An example of SAR-derived image segmentation for landslides detection

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ABSTRACT

A rapid assessment of the areal extent of landslide disasters is one of the main challenges facing by the scientific community. Satellite radar data represent a powerful tool for the rapid detection of landslides over large spatial scales, even in case of persistent cloud cover. To define landslide locations, radar data need to be firstly pre-processed and then elaborated for the extraction of the required information. Segmentation represents one of the most useful procedures for identifying land cover changes induced by landslides. In this study, we present an application of the *i.segment* module of GRASS GIS software for segmenting radar-derived data. As study area, we selected the Tagari River valley in Papua New Guinea, where massive landslides were triggered by a M7.5 earthquake on February 25, 2018. A comparison with ground truth data revealed a suitable performance of *i.segment*. Particular segmentation patterns, in fact, resulted in the areas affected by landslides with respect to the external ones, or to the same areas before the earthquake. These patterns highlighted a relevant contrast of radar backscattering values recorded before and after the landslides. With our procedure, we were able to define the extension of the mass movements that occurred in the study area, just three days after the M7.5 earthquake.

KEYWORDS

Synthetic Aperture Radar (SAR), Sentinel-1, Backscattering, Change Detection, Image Segmentation, Landslides, Papua New Guinea

INTRODUCTION

Optical and radar satellite imagery allow obtaining information on changes in land cover induced by anthropic activities or natural phenomena (e.g., wildfires, floods, landslides). Synthetic Aperture Radar (SAR) sensors have the unique advantage to transmit electromagnetic radiations in the microwave wavelength region, and to receive the backscattered signal without the cloud cover disturbance. Amplitude of the backscattered signal is influenced by the type of target and vary according to several factors, such as the land use (e.g. water bodies, ice cover, forest type, bare soil), surface roughness, terrain slope. By comparing amplitudes of signals acquired in different times, it is possible to get valuable evidences of the land cover changes occurred in a specific area.

Amplitude-based methods have been successfully applied for the detection of landslides inducing sharp modifications of the land cover (Mondini, 2017; Tessari et al., 2017; Konishi & Suga, 2018). Generally, extraction of landslide information from amplitude radar images is performed by means of segmentation and classification procedures. Segmentation aims at redefining the basic spatial unit from a single grid cell to a group of adjoining cells characterized by similar properties, and referred to as objects. This is a crucial operation, given that unreliable segmentation algorithms could lead to inaccurate identification of objects and to a wrong classification of them.

The current study focuses on the segmentation of radar-derived images by means of the segmentation module *i.segment* (Momsen & Metz, 2017), included in the open-source GRASS GIS software. As test site, we selected part of the Tagari River valley in Papua New Guinea (Fig. 1), which was struck by a M7.5 earthquake on February 25, 2018. The earthquake triggered massive landslides that killed dozens of people and caused relevant geomorphic effects (e.g., river dams). Segmentation was thus aimed at identifying areas affected by landslides, starting from multi-temporal radar images, and at exploring the performance of *i.segment* with this type of data.

The research activities described in this manuscript have been developed in the framework of STRESS (Strategies, Tools and new data for REsilient Smart Societies), a project focusing on the designing, implementing and testing of a Spatial Information Infrastructure (SII), as a support for spatial planners and risk managers involved in the analysis of hazard and impact assessment of geo-hydrological phenomena.

MATERIALS & METHODS

Data used in this study are C-band SAR images acquired by the Sentinel-1 satellites in Interferometric Wide swath (IW) mode, with a VV+VH dual polarization. A total of 5 Level-1 single look complex (SLC) consecutive images were downloaded from the ESA Sentinel Data Hub (https://scihub.copernicus.eu): two images were related to the period preceding the reference earthquake (February 25, 2018) and three images were related to the following time span. All the images were acquired along the satellite track n.82 in ascending orbit. Each image was pre-processed by means of the graph processing tool (GPT) of the ESA's Sentinel-1

Toolbox (S1TBX), a module of the Open Source software SNAP (version 6.0). Pre-processing consisted in the following stages: (1) thermal noise removal, (2) radiometric calibration (β_0), (3) TOPSAR deburst, and (4) Multilooking. For each couple of images, a co-registration procedure was carried out by using as support the Shuttle Radar Topography Mission (SRTM) 1 Sec Digital Elevation Model (DEM), auto-downloaded from the SNAP software. After the co-registration, a change detection analysis was performed by calculating the Log-Ratio (LR) index as in Mondini (2017), with the following formula:

$$LR = ln\,(\frac{\beta_{0,i}}{\beta_{0,i-1}})$$

where i is the image index, with i ranging from 2 to the number of images, *ln* the natural logarithm and β_0 is the radiometric calibrated backscatter. This index provides a measurement of land cover changes occurred in a specific time interval. For each couple of images, a LR layer was thus produced.

Each LR layer was segmented by means of the *i.segment* module of GRASS GIS 7.4, by selecting the “mean shift” as algorithm, together with the “adaptive spectral bandwidth” option. The mean shift is a kernel-based nonparametric technique for finding the modes (i.e. local maxima) of probability density estimations (Fukunaga & Hostetler, 1975; Comaniciu & Meer, 2002). In *i.segment*, the mean shift is implemented as an iterative two-step procedure, consisting in the anisotropic filtering and clustering of pixels. Basically, the mean shift algorithm recalculates cell values (shifted to the segment's mean) until a user-defined maximum number of iterations is reached, or until the largest shift is smaller than a threshold (convergence). The threshold must be larger than 0.0 and smaller than 1.0: a threshold of 0 would allow only identical valued pixels to be merged, while a threshold of 1 would allow everything to be merged (Momsen & Metz, 2017). A more or less conservative threshold needs to be selected taking into account spectral properties of the analyzed images.

The *i.segment* module requires h_s and h_r parameters, selected by the user, corresponding respectively to the spatial and range bandwidths, as indicated by Mahmood et al. (2012). With the adaptive bandwidth option, the h_s is fixed whereas the h_r can vary depending on the local data.

After convergence is reached, the second step of segmentation is the clustering of filtered data. Clusters are delineated starting from the basins of attraction of the corresponding modes. Pixels falling in such basins, consisting in the data points visited by all the mean shift procedures converging to that mode (Comaniciu & Meer, 2002), are grouped together in the same cluster. The cluster boundaries are then identified as loci where the force vectors diverge (Comaniciu & Meer, 2002).

To reduce “the salt and pepper” effect, the segments (i.e. clusters) containing less than the preferred minimum number of pixels can be eliminated, by specifying the *minsize* parameter within the *i.segment* command.

After clustering, a new layer showing the calculated segments is produced.

In this study, preliminary segmentation parameters were defined taking into account the spatial and spectral properties of the LR layers to segment, as well as the shape and size of the expected landslides. The selected parameters were then refined by using a "trial-and-error" approach relied on the visual assessment of the "pre-post earthquake" LR layer segmentation. The selected parameters resulted as follows: h_s=10, h_r=0.002, threshold=0.004, minsize=2, max number of iterations=100.

RESULTS

As shown in Figure 1, the Tagari River valley was affected by large-scale mass wasting processes triggered by the M7.5 earthquake and related aftershocks, with a consequent formation of river dams.

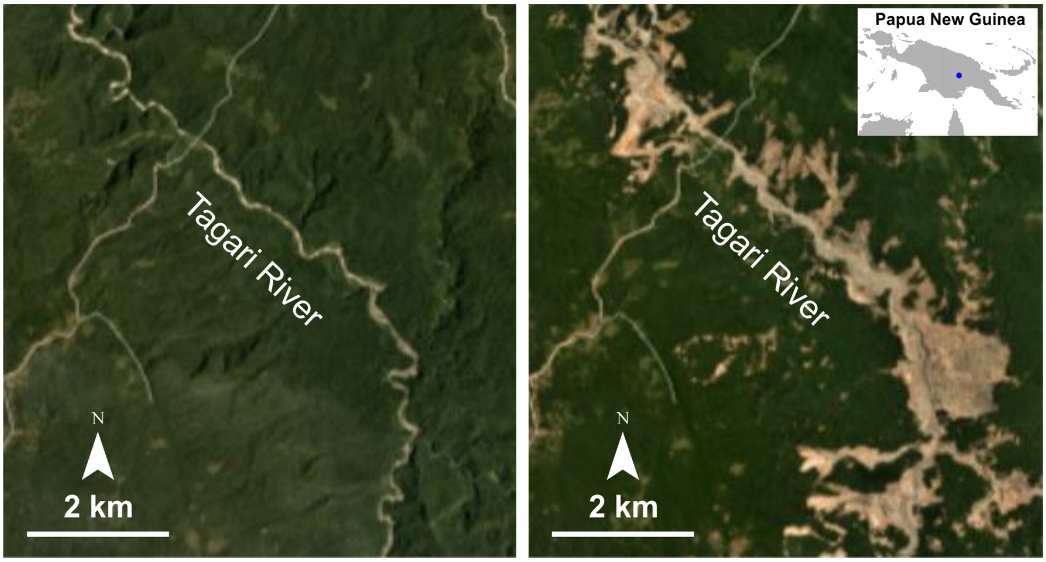

Figure 1: The Tagari River valley (Papua New Guinea). Optical satellite images before (on the left) and after (on the right) the severe earthquake. Images were collected on the Planet explorer application (Planet, 2017).

Both LR and segmentation layers derived from the change detection analyses are shown in Figure 2. In the two LR layers related to the time period between February 16 and March 12 (which include the major earthquake shaking), the evidences of land cover changes (landslides) are highlighted. In the corresponding segmentation layers, some "objects" are delineated where those changes are observed. Those objects are made by a relevant amount of very small segments, which are probably delineated due to the high local variance of the values of the underlying LR layers (1.70 and 1.46 respectively for the 02/16 - 02/28 and 02/28 - 03/12 periods). In the same areas of the preceding (02/04 - 02/16) and following (03/12 - 03/24) time periods, the variance of the LR values is significantly lower (0.24 and 0.33 respectively) and small segments are not created.

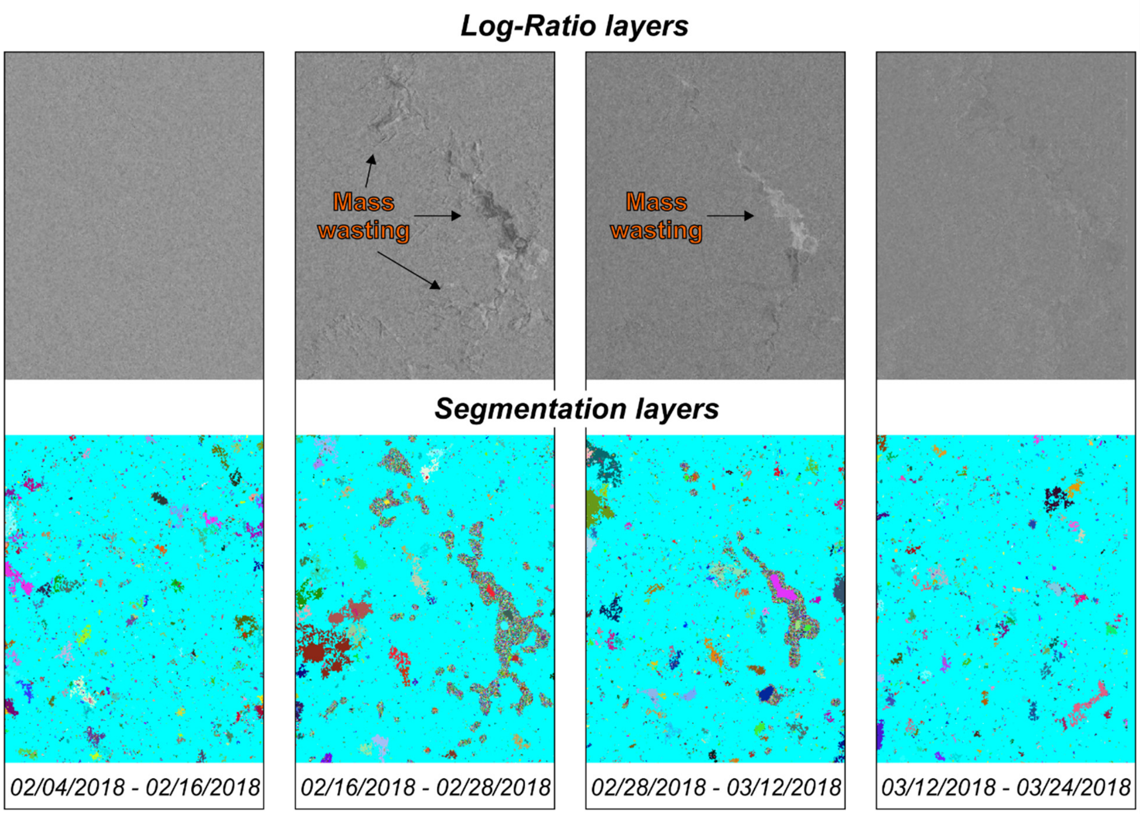

Figure 2: The Tagari River valley. Log-Ratio and Segmentation layers resulted from the change detection analyses. Extension of the area is the same of Figure 1.

DISCUSSION AND CONCLUSIONS

The segmentation of the Log-Ratio maps obtained through the GPT pre-processing chain of Sentinel 1 data seems promising for the development of automatic procedures aimed at monitoring a wide territory and detecting landslide events.

Values of the parameters selected for the segmentation procedure are user-defined and their tuning is generally related to different factors, such as the type of the images, their spatial and spectral resolution, the shape and size of the objects to be segmented. A 'trial-and-error' approach based on the visual assessment of the segmentation is therefore necessary to calibrate the parameters. The use of radar images allowed us to identify landslides after the most powerful earthquake (i.e. 02/28/2018). It is worth underlining that such products are not dependent from the cloud cover, as for example the optical images that are usually available several weeks after landslide occurrence. Following landslide disasters, maps showing the extension of the affected areas are crucial for the emergency operations. However, in remote areas of the world, like Papua New Guinea, it can be very difficult to obtain affordable data in a short time because of several reasons, including a limited availability of properly equipped helicopters/airplanes, adverse weather conditions, and road damages. In these cases, the use of SAR satellites can be therefore essential.

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