

Action 2019-3-27: Development of downstream applications supporting Sectoral Information system under Copernicus Climate Change Service

Pilot Greece – Progress so far and future work

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1 Introduction

The current report sums up the actions, so far, taken from AUTH in the context of FPCUP to define and produce the degradation metrics as well as the synthetic index of degradation status in selected test sites in Greece and Poland. First of all, AUTH team was successfully completed the **questionnaire analysis** from where critical conclusions by the end users extracted.

Based on the questionnaire analysis and our expertise we ended up with the prediction through machine learning techniques and simulation models of the following land degradation metrics:

- Soil erosion
- Soil Organic Carbon (SOC) content
- Clay content

In the following section we provide the final land degradation metrics, produced so far, and the methodological framework in which they were developed.

Furthermore, we would like to inform you that AUTH team participated, with a work¹ based on a part of this research, in the **Online Workshop on Soil Erosion for the EU²³**, 20-22 June 2022, JRC Ispra, with a reference to FPCUP and our action.

2 Estimating Soil Organic Carbon and Clay content based on open access data

2.1 Imathia Regional Unit Greece

The current section provides the methodological framework in order to produce topsoil estimations of Soil Organic Carbon and Clay content based on Remote Sensing data and especially on Sentinel-2 optical imagery, and LUCAS 2015 soil survey. To this end, a 5-years long timeseries of multispectral imagery has been created, covering the Imathia Regional Unit of Central Macedonia, Greece. The predictor variables used are the Sentinel-2 bands which are openly accessible and retrieved from [Copernicus Open Access Hub](https://copernicus.openaccess.eu/), while the topsoil analysis from LUCAS 2015 soil survey were used as target variables.

Data collected were filtered and combined, aiming to derive representations of exposed soil composites over the region of interest. This filtering took place in two stages; the first is based on the Level-2A processed data of Copernicus Open Access hub and more concretely is:

- Filtering out images with high cloud coverage through the filter **Cloud Coverage<10%**
- Filter out land cover irrelevant to cropland through Scene Classification Layer **SCL=4 & SCL=5**, where 4 indicates exposed soil and 5 vegetated soil

The second stage of the methods for creating composites of exposed soils is the filtering procedure that entails exposed soil masking as suggested by (J.A.M. Dematte, et al., 2009) and includes the following filters

¹

<https://www.researchgate.net/publication/361585240> Improved soil erosion predictions based on Sentinel2 and deep learning techniques

² https://esdac.jrc.ec.europa.eu/public_path/EUSO/WSEE_v1.pdf

³ https://esdac.jrc.ec.europa.eu/public_path/EUSO/proceedings_ALL.pdf

- Water filtering with **NDVI>0**, where $NDVI = \frac{NIR-Red}{NIR + Red}$
- Vegetation filtering (sparse vegetation and forestlands) with **NDVI<0.25**
- Exposed soil filtering through burnt area identification **NBR2<0.075**
- Green Vegetation Indices **B3<B4** and **B2<B3** (Dematté, Fongaro, Rizzo, & Safanelli, 2018)

The preprocessed images contain only pixels representing exposed soil in different time periods, which were then used for the calculation of the synthetic map of median exposed soil reflectance, resulting to the map shown at . For the modeling part, Caret's R wrapper Random Forest was used to derive estimations of SOC and Clay content based on LUCAS 2015 topsoil survey of Greece. The results of SOC content as shown in Figure 2, while, the distribution of Clay as predicted by the applied methodology can be found at Figure 3. The products have a spatial resolution of 10m and they can provide information even **inside the parcels level**.

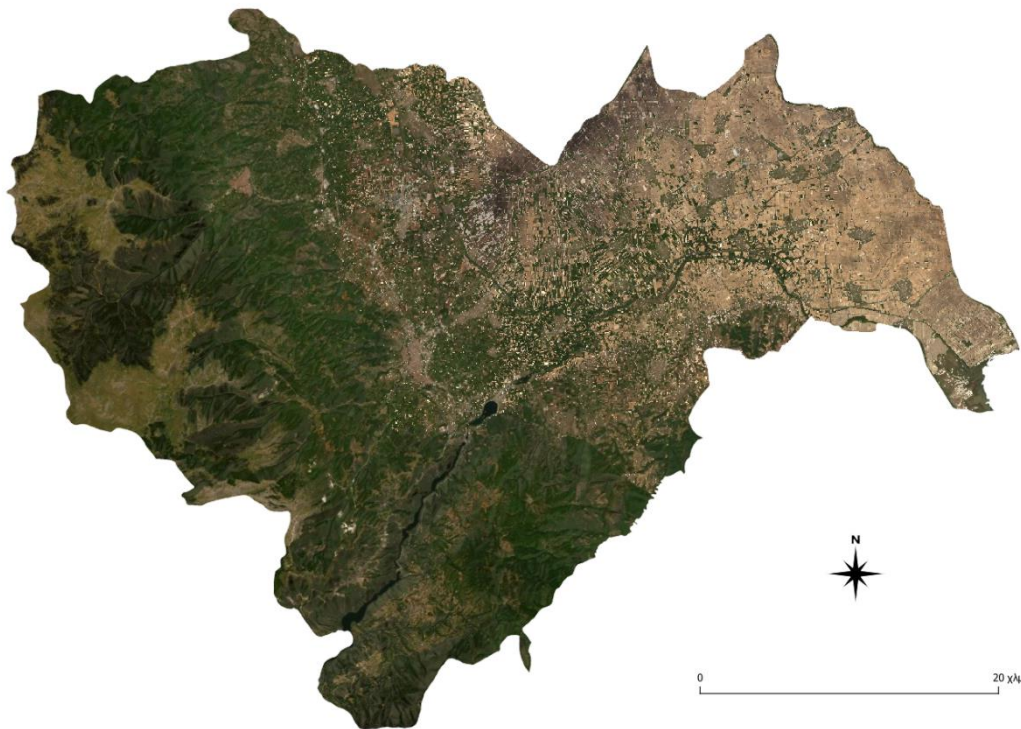


Figure 1: Imathia's true color exposed soil composite based on Sentinel-2 imagery from 2016 to 2022

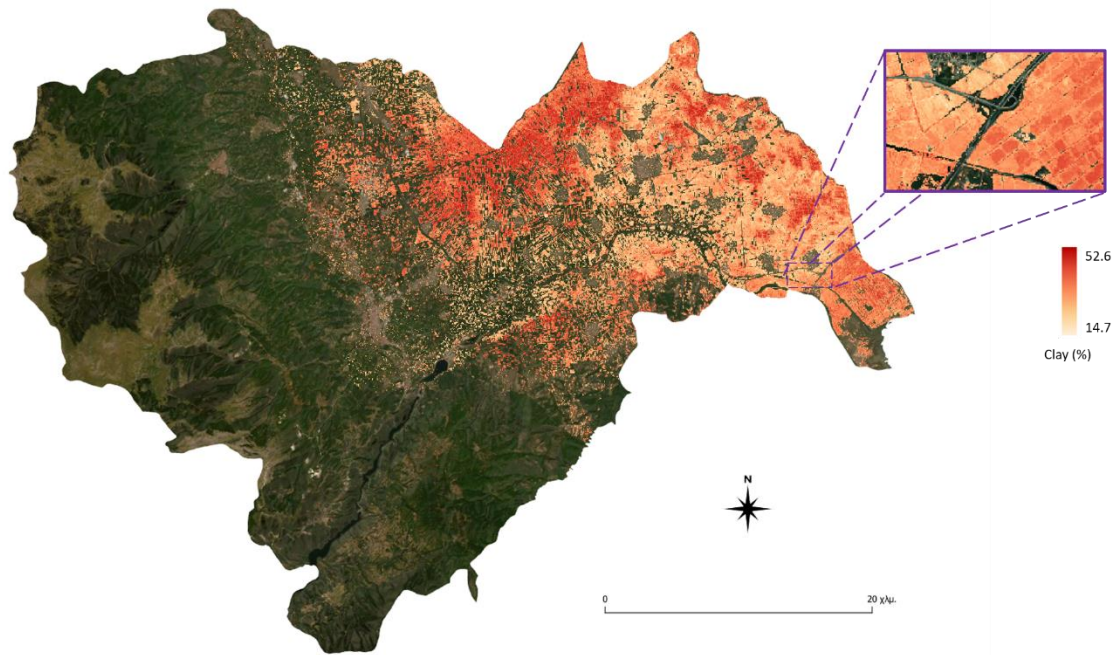


Figure 2: SOC content estimation based on LUCAS 2015 soil survey and Sentinel-2 imagery ([preview](#))

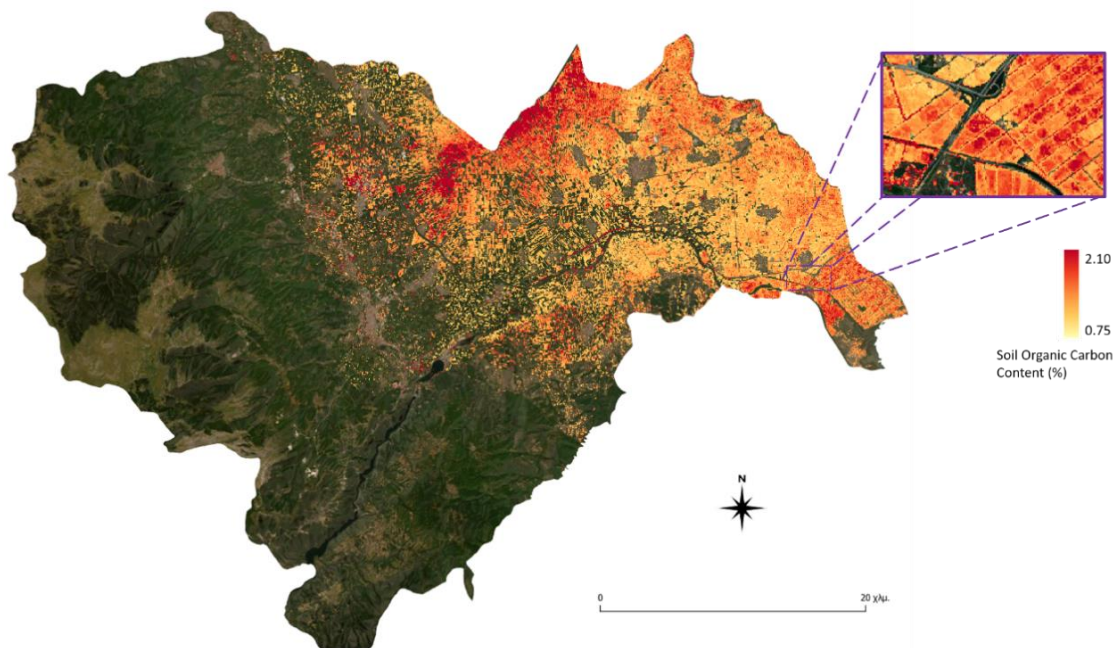


Figure 3: Clay content estimation based on LUCAS 2015 soil survey and Sentinel-2 imagery ([preview](#))

The above-presented methodology is transferable in the sense of it is not region or data restricted. In our showcase it was applied to openly accessible data (Copernicus Sentinel-2 and JRC LUCAS 2015) but can also employ or combine various data sources such as imagery retrieved from different missions and soil archives other than LUCAS, such as national soil archive.

2.2 Test site area in Poland

The same approach as described in section 2.1 was also followed in order to produce the SOC and clay content indicators for the test site in Poland.

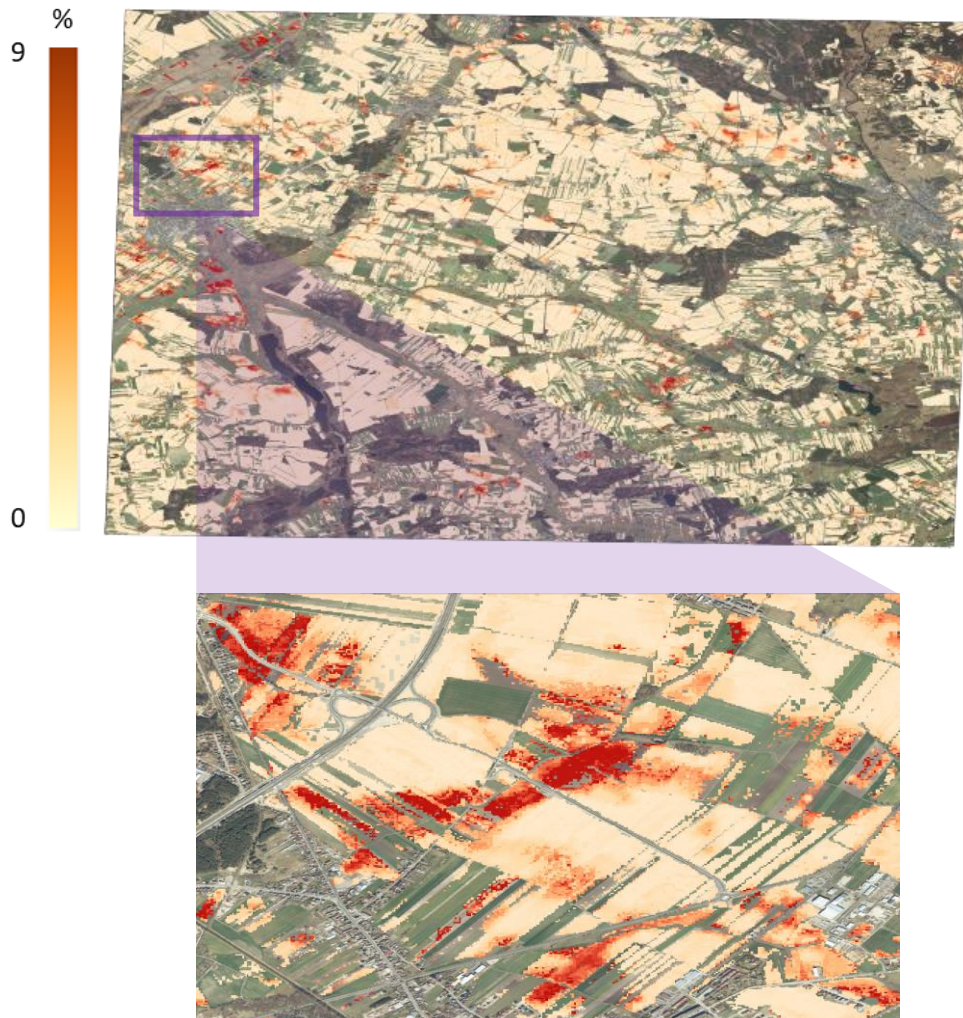


Figure 4: SOC content estimation based on LUCAS 2015 soil survey and Sentinel-2 imagery ([preview](#))

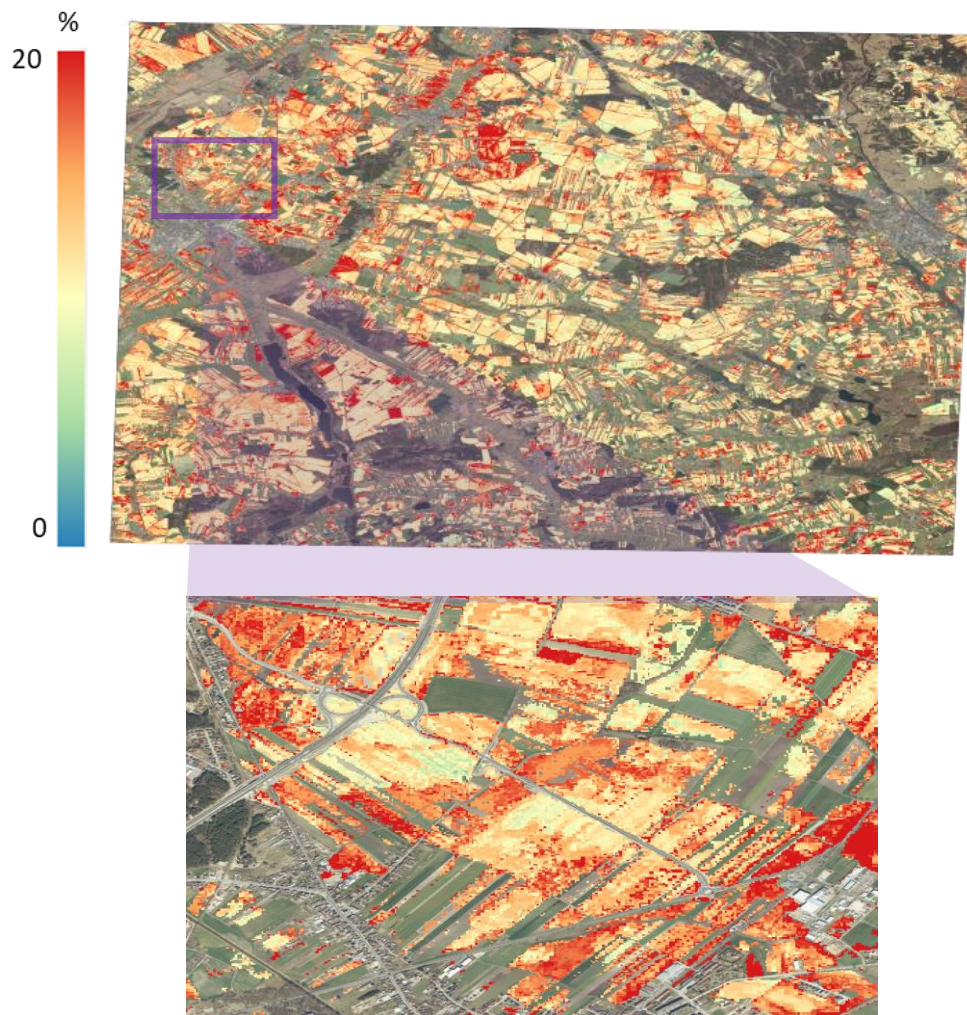
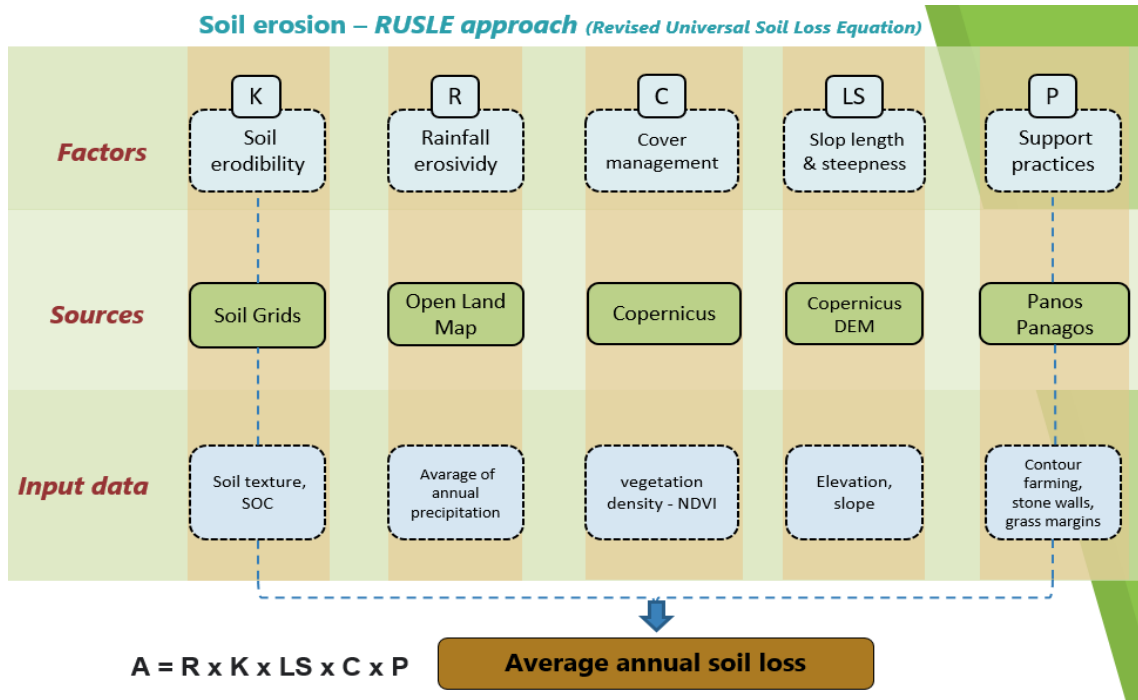


Figure 5: Clay content estimation based on LUCAS 2015 soil survey and Sentinel-2 imagery ([preview](#))

3 Estimating Soil Erosion indicator based on open access data and RUSLE

3.1 Imathia Regional Unit Greece

The current section provides the methodological framework in order to produce the soil erosion product based on Remote Sensing data and the **Revised Universal Soil Loss Equation (RUSLE)**.



C factor

In order to perform the C factor was calculate the median of the NDVI index through the bands B4 and B8 from multitemporal Sentinel-2 imagery. These bands present spatial resolution of 10 meters.

After calculate NDVI, was applied the equation described in Kazamias and Sapountzis, (2017):

$$C = \exp \left[-a \frac{NDVI}{b - NDVI} \right]$$

Where a and b are parameters that determine the shape of the curve relating the values of the NDVI and C factors.

P factor

For the P factor, was used the P factor data built by Panagos et al., (2015) for all Europe with spatial resolution of 100 meters.

LS factor

The required input data to calculate the LS factor were the slope values that was extracted from Copernicus DEM (30 meters resolution) and the flow accumulation, downloaded from https://github.com/davidbrochart/flow_acc_3s. This is a 3 seconds (30 meters spatial resolution) flow accumulation derived from HydroSHEDS.

We used the methodology built by Jian and Zheng (2008):

$$LS = 1.07 \left(\frac{\lambda}{20} \right)^{0.28} \left(\frac{\alpha}{10^\circ} \right)^{1.45}$$

Where L is the slope length factor; S is the slope steepness factor; λ is the slope length along the horizontal projection and α is the angle of inclination in degrees.

K factor

In order to calculate the K factor, we downloaded the required input data through SoilGrids (<https://soilgrids.org/>) (250 meters of resolution), including soil texture (sand, silt and clay) and soil organic carbon.

To obtain the K factor we used the equation described in Zhu, (2015):

$$K = \left\{ 0.2 + 0.3 \exp \left[-0.0256 \text{Sand} \left(1 - \frac{\text{Silt}}{100} \right) \right] \right\} \\ * \left(\frac{\text{Silt}}{\text{Clay} + \text{Silt}} \right)^{0.3} * \left[1.0 - \frac{0.25 \text{OC}}{\text{OC} + \exp(3.72 - 2.95 \text{OC})} \right], \\ * \left[1.0 - \frac{0.7 \text{SN}}{\text{SN} + \exp(-5.51 + 22.9 \text{SN})} \right] * 0.1317$$

Where Sand, Silt, Clay and OC are the percentage contents of sand, silt, clay and organic carbon. SN equates to $1 - \text{Sand}/100$.

R factor

The input data were downloaded from OpenLandMap Precipitation Monthly (developers.google.com/earthengine/datasets/catalog/OpenLandMap_CLM_CLM_PRECIPITATION_SM2RAIN_M_v01). They use data from IMERG, CHELSA Climate and WorldClim, with spatial resolution of 1 km.

In order to calculate the R factor, were downloaded all data from 2007 to 2019, then used the equation elaborated by Wichmeier and Smith, (1978):

$$R = 1.735 * 10^{(1.5 * \log\left(\frac{Pm^2}{Pa}\right) - 0.08188)}$$

Where, Pm is the monthly precipitation in mm and Pa annual precipitation in mm.

Annual soil loss

After calculating all factors, we did the calculation of annual soil loss, following the formula:

$$A = C \times P \times LS \times K \times R$$

The final product is a raster with the Annual soil losses by pixel in **ton ha⁻¹ yr⁻¹**.

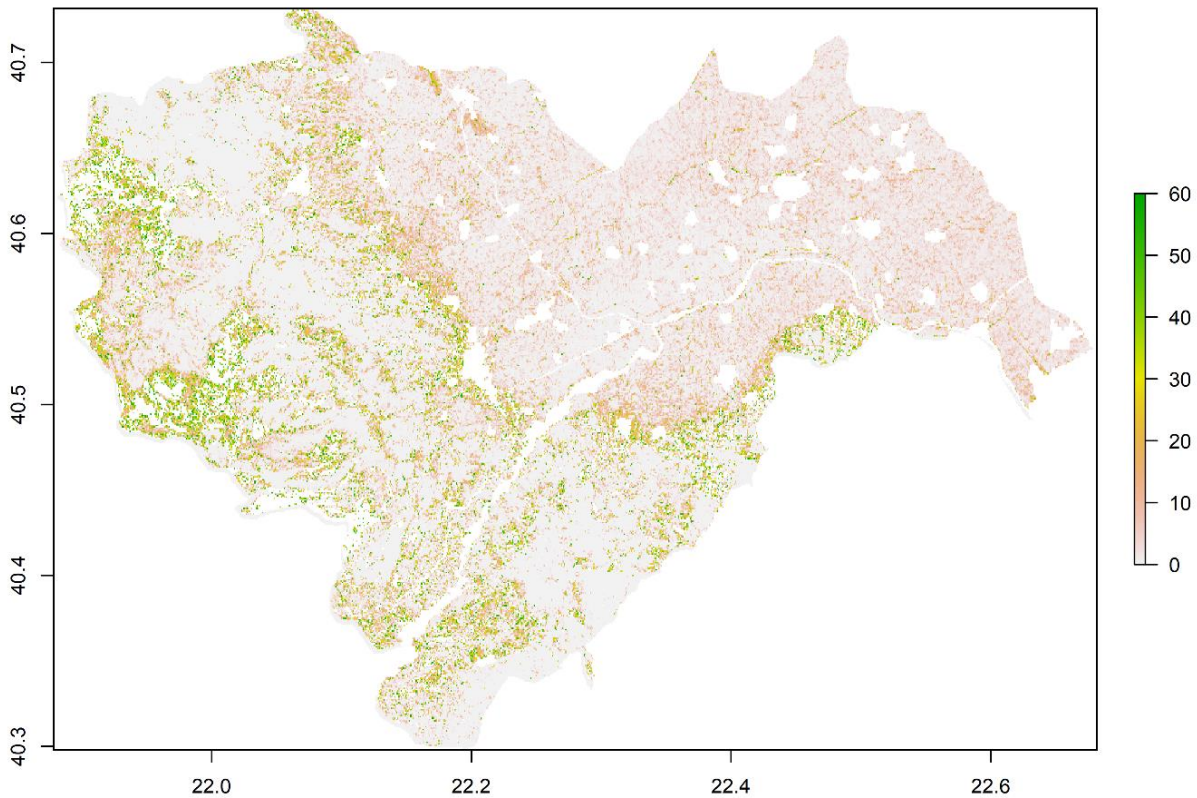


Figure 6: Soil erosion product for Imathia region for the year of 2021 ([preview](#))

3.2 Test site area in Poland

The same approach as described in section 3.1 was also followed in order to produce the soil erosion indicator for the test site in Poland.

The final product is a raster with the Annual soil losses by pixel in **ton ha⁻¹ yr⁻¹**.

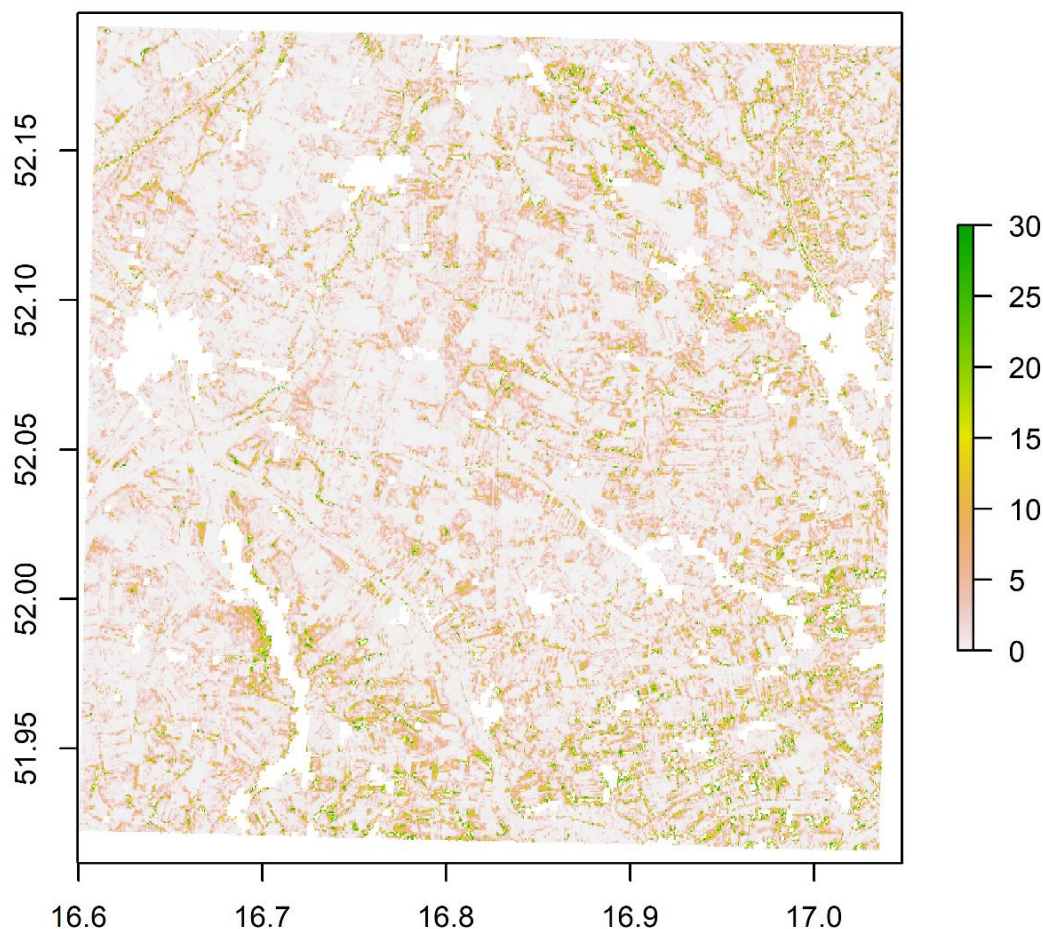


Figure 7: Soil erosion product for Poland test site area for the year of 2021 [\(preview\)](#)

4 Recommendations – Future work

4.1 Recommendations

In this section we would like to propose an idea which we believe will provide better insights in the whole project and will improve and augment the final services.

As we could understand the IGiK will provide the system for automatic **land use change** detection. If you remember we also proposed (during the January meeting) to provide the land use change product as an indicator for land degradation. At this point and in order to avoid any overlap with IGiK we would like to provide the **Clay content product**, as we already produced it, and to provide the **SOC/Clay ratio** which is strongly recognized by European policies as a vital importance indicator for land degradation. For your convenience you could see the report from EEA⁴ in subsection 2.3.3 for more information. From our point of view it is a great opportunity to focus through FPCUP also in this sub-indicator.

⁴ <https://www.eionet.europa.eu/etcs/etc-di/products/etc-uls-report-2021-soil-monitoring-in-europe-indicators-and-thresholds-for-soil-quality-assessments>

4.2 Future work

Our planned actions will focus to:

- Produce the SOC/Clay ratio product for Greece area and Poland test site.
- Combine the proposed sub-indicators (Soil erosion and SOC/clay ratio) to define and provide a synthetic land degradation index.
- Select the final 5 Pilot users.

Note: You could use also the following WMS service:

https://geoserver.ibec.org/geoserver/fpcap/wms?version=1.1.0&layers=fpcap%3AGREECE_lmathia_CLAY&bbox=21.881163690549297%2C40.30066943370122%2C22.68219142973259%2C40.7342862215198&width=768&height=415&srs=EPSG%3A4326&styles=

5 References

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