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Deliverable - D.E2.2 Hazard map of the southern Tuscany (Volterra area) test site

A deliverable of Task E: Geohazard impact assessment

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Dissemination Level		
PU	Public	x
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the Consortium (including the Commission Services)	
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EXECUTIVE SUMMARY

SAFETY is a two years research project (1 January 2016 – 31 December 2018) funded under the ECHO (European Commission's Humanitarian aid and Civil Protection department) call, “Prevention and preparedness projects in Civil Protection and marine pollution”. The mission of the project is to improve the efforts in detecting and mapping geohazards (i.e. landslides and subsidence), by assessing their activity and evaluating their impact on built-up areas and infrastructures networks. SAFETY will enhance ground deformation risk prevention and mitigation efforts in highly vulnerable geographic and geologic regions. The outcomes of the project will provide Civil Protection Authorities (CPA) with the capability of periodically evaluating and assessing the potential impact of geohazards on the selected sites.

“D.E2.2 Hazard map of the southern Tuscany (Volterra area) test site” is a deliverable of Task E “Geohazard impact assessment”, in the framework of the action Action E.2 “Susceptibility and hazard maps”. The action will focus on generating susceptibility and hazard maps using data available in the project test sites (Task D). The results of the susceptibility and hazard assessments will be used to evaluate the impact on the urban areas and infrastructures. The report will describe for the Volterra test site: i) the statistical distribution of landslide size obtained using LAND-STAT, the software for the determination of landslide statistics from inventory maps; ii) the landslide susceptibility map prepared using slope units (SU).

REFERENCE DOCUMENTS

N°	**Title**
RD1	DoW – FormT3a
RD2	

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1 INTRODUCTION

The project SAFETY aims to provide to the Civil Protection Authorities (CPA) the capability of periodically monitor and assess the impact of geohazards (landslides and subsidence, volcanos, earthquakes) on urban areas. The project's objectives are to improve the ability to detect and map landslides, to assess and forecast the impact of triggered landslide events on vulnerable elements, and to model landscape changes caused by slope failures. Safety is mainly addressed to the CPAs at different administrative levels. Action E is focused on generating susceptibility and hazard maps using data available in the project test sites (Task D). The results of the susceptibility and hazard assessments will be used to evaluate the impact on urban areas and infrastructures.

Landslide “hazard” is the probability that a landslide of a given magnitude will occur in a given period and in a given area. Landslide hazard predicts “where” a slope failure will occur, “when” or “how frequently” it will occur, and “how large” it will be (Guzzetti et al., 2005). In mathematical terms, landslide hazard consider three components that are expressed as three individual probabilities: the conditional probability of landslide size, of landslide occurrence in an established period, and of landslide spatial occurrence, given the local environmental setting. Guzzetti et all (2005) have proposed a method to obtain all the relevant information needed to apply the probabilistic model. The method is based on the systematic interpretation of multiple sets of aerial photographs of different dates, aided by historical investigations and field surveys, to obtain a detailed multi-temporal landslide inventory map. The multi-temporal inventory is then exploited to: i) obtain the spatial probability of landslide occurrence, given the local environmental setting, ii) estimate the temporal probability of landslides, from the empirical recurrence of slope failures, and iii) determine the probability of landslide size (area), considered a proxy for landslide magnitude.

For the Volterra Municipality there is no information on temporal occurrence of landslides, in other word a multi-temporal landslide inventory map is not available. For this reason, the hazard map cannot be prepared and delivered on M16. Single component of the hazard will be prepared not considering the temporal occurrence of slope failures. In particular, in this report we have analysed and described: i) the statistical distribution of landslide size obtained using LAND-STAT, the software for the determination of landslide statistics from inventory maps; and ii) a set of different landslide susceptibility maps prepared using slope units and available thematic information (Alvioli et al., 2016).

2 THE VOLTERRA MUNICIPALITY

The Volterra Municipality is located in the Tuscany region (Central Italy) and extends for about 250 km^2, between the Era and the Cecina River valleys (Figure 1). The area is characterized by hilly morphology, with moderate relief and gentle slopes, with elevations ranging from 60 to 630 meters. From a geological point of view, the area is located in the Pliocene graben-basin, known as Volterra basin, oriented NW-SE and bordered by normal faults. The territory is extensively affected by slope instability, mainly shallow slow-moving and complex landslides triggered by rainfall; falls (Volterra Crags) and gully erosion process are common in the badland landscape.

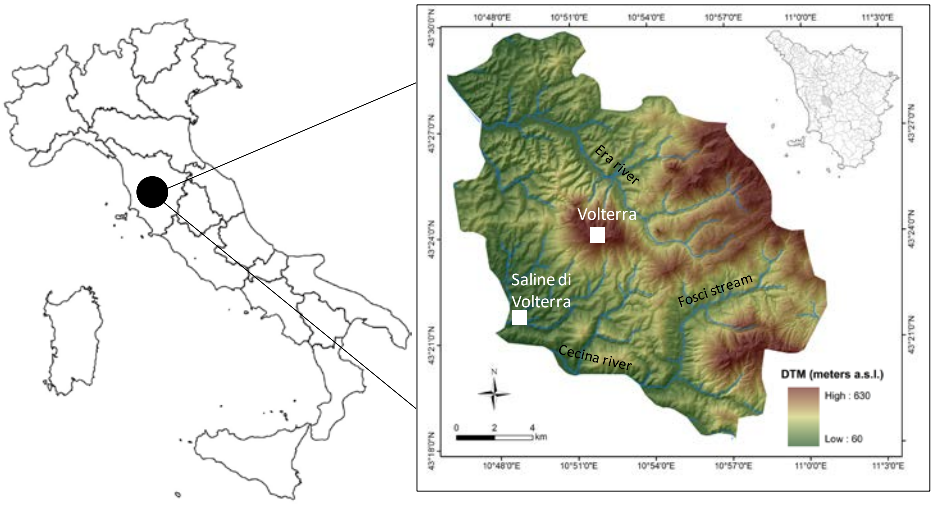

Figure 1. Location and hillshade representation of the Volterra Municipality.

To prepare the landslide susceptibility model and to evaluate the statistical distribution of landslide size, we used the following set of thematic data (The data are described in the Deliverable DD.1: Test site characterization):

- *Geological map.* The formations were grouped in lithological classes, based on the geo-mechanical properties and their predisposition to erosion.
- *Land use map.* Classes were derived from CORINE Land Cover project in Italy referred to 2006 (CLC, 2006).
- *Digital Elevation Model.* The DEM with 10 x 10 m grid resolution was obtained from TINITALY/01 DEM Project and was used to derive slope and curvature (longitudinal and profile) maps.
- *Landslide Inventory Map.* Landslides are classified based on their typology and state of activity.

This set of thematic data was used to prepare a susceptibility model and map using the pixel as mapping unit, subdividing the territory in cells with a grid resolution of 10 m x 10 m (see Deliverable - E2.1 Susceptibility map of the southern Tuscany, Volterra area test site).

2.1 The landslide inventory maps

For the test area two different landslide inventory maps are available. The first was originally compiled with the landslide inventories provided by the Tuscan region and by the Municipal Authority of Volterra. The compiled map contains data available at regional scale (IFFI, Inventario dei Fenomeni Franosi in Italia and PAI, Hydrogeological Setting Plan – Piano di assetto idrogeologico) and derived from different Urban Development Plans (in italian: Piani Strutturali). The inventory was further improved in 2013, with ERS 1/2 an Envisat PSInSAR information in the framework of the DIANA project (Dati Interferometrici per l'ANalisi Ambientale, http://www.dst.unifi.it/vp-161-progetto-diana.html). The *DIANA inventory* map includes 1211 landslides, associate with several attributes of which the main are listed in the table below:

Field	Description	Value
Typology	Type of the movement	a = undefined movement b = slide c = flow d = fall e = topple f = expansion
Activity	State of activity of the movement	a1 = undefined a1a = active a1q = dormant a1s = stabilized a1r = relict
Shape_Leng	Polygon perimeter	Value expressed (m)
Shape_Area	Polygon area	Value expressed (m^2)

The second inventory map contains 116 landslides derived from local surveys and geomorphological maps associated with the Urban Development Plan of the Volterra Municipality, year 2005. The inventory extends for about 17 km^2 nearby the Volterra city centre and the mass movements coincide only partially with the *DIANA inventory*. For six landslides located in the South West side of the Volterra town (Colombaie and Fontecorrenti), are available detailed information on the depth of the slide surface and location of the boundaries derived from field surveys and inclinometric measures. In the southwestern side of the Volterra city ("Le Colombaie-Il Cipresso" and "Fontecorrenti" sites), many translational and rotational slides are mapped, involving blue clays and colluvial deposits.

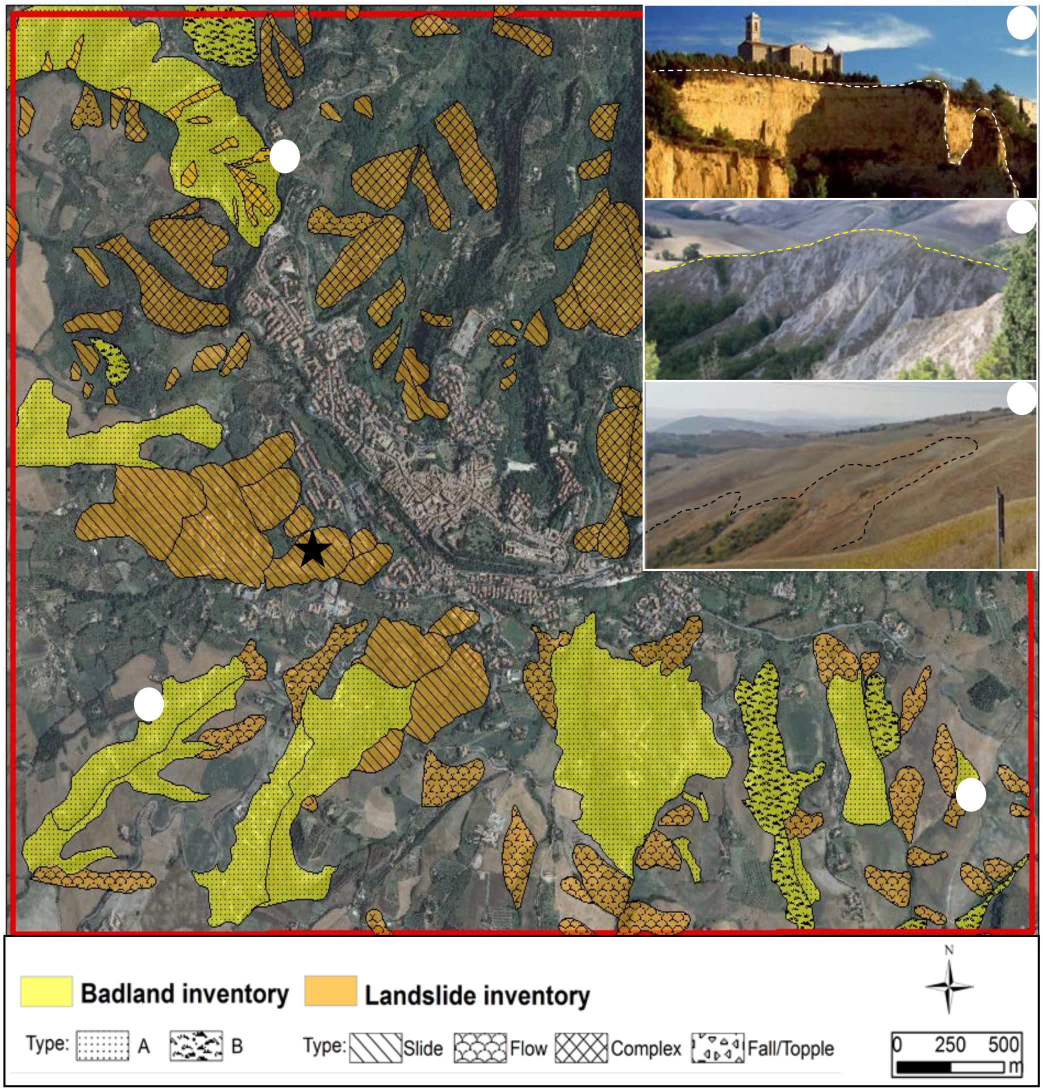

Figure 2. Detail of the landslide inventory map prepared for about 17 km^2 nearby the Volterra city.

3 STATISTICAL DISTRIBUTION OF LANDSLIDE SIZE

The statistical distribution of landslide size can be used as a proxy for landslide magnitude, a component of the landslide hazard assessment. Different statistical models can be used to estimate the probability of occurrence of landslides of a given size as part of a triggered event or a geomorphical inventory. In the literature, two frequency-area probability models have been proposed: the Double Pareto distribution (Stark & Hovius, 2001) and the Inverse Gamma distribution (Malamud et al., 2004). Both models are able:

i) to describe the right tail (i.e. the medium and largest landslides) of the landslide size distribution with an inverse power-law;

ii) to reproduce the fact that as the landslide area decreases, occurrence increases, until a landslide area of several hundred square meters arrives at a maximum probability ("rollover", i.e. the modal or the most frequent landslide size value);

iii) to decrease the occurrence probability, as the landslide area continues to be smaller.

The main difference between the two statistical models is the description of the left tail (i.e., smaller landslide areas). In the Double Pareto, the left tail consists of another power law function (this time not inverse) that gradually censors the upper tail Double Pareto from the "rollover" to the smaller landslide area values. In the Inverse Gamma, the lower tail is described by an exponential rollover. While the Inverse Gamma must have a maximum (i.e., assumed by definition a rollover), the Double Pareto does not. These two different mathematical representations of the landslide size distribution can converge to similar probability density function estimates.

In the Volterra test site, landslide statistics was computed and evaluated using LAND-Stat, a software implemented in R (a free software environment for statistical computing, http://www.r-project.org/), that consists of algorithm for the determination of statistics of landslide size (area) derived from inventory maps. LAND-Stat is described in detail in the project deliverable "D.E1: Report on tailoring existing knowledge and tools".

The LAND-Stat software implements the following parametric and non-parametric approaches to estimate the parameters of the probability density functions:

i) Histogram Density Estimation
ii) Kernel Density Estimation
iii) Maximum Likelihood Estimation

Each approach exploits different optimization procedures thus can give slightly different results. For each parameter the tool gives:

i) an estimate of its value
ii) standard error (Std. Err.),
iii) the estimated error variance (t_value), and
iv) the correlations among the parameters (Pr(>|t|)).

The latter in particular could be useful in cases of difficulty in producing a solution: very high correlations between parameters are indicative of ill-conditioning. The tool estimates the exact rollover position (r) a useful information for the landslide inventory comparison.

For the Volterra test site, landslide statistics were computed considering the following landslide data set:

a) all landslide types of the *DIANA inventory*;

b) only the “slide” type landslides of the *DIANA inventory*;
c) only the “flow” type landslides of the *DIANA inventory*;
d) all the landslides from the detailed inventory map prepared for an area around the Volterra town.

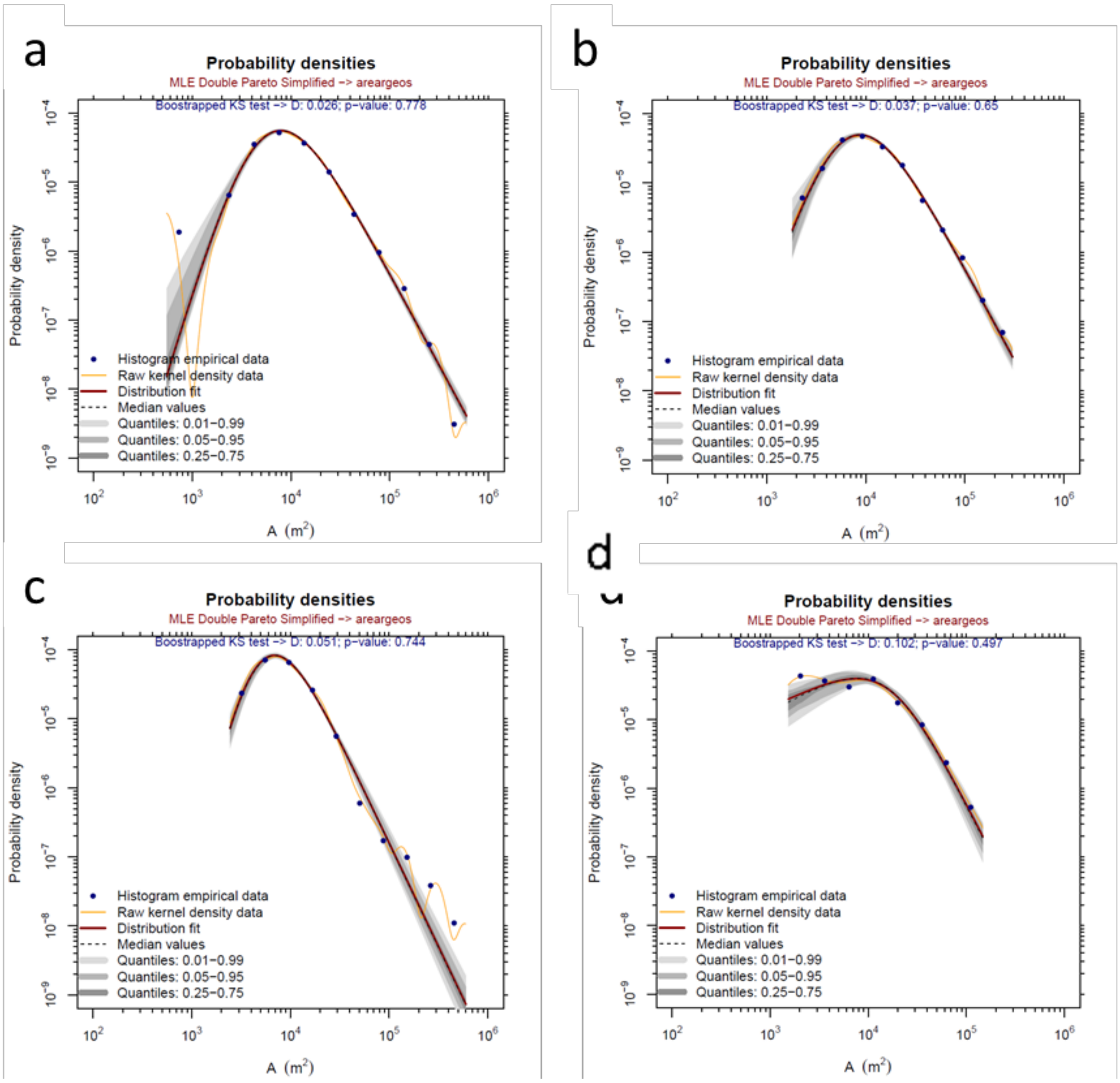

Figure 3 shows for the selected landslide data set, the probability density function and relative uncertainty estimated with the Double Pareto simplified distribution model and the Maximum Likelihood Estimation method.

The analysis of the histograms and of the row kernel density data (Figure 3) reveals anomalous values along the right tails in the three *DIANA inventory* selections and in the left tail when considering all the landslide types of the *DIANA inventory*. These anomalies can be explained by the technique used to map the mass failures that do not consider the real dimension of the single overlapping failures.

Table 1 shows the parameters estimated by the LAND-Stat software, using the Double Pareto simplified distribution model and Maximum Likelihood Estimation method for the selected landslide data set.

		Estimate	Std. err.	t_value	Pr(>|t|)
Data set a	**α**	1.6	0.03	47.5	0
	β	5.7	0.24	23.2	3.2 e-119
	t	5535.4	0.0002	21184250.8	0
	r	7900	-	-	-
Data set b	**α**	1.6	0.04	37.5	5.5 e-308
	β	5.2	0.2	18.9	1.7 e-80
	t	6581.4	0.0002	30629288.4	0
	r	8800			
Data set c	**α**	2.0	0.07	25.8	7.2 e-148
	β	7.5	0.6	12.2	1.5 e-34
	t	4703.1	0.001	3862592.6	0
	r	6900			
Data set d	**α**	1.8	0.1	11.4	3.6 e-30
	β	1.6	0.1	9.9	2.6 e-23
	t	16618.5	1.1 e-05	1494814209.3	0
	r	7600			

4 LANDSLIDE SUSCEPTIBILITY MODEL

A fundamental step for the evaluation of landslide susceptibility is the definition of a proper mapping unit. In this analysis, we have chosen the slope unit (SU) as a basic geographic area. SUs are terrain units defined by two basic requirements: i) represent a segmentation of the territory which maximizes intra-unit homogeneity and extra-unit inhomogeneity; ii) are a hydrological partition of the territory, delimited by drainage and divide lines. The software *r.slopeunits* (http://geomorphology.irpi.cnr.it/tools/slope-units), based on the algorithm of Alvioli et al., (2016), performs an automatic delineation of SUs based on a DEM and a few input parameters. Different values of such parameters correspond to SUs with different shapes and sizes, all of them fulfilling the requirements i) and ii).

SUs with different shapes and sizes represent a partition of the territory according to different granularity, or pixel aggregation level. The purpose of the study should dictate the correct level of granularity. In landslide studies, one can formulate the generic requirement that most of the landslide in a given inventory are contained within SU polygons, minimizing intersections between landslide bodies and slope unit borders. One can immediately envision that SUs suited for studying shallow landslides are, in average, smaller than SUs suited for deep-seated landslides, due to the different size of the two phenomena. This can be translated into an objective procedure to select proper values for the input parameters of the slope unit delineation software, based on a quantitative measure of performance.

Alvioli et al., (2016) suggested an optimization procedure of SU parameters based on the combination of two metrics, or objective functions, as a function of the two most important numerical inputs of the *r.slopeunits* software. The two parameters are circular variance, $0 \le c \le 1$, a measure of the variability of aspect direction within each SU polygon, and a (in m^2), the tentative SU minimum area. Optimization with respect to the a, c input parameters of *r.slopeunits* is performed by simultaneously maximizing two objective functions, namely: 1) an aspect segmentation metric F(a, c), measuring the quality of the segmentation of a generic image (Espindola et al., 2006); 2) the AUC_{ROC} metric R(a, c) (Fawcett, 2006), measuring the performance of the landslide susceptibility model.

The segmentation metric F(a, c) is obtained by means of the local aspect variance V, and the autocorrelation index I, defined as follows:

$$V = \frac{\sum_n c_n s_n}{\sum_n s_n}$$

and

$$I = \frac{N \sum_{n,l} \omega_{n,l} (\alpha_n - \bar{\alpha})(\alpha_l - \bar{\alpha})}{(\sum_n (\alpha_n - \bar{\alpha})^2) \sum_{n,l} \omega_{n,l}}$$

where $1 \le n \le N$ labels the SUs in the given set; c_n, s_n and α_n are the circular variance of the aspect, the surface area and the average aspect of the n-th SU; $\bar{\alpha}$ is the average aspect of the whole study area; ω_{nl} is an indicator for spatial proximity, equal to unity if SU polygons n and l are adjacent, zero otherwise. Both the functions V and I depend on the (a, c) parameters, by construction; V(a, c) measures internal aspect variance and assigns more importance to large SUs avoiding numerical instabilities produced by small ones, while I(a, c) measures external aspect variance and has minima for SU sets exhibiting well-defined boundaries between adjacent SUs.

The overall aspect segmentation metric is defined as:

$$F(a,c) = \frac{V_{max} - V(a,c)}{V_{max} - V_{min}} + \frac{I_{max} - I(a,c)}{I_{max} - I_{min}},$$

where the maximum and minimum of both V and I functions are calculated within the (a, c) region considered in the analysis. We used circular variance, c, values ranging from 0.01 to 0.6, and minimum area, a, in the range from 25,000 m^2 to 400,000 m^2, for a total of 64 different (a, c) combinations. The resulting values of the F(a, c) metric are shown in Figure 4. The maximum of the aspect segmentation metric is shown to occur for (a, c) = (50,000 m^2, 0.3).

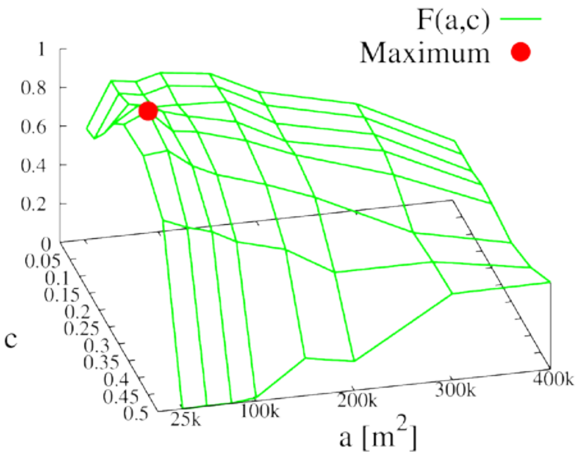

Figure 4. The aspect segmentation function described in the text, plotted as a function of the input parameters (a, c) of the software r.slopeunits (Alvioli et al., 2016). The red dot represents the maximum of the (normalized) function, occurring at (a, c) = (50,000 m^2, 0.2).

The optimization procedure devised in Alvioli et al., (2016) considers the AUC$_{ROC}$ as an additional metric for optimization.

To evaluate the landslide susceptibility in the Volterra Municipality, we used the logistic regression model (LRM) as implemented by Rossi et all (2010) and recently upgraded by Rossi and Reichenbach (2016). Landslide locations from the *DIANA inventory map* was used as LRM independent variable and the following morphometric and thematic variables as model dependent variables: slope, longitudinal curvature, tangential curvature, lithology and land use. For each morphometric variable, we used both mean and standard deviation in each SU as a different variable. For each class of the thematic variables, we calculated the percentage contained in each SU and used it as a different variable. We have run one instance of the LRM model for each of the 56 SU sets, corresponding to the different combinations of the (a, c) input parameters of *r.slopeunits*. The resulting 56 susceptibility maps are shown in Figure 5.

Figure 6 shows the resulting AUC$_{ROC}$ values, as a function of a and c. The AUC$_{ROC}$ results show a mild dependence on the a, c parameters. The figure also shows the combined objective function, S(a, c) = F(a, c) R(a, c) (Alvioli et al., 2016), which we maximize to obtain the final value of the (a, c) SU parameters.

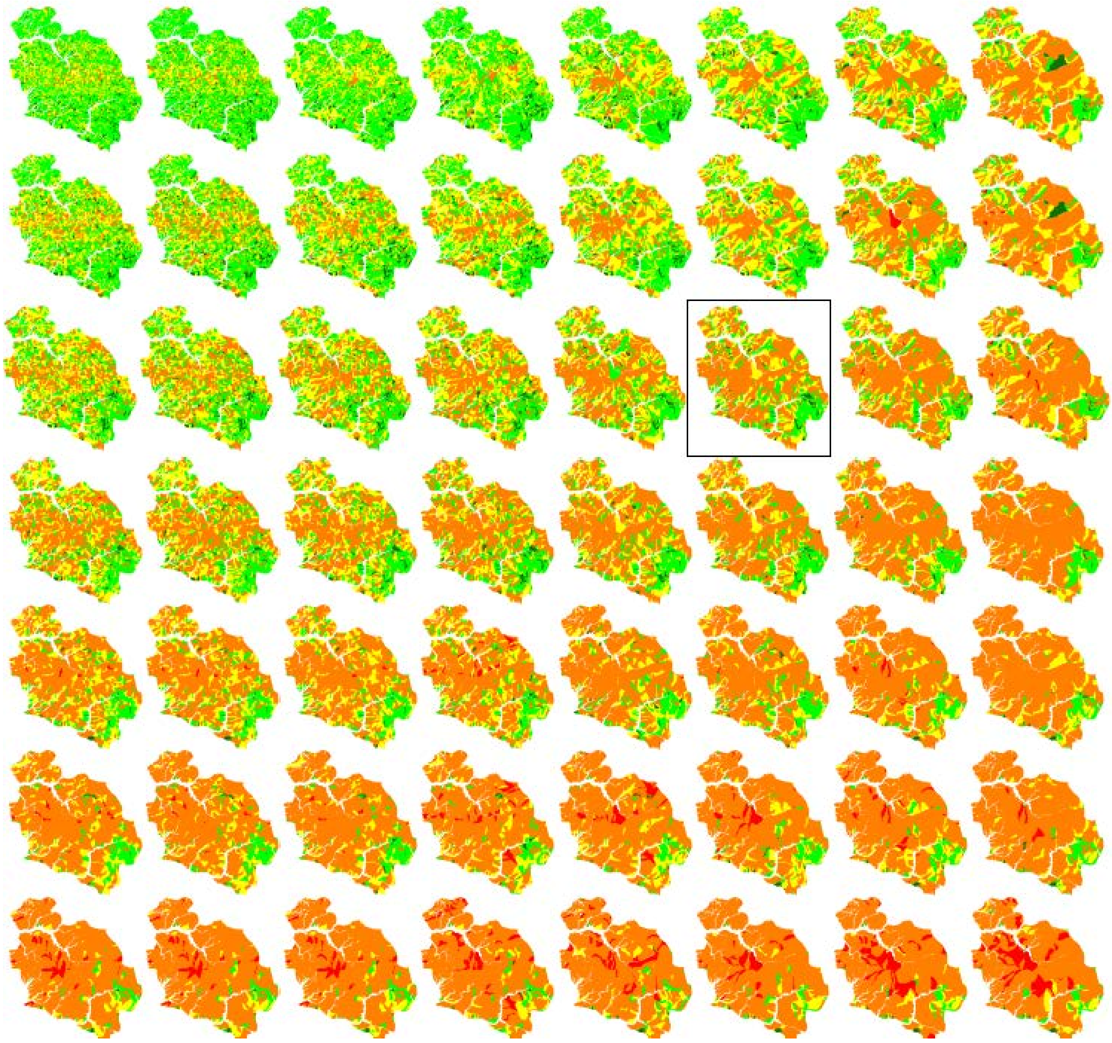

Figure 5. The 56 susceptibility maps resulting from applying the LRM to the 56 different combinations of the *r.slopeunits* input parameters. The optimal map, obtained by maximizing the S(a, c) function shown in Figure 6 and described in the text, is shown in the box and it is also shown in more detail in Figure 7.

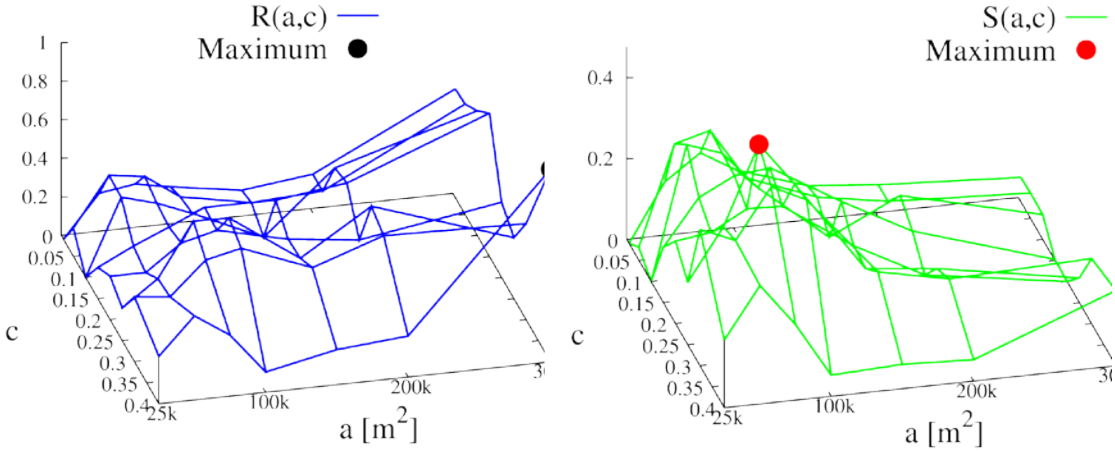

Figure 6. Left: AUC$_{\mathrm{ROC}}$ result; right: combined S(a,c) metric described in the text. Both functions are plotted as a function of the input parameters (a, c) of the software *r.slopeunits*. The black dot represents the maximum of the R(a,c) metric, occurring at (a, c) = (300,000 m^2, 0.4). The red dot represents the maximum of the S(a,c) metric, occurring at (a, c) = (75,000 m^2, 0.25), which is our final optimal result. The corresponding susceptibility map is shown in Fig. 7.

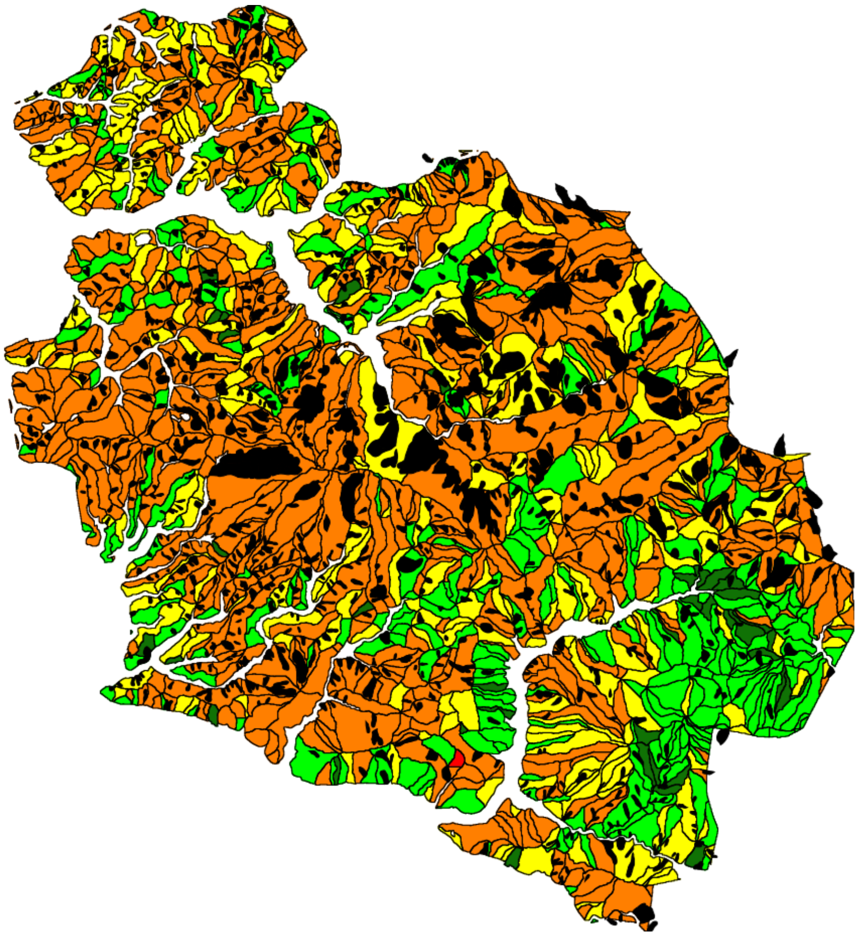

Figure 7. The final SU-based susceptibility map. The set of landslides used in the modelling is shown as black polygons. Dark green: 0 ≤ P < 0.2; light green: 0.2 ≤ P < 0.45; yellow: 0.45 ≤ P < 0.55; 0.55 ≤ P < 0.8; red: 0.8 ≤ P ≤ 1.0.

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