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D1.1.5: Indicators on climate change mitigation

Estimated CO2 emissions from electricity generation: methodological note (Bertolini, Duttilo and Lisi, UNIPD)

Landslide Susceptibility Map of Italy (Ceccato and Qadri, UNIPD)

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Summary

This document includes the description of two separate datasets submitted as deliverables for the GRINS Project on part of Spoke 6 - WP1.

The first section describes the methodology used for the CO2 emissions from electricity generation in Italy.

The second section describes the Landslide Susceptibility Maps created for Italy.

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Estimated CO_2 emissions from electricity generation: methodological note

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This note documents the methodology used for the estimation of CO2 emissions from hourly electricity generation in Italy, produced by the authors in the framework of the GRINS - Growing Resilient, INclusive and Sustainable project (GRINS PE00000018 - CUP C93C22005270001), European Union - NextGenerationEU.

Data source and estimation method

The hourly electricity generation $G^z_{i,h}$ is the actual aggregated net generation output (MW) per production type i, and physical zone z in the Italian day-ahead market (MGP). Data are collected for the years 2016-2023 with hourly time frequency (h). The source of this information is ENTSO-E, the European Network of Transmission System Operators (ENTSO-E, 2023).

The hourly CO_2 emissions are estimated according to the IPCC guidelines (IPCC, 2006),

$$E^z_{i,h} = G^z_{i,h} EF_i \tag{1}$$

where $E^z_{i,h}$ are the estimated CO2 emissions (tCO_2) per production type i, and physical zone z, while EF_i is the emission factor per production type i (MW/tCO_2). The latter is a coefficient that quantifies the amount of tCO_2 released into the atmosphere per unit of generated energy (MW). The country-specific emission factors are provided by ISPRA (2023) and are in line with those of the IPCC (2006). For each production type the average emission factor 2016-2022 is considered. Similar study that apply the same methodology are Malla (2009); Aliprandi et al. (2016); Eberle and Heath (2020); Wang et al. (2021).

Table 1: Emission factor coefficients.

Unit	Coal	Fossil gas	Fossil oil	Derived gas
TJ/tCO_2	94.13	56.38	76.59	163.36
MW/tCO_2	0.34	0.20	0.28	0.59

Notes. The emission factor of derived gas is the average of three emission factors: oxygen steel mill gas, blast furnace gas and coke oven gas. Conversion: 1 TJ are 277,7778 MW.

References

Aliprandi, F., Stoppato, A., and Mirandola, A. (2016). Estimating co2 emissions reduction from renewable energy use in italy. *Renewable Energy*, 96:220–232.

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ISPRA (2023). Emission factors for the production and consumption of electricity in italy.

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Landslide Susceptibility Map of Italy

PRESENTATION AND DESCRIPTION OF THE RESEARCH ACTIVITY UNDERTAKEN

Landslide Susceptibility (LS) maps are important instruments to manage landslide risk especially in a climate changing environment. The goal of this research is to produce a LS map that can automatically update to account for the changes of the environment. To this purpose we apply Google Earth Engine (GEE), which is a digital tool that integrates various datasets, including satellite imagery, DEMs, rainfall data, and land cover maps, for landslide susceptibility modeling. It offers geospatial analysis, machine learning algorithms, and statistical models, allowing for regional to global mapping at low computational costs. GEE can also analyze temporal trends in land cover changes, vegetation dynamics, and terrain evolution, making it a cost-effective and efficient solution for assessing landslide hazard on a national level.

The framework proposed in this study includes:

(i) Collecting relevant data such as satellite imagery, elevation data, soil type, precipitation, and any other relevant environmental covariates needed for landslide susceptibility mapping;
(ii) Preprocess and prepare the data for analysis using the cloud-based vast repositories of Google Earth Engine;
(iii) Develop a landslide susceptibility model using machine learning algorithms, such as Random Forest or Support Vector Machine;
(iv) Training of the model using historical landslide data and covariates using landslide inventories;
(v) Apply the model to the area of interest.

Note that some of the features used for LS mapping are also closely related to carbon emission and carbon stocks such as vegetation index (NDVI), land cover and land use. Future development of the research will investigate the effect of changes of these factors on LS.

RELATIONSHIP WITH THE EXISTING LITERATURE ON THE TOPIC

Landslides Susceptibility evaluation models can be qualitative or quantitative, based on expert knowledge. Qualitative methods include geomorphological analysis, heuristic approaches, and variable mapping. Quantitative methods include statistical analysis, machine learning methods, and deep learning. Different types of deep learning methods perform similarly well in prediction accuracy and evaluation. The quality of a LS map produced by a model relies heavily on the accuracy, scale, and number of driving factors considered. Considering a significant number of driving factor and work on large areas have always been challenging and computing-resources-consuming, but emerging cloud-computing resources offer new possibilities. This research applies deep learning methods to develop a LS map for Italy considering 18 factors and it explores how GEE serves as a digital twin for landslide susceptibility mapping, offering a cost-effective and efficient solution for assessing landslide hazard on a national level. While previous research has employed GIS and satellite data for similar purposes, the national-scale utilization of GEE stands out as an innovative approach.

RESEARCH OUTPUT (interim or final)

Landslide susceptibility map is prepared based on Machine learning Algorithm using cloud-based platform to deal with large scale data at national level and to serve as digital twin with the upgradation and addition of the new data.

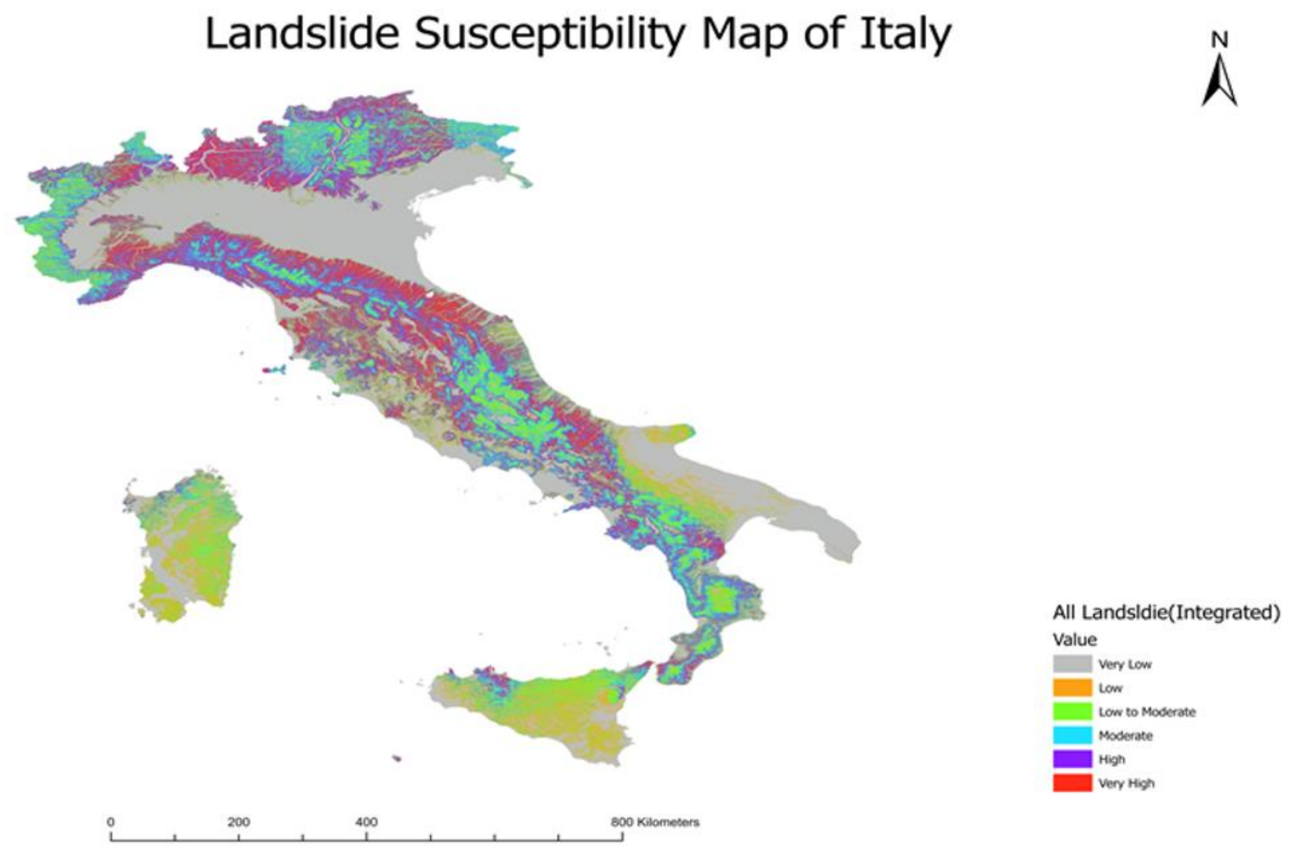

Figure 1 Landslide susceptibility map for Italy

A landslide susceptibility map divides areas into six classes based on their likelihood of experiencing landslides: "Very Low," "Low," "Low to Moderate," "Moderate to High," "High," and "Very High" susceptibility. "Very Low" areas have stable geological conditions and minimal landslide history, while "Low" areas pose a slightly higher risk. "Low to Moderate" areas indicate a moderate increase in risk, while "Moderate to High" areas suggest a more substantial likelihood of landslides. "High" areas have steep slopes and unstable geology, and "Very High" areas present the highest risk due to extremely steep terrain and frequent landslides. These classifications guide land use planning, infrastructure development, and risk mitigation efforts in landslide-prone regions, helping to minimise potential damage and protect lives and property.

Variable importance indicates the contribution of each variable to the accuracy of the model in predicting landslides or other phenomena. In this scenario, the importance ranking suggests that rainfall is the most influential variable in predicting landslides, as it occupies the first position. This is reasonable since rainfall plays a significant role in triggering landslides by saturating the soil and increasing pore water pressure. Following rainfall, the Normalized Difference Vegetation Index (NDVI) indicates its importance in assessing vegetation health and its potential correlation with slope stability. Elevation comes third, which is also logical since terrain elevation can influence slope steepness and soil moisture distribution. The HAND (Height Above the Nearest Drainage) variable follows, likely because it captures topographic features related to drainage networks, which affect soil saturation and landslide susceptibility. Slope, ranked fifth, is crucial as steeper slopes generally exhibit higher landslide potential. Soil density, occupying the seventh position, reflects the importance of soil properties in determining landslide susceptibility. Lastly, the shape index ranks eighteenth, suggesting it has the least influence among the variables considered. This ranking underscores the significance of topographic and environmental factors, particularly rainfall, vegetation, and terrain characteristics, in landslide prediction using the random forest model in GEE.

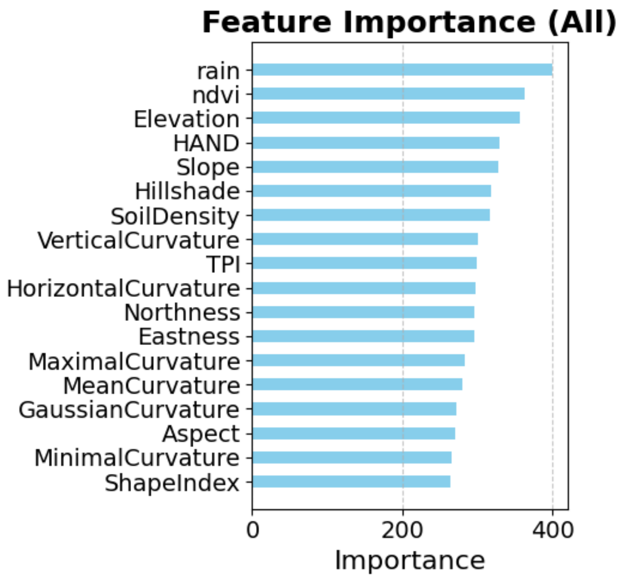

Figure 2 Feature importance

Submitted files:

- **LSM_All.jpg: this is a raster that can be opened with a figure visualizer**
- **LSM_All.tiff: this is a georeferenced raster plotting hazard levels with a resolution of 30m and can be opened with GIS. Hazard level ranges from 0 to 100 and we can say that in the range 0-10 hazard is very low, 10-24 low, 25-39 low to moderate, 40-64 moderate, 65-84 high, 85-100 very high.**

POLICY IMPLICATIONS

These Landslide susceptibility classifications help planners, engineers, and policymakers make informed decisions about land use, infrastructure development, and disaster risk reduction strategies in landslide-prone areas. Another interesting feature is the availability of time series, indeed temporal trends in land cover changes, vegetation dynamics, and terrain evolution can be analysed to assess landslide susceptibility over time, and predict possible future scenarios. This is particularly relevant in a rapidly changing environment. The Google Earth Engine Landslide Susceptibility Mapping algorithm can be viewed as a Digital Twin, meaning that it can automatically collect the most up-to-date relevant data, process them, and offer an effective visualization.