Scaling properties of rainfall induced landslides predicted by a physically based model

Massimiliano Alvioli, Fausto Guzzetti, Mauro Rossi

Abstract

Natural landslides exhibit scaling properties revealed by power law relationships. These relationships include the frequency of the size (e.g., area, volume) of the landslides, and the rainfall conditions responsible for slope failures in a region. Reasons for the scaling behavior of landslides are poorly known. We investigate the possibility of using the Transient Rainfall Infiltration and Grid-Based Regional Slope-Stability analysis code (TRIGRS), a consolidated, physically-based, numerical model that describes the stability/instability conditions of natural slopes forced by rainfall, to determine the frequency statistics of the area of the unstable slopes and the rainfall intensity (I) – duration (D) conditions that result in landslides in a region. We apply TRIGRS in a portion of the Upper Tiber River Basin, Central Italy. The spatially distributed model predicts the stability/instability conditions of individual grid cells, given the local terrain and rainfall conditions. We run TRIGRS using multiple, synthetic rainfall histories, and we compare the modeling results with empirical evidences of the area of landslides and of the rainfall conditions that have caused landslides in the study area. Our findings revealed that TRIGRS is capable of reproducing the frequency of the size of the patches of terrain predicted as unstable by the model, which match the frequency size statistics of landslides in the study area, and the mean rainfall I-D conditions that result in unstable slopes in the study area, which match rainfall I-D thresholds for possible landslide occurrence. Our results are a step towards understanding the mechanisms that give rise to landslide scaling properties.

1. Introduction

There is accumulating evidence that natural landslides exhibit scaling properties (Hergarten, 2000, 2002; Turcotte et al., 2002; Chen et al., 2011), including the area and volume of the slope failures (Pelletier et al., 1997; Stark and Hovius, 2001; Guzzetti et al., 2002; Malamud et al., 2004; Van Den Eeckhaut et al., 2007; Brunetti et al., 2009a), and the amount of rainfall required for the initiation of landslides in a region (Caine, 1980; Innes, 1983; Aleotti, 2004; Guzzetti et al., 2007, 2008). The scaling properties of landslides are revealed by power law dependencies, and are considered evidence of the critical state of landscape systems dominated by slope wasting phenomena (Hergarten, 2002; Turcotte et al., 2002).

It is known that, regardless of the physiographic or the climatic settings, the probability (or frequency) density of event landslides increases with the area of the landslide up to a maximum value, known as the “rollover”, after which the density decays along a power law (Stark and Hovius, 2001; Malamud et al., 2004; Van Den Eeckhaut et al., 2007). The length scale for the rollover, and the rapid decay along a power law, are conditioned by the mechanical and structural properties of the soil and bedrock where the landslides occur (Katz and Aharonov, 2006; Stark and Guzzetti, 2009), and are independent of the landslide trigger (Malamud et al., 2004). The probability (or frequency) density of the landslide volume obeys a negative power-law, with a scaling controlled by the type of the landslides (Brunetti et al., 2009a). The dependence of landslide volume on landslide area was also shown to obey a distinct scaling behavior over more than eight orders of magnitude (Guzzetti et al., 2009; Larsen et al., 2010; Klar et al., 2011).
Rainfall is a recognized trigger of landslides, and early investigators have recognized that empirical rainfall thresholds can be established to determine the amount of rainfall required to initiate landslides in a region [Endo, 1970; Caine, 1980; Govi and Sorzana, 1980; Innes, 1983; Moser et al., 1983; Cancelli et al., 1985]. Different types of empirical thresholds that use combinations of rainfall measurements obtained from the analysis of rainfall events that resulted (or did not result) in landslides were proposed in the literature, including mean intensity - duration (I-D) and rainfall cumulated event - duration (E-D) thresholds, and their variations [Guzzetti et al., 2007, 2008]. With a few exceptions [Wieczorek, 1987; Cannon and Ellen, 1985; Crosta and Frattini, 2003] all the empirical rainfall thresholds are represented by power law models, indicative of the self-similar behavior of the rainfall characteristics responsible for landslide occurrence.

Despite the abundant empirical evidence, the reasons for the scaling behaviors of landslide phenomena are poorly known, and only a few attempts were made to interpret the empirical evidences with deterministic or physically based models [Katz and Aharonov, 2006; Stark and Guzzetti, 2009]. In this paper, we show that a relatively simple, physically based model that describes the stability/instability conditions of slopes forced by rainfall, when applied to a sufficiently large geographical area produces results that are in agreement with two known scaling properties of landslides, namely: (i) the rainfall conditions that result in unstable slopes, which match regional empirical I-D thresholds for possible landslide occurrence [Guzzetti et al., 2007, 2008], and (ii) the frequency distribution of the area of the patches of terrain predicted as unstable by the model, which matches the statistics of landslide area for event landslides [Pelletier et al., 1997; Stark and Hovius, 2001; Malamud et al., 2004; Van Den Eeckhaut et al., 2007].

The paper is organized as follows. In Section 2 we describe the geographical area in Central Italy where we have conducted our experiments (Fig. 1), and in Section 3 we provide general information on the Transient Rainfall Infiltration and Grid-Based Regional Slope-Stability analysis code (TRIGRS, version 2.0; Baum et al., 2008) that we adopted for the experiments. Next, in Section 4 we compare the I-D conditions capable of producing slope instability in the study area predicted by TRIGRS, with empirical rainfall I-D thresholds for possible landslide occurrence in Central Italy. This is followed by a comparison of the probability density of the area of the patches of terrain predicted as unstable by TRIGRS in the study area with the probability density of natural landslides in the same general area, and by a discussion about the possible relations of this work to other existing approaches for the description of landslide scaling phenomena. We conclude, in Section 7 summarizing the lessons learnt.

2. Study area and data

The Upper Tiber River basin (UTRB) extends for 4,098 km² in Central Italy, with elevation in the range from 163 m at the basin outlet to 1571 m along the divide between the Adriatic Sea and the Tyrrhenian Sea (Fig. 1). In the area the landscape is hilly or mountainous, with open valleys and intra-mountain basins. In the mountains and the hills, the morphology is conditioned by lithology and the attitude of the bedding planes. Climate is Mediterranean, with most of the precipitation falling from October to December and from February to April [Cardinali et al., 2001; Guzzetti et al., 2008].

For the UTRB two digital representations of the terrain elevation (DEM) were available to us. A coarser DEM, with a ground resolution of 25 \times 25 m, was obtained through the linear interpolation of elevation data along contour lines shown on 1:25,000 topographic base maps [Cardinali et al., 2001]. A finer DEM, with a ground resolution of 10 \times 10 m, was prepared by the Italian National Institute for Geophysics and Volcanology through the interpolation of multiple sources of elevation data [Tarquini et al., 2007, 2012].

Five lithological complexes, or groups of rock units, crop out in the UTRB [Cardinali et al., 2001; Guzzetti et al., 2008], including, from younger to older: (a) recent fluvial and lake deposits, which crop out mostly along the valley bottoms, (b) unconsolidated and poorly consolidated sediments pertaining to a continental, post-orogenic sequence, Pliocene to Pleistocene in age, (c) allochthonous rocks, lower to middle Miocene in age, (d) sediments pertaining to the Tuscan turbidites sequence, Eocene to Miocene in age, and to the Umbria turbidites sequence, Miocene in age, and (e) sediments pertaining to the the Umbria-Marche stratigraphic sequence, Lias to lower Miocene in age. Soils reflect the lithological types, and range in thickness from less than 20 cm to more than 1.5 m. Landslides are abundant in the area, and cover
Fig. 1. The Upper Tiber River Basin (UTRB), in Central Italy. Colours in (A) show five lithological complexes (Cardinali et al., 2001; Guzzetti et al., 2008): (a) Fluvial and lake deposits, recent in age. (b) Continental, post-orogenic sediments, Pliocene to Pleistocene. (c) Allochthonous rocks, lower to middle Miocene. (d) Tuscany and Umbria turbidites sequences, Eocene to Miocene. (e) Umbria-Marche sedimentary sequence, Lias to lower Miocene. Black box in (A) shows location of enlargement portrayed in (B) where black lines show hydrological sub-basins derived automatically from a 25 × 25 m DEM; the only lithological area shown in colour in (B) is b of (A), and in (B) two sample sub-basins are shown in red and blue. Black box in (B) shows location of Fig. 2.

Fig. 2. Result of the TRIGRS numerical modeling for two sub-basins where unconsolidated and poorly consolidated sediments composed of clay, silt, sand (b in Fig. 1A) crop out. Values for the factor of safety $F_s$ are shown with a color ramp ranging from large values (green) to small values (red). $F_s$ values smaller than unity (shown in blue) represent cells predicted unstable by the model.

523 km$^2$ (12.8% of the catchment), for a total estimated landslide volume of $5.9 \times 10^9$ m$^3$ (Guzzetti et al., 2008).

For the numerical experiments we selected the area in the UTRB where unconsolidated and poorly consolidated continental sediments crop out (green area in Fig. 1). This is the lithological complex where shallow landslides are more frequent in the study area (Cardinali et al., 2000, 2006; Guzzetti et al., 2008), and where the TRIGRS conceptual landslide scheme is best suited to model the stability/instability conditions of slopes forced by rainfall. The geotechnical properties for the soils in this lithological complex used for the numerical modeling are listed in line (b) of Table 1.

3. Distributed slope stability model

As noted, we adopted TRIGRS version 2.0 (Baum et al., 2008). The software implements a grid-based, spatially distributed slope stability model coupled with an infiltration model capable of simulating the infiltration of rainfall in the terrain, modulating the stability/instability conditions
Probability Density

Area [m²]

Fig. 3. Distribution of the area of the sub-basins resulting in well-defined rainfall thresholds, shown in Figs. 4, 5, and 6.

TRIGRS adopts a grid-based representation of a real landscape based on a DEM, and uses local terrain characteristics as an input for the solution of a system of equations whose output is the factor of safety $F_s$ i.e., a positive number representing the balance of the driving and the resisting forces acting in each grid cell. For stable conditions, where the resisting forces exceed the driving forces, $F_s > 1.0$. $F_s = 1.0$ represents the metastable condition where the driving and the resisting forces are equal, and $F_s < 1.0$ represents the physically unrealistic condition where the driving forces exceed the resisting forces, and the slope fails.

For the modeling, TRIGRS exploits an infinite slope approximation i.e., a rigorous, lowest order approximation of a multi-dimensional landslide geometry. This approximation is adequate where $H << L$, where $H$ is the depth of the slip surface and $L$ is the landslide linear dimension (Iverson 2000). An upper bound for $H$ can be identified on the basis of the lithological setting, where stronger rocks underly a weaker layer of soil or regolith. This is an assumption for shallow landslides for which depth is significantly smaller than width, or length. For simplicity, TRIGRS neglects all the lateral stresses and the inter-cell forces, and the stability of each grid cell is governed solely by the balance of the vertical component of gravity, against the resisting stress due to the basal Coulomb friction, plus the pore pressure (Richards 1931). Failure occurs at depth $Z$, measured vertically from the topographic surface, if at that depth (Iverson 2000):

$$F_s = F_f + F_w + F_c = 1.$$  

where, $F_s$ is the ratio of resisting to driving forces, and the individual components in Eq. (1) can be written as a function of the local cell characteristics (Iverson 2000):

$$F_f = \tan \varphi / \tan \alpha,$$

$$F_w = -\psi(Z,t) \gamma_w \tan \varphi / \gamma_s Z \sin \alpha \cos \alpha,$$

$$F_c = c / \gamma_s Z \sin \alpha \cos \alpha,$$

where: $c$ is the soil cohesion, $\varphi$ is the soil internal friction angle, $\gamma_w = 9800$ N m⁻³ is the unit weight of water, and $\alpha$ is the local angle of the terrain with respect to the horizontal. The model assumes that rainfall modulates the water table height and groundwater

Fig. 4. Rainfall intensity – duration ($I–D$) thresholds. Colored lines are thresholds applicable to the UTRB obtained from: A (red) $I = 14.82 D^{-0.39}$ (Caine 1980), B (green) $I = 12.17 D^{-0.64}$ (Brunetti et al. 2010), and C (blue) $I = 7.5 D^{-0.62}$ (Peruccacci et al. 2012). Exponents for the black lines are in the range $-0.54 \pm 0.09$, obtained fitting each threshold line with a power law, averaging the exponents, and combining in quadrature the uncertainties given by the fits.
Fig. 5. Dependence of the modeled rainfall $I$–$D$ thresholds on the (mean) terrain gradient for 91 sub-basins in the study area (b in Fig. 1A). Slope increases from (A) to (F). Insets show geographical location of the sub-basins for which the rainfall thresholds are shown in each plot. Square bracket indicates value is included and round bracket indicates value is not included.

Flow parallel to the slope, and that sub-surface flow is one-dimensional (Iverson, 2000). When rainfall hits the ground, due to water infiltration the driving force described by Eq. (3) is modulated, $F_s$ varies with $Z$ and $t$, and $\psi(Z,T)$ is the pressure head as a function of depth $Z$ and time $t$. In Eq. (3), the effects of variation is determined for each cell by solving the Richards equation (Richards, 1931):

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial Z} \left( K(\psi) \frac{1}{\cos^2 \theta} \frac{\partial \psi}{\partial Z} - 1 \right),$$

(5)

where $\theta$ is the soil water content, and $K(\psi)$ is the soil hydraulic conductivity.

In TRIGRS, Eq. (5) is linearized and solved at discrete time steps and in the vertical coordinate. The linearization procedure relies on the identification of two different time scales (Iverson, 2000). For each grid cell, $A$ is the upslope contributing area i.e., the cumulated area of all the upslope cells draining in the considered cell, and $D_0 = K_S/S$ is the soil diffusivity in the cell, where $K_S$ is the saturated hydraulic conductivity (see Table 1) and $S$ is the specific water storage. The first time scale can be identified with $A/D_0$ as the time for lateral pore pressure transmission from the upstream area to the grid cell. The second time scale is $H^2/D_0$, the time needed for pore pressure transmission from the surface to the depth $H$ (Iverson, 2000). One can then build the length scale ratio $\varepsilon$:

$$\varepsilon = \sqrt{\frac{H^2}{D_0}} \frac{A}{A/D_0} = \frac{H}{\sqrt{A}}.$$  

(6)

Under the condition $\varepsilon \ll 1$, Eq. (5) can be simplified identifying long-term and short-term response terms (Iverson, 2000) used in the numerical implementation of Baum et al. (2008). Eq. (6) is also used to identify the approximate limits of applicability of the model implemented by TRIGRS. When rainfall intensity exceeds the local infiltration capacity, the excess water in the single grid cells is routed downslope to the nearest cells (Baum et al., 2008; Raia et al., 2013). TRIGRS accepts as input complex rainfall histories (i.e., spatially and temporally varying), permitting a realistic modeling of the slope stability/instability conditions driven by real rainfall events.

Fig. 2 shows the result of the TRIGRS modeling for two representative sub-basins in the study area. The map portrays, superimposed on a shaded relief image showing the terrain morphology, the geographical distribution of the $F_S$ calculated using typical values for the mean rainfall intensity and
Fig. 6. Dependence on the modeled rainfall $I$–$D$ thresholds on the (mean) soil depth for 91 sub-basins in the study area (b in Fig. 1A). Soil depth increases from (A) to (F). Insets show geographical location of the sub-basins for which the rainfall thresholds are shown in each plot. Square bracket indicates value is included and round bracket indicates value is not included.

the rainfall duration. Shades of colours, from red ($F_S = 1$) to green, show the values of $F_S$ calculated for each grid cell. Single unstable cells, or clusters of unstable cells with $F_S < 1$ are shown in blue.

4. Investigating the rainfall intensity – duration dependence

To investigate the relationship between the magnitude of the rainfall trigger (i.e., $I$ and $D$) we first partitioned the study area into sub-basins i.e., hydrological ensembles of slope units, where a slope unit is a hydrological region bounded by drainage and divide lines (Carrara et al., 1991; Guzzetti et al., 1999). To obtain the sub-basins we exploited the 25 × 25 m resolution DEM, and we used the r.watershed command in the GRASS GIS, release 7.0 (www.grass.org). Sub-basins with a surface area smaller than 2,500 m$^2$ (i.e., four grid cells) were identified and excluded from the analysis. Fig. 3 shows the statistical size-distribution of the slope units in the study area i.e., where post-orogenic sediments crop out in the UTRB (green areas in Fig. 1). Next, we forced the individual sub-basins in the study area with a uniform rainfall of a given intensity $I$, for a given period of time $D$. We then studied the rainfall conditions that have resulted in unstable cells in the sub-basins. For simplicity, we considered only (nearly) mono-lithological sub-basins i.e., sub-basins for which at least 50% of the area is covered by unconsolidated and poorly consolidated continental sediments. This reduced the complexity that the presence of multiple rock types in a sub-basin may introduce. We further considered unstable the sub-basins with at least 10% of the grid-cells with $F_S < 1$. This is a reasonable assumption for rainfall-triggered landslides in the study area (Cardinali et al., 2006). The results depend only weakly on the proportion of cells in a sub-basin necessary to consider a sub-basin as unstable.

The first set of experiments was conducted adopting the following procedure. For each sub-basin, we started with a given (reasonable e.g., Guzzetti et al. 2007, 2008) set of $D$ and mean $I$ conditions, and we checked if these conditions resulted in landslides i.e., if at least 10% of the grid-cells in the sub-basin had $F_S < 1.0$. Next, we increased $I$ maintaining $D$ constant, and we checked if the new rainfall conditions had resulted in landslides. The procedure was repeated for different, increasing rainfall durations. For the modeling, we used (i) $I = 1$ mm h$^{-1}$
to $I = 200\ \text{mm h}^{-1}$ with steps of $2\ \text{mm h}^{-1}$, and (ii) $D = 1$ hour to $D = 100$ hours, with steps of 1 hour for the 1-10 h range, and steps of 10 hours for the 10-100 h range. At the end of the procedure, for each of the considered sub-basins we obtained a set of rainfall ($D, I$) conditions that had resulted in (predicted) slope instabilities ($10\%$ or more of the grid-cells with $F_s < 1.0$). We plotted these rainfall conditions in a $D, I$ plot, in log-log coordinates. The result is shown in Fig. 4 where each black line represents the threshold above which a single sub-basin in the study area is unstable.

Visual inspection of Fig. 4 reveals that the rainfall ($D, I$) conditions that have resulted in unstable conditions in each sub-basin follow power laws that represent rainfall thresholds for slope instability in the sub-basins. The lines are equivalent to rainfall thresholds for possible landslide occurrence (Guzzetti et al. 2007). Not all the sub-basins in the study area resulted in an instability threshold curve, because: (i) a number of sub-basins contained less than $50\%$ of continental, post-orogenic sediments, and were excluded from the analysis, (ii) the percentage of unstable cells in a sub-basin was less than $10\%$, regardless of the rainfall conditions, and where not considered as failed slopes, and (iii) the instability threshold curve was outside of the ranges of rainfall intensity and duration considered for the modeling.

Further inspection of Fig. 4 reveals that the threshold lines are well defined, and obey distinct power law trends for a significant range of rainfall durations ($1 \leq D \leq 100$ hours) known to initiate landslides (Guzzetti et al. 2007, 2008). Significantly, the slope of the threshold curves is in agreement with the slope of empirical rainfall thresholds for possible landslide occurrence established for central Italy (Peruccacci et al. 2012) and for Italy (Brunetti et al. 2010), considering the uncertainty associated with the empirical thresholds (Peruccacci et al. 2012). The position of the threshold curves in the $D, I$ plane depends on the location and geomorphological characteristics of the individual sub-basins, but all of the threshold curves lay above the empirical thresholds proposed in the literature and applicable to the study area (e.g., Caine 1980, Brunetti et al. 2010, Peruccacci et al. 2012). This is because empirical thresholds are defined as lower boundaries of $I, D$ conditions in a large area, while in our case each curve corresponds to a specific (local) morpho-lithological setting. We stress that the result was obtained using reasonable values for the model parameters, but without any attempt to fine-tune the parameters, and specifically the geotechnical parameters (Table 1). Also, no attempt was made to optimize the modeling parameters using

Fig. 7. Probability density of the area $A_L$ of the patches of connected grid cells predicted as unstable by TRIGRS ($F_s < 1.0$). (A) shows dependence of the results on rainfall intensity. (B) shows dependence of the results on rainfall duration. See text for explanation. Grey dots show the probability density of the area of natural landslides in the UTRB (Cardinali et al., 2000; Guzzetti et al., 2008). Grey line shows the general probability density curve for event landslides proposed by Malamud et al. (2004).
e.g., a probabilistic modeling approach (Raia et al., 2013). We maintain that this indicates that the scaling behavior of the rainfall conditions responsible for shallow landslides in the UTRB emerged from the physical modeling, and is dependent on the local geomorphological setting and the rainfall trigger.

To further investigate the position of the obtained threshold curves in the $D, I$ plane with the local terrain slope and the soil depth, two key variables that control the modeling (Iverson, 2000; Baum et al., 2008), we separated the threshold curves based on classes of terrain slope (Fig. 5) and soil depth (Fig. 6) in the sub-basins. Visual inspection of Fig. 5 reveals that the $I-D$ threshold curves for sub-basins characterized by steep slopes are lower than the thresholds for sub-basins characterized by gentle slopes. This was expected (Iverson, 2000; Baum et al., 2008). Analysis of Fig. 5 indicates that thinner soils fail with less severe rainfall conditions (lower thresholds) than the thicker soils. This was also expected (Iverson, 2000; Baum et al., 2008). We attribute the dispersion of the threshold lines in the different classes of terrain slope and soil depth to natural variability i.e., to the terrain variability that characterizes the sub-basins in the study area. In Figs. 5 and 6 the maps show the geographical location of the sub-basins for which the threshold lines shown in the same panel were calculated. Inspection of the maps reveals that the sub-basins are distributed throughout the study area, with no geographical trend or bias. This is an indication that the results are independent of a specific location or geomorphological setting.

5. Investigating the distribution of the size of the landslides

We determined the probability density of the area $A_L$ of the patches of terrain predicted as unstable by TRIGRS, and we compared the probability density of the patches to the probability density of natural landslides in the UTRB (Malamud et al., 2004; Guzzetti et al., 2008). We defined a patch of unstable terrain a cluster of contiguous grid cells that individually have $F_S < 1.0$. To identify the unstable grid cells, we ran TRIGRS with a fixed rainfall duration $D = 1$ hour, increasing the rainfall intensity $I$ from 25 to 100 mm h$^{-1}$. Next, we repeated the calculations with a fixed rainfall intensity $I = 100$ mm h$^{-1}$, and we varied $D$ from 1 to 10 hours. The remaining model parameters were kept constant for all the model runs (see Table 1). Results are summarized in Fig. 7. For the experiment shown in Fig. 7 we used the finer resolution (10 $\times$ 10 m) DEM (Tarquini et al., 2007, 2012).
Fig. 9. Relationship between the area of the slope units $A_{SU}$, and the area of the individual landslides $A_L$ in the UTRB, or the area of the patches of connected grid cells predicted as unstable by TRIGRS, where post-orogenic sediments crop out (b in Fig. 1A). (A) shows results for landslides mapped by Guzzetti et al. (2008) in the UTRB; (B) shows results of TRIGRS using $D = 1$ h, $I = 25$ mm h$^{-1}$, and (C) shows results of TRIGRS using $D = 5$ h, $I = 100$ mm h$^{-1}$. The probability distribution for the results in (B) and (C) are shown in Fig. 7; some DEM resolution effect is clearly seen in the lower region of both plots.

Visual inspection of Fig. 7 reveals a good agreement between the probability density of the area of the patches of unstable terrain, and the corresponding probability density of event landslides in the UTRB (Cardinali et al., 2000, 2006), and with the general probability density curve for event landslides prosed by Malamud et al. (2004). The agreement is best for medium to low rainfall intensities ($I = 25$ to $50$ mm h$^{-1}$) and for medium rainfall durations ($D = 5$ h). These rainfall conditions are known to initiate landslides in the UTRB and in similar physiographic regions in Umbria (Cardinali et al., 2006) and in Central Italy (Peruccacci et al., 2012). Higher rainfall intensities and shorter rainfall periods result in a poorer match between the modeled and the empirical probability densities.

For small and very small unstable patches which we identify as single landslides, with area $A_L < 10^{-3}$ km$^2$, the probability density is lower than prescribed by a simple negative power law. Interestingly, the reduced density occurs at the same size $A_L$ for which the probability density of the natural landslides exhibits a distinct rollover, which was recognized to be a physical characteristic of populations of event landslides (Malamud et al., 2004), and was attributed to the mechanical properties of the soil and regolith where the small landslides occur (Katz and Aharonov, 2006; Stark and Guzzetti, 2009). However, the smooth rollover for small and very small landslides typical of event landslides is not clearly reproduced by the model. We cannot exclude a priori that the result is related to the strategy used to decide the size of the patches of instability, or to the resolution of the DEM used for the modeling.

To investigate this possibility, we tested different strategies to identify the patches of unstable terrain, and we studied the effects of the different strategies on the probability density of the area of the patches. The simplest strategy consisted in considering all the grid cells in a sub-basin with $F_S < 1.0$ that shared a boundary or a corner as belonging to a single landslide. In this strategy, a single unstable cell not connected to any other unstable grid cell represents an unstable patch with the smallest possible area, $A_L = 100$ m$^2$ for a $10 \times 10$ m DEM. An alternative strategy consisted in smoothing the grid map of the computed $F_S$ values prior to searching for the contiguous cells. For the purpose, we passed a $3 \times 3$ kernel over the grid map, and decided that the central pixel was unstable ($F_S < 1.0$) if at least two (of the nine) cells in the kernel had $F_S < 1.0$. Another strategy consisted in passing the same $3 \times 3$ kernel over the $F_S$ grid map, and in deciding that the central pixel is unstable if it has $F_S < 1$ and if the average $F_S$ value of the nine pixels in the kernel was smaller than 5, a figure determined heuristically through an iterative procedure. The first strategy provided the best result (Fig. 7A), with the other strategies deviating significantly from the
landslide field data. For the first strategy, the agreement between the area of the modeled patches and the area of the event landslides in the UTRB is best for $2 \times 10^{-3} < A_L < 2 \times 10^{-2}$ km$^2$. The density deviates slightly for larger areas ($A_L > 2 \times 10^{-2}$ km$^2$). We attribute the deviation to the fact that very large unstable patches correspond to large, deep-seated landslides that are not modeled by TRIGRS.

We investigated the dependence of the model results to the resolution of the DEM. For the purpose, we repeated the model runs using the coarser $25 \times 25$ m DEM. The results are shown in Fig. [3B], and were obtained using the same rainfall intensity, rainfall duration, and geotechnical parameters, changing the resolution of the DEM. Inspection of the plot shows that the probability density of the area of the patches of unstable grid cells obtained using the finer resolution (10 × 10 m) DEM follows nicely the probability density of the area of event landslides in the UTRB, for $A_L < 2 \times 10^{-2}$ km$^2$. Again, we attribute the observed deviation for larger areas to the fact that the very large patches correspond to deep-seated landslides that are not modeled by TRIGRS. Instead, the results obtained using the coarser resolution ($25 \times 25$ m) DEM follows a steeper power law trend that deviates from the probability density of the natural landslides in the UTRB [Malamud et al., 2004]. We repeated the simulations with the coarser DEM using larger intensity and duration values, obtaining curves with a lower slope, with a limit to the correct one. However the resulting probability densities as a function of $A_L$ (not shown in Fig. [8]) were higher than the curves obtained using the finer resolution DEM. We conclude that the resolution of the coarser DEM is insufficient to model the stability/instability conditions of shallow landslides in the study area.

Lastly, we investigated the relationship between the size of the patches predicted unstable by the TRIGRS model (Fig. [3]) and the size of the slope units in the UTRB (Fig. [9]). We find that the size distribution of the predicted unstable patches covers the same size range of the landslides mapped in the UTRB, and that the relation between the size of the unstable patches and the size of the slope units depends on the (synthetic) I-D rainfall conditions. The differences between the modelled and the empirical distributions have multiple causes, including the method used to cluster the unstable cells, and the fact that our modeling results were obtained for the portion of the UTRB where the post-orogenic sediments crop out (area b in Fig. [1]).

6. Comparison with other modeling approaches

We attempted a comparison between the results obtained in our study area using the physically-based model TRIGRS [Baum et al., 2008], and other attempts conducted to exploit numerical, simplified (i.e., “toy”), or conceptual models to simulate the rainfall conditions responsible for slope failures, and the frequency-size distribution of the landslides. We concentrate on simplified, conceptual models, and we exclude the use of physically-based geo-mechanical models such as those proposed by Katz and Aharonov (2006) or by Stark and Guzzetti (2009) to describe the frequency-size statistics of slope failures, or other physically-based spatially distributed slope stability models e.g., SHALSTAB [Montgomery and Dietrich, 1994], Dietrich and Montgomery [1998], SINMAP [Pack et al., 1998], SHETRAN [Burton and Bathurst, 1998], STARWARS [Malet et al., 2005], GEOtop-FS [Rigon et al., 2006] Simoni et al., 2008), and CHLT (von Ruette et al., 2013).

We are not aware of any attempt to describe the scaling behaviour of rainfall thresholds for possible landslide occurrence executed using simplified or conceptual models. The results obtained in this work represent a preliminary attempt to provide a physical background to the empirical rainfall thresholds for the prediction of possible landslide occurrence. This is important for the application of rainfall thresholds in landslide warning systems such as CHLT (von Ruette et al., 2013), and CHLT (von Ruette et al., 2013). We attempted a comparison between the results obtained in our study area using the physically-based model TRIGRS [Baum et al., 2008], and other attempts conducted to exploit numerical, simplified (i.e., “toy”), or conceptual models to simulate the rainfall conditions responsible for slope failures, and the frequency-size distribution of the landslides. We concentrate on simplified, conceptual models, and we exclude the use of physically-based geo-mechanical models such as those proposed by Katz and Aharonov (2006) or by Stark and Guzzetti (2009) to describe the frequency-size statistics of slope failures, or other physically-based spatially distributed slope stability models (e.g., SHALSTAB [Montgomery and Dietrich, 1994], Dietrich and Montgomery [1998], SINMAP [Pack et al., 1998], SHETRAN [Burton and Bathurst, 1998], STARWARS [Malet et al., 2005]), GEOtop-FS [Rigon et al., 2006] Simoni et al., 2008), and CHLT (von Ruette et al., 2013).

Investigators have attempted to simulate the self-similar scaling behaviour of landslide size using Cellular Automata (CA) models (see e.g., Hergarten and Neugebauer, 1998, 2000; Hergarten, 2000, 2002; Piegari et al., 2006a,b, 2009). The interest in the use of CA models to investigate landslide sizes is motivated largely by the analogy between landslides in a landscape and avalanches in the “sandpile” model, the first theoretical and practical realization of a Self-Organized Critical (SOC) system (Bak et al., 1987, 1988). In the sandpile model, the meta-stable condition is controlled by a critical slope, which gives rise to relaxation of the system i.e., movements of single or multiple grains between cells that result in an avalanche-like behaviour. SOC systems
are implemented numerically in a number of variants, choosing different dynamical variables or combination of variables to simulate the interactions between the slope and its time-dependent weakening (Hergarten, 2000). Typically, the critical conditions are controlled by conservative or dissipative relaxation rules and by the boundary conditions, leading to an SOC behaviour. When applied to the investigation of the statistics of landslide sizes, a limitation of CA models consists in the fact that the exponents controlling the scaling of the distributions obtained through the CA models are significantly smaller (e.g., Hergarten 2000, 2002) than the corresponding exponents obtained modeling empirical data taken from landslide inventory maps (e.g., Pelletier et al., 1997; Stark and Hovius, 2001; Malamud et al., 2004; Van Den Eeckhaut et al., 2007). The frequency distributions obtained from CA models are also very sensitive to the rules used to set up and run the models, and to the initial and boundary conditions (Piegari et al., 2006a, b; 2009; Guzzetti et al., 2002) hypothesized that an inverse cascade model could explain the power-law behavior of natural landslides and of SOC models of slope instability, but did not demonstrate a link between the scaling of the empirical and modeled distributions.

In a recent paper, Hergarten (2012) proposed a criticality-inspired numerical model to explain the frequency-size distribution of large rockfalls, and to estimate the size and frequency of the largest possible failures in a region. The model uses a DEM to calculate local terrain slope, and exploits random perturbations to mimic natural fractures that control the location and size of the rockfalls. Results obtained for the Alps revealed that the frequency distribution of the modelled failure volumes obeys a power-law with a scaling exponent in the range of the known empirical values (Brunetti et al., 2009a), and exhibits a distinct “rollover” for small size failures. Chen et al. (2011) proposed an alternative way for describing the scaling properties of landslide sizes exploiting non-extensive statistical mechanics, or Tsallis statistics (Tsallis, 1988, 1999, 2011), a formal extension of the Boltzmann-Gibbs statistics. This approach relies on the postulate that a system composed by two independent statistical systems has an entropy given by the entropies of the two subsystems plus a correction term dependent on a parameter that controls the degree of non-additivity. Despite criticisms (Lee et al., 2012), the approach proved capable of describing quantitatively the frequency-size distributions typical of empirical landslide datasets, including the scaling exponents and the “rollover” observed for small landslide sizes (Malamud et al., 2004). When applied to simulate the frequency-size statistics of landslides, the postulate of non-additivity of entropy implied by the Tsallis statistics is interpreted with the redistribution of the soil materials in different (larger) volumes when a landslide occurs, which increases the entropy in the final system composed of a different distribution of the initial sub-systems. The advantage of the approach is that the statistical distribution of the landslide size can be derived in an analytic way, starting from general principles (Chen et al., 2011).

As discussed before, our results indicate that a relatively simple, physically-based model for simulating the stability/instability conditions of natural slopes forced by rainfall, when applied to a sufficiently large area, is for reproducing well the frequency-area distribution of the natural landslides in the same area. This proves that the observed self-similar scaling behaviour of the landslide areas, and its deviation from the main trend observed for small landslides, are the results of physical characteristics of the landscape and of the slope instabilities in it.

Further, application of the physically-based model revealed the presence of both scaling properties of landslides i.e., of the intensity of the driving forces (the mean rainfall intensity and the rainfall duration responsible for the slope instabilities) and of the magnitude of the consequences (the relative proportion of landslides of different sizes). The result was obtained selecting reasonable values for the model parameters, without changing or optimizing them. This result indicates a functional link between rainfall and landslides, and opens to the possibility to quantify the link.

TRIGRS reproduced well the statistical distribution of landslide areas and the rainfall conditions that have resulted in landslides in our study area. This is not a trivial result, because the landslide scaling properties captured by the numerical model are not keyed in the equations governing the model. We maintain that the fact that the distribution of landslide size and the rainfall thresholds for landslide occurrence are reproduced well by the model is evidence that the model uses the correct dynamics and variables. Our results open to the possibility of establishing rainfall thresholds for landslide occur-
Table 1. Geotechnical properties for the soils in the lithological complexes cropping out in the UTRB (Fig. 1, Cardinali et al., 2001). $c$ is the soil cohesion, $\varphi$ is the soil internal friction angle, $\gamma_s$ is the wet soil unit weight, $D_0$ is the soil diffusivity, and $K_s$ is the soil saturated hydraulic conductivity. See Section 3 for details. The codes (a) to (e) match the corresponding color codes in Fig. 1 for the different lithological complexes.

| Unit | $c$ [kPa] | $\varphi$ [deg] | $\gamma_s$ [N m$^{-3}$] | $D_0$ [m$^2$ s$^{-1}$] | $K_s$ [m s$^{-1}$] |
|------|-----------|----------------|---------------------|-----------------|-----------------|
| a    | 2.5       | 10.0          | 15,000              | $4.7 \times 10^{-3}$ | 1.0 $\times 10^{-4}$ |
| b    | 3.0       | 15.0          | 15,000              | $4.7 \times 10^{-3}$ | 1.0 $\times 10^{-4}$ |
| c    | 50.0      | 25.0          | 15,000              | $8.3 \times 10^{-6}$ | 1.0 $\times 10^{-6}$ |
| d    | 50.0      | 30.0          | 15,000              | $8.3 \times 10^{-6}$ | 1.0 $\times 10^{-6}$ |
| e    | 75.0      | 35.0          | 22,000              | $8.3 \times 10^{-6}$ | 1.0 $\times 10^{-6}$ |

ference for individual slopes or groups of slopes, reducing the geographical uncertainty associated with empirical rainfall thresholds, which are most commonly defined for large to very large areas (Guzzetti et al., 2007, 2008; Peruccacci et al., 2012). A reduced geographical uncertainty of the thresholds may improve the performance of landslide warning systems based on rainfall thresholds. Further, the results open to the possibility of predicting the magnitude of landslide triggering meteorological events, and the impact of rainfall induced landslides on the landscape. Accurate information on the expected impact of landslides may be important for landscape evolution studies, and for improved landslide hazard and risk assessments.

7. Conclusions

We used the consolidated Transient Rainfall Infiltration and Grid-Based Regional Slope-Stability analysis code (TRIGRS, version 2.0; Baum et al., 2008) to investigate two scaling properties of landslides, namely: (i) the rainfall intensity – duration ($I$-$D$) conditions responsible for slope instability and landslide occurrence (Guzzetti et al., 2007, 2008), and (ii) the probability density of the area of rainfall induced landslides (Stark and Hovius, 2001; Malamud et al., 2004). Our results, obtained for a significantly large area in Central Italy where landslides are abundant and frequent (Cardinali et al., 2001, 2006; Guzzetti et al., 2008), indicate that the physically based model was capable of reproducing the two landslide scaling behaviors. More specifically, the numerical modeling revealed the followings:

- The scaling exponent of the power-law curves describing the mean rainfall intensity vs. rainfall duration conditions that produced slope instability in the studied (quasi) monolithological sub-basins, where unconsolidated and poorly consolidated sediments crop out was almost identical to the scaling exponent of empirical $I$-$D$ rainfall thresholds for possible landslide occurrence defined for Central Italy (Peruccacci et al., 2012), and for Italy (Brunetti et al., 2010). The finding is important because it reconciles the physically-based and the statistically-based approaches to the prediction of rainfall induced landslides (Crosta and Frattini, 2003; Aleotti, 2004; Guzzetti et al., 2007, 2008). This is relevant for landslide warning systems based on rainfall thresholds (Chleborad, 2003; Aleotti, 2004; Godt et al., 2006; Guzzetti et al., 2008; Brunetti et al., 2009b; Bach Kirschbaum et al., 2012).

- The probability density distribution of the area of the patches of grid cells predicted as unstable by the TRIGRS model (i.e., grid cells with $F_s < 1.0$) in the study area was similar to the frequency density of the area of natural event landslides in the UTRB (Cardinali et al., 2001; Guzzetti et al., 2008), and to the general probability density distribution for event landslides proposed by Malamud et al. (2004), for areas $A_L > 2 \times 10^{-2}$ km$^2$. For smaller areas, the probability density of the patches of unstable cells deviates from the power law trend. This is similar to the “rollover” observed in statistically complete populations of event landslides (Malamud et al., 2004). The finding is relevant because it provides a physical basis to the
statistics of landslide areas in a large and geomorphologically complex region.

We consider the results of this work as a starting point for investigating the underlying mechanisms giving rise to the scaling properties of landslide phenomena.

Acknowledgments

We thank R.L. Baum and J.W. Godt (USGS) for valuable discussion. We are grateful to the Editor (T. Oguchi), S. Hergarten and an anonymous reviewer for their constructive comments. MA was supported by grants provided by the Regione Umbria, under contract POR-FESR Umbria 2007-2013, asse ii, attività a1, azione 5, and by the Dipartimento della Protezione Civile, Italy.

References

Aleotti, P., 2004. A warning system for rainfall-induced shallow failures. Engineering Geology 7, 247-265.

Bach Kirschbaum, D., Adler, R.F., Hong, Y., Kumar, S., Peters-Lidad, C., Lerner-Lam, A., 2012. Advances in landslide nowcasting: evaluation of a global and regional modeling approach. Environmental Earth Sciences 66, 1683-1696.

Bak, P., Tang, C., Wiesenfeld, K., 1987. Self-organized criticality: an explanation of 1/f noise. Physical Review Letters 59, 381-384.

Bak, P., Tang, C., Wiesenfeld, K., 1988. Self-organized criticality. Physical Review A 38, 364-374.

Baum, R., Savage, W., Godt, J.W., 2008. TRIGRS - a FORTRAN program for transient rainfall infiltration and grid-based regional slope-stability analysis, version 2.0. U.S. Geological Survey Open-File Report 2008-1159, 75p.

Brunetti, M.T., Guzzetti, F., Rossi, M., 2009a. Probability distributions of landslide volumes. Nonlinear Processes in Geophysics 16, 179-188.

Brunetti, M.T., Peruccacci, S., Rossi, M., Guzzetti, F., Reichenbach, P., Ardizzone, F., Cardinalli, M., Mondini, A.C., Salvati P., Tonelli, G., Valigi, D., Luciani S., 2009b. A prototype system to forecast rainfall induced landslides in Italy. In: Proceedings of The First Italian Workshop on Landslides, Naples, 8-10 June 2009, Vol. 1, 157-161.

Brunetti, M.T., Peruccacci, S., Rossi, M., Luciani, S., Valigi, D., Guzzetti, F., 2010. Rainfall thresholds for the possible occurrence of landslides in Italy. Natural Hazards and Earth System Sciences 10, 447-458.

Burton, A., Bathurst, J., 1998. Physically based modelling of shallow landslide sediment yield at a catchment scale. Environmental Geology 35(2-3), 49-99.

Caine, N., 1980. The rainfall intensity-duration control of shallow landslides and debris flow. Geografiska Annaler A62, 23-27.

Cancelli, A., Nova, R., 1985. Landslides in soil debris cover triggered by rainstorms in Valtellina (Central Alps, Italy). Proc. 4th International Conference and Field Workshop on Landslides, Tokyo, pp. 267-272.

Cannon, S. H., Ellen, S., 1985. Rainfall conditions for abundant debris avalanches, San Francisco Bay region, California. California Geology, 267-272.

Cardinali, M., Ardizzone, F., Galli, M., Guzzetti, F., Reichenbach, P., 2000. Landslides triggered by rapid snow melting: the December 1996-January 1997 event in Central Italy. Proceedings of the EGS Plinius Conference on Mediterranean Storms, Maratea, Italy, pp. 439-448.

Cardinali, M., Antonini, G., Reichenbach, P., Guzzetti, F., 2001. Photo-geological and landslide inventory map for the Upper Tiber River basin. CNR, Gruppo Nazionale per la Difesa dalle Catastrofi Idrogeologiche, Publication n. 2154, scale 1:100,000.

Cardinali, M., Galli, M., Guzzetti, F., Ardizzone, F., Reichenbach, P., Bartoocci, P., 2006. Rainfall induced landslides in December 2004 in south-western Umbria, central Italy: types, extent, damage and risk assessment. Natural Hazards and Earth System Sciences 6, 237-260.

Carrara, A., Cardinali, M., Detti, R., Guzzetti, F., Pasqui, V., Reichenbach, P., 1991. GIS techniques and statistical models in evaluating landslide hazard. Earth Surface Processes and Landforms 16, 427-445.

Chen, C.-C., Telesca, L., Lee, C.-T., Sun, Y.-S., 2011. Statistical physics of landslides: new paradigm. EPL 95, 49001.

Chen, C.-C., Telesca, L., Lee, C.-T., Sun, Y.-S., 2012. Reply to comment by L.P. Li et al. EPL 100, 29002.

Chleborad, A.F., 2003. Preliminary evaluation of a precipitation threshold for anticipating the occurrence of landslides in the Seattle, Washington, Area. US Geological Survey Open-File Report 03-463.

Crosta, G.B., Frattini, P., 2003. Distributed modelling of shallow landslides triggered by intense rainfall. Natural Hazards and Earth System Sciences 3, 407-422.

Dietrich, W.E., Montgomery, D.R. 1998. SHALSTAR: a digital terrain model for mapping shallow landslide potential. NCASI (National Council of the Paper Industry for Air and Stream Improvement) Technical Report.

Endo, T., 1970. Probable distribution of the amount of rainfall causing landslides. Annual report, Hokkaido Branch, Govern, Forest Experiment Station, Sapporo, pp. 123-136.

Godt, J.W., Baum, R.L., Chleborad A.F., 2006. Rainfall characteristics for shallow landsliding in Seattle, Washington, USA. Earth Surface Processes and Landforms 31, 97-110.

Godt, J.W., McKenna, P., 2008. Numerical modeling of rainfall conditions for shallow landsliding in Seattle, Washington. Reviews in Engineering Geology 20, 121-136.

Godt, J.W., Schulz, W.H., Baum, R.L., Savage, W.Z., 2008b. Modeling rainfall conditions for shallow landsliding in Seattle, Washington. Reviews in Engineering Geology 20, 137-152.

Govi, M., Sorzana, P.F., 1980. Landslide susceptibility as function of critical rainfall amount in Piedmont basin (Northwestern Italy). Studia Geomorphologica Carpatho-Balcanica 14, 43-60.

Guzzetti, F., Ardizzone, F., Cardinali, M., Galli, M., Reichenbach, P., Rossi, M., 2008b. Distribution of landslides in the Upper Tiber River basin, central Italy. Geomorphology 96, 105-122.

Guzzetti, F., Ardizzone, F., Cardinali, M., Rossi, M., Valigi, D., 2009. Landslide volumes and landslide mobilization rates in Umbria, central Italy. Earth and Planetary Science Letters 279, 222-229.

Guzzetti, F., Carrara, A., Cardinali, M., Reichenbach, P., 1999. Landslide hazard evaluation: a review of current
techniques and their application in a multi-scale study, Central Italy. Geomorphology 31, 181-216.

Guzzetti, F., Reichenbach, P., Malamud, B.D., Turcotte, D.L., 2002. Power-law correlations of landslide areas in Central Italy. Earth and Planetary Science Letters 195, 169-183.

Guzzetti, F., Peruccacci, S., Rossi, M., Stark, C.P., 2007. Rainfall thresholds for the initiation of landslides in central and southern Europe. Meteorology and Atmospheric Physics 98, 239-267.

Guzzetti, F., Peruccacci, S., Rossi, M., Stark, C.P., 2008a. The rainfall intensity-duration control of shallow landslides and debris flows: an update. Landslides 5, 3-17.

Hergarten, S., 2000. Landslides, sandpiles and self-organized criticality. Natural Hazards and Earth System Sciences 3, 505-514.

Hergarten, S., 2002. Self-Organized Criticality in Earth Systems Springer-Verlag, Berlin, pp. 275.

Hergarten, S., 2012. Topography-based modeling of large rockfalls and application to hazard assessment. Geophysical Research Letters 39, L13402, doi:10.1029/2012GL052909.

Hergarten, S., Neugebauer, H.J., 1998. Self-organized criticality in a landslide model. Geophysical Research Letters 25, 801-804.

Hergarten, S., Neugebauer, H.J., 2000. Self-organized criticality in two-variable models. Physical Review E 61, 2382-2385.

Kata, O., Aharonov, E., 2006. Landslides in vibrating sand box: what controls types of slope failure and frequency magnitude relations? Earth and Planetary Science Letters 247, 280-294.

Klar, A., Aharonov, E., Kalderon-Asael, B., Kata, O., 2011. Analytical and observational relations between landslide volume and surface area. Journal of Geophysical Research 116(F2), F02001, doi: 10.1029/2009JF001604.

Innes, J.L., 1983. Debris flows. Progress in Physical Geography 7, 469-501.

Iverson, R.M., 2000. Landslide triggering by rain infiltration. Water Resources Research 36, 1897-1910.

Larsen, I.J., Montgomery, D.R., Korup, O. 2010. Landslide erosion controlled by hillslope material. Nature Geoscience 3, 247-251.

Lee, L.P., Lan, H.X., Wu, Y.M., 2012. Comment on ‘Statistical physics of landslides: new paradigm’ by Chen C.-C. et al. EPL 100, 29001.

Malamud, B.D., Turcotte, D.L., Guzzetti, F., Reichenbach, P., 2004. Landslide inventories and their statistical properties. Earth Surface Processes and Landforms 29, 687-711, doi:10.1002/esp.1064.

Malet, J.-P., Van Asch, T.W., Van Beek, R., Maquaire, O., 2005. Forecasting the behaviour of complex landslides with a spatially distributed hydrological model. Natural Hazards and Earth System Science 5, 71-85.

Montgomery, D.R., Dietrich, W.E., 1994. A Physically-Based Model for the Topographic Control on Shallow Landsliding. Water Resources Research 30, 1153-1171.

Moser, M., Hohensinn, F., 1983. Geotechnical aspects of soil slips in Alpine regions. Engineering Geology 19, 285-211.

Newman, M.E.J., 2005. Power laws, Pareto distributions and Zipf’s law. Contemporary Physics 46, 325-351.

Pack, R., Tarboton, D., Goodwin, C., 1998. The SINMAP approach to terrain stability mapping. In: 8th Congress of the International Association of Engineering Geology, Vancouver, pp. 21

Pelletier, J.D., Malamud, B.D., Blodgett, T., Turcotte, D.L. 1997. Scale-invariance of soil moisture variability and its implications for the frequency-size distribution of landslides. Engineering Geology 5, 255-268.

Peruccacci, S., Brunetti, M.T., Luciani, S., Vennari, C., Guzzetti, F., 2012. Lithological and seasonal control on rainfall thresholds for the possible initiation of landslides in central Italy. Geomorphology 139-140, 79-90.

Piegari, E., Cataudella, V., Di Maio, R., Milano, L., Nicodemi, M., 2006a. Finite driving rate and anisotropy effects in landslide modeling. Physical Review E 73, 026123-026129.

Piegari, E., Cataudella, V., Di Maio, R., Milano, L., Nicodemi, M., 2006b. A cellular automaton for the factor of safety field in landslides modelling. Geophysical Research Letters 33, L01403, doi:10.1029/2005GL024759.

Piegari, E., Di Maio, R., Milano, L., 2009. Characteristic scales in landslide modelling. Nonlinear Processes in Geophysics 16, 515-523.

Raia, S., Alvioli, M., Rossi, M., Baum, R.L., Godt, J.W., Guzzetti, F., 2013. Improving predictive power of physically based rainfall induced shallow landslides models: a probabilistic approach. Geoscientific Model Development Discussion 6, 1367-1426.

Richards, L.A., 1931. Capillary conduction of liquids in porous media. Physics 1, 318-333.

Rigon, R., Bertoldi, G., Over, T., 2006. GEOtop: A distributed hydrological model with coupled water and energy budgets. Journal of Hydrometeorology 7, 371-388.

Simoni, S., Zanotti, F., Bertoldi, G., Rigon, R., 2008. Modelling the probability of occurrence of shallow landslides and channelized debris flows using GEOtop-FS. Hydrological Processes 22, 542-545.

Stark, C.P., Guzzetti, F., 2009. Landslide rupture and the probability distribution of mobilised debris volumes. Journal Geophysical Research 114, F00A02, doi: 10.1029/2008JF001008.

Stark, C.P., Hovius, N., 2001. The characterization of landslide size distributions. Geophysical Research Letters 28, 1091-1094.

Tarquini, S., Isola, I., Favalli, M., Mazzarini, F., Bisson, M., Pareschi, M.T., Boschi, E., 2007. TINITALY/01: a new Triangular Irregular Network of Italy. Annales Geophysicae 50, 407-425.

Tarquini, S., Vincè, S., Favalli, M., Doumaaz, F., Fornaciari, A., Namipieri, L., 2012. Release of a 10-m-resolution DEM for the Italian territory: Comparison with global coverage DEMs and anaglyph-mode exploration via the web. Computers and Geosciences 38, 168-170.

Tsallis, C., 1988. Possible Generalization of Boltzmann–Gibbs Statistics. J. Statist. Phys. 52, 479-487.

Tsallis, C., 1999. Nonextensive statistics: Theoretical, experimental and computational evidences and connections. Braz. J. Phys. 29, 1-35.

Tsallis, C., 2011. Nonextensive statistical mechanics: Applications to high energy physics. EPJ Web Conf. 13, 05001, doi:10.1051/epjconf/20111305001.

Turcotte, D.L., Malamud, B.D., Guzzetti, F., Reichenbach, P., 2002. Self-organization, the cascade model, and natural hazards. Proceedings of the National Academy of Sciences 99, Supp. 1, 2530-2537, doi:10.1073/pnas.012582199.
hilly region. Earth and Planetary Science Letters 256, 588-603.

Von Ruette, J., Lehmann, P., Or, D., 2013. Rainfall-triggered shallow landslides at catchment scale – threshold mechanics-based modeling for abruptness and localization. Water Resources Research 49, 1-20.

Wieczorek, G.F., 1987. Effect of rainfall intensity and duration on debris flows in central Santa Cruz Mountains, California. In: Costa, J.E., Wieczorek, G.F. (eds) Reviews in Engineering Geology 7, Geological Society of America, Boulder, Colorado, pp. 93-104.