Towards a paradigm shift on mapping muddy waters in water reservoirs with Sentinel-2 using Machine Learning



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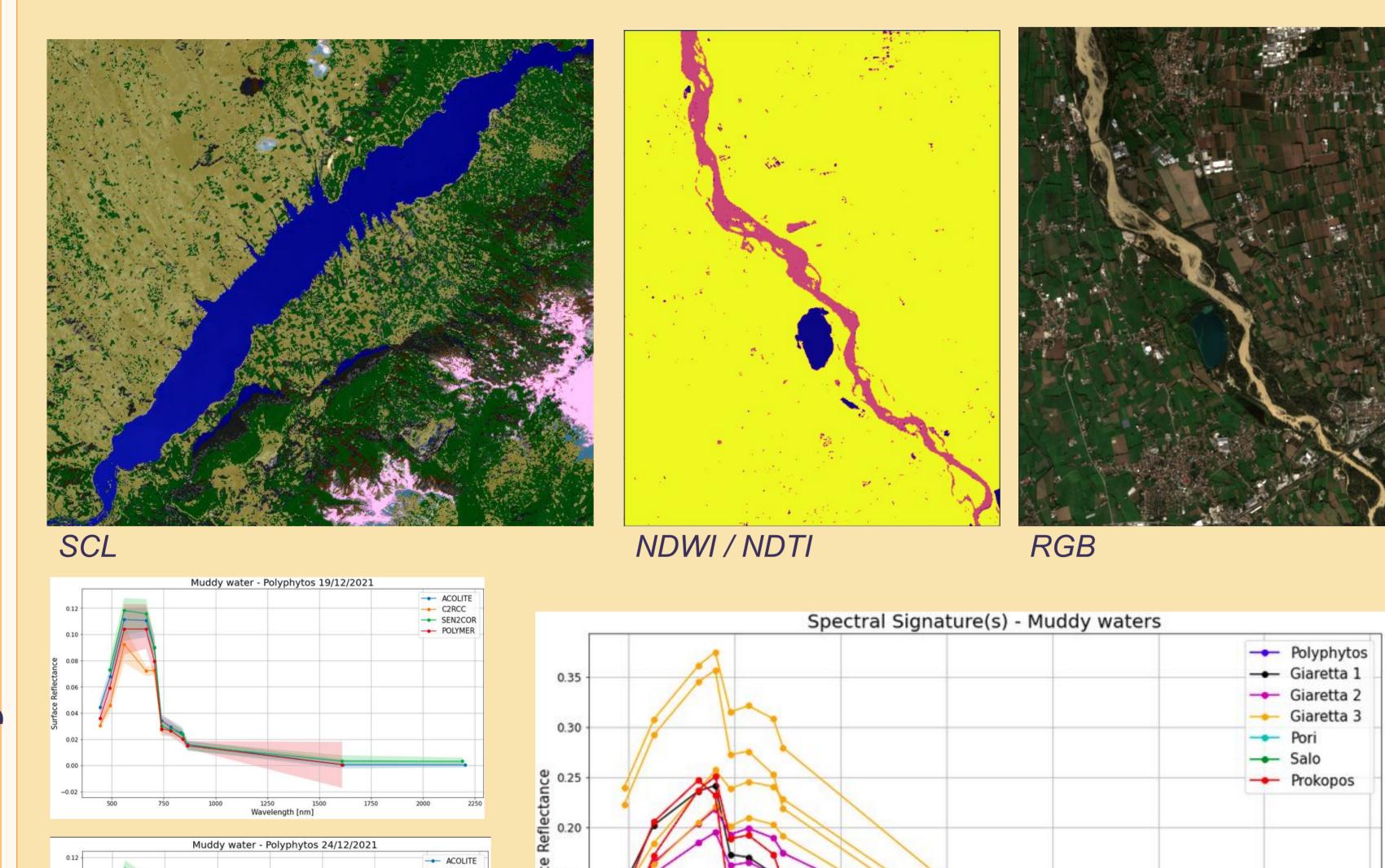
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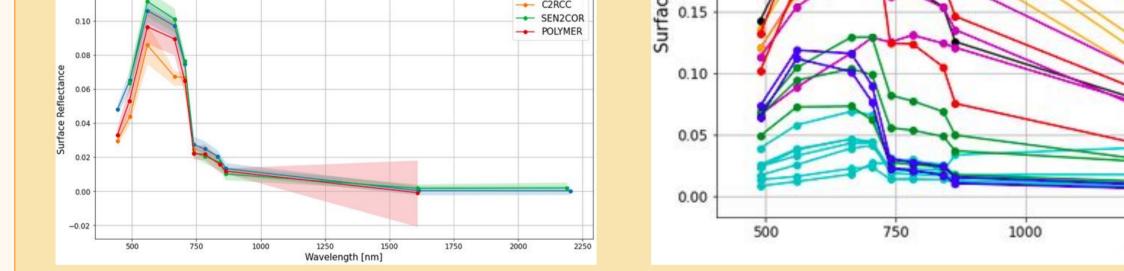
**Heavy rainfall** comprises a rising **extreme event** due to climate change, which induces increased run-off, high-flow, **flooding** and **erosion** leading to increased sediment particles in the water. The erosion is especially high when soil is exposed in regions such as construction/mining sites, burned areas, or areas with poor agricultural/forestry practices, which in turn results in **large volumes of sediment** entering the water abruptly, constituting it as **"muddy"**. Some **negative implications** are on i) a **lake ecosystem** (e.g., altering the physicochemical regime) ii) **human infrastructure** (e.g., dams, water utilities hardware) and iii) the **local economy** (e.g., when used for recreational purposes), hence the importance to monitor with **high spatial resolution** and **frequency**.

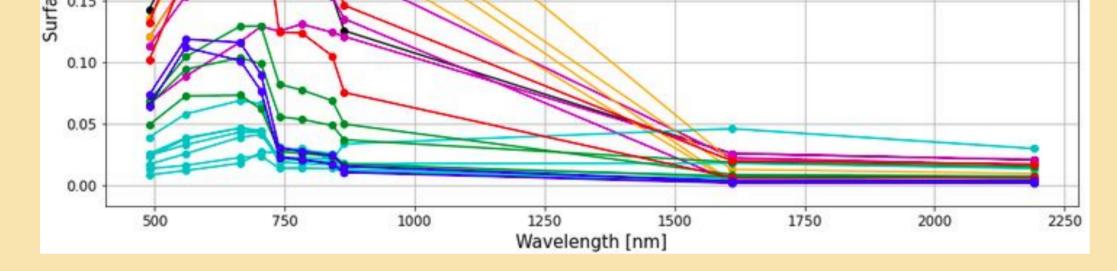


## 2. Methodology

## Data:

- Sentinel-2 Level-1 (10m, ~5 days)
   Annotation:
- Scene Classification Layer (SCL)
- Combination between NDWI and NDTI
- Expert knowledge based on RGB / FCCs
   Preprocessing:
- Select various scenes (Greece, Finland) with inland / coastal muddy water presence
- Apply Atmospheric Correction (Sen2Cor)
- Resample to 10m (bilinear interpolation)
- Subset / Rescale

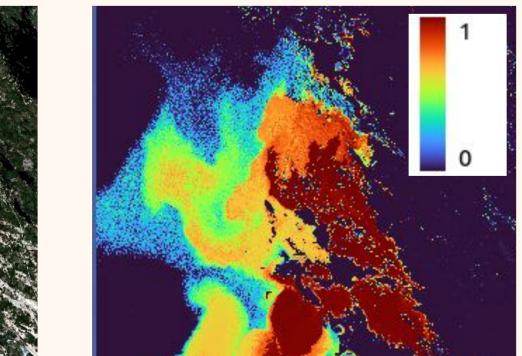


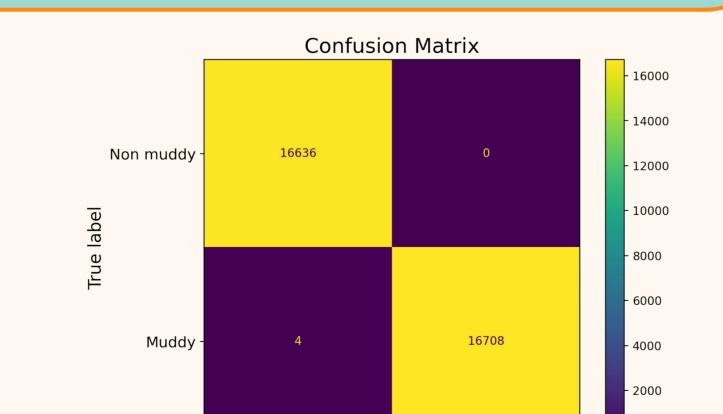


ACs comparison for the muddy water class for 2 scenes (left) & evaluation of annotated pixels (right)

- Classification metrics > 98% (F1-score, Precision, Recall, Accuracy, AUC)
- Good performance in unseen cases
- Overestimation in areas with high chlorophyll
- Highest feature contribution: B11, B12, B4, B8A, B5 (owed to e.g., clouds, vegetation, soil samples)



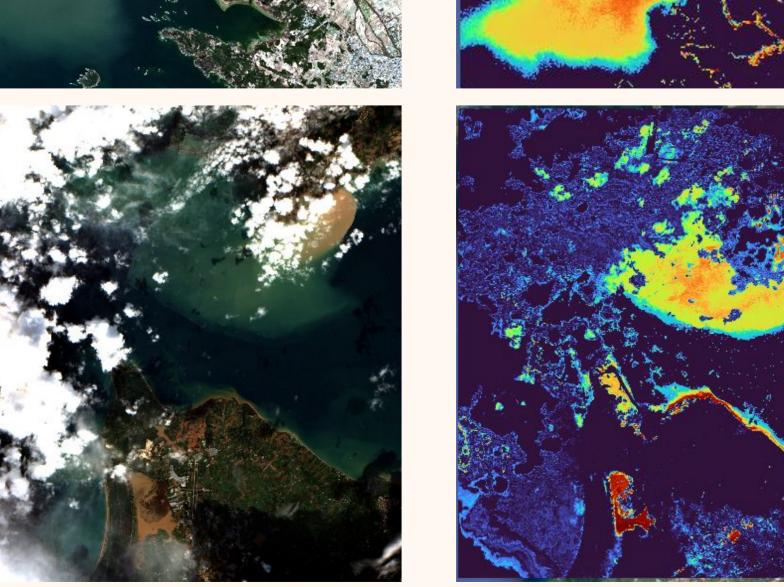




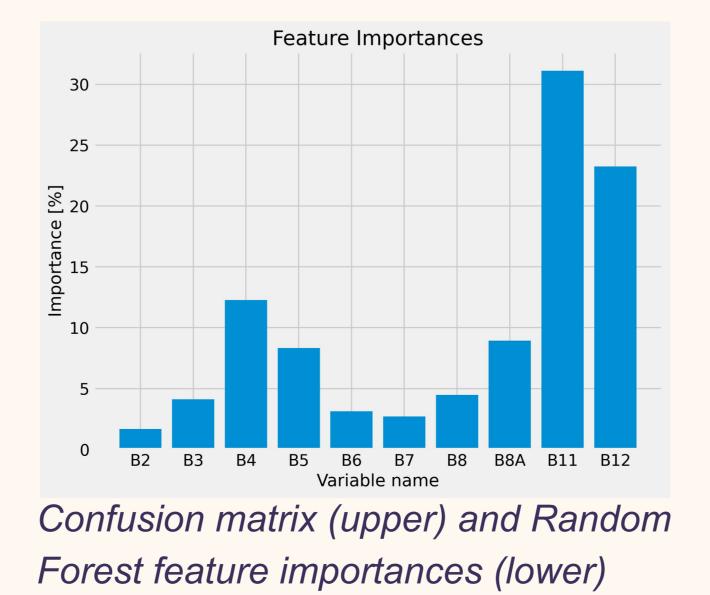
Muddy

## Model / Training:

- Input: Bands  $\rightarrow$  B{2-8}, B8A, B{11-12}
- Random Forest model
- Samples:
  - Total: 166738
  - Training: 133390
  - Test: 33348
- Hyper-parameter tuning based on:
  - Grid Search:
    - Tree depth [4, 5, 6, 8,10, 20, 30, 60, 100, 120, 150]]
    - Number of trees [5, 6, 7, 10, 20, 50, 100, 150, 200]
    - Class balance with weights [sample balance, none]
  - 5-Fold Cross Validation with 5 repeats
  - F1-score
  - Total number of fits:7425



RGB images (left) and prediction probabilities (right)



Predicted label

## 5. Conclusion & Prospect

Quick muddy water mapping without any calibration is feasible, while room for improvement still exists
An image-based dataset including global variability will increase model generalization ability
Comparison of model outputs with water quality parameters (e.g., total suspended sediment)

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