Image-based mapping of surface fissures for the investigation of landslide dynamics

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2 **dynamics**

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12

13 **Abstract**

14 The development of surface fissures is an important indicator for understanding and forecasting slope

15 movements. Landslide investigations therefore frequently include the elaboration and interpretation of

16 maps representing their spatial distribution, typically comprising intensive field work and

17 instrumentation. Only recently aerial photography with sub-decimetre spatial resolution is becoming more

18 commonly available and opens a window to analyse such features from a remote sensing perspective.

19 While these data are in principle helpful to elaborate maps from image interpretation techniques, there is

20 still no image processing technique available to extract efficiently these geomorphological features. This

21 work proposes a largely automated technique for the mapping of landslide surface fissures from very-high

22 resolution aerial images. The processing chain includes the use of filtering algorithms and post-processing

23 of the filtered images using object-oriented analysis. The accuracy of the resulting maps is assessed by

24 comparisons with several expert maps in terms of affected area, fissure density and fissure orientation.

25 Under homogenous illumination conditions, true positive rates up to 65% and false positive rates

26 generally below 10% are achieved. The resulting fissure maps provide sufficient detail to infer

27 mechanical processes at the slope scale and to prioritize areas for more detailed ground investigations or

28 monitoring.

29

30 **Keywords:**

31 Landslide; Fissure; Geomorphological mapping; Remote sensing; Image filtering; UAV

32

33

34 **1   Introduction**

35 Observations of features and structural patterns of earth surface landforms can reveal information on the

36 origin and mechanisms controlling the geomorphological processes. Structural geology and

37 geomorphology have developed comprehensive concepts to delineate geomorphological units and

38 structure types from remote sensing images, and infer about mechanical processes without necessarily

39 measuring displacement, deformation or the applied forces directly (Melton 1959; Davis and Reynolds,

40 1996; Passchier and Trouw, 2005; Pollard and Fletcher, 2005). Surface discontinuities observed in rocks

41 and sediments have proven to be valuable indicators of the deformation history and stress pattern of the

42 slope. For landslide analysis, their observation and interpretation can contribute to a better understanding

43 of the controlling physical processes and help in the assessment of the related hazards (McCalpin, 1984;

44 Fleming and Johnson, 1989; Parise, 2003). In hard-rock slopes, the analysis of structural discontinuities

45 (faults, bedding planes, joints, fractures) allows to characterize potentially unstable areas (Hoek and Bray,

46 1981; Matheson, 1983; Priest, 1993; Selby, 1993; Günther et al., 2004; Jaboyedoff et al., 2004; Glenn et

47 al., 2006). In soft-rock slopes and sediments, the analysis of surface fissures may indicate the

48 development of future failures (Krauskopf et al., 1939; Shreve, 1966; Chowdhury and Zhang, 1991;

49 Abramson et al., 2001; Khattak et al., 2010) and is often considered as a geo-indicator of the activity stage

50 of a landslide. In sediments, the surface fissure characteristics also influence water infiltration and

51 drainage, which in turn affect the ground-water system and the kinematic response of slopes to

52 hydrological events (Malet et al., 2003; Malet et al., 2005b; van Asch et al., 2009).

53   Maps of surface deformation features can be obtained by extensive field surveys either through the direct

54   visual observation of the topography (Fleming et al., 1999; Meisina, 2006) or through the indirect

55   measure of seismic wave propagation in tomography setups (Grandjean et al., 2011; Bièvre et al., 2012).

56   Relatively large fissures on landslides may also be discernible in Very-High-Resolution (VHR)

57   spaceborne images (Glenn et al., 2006; Youssef et al., 2009) but typically those structures reach widths in

58   the decimetre-range and at present only airborne photographs provide sufficient detail for their detection

59   in the centimetric range. Recent studies (Eisenbeiss, 2009; Niethammer et al., 2011a) have shown that

60   VHR images acquired from Unmanned Aerial Vehicles (UAVs) are cost-efficient data sources for the

61   monitoring of landslide surfaces with sub-decimetric image resolution. Especially small UAVs with

62   payloads below 5 kg and operating altitudes below 2000 m are expected to be employed much more

63   frequently in coming years (Frost & Sullivan, 2007) though more specific regulations for their specific

64   operational use are being discussed at national and international levels (Prats et al., 2012; Watts et al.,

65   2012).

66   Visual interpretation of VHR imagery is a classical method in geomorphology, but it remains subjective,

67   and rather impractical for repetitive observations or the inspection of large areas. An increasing number of

68   studies therefore targeted the development of automated techniques to extract relevant features from

69   imagery (Graham et al., 2010; Martha et al., 2010; Stumpf and Kerle, 2011). Although, the detection and

70   extraction of linear features is a fundamental operation in digital image processing (Quackenbush, 2004;

71   Mendonca and Campilho, 2006; Papari and Petkov, 2011), relatively few studies have explored the

72   application of automatic approaches for the mapping of geomorphological relevant linear features

73   (Baruch and Filin, 2011; Shruthi et al., 2011).

74   Considering the increasingly widespread availability of sub-decimetre resolution images from UAVs and

75   other airborne platforms, this study targeted the development of a semi-automatic image analysis

76   technique to support geomorphologists in the detection, mapping and characterization of landslide surface

77   fissures from VHR aerial images. In this context the term "semi-automatic" expresses that the technique

78   requires user input to be adapted for different image types and environmental settings. The developed

79   method is based on a combination of Gaussian directional filters, mathematical morphology and object-

80   oriented image analysis (OOA) and was tested on a set of multi-temporal VHR images acquired at the

81   Super-Sauze landslide (Southeast French Alps). The obtained results were compared to manual mappings

82   carried out by experts combining image interpretation and field surveys.

83

84   **2   Types of surface fissure observed on landslides**

85   Detailed observations of landslide surface fissures were provided by Krauskopf et al. (1939) who adapted

86   analogies from structural geology for their interpretation and distinguished between strike-slip structures,

87   normal faults, graben structures and compression structures. Also Ter-Stephanian (1946) noticed the

88   mechanical significance of surface fissures and elaborated a classification scheme relating fissure

89   morphology and location within the landslide mass to corresponding mechanical processes. This included

90   a first-order differentiation between upper extension, side friction, central compression, and lower creep-

91   on cracks. Although some authors used similar classification schemes (Bombard, 1968), the adopted

92   terminology varies among different authors and affected lithologies (Fleming and Johnson, 1989; Cruden

93   and Varnes, 1996; Fleming et al., 1999; Walter et al., 2009) and the terms crack and fissure are often used

94   synonymously to refer to a variety of surface discontinuities.

95   Here, *fissure* is adopted as a generic term for open fractures on the topographic surface of a natural slope.

96   At first instance, *transversal, longitudinal and diagonal fissures* are distinguished according to their main

97   orientation axes relative to the dip of the slope. This terminology can be used *ad hoc* to classify fissures

98   solely based on geometric properties observed in the field or in an image. A more refined mechanical

99   classification such as provided in Ter-Stephanian (1946) will generally require considerations of the

100 fissure patterns, the involved material and the local geometry of the slip surface. The term *crack* is used in

101 this manuscript when referring to genetic processes described within classical fracture mechanics

102 (Anderson, 2005). It should be noted that the term *crack* is also often adopted to refer to shrinking-

103 swelling induced fractures (Malet et al., 2003) which are not the objective of this study.

104 Classical fracture mechanics postulates tensile opening, sliding and tearing as the three basic modes for

105 crack propagation (Fig. 1a). The concept has been developed for brittle material but is also adopted to

106 explain fracturing of plastic materials at high deformation rates (Schulson and Duval, 2009). Surface

107 fissures may develop from a combination of all three modes, whereas in practice, considering the

108 relatively low tensile fracture toughness of most geomaterials (Backers, 2004; Ke et al., 2008; Schulson

109 and Duval, 2009), tensile fracturing can be expected to dominate the formation of fissures at the free

110 surfaces of a landslide. However, interpreting tension cracks as a direct indicator for a purely tensile stress

111 regime may often fall too short. In fact, tensile fracturing may also result from relaxation of tensile

112 stresses that originate from deformation induced by shearing and compression as well (Wang and Shrive,

113 1995). A mechanical interpretation and classification of the fissures must therefore consider the fissure

114 pattern, the material and the landslide geometry.

115

116

117 FIG. 1 SOMEWHERE HERE

118

119 Fig. 1b-d illustrates three typical fissure patterns that are frequently used as geoindicators of specific

120 deformation processes in the above-cited studies. One commonly observed example for such patterns is

121 the formation of *en-echelon* fissure arrays (Fig. 1c), often also termed *Riedel* shears (Riedel, 1929). They

122 accommodate tensile stress and shear stress typically resulting from shear in the bounding zone of blocks

123 moving with different displacement rates. Certain patterns such as arrays of transversal fissures (Fig. 1b)

124 are typically associated with tension in the steeper upper slopes, whereas fissures resulting from

125 compression and lateral extension (Fig. 1d) are more typically associated with gentler slopes in the transit

126 and accumulation zones of landsides (Sowers and Royster, 1978). For landslides with a complex

127 geometry, the position of those fissure patterns may however deviate considerably from this simple

128 scheme (Niethammer et al., 2011a).

129

3   Study site and data

The Super-Sauze mudslide is an active slow-moving landslide located in the Barcelonnette Basin in the Southern French Alps (Fig. 2) that developed in weathered black marls in the 1960s, and features highly variable displacement rates (from 0.01 m.day^{-1} to 0.40 m.day^{-1}) controlled by the local hydrological conditions (Malet et al., 2005b). The landslide measures 950 m from the main scarp to the toe, and is up to 150 m wide. The moving mass has a clay-rich matrix containing up to 30% coarse gravel as well as larger boulders and blocks (Malet et al., 2005b). The surface displays the signs of deformation in the form of ridges, bulges, lobes and fissures but also markers of surface erosion such as rills and small gullies. Unlike surrounding stable areas the landslide surface is largely bare and only at a few locations, especially at its toe, cushion plants form small vegetation patches. Fissure widths of 0.01-0.40 m, lengths of more than 1.00 m and depths of up to 1.50 m (Espinosa, 2009) can be observed in the field (Fig. 4b). During the last 15 years, the landslide has been investigated through numerous monitoring campaigns including *in-situ* geophysical measurements, terrestrial and airborne LiDAR (Light-Detection and Ranging) and the acquisition of VHR optical imagery. In the VHR airborne optical images, the fissures can be recognized as dark curvilinear structures (Fig. 2c-e) as soon as their width approaches one pixel in size. Previous studies (Malet, 2003; Niethammer et al., 2011a; Walter et al., 2012) already discussed relationships between the observed fissure patterns (Fig. 2c-e) and strain resulting from a spatially heterogeneous displacement field and interactions between moving mass and the stable bedrock. However, a full reconstruction of the complex bedrock geometry that may allow for a more detailed characterisation of the underlying deformation mechanisms has been completed only recently (Travelletti and Malet, 2012).

FIG. 2 SOMEWHERE HERE

154 *3.1   Airborne acquisitions of VHR optical imagery at the Super Sauze landslide*

155   Between April 2007 and October 2009, diverse imaging systems and airborne platforms were used to

156   acquire VHR images of the landslide at five different dates (Fig. 3). In July 2008, October 2008, and

157   October 2009, a low-cost UAV system equipped with compact camera was operated at flight heights

158   between 100 m and 250 m yielding images of the surface with a ground resolution between 0.03 m and

159   0.10 m. The individual images were corrected for barrel lens distortion, rectified according to ground

160   control points (GCPs) measured with differential GPS (DGPS), and finally merged into one large

161   orthomosaic. Further details on the image acquisition and processing were provided by Niethammer et al.

162   (2010; 2011b) who quantified the residual positional error (x-y) for the October 2008 images with

163   0.5 ± 0.57 m within the boundaries of the sliding area. The UAV images for July 2008 and October 2009

164   are expected to provide better positional accuracies because they were orthorectified using elevation

165   models that were generated from a photogrammetric analysis of the images.

166   During the airborne LiDAR surveys (see § 3.2) of, respectively May 2007 and July 2009, two

167   orthomosaics of optical images with full coverage of the landslide were recorded using medium format

168   cameras (Fig. 3) mounted on, respectively an airplane and a helicopter. The surveys used fully integrated

169   systems for direct georeferencing and orthorectification with LiDAR surface models (see § 3.2), which in

170   general provide sub-decimetre positional accuracy in the x-y plane (Vallet, 2007).

171   For the study presented here, additionally 60 homologous tie points on stable areas were manually

172   selected in the available images and showed a mean relative alignment error of 0.76 ± 0.82 m among the

173   different acquisitions.

174   Further details on the adopted camera systems and the resolutions of the images resulting from the five

175   surveys are summarized in Fig. 3. The figure also illustrates the considerable radiometric differences

176   among the five images originating from illumination changes, seasonal variations and the distinct

177   characteristics of the sensors. The scenes for May 2007, October 2008 and October 2009 were acquired

178   under cloudy conditions with diffuse sky radiation and consequently show a more homogenous

179   illumination of the surface. The scenes for July 2008 and July 2009 in contrast were recorded under sunny

180 sky yielding strong contrast and many cast shadows. The latter are more prominent in the image for July

181 2008 which was recorded in the morning hours, at a relatively low sun angle. Available methods for

182 absolute and relative radiometric correction can be employed for the radiometric alignment of satellite

183 images (Hong and Zhang, 2008; Vicente-Serrano et al., 2008) but, to the best of our knowledge, no

184 approach exists to accurately align the radiometry of sub-decimetre images from different sensors, with

185 substantial changes in illumination, a complex topography and changing surface characteristics. Initial

186 test using histogram-matching, linear-regression (Schott et al., 1988) and iteratively re-weighted

187 regression (Canty and Nielsen, 2008) did not provide satisfactory results. Consequently no radiometric

188 normalization was performed and the image analysis technique was designed and tested with radiometric

189 diverse imagery.

190 In order to calibrate adjustable parameters of the detection algorithm to the targeted fissures and the

191 variable scene characteristics, the processing was first tested on a subset of the terrain covering ~

192 14.000 m^2 in the central part of the landslide (Fig. 2a, Fig. 3). This section was characterized by different

193 fissure patterns and recorded during all surveys (including July 2008 and October 2009 which did not

194 yield full coverage of the surface). Subsequently, the developed workflow was applied on the full scenes

195 for a comprehensive mapping and analysis of the fissure distribution. Corresponding results for the full

196 extent of the Super-Sauze landslide and their mechanical significance are discussed in section § 5.2.

197

198 FIG. 3 SOMEWHERE HERE

199

200 *3.2 LiDAR DTM*

201 Two airborne LiDAR surveys were conducted in May 2007 and July 2009, respectively. The first survey

202 used a Riegl LMS-Q560 laser scanner mounted on an airplane flying 600 m above the ground and

203 resulted in a mean point density of 0.9 pts.m^{-2} after vegetation filtering. The residual 3D positional error

204 of the ground points was quantified as 0.12 m. The second survey was conducted with a Riegl Q240i laser

205 scanner mounted on a helicopter and after vegetation filtering resulted in a mean point cloud density of

206 3.2 pts.m^{-2}. The residual 3D positional error of the ground points was 0.07 m. Continuous surface raster

207 with a pixel size of 0.5 m were interpolated from the respective point clouds using Delaunay

208 triangulation. The resulting surface was then adopted for the extraction of the principal hydrological

209 drainage lines.

210

211 *3.3   Reference datasets: expert maps of surface fissures*

212 Reference mappings of the fissure characteristics (type, distribution) were elaborated by an expert

213 geomorphologist familiar with the study site. The fissures were first identified on-site during a field

214 survey carried out in October 2009 at the same time as the acquisition of the UAV images. The position

215 of the fissures was mapped using a dGPS survey and terrestrial photographs. Then image interpretation

216 rules were defined to identify and digitize the fissures on the images as polyline vectors using a 2D view

217 and at a scale of 1:250. The image interpretation rules were then applied to the four other images in order

218 to elaborate an expert fissure map for each date. The resulting five maps were adopted as a reference to

219 assess the performance of the semi-automatic method.

220

221 **4   Image processing methods**

222 While first generic edge detection operators were already proposed in the 1980s (Marr and Hildreth,

223 1980; Canny, 1986), the extraction of linear features from imagery remains a challenging task in many

224 disciplines such as medical research (Mendonca and Campilho, 2006), earth science (Shao et al., 2011;

225 Shruthi et al., 2011) or signal processing (Lampert and O'Keefe, 2011). For our focus, the specific

226 challenges posed for an automation of fissure detection can be summarized as follows:

227 • The approach should be scalable to apply for variable fissure sizes and image resolutions, and as

228   insensitive as possible to variable radiometric image characteristics;

229 • The technique should not respond to edges but enable the detection of dark curvilinear structures that

230   may be oriented at any direction. Classical techniques such as Sobel operator and the Canny detectors

231 (González and Woods, 2008) have been designed specifically for edge detection and are not directly

232 applicable;

233 • The complex micro-topography, the presence of rock blocks and gravels as well as small patches of

234 vegetation yield highly textured images. Consequently, the approach should enable to smooth out

235 spurious signals from the noisy background while still retaining small partially disconnected linear

236 features of interest. Contextual scene information should be taken into account to resolve ambiguities

237 of the local features.

238 Considering these challenges, a processing workflow including three main stages was developed. Firstly,

239 a set of scalable Gaussian filters is applied to detect fissure candidates and suppress responses at edges.

240 Secondly, a set of morphological filters is used to close small gaps along the extracted candidates.

241 Thirdly, an object-oriented procedure is followed to eliminate some of the false positives exploiting

242 higher-level scene information with contextual rules.

243

244 FIG. 4 SOMEWHERE HERE

245

246 *4.1   Stage 1: Extraction of fissure candidates using a Gaussian matched filtering algorithm*

247 A particularly well-studied example for the detection of dark curvilinear structures is the extraction of

248 dark blood vessels in photographs of the human retina. Based on the observation that the cross-profiles of

249 the vessels resembles a Gaussian distribution, Chaudhuri et al. (1989) proposed the use of a matched filter

250 (MF) that is essentially a Gaussian convolution kernel subtracted by its own mean value. As illustrated in

251 Fig. 4a, the cross-sections of surface fissures can be approximated with a Gaussian distribution and an

252 MF scaled to the size of the fissure will give a peak response when crossing the fissure at an angle of

253 approximately 90°. Because the MF still yields errors such as false detections at step edges (Fig. 5a,c)

254 numerous extensions (Hoover et al., 2000; Sofka and Stewart, 2006) and alternative approaches

255 (Mendonca and Campilho, 2006; Soares et al., 2006) have been developed. Recently, Zhang et al. (2010)

256 proposed modification to the original MF filtering approach integrating a first order derivative of a

257   Gaussian function (FDOG) to locally adapt the thresholds separating dark line from non-target features.

258   Compared to other state-of-the-art algorithms their approach provided competitive accuracies while being

259   a computationally efficient and hence easier to apply on the large images resulting from VHR remote

260   sensing.

261   For this study, a similar approach was implemented in ENVI-IDL 4.8 (ITT Visual Information Solutions).

262   The algorithm and its parameterization are detailed below.

263

264

265   FIG. 5 SOMEWHERE HERE

266

267   The MF is a two dimensional kernel defined in the x-direction by an inverted Gaussian profile (Fig. 5b),

268   and in the y-direction by replicates of the same profile (Fig. 5d). It may be denoted as:

269

270    $MF = g(x, y; \sigma) = -\frac{1}{\sqrt{2\pi}\sigma} e^{\left(-\frac{x^2}{2\sigma^2}\right)} - m$, for |x|≤3σ, |y|≤L/2   Eq. 1

271

272   where σ denotes the standard deviation of the Gaussian functions and relates to the width of the targeted

273   feature. To centre the kernel on zero, it is subtracted by its own mean m. The extent of the kernel in the x-

274   direction is typically constrained to 3σ, whereas L defines the extent of the kernel in the y-direction and

275   can be related to the length of the fissures. Because the matched filter still yields false responses at dark

276   and bright step edges (Fig. 5c) Zhang et al. (2010) proposed to use the response of the FDOG to locally

277   adjust the thresholds which are applied to classify the MF response into fissure and non-fissure structures.

278   In analogy to Eq. 1, the first order derivative filter may be denoted as:

279

280    $FDOG = g'(x, y; \sigma) = -\frac{1}{\sqrt{2\pi}\sigma^3} e^{\left(-\frac{x^2}{2\sigma^2}\right)}$, for $|x| \leq 3\sigma, |y| \leq L/2$ Eq. 2

281

282   Fig. 5f illustrates that the FDOG responds with a single peak to edges but with a zero crossing at the

283   centre of the idealized fissure. A simple mean filter can be applied to broaden the zero crossing into a

284   plateau covering the whole width of the fissure (Fig. 5f). Subtracting the smoothed FDOG response from

285   the MF response will attenuate the signal at edges while at the position of the fissure the full response is

286   retained (Fig. 5h).

287   Since the orientation of the fissures is *a priori* unknown, multiple rotated versions of the Gaussian filters

288   are applied on the image and for each pixel only the maximum response value is retained. This

289   corresponds to finding the angle $\theta_{max(x,y)}$ which maximizes the filter response at a given position in the

290   image $I_{(x,y)}$ using Eq. 3:

291

292    $\theta_{\max(x,y)} = \arg\max \left(I_{(x,y)} \otimes MF_\theta \right), \text{ for } 0 < \theta_i \le \pi$ Eq. 3

293

294   where $\otimes$ denotes the convolution operator and θ the orientation of the MF.

295   The calculation of the maximum response image R can then be obtained with Eq. 4:

296

297    $R_{(x,y)} = [I_{(x,y)} \otimes MF_{\theta_{\max(x,y)}}] > 0$ Eq. 4

298

299   where all negative response values are automatically set to zero and only values greater than zero are

300   retained. The FDOG filter is rotated according to the determined $\theta_{\max(x,y)}$ and the corresponding

301   response image D can be derived by Eq. 5:

302

303    $D_{(x,y)} = \left| I_{(x,y)} \otimes FDOG_{\theta_{\max(x,y)}} \otimes M \right|$ Eq. 5

304

305   where M denotes the above-mentioned mean filter used to broaden the zero crossing to the width of the

306   fissures.

307   While Zhang et al. (2010) used a very broad mean filter with a fixed size, we suggest to use a kernel size

308   that matches the width of the Gaussian kernel (6σ) and is thereby related to the width of the targeted

309   features (Fig. 5a,f). In contrast to early studies where the FDOG response was used to locally adapt the

310   threshold (Zhang et al., 2010) the final response image $\bar{R}$ is obtained by subtracting the FDOG from the

311   GMF response using Eq. 6:

312

313    $\overline{R_{(x,y)}} = R_{(x,y)} - Ct * D_{(x,y)}$ Eq. 6

314

315   where Ct denotes a user defined trade off parameter to adjust the sensitivity of the detection with typical

316   range of values between 3 and 4. A threshold T is defined by Eq. 7:

317

318    $T = \mu_{\bar{R}} + 2\,\sigma_{\bar{R}}$ Eq. 7

319

320   where $\mu_{\bar{R}}$ is the mean of the response image $\bar{R}$ and $\sigma_{\bar{R}}$.

321

322   A binary fissure candidate map F_{map} is obtained by applying the threshold T on the response image $\bar{R}$

323   using Eq. 8:

324

325    $\overline{R_{(x,y)}} \geq T_{(x,y)} : F_{\text{map}} = 1$ and $\overline{R_{(x,y)}} < T_{(x,y)} : F_{\text{map}} = 0$ Eq. 8

326

327   The thresholding after subtraction of the FDOG response was found to provide a generally more robust

328   attenuation of undesired edge responses than the technique previously applied by Zhang et al. (2010).

329   In summary, the user needs to specify four simple parameters, namely (1) the scale of the filter kernels in

330   terms of σ, (2) the length L of the kernel, (3) the constant Ct of the thresholding sensitivity and (4) the

331   number of orientations n_θ at which the filters are calculated. In this study, n_θ was kept constant at 36 for

332   all experiments, whereas, if computational time becomes an issue, the angular resolution may be reduced

333   to 12 steps without major losses of accuracy. To determine σ a tool was created,which allows drawing

334   profiles on the image and automatically estimates the fitting Gaussian function (Fig. 4). Cross-profiles of

335   the smallest fissures visible in the image with the coarsest resolution (0.1 m.pixel^{-1} resolution) were best

336   fitted by Gaussian curves with $\sigma \approx 0.6$. To ensure a homogenous scale of the detected features among all

337   images, the kernel can be scaled by changing σ relative to the image resolution. If, for instance, the image

338   resolution is increased to 0.08 m.pixel^{-1}, a value of $\sigma \approx 0.75$ yields a kernel with the same physical size

339   (Table 1). The same applies for the filter length L which was estimated as 1 m corresponding to the

340   typical minimum length of the fissures. Resampling of the images can thereby be avoided. In our

341   experience, σ establishes the lower bound for the width of the targeted features, whereas the filters still

342   remain sensitive to features which are up to 5 times larger. For the choice of σ it is also helpful to note

343   that the discrete kernel cannot represent FDOG functions with $\sigma \leq 0.5$.

344   To assess the sensitivity of the parameters and to determine a suitable threshold parameter Ct, a

345   sensitivity analysis was carried out on a subset of the October 2008 image. Based on a visual assessment,

346   values of $L = 1$ m and $\sigma = 0.75$ were found suitable for the detection of the fine fissure structures. The

347   preliminary analysis also showed that increasing the parameters L and σ directs the detection towards

348   more elongated and broader features, whereas in general the sensitivity of those parameters is rather low

349   compared to the influence of the threshold Ct. Values of $Ct = \{0.0, 1.0, 2.0, 3.0, 4.0\}$ were tested and

350   based on a visual assessment of the outputs a value of $Ct = 3$ was established for an optimal trade-off

351   between detection rate and the amount of false positives. The final parameter set is summarized in Table

352   1.

353

354   TABLE 1 SOMEWHERE HERE

355

356   *4.2   Stage 2: Connection of broken lines using structuring elements*

357   The highly textured surface of the landslide constitutes a noisy background that affects the detection

358   especially at section where the fissures are very thin or partially occluded. While a human operator can

359   easily interpolate broken lines through perceptual grouping (Metzger, 1975), this needs special attention

360   for a semi-automated mapping technique.

361   To close small gaps between broken line segments of the detected candidates, a hit-or-miss transform

362   algorithm (Serra, 1982) was used. The transform assigns a value of 1 to each pixel whose local

363   neighbourhood fulfils the criteria defined by hit- and miss structures (Fig. 6a), also known as structuring

364   elements. They were defined to address all plausible 3-by-3 neighbourhoods representing small gaps in

365   the detection starting from four prototype hit-structures shown in Fig. 6b. The respective miss-structures

366   (Fig. 6c) are typically derived by simply inverting the prototype hit-structures, and both elements were

367   rotated (Fig. 6d) to test for a total number of 24 possible neighbourhood arrangements. Exceptional cases

368   were thereby the structuring elements for closing directly diagonal gaps, where an extended

369   neighbourhood was used for the hit-and miss structures (Fig. 6b, c) to prevent connections of lines

370   running parallel to each other.

371

372   FIG. 6 SOMEWHERE HERE

373

374   The connectivity of the line segments was also particularly important for the subsequent object-oriented

375   post-processing, where objects constitute from pixels groups connected in a Von Neumann

376   neighbourhood (4 adjacent pixels at each side), and small isolated objects could be disregarded as noise.

377

378   *4.3   Stage 3: Object-oriented analysis for false positive removal*

379   Due to visually similar objects, such as linear erosion features (rills, small gullies) and elongated shadows

380   induced by the micro-topography, the fissure candidates resulting from the described filtering routine may

381   still comprise numerous false positive detections. While a human interpreter can differentiate most of the

382   false positives assessing the geospatial context of the scene, the efficient use of such information with

383   automated systems is a challenge for object-oriented image analysis. To exploit the contextual scene

384   information for an automatized refinement of the extracted fissure candidate maps, an object-oriented

385   routine that integrates spatial reasoning into an explicit form was elaborated and implemented using

386   eCognition 8.64 (Trimble, 2011). The elaborated routine included the following steps:

387   1)   The ratio of shadow around the detections is evaluated and candidates with a ratio of shadow pixels

388   in their smallest enclosing circle above 33% are regarded as false detections induced by shadings of

389   the micro-topography. This ratio threshold was determined empirically through visual inspection of

390   the candidate fissures, and selected to capture elongated false detections with one side lying fully in

391   shaded zones. The threshold for shadow can thereby be adjusted according to the illumination

392   conditions and the dynamic range of the image (Table **2**).

393   2)   Further false detections may result from vegetation which typically shows a lower reflectance in the

394   green and red channel compared to the blue. The blue ratio in the sum of all channels is consequently

395   typically below one third for vegetated areas. The suitable value varies slightly with the illumination

396   conditions and the season, and Otsu's method (Otsu, 1979) was employed to automatically adapt to

397   such changes. Through an iterative testing of all possible values, Otsu's method determines threshold

398   value that maximizes variance between two classes in an image. Hence, constraining the search

399   space to all pixels with a ratio blue below 33%, the algorithm was used to determine the thresholds

400   that maximize the contrast between vegetation and the background (Fig. 7). Fissure candidates

401   covered by the resulting vegetation class, or having a relative border length larger than 0.15, were

402   subsequently removed.

403

404   FIG. 7 SOMEWHERE HERE

405

406   3)   Another class of frequent false detections resulted from linear objects such as rills, gullies and nearly

407   vertical steps at the landslide flanks, which may locally obtain similar characteristics as the targeted

408   fissures. To test for the presence of larger linear features and evaluate their relationship with fissure

409   candidates, a strategy to suppress additional false positives was required. For the mapping of the

410   larger linear elements two sources were adopted. First drainage lines were extracted from the LiDAR

411   DTMs using hydrological standard tools (Tarboton et al., 1991) and enlarged with a surrounding

412   buffer of 0.5 m. A second approach was to repeat the Gaussian filtering with the parameter set

413   indicated in Table 1, but with a two times increased scale σ and a 5 times coarser image resolution

414   (resampled with bilinear interpolation). This is equivalent to a search with a 10 times larger scale

415   providing a sufficiently large scale difference to assure that none of the detected linear features

416   would correspond to fissures. The linear objects extracted with both approaches were virtually

417   overlaid with the fissure candidates, and the difference of the orientations of their respective centre

418   lines was adopted as criteria to evaluate if the fissure candidate was in fact part of a larger linear

419   object or constitutes an independent structure (Fig. 8). Image-based measurements of the angular

420   offset of the fissured indicated a minimum offset of about ± 13°. Considering that the lowest

421   effective friction angle values measured for the landslide material are $\alpha' = 26°$ (Malet et al., 2005a),

422   the thresholds are consistent with the orientation of $\alpha'/2$ that the Coulomb criterion predicts for the

423   orientation of shear fissures at the landslide boundary (Tchalenko, 1970).

424

425   FIG. 8 SOMEWHERE HERE

426

427   4)   A last filtering step was implemented by removing all candidates with length not longer than 0.4 m

428   and an area smaller than 0.1 m^2. Finally all fissure candidates falling in areas with a fissure class

429   density lower than 1% in a surrounding neighbourhood of 10 m^2 were considered as noise and also

430   removed.

431   Table 2 displays that most adopted thresholds were kept the same among all the images and only the

432   classification rule for the shadow areas was adapted in order to compensate radiometric differences in the

433   input images.

434

435   TABLE 2 SOMEWHERE HERE

436

437   **5   Results**

438

439   *5.1   Comparison with multi-temporal manual mappings*

440   The primary output of the developed processing routine is a map of the detected fissures represented by

441   polygons. Applying a Delaunay triangulation that extracts the skeleton of those polygons (Trimble, 2011),

442   a 2D line representation, which enables a more immediate comparison with expert mappings, can be

443   obtained.

444

445   FIG. 9 SOMEWHERE HERE

446

447   Fig. 9 displays an example of comparison between an expert map and the result of the semi-automatic

448   detection. A first visual assessment of the obtained maps suggested better agreement of the fissure

449   patterns in areas with high contrast and low texture (Fig. 9a), whereas false positives and false negatives

450   concentrated in sections with low contrast and increased surface texture (Fig. 9b).

451   For a quantitative assessment of the mapping accuracy the obtained results were compared with the expert

452   mappings in the central part of the landslide (Fig. 9c) at all five dates. While several accuracy measures

453   for geographic line datasets have been already proposed, there is still no consensus about one generally

454   applicable technique and the metrics should be selected according to the problem at hand (Ariza-López

455   and Mozas-Calvache, 2012). Here, we focused on three crucial aspects of the map accuracy that may have

456 direct implications for their further use, namely the size of the affected (e.g. fissured) area, the length and

457 density of the fissures, and their orientation.

458

459 *5.1.1   Size of the fissured area*

460 Tveite and Langaas (1999) suggested an accuracy measure for line datasets based on repeated buffering

461 and overlay operations of detected and reference line datasets. A similar strategy was adopted in this

462 study by repeatedly calculating true positive and false positives rates from two raster representing the

463 detections and the expert mapping at increasingly coarser resolutions. Raster were calculated at 10 cm

464 steps for resolutions between 0.10 m and 1.00 m, and each pixel was assigned as fissured or non-fissured

465 area according to the presence or absence of a fissure in the detections and the reference map,

466 respectively. The resulting Receiver Operating Characteristics (ROC) plots are presented (Fig. 10). The

467 analysis showed a correspondence with the expert maps at true positive rates typically above 40% and up

468 to 65%. The false positive rates were below 5% except for the scenes recorded with full sunlight where

469 false positive rates up to 9% could be observed (Fig. 10).

470

471 FIG. 10 SOMEWHERE HERE

472

473 *5.1.2   Fissure length and density*

474 Hydrological models that integrate the influence of surface fissures on infiltration and preferential flow

475 have demonstrated that the fraction of fissures per unit area is an important parameter with considerable

476 influence on the modelled water storage (Malet et al., 2005b; Krzeminska et al., 2011). Such models are

477 typically generated at slope scale with grid resolutions below 10 m. To assess the accuracy of the

478 extracted maps with respect to this potential application, the fissure density was calculated as the line

479 length in circular sliding windows with diameters between 2 and 10 m, and compared among automated

480 detection and expert mappings.

481

482   FIG. 11 SOMEWHERE HERE

483

484   The regression plots in Fig. 11 illustrate the correlation of the fissure density estimates with a 5 m circular

485   sliding window yielding coefficient of determination (R^2) typically above 0.5. The regression analysis

486   further indicated generally higher densities resulting from the semi-automatic detection originating from

487   false positive detections but also from a stronger generalization of the fissure line drawings within the

488   expert mapping. Exceptions from this general trend are the results obtained from the image of July 2008

489   which was recorded at a low sun incidence angle leading to a relatively low $R^2_{5m} = 0.36$. The bar plots in

490   Fig. 11 display the generally higher R^2 values at increasing resolutions of the density raster. This is a well-

491   known effect of spatial aggregation on correlation statistics (Gotway and Young, 2002) but also reflects

492   the contrast between stronger discrepancies of local details and a better correspondence of the global

493   fissure pattern pictured in the respective maps. The highest correlation was observed among the mappings

494   for May 2007 with $R^2_{10m} = 0.88$ indicating that the lower resolution of the corresponding input image

495   was not an important factor for the accuracy of the detection.

496

497   *5.1.3   Fissure orientation*

498   As outlined in the introductory section, different fissure patterns may signal respective mechanical

499   processes and statistics of the principal fracture orientation often allow to estimate the directions of the

500   principal stresses (Pollard and Fletcher, 2005). The fissure orientations were quantified as a third factor to

501   assess the accuracy of the extracted maps using rose diagrams frequently employed for the analysis and

502   interpretation of two dimensional orientation data (Jammalamadaka and SenGupta, 2001). Rose diagrams

503   with a bin width of 10° were computed on a 10 m regular grid for the semi-automatic detections and the

504   expert mappings at all five dates. Considering the length and direction of each bin expressed as a

505   respective vector the preferred fissure orientation within a grid cell can be calculated by summing the

506   vectors over all bins. Taking into account all cells containing fissures in both the expert map and the

507 semi-automatic detection, the Mean Absolute Error (MAE) of the mean orientations provides a

508 quantitative measure for the orientation accuracy.

509 The rose diagrams plots and error statistics in Fig. 12 depict MAEs between 9.7° and 22.5° for the five

510 dates. The detections on the three scenes recorded under cloudy sky resulted in MAE not larger than

511 10.7°, whereas the error rate clearly exceeded 20° with the scenes of July 2008 and 2009 recorded with

512 full sunlight at the surface. The lower orientation accuracies are largely consistent with the relatively low

513 accuracies in terms of area (see § 5.1.1) and density (see § 5.1.2) resulting from the detection at the latter

514 two dates.

515

516

517 FIG. 12 SOMEWHERE HERE

518

519 *5.2 Fissure patterns as possible geoindicators of deformation processes*

520 For a comprehensive interpretation of the detected fissure patterns at the scale of the entire slope, the

521 scenes of May 2007, October 2008 and July 2009 offering a full coverage of the landslide, have been

522 analysed. However, considering the relatively low detection accuracy on the sunlit images of July 2009,

523 the interpretation was focused essentially on the scenes of 2007 and 2008 spanning also over a period

524 with displacement rates significantly above the average annual rates (Travelletti, 2011).

525 Comparing the detection results of May 2007 (Fig. 13a) and October 2008 (Fig. 13b), a significant

526 increase in the abundance of fissures could be noted for the entire landslide. This can be attributed to a

527 phase of strongly increased displacement rates (up to 3.5 m.day^{-1}) in early June 2008 (Travelletti, 2011)

528 preceding the UAV survey in October 2008. Though, in October 2008, the displacement rates already

529 consolidated again at average rates between 0.01 and 0.03 m.day^{-1}, most of the fissures induced in June

530 were preserved and evolved at the surface until October. This view is supported by the results obtained

531 for the test area with the five scenes (Fig. 10, Fig. 11) picturing rather a transient evolution than a

532 complete reorganization of the fissure patterns. Despite partially strong disagreement in the absolute

533 measured fissure density, both expert maps and semi-automatic mapping showed an increase in fissure

534 density after May 2007, with higher values in October 2008 (Fig. 11) than directly after the peak

535 displacement in spring. Pluviometric records for the area in 2008 show relatively dry summer season with

536 cumulative rainfall of 110 mm for the month of July, August and September, suggesting that the

537 increased fissure density in October is partially caused by an increased brittleness of the upper soil layer

538 that dried out during summer.

539 Besides the general increase in the amount of fissures, it is intriguing to observe that at several local plots,

540 similar fissure patterns can be observed at approximately the same positions through time (Fig. 12, Fig.

541 13a,b), despite maximal displacements of up to 55 m between October 2008 and October 2009

542 (Niethammer et al., 2011a). This indicates the recurrent continuous *in-situ* formation where the fissures

543 provide a close representation of the local strain field, similar as observed for the evolution of glacier

544 crevasses (Harper et al., 1998).

545 Previous studies (Malet, 2003; Niethammer et al., 2011a; Walter et al., 2012) already observed close

546 relationships between the occurrence of fissures and the geometry of the stable bedrock at the Super-

547 Sauze landslide. They also noted a general contrast between higher water content and rather ductile

548 behaviour in the lower subsurface (< 1m) and typically lower water content of the topsoil yielding more

549 brittle behaviour at the surface. The surface fissures can therefore be understood as the response to

550 stresses induced in the topsoil through coupling with ductile strain in the deeper subsurface. A similar

551 model was already described by Fleming and Johnson (1989) and adopted as a basis to qualitatively

552 estimate the patterns of flow and stresses from a joint-interpretation (Fig. 13) of the detected fissure

553 patterns and a geometrical model of the stable bedrock (Travelletti and Malet, 2012).

554 Considering the bedrock geometry and a formation of the open fissures normal to the direction of the least

555 compressive stress (Pollard and Fletcher, 2005), three different flow field patterns leading to the fissure

556 formation at the Super-Sauze landslide can be suggested. First, lateral shear at external and internal

557 landslide boundaries aligned with the general flow field leads to the formation of diagonal shear fissure

558 arrays (Fig. 13e). Second, longitudinal compressive and tensile strain related to abrupt changes in the

559 slope of the sliding surface induces tensile stresses at the surface that results in transversal fissure arrays

560 (Fig. 13c). Third, divergence of the flow field over topographic ridges and at the outlets of confining

561 topographic channels induces lateral extension and tensile stresses resulting in longitudinal fissure arrays

562 (Fig. 13d). At several locations, those processes overlap and lead to the formation of mixed structures

563 such as a radial fissure patterns displayed in Fig. 4 and Fig. 13c, resulting from lateral shear and

564 longitudinal strain, and from local divergent stress field, respectively.

565

566 FIG. 13 SOMEWHERE HERE

567

568 **6   Discussion**

569 Deformation patterns at the surface of landslides are important indicators for the mechanical processes,

570 whereas the elaboration of detailed maps of such features remains a challenging and time-consuming task.

571 While Sowers and Royster (1978) still argued that aerial photographs do not reach sufficient resolution

572 for such mappings, modern digital sensors and new aerial platforms such as UAVs today provide the

573 necessary level of detail. Furthermore, this study demonstrated the possible use of a semi-automatic

574 image processing chain for the extraction of surface fissure maps.

575 The accuracy of the method was assessed by comparisons with expert maps and demonstrated

576 heterogeneous areal accuracies with true positive rates of up to 65% and false positive rates generally

577 below 10%. Also, the orientation accuracy showed a variable quality of the resulting maps with mean

578 deviations between 9.7° and 22.5°. The fissure densities derived from both maps have significant

579 correlations (R^2 between 0.36-0.78), whereas the semi-automatic detections yield typically higher

580 estimates. Interestingly, this difference is more pronounced with the images of 2009 (Fig. 10) reflecting

581 the contrast between increased semi-automatic detection rates at higher resolutions and the fixed scale of

582 the expert mapping. Contrariwise, the best agreement among detection and expert maps was measured for

583 the scene of May 2007 showing that the lower resolution does not necessarily yield lower accuracies.

584 Generally lower accuracies were observed for the scenes recorded with full sunlight at the surface in July

585   2008 and 2009 and the worst results were obtained for July 2008 when images were recorded at a

586   relatively low sun incidence angle. Since the direct sunlight induces shading that affects the local contrast

587   and global image normalization methods cannot alleviate this problem and image acquisition with diffuse

588   skylight appears to be the generally better option.

589   In the initial stage of the processing chain, a low-level linear feature detector is used. Similar techniques

590   yield competitive results in medical image analysis (Zhang et al., 2010), whereas the accuracies achieved

591   with aerial images in this study are still significantly lower. This must be attributed to the generally higher

592   complexity of outdoor scenes and at the moment still requires additional steps and parameters to take the

593   contextual scene information into account. The use of an OOA heuristic-based post-processing technique

594   proofed useful for the removal of false positives and helped to objectify the image analysis by transferring

595   expert knowledge in an explicit form. The analysis still relies on a number of fixed thresholds which may

596   hinder an easy transfer of the entire processing chain to a different geographic area. This concerns

597   especially parameters that require knowledge of the local processes (e.g. minimum fissure length,

598   effective friction angle) while thresholds that can be determined directly from the image (e.g. shadows,

599   vegetation) may be adjusted more effortless.

600   The development of surface fissures precedes and accompanies especially slow- and very slow-moving

601   landslides (Cruden and Varnes, 1996) making the developed technique particularly applicable to such

602   types of landslides and to potentially unstable slopes. However, the spatial resolution of the acquired

603   images must at least match, or should ideally exceed, the width of the targeted fissures, and the vegetation

604   must be sufficiently sparse to permit direct view on the bare ground. The results of this study

605   demonstrated that if those requirements are met, the obtained fissure maps can already provide sufficient

606   accuracy to infer the landslide dynamics and mechanical processes (see § 5.2.) at the slope scale. Density

607   maps from both semi-automatic and expert mappings show a strong spatial and temporal variability of the

608   fissure abundance pointing toward important local and temporal contrasts in the infiltration capacity

609   which may need considerations in the design of hydro-mechanical models. An analysis of the evolution

610   and mechanics of individual fissures will however require higher temporal resolution and terrestrial

611 cameras have recently been installed at the surface of the landslide to record imagery for further research

612 in this direction. It would also be desirable to test the developed technique for the investigation of other

613 landslides with different characteristics in order to validate a more general applicability of the approach

614 and the mechanical interpretation of the observed fissure dynamics.

615 The OOA heuristics already considers multi-scale information to some degree (see § 4.33), whereas for

616 further methodological improvements an explicit integration of an automatic scale selection technique at

617 the low-level filtering stage appears as a promising approach to further reduce heuristics and tuneable

618 parameters (Stumpf et al., 2012). The first and second stages of the proposed method are generic for the

619 detection of dark linear features and could in principle also be applied to detect other geomorphological

620 and geological structures with similar characteristics. The proposed technique might be of interest for the

621 mapping of erosion gullies (Shruthi et al., 2011), geological lineaments (Mallast et al., 2011), ice-glacier

622 crevasses (Vaughan, 1993) or tectonically induced fractures (Allmendinger and González, 2010),

623 sufficiently larger to be depicted in sub-metre satellite images.

624 Considering the intrinsic disagreement in expert mappings of linear features, especially in the inter- and

625 extrapolation of lines (Sander et al., 1997), further studies should also include an assessment of the

626 uncertainties of reference maps since their quality can strongly bias the evaluation of different alternative

627 approaches (Lampert et al., submitted).

628

629 **7   Conclusions**

630 This study developed an image processing chain to extract surface fissures from heterogeneous sets of

631 VHR aerial images and tested the approach with a challenging multi-temporal set of images recorded at

632 the Super-Sauze landslide for five different dates. The first two stages of the developed workflow

633 combine families of Gaussian matched filters and morphological filters and are followed by an object-

634 oriented analysis to reduce the amount of false positive detection using contextual information and

635 auxiliary topographic information. The detection results can be represented in raster maps or optional by

636 centre skeleton lines.

637 Under homogenous illumination conditions a comparison of the results with expert mapping

638 demonstrated detection rates of up to 65% and orientation errors below 10°. Contrary, the technique is

639 relatively sensitive to shading effects at full sunlight and prone to errors especially at low sun incidence

640 angle.

641 A joint-interpretation of obtained fissure maps and of a 3D geometrical model of the stable bedrock

642 demonstrated their complementary use for a better understanding of the geomorphological and

643 geomechanical processes, such that the detected fissure pattern may be used for first approximation for

644 mechanical processes in the recent deformation history of a slope.

645 Possible directions for further research are the reduction of tuneable parameters and a more immediate

646 exploitation of multi-scale information, as well as an adaption of the technique to other linear features

647 with geomorphological and geological relevance.

648

649

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868

869   **Fig. 1.** Generic types of surface fissures and their typical spatial occurrence within a landslide mass. (a)

870   Modes of fracture propagation: mode I (opening), II (sliding) and III (tearing). (b) Fissures developing

871   predominately in mode I and resulting from tensile stress. (c) Fissures developing predominately in mode

872   I and resulting from shear stress. (d) Fissures developing predominantly in mode I resulting from

873   compressive stress and lateral expansion. The central figure is adapted from (Sowers and Royster, 1978).

874

875   **Fig. 2**. Oblique view of the Super-Sauze landslide combining a hillshade image derived from an airborne

876   LiDAR DTM (July 2009) and a UAV image (October 2008). (a) The main scarp (hashed black line),

877   transport and accumulation zone (black outline), and the area of interest for the multi-temporal analysis

878   (white square) are indicated. UAV image subsets show (b) compression ridges, (c) longitudinal fissures,

879   (d) diagonal fissures at the boundary of the active part, and (e) and transversal fissures.

880

881   **Fig. 3.** Subsets of orthophotographs (see location in the white bounding box in Fig. 2a) acquired at five

882   different dates with details of the acquisition systems and image ground resolutions.

883

Fig. 4. (a) Subset (see extent in Fig. 3) of the UAV image from October 2008 showing typical fissure patterns and (I-IV) grey-value profiles (green channel) approximated with Gaussian curves. (b) Field terrestrial photograph taken in October 2009.

Fig. 5. Illustration of the principles of the Gaussian filtering for (a-c, f-h) a simplified 1-D case, (d, i) a 3D visualization of 2D filters and (e, j) the filter responses for the image subset in Fig. 4a. See text for details.

Fig. 6. Strategy used to connect broken line segments. (a) Working principle of the hit- and miss transform, (b) hit structures, (c) miss structures and (d) respective rotations used for the plausible pixel neighbourhoods.

Fig. 7. Illustration of the automatic threshold detection for the intermediate mapping of vegetation. (a) Subset of the October 2008 image at the toe of the landslide. (b) Ratio blue. (c) Initial thresholding at ratio blue < 0.33 to obtain vegetation candidates (yellow). (d) Histogram of the vegetation candidates with the automatically selected threshold. (e) Final map of the vegetation (green).

Fig. 8. Illustration of the object-oriented post-processing routine. (a) Fissure candidates that overlapped with linear structures. (b) Linear structure detected at a ten times greater filter scale. The fissure candidates aligned with the linear structures at angles below ± 13° were removed.

Fig. 9. Example of comparison of the obtained fissure maps with the expert mapping for October 2010 (fissures in red). (a) Area with relatively high agreement of the mapped fissure patterns. (b) Area with relatively high rate of false negatives and false positives. The scale of the representations corresponds approximately to the scale used for the expert mapping (1:250).

908

909 **Fig. 10:** Receiver operating characteristics (ROC) plots for the fissured area at different map resolutions.

910 The sky conditions for the five different dates are indicated.

911

912 **Fig. 11.** Correlation between fissure density estimates at 5 m raster resolution based on semi-automatic

913 detections and expert mappings from the five images. The bar plots at the bottom display the R^2

914 coefficient at different raster resolutions.

915

916 **Fig. 12.** Rose diagram plots with mean orientation (red line) and error statistics for the mean fissure

917 orientation per 10 m grid cell for the test area at the five different dates. For visualization, the rose

918 diagrams where plotted over a hillshade of the landslide surface and the scatterplot angles were centred at

919 90°.

920

921 **Fig. 13.** Pseudo 3D view showing the landslide dynamics inferred from the fissure patterns detected in the

922 aerial images of (a) May 2007 and (b) October 2008. (c, d, e) Close up views for October 2008 showing

923 inferred landslide dynamics and stress vectors. The results are overlaid on a hillshade model of the

924 topography of the stable bedrock proposed by (Travelletti and Malet, 2012).

925

926 **Table 1**

927 Parameter set of the Gaussian filters scaled according to the respective image resolution.

928

929 **Table 2**

930 Summary of the thresholds adopted in the object-oriented post-processing routine. See text for details.

931