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4 Characteristics of landslide path dependency revealed through 5 multiple resolution landslide inventories in the Nepal 6 Himalaya

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14 Abstract

15 Recent research in Umbria, Italy, has shown that landslide susceptibility is controlled by a process
16 called path-dependency, which describes how past landslides control the locations of future landslides.
17 To date, landslide path-dependency has only been characterised in Italy. This raises the question of
18 whether this process occurs in other geomorphic settings, and thus whether path-dependency should be
19 more universally included in landslide susceptibility assessments. Therefore, the main aim of this paper
20 is to investigate and quantify landslide path dependency in the Nepal Himalaya. This is achieved by
21 applying several path dependent metrics to three monsoon-triggered landslide inventories for the
22 central-eastern Nepal Himalaya. These inventories were developed at two different spatial and temporal
23 resolutions. As such, we aim not just to quantify landslide path-dependency, but also assess whether
24 path dependency characteristics are resolution-dependent. We find strong evidence that landslide path

25 dependency is occurring in Nepal, with all three inventories having more overlap between past and new
26 landslides than expected from a random distribution, and a tentative observation that the expected
27 degree of overlap between landslides decreases with time. Finally, whilst path-dependency is
28 observable across both of the investigated inventory resolutions, we find that the rates and magnitudes
29 of the quantified path dependent metrics are sensitive to inventory length, study region size and the
30 size/type of landslides mapped. Overall, our results corroborate the path-dependency observations from
31 Italy, confirming that this process does occur in other geomorphic settings, and thus suggesting that
32 path-dependency should be explicitly and universally considered in landslide susceptibility approaches.

33 Keywords: Landslides, Nepal, Himalaya, Path dependency, Landslide Susceptibility

34

35 1.0 Introduction

36 Landslides are a ubiquitous hazard in areas with mountainous terrain and frequent trigger events that
37 can create significant risk when near populations and critical infrastructure. From January 2004 to
38 December 2016, 55,997 people were killed globally in 4862 landslide events (Froude and Petley, 2018).
39 Furthermore, the impacts of landslides are typically greater in less economically developed countries
40 owing to increased vulnerability and decreased resilience (Kjekstad and Highland, 2009). It is clear that
41 landslides are a significant global hazard, and that further research is required to reduce the economic
42 and societal toll of landslide occurrences.

43 Landslide mitigation typically relies upon assessments of landslide susceptibility, which quantifies the
44 likely locations of future landslides (Guzzetti et al., 2006). Typical landslide susceptibility approaches
45 are time-independent, meaning that landslide susceptibility is assumed to be stationary through time
46 (Aleotti and Chowdhury, 1999; Samia et al., 2017; Varnes, 1978). However, this assumption is
47 challenged by recent research showing that several processes impart time-dependent controls on
48 landsliding. For example, it is now well-described that the damage signature of large magnitude
49 earthquakes can transiently precondition landscapes such that they experience an increased likelihood
50 of landslide occurrence for years to decades after the event (Marc et al., 2015; Parker et al., 2015).

51 Furthermore, recent analysis of a long-term landslide record in Italy suggests that past landslide events
52 can transiently influence future landslide occurrence via a non-linear process defined by Samia et al.
53 (2017) as path dependency (Samia et al., 2018, 2017; Temme et al., 2020). As established by Samia et
54 al. (2017), path dependency describes how pre-existing landslides can impart a legacy effect that
55 controls the occurrence and size of new landslides. Specifically, this legacy effect increases the
56 propensity of new landslides to overlap or be contiguous with pre-existing landslides. Such path-
57 dependent landslides are termed here as spatially associated landslides, whilst new landslides that do
58 not overlap a pre-existing landslide are termed as spatially unassociated landslides. It is also observed
59 that spatially associated landslides can have different geometric characteristics to spatially unassociated
60 landslides, with the former being less round and larger on average (Samia et al., 2017).

61 Furthermore, it has since been shown that the inclusion of time-dependent path dependency in landslide
62 susceptibility models, via various approaches, can significantly improve model performance (Samia et
63 al., 2018; 2020). However, the wider applicability of using path dependency in landslide susceptibility
64 modelling remains uncertain, as path dependency is yet to be rigorously tested in other regions. As such,
65 quantifying whether landslides exhibit path dependent behaviour in other geomorphic regions should
66 be considered vital (Samia et al., 2017). One of the main reasons why this process has yet to be widely
67 investigated is that it is thought to require large-scale multi-temporal landslide inventories to observe.
68 For example, the path dependency characteristics quantified by Samia et al. (2017) in Italy were derived
69 from a 60-year multi-seasonal inventory across a 78.9 km² region. These landslides were mapped using
70 stereoscopic aerial photographs ranging from 1:13,000 to 1:33,000 for the period 1941 – 1997, and
71 using field surveys and satellite imagery with better than 1 m resolution for subsequent years (Samia et
72 al., 2017). Unfortunately, such regional multi-temporal inventories are uncommon as they are time-
73 consuming to develop, particularly over very large (> 100 km²) regions (Reichenbach et al., 2018). As
74 such, if path dependency is to be investigated more widely, it would be beneficial to have a greater
75 understanding of what spatial and temporal resolution datasets are required to fully describe its
76 behaviour. For example, over what time period should landslide data be collected and across how many
77 time-slices? What size study region is required? At what resolution should landslides be mapped? A

78 better understanding of these questions would allow other studies to target landslide data collection
79 more efficiently for the purpose of investigating path dependency.

80 Therefore, this paper has two main aims. First, to investigate whether monsoon-triggered landslides
81 exhibit path-dependency in the Nepal Himalaya and, if so, to quantify the characteristics of this process.
82 Path dependency will be tested using several metrics that quantify the degree of overlap between new
83 and pre-existing landslides following the approach of Samia et al. (2017). In addition, we hypothesise
84 that, as observed in Italy (Samia et al., 2017), spatially associated landslides in the Nepal Himalaya will
85 have different spatial and size characteristics to spatially unassociated landslides. Second, we
86 investigate the spatial and temporal resolutions of landslide data that are required to observe landslide
87 path-dependency. We do this by quantifying landslide path-dependency across three regions with two
88 different resolution landslide inventories. One region with landslide data collected across a 45,000 km²
89 region and 29-time slices, but with landslides mapped at a relatively low resolution of 15 – 30 m. And
90 two regions with landslide data collected across smaller (513 and 608 km²) regions and just five time
91 slices, but with landslides mapped at a higher (5 m) resolution.

92 2.0 Regional Setting

93 The main region selected for this study is a 45,000 km² area of the central-eastern Himalaya, Nepal
94 (Fig. 1). Nepal was selected because it has an annual monsoon season that facilitates the systematic
95 development of multi-temporal landslide inventories. Nepal also suffers frequently from other landslide
96 trigger events such as earthquakes, storms and floods which, combined with its high relief, makes
97 landslides and associated hazards pervasive (Cook et al., 2018; Dhital, 2003; Marc et al., 2015; Petley
98 et al., 2007). The specific size and location of the main region was selected to ensure that our inventory
99 included landsliding across a range of geomorphological and geological settings. The selected region
100 includes catchments in all four of the main tectonic units that comprise the Nepal Himalaya: the Sub,
101 Lesser, Greater and Tethyan Himalaya (DeCelles et al., 2001). These tectonic units have distinctly
102 different geomorphologies and geologies across the study region. For example, the Tethyan Himalaya
103 is dominated by granitic complexes (DeCelles et al., 1998) and has high average elevations of ~5000 m
104 (Lavé and Avouac, 2001). Consequently, the Tethyan Himalaya are strongly influenced by glacial and

105 periglacial processes, with diverse landforms such as active glaciers, moraines, alluvial fans, landslides
106 and rock avalanches (e.g. Jones et al., 2020). In contrast, the bedrock geology of the Greater and Lesser
107 Himalaya is composed of lower-grade metamorphic, metasedimentary and sedimentary rocks
108 (Robinson et al., 2001; Upreti, 1999). Topographically the Greater and Lesser Himalaya are
109 characterised by steep, fluvially incised valleys, including the Mahabharat Mountains and higher peaks
110 to the north, which range from ~2000 – 7000 m (Lavé and Avouac, 2001). Finally, the Sub-Himalaya
111 are composed of Quaternary sandstones and conglomerates (Decelles et al., 2001; Robinson et al.,
112 2001), with a topography that extends from the flat lowlands of the Indo-Gangetic Plain to the Siwalik
113 Hills. Overall, by selecting a main region with a diverse set of landscapes, we can be confident that any
114 observed path-dependency is not unique to any specific geomorphic setting, which, as described above,
115 is a key aim of this paper.

116 Whilst the main study region allows us to investigate path-dependency across a range of geomorphic
117 settings, we selected two-sub regions within the main region to assess how different inventory
118 resolution impacts path-dependency results. These sub-regions are a 609 km² area following the Pasang
119 Lhamu highway to Rasuwa Ghadhi (sub-region 1; Fig 1a and b) and a 513 km² area following the
120 Araniko highway from Kathmandu to Kodari (sub-region 2; Fig 1a and c). These sub-regions were kept
121 a similar size to allow the two to be easily compared, whilst their extents were defined within the main
122 region to ensure that any differences between the main and sub regions are due to data resolution, rather
123 than a change in landslide process. As with the main region, the specific locations of these two sub-
124 regions were selected largely for their geomorphological and geological diversity, as well as their high
125 landslide densities. The topography of both regions is extreme, with elevations ranging from 600 to
126 5800 m in sub-region 1 and 850 to 5900 m in sub-region 2, and hillslope angles in both regions ranging
127 from 0 to 77° with an average of 32°. Across the two sub-regions there are seven lithologies: dolomites;
128 granites; gneisses; phyllites; schists; quartzites, and shales. These rock types are characteristic of the
129 Higher Himalaya Central Crystalline zone (Stöcklin, 1980). Both sub-regions contain large areas of
130 granites and gneisses in the north, whilst the lithologies in the southern portions of both areas are more
131 heterogeneous. This geomorphological and geological diversity allows investigation into how landslide
132 distributions vary across a variety of spatially heterogeneous landslide control factors.

133 3.0 Methodologies

134 3.1 Data collection

135 To investigate landslide path dependency, the methods of Samia et al. (2017) were followed using three
136 newly developed multi-temporal landslide inventories for each region described above. The following
137 sections describe the main data collection and analysis methodologies used throughout this paper.

138 3.2 Landslide inventory mapping

139 Three monsoon-triggered landslide inventories were developed across central-eastern Nepal (Fig. 1).
140 The first, referred to as the “main region” inventory, was a multi-seasonal inventory developed for the
141 ~45,000 km² main region described in section 2.0, using 15 – 30 m Landsat 4/5/8 satellite imagery. This
142 inventory included landslides mapped within 29 distinct time-slices across a 30 year period, where each
143 time-slice encompassed a single monsoon season between 1988 and 2018, excluding 2011 and 2012
144 which could not be mapped due to Landsat 7 scanline errors (Alexandridis et al., 2013). In total, the
145 main region inventory included 12,901 monsoon-triggered landslides (Supplementary Table 1). The
146 second and third inventories, referred to as the “sub-region 1” and “sub-region 2” inventories, were
147 developed across the two smaller sub-regions described in section 2.0. These sub-regions both fell
148 within the main region, where sub-region 1 covers 609 km² along the Pasang Lhamu Highway, and sub-
149 region 2 covers 513 km² along the Araniko Highway (Fig. 1a – c). Both sub-region inventories were
150 developed using 5 m resolution RapidEye satellite imagery and included landslides mapped within 5
151 distinct time-slices, where each time-slice encompassed two monsoon seasons (and the month’s in-
152 between) from 2009 and 2019. This resulted in a total of 623 landslides in Sub-region 1 and 569
153 landslides in Sub-region 2 (Supplementary Tables 1 and 2). For all three inventories, landslides in a
154 given time-slice were mapped through the visual comparison of pre- and post-time-slice satellite
155 imagery. All used satellite images had < 15% cloud cover and were obtained during the Nepalese dry
156 season (1st October – 31st March). The specific satellite types and imagery dates used to map each
157 individual landslides are shown in Supplementary Tables 1 – 3. Landslides were mapped as polygons
158 that included the scar, deposition and runout zones of each event, with care taken to avoid landslide
159 amalgamation (Marc and Hovius, 2015) and mass-wasting due to anthropogenic activity such as cut-

160 and-fill practices, land-clearing and road-tipping. For both resolution inventories, road-tipping events
161 were identified as any mass-wasting event that occurred below and concurrently with a new road. We
162 also ensured that our monsoon-triggered inventories did not include any of the coseismic landslides
163 triggered by the 2015 Gorkha earthquake by discounting any landslides included in the comprehensive
164 coseismic inventory of Roback et al., (2018).

165 Within all three inventories, landslide spatial associations were classified into three categories (Fig. 2)
166 using the ArcGIS functions: outside, partial, and inside. The outside function selected any landslide
167 which at the time of its occurrence made no contact with an earlier landslide polygon. I.e., it defined all
168 spatially unassociated landslides. The partial function selected any landslide which crossed the outline
169 of an earlier landslide polygon, whilst the inside function selected any landslide which occurred fully
170 within an earlier landslide polygon. I.e., these functions defined all spatially associated landslides,
171 which were subdivided into spatially associated (partial) and spatially associated (inside) respectively.
172 Example landslides of each path-dependency type are shown in Figure 2.

173 *3.3 Size-frequency and roundness analysis*

174 Assessment of landslide size has important implications for the design and implementation of
175 appropriate hazard mitigation and management strategies. In this case, it would be particularly useful
176 to understand whether spatially associated landslides have similar size-frequency distributions to
177 spatially unassociated landslides, and thus whether they need to be managed differently. As such, prior
178 to analysing to landslide path dependency metrics, for our main inventory and combined sub-inventories
179 we quantify the landslide area-frequency distributions for all landslide data and subsets of both the
180 spatially unassociated and spatially associated (partial) landslide types. It should be noted that we did
181 not calculate distributions for the spatially associated (inside) landslide types as there were very few
182 cases of these within the inventories (46 in the main inventory and none in the sub-inventories).

183 Landslide size-distributions are typically characterised according to the probability density function of
184 landslide areas $p(A_L)$, which is defined by Equation 1 (Malamud et al., 2004):

$$185 \quad p(A_L) = \frac{1}{N_{LT}} \frac{\partial N_L}{\partial A_L} \quad (\text{Equation 1})$$

186 Where N_{LT} is the total number of landslides in the inventory, A_L is landslide area, δN_L is the number of
187 landslides with areas between A_L and $A_L + \delta A_L$. Probability density functions of landslide area are
188 commonly observed to exhibit a power-law decay and exponential roll-over at smaller areas that can be
189 modelled by a three-parameter inverse-gamma distribution (Malamud et al., 2004), as defined by:

$$190 \quad pdf(A_L | \alpha, \eta, \lambda) = \frac{\lambda^{2\alpha}}{\Gamma(\alpha)} \left[\left(\frac{1}{x + \eta^2} \right)^{(\alpha+1)} \right] \exp \left[-\frac{\lambda^2}{x + \eta^2} \right] \quad (\text{Equation 2})$$

191 Where α controls the exponent of the inverse-power law (i.e., the steepness of the right tail of the
192 probability density function), η controls the bend of the left tail of the probability density function, and
193 λ controls the position of the rollover. The position of the rollover, which represents the size of the most
194 frequent landslides, is typically used as a means of comparing the completeness of different inventories,
195 as it indicates the landslide area below which landslide frequency-density values begin to decrease
196 (Tanyaş et al., 2019). The exponent of the inverse power-law describes the rate at which the probability
197 of getting larger landslides decreases. A larger exponent indicates that the probability of getting larger
198 events is decreasing quickly, and thus that larger landslides are contributing less to each inventory.
199 Conversely, a smaller exponent indicates that the probability of getting larger events is decreasing more
200 slowly, and thus that larger landslides are contributing more to each inventory (Borgomeo et al., 2014;
201 Van Den Eeckhaut et al., 2007).

202 Here, we use the LANDSTAT software (version 10) to fit the three-parameter inverse gamma
203 distribution (Malamud et al., 2004; Equation 2) to the probability density functions of the area-
204 frequency data for three subsets (all landslides, spatially unassociated landslides, and spatially
205 associated (partial) landslides) of our main inventory and combined sub-region inventories. This
206 software uses Maximum Likelihood Estimation (MLE) to optimise the parameters of equations 1 and
207 2, and a bootstrapped (here with 1000 simulations) Kolmogorov-Smirnov (K-S) test to estimate
208 parameter uncertainties and overall goodness of fit of the inventory data to the fitted distributions.

209 Finally, we also calculated the roundness of the landslides in both inventories. This was done using the
210 methodology outlined by Samia et al. (2017), whereby roundness is defined as the ratio between the

211 actual perimeter of a landslide, and the theoretical perimeter a landslide would have if it were a perfect
212 circle with the same area.

213 *Path dependency analyses*

214 To quantify path dependency in the Himalaya, we apply the methods of Samia et al. (2017) to our three
215 inventories. These methods are the overlap index, the unaffected area, and the number of overlaps. The
216 overlap index quantifies the degree of overlap between landslides in two different inventory time slices
217 according to equation 3 (Samia et al., 2017).

$$218 \text{Overlap index}_{t-t+n} = \frac{AL_t \cap AL_{t+n}}{AL_t + AL_{t+n} - (AL_t \cap AL_{t+n})} \quad (\text{Equation 3})$$

219 Where, t is the average time of the first time slice, t + n is the average time of the second time slice, and
220 \cap is the geometric intersection (overlapping area) between two time slices. Average times were taken
221 as the middle of the monsoon period for the main inventory and the middle of the two-year time slice
222 period for the sub-region inventories. By plotting the overlap index values against the respective time
223 interval between time slices, the relationship between the overlap of earlier and new landslides and time
224 since an earlier landslide can be established. For each inventory, the overlap index was calculated for
225 every possible combination of time-slices, as well as between each year in each inventory and the 2015
226 Gorkha earthquake coseismic landslides of Roback et al. (2018). This gave 435 overlap index values
227 for the main region inventory and 15 for each of the sub-region inventories.

228 The unaffected area method compares the actual area of land unaffected by landsliding to the theoretical
229 area of land that would be unaffected by landsliding if no overlapping of landslides in different time
230 slices occurred. The Actually Unaffected Area (AUA) is given by equation 4 (Samia et al., 2017):

$$231 \text{Actually unaffected area}_t = \left(\bigcup_{i=1}^t AL_{Ti} \right) / AS \quad (\text{Equation 4})$$

232 Where, t is the time slice number, AL_{Ti} is the total area of landsliding in time slice i, AS is the area of
233 the study region, and U is the union of all landslides between time slice i =1 and time slice t. In other
234 words, this metric calculates the total area of landsliding up to a given time slice, after accounting for
235 overlaps, as a dimensionless fraction of the size of the study region.

236 Conversely, as shown in equation 5 (Samia et al., 2017) the Theoretically Unaffected Area (TUA) does
237 not account for overlaps:

$$238 \textit{Theoretically unaffected area}_t = (\sum_{i=1}^t AL_{Ti})/AS \quad (\text{Equation 5})$$

239 This metric essentially calculates the total area of landsliding up to a given time slice, without
240 accounting for overlaps (i.e., assuming all landslides are spatially unassociated), as a dimensionless
241 fraction of the size of the study region. As such, if spatially associated landslides are occurring, when
242 the AUA and TUA are plotted against one another through time, we would expect the AUA to plot
243 progressively lower than the TUA, with the distance between the two indicating the degree to which
244 landslides are overlapping across the study region. These metrics were calculated at every time slice of
245 each of our three inventories, i.e., calculated 29 times between 1988 and 2018 for the main region
246 inventory, and 5 times between 2009 and 2019 for the two sub-region inventories.

247 The number of overlaps method compares for each inventory the actual area of landsliding at different
248 degrees of overlap to the area of landsliding predicted at each degree of overlap by a random model.
249 The actual number of overlaps in each inventory was calculated by first converting the landslide
250 polygons in each time slice into rasters using the ArcGIS 'Feature to Raster' tool. These time slices
251 were rasterised at the same resolution as the landslide mapping (i.e., 30x30 m cells for the main region
252 inventory and 5x5 m cells for the sub region inventories). All landslide presence cells were given a
253 value of 1, whilst landslide absence cells were given values of zero. Then, by summing all time-slice
254 rasters for each inventory, the total number of landslide presence cells (and thus area of landsliding) at
255 different degrees of overlap were calculated for each inventory. The random model used a random
256 number generator in Matlab to randomly assign the same number of landslide presence cells as existed
257 in each time slice of the actual inventories to a grid with the same number of cells as each study region.
258 The randomly assigned time slices were then summed to count the total number of landslide presence
259 cells (and thus area of landsliding) at different degrees of overlap for the random model. Each random
260 model was run 50 times per inventory to get a mean number of overlaps. If landslides in each inventory
261 are exhibiting path dependency, it would be expected that the actual data will show a greater area of
262 landslides at higher degrees of overlap than is predicted by the random model.

263 *3.4 Landslide control factor analysis*

264 The second hypothesis to be tested in this paper is that spatially associated and spatially unassociated
265 landslides have different spatial distributions and size characteristics. To investigate the spatial
266 distributions, we first used standard ArcGIS tools to extract the slope, elevation, aspect, and lithology
267 at the centroid of each landslide in each inventory, where all topographical data were derived from the
268 ALOS World 3D-30m (©JAXA) product. We then split each of our inventories into four subsets: all
269 data, just spatially unassociated landslides and just spatially associated (partial) landslides. Again,
270 owing to the low number of cases, we do not include the spatially associated (inside) landslides in this
271 analysis. We then used standard ArcGIS zonal statistics tools to calculate for each subset of the main
272 inventory and the combined sub-region inventories, the percentage of landslides that occurred across
273 different bins of each control factor. The percentages of the main inventory study region landscape and
274 combined sub-region inventory landscapes that fell within each bin were also calculated. Finally, for
275 the main inventory and combined sub-region inventories, the percentage distributions of each landslide
276 subset were plotted against each other and the percentage distribution of the respective study region
277 landscapes to compare how their distributions across each control factor varied.

278

279 **4.0 Results**

280 *4.1 Landslide inventory, area-frequency and roundness*

281 The main region landslide inventory contained 12,901 landslides; 11,031 of which were spatially
282 unassociated landslides, 1,824 of which were spatially associated (partial) landslides and 46 of which
283 were spatially associated (inside) landslides. These landslides had a mean area of 12,616 m², with a
284 minimum area of 198 m² and a maximum area of 684,780 m² (Table 1). Sub-region 1 contained 623
285 landslides, of which 545 were spatially unassociated landslides and 78 were spatially associated (partial)
286 landslides, with no inside cases. These landslide areas varied from 190 m² to 71,000 m² with a mean of
287 5,980 m² (Table 1). Sub-region 2 contained 569 landslides, of which 483 were spatially unassociated

288 landslides and 86 were spatially associated (partial), with no inside cases. These landslide areas varied
289 from 170 m² to 45,780 m², with a mean of 4,995 m² (Table 1).

290 To investigate whether spatially associated and spatially unassociated landslides have different size
291 characteristics, three parameter inverse gamma distributions were fitted to the probability density
292 functions of landslide area for all of the data, just the spatially unassociated landslides, and just the
293 spatially associated (partial) landslides for both the main inventory and the combined sub-region
294 inventories (Fig. 3). The scaling parameters and rollover values of these distributions are shown in Table
295 1 alongside the mean, minimum and maximum landslide areas for each case. This highlights several
296 significant differences between both the two inventory types and the two landslide path-dependent
297 types. In terms of the inventory types, we see that the main region distributions have higher scaling
298 exponents (α) of 1.62 – 1.83 compared to the Sub-region distributions, which have exponents of 1.35 –
299 1.45. Similarly, the main region distributions have higher mean landslide areas (12,000 – 16,400 m²)
300 and rollover values (3260 – 3440 m²) compared to the sub-region inventory mean areas (5300 – 6860
301 m²) and rollovers (1090 – 1170 m²). In terms of spatially associated versus spatially unassociated
302 landslides, we see that for both inventories the spatially associated (partial) landslides have higher mean
303 areas and rollovers than the spatially unassociated landslides. In the case of the main region inventory,
304 the spatially associated (partial) landslides have a mean area of 16,410 m² compared to 12,017 m² for
305 the spatially unassociated landslides, and rollovers of 3444 m² compared to 3256 m². Likewise, for the
306 sub-region inventories, the spatially associated (partial) landslides have mean areas of 6861 m²
307 compared to 5295 m² for the spatially unassociated landslides, and rollovers of 1171 m² compared to
308 1087 m². The spatially associated (partial) landslides also have lower scaling exponents than the
309 spatially unassociated landslides, with a value of 1.62 compared to 1.83 in the main region, and a value
310 of 1.35 compared to 1.45 in the sub-regions.

311 Landslide roundness was also determined to compare differences between spatially associated and
312 unassociated landslides, as well as between the main region and sub-regions to highlight inventory
313 resolution differences (Fig. 4). The main region contains landslides with a higher average roundness
314 than the sub-regions. The average landslide roundness is ~0.78 in the main region and ~0.65 in the sub-

315 regions. In terms of spatial associations, spatially unassociated landslides have slightly larger average
316 roundness than spatially associated landslides in both regions. This difference is most pronounced in
317 the main region data, where spatially associated landslides have a mean roundness of 0.76 compared to
318 0.8 for those that are spatially unassociated.

319 *4.2 Path dependency*

320 Path dependency was investigated for all of our inventories using three metrics proposed by Samia et
321 al. (2017); number of overlaps, overlap index, and unaffected areas. In terms of number of overlaps, all
322 inventories are found to have a greater area of landsliding at higher degrees of overlap than is expected
323 based on the random model (Fig. 5). This is particularly evident in the main region, where the random
324 model never observes more than three degrees of overlap, compared to five degrees of overlap in the
325 actual data. Furthermore, whilst the two sub-regions do not have more degrees of overlap than predicted
326 by the random model, the actual data have 3-4 times more area of landsliding at three degrees of overlap
327 than predicted, and approximately 1.5 times more landslide area at two degrees of overlap than
328 predicted.

329 From the overlap index analysis, it is apparent that there is a weak negative coincidence between amount
330 of overlap between landslides in two time-slices and the time period between those time-slices (Fig. 6).
331 In the main region, as time increases between time-slices the overlap index decreases gradually from
332 0.01 – 0.02 at one year between time slices to 0 – 0.005 at 30 years between time slices (Fig. 6a). The
333 two sub regions show a similar trend, with a gradual decrease in overlap index from 0.01 – 0.05 at one
334 year between time slices to 0 – 0.001 at eight years between time slices (Fig. 6b – c). Time-slices
335 compared to the Roback (2018) Gorkha earthquake landslide inventory show a generally lower overlap
336 index in the main region whilst maintaining a similar overlap index in the sub-regions (Fig. 6a – c).
337 Interestingly, whilst both the main region and sub-regions show the same overall trend, the
338 characteristics of the trends appear to be resolution dependent, with the negative trend of the index
339 values for sub-regions 1 and 2 significantly steeper than the trend in the main region (Fig. 6d). However,
340 these observations are tentative, with significant variation in overlap index at different time intervals,
341 and thus no conclusive R^2 values.

342 In terms of the unaffected area method, in the main region and sub-region 1, the actually unaffected
343 area (AUA) gradually falls below the theoretically unaffected area (TUA) as time increases (Fig. 7a –
344 b). However, the divergence between the AUA and TUA in both regions is small, with a maximum
345 difference of 3×10^{-4} in the main region and 6×10^{-5} in sub-region 1. Furthermore, in sub-region 2, the
346 AUA and TUA remain similar throughout, with almost negligible divergence between the two metrics
347 (Fig. 7c). It should also be noted that all three regions exhibit large perturbations in both the AUA and
348 TUA that are coincident with cloud outburst storms in 1993 and 2002 (Fig. 7a) and the Gorkha
349 earthquake in 2015 (Fig. 7a – c).

350 *4.3 Landslide control factor distributions*

351 To test whether spatially associated and spatially unassociated landslides have different spatial
352 characteristics, the spatial distributions of the spatially associated and unassociated landslides in the
353 main region and combined sub-region inventories were quantified with respect to four potential
354 landslide controlling factors: elevation, hillslope angle, aspect, and geology (Fig. 8a – h).

355 It is apparent that the sub-regions have higher average elevations than the main region, with most
356 frequent elevations of 2000 – 2400 m compared to 800 – 1200 m (Fig 7a - b). This is unsurprising given
357 that the main region encompasses large parts of the Sub and Lesser Himalaya, whereas the two sub-
358 regions are located towards the north of the main region in the more topographically extreme Greater
359 Himalaya. Despite these differences, overall landslides are distributed similarly across both the main
360 and sub-regions, with landslides typically occurring between 400 – 3600 m. In the main region, this
361 elevation distribution is similar for all landslides and both the spatially associated and unassociated
362 landslide subsets (Fig. 8a). However, in the sub-regions, it is apparent that the spatially associated
363 (partial) landslide types are 5 – 10% more likely to occur at elevations of 2000 – 2800 m than spatially
364 unassociated landslides, and 2 – 5% less likely to occur at higher elevations of 2800 – 3600 m (Fig. 8b).

365 In terms of hillslope angle, both the main region and sub-regions have similar slope distributions that
366 are normally distributed around 30 – 35° (Fig. 8c – d). In both the main and sub-regions, landslides also
367 show a normal distribution with respect to slope, though shifted 5 – 10° higher than the study region
368 distribution, such that landslides are 5 – 10% more likely to occur at slope angles of 35 – 55° and less

369 likely at lower slope angles. Spatially unassociated and spatially associated (partial) landslides occur
370 on similar slopes in the main region (Fig. 8c). However, in the sub-regions, spatially associated (partial)
371 landslides are 2 – 4% less likely to occur at slope angles of 0 – 20° than spatially unassociated landslides,
372 but 2 - 5% more likely to occur at slope angles of 25 – 30° and at slope angles > 50° than spatially
373 unassociated landslides (Fig. 8d).

374 Hillslope aspect across both the main and sub-region study areas is evenly distributed across all
375 orientations, with almost negligible amounts of flat terrain (Fig. 8e – f). However, landslides in both
376 regions are 15 – 20% more likely to occur on S and SE aspects. In the sub-regions (Fig. 8f), spatially
377 associated (partial) landslides are ~5% less likely than spatially unassociated landslides on SE aspects,
378 but up to 10% more likely on S – SW aspects.

379 Lithological variability is largely similar between the main region and sub-region study areas, with
380 granites and phyllites dominating, though the sub-regions do not contain significant occurrences of
381 marble, schist, quartzites, shales, or Quaternary sandstones and conglomerates (Fig. 8g – h). Generally,
382 landslides in both regions are 10 – 20% more likely to occur in phyllites, but 20 – 30% less likely to
383 occur in granites. In the sub-regions, spatially associated and unassociated landslides are similarly
384 distributed across the different lithologies (Fig. 8h). Spatially associated (partial) landslides are slightly
385 less likely than other types in Quaternary conglomerates and sandstone, but up to 5% more likely in
386 granites and phyllites (Fig. 8g).

387

388 5.0 Discussion

389 *5.1 Does landslide path dependency occur in the Nepal Himalaya?*

390 The first aim of this paper was to investigate whether landslides exhibit path-dependency in the Nepal
391 Himalayas. To complete this aim we quantified the three path dependent metrics used by Samia et al.
392 (2017) (number of overlaps, overlap index and unaffected area) for three multi-temporal landslide
393 inventories that covered the central-eastern Nepal Himalaya. For all three landslide inventories, these
394 metrics suggest that there is strong evidence of path dependency in this region.

395 In terms of number of overlaps, all three of our inventories for central-eastern Nepal are found to have
396 larger areas of landsliding at higher degrees of overlap than is predicted by a random model (Fig. 5a –
397 c). In other words, this shows that new landslides overlap with earlier landslides to a greater extent than
398 would be expected if the spatial distributions of landslides through time were random. This result is
399 indicative of path dependency and follows a similar general trend to that found by Samia et al. (2017)
400 in Collazzone (Italy), who also found that the number of overlaps was greater than would be expected
401 from a random model.

402 Yet, whilst the general trend in Collazzone may be similar to Nepal, there are some subtle differences.
403 Notably, the rate of decrease of landslide area with higher degrees of overlap in Collazzone is
404 approximately half that observed in Nepal (-0.62 compared to -1.2 – -2.0), suggesting that the
405 Collazzone region has the potential to generate greater degrees of overlap given enough time, but that
406 Nepal has a greater area of overlap than expected at lower degrees of overlap. It is unclear whether this
407 reflects physical processes that differ between the two regions, or is simply an artefact of the different
408 inventory characteristics used between the two studies. For example, one explanation could be due to a
409 difference in landside typology and size between the two regions. In Italy, ancient deep-seated
410 landslides are common (Cardinali et al., 2002) and included within the Samia et al. (2017) inventory.
411 Conversely, our inventories for Nepal are dominated by the shallow rockfalls and slides that are
412 pervasive across the Himalaya (Dahal et al., 2013), with deep-seated relict events not included. Deep-
413 seated landslides are generally larger than shallow movements because there is more material available
414 to be mobilised (Zêzere et al., 2005) and as such could have greater potential for higher degrees of
415 overlap with new landslides. Therefore, it is possible that if we had included much older, large, deep-
416 seated landslides in our inventory we would have seen a similar rate of decrease to Collazzone.

417 However, if it is the inclusion of larger landslides causing the disparity, then we would expect the mean
418 and maximum sizes of the Samia et al. (2017) inventory to be larger than ours. Yet this is not the case,
419 with the Samia et al. (2017) inventory having larger average sizes than our sub-region inventories, but
420 much smaller average and maximum landslide sizes than for our main inventory. An alternative
421 explanation is that the rate of decrease of landslide area with degree of overlap is an artefact of inventory

422 length. We note that the rate of decrease appears sensitive to inventory length, with the Samia et al.
423 (2017) inventory, our main inventory and our two sub-inventories having decreasing time-spans and
424 decreasing rates. This is logical, as the longer the inventory, the greater the likelihood of observing
425 increasing degrees of overlap.

426 Whilst the number of overlap results confirm that the Himalaya has more landslide overlap than
427 expected if landslide occurrence was random, the overlap index and theoretical area analysis provide
428 further quantification of the actual extent and characteristics of landslide overlap (and thus path
429 dependency). The overlap index results tentatively support that path dependency occurs within the
430 Himalaya, with a weak negative correlation between time between time-slices and overlap index across
431 all three Nepal inventories (Fig. 6a – c). This trend suggests that the occurrence of spatially associated
432 (i.e., overlapping) landslides relates to the time since earlier landsliding, with the likelihood of a new
433 landslide overlapping with an earlier landslide decreasing with time. However, it should be noted that
434 this relationship is not statistically significant, with overlap index showing large variations, particularly
435 at 5 – 15 years between time slices.

436 Again, these results follow a similar trend to those reported by Samia et al. (2017), who also observed
437 a weak negative correlation between overlap index and time passed between time slices. However, the
438 overlap index in the Collazzone region is at least a factor of 10 larger than in any of the Nepal Himalaya
439 regions investigated here. As with the number of overlap results, we suggest that this is due to inventory
440 differences in landslide typology and size. Indeed, whilst we did observe more overlaps than expected
441 given a random distribution, as we only mapped recent shallow landslides, the overlaps between
442 landslides were limited in their absolute potential area. Conversely, the first Samia et al., (2017) time-
443 slice contained substantial relict deep-seated events, meaning that subsequent landslides had a high
444 likelihood of occurring fully within these early failures. Whilst our main inventory and the Roback
445 (2018) Gorkha coseismic inventory do include a couple of very large failures (e.g. the Langtang
446 avalanche (Jones et al., 2020) and the Jure landslide (Regmi et al., 2017)) these occurred late in our
447 time series, so there was less potential for subsequent large degrees of overlap. Interestingly, overlap
448 index values between the Roback (2018) inventory and the time slices from the main region inventory

449 are typically smaller than the index values between different slices of the main region inventory. This
450 may be explained by the fact the Gorkha coseismic landslides had an overall smaller size distribution
451 than expected for an earthquake of that magnitude (Collins and Jibson, 2015).

452 The unaffected area results also suggest that path dependency is occurring across Nepal, with the main
453 region and sub-region 1 inventories showing that the AUA area diverges below the TUA over time (Fig.
454 7a – b). In other words, this shows that the occurrence of overlapping landslides is reducing the actually
455 affected area of landsliding, as if landslides never overlapped then the actually and theoretically
456 unaffected areas would be identical. Again, this result follows the same general trend as that observed
457 in Collazzone. Interestingly, we find that sub-region 2 shows almost no divergence between the AUA
458 and TUA. The cause of this lack of divergence remains unclear, and so should be considered in future
459 work.

460 It is notable that the relative area values are several orders of magnitude higher in Collazzone than they
461 are in the Nepal Himalaya, with a larger observed divergence between the actually and theoretically
462 unaffected areas. This discrepancy is again likely explained by the difference in study region size and
463 landslide inventories of our study and that of Samia et al. (2017). The region studied by Samia et al.,
464 (2017) was relatively small ($\sim 78 \text{ km}^2$) and their analysis included very large relict deep-seated events.
465 Conversely, our main study region was $\sim 45,000 \text{ km}^2$, whilst our sub-regions were $\sim 513 - 609 \text{ km}^2$, and
466 we only mapped recent small-scale landslides. Consequently, the landslide number densities per time-
467 slice in Collazzone ranged from $0.21 - 8.88 \text{ N/km}^2$, whereas ours ranged from $0.003 - 0.54 \text{ N/km}^2$. As
468 such, as this metric is proportional to study region size, the lower densities of landsliding in Nepal
469 explain why our relative area values are so much lower. This also explains why the divergence between
470 the actually and theoretically unaffected areas is lower for Nepal, because even though there are more
471 overlaps than expected across both regions (e.g. Fig. 5), as a proportion of the study region size the
472 actual area affected by overlaps is small.

473 Furthermore, it is also observed that in all of the Nepal landslide inventories, major increases in both
474 the AUA and TUA are coincident with cloud outburst storms in 1993 and 2002 (Fig. 7a) and the Gorkha
475 earthquake in 2015 (Fig. 7a – c). This observation highlights that the occurrence of new landslides and

476 the reactivation of pre-existing landslides is largely driven by extreme triggering events, rather than just
477 gravitational processes. This observation corroborates other studies that have shown that shallow
478 landsliding is commonly perturbed by infrequent, high magnitude landslide drivers such as earthquakes
479 and storms (Chen et al., 2020; Dadson et al., 2004; Marc et al., 2015; Martino, 2015; Rathburn et al.,
480 2017; Wolman and Miller, 1960). For example, the 2008 Wenchuan earthquake was observed to cause
481 significant increases in post-earthquake landslide reactivation rates (Chen et al., 2020; Tang et al., 2016;
482 Zhang et al., 2014). Therefore, our new data support previous observations showing that significant
483 increases in rates of landslide reactivation, and thus path dependency, are most likely following extreme
484 events.

485 *5.2 Do spatially associated and unassociated landslides have different size, roundness and spatial*
486 *distributions?*

487 Overall, the number of overlaps, overlap index and theoretical area analysis show that landslide path
488 dependency is occurring within the Nepal Himalaya. The second testable hypothesis is that path
489 dependent (spatially associated) landslides will have different size and spatial distributions to spatially
490 unassociated landslides, as found by Samia et al. (2017) in Collazzone,

491 To investigate differences in spatial distributions we quantified how different landslide subsets (all
492 landslides, spatially associated (partial) and spatially unassociated) in our main inventory and combined
493 sub-region inventories were distributed according to four typical landslide control factors; elevation,
494 slope, aspect and lithology. The first control factor to be considered is elevation; all landslides are
495 proportionately more likely to occur at lower elevations (800 – 2800 m) than at higher elevations (2800
496 – 6000 m) in both study areas (Fig. 8a –b). This is unsurprising given that our inventories are of
497 monsoon-triggered landslides, and that the lower elevation regions in the Himalaya typically experience
498 more rainfall due orographic effects (Ichiyanagi et al., 2007). Furthermore, particularly across the main
499 region, it is noted that landslide occurrence falls to zero by ~4500 m, despite there being significant
500 areas of land at higher elevations. We suggest that this cut-off in landslide occurrence is owing to the
501 onset of permanent snow, ice and permafrost, all of which become pervasive at elevations of ~5000 m
502 (Chauhan and Thakuri, 2017; Fukui et al., 2007). Glacial, paraglacial and periglacial processes are

503 unlikely to influence landslide occurrence across the sub-regions as there is little coverage of elevations
504 greater than ~5000 m in these areas (Fig. 8b).

505 Secondly, with respect to hillslope angle, all landslide occurrences typically follow a normal
506 distribution that peaks at 35 – 40°. This result is expected given that higher slope gradients are a
507 significant control on slope stability (Hasegawa et al., 2009; Regmi et al., 2013). Within the sub-regions,
508 spatially associated (partial) landslides are more likely than spatially unassociated landslides to occur
509 at slope gradients > 50°. This is likely because hillslopes above their natural threshold angle are
510 inherently more unstable (Blöthe et al., 2015), so past landslide material that remains on high angle
511 slopes is more likely to fail again or be remobilised in the future.

512 The third control factor is aspect; all landslides across both regions are most likely to occur on south
513 east, south, and south-west facing hillslopes (Fig. 8e - f). One explanation for this distribution could be
514 due to thermal weathering, whereby south-facing hillslopes experience greater expansion and
515 contraction as a result of high insolation, causing higher rates of rock and regolith damage, and therefore
516 an increase in landsliding (Collins and Stock, 2016). Another potential explanation is the Nepal summer
517 monsoon. The Asia Summer Monsoon typically travels from southeast to northwest (Nayava, 1974),
518 causing more rainfall to be deposited on south and southeast facing slopes. Consequently, these aspects
519 become saturated faster and will experience higher pore water pressures than north facing, more
520 sheltered, hillslopes. This explanation is corroborated by Dahal et al. (2008) who also found increased
521 landsliding on SE – SW facing slopes, and attributed this to the monsoon. In terms of the difference
522 between spatially associated and spatially unassociated landslides, in the sub-regions, we see that
523 spatially associated (partial) landslides are 10% more likely than spatially unassociated landslides to
524 occur on S-facing hillslopes. This implies that spatially associated landslides are more strongly affected
525 by the monsoon (and insolation). This interpretation is logical, as infiltration of rainwater and
526 subsequent increases in pore pressure and decreases in hillslope stability will be exacerbated where
527 failures have occurred in the past, thus leading to more failures in the same location going forward
528 (Iverson, 2000). We would expect this effect to be particularly potent in the years immediately following

529 a past failure, when bedrock and regolith may still be exposed to the elements (i.e., not yet revegetated)
530 decreasing slope stability (Löbmann et al., 2020).

531 Finally, when considering the influence of bedrock geology on spatial distributions, landslides of all
532 types and across both study regions are more likely to occur in phyllites, dolomite, and Quaternary
533 conglomerates and sandstones, but less likely to occur in granites. This is unsurprising, given that
534 landslides would be expected more frequently where hillslope strength is lower, and that Quaternary
535 sandstones and phyllites in Nepal are estimated to have Uniaxial Compressive Stresses (UCS) of ~ 27
536 MPa (Tamrakar et al., 2007) and 46 MPa (Samadhiya and Jain, 2003), respectively. Whereas granites
537 are estimated to have higher UCS values of ~ 58 MPa (Tandon and Gupta, 2015). In addition, spatially
538 associated (partial) landslides in both the main and sub-regions are more likely than spatially
539 unassociated landslides to occur in phyllites.

540 In terms of size distributions, it is observed that the main region average landslide size is larger than it
541 is for the sub-regions. This is likely a direct result of inventory resolution, with the higher resolution
542 sub-region results being a more reliable reflection of true average landslide size. However, for both the
543 main region inventory and combined sub-region inventories, we see that spatially associated (partial)
544 landslides have larger mean areas and rollover values, but lower power-law scaling exponents. The
545 higher rollover values for the spatially associated landslides indicates that the most frequent landslide
546 area, and the area below which the frequency density of landslides begins to decrease, is greater.
547 Likewise, the lower power-law exponent for the spatially associated landslides indicates that larger area
548 landslides contribute more to the overall distribution than they do for spatially unassociated landslides.
549 This result is similar to that found by Samia et al. (2017) in Collazzone, Italy, where it was found that
550 there was a decrease in landslide size with decreasing degree of spatial association.

551 There are two potential explanations for this observation. One, that it reflects a physical tendency for
552 spatially associated landslides to be larger. As posited by Samia et al. (2017) this could be due to
553 boundary effects, whereby the edges of a past landslide have high instabilities due to over-steepening,
554 decreased cohesion and shear strength, and increased infiltration, which make subsequent landslides in
555 those locations larger. This explanation is supported by our control factor analysis, which shows that

556 spatially associated (partial) landslides are more likely than spatially unassociated landslides at slope
557 angles $> 50^\circ$. Alternatively, this could be an artefact of landslide mapping procedure. Landslides are
558 identified via the visual comparison of pre- and post-time slice imagery. Typically, the easiest landslides
559 to observe and map are those that replace vegetation with fresh bare earth, as these have high reflectivity
560 differences that is easily picked up by optical imagery. However, spatially associated landslides are by
561 definition occurring fully within or overlapping with a past landslide that may or not have been re-
562 vegetated. If the past landslide has not been revegetated, then new landslides overlapping it may be
563 difficult to identify, particularly if they are small, as the reflective difference between weathered bare
564 earth and fresh bare earth is less evident than the difference between vegetation and fresh bare earth.
565 As such, smaller spatially associated landslides may be under sampled within the inventory compared
566 to similarly small spatially unassociated landslides, an artefact that will be more pronounced in the
567 lower resolution main region inventory.

568 Finally, differences in average roundness between the main and sub-regions is likely a resolution
569 artefact. On average, the main region contains landslides with higher roundness values, which could be
570 caused by lower inventory resolution making landslide shapes appears rounder. However, despite the
571 differences between the two inventory types, in both cases, spatially unassociated landslides show a
572 higher average roundness than spatially associated landslides. This supports Samia et al. (2017), who
573 showed that spatially associated landslides were typically more elongated. Lower roundness values and
574 thus more elongate landslides are typically associated with a debris flow like typology (Parise and
575 Jibson, 2000), suggesting that spatially associated landslide events are more likely to be reactivated
576 material failing as a debris flow than spatially unassociated events.

577 *5.3 What spatial/temporal data are required to observe path dependency?*

578 The second aim of this paper was to assess what spatial and temporal data are required to observe path
579 dependency. This is a useful question to answer as it will allow future studies on this topic to target
580 landslide data collection more efficiently for the purpose of investigating path dependency.

581 Our results and those of Samia et al. (2017) show that path dependency can be observed across a range
582 of spatial and temporal scales. Here, we used two inventory types, one covering 30 years with annual

583 time slices and landslides mapped at 15 – 30 m resolution, and two others covering 10 years with bi-
584 annual time slices and landslides mapped at 5 m resolution. The fact that path-dependency was observed
585 across both inventory types suggests that only a small number of time-slices (at least 5) and landslides
586 mapped at a low (15 – 30 m) resolutions are required to determine whether path dependency is
587 occurring.

588 However, we also observe that some path dependent results may be scale dependent. For example, we
589 find that the rate of decrease of landslide area with degree of overlap is sensitive to inventory length.
590 Likewise, whilst the general trends in the overlap index and unaffected area results were similar across
591 all spatial and temporal scales, the magnitudes of these metrics were strongly related to landslide
592 density, which was itself a product of study region size and the type and scale of landslides included in
593 an inventory; specifically, whether large relict deep-seated landslides are included. Thus, higher
594 resolution mapping over smaller spatial scales combined with the inclusion of large deep-seated events
595 will lead to inventories with a higher landslide density, and therefore a greater magnitude overlap index
596 and TUA / AUA relative area. Furthermore, for the overlap index specifically, we conclude that longer
597 inventories with more time-slices will be increasingly accurate, as they allow for greater inter- time
598 slice comparisons, and thus will ensure that any short-term anomalous variations (such as that observed
599 in Fig. 6) do not mask the overall trends in path dependency.

600 In addition, the results from Section 4.3 highlight that inventory resolution has a strong impact on the
601 apparent influence of landslide control factors. Specifically, figure 7 shows that, when using the lower
602 resolution main inventory data, the spatially associated and spatially unassociated landslides appear to
603 have similar control factor distributions. In contrast, the higher resolution sub-region data suggest that
604 spatially associated and unassociated landslides actually have slightly different control factor
605 distributions. This highlights that whilst lower resolution landslide inventory data can detect overall
606 rates of path-dependency, such data may not be sufficient to undertake a detailed quantification of path-
607 dependency characteristics. Consequently, when investigating path-dependency for the purpose of
608 undertaking landslide susceptibility, where an understanding of control factor is vital (e.g. Samia et al.,
609 2018) the use of higher resolution, and thus more accurate, inventories is recommended.

610 6.0 Conclusions

611 The main aims of this paper were twofold. Firstly, to use the methods of Samia et al. (2017) to quantify
612 if, and if so how, landslide path dependency occurs in the Nepal Himalayas, and thus provide evidence
613 that the path dependency observed in Italy is also present in other geomorphic regions. As part of this
614 aim, we also investigated whether path dependent (spatially associated) landslides have different size
615 and spatial distributions to spatially unassociated landslides. Secondly, to provide insight into the spatial
616 and temporal resolution of data required to observe and quantify path-dependency.

617 We find that there is strong evidence for landslide path dependency in Nepal, with all Nepal inventories
618 having more overlaps between earlier and new landslides than would be expected from a random
619 distribution. Furthermore, the unaffected area results show that the actual area of the study regions
620 unaffected by landsliding is lower than the theoretical area that would be unaffected if there was no
621 landslide overlapping, whilst the overlap index tentatively suggests that the amount of overlap between
622 landslides in two time-slices decreases with time. This corroborates the results of Samia et al. (2017),
623 suggesting that their recommendation for this process to be included in landslide susceptibility
624 modelling should apply to geomorphic regions outside of Italy.

625 We also conclude that spatially associated landslides have larger size distributions than spatially
626 unassociated landslides, and are more likely at slope angles $> 50^\circ$ and south-facing aspects. This further
627 supports the idea that path-dependency and path-dependent landslides should be treated more explicitly
628 within landslide susceptibility models.

629 Finally, by investigating path dependency using inventories with two different spatial and temporal
630 resolution landslide inventories, we confirm that path dependency can be observed with 2-year long
631 time slices over 10-years and 30 m resolution landslide data. However, we also find that the rates and
632 magnitudes of path dependent metrics are sensitive to inventory length, study region size and the
633 size/type of landslides mapped, so these must be considered when interpreting path-dependent results.

634

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640

641 Data Availability Statement

642 Supplementary Tables 1 – 3 show the satellites used to map each landslide in each inventory, as well
643 as the perimeters, areas and path-dependency classifications of each landslide in each inventory. The
644 full landslide inventory data are available from the corresponding author on request.

645

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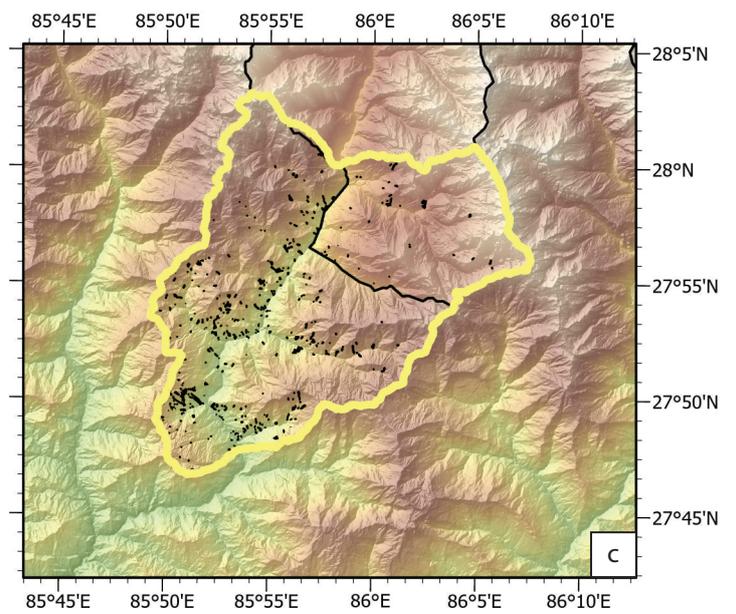
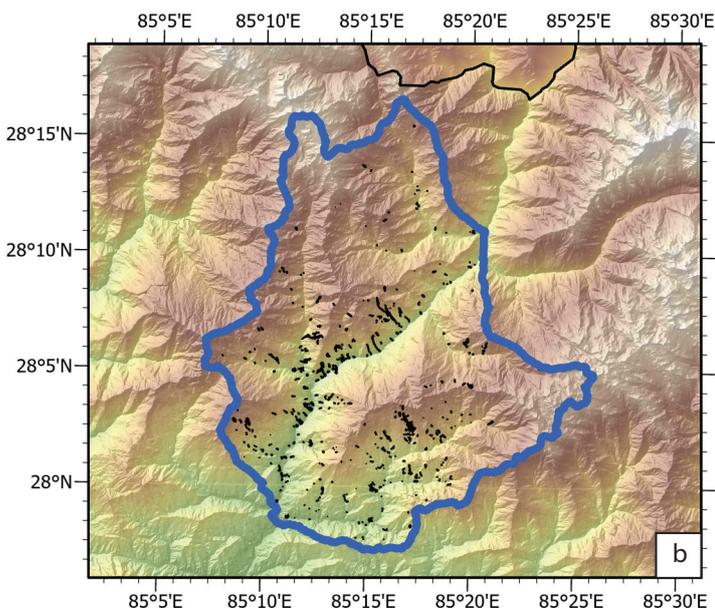
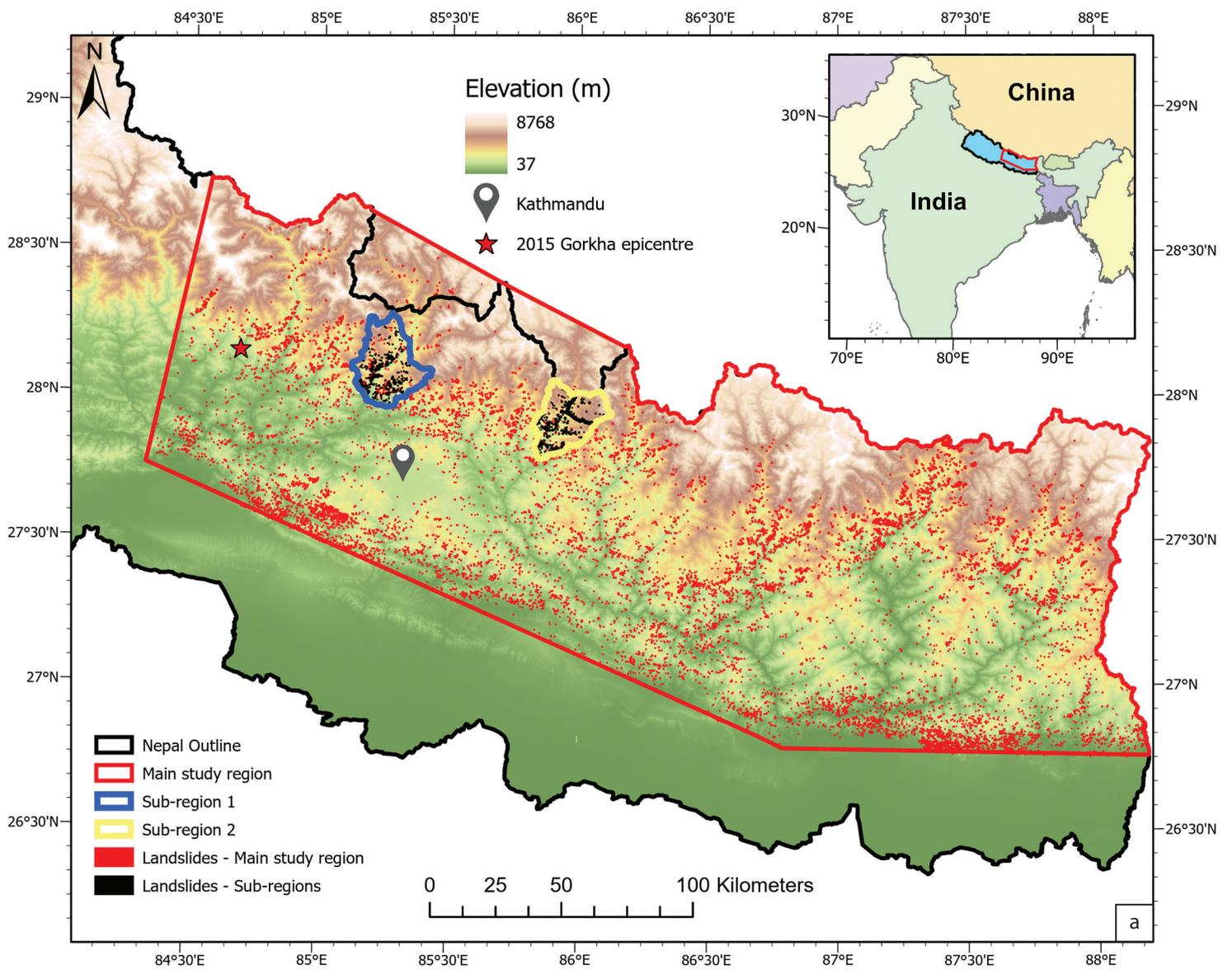


Figure 1. a) Regional locations of Nepal and our main study region. b) the specific locations of our main and two study regions, including all mapped landslide polygons, the 2015 Gorkha earthquake epicentre and Kathmandu. c – d) larger scale maps showing only the landslides mapped in sub-regions 1 and 2 respectively.

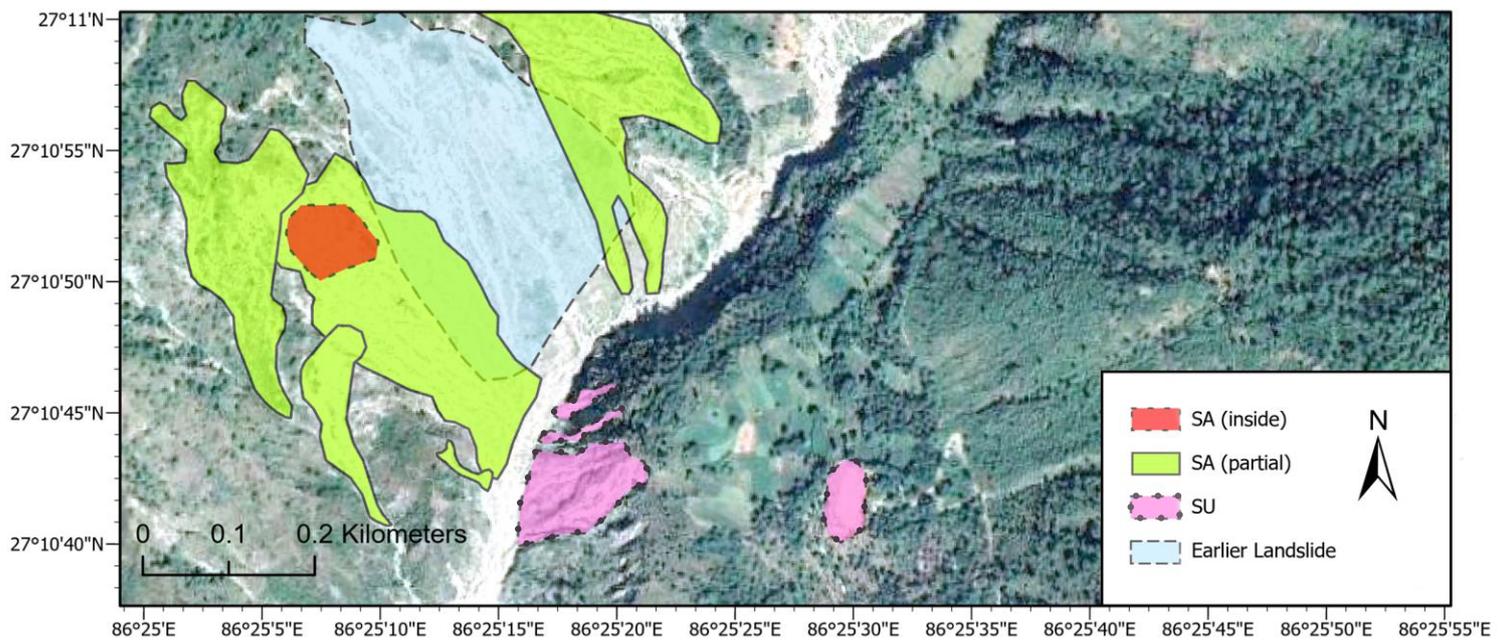


Figure 2. Examples of the spatial associations between landslides in different time-slices *using google Earth imagery* (GoogleEarth, 2020). Note, the landslide polygons presented in this figure are used to illustrate the path-dependent types in high resolution imagery, and are not polygons from any of the inventories presented in this paper. Spatial associations include: Spatially Associated (SA) (inside), which are landslides that occur fully within an earlier landslide. Spatially Associated (SA) (partial), which are landslides that occur partially within (i.e. across a boundary of) an earlier landslide. Spatially Unassociated (SU), which are landslides that have no geometric intersection with any earlier landslides.

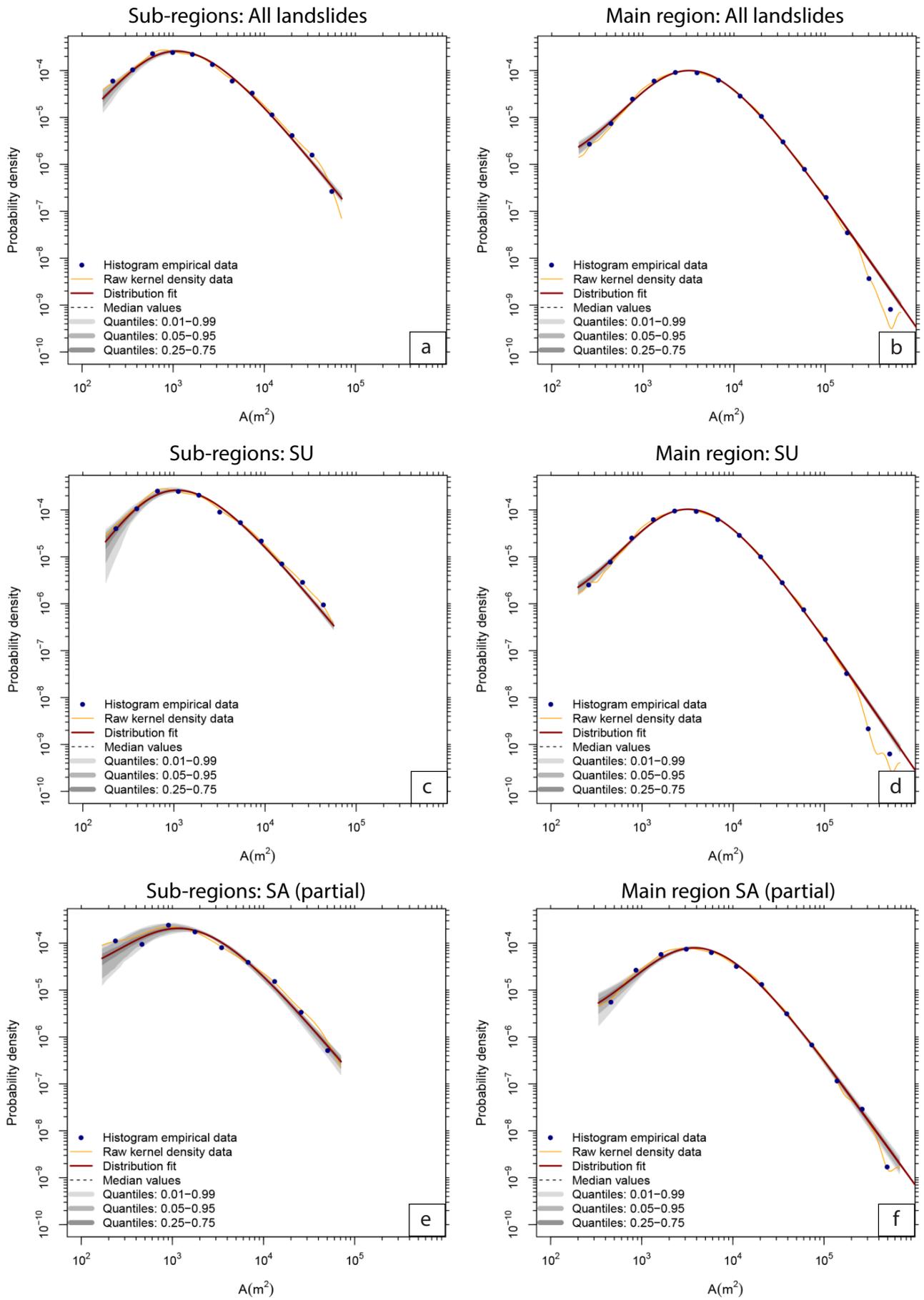


Figure 3. The three-parameter inverse power-laws fitted to the probability density functions of: all landslides in the two sub-regions (a) and main region (b), all Spatially Unassociated (SU) landslides in the two sub regions (c) all main region (d), and all Spatially Associated (SA) (partial) landslides in the two sub-regions (e) and main region (f).

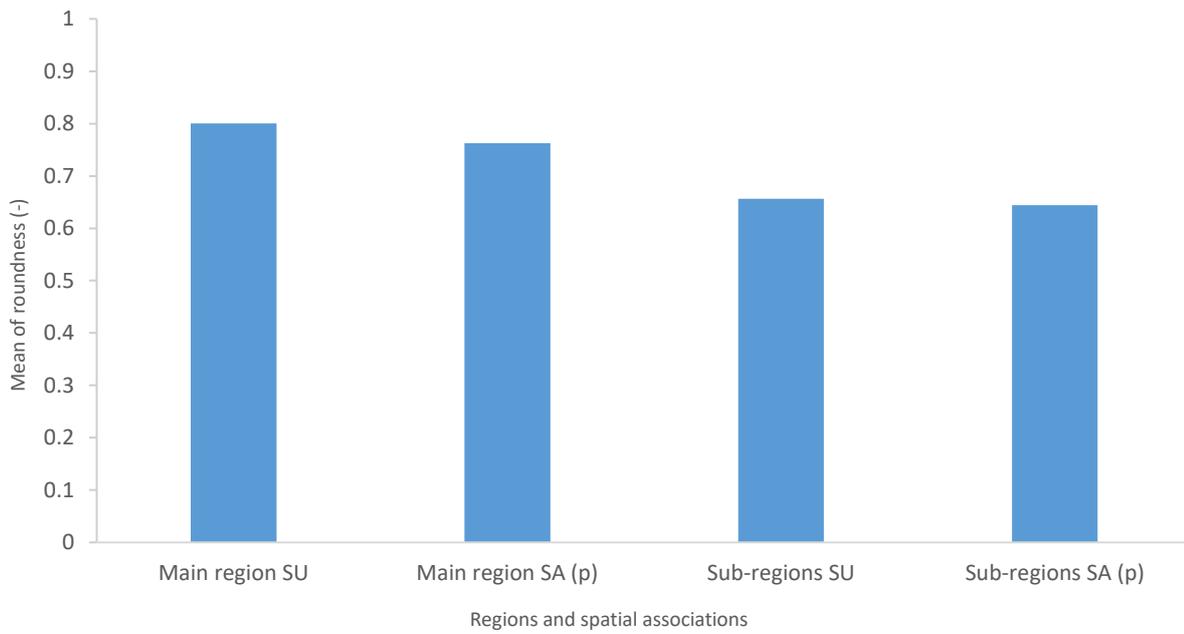


Figure 4. Mean of roundness for different regions and classes of spatial association (Main region spatially unassociated, main region spatially associated (partial), sub-regions spatially unassociated, and sub-regions spatially associated (partial)).

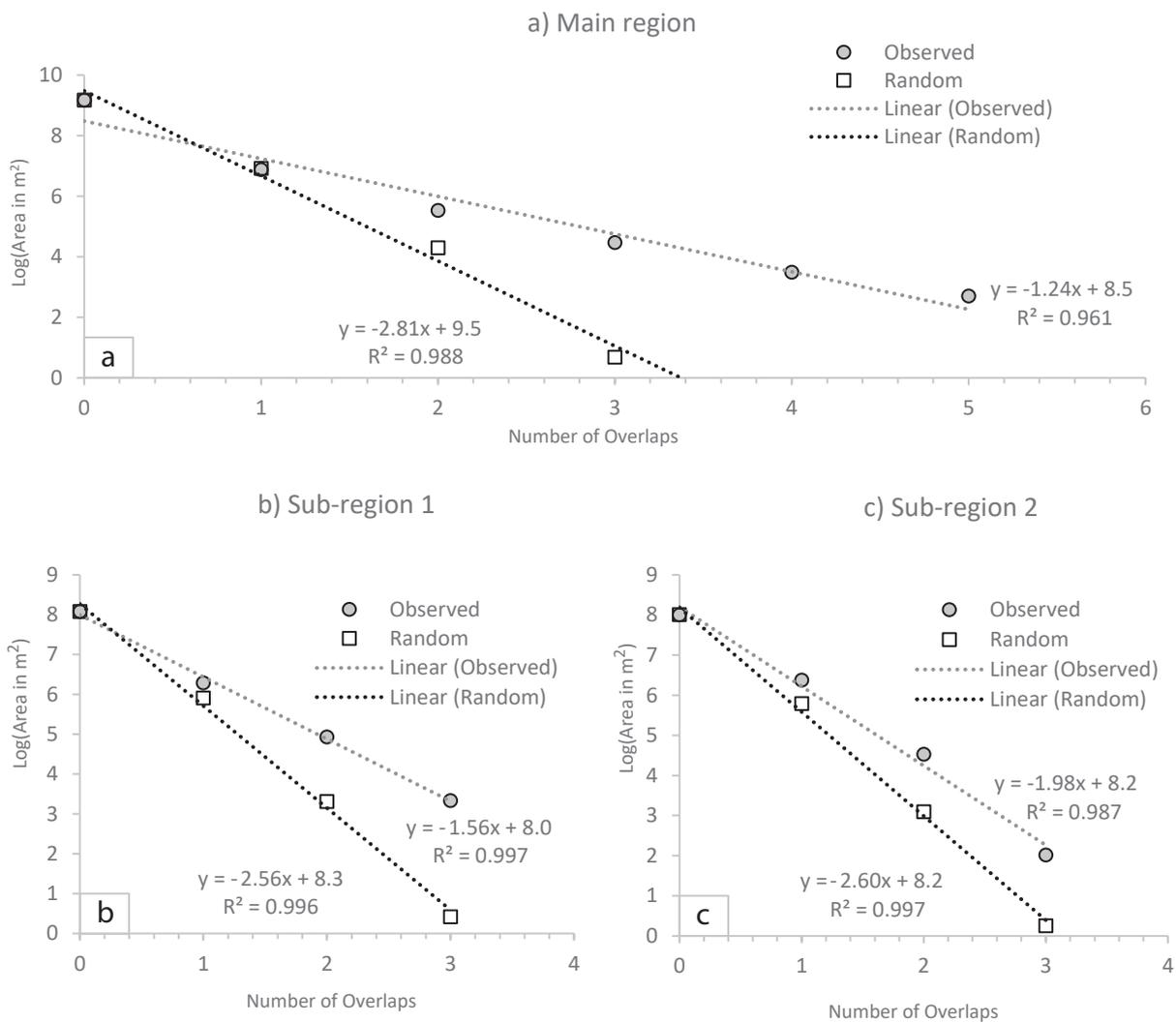


Figure 5. The area of landslides at different degrees of overlap for: a) the main inventory, b) sub-region 1, c) sub-region 2.

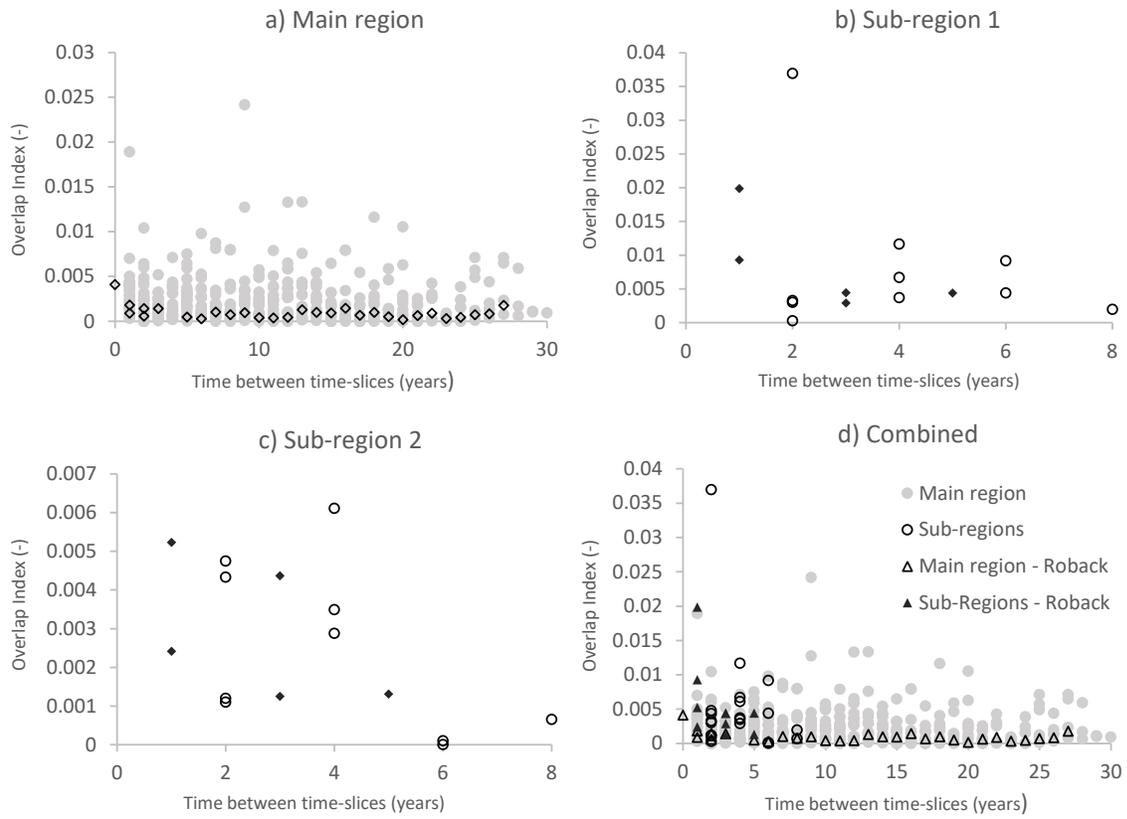


Figure 6. Overlap Index versus time between time-slices for: a) the main inventory, b) sub-region 1, c) sub-region 2.

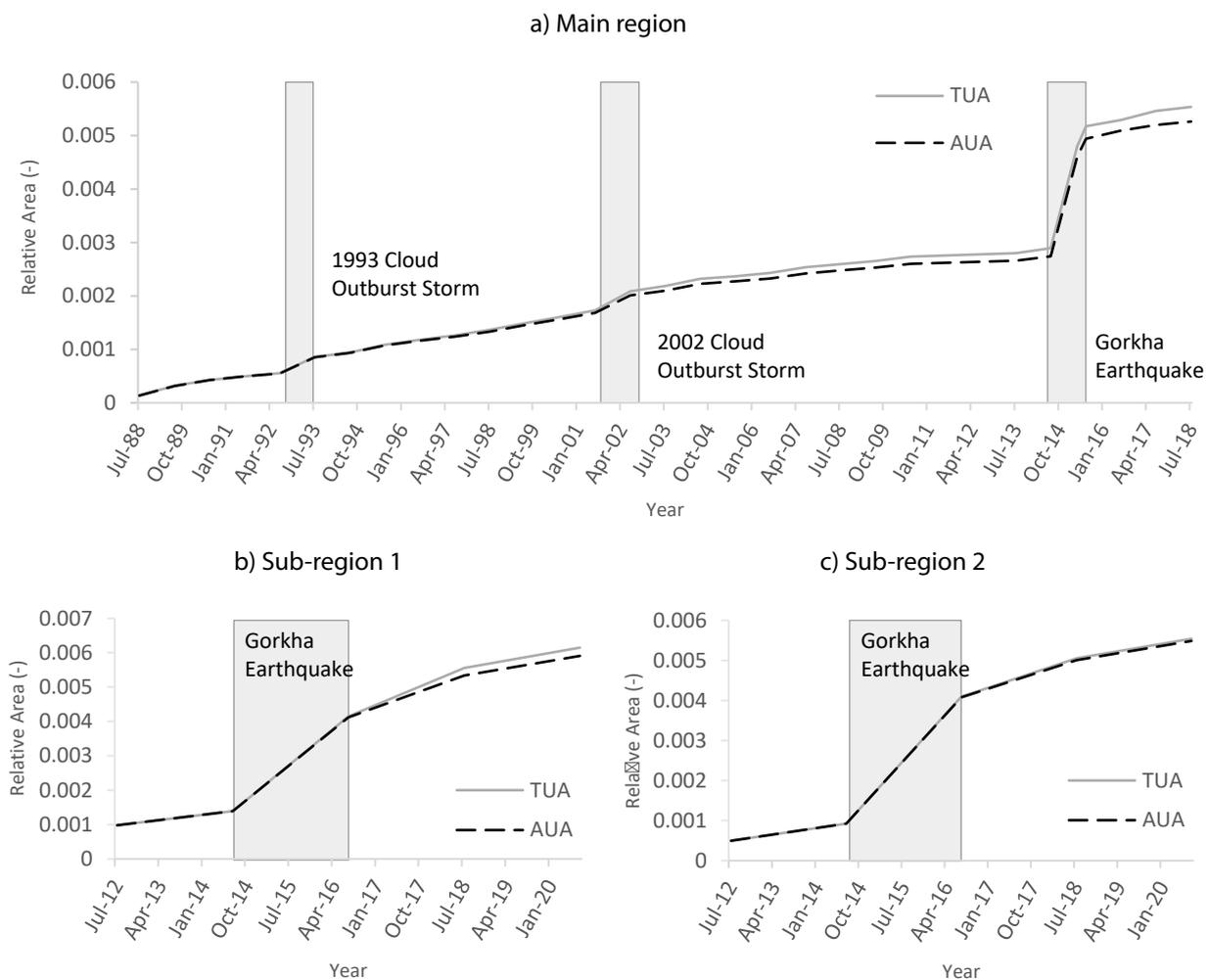


Figure 7. The Theoretical (TUA) and Actual (AUA) areas unaffected by landslides for: a) the main inventory, b) sub-region 1, c) sub-region 2.

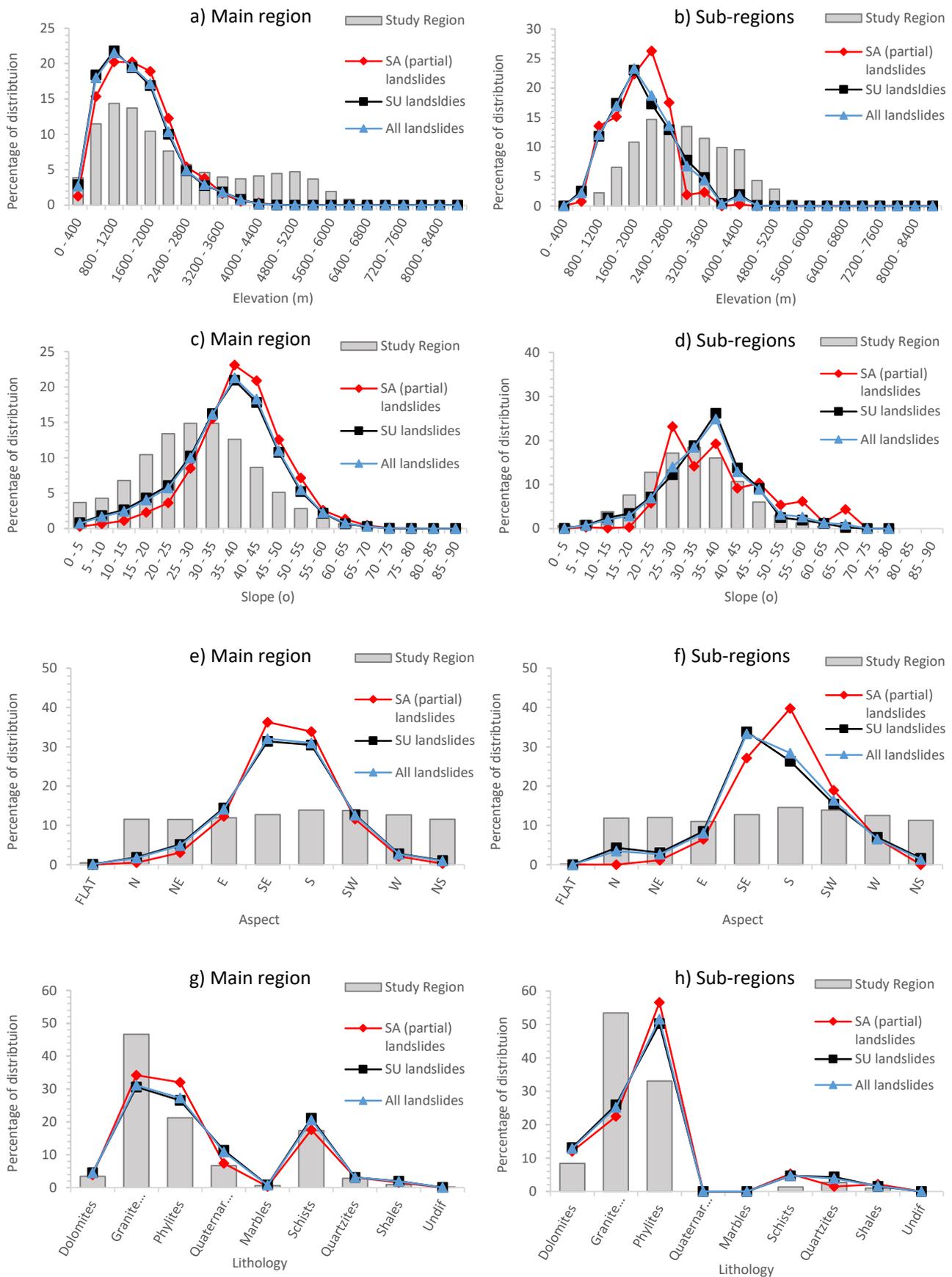


Figure 8. Landslide distributions by subtype (all landslides, Spatially Associated (SA) (partial), and Spatially Unassociated (SU)) with respect to: a) elevation (main inventory), b) elevation (sub-region inventory), c) slope (main inventory), d) slope (sub-region inventory), e) aspect (main inventory), f) aspect (sub-region inventory), g) lithology (main inventory), h) lithology (sub-region inventory).

	All (Main region)	SU (Main region)	SA (partial) (Main region)	(Sub-regions 1 / 2)	SU (Sub-regions 1 / 2)	SA (partial) (Sub-regions 1 / 2)
n	12901	11031	1824	1192	1028	164
Mean Area (m²)	12616	12017	16410	5510	5295	6861
Minimum Area (m²)	198	198	334	169	178	169
Maximum Area (m²)	684783	684783	680500	71009	56720	71009
α	1.79 +/- 0.032	1.83 +/- 0.036	1.62 +/- 0.074	1.44 +/- 0.079	1.45 +/- 0.087	1.36 +/- 0.20
η	29 +/- 0.89	29.1 +/- 0.97	29.3 +/- 2.41	16.63 +/- 1.72	15.72 +/- 1.91	21.88 +/- 4.52
λ	107 +/- 1.58	108 +/- 1.73	106 +/- 4.02	57.79 +/- 2.70	57.24 +/- 2.89	62.37 +/- 8.16
Rollover	3266	3256	3444	1094	1087	1171
	0.223	0.374	0.801	0.296	0.259	0.734

Table 1. Summary size statistics for all landslides, Spatially Associated (SA) partial landslides, and Spatially Unassociated (SU) landslides in both the main region and combined sub-regions. For each case, the statistics include: the number of landslides (n), the mean, minimum and maximum landslide areas, the exponent of the three-parameter inverse power law fitted to the right tail of the probability density function (α), the bend of the left tail of the three-parameter inverse power law (η), the constant controlling the position of the rollover (λ), the rollover area (i.e. the landslide area below which landslide sizes become less frequent) and the p-value of data fit to the three-parameter power-law.