Variation in landslide-affected area under the control of ground motion and topography

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A B S T R A C T

Earthquake-Induced Landslide (EQIL) inventories are the key to improve our understanding of the relationship between landslides and their causes, including environmental settings and ground shaking parameters. However, creating a high-quality inventory can take years. As a result, reliable information on landslide-affected areas typically remains unknown until a complete inventory is compiled. In this paper, we analyze 20 digital EQIL inventories of varying quality and completeness that represent a range of geologic and climatic settings around the globe. We examine the landslide-affected area with respect to Peak Ground Acceleration (PGA) and topography, and develop a statistical model to estimate the landslide distribution without prior knowledge of the actual landslide triggering locations.

For each EQIL inventory, we initially calculated the PGA contours where 90% of the total landslide population fell into. Subsequently, we define landslide susceptible areas as those pixels with slope > 5° and local relief > 100 m. The latter is used to normalize the total landslide-affected area and to compute correlations with local PGA values. We find that the landslide-affected area may be predicted from PGA values only, with the mean error ranging from −20.0% to +7.1%, with respect to total landslide population. This relationship can be used immediately following a disaster to identify areas of greatest landslide impact and to prioritize emergency response actions, even without a landslide inventory.

1. Introduction

The estimation of Earthquake-Induced Landslide (EQIL) hazard is an important component of risk mitigation in seismically active areas, which aims at reducing casualties and economic losses (Wasowski et al., 2011). In addition to predicting the location and the temporal probability of EQIL, other parameters such as the intensity, volume and area (or landslide-affected area) are also significant in EQIL studies (Wasowski et al., 2011). In this contribution, we focus on identifying the spatial boundaries where EQILs are likely to be triggered, which we refer to as landslide-affected areas. This concept should be distinguished from the total landslide area, which is the sum of all landslide surface areas. An estimate of landslide-affected area is essential in near real-time hazard assessment to guide disaster responses. Notably, this is time-critical, before landslide inventory maps are compiled, which typically take months or years. Predicting landslide-affected areas can inform the spatial extent of landslide mapping and provide estimates of inventory completeness.

Several globally applicable models provide probabilistic estimates of landslide locations without an explicit spatial limit (e.g. Nowicki et al., 2018; Tanyaş et al., 2019a). Others provide quantitative assessments of total volume and total area without providing an estimate of landslide locations (Keefer, 1984; Marc et al., 2016a; Rodriguez et al., 1999). However, a globally applicable model to predict the spatial limits of the landslide-affected areas does not exist. One of the few available methods was initially proposed by Keefer (1984) and subsequently updated by Rodriguez et al. (1999) based on the relation between earthquake magnitude and the maximum landslide distance, either from the epicenter or from the rupture zone. However, Jibson and Harp (2012) found that the landslide distance limits proposed by Keefer (1984) differ between plate-boundary earthquakes and intraplate earthquakes, where seismic-wave attenuation is generally much lower. Moreover, the proposed relations can only provide a one-dimensional measure, which returns the distance from the epicenter or rupture zone to the furthest individual landslide. Therefore, this information is not sufficient to clearly define the geometry of landslide-affected areas.

An alternative to this one-dimensional measure uses the peak ground acceleration (PGA) contour, which has been shown to correlate with landslide density (e.g. Meunier et al., 2007). This was first...
investigated by Wilson and Keefer (1985). Based on the analysis of 40 earthquakes from Keefer (1984), they proposed a minimum threshold of 0.05 g to define the limits of the landslide-affected area. However, Tanyaş et al. (2017) noted that only a small part of the 40 earthquakes in Wilson and Keefer’s (1985) study have a corresponding landslide inventory. And for many, information on landslide impact was limited, gathered from partial information (Keefer and Tannaci, 1981). This highlights the need for further work, to test the proposed threshold with more EQIL inventories.

Studies have also investigated the minimum PGA thresholds which cover all triggered landslides for individual EQIL inventories. For instance, the boundary corresponding to the 0.01 g PGA isoline included the vast majority of landslides triggered during the 1980 Irpinia earthquake (Del Gaudio and Wasowski, 2004). Furthermore, the 0.02–0.04 g isolines were recognized to have a similar role for the Mineral, Virginia earthquake (Jibson and Harp, 2012). More recently, Jibson and Harp (2016) investigated the best PGA boundary which encompassed every landslide up to very small mass movements (volume < 1 m³). For four inventories obtained through field mapping, all landslides occurred within isolines ranging from 0.02–0.08 g. For two additional inventories, generated from high quality orthophotos and thus including even very small landslides, the PGA range 0.05–0.11 g corresponded to the outermost limit.

Jibson and Harp (2016) stated that the proposed outermost limits of triggered landslides can only be valid where susceptible slopes characterize the entirety of the landscape. Critically, the actual area affected by landslides depends on the local topographic, lithologic, climatic and land cover settings. These conditions are different across each earthquake site, and vary with time. The interaction between them and the ground shaking controls the specific landslide distribution. Thus, for some environments, the outermost PGA boundary could be considerably larger than the actual landslide-affected area, where susceptible slopes are limited in space.

Marc et al. (2017) proposed an alternative analytical expression to calculate the landslide-affected area by gathering geophysical information and estimates of the landslide distribution for 83 earthquakes. However, they noted that only 10 out of the 83 earthquakes were associated to a detailed EQIL inventory. The remaining 73 only provided rough estimates of the landslide-affected areas. The expression proposed by Marc and co-authors is based on scaling laws relating

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### Table 1

<table>
<thead>
<tr>
<th>ID</th>
<th>Location</th>
<th>Date</th>
<th>Earthquake magnitude</th>
<th>Quality of shakemap (Grade)</th>
<th>Reference study</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Guatemala</td>
<td>1976-02-04</td>
<td>7.5 (Mw)</td>
<td>A</td>
<td>Harp et al., 1981</td>
</tr>
<tr>
<td>2</td>
<td>Friuli (Italy)</td>
<td>1976-05-06</td>
<td>6.5 (Ms)</td>
<td>A</td>
<td>Govi, 1977</td>
</tr>
<tr>
<td>3</td>
<td>Cooinga (USA)</td>
<td>1983-05-02</td>
<td>6.7 (Mwce)</td>
<td>A</td>
<td>Harp and Keefer, 1990</td>
</tr>
<tr>
<td>4</td>
<td>San Salvador (El Salvador)</td>
<td>1986-10-10</td>
<td>5.7 (Mw)</td>
<td>C</td>
<td>Ryner, 1987</td>
</tr>
<tr>
<td>5</td>
<td>Limon (Costa Rica)</td>
<td>1991-04-22</td>
<td>7.6 (Mw)</td>
<td>B</td>
<td>Marc et al., 2016b</td>
</tr>
<tr>
<td>6</td>
<td>Northridge (USA)</td>
<td>1994-01-17</td>
<td>6.7 (Mw)</td>
<td>A</td>
<td>Harp and Jibson, 1995</td>
</tr>
<tr>
<td>7</td>
<td>Hyogo-ken Nanbu (Japan)</td>
<td>1995-01-16</td>
<td>6.9 (Mw)</td>
<td>A</td>
<td>Uchida et al., 2004</td>
</tr>
<tr>
<td>8</td>
<td>Chi-chi (Taiwan)</td>
<td>1999-09-20</td>
<td>7.7 (Mw)</td>
<td>A</td>
<td>Liao and Lee, 2000</td>
</tr>
<tr>
<td>9</td>
<td>Denali Alaska</td>
<td>2002-11-03</td>
<td>7.9 (Mw)</td>
<td>A</td>
<td>Gorum et al., 2014</td>
</tr>
<tr>
<td>10</td>
<td>Kashmir (India-Pakistan)</td>
<td>2005-10-08</td>
<td>7.6 (Mw)</td>
<td>A</td>
<td>Marc et al., 2016b</td>
</tr>
<tr>
<td>11</td>
<td>Wenchuan (China)</td>
<td>2008-05-12</td>
<td>7.9 (Mw)</td>
<td>A</td>
<td>Xu et al., 2014b</td>
</tr>
<tr>
<td>12</td>
<td>Iwate-Miyagi Nairiku (Japan)</td>
<td>2008-06-13</td>
<td>6.9 (Mw)</td>
<td>A</td>
<td>Yagi et al., 2009</td>
</tr>
<tr>
<td>13</td>
<td>Haiti</td>
<td>2010-01-12</td>
<td>7.0 (Mw)</td>
<td>A</td>
<td>Harp et al., 2016</td>
</tr>
<tr>
<td>14</td>
<td>Sierra Cacapah (Mexico)</td>
<td>2010-04-04</td>
<td>7.2 (Mw)</td>
<td>A</td>
<td>Barlow et al., 2015</td>
</tr>
<tr>
<td>15</td>
<td>Yubu (China)</td>
<td>2010-04-13</td>
<td>6.9 (Mw)</td>
<td>C</td>
<td>Xu et al., 2013</td>
</tr>
<tr>
<td>16</td>
<td>Lushan (China)</td>
<td>2013-04-20</td>
<td>6.6 (Mw)</td>
<td>C</td>
<td>Xu et al., 2015</td>
</tr>
<tr>
<td>17</td>
<td>Minxian-Zhangxian (China)</td>
<td>2013-07-21</td>
<td>5.9 (Mw)</td>
<td>C</td>
<td>Xu et al., 2014a</td>
</tr>
<tr>
<td>18</td>
<td>Ludian (China)</td>
<td>2014-08-03</td>
<td>6.2 (Mw)</td>
<td>C</td>
<td>Tian et al., 2015</td>
</tr>
<tr>
<td>19</td>
<td>Gorkha (Nepal)</td>
<td>2015-04-25</td>
<td>7.8 (Mw)</td>
<td>C</td>
<td>Roback et al., 2017</td>
</tr>
<tr>
<td>20</td>
<td>Kumamoto (Japan)</td>
<td>2016-04-15</td>
<td>7.0 (Mw)</td>
<td>A</td>
<td>NIED, 2016</td>
</tr>
</tbody>
</table>
They noted that their model explains 56% of the variance in the dataset. For some earthquakes the model significantly overpredicts landslide-affected areas whereas, for others, it does not capture the along-strike asymmetry. They concluded that 0.15 g can be considered as a threshold value capturing the region where 95% of the total landslide area is concentrated.

Our study aims at further investigating the minimum PGA isoline to determine landslide-affected areas. In particular, we consider topographic features associated with landslide-susceptible areas and account for their asymmetry to better define the PGA boundary. From the USGS ScienceBase repository (Schmitt et al., 2017), we analyze 20 digital EQIL inventories situated in different geographic locations. We analyze these inventories in relation to the deterministic estimates of PGA generated by the U.S. Geological Survey (USGS) ShakeMap system (Garcia et al., 2012). Based on our results, we propose an update to the PGA-dependent approach of Jibson and Harp (2016).

2. Input data

We use the global EQIL inventory database collated and presented by Tanyaş et al. (2017). Sixty-four digital EQIL inventories are available for 46 earthquakes of varying quality and completeness levels. The term completeness here refers to whether an EQIL inventory includes all landslides above a specified size triggered by a specific earthquake (Guzzetti et al., 2012). However, evaluating the completeness of EQIL inventories is not a straightforward task because usually we do not always have sufficient information on how inventories are compiled (Tanyaş et al., 2017). In our study, we only consider inventories for which an adequate completeness can be determined, based on the information provided by the authors (Tanyaş et al., 2017) and the following criteria.

We include EQIL inventories for which we know that: (i) the entire landslide-affected area was systematically surveyed and mapped; (ii) the landslide-affected area was not hit by multiple earthquakes; (iii) the landslides were triggered by an earthquake whose epicenter with an
onshore epicenter; and (iv) the corresponding earthquake has moderate or high quality ShakeMaps (our reference data for ground motion) and does not suffer from high uncertainties according to the USGS quality grading system developed by Wald et al. (2008).

Where more than one EQIL inventory is available for a single earthquake, we include the inventory with the highest landslide count and which captures the largest affected area. As a result, we eliminate several inventories out of the initial 64 to increase the reliability of the analyses presented in this contribution.

In Table 1, we list all the inventories used in this study and the associated ShakeMap Grade.

### 3. Methodology

Deterministic estimates of PGA are generated by the U.S. Geological Survey (USGS) ShakeMap system (Garcia et al., 2012) in near real-time. The initial estimates of the ShakeMap system are based on simplified point source earthquake models and they are updated over time via data acquired on fault rupture geometry and mechanism. Therefore, especially for big earthquakes with large ruptures, the near real-time estimates may have considerable uncertainties before the data is refined, hours or days after the event (Allstadt et al., 2018). Despite this, the ShakeMap system still provides useful information regarding ground motion parameters in near real-time for many earthquakes. As a result, if one can find a relationship between PGA and landslide-affected area, it should be possible to provide valuable information to estimate the landslide-affected area just after the occurrence of an earthquake by using the PGA. According to this rationale, we sought a PGA contour that covers the large majority of landslides for various earthquake events. In this study, we use the USGS ShakeMaps in the form of rasterized PGA values.

We assume that the optimal boundary representative of the main landslide-affected area should correspond to the PGA isoline in which 90% of the total landslides are contained. Similar assumptions to identify the majority of landslide population are already available in the literature (e.g., Marc et al., 2017; Tanyaş et al., 2019b). The remaining 10% of the landslide population is usually triggered very far from the rupturing region and may be due to very local conditions rather than reflecting the general ground motion effect. In other words, we consider these 10% mass movements as outliers with respect to the general landslide spatial distribution (e.g., Hancox et al., 2002; Marc et al., 2017).

A clear example of how large the variation in PGA can be between the isoline containing 90% and 100% of the total landslide population is represented by the 2002 Denali earthquake inventory (Gorum et al., 2014). In our dataset, we find several situations where choosing the PGA containing the total population results in a much wider and non-informative area. Here we select the Denali earthquake as a striking example to support our assumption (Fig. 1). In this case, the vast majority of the landslide population clusters within a 15 km wide corridor extending along the surface rupture zone (Jibson et al., 2006). However, during the Denali earthquake a single landslide was triggered approximately 35 km from the rupture zone. By ignoring this outlier, a PGA contour of 0.2 g is sufficient to cover the entire landslide population. Otherwise, the 0.11 g contour is required. Hancox et al. (2002) already recognized this issue and introduced the term “main area affected by landslides” to refer to the core of the landslide population which does not include outliers. However, the authors introduce the term without investing additional efforts to define it in detail. We use a similar assumption and choose a 90% (out of the total landslide population) spatial bin to express the same concept. A justification for such a threshold will be provided at the end of Section 4.

Analysis in this study is structured as a six-step procedure presented in Fig. 2. In step 1, for each of the 20 inventories, we systematically calculate the percentage of landslides contained within a range of PGA contours. We start from the overall landslide distribution and extract the PGA contours that would contain from 10% to 100% of the total landslide population results in a much wider and non-informative area. Here we select the Denali earthquake as a striking example to support our assumption (Fig. 1). In this case, the vast majority of the landslide population clusters within a 15 km wide corridor extending along the surface rupture zone (Jibson et al., 2006). However, during the Denali earthquake a single landslide was triggered approximately 35 km from the rupture zone. By ignoring this outlier, a PGA contour of 0.2 g is sufficient to cover the entire landslide population. Otherwise, the 0.11 g contour is required. Hancox et al. (2002) already recognized this issue and introduced the term “main area affected by landslides” to refer to the core of the landslide population which does not include outliers. However, the authors introduce the term without investing additional efforts to define it in detail. We use a similar assumption and choose a 90% (out of the total landslide population) spatial bin to express the same concept. A justification for such a threshold will be provided at the end of Section 4.

For each of the 20 EQIL inventories we identify what we refer to as event-specific PGA isoline, which contains 90% of the population. In doing so, we also record the changes in areal extent from one spatial bin to another. In step 2, we examine the 20 event-specific PGA values. From these values, we compute the minimum out of the 20 event-specific PGAs as the most conservative measure; this corresponds to the largest areal extent. Throughout the paper, we consider this measure as the baseline to explain the landslide distribution across all the...
inventories and we refer to it as the common PGA contour. At this stage, its calculation is not related to topographic features. Notably, the common PGA contour may perfectly include the 90% of the population in few cases but it over estimates other 90% landslide bins across the 20 samples considered in the present study. However, to find a common measure or rule, we have to make an approximation at some point which we choose to be the worst-case scenario.

Once we select our common PGA contour, we focus on landslide-affected areas in step 3. The extent of these areas depends on ground motion as well as local topographic, lithologic, climatic and land cover conditions. These conditions are different for each landscape, and the interaction between them and the ground shaking influences the specific susceptibility and resulting landslide distribution pattern. To classify susceptible terrains across the 20 inventories we opt for a simple rule-based criterion based on Tanyaş et al. (2017). We define landslide-susceptible areas by eliminating flat regions via a combination of two morphometric parameters: slope and local relief.

Eliminating non-susceptible zones to landsliding by disregarding flat regions is a generally accepted approach (e.g., Jibson et al., 2000; Meunier et al., 2007; Marc et al., 2017). Specifically, Tanyaş et al. (2017) presented frequency distributions of topographic factors and associated intervals of unstable slopes and local reliefs for 66 EQIL inventories (Fig. 3). However, here we also eliminate the outliers shown in the aforementioned frequency distributions by defining omitting-
thresholds for the bins with the lowest reasonable frequency. Based on these descriptive statistics, we assume unstable areas when slope is larger than 5° and local relief is larger than 100 m. These choices exclude <2% of the entire landslide population by using both of the defined constraints (Fig. 3).

Up to this stage, we extracted the common PGA contour and the landslide-susceptible areas. In step 4, we compute the ratio between the two to obtain the areal coverage of landslide-susceptible areas (ACLSA) within the common PGA contour (Fig. 2). The ratio is meant to normalize the area exposed to ground motion by the actual terrain where landslide may occur under topographic control.

In step 5, we check if a significant asymmetry is observed in landslide-susceptible areas. We define as significant asymmetry those cases where a large portion of the area is flat and completely confined to one side of a given landscape which underwent seismic stress; and, where the remaining landslide-susceptible area extends towards the other side. In such cases, all landslides would be anisotropically distributed over space, which makes our global approach unsuitable to explain the local situation. In fact, asymmetry in landslide-susceptible areas can introduce noise in our approach. In other words, even if we normalize by the extent of the landslide-susceptible areas, the PGA contour required to encompass the 90% of landslides would exhibit a much larger areal extent than those associated with inventories occurring in topographically or near-topographically symmetric conditions. To overcome this problem, in each case, we divide the landslide-affected area into two approximately equal-sized halves passing a line through the highest ground motion location. For each half, we then calculate the ACLSA value. However, the line passing from the highest PGA value can assume infinite directions. Thus, we opt for the direction which maximizes the difference in percentage of susceptible terrain over the common PGA. In other words, the final symmetry line separates the given landscape by maximizing the difference in ACLSA between the two halves. In turn, we define asymmetry in landslide-susceptible areas when the difference between the two ACLSA values is equal or > 50%.

To prepare the dataset for the subsequent step, we proceed as follows. By using the symmetric line, if the difference in ACLSA between areas is lower than 50% (see Supplementary Material Fig. S1e), then we compute the ACLSA for the entire landscape. If the difference is equal or > 50%, then we construct our dataset assigning the largest ACLSA, disregarding the half where flat conditions dominate the landscape (see Supplementary Material Fig. S1d, where we disregard the region with a 1% ACLSA and we only pass to the subsequent analyses the region and associated ACLSA of 75%). As a result, this criterion is meant to ensure that landslide-susceptible areas are distributed isotropically or near-isotropically within the considered halves even for earthquakes where the landscape was not originally symmetric. And, it also ensures that anisotropic flat regions would not inflate the necessary area which encompasses the landslide population and therefore the associated PGA.

In step 6, we compare ACLSA computed in step 5 to the initial event-specific PGA (PGA isoline encompassing 90% of the landslide population) values obtained from step 1 (Fig. 2). As a result, we derive a relationship between PGA values and ACLSA which test for predicting landslide-affected area without the need of an actual inventory.

Our general view is that event-specific PGA is a consequence of the physical response of a single landscape to the seismic stresses (as also reported by Jibson and Harp, 2016). However, instead of treating each landscape separately, if we take a more general perspective on mass-wasting processes, we assume that there may be some commonality across different landscapes for the physics behind should be the same, irrespective of the single earthquake event. Here, we try to capture this commonality or shared behavior through the ACLSA. The ACLSA should be able to capture the general landscape response because it should represent a constraint to the overall landslide distribution. Hence, the deviation of the ACLSA from the event-specific PGA should only be due to local geographic setting.
4. Results

We examine the distributions of PGA values for each percentage of landslide population and for each of the 20 EQIL inventories (Fig. 4). The dark green bins shown to the left side of each black bars in Fig. 4 represents the PGA which encompasses all landslides for that event; thus, the interval between the minimum (0.05 g) and the maximum (0.57 g) PGA contains 100% of the entire population of landslides considered in the present study. This PGA range corresponds to the 1999 Chi-Chi (Liao and Lee, 2000) and to the 1995 Hyogo-ken Nanbu (Uchida et al., 2004) inventories, respectively. Notably, the Hyogo-Ken Nanbu minimum PGA is ten times larger than the Chi-Chi one and more generally, a large variability characterizes the extent of landslide-affected areas.

Fig. 8. Examples showing: 1) common PGA (0.12 g) contours (black lines), 2) event-specific PGA contours (red lines), 3) estimated landslide-affected areas (white lines), 4) symmetry axis (purple dashed lines), 5) ACLSA values calculated for the both halves overlaid with landslide-susceptible areas, 6) landslide locations (cyan points), 7) ground motion patterns and 8) dark hillshaded masks corresponding to landslide-susceptible landscapes for (a) Hyogo-Ken Nanbu; (b) Chi-Chi; (c) Coalinga; (d) Northridge; (e) Wenchuan; and (f) Haiti earthquakes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
To further examine this variability in a particular case, we present a summary of the Northridge earthquake in Fig. 5. Here, PGA contours of 0.133 g, 0.267 g, 0.304 g and 0.380 g contain 100%, 90%, 80%, and 70% of the Northridge inventory (Harp and Jibson, 1995), respectively. From one landslide population to the other, the absolute difference in PGA is 0.134 g (0.267 g – 0.133 g), 0.037 g (0.304 g – 0.267 g), and 0.076 g (0.380 g – 0.304 g). Remarkably, the first difference (100% – 90%) in PGA is four times larger than the subsequent bin and represents the largest jump considering all the bins.

By noticing this jump for the Northridge case, we opted to investigate whether a similar situation repeats itself for the other 19 earthquakes. This information is compressed in Fig. 6. Here, the global and largest gradient is also found from 90% to 100% of landslide populations. This indicates that explaining the last 10% of each landslide population requires a large average jump in PGA. In other words, the average distribution of landslide outliers (10%) is scattered over very large areas compared to the corresponding nine 10% bins. We interpret such a large difference as a potential result of site-specific factors which locally increase the susceptibility despite the relatively low ground motion disturbance. These kind of factors may not be capturable with a model generated at a global scale.

Having confirmed our assumption that the 90% PGA bin is the most appropriate reference to study EQIL inventories over space, we then focus on the single 90% bins for each earthquake and consider them as our reference event-specific PGA values. These values range from 0.120 g to 0.711 g (and correspond to the black bars shown in Fig. 4). The 0.120 g PGA represents the minimum PGA containing 90% of the landslides for any of the 20 earthquakes and falls within the range Jibson and Harp et al. (2016) reported as well. We define this minimum PGA as the common PGA contour and use it in the rest of the paper as our reference.

We also identify the landslide-susceptible areas by selecting the combined slopes > 5° and local relief values > 100 m. These pixels are added up for each of the 20 inventories to obtain a measure of the total extent of potentially susceptible areas. As a result, we calculate the ratio between landslide-susceptible areas and the area covered by the common PGA to obtain the Areal Coverage of Landslide-Susceptible Area (ACLSA). In Fig. 7a, we plot all the ACLSAs ranging from 3% to 94% corresponding to the 2010 Sierra Cucapah (Barlow et al., 2015) and the 2013 Minxian (Xu et al., 2014a) inventories.

For the Sierra Cucapah the 3% ACLSA indicates that the common PGA overestimates the landslide-affected areas (see Fig. 7b), whereas the 94% found for Minxian suggests that the two measures almost perfectly overlap (see Fig. 7c).
We detect asymmetric distribution of landslide-susceptible areas in Coalinga (Fig. 8c) and Limon (see Supplementary Materials) cases. For instance, in Coalinga, landslide-susceptible area confined to the West (ACLSA = 74%) whereas the remaining flat area extends towards the East (ACLSA = 2%). The difference between ACLSA values is larger than 50%. As a result, we ignored the flat areas causing asymmetry and used the 74% ACLSA values to represent this particular case.

To test the joint effect of topography and seismic stress on the areal extent of landslide occurrences, we examine the difference between the ACLSA and event-specific results. At this stage, we present these differences via linear fitting procedures.

The fitting results are shown in Fig. 9 where an increase in the proportion of landslides-susceptible areas corresponds to a decrease in the event-specific PGA. This implies that by theoretically assuming a constant shaking level over space, the main landslide-affected area will be proportionally larger to the extent of susceptible terrains. Our approach takes into account the signal brought by the susceptible terrain distribution and the shaking patterns to constrain the actual landslide-affected area solely on the basis of these two parameters. Details on the linear relations are discussed in Section 5.

5. Discussion

In Fig. 9, we report the linear fits between ACLSA and event-specific PGA (let us recall it contains 90% of the landslide population). The blue line corresponds to our initial attempt to explain all the 20 earthquakes. However, Hyogen-Ken Nanbu and Kashmir inventories do not follow the general trend of the data distribution which is also summarized by the low coefficient of determination ($R^2 = 0.40$), although we still visually recognize a trend (light blue line in Fig. 9a). This may be due to the incompleteness of inventories which would naturally lead to overestimate the event-specific PGAs (for the two outliers) and the
associated landslide populations. However, due to several sources of approximations affecting our model, finding a specific explanation was not a straightforward task. The quality of the ShakeMap can also affect the data and the conclusions arising from our approach. In fact, by reading the PGA values provided by USGS ShakeMap system, the uncertainty of the deterministic PGA estimates has a direct effect on our analysis. As shown in Table 1, for some of the earthquakes (such as the 1986 San Salvador, the 2010 Yushu, the 2013 Min-xian, the 2014 Ludian and the 2015 Gorkha) we worked with relatively poor quality ShakeMaps. All ground motion parameters we used here were already updated and refined by US Geological Survey ShakeMap system using bothrupturing geometry and mechanism. However, for future applications of our method, data received in near-real time may not produce compatible results to those obtained with refined ShakeMaps, especially for large earthquakes (Allstadt et al., 2018). This needs to be noted as a possible limitation of our methodology.

Having disregarded problems related to unreliable PGAs, we went through each of the inventories looking for other possible factors controlling the landslide distribution.

By examining the inventories, we realized that all the landslides for the Hyogen-Ken Nanbu and Kashmir cases are concentrated close to the main epicentral area, with a very limited spread moving towards the peripheral shaking regions. We assume this to be conditioned by very localized factors which may have focused all landslides within a very small sector (Meunier et al., 2013). This could have been the case for local relief. Fig. 10a-b seems to confirm this hypothesis. In fact, the landslides belonging to the Hyogen-Ken Nanbu earthquake are clustered within acidic plutonic rocks. Similarly, the landslides belonging to the Kashmir earthquake cluster within recent siliciclastic sedimentary deposits (see Fig. 10c-d).

Having recognized the localized behavior responsible for the deviation from the general trend shown in Fig. 9a, we opted to remove the two inventories. As a result, the general relation between ACLSA and event-specific PGA improved substantially, reaching a R² of 0.57 (red line). This is still not a well-constrained relation although it supports our argument that a trend actually exists.

In Fig. 9a we essentially check the existence of a relation which explains the event-specific PGA as a function of the ACLSA. In other words, assuming this relation to be reliable, it could be used to estimates the PGA which describes the area where 90% of landslides fall into, solely from the ACLSA. However, testing whether the estimation of event-specific PGAs is realistic or not is not a straightforward task when expressed directly via PGAs. For this reason, we use the same relation and calculate the actual landslide population estimated via the inferred event-specific PGAs. This is shown in Fig. 9b where the red line now shows the estimated landslide population and the vertical bars report the actual landslide population in the raw data.

Irrespective of how we express the relation between ACLSA and event-specific PGA, the data shown in Fig. 9a and b splits 50% above the regression line (confined in a 0.29 g interval) and 50% of the cases correspond to underestimations (confined in a 0.24 g interval). Despite this variation, the corresponding deviation from the 90% of the total landslide populations shown in Fig. 9b is not as bad as the difference in PGA reflects in Fig. 9a. Fig. 9b also shows that among the underestimations, the worst case is Ludian where our global fit estimates the area containing 60.1% of the total landslides. We recall here that Ludian is one of the cases for which the USGS reports a low quality PGA estimate. To summarize the error, we separately investigated underestimations and overestimations as they correspond to completely different problems in reality. For the underestimated cases (worst-case
scenario), we compute the average of the extrapolated population for each earthquake, this being 72.7%. In other words, our model estimates 72.7% instead of the 90%. As for the 10 overestimations, 7 of them are still within 100% of the real landslide population (mean = 96.8% and maximum = 99.5% in Friuli), leaving only one case (Limon) where our expected areas slightly exceed the limits of the entire landslide dataset (Hyogen-Ken Nanbu and Kashmir are not considered for they have been removed in a previous stage).

Therefore, not considering Limon, Hyogen-Ken Nanbu and Kashmir Overall, the error in our fit ranges from −29.9% to +9.5% with respect to our 90% target.

At this stage, all the results come from a fitting procedure where the relation between ACLSA and event-specific PGA is derived by using 18 earthquakes (red line in Fig. 9a,b).

We extend the explanatory assessment of our model by testing it for predictive purposes. Fig. 11 shows the result of the leave-one-out crossvalidation (CV) we performed: we fit the data to 17 earthquakes and alternatively predicted the remaining one. Here, the ideal fit (dashed blue line) is shown to be included within the 95% credible interval of the 18 cross validated linear fits.

Fig. 12 complements this information by providing the residuals between the observed and predicted values obtained with respect to the 90% landslide population (separately for the 10 underestimations below the regression line and the 8 overestimations above).

Fig. 12a reports the residuals in terms of PGA, the panel b shows the same for the population whereas the panel c shows the difference in term of linear distance. Ultimately, we carry this information in Fig. 13. Here, we graphically show both the performances for the fit and leave-
one-out CV with respect to the observed data as differences between the observed and estimated: i) population (with target being 90%) and ii) average Euclidean distance between the observed PGA isoline containing 90% of the landslides and the estimated PGA isoline from our model. The variation around our fitted isoline ranges from -12 km (Coalinga) to +26 km (Wenchuan), whereas the averages calculated separately for underestimations and overestimations are -7 km (dashed red line in Fig. 12) and +7 km (dashed green line in Fig. 12), respectively. Three overestimations in the predicted landslide limits stand out in Fig. 13, where Limon (+8 km for the fit and +8 km for crossvalidation), Hyogen-Ken Nanbu (+8 km for the fit and +9 km for crossvalidation) and Kashmir (+26 km for the fit and +26 km for crossvalidation) are plotted outside the colorcoded wedge. Here, the fit and predictive performances do not significantly differ from each other, although it should be noted that the radial plot is expressed in logarithmic scale. Nevertheless, the performances related to the population appear quite stable. In fact, for the CV, the variation with respect to the target 90% is bounded between -35.1% and +9.6% (let us recall that the same for the fit ranged between -29.9% to +9.5%).

These findings show that the global relation we proposed helps us to make a reasonable estimation regarding landslide-affected area. We actually used a linear best fit in Fig. 9a, although we also propose a quadratic fit as reported in Fig. 9b (dashed line). This relation would lead to no or negligible underestimation which correspond to the most “dangerous” cases in any natural hazard context. And, it would essentially trade False Positives for False Negatives, which is usually the preferred cases.

6. Conclusions

We propose an update to the paper of Jibson and Harp (2016) and an alternative to Marc et al. (2017). With respect to these contributions, here, we extend our survey to 20 inventories and try to generalize a global relation for landslide-affected areas (accounting for ground shaking and susceptible terrains).

We examine inventories with various quality and completeness levels from regions across the globe. We show that the outermost 0.05 g contour is the minimum PGA value covering the entire landslide population considered among all the investigated inventories. Inside our 0.05 g boundary, a scattered landslide pattern is generally observed far from the main landslide-affected area. Thus, we focus on defining a PGA boundary containing 90% (event-specific PGA) of the landslide population for each earthquake separately. And, we identify the 0.12 g as the global minimum PGA (common PGA contour) containing at least 90% of the landslides, for all the inventories at the same time.

For each earthquake, we divide the total surface of susceptible terrains by the area of the common PGA contour to define the ACLSA.

We then derive a relation between the ACLSAs and event-specific PGA isolines which is able to explain 60% of the variability in the data, with an associated uncertainty of -29.9% to +9.5% in the corresponding landslide population. These fitted results are reached despite all the uncertainties and the methodological simplifications we made. We test the same relation as a predictive tool by performing a leave-one-out cross-validation. Hence, we measure that the predictive uncertainty ranges between -35.1% and +9.6% in population estimates with respect to our 90% population target.

The differing level of completeness for the inventories we used and the relatively poor quality of ShakeMaps for some of the earthquakes we considered can act as noise on a global assessment. It may not be a coincidence that all our underestimations namely, Ludian (60.1%), Yushu (70.3%), San Salvador (70.5%), Minxian (72.4%), Gorkha (83.8%), Lushan (86.1%) correspond to earthquakes for which the USGS has reported as C grade (see Table 1). However, this could be a lesser problem in the future, for seismic networks across the globe have gotten denser in the last decades and they are foreseen to improve.

Another source of error may come from the approximation of the landslide susceptible landscape. We chose a simple rule-based classification, but we envision to polish our approach even further by implementing state-of-the-art statistical models to assess landslide susceptibility for each of the 20 inventories.

Despite all the limitation listed above, we can still recognize a pattern linking the increase of the areal coverage of landslide-susceptible areas to the decrease of the corresponding PGA covering the large majority of landslide activations. This is not a trivial relationship because by defining a-priori the PGA where landslides are expected to be concentrated, we can extract the most appropriate spatial boundary upon which researchers can focus on to build an inventory in the post-disaster phase. Furthermore, the predicted landslide-affected areas should be a proxy for the region where most of the damages by landslide should take place. And by knowing it in near real-time, when the PGA estimates are made available to the public, prioritization in post-disaster emergency could be made in the narrow time window when the affected communities need this information the most.

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Appendix A. Supplementary data

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References
