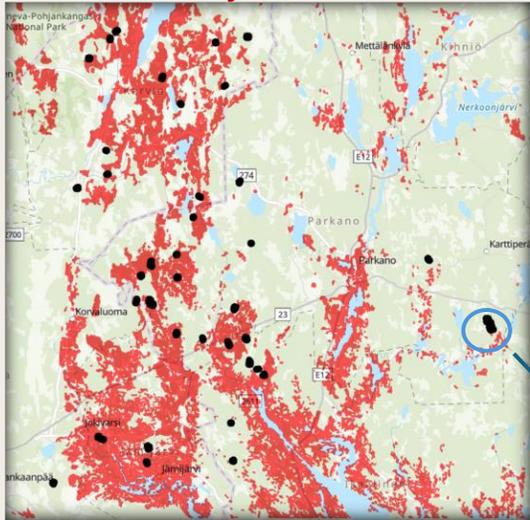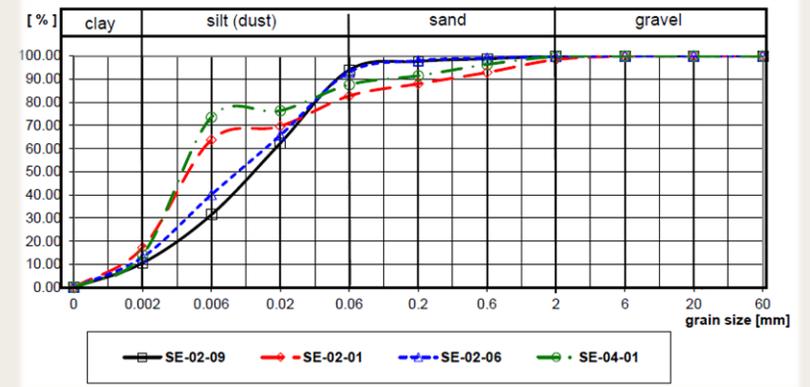
# Forest Segments (Zones)

- Tree species classification
- Tree clumping
- Segmentation
- Segments/ Zones



Open Source Data

CHM (LiDAR)

IR-image (Nir-R-G)

CHM-NIR-R-G

PSPNET

Single Trees (up 60,000)

Segments
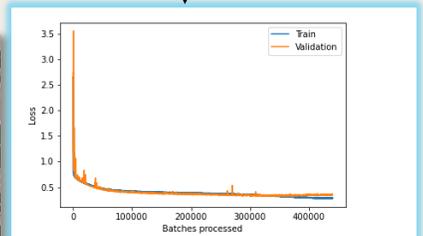
- Training data: patches 64 ×64
- Training models: Pretrained models
- Evaluate model

**Analysis of the model**

Per class metrics:

| | NoData | Pine 1 | Spruce 2 | Birch 3 | Aspen 4 | Open 5 |
|---|---|---|---|---|---|---|
| precision | 0 | 0.859644 | 0.775792 | 0.802361 | 0.897426 | 0.885280 |
| recall | 0 | 0.875057 | 0.771236 | 0.786544 | 0.858977 | 0.879011 |
| f1 | 0 | 0.867282 | 0.773508 | 0.794374 | 0.877781 | 0.882134 |
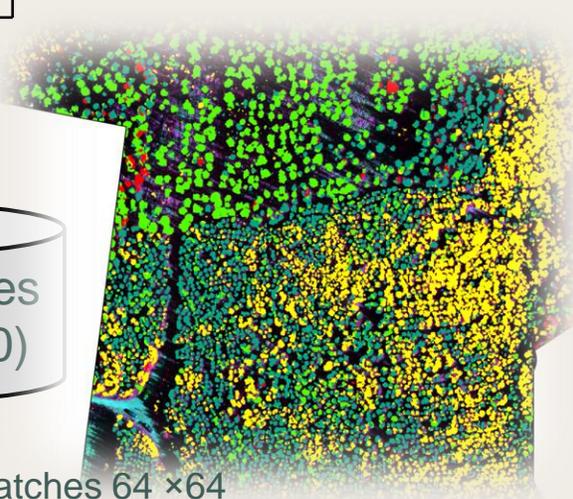
# Soil Covariates

## Geomorphometry

*Accumulation Curvature*
*Curvedness*
*Gaussian Curvature*
*Horizontal Excess Curvature*
*Vertical Excess Curvature*
*Tangential Curvature*
*Ring Curvature*
*Plan & Profile Curvature*
*Difference Curvature*
*Mean & Total Curvature*
*Min & Max Curvature*
*Rotor*
*Ruggedness Index*
*Shape Index*
*Slope*
*Standard Deviation of Slope*
*Unsphericity*
*Aspect*
*Diff From Mean Elev*
*Downslope Index*
*Wetness Index*
*Roughness*
*Openness*
*Elevation (Breach Dep.)*

## Hydrology

*Average Flowpath Slope*
*Average Upslope Flowpath Length*
*Quinn Flow Accumulation*
*Hydrologic Connectivity (Upslope & Downslope)*

## Trees

*Mean Height*
*Max Height*
*Crown coverage*
*Majority of Species*
*Diversity of Species*

LiDAR (5 P)

## Soil indices

$$bi = \sqrt{(R^2 + G^2)/2}$$

$$bi2 = \sqrt{(R^2 + G^2 + NIR^2)/3}$$

$$bsi = \frac{(SWIR2 + R) - (NIR + B)}{(SWIR2 + R) + (NIR + B)}$$

$$SATVI = \left(\frac{SWIR1 - R}{SWIR1 + R + L}\right) \times (1 + L) - \frac{SWIR2}{2}$$

$$Clay \; \text{Index} = \frac{SWIR1}{SWIR2}$$

➤ Time series 2017- 2023 (May – November)
➤ Mask green vegetation (NDVI: - 0.15 – 0.20)
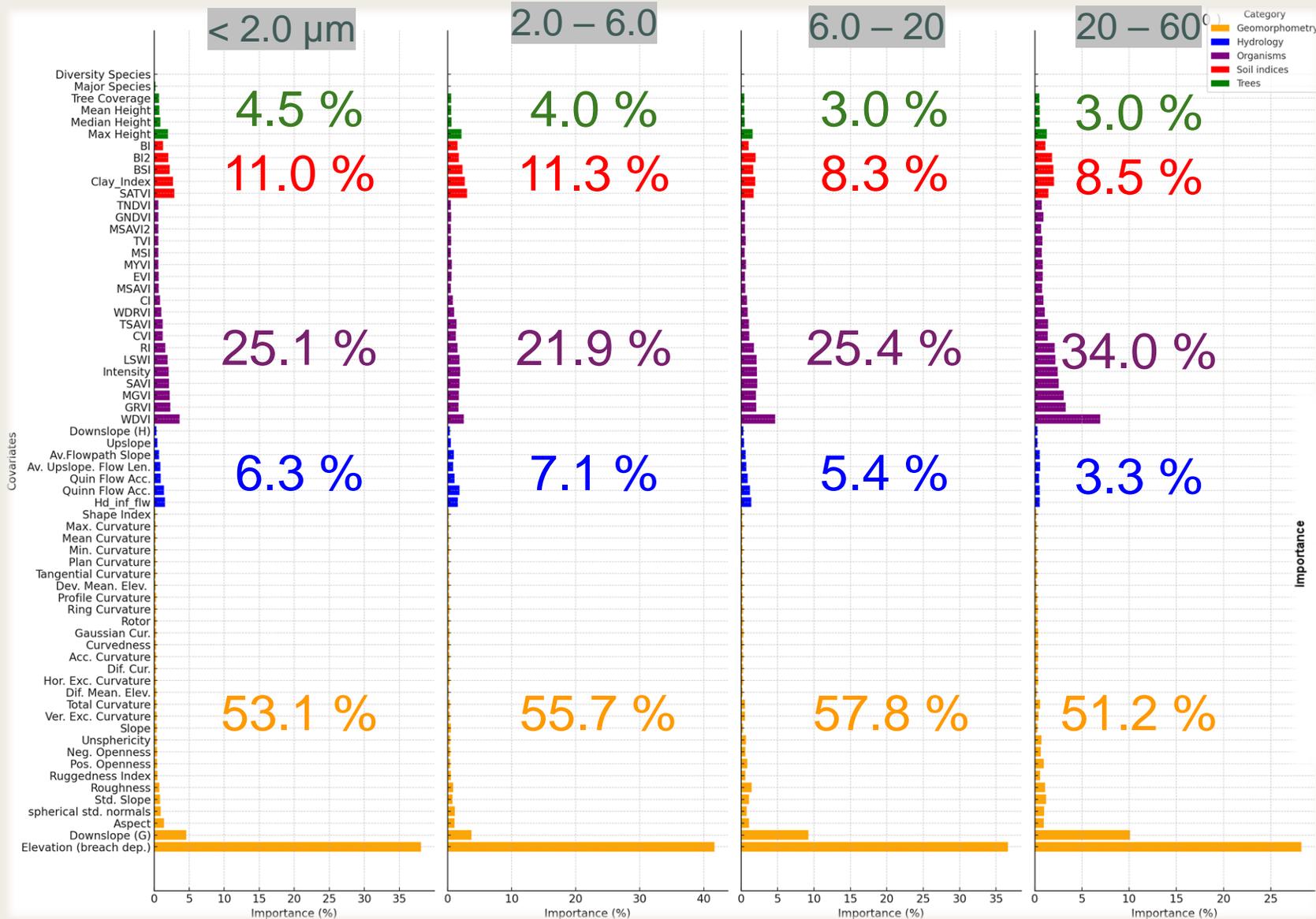➤ Mask residuals (NBR2: - 0.15 – 0.15)

## Organisms

*TVI*
*EVI*
*SATVI*
*SAVI*
*MSI*
*GNDVI*
*GRVI*
*LSWI*
*TSAVI*
*MSAVI*
*MSAVI2*
*WDVI*
*RI*
*CI*
*TNDVI*
*WDVI*
*WDRVI*
*MYVI*
*MGVI*
*Intensity*
*CVI*

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# GeoAI-based Models for Prediction of Soil Particle Sizes

Evaluation: ME, RMSE and $R^2$
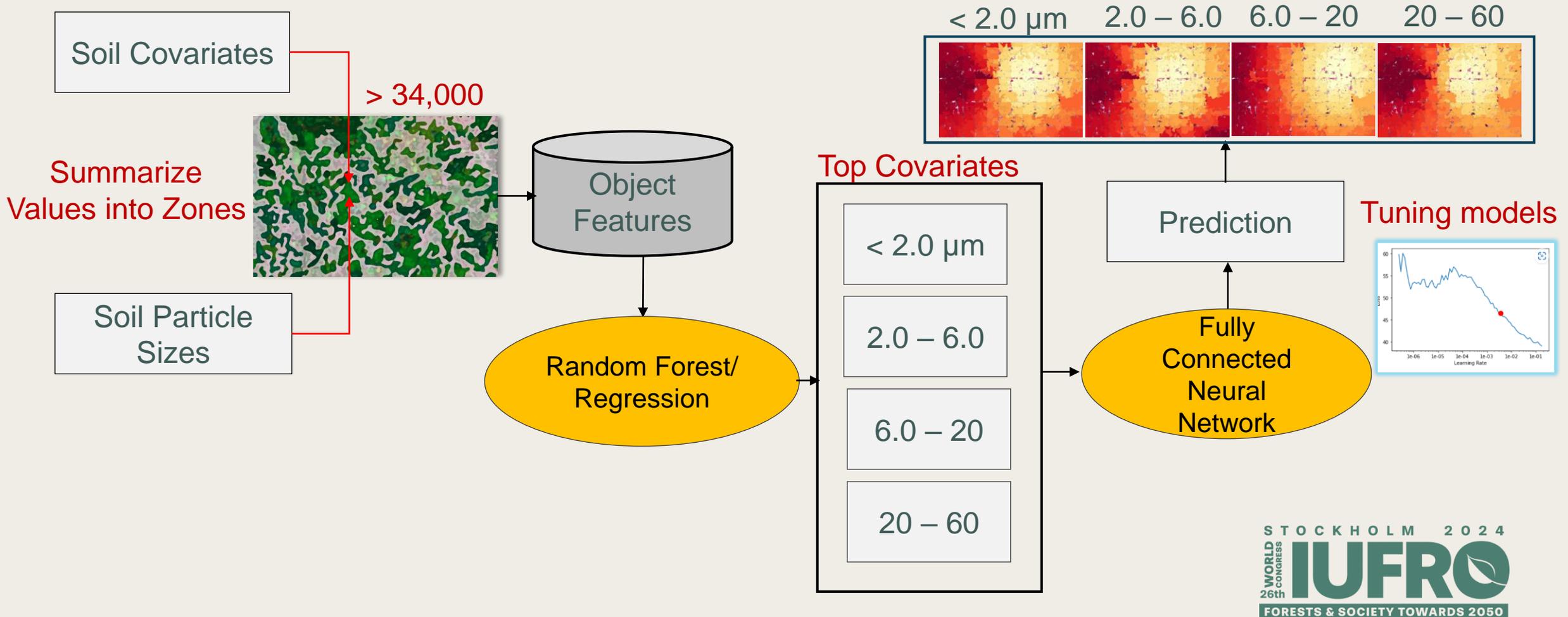
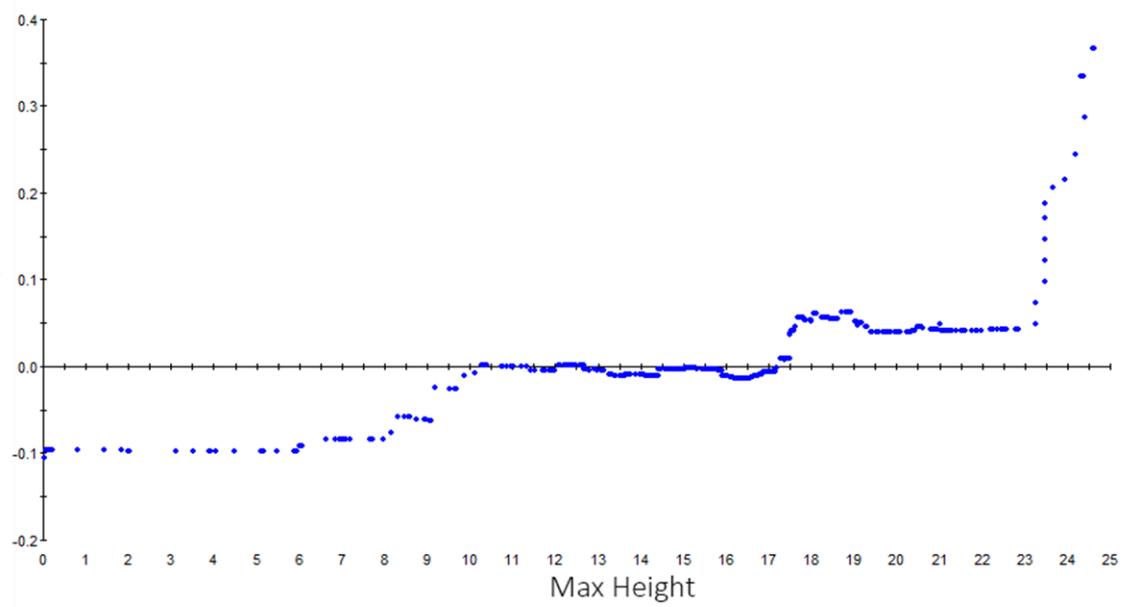# The Importance of Covariates
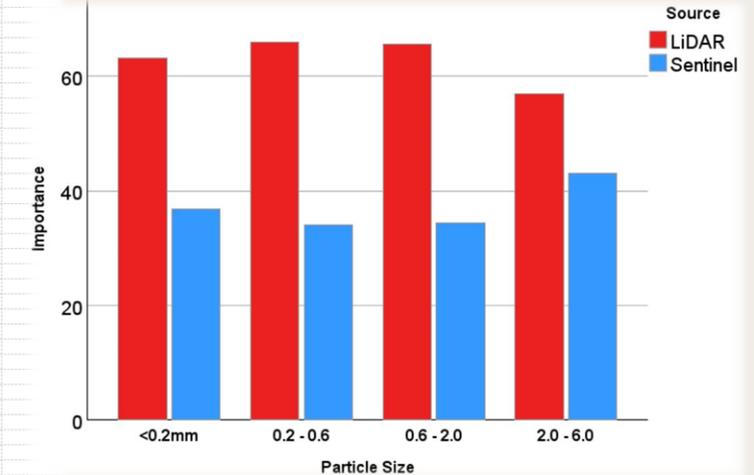
# Partial Dependency of Covariates (< 2 µm)
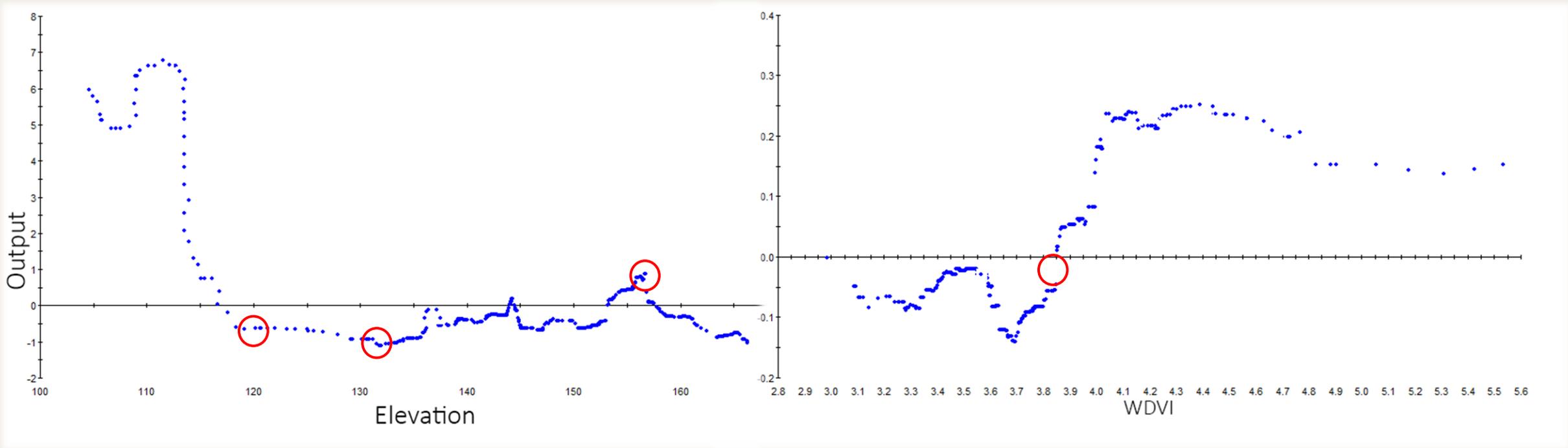
# Partial Dependency of Covariates (< 2 µm)
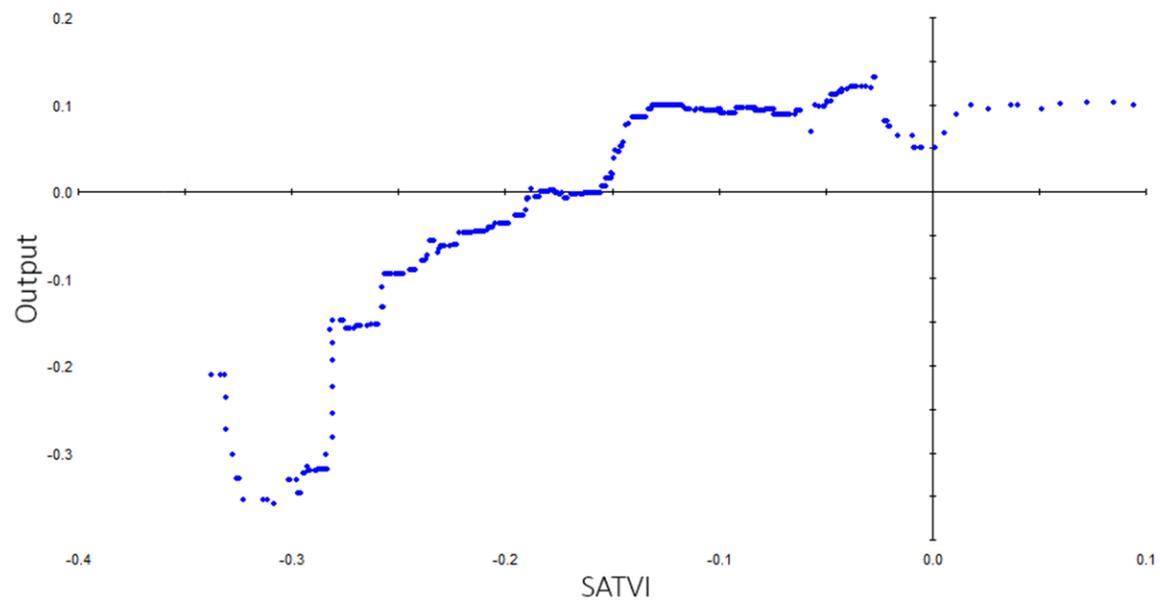
# Performance of FCNN



< 2.0 µm

$R^2 = 0.897$

2.0 − 6.0

$R^2 = 0.885$

6.0 − 20

$R^2 = 0.870$

20 − 60

$R^2 = 0.874$

# Prediction Maps (FCNN)



< 2.0 μm      **ME**: 0.075   **RMSE**: 0.703

2.0 – 6.0      **ME**: 0.0411   **RMSE**: 0.825

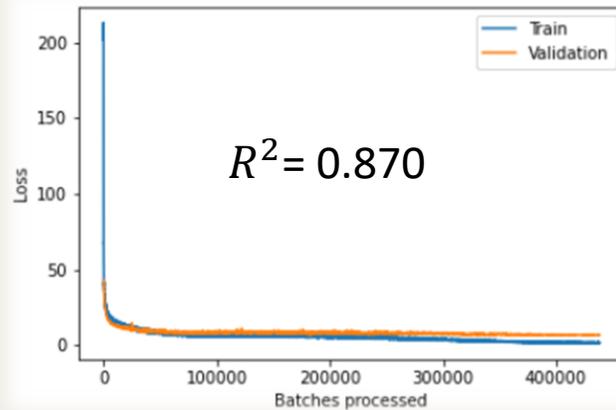6.0 – 20      **ME**: 0.039   **RMSE**: 0.862

20 – 60      **ME**: 0.087   **RMSE**: 1.28

Prediction (%)

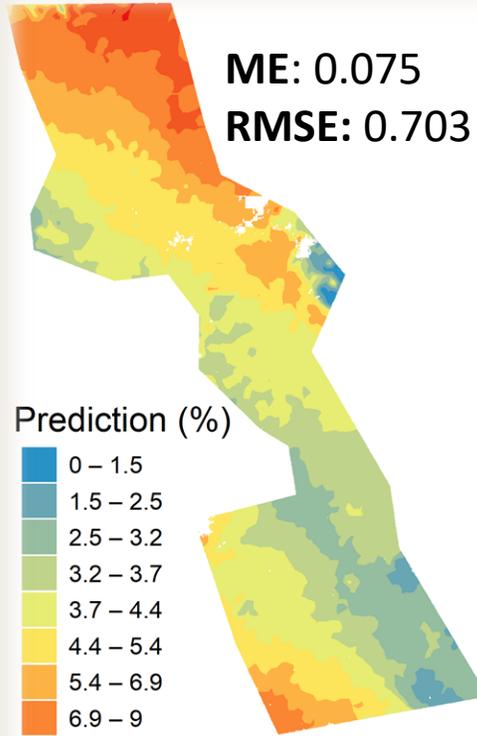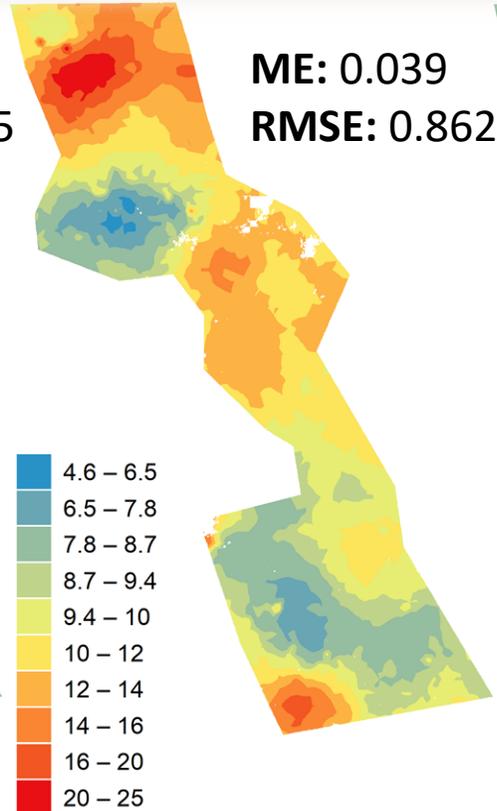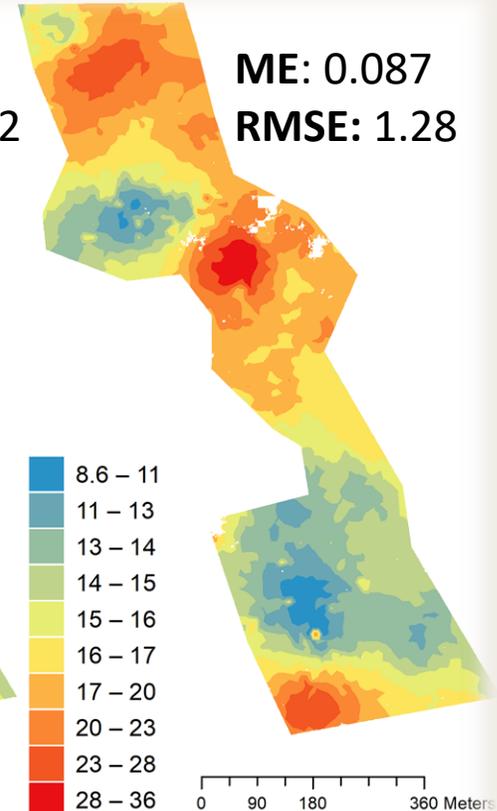| < 2.0 μm | 2.0 – 6.0 | 6.0 – 20 | 20 – 60 |
|---|---|---|---|
| 0 – 1.5 | 2.4 – 3.7 | 4.6 – 6.5 | 8.6 – 11 |
| 1.5 – 2.5 | 3.7 – 4.4 | 6.5 – 7.8 | 11 – 13 |
| 2.5 – 3.2 | 4.4 – 4.8 | 7.8 – 8.7 | 13 – 14 |
| 3.2 – 3.7 | 4.8 – 5 | 8.7 – 9.4 | 14 – 15 |
| 3.7 – 4.4 | 5 – 5.4 | 9.4 – 10 | 15 – 16 |
| 4.4 – 5.4 | 5.4 – 6.1 | 10 – 12 | 16 – 17 |
| 5.4 – 6.9 | 6.1 – 7.4 | 12 – 14 | 17 – 20 |
| 6.9 – 9 | 7.4 – 9.8 | 14 – 16 | 20 – 23 |
| 9 – 12 | 9.8 – 14 | 16 – 20 | 23 – 28 |
| 12 – 17 | 14 – 23 | 20 – 25 | 28 – 36 |

0  90  180  360 Meters
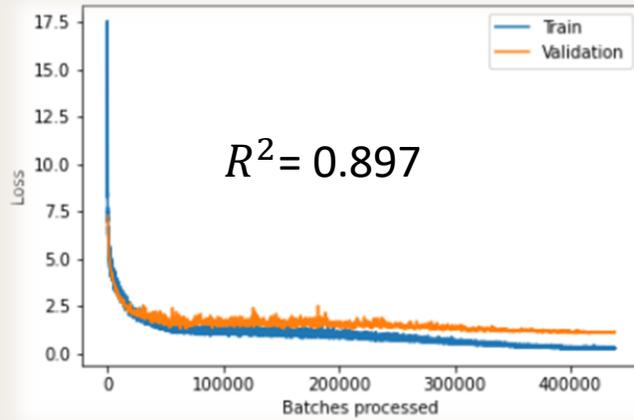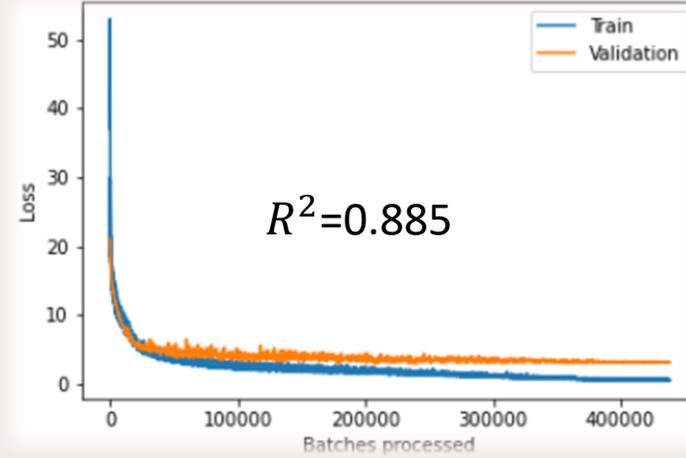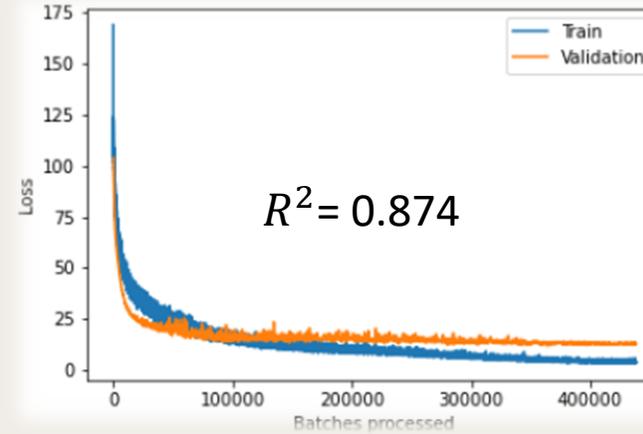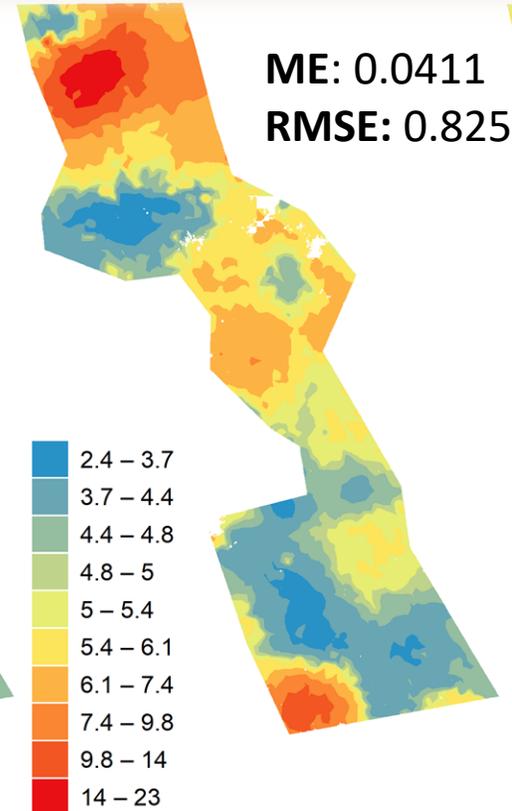
# Summary

o Local predictions of soil particle sizes have enhanced the potential for augmenting soil training data for mapping via machine learning and deep learning techniques

o LiDAR data significantly improved the extraction of various soil covariates related to geomorphometry, hydrology, and tree attributes

o Organisms-derived variables demonstrated substantial importance in mapping all fine-grained particle sizes of soil, particularly those in the 20 – 60 μm range

o The digital elevation model, after removing depressions (Breach Depression) and incorporating downslope covariates, is crucial for predicting all fine-grained particle sizes of soil

o The Random Forest model exhibited high performance in selecting top covariates for soil mapping

o The FCNN performed well in mapping fine-grained soils; however, its performance slightly declined with an increase in particle size

o Our trained models have high potential for precision harvesting, particularly in predicting soil bearing capacity

**Thank you!**

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