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Object-based landslide mapping using ML and UAS photogrammetric products

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Modeling natural hazards in 3D space constitute a significant step for managing and planning our living environment. The creation of precise maps is needed to document the impact of natural hazards such as landslides (Picarelli, 2009). Loss of life, natural resources or property transform landslide phenomenon to a natural disaster. In landslide analysis different factors can be incorporated and studied such as landslides occurrence and occurrence, their distribution, mechanisms, pattern of failures. The development of detailed and reliable maps is also crucial for determining landslide susceptibility and risk (Guzzeti, 2012). Only recently, the emerging geospatial technologies are capable to produce and combine different types of 2D and 3D data. Unmanned Aerial Vehicle (UAV) or Unmanned Aerial Systems (UAS), support the acquisition of ultra-high detailed resolution geospatial data in the 3D environment (Giordan et al. 2020). Those systems are flexible in data acquisition, with a high temporal frequency, while it is limited for site specific mapping purposes. The exploitation of 3D point-clouds has been proven remarkably efficient for analyzing data in the field of geoscience. Point cloud advantages of documenting in 3D space, data of hazardous sites at low cost and effective performance identifies them as leading primitives for site-specific 3D landslide modelling. Given the gaps between the computer vision capabilities and their applications in landslide assessment in site-specific scale, the proposed work aims at developing a general framework of predefined workflows in an object-based (Object-Based Image Analysis- OBIA) programming environment for detection (Fig.1) and characterization of landslide phenomena from ultra-high-resolution UAV-derived data.

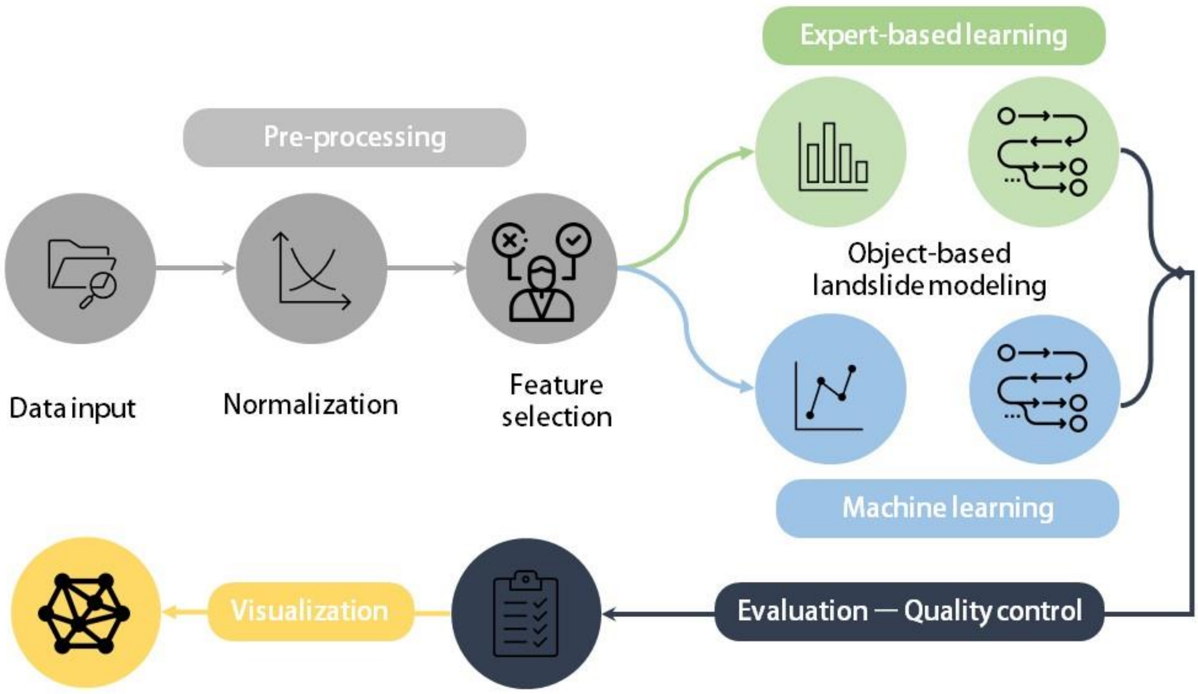

Figure 1. Developed object-based classification scheme for landslide object characterization.

The framework is built up in four distinct research phases: (a) on-site data collection, (b) data preprocessing, (c) OBIA (segmentation and classification), and (d) evaluation. These phases result in various novel component-wise solutions, which particular focus on the optimization phase of OBIA for landslide assessment. Different flight acquisition configurations were tested by varying the number of images, image overlap, flight height and focal length for selecting the optimal workflow for imagery collection always considering the site specifications (topography, landslide mechanism). Structure-from-Motion (SfM) photogrammetry has been used to provide dense 3D point clouds describing surface morphology of landslide environments. The proposed methodology has been developed based on OBIA and fusion of multivariate data resulted from photogrammetric processing in order to take full advantage of its productivity. Several quantifiable comparative studies have been conducted to analyze the influence of topographic information, scale segmentation and evaluate the object-based classification of landslide ontologies with three state-of-the-art Machine Learning classifiers, KNN (Cover and Hart, 1967), DT (Breiman et al. 1984) and RF (Breiman, 2001) with the inclusion of spectral, spatial, and contextual characteristics. Results highlight higher performances for landslide mapping with RF when DSM information was integrated (Fig.2). Transferability constitutes a critical issue in image classification. Thus, RF presented higher predictive performance when the model was fitted and applied to a different study area. For the ML classification of landslide zones, 60% of the reference segments have been used for training and 40% for validation of the models. From all configurations tested, 54 classifications were exceed in an agreement of higher than 75% with the highest performance being with the RF classifier.

Figure 2. a) Orthophoto overlaid by the reference data, b) segmentation result and c) the final classification after refinement of the rule-based method (green: non-affected, light brown: depletion, dark brown: scarp).

Since the ultimate goal is to provide a ready-to-use landslide mapping tool, a transferability study of the final classification workflow needs to be conducted. The same object features and processes for segmentation and classification needs to follow for keeping a uniform implementation approach. Based on the F1 metrics, the RF model showcased great superiority compared with other classifiers. The proposed work illustrates the effectiveness of UAS platforms to acquire accurate photogrammetric datasets from complex surface topographies and provide an efficient and transferable objectbased framework to characterize the failure site based on semantic classification of the landslide elements on site specific scales. The outcome can be useful for prioritizing efforts to moderate the adverse consequences of landslides and provide future mitigation strategies following landslide ontologies. Complementary to the developed workflow the accomplished real-world application, this work has shown the great potential of coupling UAS photogrammetry with object-based methods for assessing the landslide features in different hierarchical scales and provide a detailed automatic classification. Desirable data for further landslide analysis and OBIA include cohesion, friction angle, plasticity values, and groundwater data. In view of the long-term and permanent nature of the landslide hazard, and the resulted risk, the only practical method of landslide mitigation is to assist local authorities and inhabitants to understand the problem and how to avoid or prepare for an event.

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