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Spatial patterns of landslide dimension: A tool for magnitude mapping

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ABSTRACT

The magnitude of mass movements, which may be expressed by their dimension in terms of area or volume, is an important component of intensity together with velocity. In the case of slow-moving deep-seated landslides, the expected magnitude is the prevalent parameter for defining intensity when assessed as a spatially distributed variable in a given area. In particular, the frequency–volume statistics of past landslides may be used to understand and predict the magnitude of new landslides and reactivations. In this paper we study the spatial properties of volume frequency distributions in the Arno river basin (Central Italy, about 9100 km^2). The overall landslide inventory taken into account (around 27,500 events) shows a power-law scaling of volumes for values greater than a cutoff value of about 2×10^4 m^3. We explore the variability of the power-law exponent in the geographic space by setting up local subsets of the inventory based on neighbourhoods with radii between 5 and 50 km. We found that the power-law exponent α varies according to geographic position and that the exponent itself can be treated as a random space variable with autocorrelation properties both at local and regional scale. We use this finding to devise a simple method to map the magnitude frequency distribution in space and to create maps of exceeding probability of landslide volume for risk analysis. We also study the causes of spatial variation of α by analysing the dependence of power-law properties on geological and geomorphological factors, and we find that structural settings and valley density exert a strong influence on mass movement dimensions.

1. Introduction

A number of natural hazards are known to occur as stochastic processes whose magnitude frequency follows a non-normal distribution. Often, such a distribution assumes a form compatible with a power-law, an exponential or an extreme-value distribution. Widely known examples are e.g. the distribution of earthquakes, snow avalanches, landslides, volcanic explosions, epidemic spreading, meteorite impacts, forest fires and floods (Malamud and Turcotte, 1999; Malamud and Turcotte, 2006; Turcotte and Malamud, 2004; Clauset and Shalizi, 2009). The exponential decrease of frequency with increasing magnitude seems to be connected to patterns of self-organized criticality in complex systems as well as to the tendency towards optimal energy expenditure configurations (Bak et al., 1988; Rodriguez-Iturbe and Rinaldo, 1997), ubiquitous in natural systems. Sediment transfer pulses, including mass movements, do not seem to deviate from such a behaviour, even though the power-law form of magnitude–frequency distribution (MFD) is regarded as being mainly applicable to medium and large size occurrences.

Several studies address the statistical properties of MFDs making use of specific databases of landslides collected in several parts of the world (Guzzetti et al., 2002; van den Eeckhaut et al., 2007; Guzzetti et al., 2009; Trigila et al., 2010). In most cases such datasets constitute the sum of occurrences over large time spans and are thus called “historical inventories”. In other cases, conversely, the properties of landslide ensembles triggered by a unique meteorological or seismic event are studied (Larsen and Torres-Sanchez, 1998; Dai and Lee, 2001). In the majority of the published material, the authors find a portion of the area (or volume) distribution (usually the higher tail) to follow a single or double power-law, expressed, according to the different cases, as a Gamma, Double Gamma, 3-parameters Gamma, Pareto, Generalized Pareto or Double Pareto distribution with a lower cutoff M_{min}. According to some views (see e.g. Stark and Hovius, 2001; Guthrie and Evans, 2004) the left part of the MFD (i.e. magnitude $m < M_{min}$) may be modelled as a positive-exponent power-low, but suffers from deviations and noise due to possible undersampling effects (Guzzetti et al., 2002; Malamud et al., 2004). Small occurrences are easily missed by field surveys or rendered invisible by vegetation regrowth, human activities and weathering processes on hillslopes (Guzzetti et al. 2002). This is especially true in historical inventories, where mass movements of different age are mapped together thus producing a statistical oversampling of the medium-large size events compared to smaller ones (Malamud et al., 2004).

Malamud et al. (2004) and Guzzetti et al. (2002) hypothesized that the left part of the distribution can be modelled by a different form of the same relationship, such as e.g. a power-law with different parameters and, possibly, a positive exponent. This inverse trend would be

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explained by the prevalence of cohesive over frictional forces in the soil at small scales (Malamud et al., 2004; Van den Eeckhaut et al., 2007; Stark and Guzzetti, 2009). In such a case, the authors model the MFD of mass movements by supposing the presence of a double power-law distribution with different parameters (both with negative α_1 and α_2 exponents) across a characteristic cutoff scale $M_{\min}$ whilst, for dimensions smaller than a second cutoff $M^*_{\min}$, by using a positive power-law ($\beta > 0$), in which the increasing influence of cohesion forces for smaller scales limits the number of mass movements that can develop.

The ubiquitous tendency of landslide hazard to occur according to this power-law scaling offers important insights on the underlying mechanisms for mass movement triggering and evolution, making it possible to predict the overall impact of climate changes in the near future trends for landslide-related risks (Convertino et al., 2013). Another important aspect of using known MFDs for mass movements is that they may be used as a robust basis for the forecasting of the magnitude (and thus of the intensity as defined by Fell et al., 2008 and Hungr, 1997), a fundamental step in natural hazard and risk prediction. In fact, for large areas, where slope-scale single-landslide intensity estimation is not possible, a statistical approach may often be the best solution, based on the MFD of area or volume. However, to be able to actually implement this approach, more quantitative information on the spatial variability of the MFDs of landslides in the geographical space is needed, a topic almost totally lacking in the relevant literature. In fact, in almost all cases (see e.g. Van den Eeckhaut et al., 2007 for a comprehensive listing) an entire landslide inventory is taken as a whole to produce a single MFD to be modelled by a given power-law scaling. This has been done for study areas ranging from 10^1 to 10^4 km^2 where very different geophysical and environmental conditions leading to sediment loss may coexist. Therefore, some important questions are still unanswered so far, such as: how well do such general MFDs depict local patterns of landslide magnitude? What happens to a scaling relationship when progressively moving from an area to an adjacent one with different geophysical settings? Can the power-law exponents be treated as random space variables with autocorrelation properties? In this paper we attempt to give a contribution in this direction. In particular, we study the spatial characteristics of the power-law scaling in a large and well-studied landslide volume frequency distribution (Arno river basin, central Italy, counting >27,000 events over about 9100 km^2) by computing a spatially variable set of MFD parameters as random space variables. We determine the spatial autocorrelation properties of such variables and propose a new simple tool to map the magnitude exceeding probabilities as a proxy for landslide intensity or potential destructive power. Then, we analyse the relationships between MFD parameters and environmental settings to explore the possible causes of this spatial variability.

2. Materials and methods

2.1. Working hypothesis

The starting hypothesis at the basis of this work is that the MFD of area and volume of mapped landslides in a given region shows a power-law scaling, at least for medium and large sized occurrences, and it is not spatially constant but varies continuously in space. As a corollary, the overall MFD computed over the entire inventory is an average quantity, which is locally stationary only for very homogeneous environmental conditions. We will, henceforth, refer to such environmental conditions as Landslide Conditioning Variables (LCVs), which may include geology, geomorphology, local climate, vegetation, land use, geomorphometry and hydrology. The hypothesis is supported by numerous studies as summarised by Van den Eeckhaut et al. (2007) for all types of landslide collections, either event-related or historical, made up by single or mixed typologies (such as e.g. shallow or deep seated slides, falls, and debris flows), related to large or small areas. We will also test this hypothesis experimentally over the test area. The characteristics of the inventory in the study area (Catani et al., 2005) are well suited to this approach because the majority of mapped landslides has slow rates of movement according to Fell et al. (2008) (rotational earth slides and solifluctions) which implies that their kinetic energy is essentially linked to dimensions, hence volume. In particular, earth slides constitute 77.4% of the total number and, furthermore, they consistently show higher-than-average volumes (Table 1) so that the right side of the empirical MFD is almost only occupied by a single typology.

A derivation of the main hypothesis is that a suitable subsetting of the entire inventory would produce sub-inventories equally representative in statistical terms that can be separately studied to understand possible linkages to the local characteristics of the sub-area. Therefore, the power-law fitting of the subsets would present MFD parameters locally valid that could then be compared to each other and, upon verification of continuity, treated as random space functions with definite autocorrelation properties. The second hypothesis is that, once the first one is verified and the local MFD parameters for the distribution chosen are autocorrelated in space, we can use geostatistical tools to study, interpolate and map the scaling properties of landslides thus producing magnitude estimation maps. In the study area, Catani et al. (2005) and Convertino et al. (2013) have previously computed area frequency statistics for the landslide inventory described in the area section. The authors found that a power-law scaling is a valid model for explaining the frequency distribution of mapped landslide areas for values greater than a cutoff of about 10^4 m^2 (1 ha). In particular, they adopted a power-law type distribution in the continuous form:

$$p(a)da = \Pr(a \le A \le a + da) = Ca^{-\alpha}da \tag{1}$$

where a is the landslide area and C is a normalization constant. For very small values of a this probability density diverges so that there must be a limiting or cutoff value to the power-law behaviour that can be denoted by $a_{\min}$. In landslide systems, for both areas and volumes, the exponent α is always greater than unity. In this case, for landslide volume, we can find that:

$$p(v) = \frac{\alpha - 1}{v_{\min}} \left(\frac{v}{v_{\min}}\right)^{-\alpha} \tag{2}$$

where v is volume and $v_{\min}$ is the lower cutoff volume for which the power-law scaling holds. In the cumulative form:

$$P(v) = \int_v^\infty p(v\prime)dv\prime = \left(\frac{v}{v_{\min}}\right)^{-\alpha+1} \tag{3}$$

In particular, if we limit the population to the tail of the empirical distribution ($v \ge v_{\min}$) it must be:

$$P(\ge v_{\min}) = \int_{v_{\min}}^\infty p(v)dv = 1 \tag{4}$$

So that the exceedance probability for a given volume V ($\ge v_{\min}$) can be obtained by integration of the previous equation in a given interval

Table 1
Landslide typology in the Arno river basin according to the latest available inventory. Only the three typologies considered in the study are reported.

Landslide typology	Frequency (%)	Total area (m^2)	Average area (m^2)	Average volume (m^3)
Earthslides	77.4	5.9×10^8	2.9×10^4	1.7×10^5
Flows	4.7	0.2×10^8	1.5×10^4	1.5×10^4
Solifluctions	17.9	1.9×10^8	3.7×10^4	3.7×10^4