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1 SAR data and field surveys combination to update rainfall-induced 2 shallow landslide inventory

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17 18 **Abstract**

19 The *Campania* region has been recurrently hit by severe landslides in volcanoclastic deposits. The
20 city of Naples, and in particular the *Camaldoli* and *Agnano* hills (Phlegraean Fields), also suffered
21 several landslide crises in weathered volcanoclastic rocks as a consequence of intense rainfalls or
22 wildfires. To identify slope failures phenomena occurred in the winter season 2019 – 2020 an
23 innovative procedure has been proposed. The purpose of this procedure is to highlight areas where
24 major land cover changes occurred within our area of study, which can be potentially related to mass
25 movements. The amplitude of spaceborne SAR images has been exploited for the change detection

26 analysis and the output derived from the segmentation procedure has been compared with field
27 observations. The amplitude-based method has been already applied in the detection of landslides,
28 but never on the event with limited extensions, such as for this application. The achieved outcomes
29 allowed the mapping of 62 new landslides that have been used to update the current landslide
30 inventory database. This type of information is expected to help decision-makers with land planning
31 and risk assessment.

32

33 **Keywords:** amplitude imagery, synthetic aperture radar, landslides, rainfall, Naples

34

35 **1. Introduction**

36 The request for additional spaces in expanding cities and villages, driven by the continuous population
37 increase, has led to deforestation and cut slopes (Altan et al. 2015; Gariano and Guzzetti 2016). These
38 processes inevitably increase the incidence of landslides, by altering hydrological processes and
39 shear-stress distribution (Wilkinson et al. 2002; Crosta and Frattini 2008). Landslide events globally
40 result in tens of billions of US\$ worth of damage and > 4300 lives lost annually (Froude and Petley,
41 2018). In Europe, and principally in Italy, slope failures represent the main cause of death produced
42 by natural hazards (Guzzetti et al. 2012; Reichenbach et al. 2018). In Italy, only in 2019, 3 deaths and
43 27 injured have been reported and approximately 3,000 people evacuated or remained homeless
44 while, from 1969 to 2020, about 1,100 deaths, 1,500 injured people and thousands of additional
45 evacuees and homeless people have been recorded (<https://polaris.irpi.cnr.it/report/last-report/>).

46 Different studies have demonstrated the importance of available up-to-date and complete risk maps,
47 which are based on Landslide Inventory Maps (LIMs), reducing the impact of these phenomena on
48 society (Guzzetti et al. 2012). To this respect, it is noteworthy to mention that Italy is one of the very
49 few countries in the world entirely covered with landslide susceptibility and risk maps since the
50 beginning of the present century. However, considering the number of events (~620,000; ISPRA,
51 2018), there still is an urgent need to develop better tools for improving landslide risk management

52 starting from the identification and mapping of landslides reported in the LIMs. The latter provides a
53 detailed picture of landslides within an area by reporting location and, if known, date of occurrence
54 and types of mass movements (Fell et al. 2008; Corominas et al. 2014). LIMs are basic elements in
55 land-use planning and represent powerfully and easily understandable tools for researchers and
56 authorities involved in landslide susceptibility analyses (Lombardo et al. 2015; Segoni et al. 2018; Di
57 Napoli et al. 2020a, 2021; Arabameri et al. 2021; Yin et al. 2021) and landslide risk management (Dai
58 et al. 2002; van Westen et al. 2006; Zhang et al. 2020). Regularly updating LIMs is a strategic activity
59 for territorial planning, also considering that landslides can reactivate over time, even after long
60 periods of quiescence (Guzzetti et al. 2012; Solari et al. 2020).

61 Over the last three decades, Remote Sensing (RS) technologies based on satellite optical and
62 Synthetic Aperture Radar (SAR, Franceschetti et al. 1992) imagery have been used for landslides
63 detection and mapping (Stumpf et al. 2017; Novellino et al. 2017; Del Soldato et al. 2018; Guerriero
64 et al. 2019). Differently from optical images, SAR sensors have the advantage to be able to gather
65 ground surface information regardless of weather and illumination conditions. Geoscientists have
66 widely exploited Interferometric SAR (InSAR, Gabriel et al. 1989) techniques to resolve the spatial
67 distribution and temporal evolution of ground instabilities by considering phase values associated
68 with SAR scenes (Novellino et al. 2015; Confuorto et al. 2017; Raspini et al. 2017; Spinetti et al.
69 2019). Due, to the inherent limitations of current space observation systems and data processing
70 techniques (Colesanti and Wasowski 2006; Wasowski and Bovenga 2014), InSAR approaches are
71 mostly applicable to extremely slow ($<16\text{mm/yr}$) and very-slow movements ($\geq 1.6\text{mm/yr}$ and
72 $\leq 16\text{mm/yr}$) landslides (Cruden and Varnes 1996) which typically correspond to deep-seated
73 gravitational slope deformations, creep, and, in some cases, slides and complex landslides (Saroli et
74 al. 2005; Di Martire et al. 2016; Bozzano et al. 2017). Recent studies have used interferograms to
75 detect precursor signals of fast movement landslides (falls and topples) or to identify areas where a
76 mass movement has potentially occurred (Barra et al., 2016; Casagli, 2017; Kyriou &
77 Nikolakopoulos, 2018).

78 To map deformations induced by relatively rapid landslides, the analysis of amplitude signal
79 associated with the SAR images can be an effective alternative (Mondini et al. 2019). Amplitude-
80 based methods analyse the changes across two images (pre-and post-event) induced by a landslide.
81 Despite changes in SAR amplitude have been already used to monitor land cover (Freitas et al. 2008;
82 Qi et al. 2012), many studies have demonstrated the valuable contribution of this approach to detect
83 landslides (Mondini et al. 2017). Still, fewer are applications of polarimetric SAR based on amplitude
84 information data for landslides mapping which are limited to large landslides, typically in the order
85 of km² of extension (Shimada et al. 2014; Plank et al. 2016). In this work, amplitude-based methods
86 were explored to map landslides with limited extension (hundreds of square meters).

87 Such a semi-automatic procedure aims at highlighting land cover changes (potentially related to
88 rapid-moving landslides) by exploring radar backscattered signals differences in consecutive
89 spaceborne SAR images. The mass movement phenomena occurred during the 2019 – 2020 winter
90 season in the *Agnano* plain and *Camaldoli* hill located within the city of Naples (*Campania* region,
91 southern Italy, Figure 1) were analysed. Most of these events-were triggered by high-intensity and
92 short-duration precipitations or prolonged rainfalls affecting the most superficial loose pyroclastic
93 deposits.

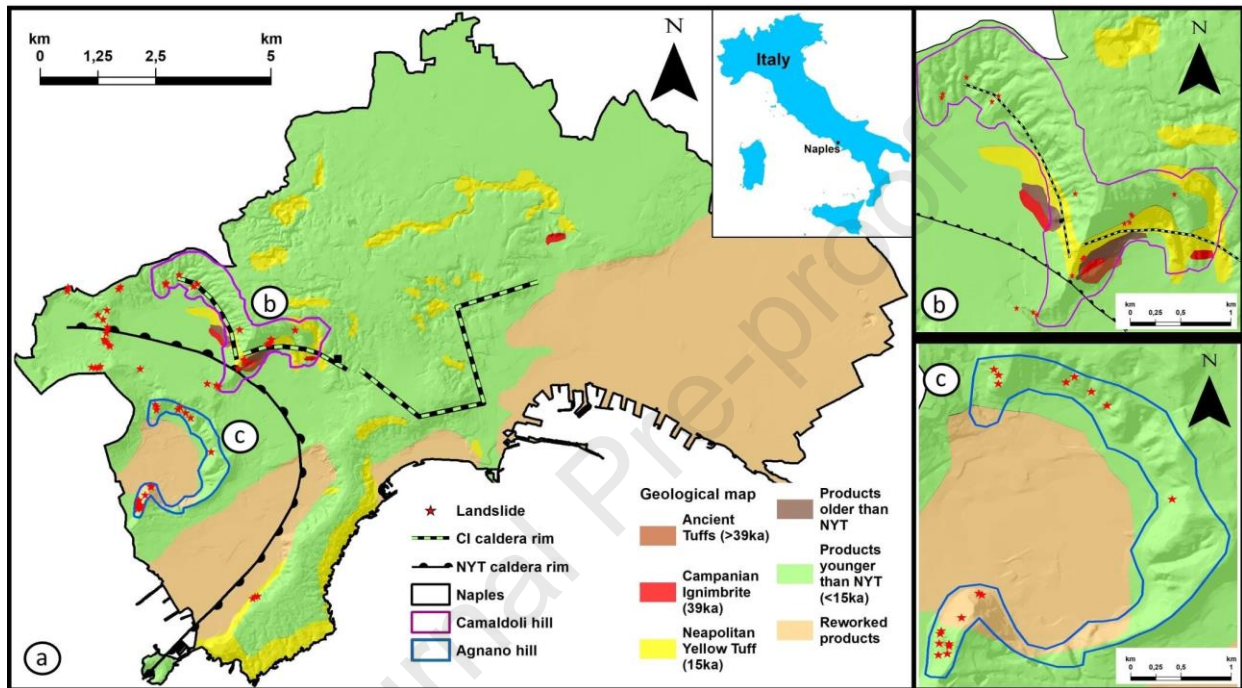
94 The paper is organized as follows: first, the geological and geomorphological setting of Naples'
95 municipality area is presented. The data and methods used in the work are successively analysed.
96 Further, an overview of basic concepts of the polarimetric SAR amplitude technique is described.
97 Finally, polarimetric outcomes are compared with field surveys data to evaluate the applicability of
98 the semi-automatic procedure to landslide detection.

99

100 **2. Study area**

101 The *Agnano* plain and *Camaldoli* hill are located in the eastern sector of the Phlegraean Fields, a ~450
102 km² active volcanic area located in the western sector of the city of Naples. The area has experienced
103 numerous eruptions from monogenic volcanoes over the past 70,000 years (Scarpati et al. 2013, 2015,

104 Figure 1) with the local landscape and bedrock geology mainly shaped by two eruptions: Campanian
 105 Ignimbrite eruption (CI - occurred 39,000 years; Rolandi et al., 2020) and the Neapolitan Yellow
 106 Tuff eruption (NYT- occurred 15,000 years ago; Scarpati et al., 2013). These sequences are covered
 107 by pyroclastic, anthropogenic, and epiclastic deposits with abrupt variations in thickness and facies
 108 that have proven to be very susceptible to landslides (Calcaterra et al., 2007).



109
 110 **Figure 1.** a) Geological sketch map of the urban area of Naples (modified from Scarpati et al. 2015); b) and c) detailed
 111 view of *Camaldoli* hill and *Agnano* plain, respectively (western sector of city of Naples, purple and blue bold lines in a).

112 The morphology of the whole Phlegraean area reflects the evidence of volcano-tectonic Quaternary
 113 events and the slopes are the remains of ancient volcanic buildings. These hills consist of several tens
 114 of metre thick NYT and are generally covered by younger (< 15 ka) loose and unconsolidated
 115 pyroclastic deposits (Ascione et al. 2020). Additionally, the energy of relief is quite high where local
 116 hills are characterized by high slope angles (> 30°). The caldera inner slopes have typical semi-
 117 circular planar shapes and steep profiles that make them prone to landsliding (Calcaterra et al. 2007;
 118 Ascione et al. 2020). Also, the drainage network presents a pronounced structural control, where low-
 119 order straight channels are exposed (Di Martire et al. 2012). Sea level variations also greatly

120 contributed to the present morphological setting. These conditions have represented predisposing
121 factors for the development of landslides since the Roman era (Morra et al. 2010).

122 Landslides are the main geomorphic processes within Naples municipality. Although landslides have
123 generated disruption and damage over time, only in recent decades more attention has been posed to
124 these phenomena, following the February 1986 rainfall event, representing a threshold between
125 historical and recent mass movements (Beneduce et al. 1988; Calcaterra et al. 2002; Di Martire et al.
126 2012) which led to complete landslide inventory in the Phlegraean area (Carratù et al. 2015; Finicelli
127 et al. 2016). The inventories reveal that landslides mostly affect the shallow pyroclastic cover and
128 have thicknesses in the order of 0.5 to 2 m (Calcaterra et al. 2007) and are characterized by relatively
129 low mobility.

130

131 **3. Materials and methods**

132 The procedure for the individuation and validation of the landslides consists in two independent steps.
133 The former includes the identification of slope failures through field surveys and Google Earth images
134 inspection leading to a creation of a landslide inventory, while the latter is characterized by the
135 collection and processing of radar polarimetric satellite images for the development of another
136 landslide inventory. Finally, the two outputs have been compared to assess the results (Figure 2).

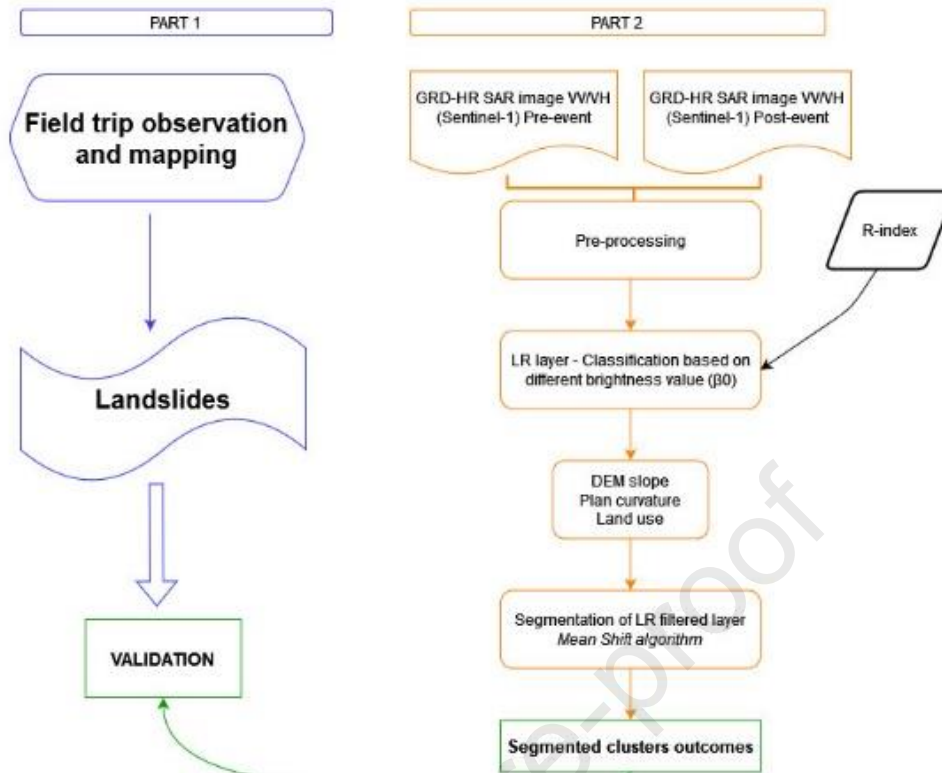


Figure 2. Flowchart of the proposed methodology. Additional information on part 2 are provided in Section 3.2.

3.1 On-site investigation data

Landslide inventories represent essential input data to implement any study on landslide susceptibility, hazard or risk assessment. Very often this data is missing or not homogeneous in space and time, leading to an incorrect evaluation of the above-mentioned analyses. In the investigated area, several studies have already compiled a partial census of landslide phenomena (Calcaterra et al. 2002; Di Martire et al. 2012; Carratù et al. 2015; Finicelli et al. 2016) in addition to the *I.F.F.I.* (Landslide Inventory in Italy) national landslides database.

This database covers a time span of about two centuries (1816 - 2015) and is based upon field surveys, aerial photo interpretation and local and national archival research of relevant sources (Di Martire et al., 2012). As a result, about 1300 landslides were inventoried and classified as “historical” or “recent” conventionally using the February 1986 event as a temporal divide. The main flaw of this

151 database is the lack of consistency in space and time, the different methodologies adopted and the
152 different classification criteria used.

153 Winter season 2019 – 2020 has been characterized by the occurrence of several high-intensity and
154 short-duration rainfalls, where one of the most severe recorded values of 66 mm of cumulative
155 rainfall in 30 minutes. Such events have triggered many slope failures and undermining surface
156 drainage systems in urban areas. As a consequence, visual interpretation of Google Earth images
157 integrated by geomorphological field survey observations were performed to validate and update the
158 landslide inventory with the latest mass movements that occurred in the area. Field surveys were
159 carried out on topographical maps at 1:5,000 scale from December 2019, following the intense
160 rainfall phenomena that occurred in the Phlegraean area. Based on the adopted scale, only landslides
161 larger than 25 m² were considered.

162

163 **3.2 Visibility maps**

164 SAR images are very useful tools for detecting and monitoring land cover changes but, being sensed
165 in a side-looking configuration (Kropatsch and Strobl 1990), it is important to predict if the
166 measurements over the study area might be affected by geometrical distortions before any processing.
167 A preliminary analysis was carried out to obtain the Range Index (RI) (Notti et al. 2012, 2014), the
168 latter is a pixel-by-pixel representation of the relationship between the geometry of acquisition of the
169 satellite (slant range) and the topography Slope angle (S) and slope Aspect (A); (Plank et al. 2012;
170 Del Soldato et al. 2021). The RI was applied to the Level-1 GRD products before part 1 in order to
171 assess the quality of the pixels in the area of interest and to select the most effective stack to process.
172 The elements needed to calculate the RI are a DEM and the satellite Line of Sight (LoS) parameters,
173 namely the incidence angle (α) and heading (θ). The maximum value of RI is 1. This occurs when the
174 slope is parallel to the LoS. This is the best geometry to obtain SAR features in mountainous areas.
175 On the contrary, the lowest value of RI occurs in the case of foreshortening ($0 < RI < 0.3$) or

176 layovering ($RI < 0$) effects. Obtained outcomes have been classified according to the four main RI
 177 classes suggested by Notti et al. (2012).

178

179 3.3 SAR images processing

180 The pre-processing procedure is based on Sentinel-1 images acquired in the Level-1 Ground Range
 181 Detected – High Resolution format (GRD-HR) and Interferometric Wide acquisition mode in VV and
 182 VH polarization (<https://scihub.copernicus.eu/>). Level-1 GRD products are focused SAR data that
 183 has been multi-looked and projected to ground range using the Earth ellipsoid model WGS84. Only
 184 the amplitude information associated with each pixel in the image was considered
 185 (<https://sentinel.esa.int/web/sentinel/missions/sentinel-1/data-products>). The resulting product has
 186 squared pixels of 10 m resolution with reduced speckle.

187 For the purpose of this work, six images were acquired shortly after the heaviest rainfall recorded in
 188 the area, both in ascending and descending orbit and covering the period between 17 September 2019
 189 and 16 January 2020 (Table 1).

190

191 **Table 1.** Analysed SAR imagery in the amplitude change detection. The listed products correspond only to images
 192 acquired in descending orbit. The whole considered imagery dataset corresponds to GRD-HR dual-pol products.

Date	Satellite platform
17 September 2019	Sentinel-1B
5 October 2019	Sentinel-1A
5 November 2019	Sentinel-1B
4 December 2019	Sentinel-1A
29 December 2019	Sentinel-1A
16 January 2020	Sentinel-1A

193 Pre-processing of the images is performed to obtain Beta Nought (β_0), namely the radar brightness
 194 coefficient in slant coordinates. This part is done using the open-source software SNAP, available
 195 through the European Space Agency (<https://step.esa.int/main/download/snap-download/>), and

196 includes the following steps: retrieving the precise orbits, removing the thermal noise and radiometric
 197 calibration (Filipponi 2019). SAR images were co-registered with a 10 m Digital Elevation Model
 198 (DEM)-assisted procedure (Tarquini et al. 2007). After the co-registration, the resulting stacked
 199 images are filtered for speckling reduction using the adaptive Frost filter (Frost et al. 1982), with a
 200 filter size in X and Y of 5 pixels, and a damping factor of 2.

201

202 **3.4 SAR amplitude changes detection**

203 SAR backscatter is dependent on a number of factors, including the polarization and wavelength used
 204 by the SAR system, the local slope orientation relative to the SAR sensor and the roughness and
 205 dielectric properties (e.g. soil moisture, presence of vegetation) of the material that the microwave
 206 energy interacts with at the Earth's surface (Burrows et al., 2022).

207 Analysing changes between pre-and post-event amplitude SAR images is based on the assumption
 208 that landslides change the local land cover and its backscattering properties. For instance, when a
 209 mass movement occurs, if the mobilised material covering the previous surface is characterized by a
 210 higher moisture content then the backscatter signal should increase (Novellino et al. 2020). Back-
 211 scattering might also increase when the surface roughness (at the scale of the used wavelength)
 212 increases (Oliver and Quegan 2004) for example as a result of trees being ripped off leaving bare soil
 213 or rock. Following the procedure defined by Mondini (2017), the Log-Ratio (LR) index was then
 214 computed in every pixel for each couple of dual-pol consecutive images. LR index estimates change
 215 in brightness that can be induced by land cover changes due to both natural (e.g., landslides, floods,
 216 snow melting) or human-induced activities (e.g., deforestation, mining activities) in a defined time
 217 interval. The obtained ratio image helps suppressing background structures and improve the
 218 detectability of potential changes from SAR data (Ajadi et al., 2016).

219 For each pair of corresponding pixels belonging to consecutive pre-processed SAR images, LR is
 220 calculated as follows (Esposito et al. 2020, Eq. 1):

$$221 \quad LR = \ln\left(\frac{\beta_{0,i}}{\beta_{0,i-1}}\right) \quad (\text{Eq. 1})$$

222 where β_0 is the reflectivity per unit area in slant range; its values are independent from the terrain
223 covered and i -th image indicate two consecutive pre-processed SAR images. LR pixels can assume
224 by positive or negative values, depending on the backscattering changes. Then, a subset of Region of
225 Interest (RoI) is extracted by using the subset tool in SNAP.

226

227 **3.5 Image segmentation and matching assessment**

228 Before the segmentation, a filtering step has been performed to mask pixels that cannot correspond
229 to landslides (i.e., flat urban areas). In fact, to obtain an LR filtered layer, areas potentially affected
230 by mass movements were separated using morphological parameters derived from slope and plan
231 curvature. Additionally, areas in shadowing and foreshortening in the RI have been masked out and
232 removed. Moreover, to ensure the correct identification of urban boundaries, land-use information
233 derived from the second level of the 2018 Corine Land Cover (CLC) program were taken into account
234 (<https://land.copernicus.eu/pan-european/corine-land-cover/clc2018>). CLC classification system is
235 hierarchical and subdivided into different levels: the second level of the CLC classification for the
236 urban group includes areas mainly occupied by dwellings and buildings used by administrative/public
237 utilities, including their connected areas (associated lands, approach road network, parking lots).

238 LR layer segmentation groups pixels with similar LR values into various unique segments. The image
239 is partitioned into regions that contain points having nearly the same properties, e.g. mean values or
240 textural properties (Tang 2010). In this work, the segmentation process is performed with the
241 “*i.segment*” module in GRASS GIS 7.8.3 using the “Mean Shift” algorithm and the adaptive
242 bandwidth option (Fukunaga and Hostetler 1975).

243 For the segmentation of the filtered LR, the algorithm requires the definition of the following
244 parameters: *i*) a selective threshold with a value between 0 and 1; *ii*) the kernel size; *iii*) the minimum
245 number of cells falling into a cluster and *iv*) the minimum number of iterations. A threshold of 0
246 would allow only pixels with identical values to be considered similar and clustered together in a
247 segment, while a threshold of 1 would allow everything to be included in a large segment (Momsen

248 and Metz 2017). Mean Shift algorithm recalculates central pixel values using the user-defined
249 maximum number of iterations or until the shift between the central pixel and pixels within the kernel
250 results is smaller than the user-defined threshold. The threshold choice depends on the purpose of the
251 application and the image resolution (Comaniciu and Meer 1999; Tao et al. 2007). To select the
252 appropriate parameter values, iterative steps have been carried out manually. According to Esposito
253 et al. (2020), the criterion for selecting the best input values is to search for the combination of values
254 that optimize, at the same time, the number of clusters and their average size concerning the expected
255 land cover changes. To avoid over-segmentation, a threshold value of 0.1 has been chosen and a
256 minimum of 3 pixels has been used as criteria to determine the presence of a cluster with the Euclidean
257 calculation method. Considering the approximate expected size of the land cover changes, the size of
258 the spatial kernel was set to 10 pixels with 200 iterations to detect significant differences in LR values
259 and to minimize the “*salt and pepper effect*” both for VH and VV polarization LR layers.
260 The obtained outcomes have been matched with the surveyed data reported in the LIM map. This
261 procedure allowed to compare the two datasets in terms of the number of landslides recognized and
262 their areal extension.

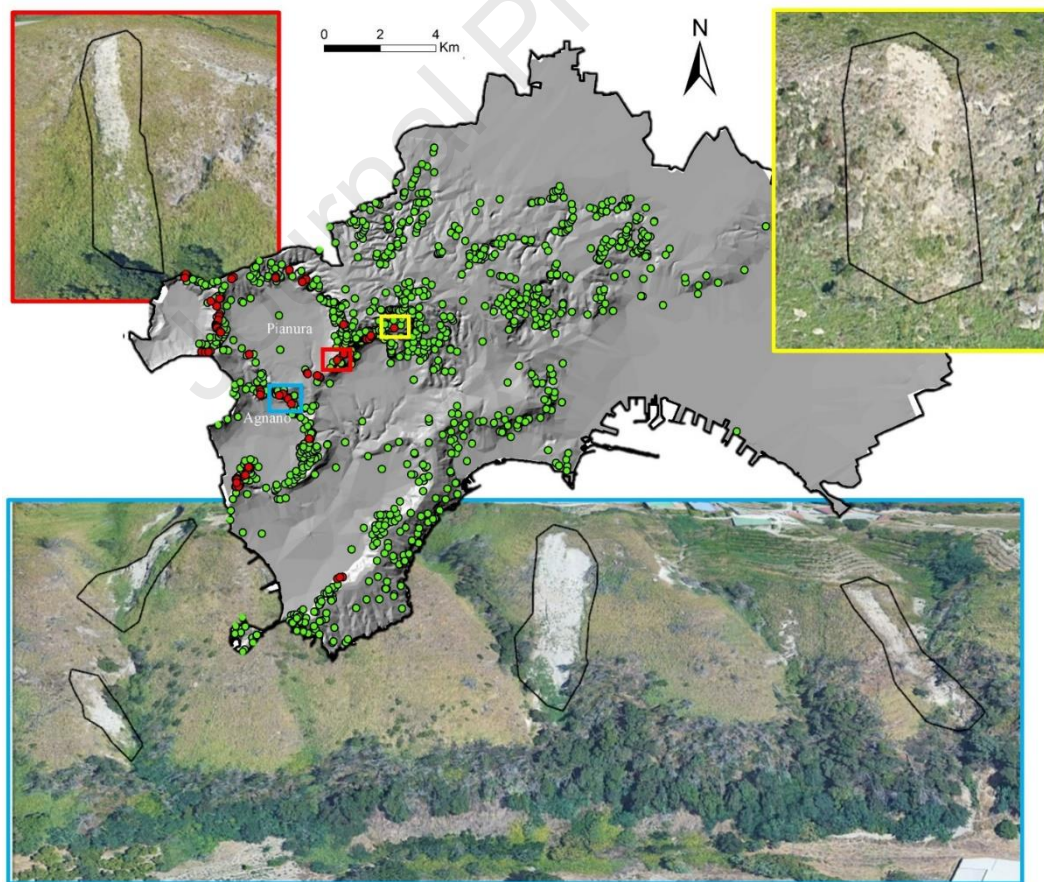
263

264 **4. Results and discussion**

265 **4.1 On-site investigation outcomes**

266 The field inspection was conducted into the whole municipality of Naples by using Google Earth
267 images as ancillary data (Figure 3). Through this examination, 62 landslides were recognized and
268 added to the previous landslide inventories available for the city of Naples (Di Martire et al, 2012;
269 Carratù et al., 2015; Finicelli et al., 2016), bringing the total number of phenomena surveyed to 1322.
270 Of the 62 new mass movements, 29 are located on the slopes of the *Agnano* plain and the *Camaldoli*
271 hill so confirming that these areas have the highest susceptibility within Naples (Figure 1b).
272 According to Cruden and Varnes (1996) classification, the detected slope failures can be classified as
273 rotational or translational slides, which are typical phenomena affecting local hilly areas, particularly

274 in case of prolonged or intense rainfall events. In fact, considering the geological and
275 geomorphological setting of the Phlegraean Field, rainfall is the main triggering factor of mass
276 movements (Calcaterra et al., 2000; Fusco et al., 2019) and between September and December 2019,
277 the *Campania* region was affected by several rainfall events of high intensity and short duration
278 (<http://centrofunzionale.regione.campania.it>). Moreover, by consulting the reports on hydrological
279 events, it was possible to note that, especially in September 2019, the city of Naples was hit by severe
280 precipitation. From field observations, it was noted that the tuffs are affected by falls and topples,
281 which move from high-angle walls and, more frequently, from cut slopes or quarry walls (Calcaterra
282 et al. 2002). Moreover, many landslides with complex evolution can be observed along the Phlegrean
283 hilly slopes. These phenomena are characterized by localized residual movements and occasional
284 reactivations.



285

286 **Figure 3.** Landslide inventory map for the Naples municipality where red dots show the new surveyed landslides,
287 whereas, green ones indicate the mass movements already obtained from official inventories. The black polygons refer to
288 the outcome obtained with the segmentation step.

289 Hence, different change detections have been accomplished to identify the number of landslides
 290 associated with the different rainfall events and to create a multi-temporal catalogue of the mass
 291 movements triggered in the study area.

292 The heavy rainfalls and severe wildfires, together with land-use changes (i.e., abandonment of
 293 agricultural practices; Figure 4) have caused a progressive increase in landslide occurrence over time.

294 These problems combined with the urban sprawl has increased the landslide risk in this context
 295 (Calcaterra et al. 2007).



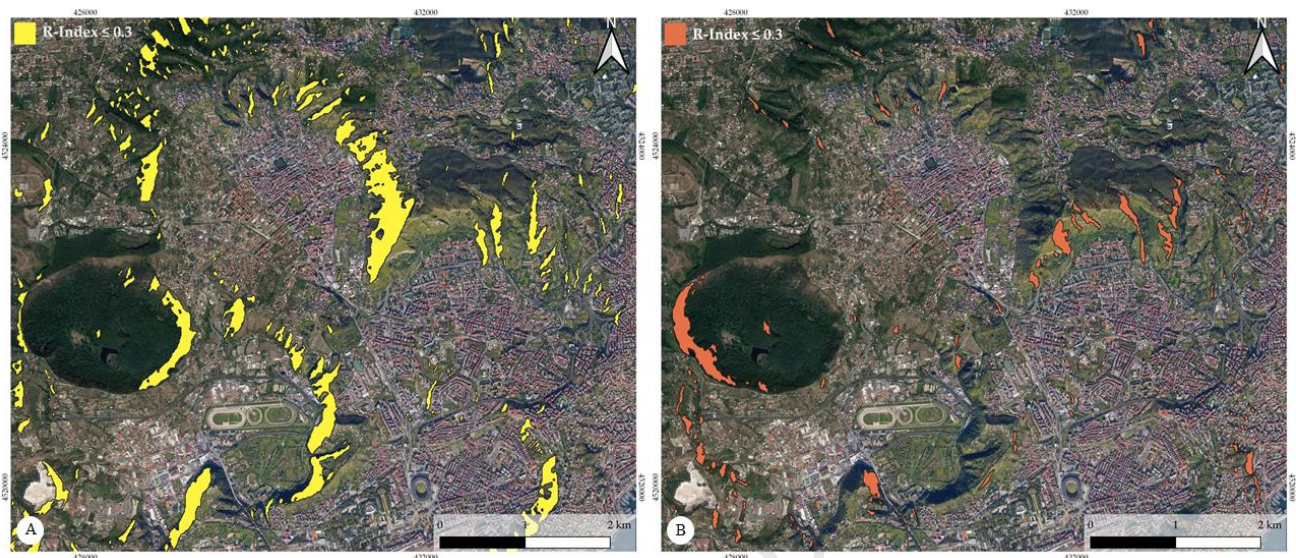
296
 297 **Figure 4.** Interaction between land-use change (green) and landslides (light red). Lateral landslides were detached at the
 298 base of the terraced areas where the agricultural practices are still active, differently from the central landslide.

299

300 4.2 Change detection analyses

301 The preliminary analysis based on the RI calculation shows that most of the slopes in the *Agnano* and
 302 *Camaldoli* areas is affected by topographic effects limiting SAR applications (Figure 5). The
 303 ascending orbit is characterized by a low RI (< 0.3) affected by foreshortening and the terrain
 304 geometry has a high impact on the backscattered signal, then limiting the effectiveness of the
 305 amplitude analysis on the ascending stack that has been, therefore, excluded. As shown in Figure 5,
 306 the western side of *Camaldoli* hill and almost all of the *Agnano* slopes fall into a low RI class. By
 307 comparing ascending and descending orbits, it is possible to note that the descending geometry is
 308 better suited for slopes facing West. On the contrary, the ascending geometry allows to better

309 investigate slopes oriented to the East. Considering the western wards landslides' directions of
 310 motion, only descending SAR images have been employed in this work.



311
 312 **Figure 5.** R-Index maps of *Camaldoli* hill and *Agnano* plain in the ascending geometry (a) and descending geometry (b).

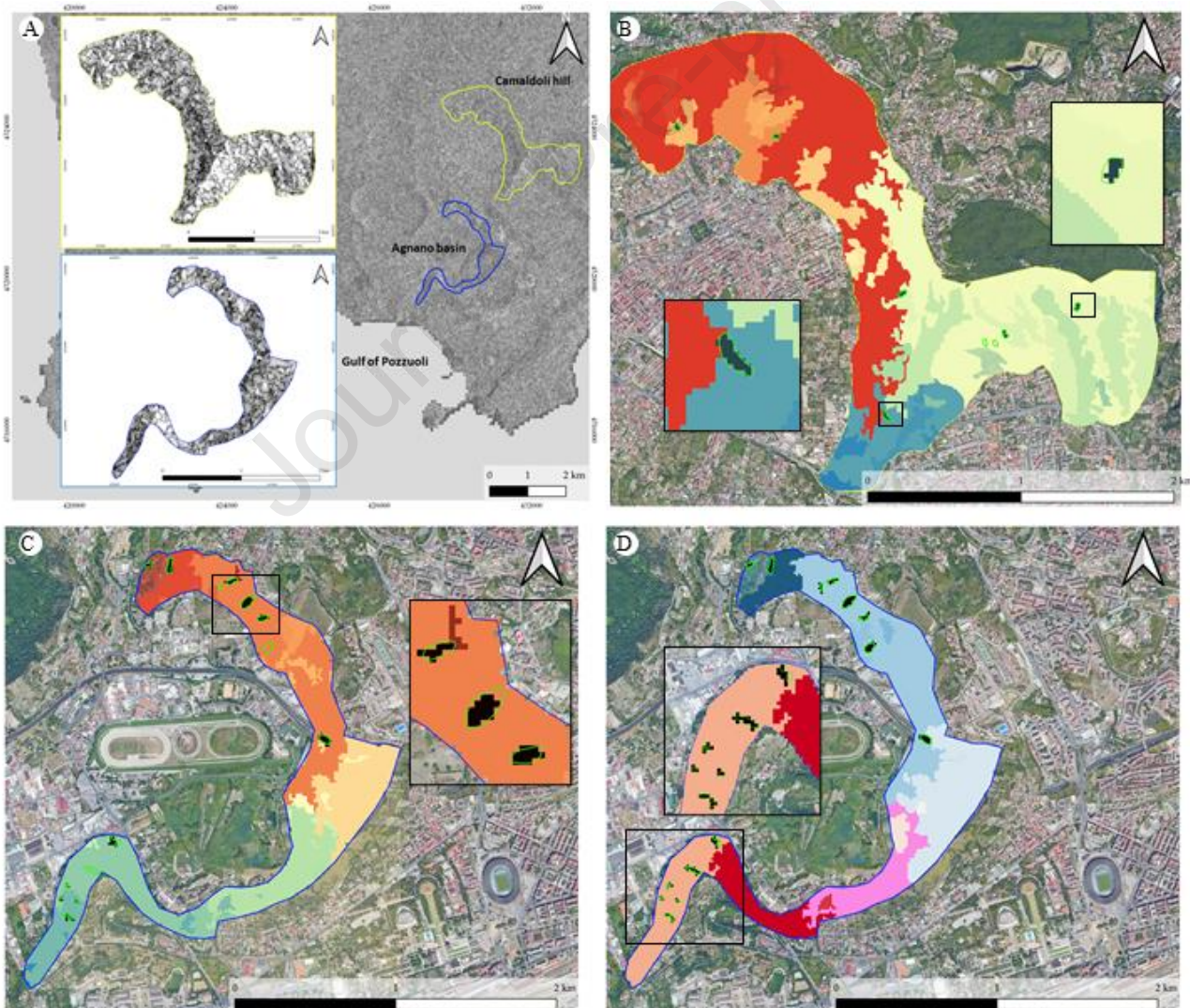
313 In ascending geometry most of the slopes are affected by layover and shadowing problems due to the topography effects
 314 and LoS parameters.

315 Subsequently, LR has been filtered by selecting out flat urban areas. In our study area, flat areas
 316 correspond to built-up zones while the unstable slopes involve only vegetated areas. For this reason,
 317 urban areas have not been considered, while acknowledging that mass movement phenomena can
 318 also be triggered in urban contexts (Di Napoli 2020b, Novellino et al., 2021, Miele et al., 2021).

319 After the segmentation of the LR filtered layer, segments with a minimum size of 3 pixels,
 320 corresponding to a minimum area of 300 m², were extracted in the RoI. The output of the
 321 segmentation algorithm returned 39 clusters in the *Camaldoli* and *Agnano* areas (Figure 6). The
 322 obtained outcomes correspond to small and isolated clusters (black pixels) in a homogeneous region,
 323 where the backscattering variations were most significant ($\Delta\beta_0$ ranging from 0.6 and 0.7). In large
 324 parts of the investigated area, there weren't significant variations in terms of the backscattered signal
 325 and these outputs have been interpreted taking into account the geometry of the cluster. Namely,
 326 clusters running perpendicular to the line of the maximum slope were not considered as well as

327 clusters that cover areas too large are not compatible with the typical landslides historically occurred
 328 in the study area.

329 Concerning the multi-temporal analysis, different change detections were analysed considering
 330 different images acquired at monthly intervals. Specifically, in the period between September and
 331 October two landslides were recorded on the *Camaldoli* hill while four phenomena were identified
 332 between October and November in *Agnano*. Between November and December, a total of five
 333 landslides were identified in *Agnano* (i.e., 3) and *Camaldoli* (i.e., 2) and finally, the eleven events
 334 were mapped between December 2019 and January 2020 on the slopes of the *Agnano* plain (Table 2
 335 and Figure 6).



336

337

338 **Figure 6.** Outputs from the segmentation step: a) LR amplitude layer of the ROI within part of Phlegrean Fields obtained
 339 stacking the last two SAR images considered (29 December 2019 and 16 January 2020) clipped around the *Agnano* plain
 340 and *Camaldoli* hill areas; b) segmentation results for the October-November period in the *Camaldoli* hill; c) results for
 341 the December-January period over the *Agnano* plain; d) results for December at the *Agnano* plain. The background
 342 different colours represent the segmentation output and green polygons correspond with the mass movements shape
 343 surveyed. Potential pixels associated with landslides, detected after the segmentation, are represented with the same colour
 344 (i.e., black).

345

346 **Table 2.** Summary of landslides recognition for each change analysis computed.

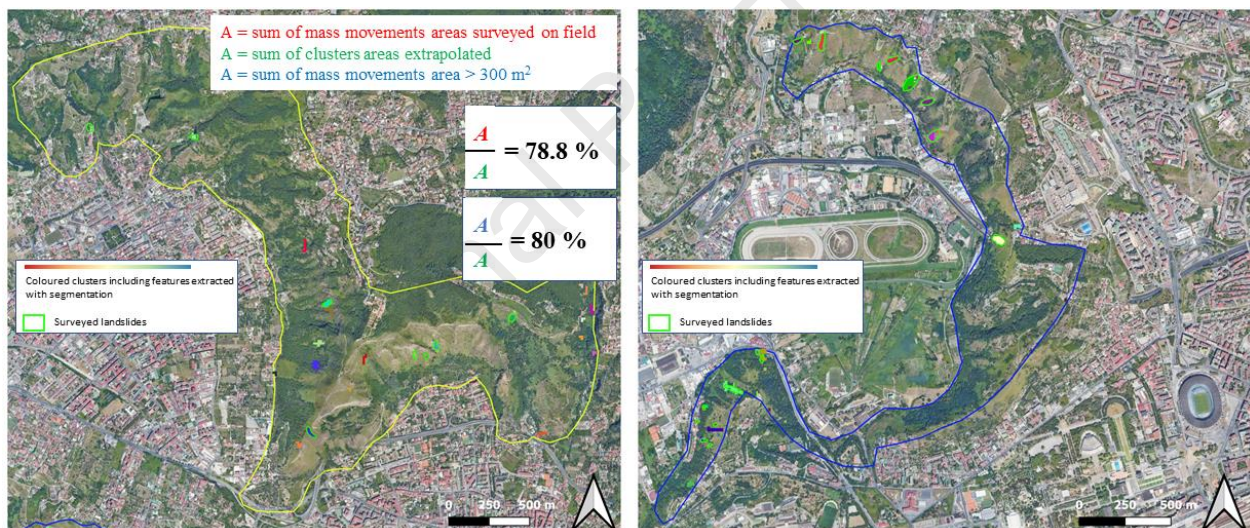
TIME SPAN	AGNANO	CAMALDOLI
SEPTEMBER/OCTOBER	-	2
OCTOBER/NOVEMBER	4	-
NOVEMBER/DECEMBER	3	2
DECEMBER/DECEMBER	-	5
DECEMBER/JANUARY	11	-
SUM OF CHANGE DETECTION	18	9

347

348 4.3 SAR and field surveys comparison

349 Twenty-seven out of the 39 clusters individuated with the segmentation process correspond to
 350 landslides detected in the field. The remaining 12 clusters could be interpreted as False-Positive (FP),
 351 because small landslides can be immediately obliterated or the amplitude-based method might detect
 352 slope failures in areas inaccessible to survey, or False-Negative (FN) due to limited spatial resolution
 353 of the SAR products. FP and FN have been also considered in the comparison analysis. Both FP and
 354 FN, as well as validated landslides, are located near the slope breaks and in correspondence of
 355 relatively high acclivity (i.e., greater than 35°). In particular, on the *Camaldoli* slopes have been
 356 identified 2 FN and 5 FP, whereas, in *Agnano* plain have been recognized 2 FN a 3 FP. True Positives
 357 (TP) correspond to 78.8% and, if landslides >300 m² are taken into account, TP increases to 80%
 358 (Figure 7).

359 The recognised clusters show an areal extent of landslide slopes larger than the areas mapped during
 360 the field survey. This overestimation is unfortunately due to the low satellite images resolution that,
 361 when small landslides occur, do not allow the exact delimitation of the landslide area (East sector of
 362 *Camaldoli* hill, Figure 7).
 363 As already discussed in a previous similar study (Barra et al., 2016), the use of interferometric
 364 processing for landslide detection was proved. The main add-on of the current study regards the
 365 amplitude-based approach to prove the likelihood to map the scars caused by the landslide. However,
 366 this approach could be particularly useful in rapid landslide investigation allowing precise
 367 identification of landslides location, especially when are present area inaccessible to field detectors,
 368 as demonstrated on *Camaldoli* hill.



369
 370 **Figure 7.** Comparison between the SAR derived segmentation map and the field investigation. In the *Agnano* plain (right)
 371 there is a good correspondence between landslides' shapes and clusters. The *Camaldoli* hill area presents many clusters
 372 corresponding to false-positive objects due to issues of visibility parameters (see visibility maps).

373

374 5. Conclusions

375 Over the last decades, remote sensing technologies have supported landslide monitoring and detection
 376 analyses at relatively low costs. Among them, amplitude-based methods have been employed in very
 377 large mass movements identification. A semi-automatic procedure to identify rapid landslide
 378 occurrence in measures of SAR amplitude changes has been tested in this work in the outskirts of

379 Naples (Italy). The scope of our method is to obtain preliminary information from radar imagery on
380 mass movements when atmospheric conditions (cloud coverage) prevent the use of optical images.
381 However, in the presented analyses all the data and software adopted are completely free-of-charge.
382 For the chosen study area, only SAR images acquired in descending orbit were considered due to the
383 geometrical constraints recorded in the ascending orbit. At the same time, extensive field surveys
384 activities have been executed in the study area. The results obtained, with 27 events confirmed by
385 field surveys, assert that SAR Sentinel-1 images are successful in capturing rapid landslides. SAR
386 images permit to obtain quick and reliable information in supporting disaster management civil
387 protection operations on landslides occurrence following a rain event. Moreover, in bibliography,
388 polarimetric applications have been already presented focusing on very huge mass movements
389 detection. As shown in the results section, it is possible to identify also landslides with limited
390 extension (hundreds of square meters) which are more likely in the Phlegrean setting. Further
391 applications could be implemented by using SAR images with a very high resolution allowing more
392 accurate results.

393 The integration between RS and conventional geological methods can represent a significant tool for
394 intervention works planning, providing the right indication on how and where to operate to reduce
395 the risk and to increase the safety of the area.

396

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398 M.D.N., A.N.; formal analysis, P.M., M.D.N., A.N.; investigation, M.D.N., D.D.M., D.C.;
399 methodology, P.M., M.D.N., A.N., D.D.M.; software P.M., A.N.; validation, M.D.N., D.D.M., D.C.;
400 writing – original draft preparation P.M., M.D.N., A.N.; writing – review and editing, D.D.M., J.M.,
401 D.C.; supervision, D.D.M. all authors have read and agreed to the published version of the
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407

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410

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Journal Pre-proof

Ethical Statement

Hereby, I Mariano Di Napoli consciously assure that for the manuscript “SAR data and field surveys combination to update rainfall-induced shallow landslide inventory” the following is fulfilled:

- 1) This material is the authors' own original work, which has not been previously published elsewhere.
- 2) The paper is not currently being considered for publication elsewhere.
- 3) The paper reflects the authors' own research and analysis in a truthful and complete manner.
- 4) The paper properly credits the meaningful contributions of co-authors and co-researchers.
- 5) The results are appropriately placed in the context of prior and existing research.
- 6) All sources used are properly disclosed (correct citation). Literally copying of text must be indicated as such by using quotation marks and giving proper reference.
- 7) All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.