DIPARTIMENTO
DI SCIENZE DELLA TERRA

SAPIENZA
UNIVERSITÀ DI ROMA

DOTTORATO DI RICERCA
IN SCIENZE DELLA TERRA

1. Research activity (max 1.000 words)

Landslide inventory maps represent a preliminary step toward landslide susceptibility, hazard, and risk assessment[1-4]. Moreover, information about the origin and geometry of slope-waste deposits, along with gravity-driven processes, are essential for estimating the landscape evolution and for planning purposes[5]. Completeness and updating of inventories are crucial elements to consider in every stage of the risk assessment, especially when landslides occur in the vicinity of human centres or infrastructures.
A spatial correlation between the geomorphological conditions in which the past events took place and expected future conditions can be established using satellite imagery in combination with geographic information system (GIS) data[6]. To date, visual interpretation of optical aerial or satellite images and DEMs remains the most common and widely used method to map mass-wasting processes, providing low-cost and up-to-date information[7]. However, depending on the extension of the area and the availability of data, analyses of remote sensing datasets are time-consuming and require extensive human labour. Thus, systematic updating of existing slope landforms inventory databases (including both landslides and slope-waste deposits) remains still challenging[1,4-5].
In recent studies, Machine Learning techniques have proven to reach outstanding and reliable performances in the automation of landslide detection and their rapid mapping from optical imagery. Since landslides are not characterized by unique spectral signatures or shapes, combining features from different approaches (*i.e.*, DEM derivatives) could prove to be a better solution in complex morphological settings such as forested areas[8-9]. Furthermore, implications on mapping slow ground deformations, often misclassified as dormant or inactive, can be inferred from interferometric data[10].
Although the promising results reached so far in landslide identification tasks, several problems remain still unsolved[11]:

1. how to combine optical, topographic, and interferometric information in a Machine Learning model?
2. how to identify and classify different types of landslides?

The first semester of my PhD was dedicated to the selection of a study area in the Central Apennines, relying on the availability of regional geological databases (i.e., PAI, IFFI and MZS). Specifically, an area encompassing Lazio, Umbria, Marche, and Abruzzo Regions has been selected, where a widespread scenario of earthquake-induced landslides occurred after the 2016-2017 seismic sequence.
In the framework of the project ReSTART, involving CERI Research Centre of Sapienza University and Autorità di Bacino Distrettuale dell’Appennino Centrale, I focused on more than 100 landslides classified with P3 or P4 (i.e., high and very high) hazard values, part of the pre-existing PAI database interacting with infrastructures and urban centres. According to this database, the most frequent landslide typology is represented by rockfall (41%), followed by earth/debris slide (15%), shallow landslides as soliflux (14%), complex landslides (12%), debris flow (8%) and non-defined landslides (10%).
The first step before the data analysis was the collection and storage of geo-spatial and multi-temporal information in a GIS georeferenced database. Such information, related to different data

types, was then grouped in the following datasets: 1) geological and lithological features (1:10.000); 2) topographical features (CTR and medium to high-resolution DEMs); 3) multi-temporal aerial imagery; 4) other pre-existing landslides inventories (IFFI, MZS, CEDIT); 5) Persistent Scatterers (PS).

Since there is neither a national nor regional standard for updating PAI inventory, I introduced a new workflow that permitted the combination of classic mapping techniques (aerial photos inspection) with the most recent ones (use of DEMs and PS) at a local scale of 1:5000.

A general overview of each slope, embracing one or more landslides, is fundamental to assess previous recordings of displacements and predisposing factors for instabilities: for this reason, considering pre-existing databases, slope morphology, and geological units outcropping provided initial hints on which landslides kinematics is likely to occur. Moreover, information about the state of activity was derived from the PS time series analysis of ERS (1992-2000) and ENVISAT (2004-2008) satellites, in order to distinguish dormant landslides from active ones.

Although the visual interpretation of aerial photos remains the most common and classic method to recognize landslides, the first attempt in updating boundaries was made using topographic surface models. Therefore, visual analysis and interpretation of a LiDAR-derived DEM of 2m-resolution (where available) and a 5m-resolution DEM generated from the 1:5000 topographical map was performed. From the latter DEM, several shaded relief maps, with variable sun azimuths, were also obtained: this permitted to avoid azimuth-bias in the interpretation of landforms and emphasize scarps, topographic changes, and other landslides elements under different illumination effects[12-13].

Modified boundaries and new landforms resulting from this step were then further refined through the multi-temporal interpretation of stereo pairs (acquired in 1953-1954), orthophotos (acquired in 1988-89, 1994-98, 2000, 2006, 2008 and 2012), and recent satellite imagery (2016-2021), which also helped in the assessment of the state of activity of each polygon.

Geomorphological field surveys were eventually carried out to validate kinematics, states of activity and, in some cases, solve misclassification due to intricate spatial relationships.

To date, results derived from this workflow are already available for Autorità di Bacino Distrettuale dell'Appennino Centrale, which will update its old inventory. During the next months, I will complete the procedure on the remaining landslides and use this dataset as a starting point for interferometric analysis and application of semi-automatic detection algorithms.

<u>REFERENCES</u>

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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., Troiani F., Milli S., Piacentini D., Mazzanti P., Zocchi M., Nadali D. (2021) - Remote sensing approach for the fluvial avulsion processes detection and mapping. Intervento presentato al convegno EGU General Assembly 2021 tenutosi a Online

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).