



1. Research activity (max 1.000 words)

In the last decades, the application of Earth Observation (EO) remote sensing data to natural risk mitigation has been extensively exploited, especially for the characterization of areas historically prone to landslides, and as support for field surveying and aerial photographs interpretation. Moreover, along with gravity-driven processes, information about the origin and geometry of slope-waste deposits are essential for assessing the landscape evolution, and for hazard prediction and planning purpose [2]. However, the detection of features useful to automatically create detailed slope landforms and deposits inventories (including landslides and slope-waste deposits) remains challenging [2, 5].

During the last years, the availability of spatial and temporal high-resolution EO data has already exponentially increased (i.e. Big Data), and the trend is expected to reach tens of Petabytes per year [11]. In this framework, it's quite impossible to perform feature extraction through supervised approaches or supervised ML algorithms (e.g. Random Forest, Support Vector Machine). Thus, to effectively enhance information from Big Data, it is necessary to take advantage of an ML algorithms sub-category, called Deep Learning – DL [4, 6].

Recently, several studies [1, 3, 8-10] proposed DL methods based on one of the most common models (i.e. Convolutional Neural Network) to extract features from EO data more rapidly than other classic techniques. Additionally, rapid features identification on multitemporal datasets could be essential to discriminate specific landslides' triggering mechanisms (e.g. Earthquake-triggered Landslides - EQtLs).

Although the promising results reached so far, and the efforts that have been made to develop efficient landslide and deposits identification methods, all the authors point out that the potentiality of DL application to EO data is still to achieve. Literature relies almost entirely on optical imagery to perform landslides detection: interferometric data and high-resolution DEMs have been exploited mostly as auxiliary information, or not exploited at all [11]. Furthermore, efforts have not been still aimed at the detection and classification of slope-waste deposits of different origin (e.g. colluvium, stratified slope deposits, debris cones or sheets, relict landslide bodies).

Therefore, with the general purpose of enhancing techniques and methodologies for the detection of gravity-driven processes and landforms, my study aims to integrate a multi-sensor and multi-temporal dataset in an ML algorithm, in order to achieve three specific objectives:

1. Detection and classification of landslides processes and related landforms, with particular emphasis to relict and/or vegetated landslide bodies;
2. Detection and mapping of slope debris deposits due to gravity and/or surface running water;
3. Discrimination and inventorying of earthquake-induced landslides, with particular emphasis on the rockfall and rock/debris slide typologies.

To investigate the potentiality of different ML algorithms, a multidisciplinary approach is mandatory. Studying ML application on various disciplines, other than Earth Sciences, will permit to choose one or more algorithms suitable for analyzing heterogeneous datasets. In addition to multi-temporal optical imagery, interferometric data and multi-resolution DEMs will be collected (global DEMs, LiDAR where possible). Starting from digital elevation data, land surface quantitative analyses will be performed in order to support the prediction of hard-to-recognize landforms (i.e. relict landslides).

A specific site in the Central Apennines will be selected to apply the ML model; the site must contain a wide spectrum of landslides (including relict and earthquake-induced landslides) and slope debris deposits in terms of typology and dimensions. Availability of detailed and updated landslides inventory in the selected study area [7] will be a fundamental factor in the reliability assessment of the model prediction capability. Moreover, considering the peculiarity of Apennine EQtLs, mostly represented by rockfalls, rockslides and debris slides [7], detection of these specific gravitational landforms will be attempted. Specific and detailed field survey is planned, to better investigate relict and forested landslides, and eventually lessen resulting false-negatives.

References

1. Chen et al., 2018; Sensors 18, 821.
2. Drăguț and Blaschke, 2006; Geomorphology 81, 330-344.
3. Ghorbanzadeh et al., 2019; Remote Sens. 11, 196.
4. Goodfellow et al., 2015; MIT Press.
5. Guzzetti et al., 2012; Earth-Science Reviews 112, 42-66.
6. LeCun et al., 2015; Nature 521, 436-444.
7. Martino et al., 2017; Geogr. Fis. Dinam. Quat. 40, 77-95.
8. Meezal et al., 2017; Applied Science 7, 730.
9. Prakash et al., 2020; Remote Sens. 12, 346.
10. Sameen and Pradhan, 2019; IEEE Access 7, 114363–114373.
11. Wang et al., 2020; Geoscience Frontiers.

2. Research products

a) Publications (ISI journals)

Iacobucci G., Troiani F., Milli S., Mazzanti P., Piacentini D., Zocchi M., Nadali D. (2020) - *Combining satellite multispectral imagery and topographic data for the detection and mapping of fluvial avulsion processes in lowland areas*. Remote Sensing 12, 2243.

b) Publications (NON ISI journals)

c) Manuscripts (submitted, in press)

d) Abstracts

Iacobucci G., Mazzanti P., Milli S., Nadali D., Troiani F., Zocchi M., Forti L. (2019) - *Holocene and historical morphodynamics of the Lower Mesopotamian waterscape: a multi-sensor remote sensing approach*. INQUA Commission: Terrestrial Processes Deposits and History, Session: Palaeohydrology and Fluvial Archives - hydrological extreme and critical events (HEX), Dublin, July 2019 (Poster).