



Geographical
Information Systems
Research Unit

AGRICULTURAL
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Estimating Top-Soil Moisture at High Spatiotemporal Resolution

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NATIONAL RECOVERY AND RESILIENCE PLAN



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Why Soil Moisture Matters

- Key variable in precision agriculture, hydrological modeling, and environmental monitoring



- Influences crop productivity, irrigation, and water resource management

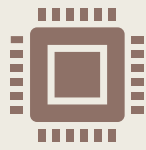


- Challenging to estimate due to spatial heterogeneity and temporal variability

Study Objective



- Develop a national-scale soil moisture estimation methodology



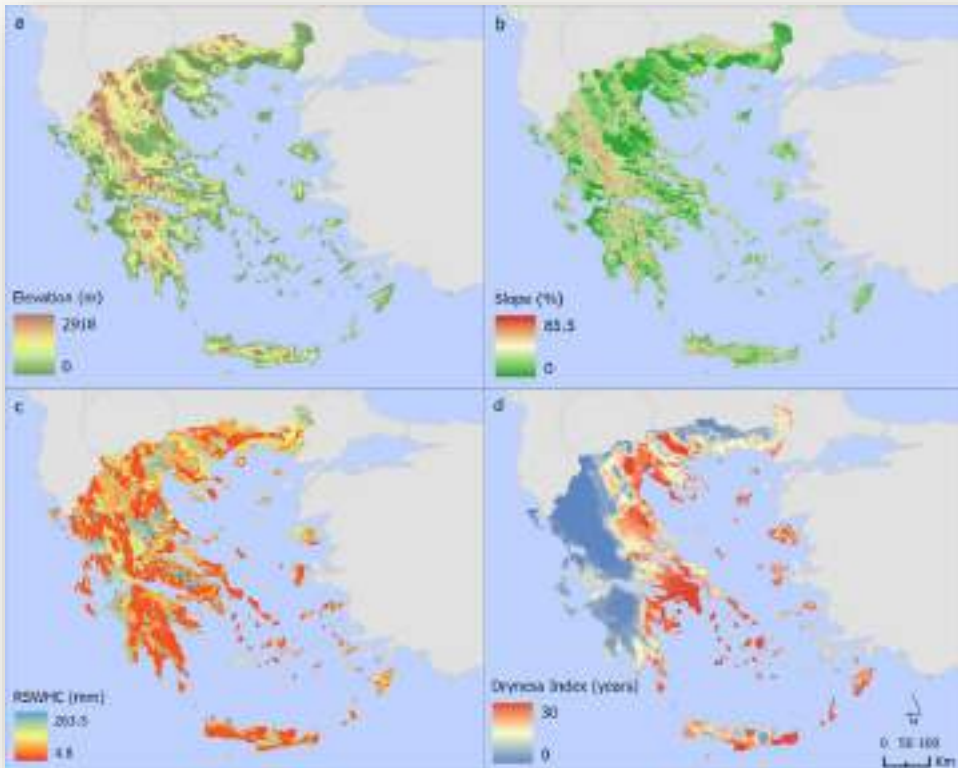
- Integrate Sentinel-1 & Sentinel-2 EO data with in-situ sensor networks



- Address challenges of heterogeneous landscapes and Mediterranean climate dynamics



Targeting Agricultural Areas in Greece



Mediterranean Climate

Hot, dry summers and mild, wet winters, influencing seasonal soil moisture variability.

Diverse Agricultural Zones

Irrigated plains, rainfed uplands, and mixed farming systems—each with distinct water demands.

Heterogeneous Soil Types

Ranges from sandy and loamy soils in lowlands to clayey and rocky soils in mountainous areas.

Complex Topography

Mountain ranges, valleys, coastal plains, and islands create microclimates and varied hydrological responses.

Vulnerable to Climate Change

Increasing frequency of droughts and extreme weather events makes efficient water management critical.

IoT-Based Soil Moisture Monitoring Network

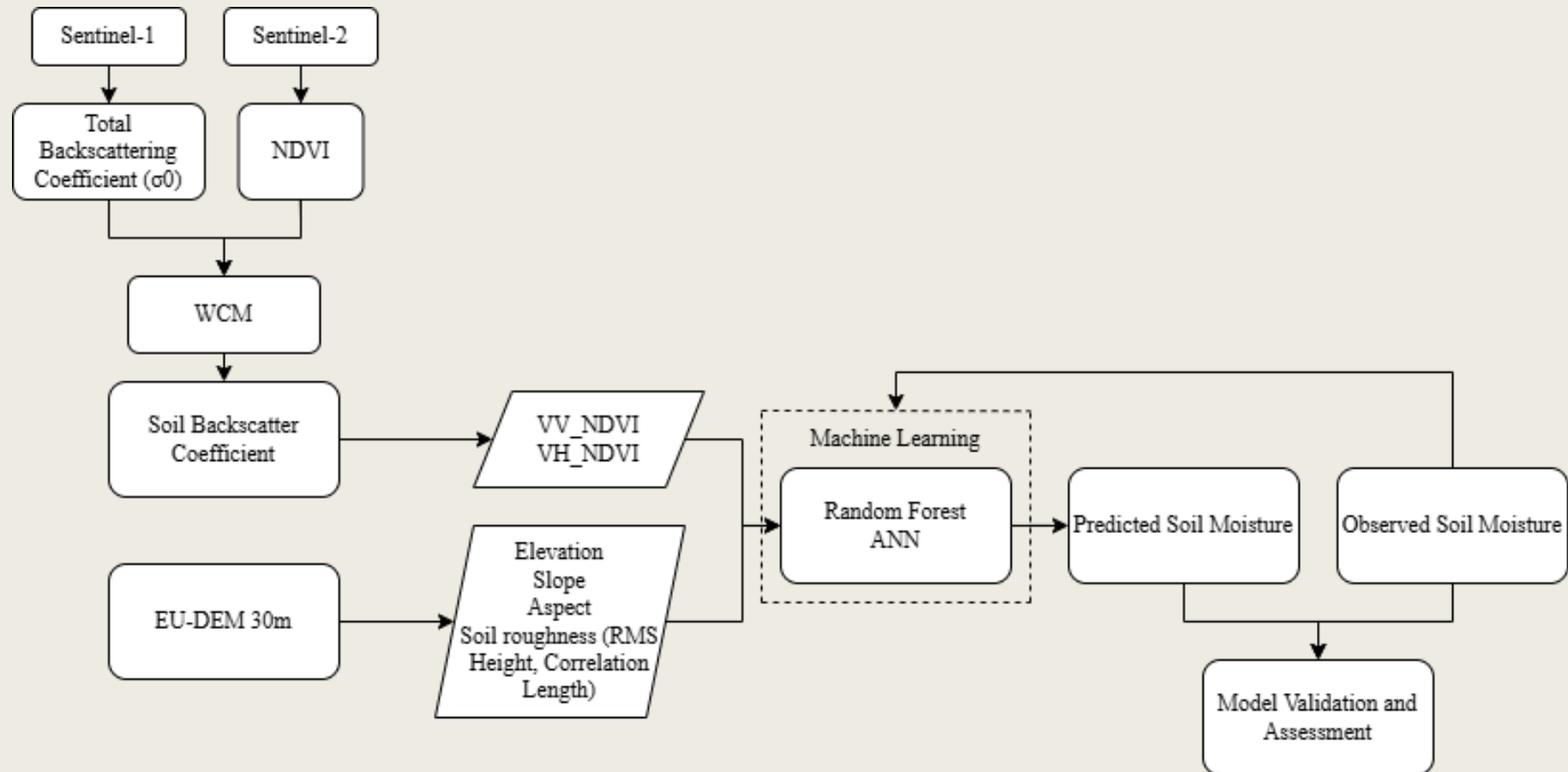
Network of IoT soil sensors at strategic locations in agricultural areas

Covers zones with different land cover and soil textures

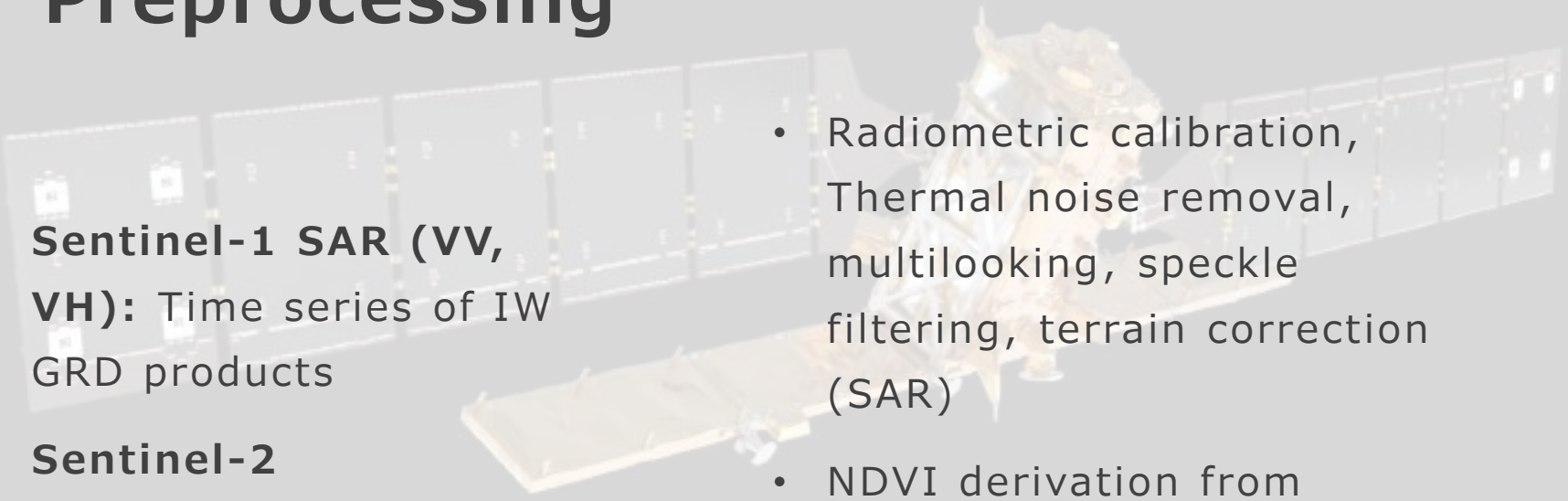
Designed using geospatial analysis based on topography, soil and climate to ensure representativeness



Methodology



Satellite Data Inputs and Preprocessing

- 
- A satellite with large solar panel arrays is shown in orbit above the Earth's blue and white horizon. The satellite is oriented horizontally, with its central body and various instruments visible.
- **Sentinel-1 SAR (VV, VH):** Time series of IW GRD products
 - **Sentinel-2 Multispectral:** Time series of cloudless (<30%) L2A products
 - **Temporal resolution:** Every 5–10 days
 - **Spatial resolution:** 10 m
 - Radiometric calibration, Thermal noise removal, multilooking, speckle filtering, terrain correction (SAR)
 - NDVI derivation from Sentinel-2
 - Corregistration & masking using AOI and cloud/topographical features masks
 - Extraction of backscatter and vegetation metrics

Vegetation Correction – Water Cloud Model

- **Purpose:** Separate vegetation and soil contributions to backscatter
- **Inputs:** NDVI from Sentinel-2 + SAR backscatter + incidence angle
- **Key Equations:**

$$\sigma_{can}^0 = \sigma_{veg}^0 + \tau^2 \sigma_{soil}^0$$

$$\sigma_{veg}^0 = AV \cos\theta(1-\tau^2)$$

$$\tau^2 = \exp(-B \cdot V^2 / \cos\theta)$$

- **Parameters A & B:** Fitted to in-situ data, vary by land cover, soil type, and season

σ_{can}^0 : total backscatter coefficient

σ_{veg}^0 : signal directly reflected by the vegetation

σ_{soil}^0 : scattered soil signal

τ^2 : attenuation coefficient of the signal attenuated twice by the vegetation

θ : the signal incident angle

V : vegetation related parameters (NDVI)

A and B : empirical parameters

Soil Moisture Estimation Model & Validation

Corrected SAR & Optical Data → ML Models

Models Used:

- Random Forest (RF)
- Artificial Neural Networks (ANN)

Training Data: In-situ measurements, land use, soil type, topography (slope, elevation, roughness)

Output: Predict soil moisture from corrected radar signal

Validation Methods:

- Cross-validation
- Performance metrics: RMSE, R^2

Robustness:

- Calibrated across different seasons, land cover, and soil types
- Addresses overfitting and generalization

Nemea region as a testing ground

Location:

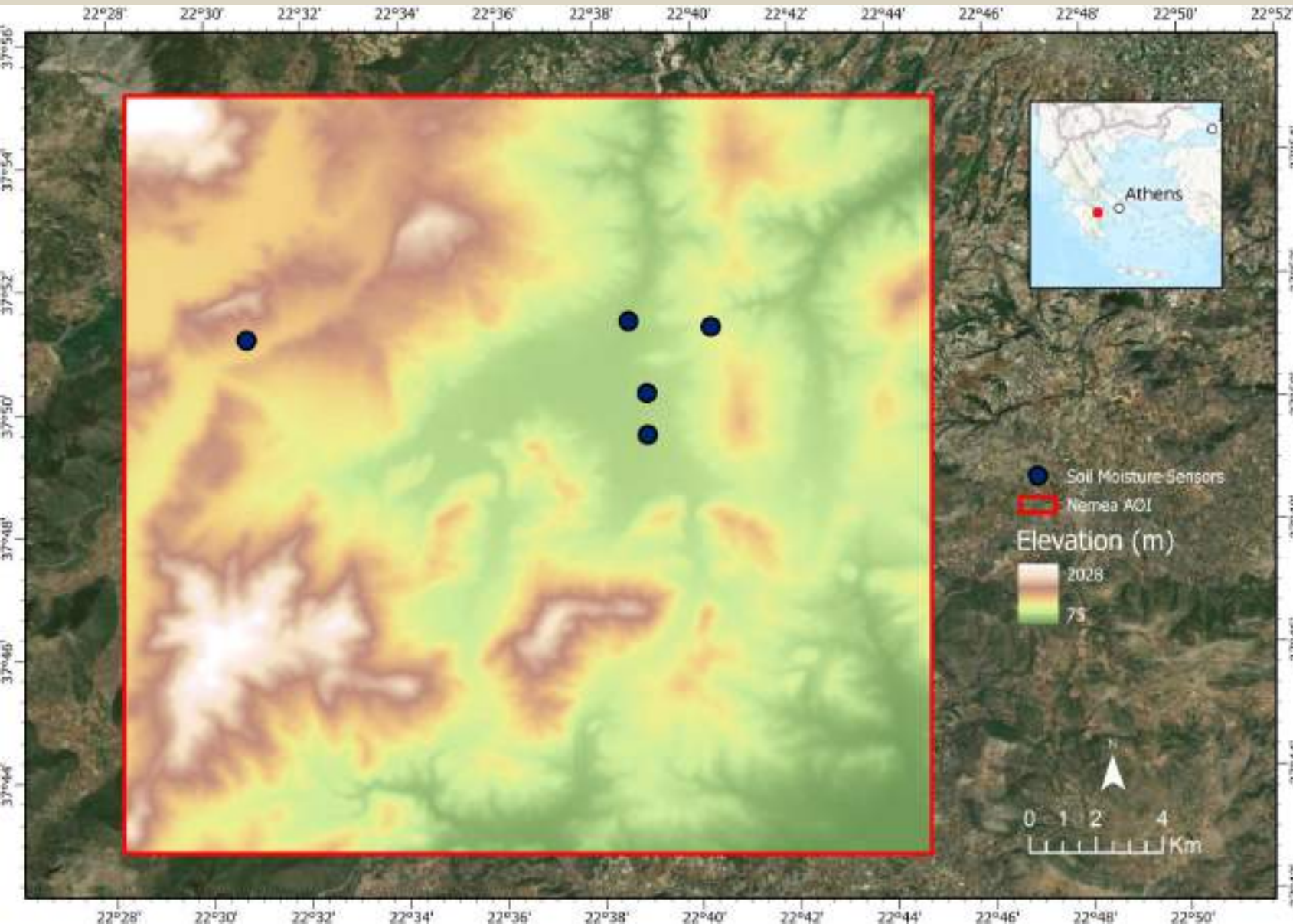
Nemea PDO wine-region,
northeastern Peloponnese
peninsula, Greece

Climate:

Mediterranean; warm, dry
summers; mild winters

Terroir:

Limestone-rich soils;
altitudes ranging from 94
m to 1072 m



Methodology implementation on Nemea

Data Collection & Preprocessing:

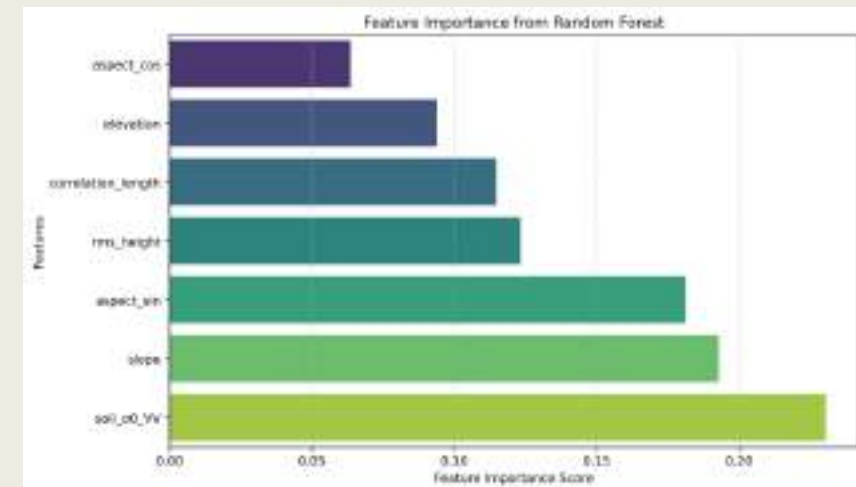
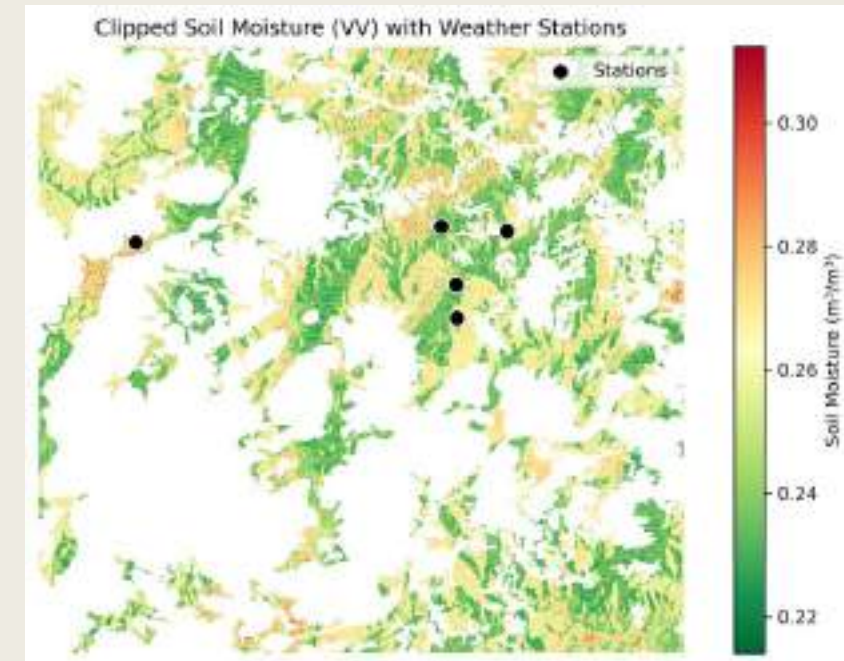
- **Soil Backscatter** extracted via the WCM using the generalized values of **A = 0.0012** and **B = 0.091** (Bindlish and Barros, 2021)
- Collected **soil moisture data from 5 sensors** across the AOI (Nemea region, Greece)
- **Matched soil moisture observations with Sentinel-1** image acquisition times to ensure **temporal consistency** (25/08/2024 – 24/03/2025)
- Acquired **Sentinel-2 imagery** for dates with **cloud cover below 30%**
- **Processed DEM-based parameters** (slope, elevation, aspect, RMS height, correlation length) to analyze terrain effects
- **Spatial alignment and standardization** of features values, including aspect (converted to sine/cosine), slope, elevation, backscatter (σ_0 VH, σ_0 VV), RMS height, and correlation length

Model Development:

- Used a **Random Forest** model for soil moisture estimation (n_estimators: 100, max depth: Default (full growth), min samples split: 2, min samples leaf: 1, Bootstrap: Enabled).
- **Trained** the model **on soil moisture station data** and features.
- Validated the results with **Leave-One-Out Cross-Validation (LOOCV)**, as well as metrics like MAE, RMSE, R^2 , (R^2 undefined in some cases due to small data size).
- Checked the **features' importance**
- **Pearson correlation** analysis

Initial Findings

- Non-agricultural areas (CLC 2018) were clipped out
- Backscatter (soil_σ0_VV) had the highest influence, followed by terrain parameters
- **Pearson correlation** analysis showed:
 - *Positive correlations with aspect_sin (0.43) and correlation_length (0.41), indicating that these factors may enhance soil moisture.*
 - *Negative correlations with soil_σ0_VH (-0.57), soil_σ0_VV (-0.62), and slope (-0.49), suggesting that rougher terrain and higher slopes tend to have lower soil moisture*
- **RMSE:** 0.07, **MAE:** 0.05, **R²:** Low (due to small data size)
- Model captures general soil moisture trends but lacks robustness due to sparse ground truth data



Conclusions - Further steps



- The developed model captures the general trends in soil moisture within the Nemea region (test area).
- The model until now is demonstrating very promising initial results.
- Over the next seven months, the model will undergo further training with an expanded dataset, incorporating both remote sensing data and soil moisture measurements collected from the newly established IoT-based monitoring network across 50 sites nationwide.

Thank You

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