Task 4
Soil erosion detection
- solution report-

With provided data:

- .jp2 file of Sentinel-2 satellite tile image
- masks with soil erosion for this tile

The challenge can be presented as ML Computer Vision task of **image segmentation**:
assigning a label to every pixel in an image (satellite tile) such that pixels with the same label share certain characteristics (areas of soil erosion).
Segmentation models provide the exact outline of the object within an image, as opposed to Classification models, where the model identifies what is in an image, and Detection models, which place a bounding box around specific objects.

The way mask data was provided would also allow for treating the problem as **instance segmentation.** Semantic segmentation treats multiple objects within a single category as one entity, whereas instance segmentation identifies individual objects within these categories.

With the provided amount of data (1 satellite tile with soil erosion mask) modeling workflow can only be proposed, for training and evaluation steps a much greater amount of data would be required.

ML Workflow

The ML Workflow should consist of steps:

DATA PROCESSING

1. DATA INGESTION, DATA ANALYSIS - see sub-chapter below
2. DATA PREPARATION
   To reduce the computational complexity we would possibly need to resize all the images. Data augmentation would also be advisable, to prevent overfitting.

MODELLING

1. MODEL PROPOSITION - see sub-chapter below
2. MODEL TRAINING and EVALUATION - conducted when bigger labeled dataset is provided

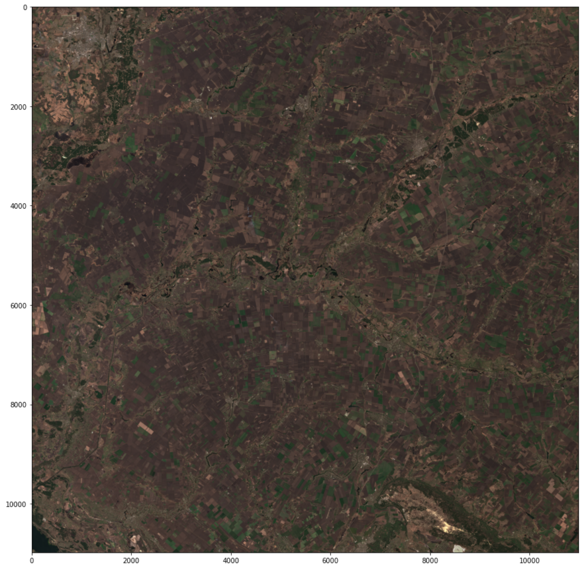
Everything should work in cycles, after evaluation step data processing and modeling steps should be readjusted.

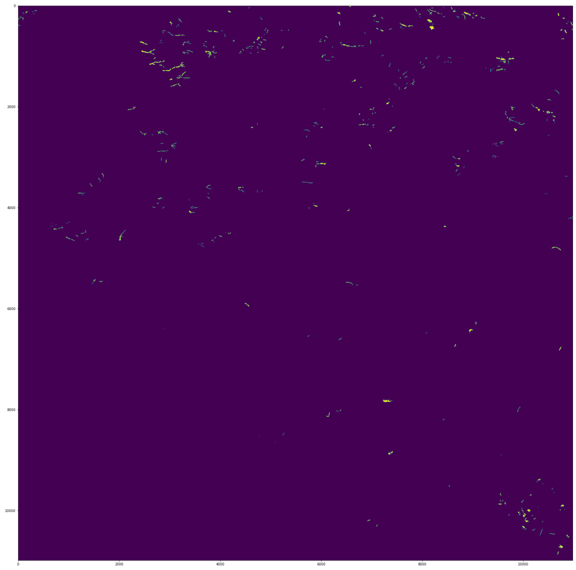
Data analysis - summary

Full data ingestion and analysis is conducted in Jupyter Notebook file.

From the provided file with mask polygons, 500 of 935 proper polygons (the ones overlapping with raster) were selected.

Below i present satellite tile image (L) and it's soil erosion mask (R)
(violet - no soil erosion; yellow - soil erosion present)
Both are presented in a graphic form obtained with pyplot (x, y axes of both plots in [px]):





Shape of satellite tile: (3, 10980, 10980)
Shape of mask: (1, 10980, 10980)

Model proposition

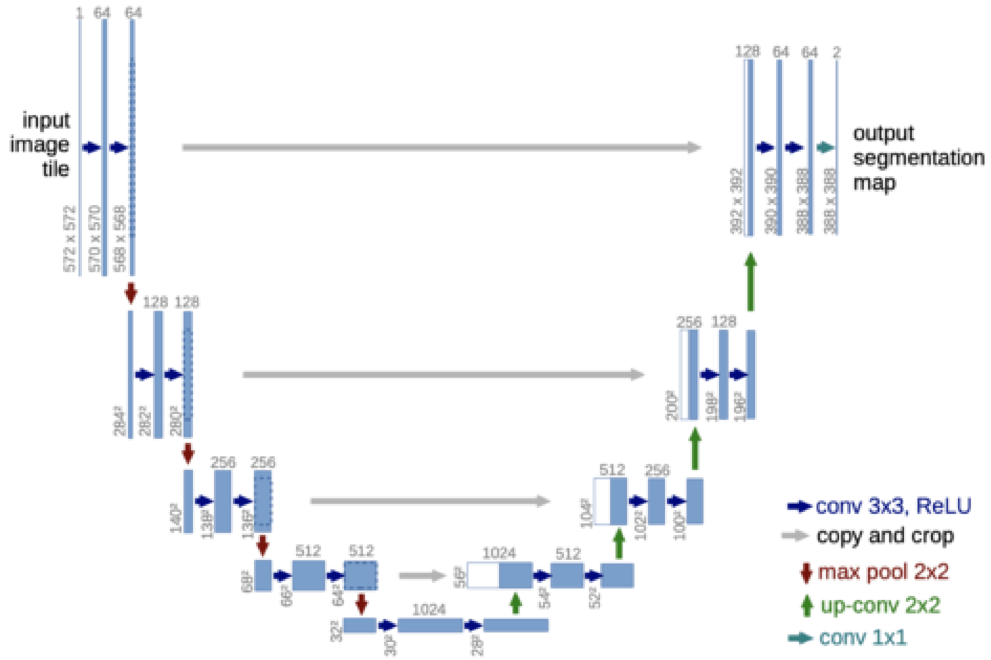
As declared above, the problem will be treated as image segmentation.

Looking at the given training example, we can assume that a problem of skewed classes will occur.

Skewed classes refer to an imbalanced dataset, where the number of training examples belonging to one class (no soil erosion pixels) out-numbers heavily the number of training examples belonging to the other (soil erosion present pixels).

The architecture I chose for the given task (image segmentation), based on articles and repositories cited in “RESOURCES” section, is U-Net (Deep Neural Network model).

U-Net was introduced in the paper, [U-Net: Convolutional Networks for Biomedical Image Segmentation]. The model architecture is fairly simple: an encoder and a decoder with skip connections. It is shaped like the letter U hence the name U-Net.



U-Net architecture (image source: [U-Net paper]).

Implementation is heavily based on implementation presented in [Article].
The adjustments made was input size change (changed to real tile size cropped to dimension dividable to 32 which is required for U-Net).

As mentioned above, the whole training and adjustment process can be conducted when a greater dataset is provided.

Soil erosion detection - Research

Freddy A. Diaz-Gonzalez, Jose Vuelvas, Carlos A. Correa, Victoria E. Vallejo, D. Patino, **Machine learning and remote sensing techniques applied to estimate soil indicators – Review**, Ecological Indicators, Volume 135, 2022. https://doi.org/10.1016/j.ecolind.2021.108517.
Access: [Link]

A review of recent studies of crop yield prediction based on the estimation of **chemical, physical, and biological soil quality indicators** (SQI), which incorporate different machine learning (ML) techniques to process data from **remote sensing** (RS) systems, is presented.
Of the 22 publications analyzed, 14 authors based their studies on **images captured with satellite** sensors to make general estimates of soil properties on a regional scale; In addition, these highlight the importance of **topographic information** (DEM and TWI), and **climatic information** (MAT and MAP) as **inputs** of great weight to ML estimation models, complementary to multispectral image.
It is recommended to use a minimum data set using multivariate statistical techniques such as **principal component analysis, redundancy analysis and discriminant analysis** for the appropriate indicators selection to reduce the redundancy of soil data in soil quality assessment.

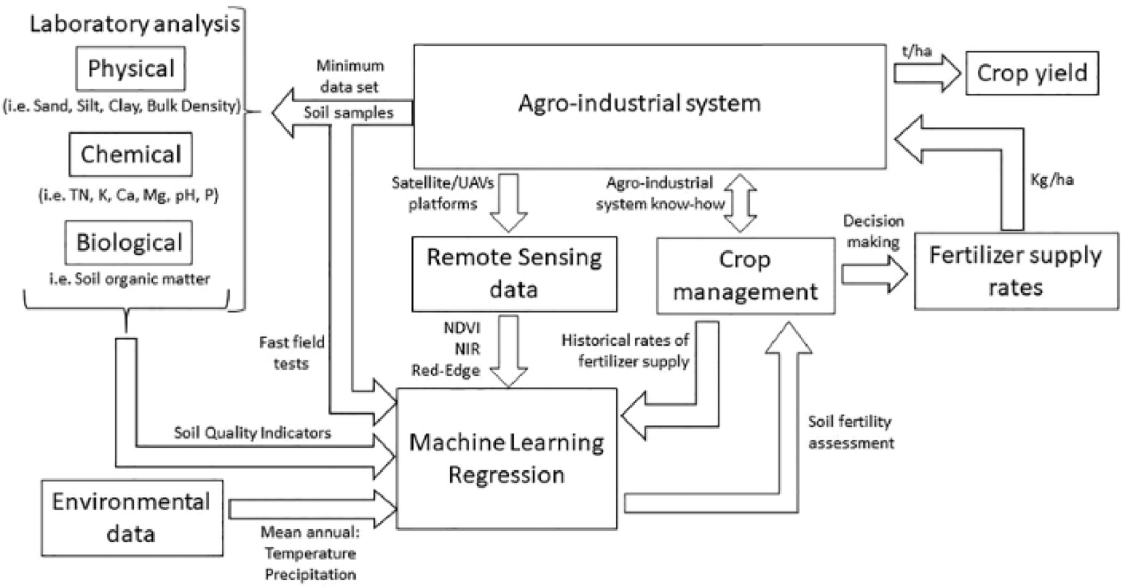


Fig. 1. Relationship between RS, ML and SQIs scheme in an Agro-industrial system.

Avand, Mohammadtaghi & Mohammadi, Maziar & Mirchooli, Fahimeh & Kavian, Ataollah & Tiefenbacher, John. (2021). **A New Approach For Smart Soil Erosion Modelling: Integration of Empirical And Machine Learning Models**. 10.21203/rs.3.rs-809330/v1.
Access: Link

Erosion-prone locations (erosion ≥16 tons/ha/year) are identified using RUSLE model.
This study uses **13 factors affecting soil erosion** in the Talar watershed, Iran, to increase prediction accuracy. The results show that **slope angle, land use/land cover, elevation, and rainfall erosivity** are the factors that contribute the most to soil erosion propensity in the watershed.
Soil-erosion map is prepared using random forest (RF), artificial neural network (ANN), classification tree analysis (CTA), and generalized linear model (GLM). The results reveal that the RF model has the highest prediction performance, outperforming the three other machine-learning models.

Rukhovich, D.I.; Koroleva, P.V.; Rukhovich, D.D.; Rukhovich, A.D. **Recognition of the Bare Soil Using Deep Machine Learning Methods to Create Maps of Arable Soil Degradation Based on the Analysis of Multi-Temporal Remote Sensing Data.** *Remote Sens.* **2022**, *14*, 2224. https://doi.org/10.3390/rs14092224
Access:Link

In this paper, a method for constructing soil maps based on a multi-temporal analysis of the bare soil surface (BSS) is proposed. It is an alternative method to the widespread use of vegetation indices.
A method for detecting degraded areas of arable land was developed, based on the recognition of bare soil surface on satellite images using deep machine learning methods and methods for calculating average long-term values of the spectral brightness of the bare soil surface of the RED and NIR bands. The indicator of soil cover degradation was the long-term average spectral characteristics of degraded lands. The **high spectral brightness of the bare soil surface** (above the average spectral brightness of the study area) is an indicator of the distribution of degraded soils. A neural network was used to automate the selection of an BSS on each RSD scene.

RESOURCES

U-net for satellite imagery segmentation:

1. https://arxiv.org/pdf/2003.02899.pdf
2. https://www.sciencedirect.com/science/article/pii/S0303243422000113
3. https://link.springer.com/article/10.1007/s11227-022-04379-6

4. https://medium.com/vooban-ai/satellite-image-segmentation-a-workflow-with-u-net-7ff992b2a56e

5. https://towardsdatascience.com/semantic-segmentation-of-aerial-imagery-using-u-net-in-python-552705238514

An extensive resource on Deep Learning on Satellite Imagery:
https://github.com/robmarkcole/satellite-image-deep-learning