Evaluating the state of activity of slow-moving landslides by means of DInSAR data and statistical analyses

L'évaluation de l'état de l'activité de lents glissements de terrain par l'intermédiaire des données DInSAR et des analyses statistiques

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ABSTRACT The paper presents an original procedure pursuing the definition of the state of activity of slow-moving landslides at medium scale (1:25,000) via the joint use of remote sensing data deriving from the differential interferometric processing of Synthetic Aperture Radar (DInSAR) images and multivariate statistical analyses carried out on available thematic maps. The procedure was tested in a portion of Benevento Province (southern Italy) where several slow-moving landslides were inventoried according to geomorphological criteria.

RÉSUMÉ Le document présente une procédure pour déterminer le statut d'activité des glissements de terrain lent à moyenne échelle (1:25,000) grâce à l'intégration de données résultant d'un traitement au moyen d'images interférométriques différentielles acquis avec Synthetic Aperture Radar (DInSAR) et les résultats de l'analyse statistique multivariée effectuée à l'aide de cartes thématiques disponibles. La procédure a été testée dans une partie de la province de Benevento (sud de l'Italie) où plusieurs glissements de terrain lent ont été inventoriés en fonction de critères géomorphologiques.

1 INTRODUCTION

Slow-moving landslides are widespread in different geoenvironmental contexts all over the world causing economic losses which are not always sustainable by the community. For instance, as far as the Italian territory is concerned, 17,500 slow-moving landslides were inventoried at 1:25,000 scale within the territory of the National Basin Authority of Liri-Garigliano and Volturno rivers – NBA-LGV – (Cascini et al., 2002) and 32,000 phenomena were mapped at 1:25,000 scale in the northern portion of the Apennines chain (Bertolini et al., 2005). Landslide characterization and mapping are fundamental steps within the landslide risk management framework (Fell et al., 2008); as a result landslide inventory maps need to be sufficiently accurate and continuously updated. To this aim, photo-interpretation and field surveys are still mainly used (Guzzetti et al., 2012), although such campaigns, if carried out over large areas, may turn out to be extremely expensive.

In the last decade the scientific community investigated the use of both space and airborne remote sensing techniques (e.g., Tofani et al., 2013). Data deriving from the processing via multitemporal interferometric analyses (Ferretti et al., 2000; Fornaro et al., 2009; etc.) of images acquired by Synthetic Aperture Radar (DInSAR) were successfully exploited for the detection, mapping and monitoring of slow-moving landslides in a number of case studies (Cascini et al., 2009, 2010; Cigna et al., 2012; Wasowski and Bovenga, 2014). These latter were favoured by the increased availability of medium-resolution DInSAR data (i.e. derived from the processing of ERS1-2 and Envisat SAR sensors) as a result of several national (e.g. in Italy, Piano Straordinario di Telerilevamento, 2010; TERRAFIRMA, 2012) and regional projects (e.g. PODIS_Tellus Project in Campania
The main advantage provided by these datasets is furnishing ground-surface displacement measurements with sub-centimetric accuracy over large areas at affordable costs over a period of time covering more than 20 years since 1992. Within activities pursuing land planning and management at both small and medium scale, the use of multivariate statistical analyses has also been increasing steadily, since the past decades, for many applicative purposes related to landslide hazard and susceptibility zoning (Carrara, 1983; Guzzetti et al., 1999; van Westen, 2004; Calvello et al., 2013). These analyses statistically correlate landslide predisposing factors (independent variables) and existing landslide distribution (dependent variable) with the aim of defining a model to be associated with a given area of interest and, then, exported to areas with similar physical, geological and hydro-geological features.

The present paper introduces an original procedure based on the joint use of the results of DInSAR data analyses and multivariate statistical analyses for the definition of the state of activity of slow-moving landslides already mapped in the available inventory.

2 THE PROPOSED PROCEDURE

The proposed procedure consists of two phases (Figure 1). In particular, during Phase I DInSAR data and statistical analyses are separately implemented over homogeneous Terrain Computational Units – TCU – (Calvello et al., 2011, 2013), which discretize the area according to a regular grid with cells of size corresponding to 1/1000 of the scale of analysis, i.e. 25m x 25m for the case at hand. The DInSAR data analysis allows each TCU (defined as covered by DInSAR data if it includes at least one interferometric measurement within its perimeter) to be assigned an averaged velocity value weighted on coherence values following the procedure described in Cascini et al. (2013). These velocity values are then compared with a movement threshold equal to 1.5 mm/year (Cascini et al., 2009), so as to distinguish the moving TCU (TCU_M) from the not moving ones (TCU_NM) within a so-called “DInSAR map”. The multivariate statistical analyses are carried out on relevant thematic maps and event maps (i.e. the landslide inventory map) in order to discriminate the active from the not active TCU (i.e. respectively TCU_A and TCU_NA). Also in this case, the results are then reported within a map, herein called “statistic map”.

In Phase II, the analyses are performed on appropriately defined Territorial Zoning Units – TZU – (Calvello et al., 2011, 2013), which in this study coincide with landslides mapped as dormant, according to geomorphological criteria, within the landslide inventory. First of all, an activity model is defined, for each TZU, according to the value of the I_{dar} Index, namely DInSAR activity ratio, corresponding to the ratio between the number of moving TCU (TCU_M) and the number of covered TCU (TCU_c) within each TZU:

\[
I_{\text{dar}} = \frac{TCU_M}{TCU_c} * 100
\]  

(1)

The values of I_{dar} index are subsequently associated with four levels of TZU proneness to activity: High (H: 100 \geq I_{\text{dar}} \geq 70); Medium (M: 70 \geq I_{\text{dar}} \geq 35); Low (L: 35 \geq I_{\text{dar}} \geq 5); Very Low (VL: 5 \geq I_{\text{dar}} \geq 0).

Following the implementation of the activity model, the results of DInSAR data analysis are combined with the results of the statistical analysis via the consistency model shown in Figure 2a. In particular, a matrix approach is used to combine “moving/not moving” TCU – derived from DInSAR analyses – with “active/not active” TCU – derived from multivariate statistical analyses – in order to distinguish the TCU for which the analyses provide consistent results (i.e. active and moving TCU or not active and not moving TCU) from those for which the results are not consistent (i.e. active and not moving TCU as well as not active and moving TCU). By focusing the attention only on the group of consistent TCU, the confidence model is subsequently applied to each TZU (Figure 2b). Two indexes are preliminary defined:

\[
I_m = \frac{TCU_{A-M}}{TCU_M} * 100
\]  

(2)

\[
I_{nm} = \frac{TCU_{NA-NM}}{TCU_{NM}} * 100
\]  

(3)
where $TCU_{A-M}$ and $TCU_{NA-NM}$ represents, respectively, an active and in movement TCU and a not active and not moving TCU.

The computation of $I_m$ and $I_{nm}$ indexes for each TZU thus provides an additional information to the four levels of proneness to activity (H, M, L, VL) previously identified by the activity model based only on the information of movement retrieved from DInSAR data. Indeed, the implementation of the confidence model allows the classification of the TZU for which the results of the joint analyses exhibit a high ($H_{hc}$, $M_{hc}$, $L_{hc}$, $VL_{hc}$) or low ($H_{lc}$, $M_{lc}$, $L_{lc}$, $VL_{lc}$) confidence level. These levels are based, respectively, on the values of the Index of movement for TZU with high and medium activity proneness ($I_m$) and on the Index of not movement for TZU with low and very low proneness to be active ($I_{nm}$).

3 RESULTS

The analyses were carried out in a test area (Figure 3) extending for 557 km$^2$ and including 21 municipalities in the Campania Region, belonging to the NBA-LGV. In the area, within the activities carried out for the PsAI-Rf project (Landslide Risk excerpt of the Hydrogeological Setting Plans, Italian Law 365/2000), 2,180 slow-moving landslides covering around 25% of the territory were inventoried at 1:25,000 scale. In particular, the area includes: 766 rotational slides; 267 rotational slide-earth flows; 1117 earth flows; 30 deep-seated gravitational movements; 158 creep phenomena; 65 earth flow-creeps; 2 rotational slide-creeps.

Two possible states of activity for rotational slides, rotational slide - earth flows and earth flows are considered in the inventory according to geomorphologic criteria: “dormant” landslides and “active” landslides, the latter including active, reactivated and suspended phenomena (Cruden and Varnes, 1996). In this regard, Figure 3 shows a predominance of dormant phenomena in the study area.

The statistical procedure used is known in the literature with the name of "information value method" (e.g. Yin and Yan, 1988) and is based on bivariate analyses between the independent variables and a dichotomous dependent variable called, in the definition of the statistical model, event map. The multivariate statistical analyses related to the case study were developed herein assuming as event map the sample of the active slow-moving landslides mapped in the inventory map of the NBA-LGV. For the purpose of the analysis 8 territorial variables were considered: three categorical (seismic classification, hydrogeological and lithological complexes) and five numeric (altitude, slope, aspect, curvature and distance from the drainage network).

Of course, not all the considered independent variables are equally significant for the statistical analysis. To define what variables could most effectively be used to calculate and produce the statistical map employed herein, two procedures were used to base this choice on a maximization of both: (i) the discriminating power of the variables, (ii) their contribution to the success of the analysis. More information on this procedures can be found in Calvello (2012). The results of this analysis indicate that the variables most statistically significant are: hydrogeological and lithological complexes, slope and altitude.

![Figure 1. Flow chart of the proposed procedure.](image-url)
Figure 2. a) Consistency model; b) Confidence model.

The map of Figure 4a synthesizes the results of the statistical analyses in a statistical map employing grid cells of 25m x 25 m as TCU and implemented with reference to the sample of dormant landslides. The map shows that about 70% out of the total number of TCU are computed as not-active by the statistical analysis (154,366) and about 30% are evaluated as active. The DInSAR data used in this study were processed using PSI (Persistent Scatterer Interferometry, Ferretti et al., 2001) techniques as part of the activities of the Piano Straordinario di Telerilevamento (2010). The dataset consists of: 208 images acquired on ascending orbit from the ERS sensor during the period September 1992 - September 2000; 134 ERS images on descending orbit (period November 1992 - December 2000). In this phase only ERS data were used since they refer to a period prior to the drawing of the NBA-LGV landslide inventory map (2001). The analysis of DInSAR data (Figure 4b) identified 1,851 covered TCU (26% moving and 74% not moving). Then, the application of the activity model (Figure 4c) to the considered sample of DInSAR covered TZU (dormant landslides) allowed the distinction of different levels of proneness to activity: 78 with a high proneness; 30 with a medium proneness; 50 with a low proneness and 180 with a very low proneness. As it is indicated in the flow-chart of Figure 1, the results of DInSAR data and multivariate statistic analyses were combined through the application of the consistency model. As a result, out of a total of 2027 TCU about 60% of them exhibit consistent information. With reference to this latter sample of TCU the confidence model was finally applied; the obtained results (Figure 4d) show that a high confidence level is exhibited by: 31 of the 78 TZU with a high proneness to activity; 10 of 30 TZU with a medium proneness to activity; 42 of 50 TZU with a low proneness to activity; 127 of the 180 TZU with a very low proneness to activity. In brief, the analyses carried out show that the results obtained for the TZU with low and very low proneness to be active (73%) attain a confidence level which is higher than that of the TZU with medium and high proneness to activity (38%).

A preliminary validation test of the proposed procedure was possible thanks to the availability of DInSAR data resulting from the processing of ENVISAT sensor images acquired in the period 2003-2010 and, therefore, following those used for the definition of the state of activity. The results of the comparison, although preliminary, showed that 48% of the landslides classified with high or medium pronen-
ness to activity in the period from 1992 to 2000 were found to have a high or medium proneness to activity also in the period 2003-2010. In addition, during the same period 80% of the landslides confirmed a low or very low proneness to activity.

4 CONCLUSIONS

The need for the availability of accurate and updated landslide inventory maps to be used within the activities aimed at managing landslide risk over large areas is leading the scientific community to find affordable and innovative methodologies to complement standardized procedures. To this aim, the present work showed a preliminary attempt to integrate DInSAR data with multivariate statistical analyses of thematic maps in order to test their contribution to the definition of the state of activity of slow-moving landslides.

The obtained results highlight that: it is possible to define the state of activity of slow-moving landslides according to the outcomes of DInSAR data analysis; additional information concerning the level of confidence of the obtained results can be derived thanks to a procedure which considers the results of multivariate statistical analyses carried out for the same phenomena. When an updated remote sensing dataset is available, one possible application of the presented procedures can be addressing as well as prioritizing in-situ surveys for updating the landslide inventory maps. In particular, the surveys should be primarily carried out in areas affected by slow-moving landslides confirmed in their high/medium proneness to be active by recent DInSAR datasets; subsequently, in those areas which were not confirmed in their low/very low proneness to be active; finally, in those areas which were not confirmed in their high/medium proneness to be active. Finally, it is worth stressing that the presented procedures can greatly benefit from the use of DInSAR data derived from the processing of high-resolution SAR sensors (COSMOSkyMed, TerraSAR-X), which provide a higher density of targeted points on the observed scene. The latter, indeed, would result in a significant increase of TCU and TZU coverage also allowing, if properly handled, the extension of the observation period to the present day.

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