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Building vulnerability to hydro-geomorphic hazards: Estimating damage probability from qualitative vulnerability assessment using logistic regression

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36

37 **Abstract**

38

39 The focus of this study is an analysis of building vulnerability through investigating impacts
40 from the 8 February 2013 flash flood event along the Avenida Venezuela channel in the city of
41 Arequipa, Peru. On this day, 124.5mm of rain fell within 3 hours (monthly mean: 29.3mm)
42 triggering a flash flood that inundated at least 0.4km² of urban settlements along the channel,
43 affecting more than 280 buildings, 23 of a total of 53 bridges (pedestrian, vehicle and railway),
44 and leading to the partial collapse of sections of the main road, paralyzing central parts of the
45 city for more than one week.

46 This study assesses the aspects of building design and site specific environmental
47 characteristics that render a building vulnerable by considering the example of a flash flood
48 event in February 2013. A statistical methodology is developed that enables estimation of
49 damage probability for buildings. The applied method uses observed inundation height as a
50 hazard proxy in areas where more detailed hydrodynamic modeling data is not available.
51 Building design and site-specific environmental conditions determine the physical vulnerability.
52 The mathematical approach considers both physical vulnerability and hazard related
53 parameters and helps to reduce uncertainty in the determination of descriptive parameters,
54 parameter interdependency and respective contributions to damage. This study aims to (1)
55 enable the estimation of damage probability for a certain hazard intensity, and (2) obtain data

56 to visualize variations in damage susceptibility for buildings in flood prone areas. Data
57 collection is based on a post-flood event field survey and the analysis of high (sub-metric)
58 spatial resolution images (Pléiades 2012, 2013). An inventory of 30 city blocks was collated in
59 a GIS database in order to estimate the physical vulnerability of buildings. As many as 1103
60 buildings were surveyed along the affected drainage and 898 buildings were included in the
61 statistical analysis. Univariate and bivariate analyses were applied to better characterize each
62 vulnerability parameter. Multiple corresponding analyses revealed strong relationships
63 between the “Distance to channel or bridges”, “Structural building type”, “Building footprint”
64 and the observed damage. Logistic regression enabled quantification of the contribution of
65 each explanatory parameter to potential damage, and determination of the significant
66 parameters that express the damage susceptibility of a building. The model was applied 200
67 times on different calibration and validation data sets in order to examine performance. Results
68 show that 90% of these tests have a success rate of more than 67%. Probabilities (at building
69 scale) of experiencing different damage levels during a future event similar to the 8 February
70 2013 flash flood are the major outcomes of this study.

71

72 **Keywords**

73 Flash flood; Vulnerability; Logistic regression; Damage probability; Risk; Arequipa

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81 **1. Introduction**

82 On February 8 2013, heavy rainfall (124.5mm within 3 hours versus a monthly mean of
83 29.3mm) triggered a flash flood event along the Avenida Venezuela channel in the city of

84 Arequipa, Peru. On this day, more than 280 buildings and 23 of a total of 53 bridges
85 (pedestrian, vehicle and railway) were affected; the partial collapse of sections of a major road
86 paralyzed central parts of the city for more than one week. Previous risk assessment studies
87 in Arequipa did not include the Avenida Venezuela channel due to its smaller size and largely
88 confined channel course. The high recurrence rate of hydro-geomorphic hazards (Martelli,
89 2011; Thouret et al., 2013, 2014), and apparent locally high vulnerability of buildings and
90 critical infrastructure in Arequipa, are major motivations for this study.

91 Risk in the context of disaster risk management is commonly defined as a potential loss for a
92 given probability function (Crichton, 1999; Kaplan and Garrick, 1981). In the standard
93 conceptual framework, risk is the product of hazard, vulnerability and exposure (Cardona,
94 2004; Carreno et al., 2006). While the hazard is generally described by its severity, e.g.
95 inundation height for a given return return period, exposure relates to the number and value of
96 elements potentially affected (Hiete and Merz, 2009). Many different definitions, concepts and
97 methods to systemize vulnerability exist in the current literature (Birkmann, 2006; Cutter, 2003;
98 Wisner et al., 2004; Thywissen, 2006; IPCC, 2007; Bründl et al., 2009). In this study we follow
99 the definition for physical vulnerability proposed by Glade (2003) and Villagran de Leon (2006)
100 as the predisposition of an element or system to be affected or susceptible to damage as the
101 result of the natural hazard's impact. Vulnerability assessment for hydro-geomorphic hazards
102 such as dilute floods, debris flows, hyperconcentrated flows etc. is inherently complex, mainly
103 as a result of the following factors (Gaume et al., 2009): (i) lack of accurate or real-time
104 observational data necessary for reliable hazard analysis; (ii) only substantial damage
105 information is generally recorded and accurate information on failure characteristics is often
106 missing (Fuchs et al., 2007b; Papathoma Köhle et al., 2011); (iii) different time and
107 geographical scales involved (Grunfest, 2009; Marchi et al., 2010); (iv) natural adjustments of
108 the environment to return to a state of equilibrium; (v) rapid intervention by technical services
109 to restore functionality of urban infrastructure reduces the time frame for damage assessment
110 in the field; (vi) site-specific triggering processes and upstream-downstream evolution of
111 debris-flow phenomena (Di Baldassarre and Montanari, 2009). If field investigations are

112 conducted to study and record structural damage following a hazard event, these data are then
113 generally correlated to the process intensity, frequently derived from deposition height or
114 inundation height, in order to develop empirical fragility curves (Fuchs et al., 2007a,b; Holub
115 and Fuchs, 2008). These curves are then employed within risk assessments to estimate
116 structural damage in future events. The lack of high-quality observational evidence and
117 uniform, i.e. non site-specific, approaches to data collection, implies that the majority of fragility
118 curves are still developed using expert judgment (Papathoma Köhle et al., 2012; Totschnig
119 and Fuchs, 2013). The compilation of field data for different sites in the European Alps, Taiwan
120 etc. published in recent studies (Totschnig et al., 2011; Holub et al., 2012; Papathoma Köhle
121 et al., 2012; Totschnig and Fuchs, 2013) has helped to develop vulnerability functions
122 applicable within the framework of risk management for specific regions (Totschnig and Fuchs,
123 2013). If the required input data are available, the method is transferable to other alpine
124 regions. However, data availability remains a major constraint in many countries (e.g.,
125 Douglas, 2007; Jakob et al., 2012; Lo et al., 2012; Totschnig and Fuchs, 2013). For Latin
126 America, very few case studies have been published with a focus on physical vulnerability
127 analysis. In contrast to many sites monitored and equipped in the European Alps, areas prone
128 to hydro-geomorphic hazards in the Andes are rarely monitored, and in the worst case, not
129 even mapped. It therefore becomes difficult to apply methods derived from European
130 experience in the same or a similar way. In addition there is a critical lack of observational data
131 collected in the immediate aftermath of disasters. For the study presented here, data to apply
132 existing vulnerability assessment methods were not available, although alternative information
133 could be collected.

134 Flash floods are common in semi-arid areas, such as Arequipa, and can, despite their
135 infrequent nature, have a devastating effect in both geomorphological and human terms
136 (Gaume et al., 2009; Jonkman and Vrijling, 2008; Martínez Ibarra, 2012). The occurrence of
137 flash floods is highly variable, both spatially and temporally, most occurring as the result of
138 localized intense storms (Graf, 1988; Reid and Frostick, 1992; Hooke and Mant, 2000). Several
139 important factors arise as a result of these characteristics. First, areas prone to flash floods

140 need to be adequately prepared. Because events usually occur unexpectedly, warning and
141 preparation are essential (Montz and Grunfest, 2002; Collier, 2007; Borga et al., 2008; Gaume
142 et al., 2009); however, because events are typically rare, the motivation to invest time and
143 resources into such activities may be lower than for more frequent hazards (Grunfest and
144 Handmer, 2001). Flash floods usually affect relatively small areas and losses resulting from
145 them do not always generate much long-term response, unless there is high loss of life.
146 However, losses per unit (acre, square mile, or kilometer) of area affected tend to be high
147 compared to other events such as riverine floods or hurricanes due to locally high intensity
148 (Gaume et al., 2009; Martínez Ibarra, 2012).

149 Vulnerability indicators for flash flood hazard are at present too site-specific to render the use
150 of vulnerability assessment broadly operational. Additionally, building structures differ
151 regionally and nationally and channel settings vary locally. The general approach to assess
152 structural vulnerability focuses on impact intensity and structural susceptibility of elements at
153 risk, assigning probabilities to different damage thresholds, from no damage through to
154 complete destruction. From this technical point of view, and as a general rule, vulnerability
155 assessment is based on the evaluation of parameters and factors such as building type,
156 construction materials and techniques, state of maintenance, and presence of protection
157 structures (Fell et al., 2008). For this reason, vulnerability values describe the susceptibility of
158 elements at risk, facing different process types, with various spatial and temporal distributions
159 of hazard intensity (e.g. flow depth, accumulation height, flow velocity and/or pressure, Fuchs
160 et al., 2007a,b; Holub and Fuchs, 2008).

161 Several recent studies (Martelli, 2011; Santoni, 2011; Ettinger et al., 2014a,b; Thouret et al.,
162 2013, 2014) examined the physical vulnerability of buildings and critical infrastructure in the
163 city of Arequipa, Peru. Thouret et al. (2014) established vulnerability indicators for buildings
164 based on experiences by Zuccaro and Ianniello (2004), Zuccaro et al. (2008) and Zuccaro and
165 De Gregorio (2013) that were calibrated on-site in Arequipa. Our research builds on this work
166 and analyzes the relationships between these parameters and their significance in terms of
167 the susceptibility of a building to experience damage. The present study aims to develop a

168 methodology for rapid estimation of potential damage of existing structures facing natural
169 hazards, in particular flood-hazard. It can be useful, in particular for developing countries, in
170 the case of inadequate hazard information, i.e. in areas where there have been no surveyed
171 hazard events or hydraulic modeling. The objectives of this research are fourfold: to (1) map
172 and characterize channel morphology in natural and built sections; (2) determine and quantify
173 the relationships between building vulnerability parameters; (3) identify the weight of each
174 parameter; and (4) apply mathematical models to calculate the damage probability for each
175 building.

176

177 **2. Geographical setting**

178

179 Arequipa, with a population of c. 900,000, is the second largest city in Peru, located at c.
180 2,300m above sea level, at the foothill of three summits of the Peruvian Andes: El Misti volcano
181 (5,821m asl) to the northeast, flanked by Mounts Chachani (6,075m asl) to the North and Pichu
182 Pichu (5,664m asl) to the East. The high altitude and semi-arid climate are responsible for
183 scarce vegetation cover in both low and high altitudes. Abundant unconsolidated volcanic
184 debris is therefore exposed on steep mountain slopes. Mean annual precipitation does not
185 exceed 150mm and rainfall occurs mainly in the form of low frequency-high intensity
186 rainstorms. These events often trigger flash floods, which sweep through the city of Arequipa
187 following one or more of the numerous channels draining the flanks of El Misti volcano. Since
188 the 1940s, the city's population has quadrupled, occupying at present a built surface of
189 approximately 5,025ha (Fig. 1). The Río Chili valley is a geographical barrier separating the
190 city in two parts; urbanization is extending the city area to the West but also to the East,
191 colonizing the lower flanks of El Misti volcano. Intense urbanization is exposing an increasing
192 number of people and built environment to flash flood hazards.

193 On 8 February 2013 the La Pampilla meteorological station, located close to the city centre
194 (Fig. 1A), recorded c. 123mm of rain over 3 hours ([SENAMHI, 2013](#)); compared with a mean
195 February total of 29.3mm. Since the beginning of pluviometric records in the 1960's, the

196 February 2013 rainfall was the highest for that month (SENAMHI, 2013; Cacya et al., 2013).
197 The high intensity of this particular rainstorm generated a flash flood that affected several
198 districts of the city (INDECI, 2013; Cacya et al., 2013). Previously conducted risk assessment
199 studies in Arequipa (Martelli, 2011; Thouret et al., 2013, 2014) considered major drainages
200 such as the Río Chili, San Lazaro and Huarangal. However, the 2013 rainfall event rainfall
201 event affected in particular the smaller Avenida Venezuela secondary drainage channel.
202 Two tributaries drain a c. 7.8km² catchment characterized by abundant non-consolidated
203 debris and feed the Avenida Venezuela channel (Fig. 1B): (1) the northern tributary drains
204 watersheds to the Northeast, upstream of the Cooperativa 14 to La Galaxia urban areas; and
205 (2) the southern tributary drains watersheds to the Southeast, upstream of the Mariano
206 Bustamante and Joven Vencedores del Cenepa urban areas. Before joining the main Río Chili
207 valley to the West, the Avenida Venezuela channel crosses the city from NE to SW. Over a
208 total length of 5.2km, the channel depth ranges from 1.3 to 6.3m, with channel widths from
209 1.63 to 20.64m.

210

211 **Figure 1A: Geographical setting and location of Arequipa city, Peru. B: The study area**
212 **Avenida Venezuela channel and six zones that will serve to illustrate observations in the**
213 **following.**

214

215 **3. Methods**

216 The general methodological approach proposed in this study benefits from data and insights
217 gained from previous exposure and vulnerability assessments carried out in Arequipa (Santoni,
218 2011; Martelli, 2011; Thouret et al., 2013, 2014). Additional data, in particular, concerning the
219 flood hazard, Avenida Venezuela channel characteristics and surrounding built environment,
220 which had not been studied before, was collected during field work in March 2013 and compiled
221 in an extensive GIS database.

222 The choice of parameters to be considered for the statistical analysis was motivated by the
223 following reasons:

- 224 (i) Information for each parameter, potentially describing vulnerability, needed to be
225 available for all of the individual buildings considered in the study.
- 226 (ii) [Thouret et al. \(2014\)](#) observed most vulnerable city blocks to be located within c.
227 100 m of river channels or in proximity to tributary confluences. Past flood events
228 and flow extension are frequently associated with overbank flow and occasions
229 where bridges acted as obstacles to flow evacuation downstream ([Martelli, 2011](#);
230 [Thouret et al., 2014](#)). The distance from the channel and from bridges was therefore
231 considered to be an important parameter to investigate.
- 232 (iii) Previous studies ([Santoni, 2011](#); [Martelli, 2011](#); [Quan Luna et al., 2011](#)) examined
233 vulnerability at the city block-scale and highlighted the importance of city block
234 shape, building density, and soil impermeability for flow propagation/deviation or
235 velocity, both in downstream direction and laterally.
- 236 (iv) The structural type of buildings as well as the number of storeys has been
237 demonstrated as decisive for survival and resistance to flow impact by numerous
238 studies ([Papathoma Köhle et al., 2011](#); [Zuccaro and Ianniello, 2004](#); [Zuccaro et al.,](#)
239 [2008](#); [Jenkins et al., 2014](#)) and was therefore considered.
- 240 (v) The building footprint was included in order to determine its dependency to other
241 building related parameters and susceptibility to damage.

242 Buildings were selected for sampling as a function of accessibility and willingness of owners
243 to grant access and document damage. Systematically, all accessible buildings in a block (city
244 block) were sampled. Surveyed characteristics regarding building design and environmental
245 characteristics were adapted from previous studies ([Thouret et al., 2013, 2014](#)).

246

247 3.1 Data collection and processing

248 As rainfall data was the most reliable information available regarding the origin of the hazard,
249 and too few additional parameters were known to realize numerical simulations of the flood
250 event, this study essentially relies on data acquired from high resolution satellite images, field
251 surveys and GIS (ArcGIS, QGIS) data processing. Pleiades satellite images from 2012 and

252 2013 at sub-metric resolution were used in ArcGIS to map the channel and built environment
253 affected by the flash flood, both before (2012) and after (2013) the hazardous event.

254 A field survey was carried out on site a five weeks after the flash flood. The survey was
255 particularly aimed at collecting data regarding inundation height and damage characteristics
256 to buildings, bridges, and training walls caused by the 8 February 2013 flood, but also helped
257 to validate and complete imagery-based measurements and mapping of post-flood channel
258 characteristics (width, depth, wetted section, river bank erosion, etc.). Measuring tape and
259 laser distance meter enabled mapping of bridge opening heights, channel depth and width.
260 Laser measurements were used in particular at sites where channel access from both
261 riversides was not possible (e.g. where building foundations represent the channel wall). GPS
262 (Trimble, handheld) data was simultaneously collected.

263 Additional data (photography, eyewitness accounts, Civil Defense reports, etc.) were also
264 gathered and compiled in the GIS database. Media images and video footage (professional
265 and social), freely available on the Internet, were invaluable in assessing hazard intensity, flow
266 impacts, damage types, affected sites and deposit types or height. Images taken the day after
267 the event were particularly useful to estimate the immediate aftermath of the inundation. This
268 complimentary data allowed us to monitor impacts in near real-time, identify areas where
269 impact assessments would be most informative and to map the spatial extent of affected areas
270 and occurrence of damage. More than 300 photographs and 15 newspaper articles were
271 studied to extract qualitative and semi-quantitative information regarding damage and flow
272 characteristics. Where flood marks were still visible at the time of our field survey, or where
273 inhabitants were willing to share their experiences, damage level and inundation height were
274 verified along the channel. Run-up measurements could be realized at the tributary confluence
275 in the upstream sector (Fig. 1), at one channel bend in the intermediate section and on a
276 building in the downstream sector. The use of [Chow's \(1959\)](#) formula ($v = 2 g\Delta h)^{0.5}$ or [Wigmosta](#)
277 [\(1983\)](#), ($v = 1.2 g\Delta h)^{0.5}$ enabled estimation of flow velocities based on the measured runup
278 height (in both formulae v is flow velocity, g is gravitational acceleration and Δh the difference
279 in mudline elevation).

280 Data describing the footprints of buildings were gathered from digital cadastral maps (mostly
281 city block scale), downscaled using the HSR images and cross-checked, where possible, with
282 Google Street View.

283 For the damage assessment of buildings, survey forms were conceived for masonry and
284 reinforced concrete structures (see Appendices A and B) following experiences from previous
285 studies concerning natural hazard impact (Zuccaro et al., 2008; Zuccaro and De Gregorio,
286 2013; Jenkins et al., 2014). The survey scheme followed in these forms relies on detailed
287 predefined categories describing different damage intensities and impact types. This
288 procedure was based here on standardized characteristics in order to optimize repeatability of
289 the survey and minimize operator bias.

290 Once integrated into the GIS database, all surveyed buildings were attributed, in preparation
291 for the statistical data analysis, one of the following four categories describing the observed
292 damage intensity: “1” for no (structural) damage, “2” for light damage, “3” for moderate
293 damage, and “4” for serious damage.

294

295

296 3.2 Statistical data analysis

297 Building data was statistically analyzed in order to: (i) visualize and quantify relationships
298 between vulnerability parameters; (ii) improve threshold estimates for the different parameter
299 levels; (iii) define the weight of each parameter; (iv) discard or add parameters as a function
300 of their significance; (v) determine significant parameters that are likely to determine whether
301 damage occurs or not; and (vi) calculate a damage probability for each building. Data
302 processing was conducted using R software packages. In order to conduct a statistical analysis
303 on the relationship between the parameters, building data first underwent a selection process
304 to eliminate all elements with one or more unknown parameter and to remove all duplicates.
305 From 1103 buildings surveyed, 898 were therefore extracted for a comparative analysis.

306 All of the nine considered parameters were initially qualitative, i.e. observational or descriptive
307 (Table 1). Four of them (“Distance from channel” and “Distance from bridge”, “Number of

308 storeys” and “Building density in a city block”) were rendered quantitative, i.e. calculated or
309 measured, in order to increase the statistical model performance. Qualitative parameters
310 include the “Inundation height”, the “Soil (im-)permeability”, the “Structural building type” and
311 the “Shape of the city block”. These explanatory parameters were then related to the
312 dependent parameter observed “Damage”. Parameters are either binary (e.g. soil permeability
313 either “permeable” or “impermeable”) or described with up to 5 value categories (levels). An
314 increased number of parameters could not be differentiated as this would have reduced the
315 total sample size of buildings to an extent where the number of cases in each corresponding
316 damage class would have been too low for a robust probabilistic assessment.

317

318 **Table 1: Vulnerability parameters concerning building characteristics, building environment**
319 **and flood hazard with their respective levels as defined for this study.**

320

321 A first step assessed the frequency distribution of buildings for each of the different parameter
322 levels: for example, concerning the parameter “Distance from channel”, the frequency
323 distribution represents the number of buildings which are part of level 1, 2, ... or 5. The
324 thresholds delimiting each parameter level were determined in order to respect a minimum of
325 45 buildings per level (5% of the total building data), necessary to render the level significant.
326 The frequency distribution was then graphically displayed in 2D histograms with the abscissa
327 representing the number of buildings and the ordinate the parameter levels of the examined
328 parameter.

329 In a second step, correspondence analysis (CA) was conducted in order to bring to light
330 relationships among the different levels of each parameter and among several parameters.

331 The CA summarizes the relationships between the different parameter levels as scores in
332 contingency tables and enables graphical representation of the latter in several 2D-plots. Each
333 graphical representation is naturally based on two axes (dimensions), each of which expresses
334 a certain percentage of information (inertia) of the contingency table. The dimensions are
335 ranked as a function of their contribution to global inertia (=100%) of the contingency table. In

336 our study, dimensions 1 and 2 have the highest contributions (from 50 to 98.9, with most of
337 that attributed to the first dimension) compared with dimension 3 (< 10).

338 The CA also provides the coordinates for each parameter level on each dimension. Here, the
339 coordinates are illustrated by (i) small boxes (for results of the simple CA) or (ii) dots (for results
340 of the multiple CA) with dimension 1 being the abscissa and dimension 2 the ordinate.

341 In graphs plotted for results of the simple CA, two parameters are opposed to each other and
342 each box represents one parameter level. The closer the boxes are, the more similar is the
343 behavior of the buildings that are part of the respective parameter levels.

344 Graphs illustrating results of the multiple CA are presented as scatter plots and individual
345 buildings are represented as dots. The color of each dot indicates the parameter level (from 1
346 to 5) that the building belongs to. Ellipses are drawn to help identify buildings that are part of
347 the same parameter level. When the ellipse centers are close to each other, they are strongly
348 related, i.e. the buildings within these groups behave in a similar way. Ellipse centers that are
349 far from each other indicate opposing behavior of the respective group members.

350 On the basis of the relationships identified between the different parameters by the CA, the
351 final objective was determining the contribution of these parameters to potential building
352 damage. This was achieved using a multinomial logistic regression. Logistic regression was
353 adopted instead of classical linear regression due to the dependent parameter "Damage" being
354 qualitative. As "Damage" levels decline with more than two parameters (level 1 to 4), the
355 logistic regression is referred to as multinomial.

356 By the use of the following equations, the multinomial dependent parameter "Damage" is
357 related to several other explanatory parameters (e.g. distance to channel, structural type of
358 building, building footprint, etc.). Numerical outputs are probability scores representing the
359 predicted values of damage related to these parameters.

360 With the hypothesis that explanatory variables are independent, we obtain an additive model,
361 i.e. a model without interactions that is expressed as follows:

362

363 $\text{logit}\left(P\left(Y = k \mid X_1, \dots, X_j\right)\right) = a_0 + a_1 X_1 + \dots + a_j X_j$ with $k = 1, \dots, K$ (1)

364

365 where a_0 is the model constant, Y the dependent parameter (Damage), k the level of the
 366 dependent parameter (Damage level), K the highest possible level of damage, j the number of
 367 explanatory parameters, X_1, \dots, X_j the respective parameter level of each explanatory
 368 parameter. The applied logit function is:

369

370 $\text{logit}(p) = \ln \frac{p}{1-p}$ (2)

371

372

373 For ease of presentation in the following, we set:

374 $S = \text{logit}\left(P\left(Y = k \mid X_1, \dots, X_j\right)\right)$ (3)

375 This implies that:

376 $P\left(Y = k \mid X_1, \dots, X_j\right) = \frac{e^S}{1 + e^S}$ (4)

377 Using the calculated coefficients and parameter level values proper to each building in Eq. (4),
 378 we can therefore define the probability of a building to experience damage at damage level k .

379 In order to obtain the damage probability at the precise level 1, 2, 3 or 4, we use

380

381 $P\left(Y = k \mid X_1, \dots, X_j\right) = P\left(Y = k \mid X_1, \dots, X_j\right) - P\left(Y = k - 1 \mid X_1, \dots, X_j\right)$ (5)

382

383 Finally, based on the Bayesian Information Criterion (BIC), the optimal model is selected. The
 384 BIC enables elimination of non-significant parameters and reduces the model to the significant
 385 parameters determining damage.

386

387 3.3 Model validation

388 Formal model validation was realized in two steps. First, using a calibration and validation data
389 set. Hereby, the original data set was split into a calibration and a validation data set. From the
390 898 totally sampled buildings, the validation data set contained 300 arbitrarily selected
391 buildings. The model was calibrated using the 598 remaining buildings and then run to test the
392 validation data set. Calculated damage probabilities obtained by the model for buildings in the
393 validation data set was then compared to observed damage in the field.

394 Second, based on the results of the validation data set, the “good classification rate” was
395 determined. This rate describes the performance of the model indicating the percentage of
396 buildings in which predicted damage corresponds to observed damage.

397

398 **4. Results**

399 **4.1 Channel characteristics**

400 Three main cross section types were observed: (1) unconfined, natural; (2) confined, both
401 sides; and (3) confined, unilateral. Type 1 is typical in upstream and downstream channel
402 segments with channel widths from 5 to 16m, characterized by predominantly natural channel
403 bed and walls, as well as frequent terraces along either left or right channel walls. Type 2
404 (confined, concrete) is characterized by narrow and straight channel sections, especially in the
405 intermediate sections. Type 3 generally corresponds to the largest channel widths (> 15m) and
406 is transitional in character between types 1 and 2, i.e. semi-natural. In confined sections, either
407 concrete (reinforced or not), or mixed material (volcanic rocks, mainly andesite or ignimbrite,
408 brick, metal tubes, etc.) are used to stabilize channel banks (table 2). On both channel sides,
409 more than 70% of counted sections have their start or end point within 15m of a bridge. Of
410 note is that only 23 of a total of 181 channel sections distinguished along the Venezuela
411 drainage are still natural and, of which, the majority are located on the right riverside (in
412 downstream direction). This corresponds to a length of c. 1.5km out of 13.8km in total (table
413 3). Mixed material bank stabilization is shown in 48% of total sections, employed more
414 frequently than concrete constructions (47%) but on shorter section lengths (table 3). While
415 concrete constructions extend over c. 58% of total section length, mixed material reaches

416 approximately 23%. This is a result of recent channel confinement work especially in the
417 intermediate section where major road works were ongoing in 2013.

418

419 **Table 2: Material types characterizing channel banks along the left and right riverside of the**
420 **Avenida Venezuela channel. Numbers indicate the frequency distribution of channel sections**
421 **in each material category and their respective distance to a bridge. The total number of**
422 **sections located at a certain distance from a bridge is illustrated in bold with, to its right, the**
423 **corresponding percentage of total channel bank length.**

424

425 **Table 3: Section lengths of channel banks as a function of construction material and location**
426 **on left and right riverside.**

427

428 The mean slope of the channel from its upstream confluence to joining the Río Chili
429 downstream is 12.54% on a recently calculated 5m-DEM based on high resolution satellite
430 imagery (Pléiades-data) versus 4.67% on a previously utilised 30m-DEM derived from SPOT5
431 images. Channel width ranges from a minimum of 1.63m to a maximum of 20.64m. Large
432 channel widths are mostly tied to a natural bed type (gravel, sand; Fig. 2, dark gray color),
433 while narrow reaches correspond to confined concrete channel sections (Fig. 2, medium gray).
434 Between the shopping mall La Negrita and the Villa Militar Salaverry area (Fig. 1B), flow
435 velocities for the February 2013 event could be estimated, based on run-up measurements, to
436 be between 7.6 and 10.9m/s (Chow, 1959) and between 5.9 and 8.5m/s (Wigmosta, 1983),
437 respectively.

438

439 **Figure 2: Longitudinal channel profile (black line) with channel width (green dots), and**
440 **sections in which erosion occurred (orange bars). The gray scale bar represents channel bed**
441 **type, i.e. natural gravel, sand (dark gray), natural with occasional concrete steps (white) and**
442 **concrete (medium gray); the channel wall material is represented by concrete (red), mixed**

443 material (concrete, brick, boulders; yellow) and natural (blue). For complementary
444 information see also table 2 to 4.

445

446 Peak flow discharge for the February 2013 event was estimated using channel cross section
447 measurements and average flow velocity to be $123.4\text{m}^3\text{s}^{-1}$ in the upstream reach and c.
448 $425\text{m}^3\text{s}^{-1}$ in the middle reach (in proximity to the La Negrita shopping mall, fig. 1B). A clear
449 delineation of areas inundated by intense surface runoff or by overbank flow of the Venezuela
450 channel was not possible in many parts along the channel, which prevents a more precise
451 estimate of the flow volume. An attempt at mapping the inundation extent resulting from
452 overbank flow was made on the basis of field survey, including observations of erosion marks
453 along the channel, flood marks on built infrastructure and eye witness accounts (Fig. 3).
454 Comparing this map with flow simulations published in previous studies (Martelli, 2011; Oehler
455 et al., 2014), the flow volume of the February 2013 flash flood can be estimated between
456 50,000 and 100,000 m^3 . There appeared to be no general rule to where erosion occurred;
457 natural bed types were affected to the same extent as concrete beds. Concerning the channel
458 wall material, concrete and mixed material sections seemed to be affected more often by
459 erosion than natural sections. For concrete sections, erosion is most likely at channel
460 contractions or expansions or where bed or channel wall materials change. When erosion
461 occurs in natural sections, the proximity to bridges with low opening height frequently
462 determines whether erosion occurs or not.

463

464 **Figure 3: Field-survey-based mapping of inundation extent resulting from overbank flow**
465 **along the Avenida Venezuela channel.**

466

467 For a flash flood event of relatively small volume such as the one of February 2013, obstacles
468 such as bridges play a major role in terms of flow propagation, extent of inundated area, and
469 the type and intensity of damage. Impact forces of this particular flood were strong enough to
470 completely erode one pedestrian bridge at the upstream border of the Palomar market (Figs.

471 2 and 5). In the case of 17 other damaged bridges along the Venezuela channel, openings
472 were either not large enough for an increased discharge or were obstructed by boulders. In
473 both cases, the consequence was similar: the flow front overtopping the bridge and caused
474 overbank flow to both sides of the obstacle (Fig. 4, zone 1 and zone 5-6). Additionally, partially
475 confined sections with an abrupt change in channel direction (e.g. close to 90° angle) were
476 particularly prone to overbank flow (Fig. 4, Zone 1).

477

478 **Figure 4: Three examples of particular channel courses and resulting damage.**

479

480 **4.2 Flood impact on channel banks**

481 Generally, an increase in the damage degree was observed from upstream to downstream
482 reaches with 64% of right channel banks (in downstream direction) affected. Plotting erosion
483 and bridge location on the longitudinal channel profile shows that there seems to be a positive
484 relationship between the presence of a bridge and the occurrence of erosion in its proximity
485 (Fig. 5, table 4). Field observations suggest that erosion in the immediate downstream region
486 of bridges is more likely than in upstream parts. However, especially in the intermediate
487 channel reach, the distance between bridges is so close that it is difficult to determine whether
488 erosion is a consequence of flow turbulence immediately upstream or downstream of a bridge.
489 Concerning the channel width, erosion was frequently related to a change from narrow to wide
490 channel sections (Fig. 2, 5). This is likely linked to increasing flow turbulence at the transition
491 from harder trained confined sections to unconfined sections and a decrease in flow velocity
492 with lateral flow expansion.

493

494 Material types of training walls were regrouped into 5 major classes (Fig. 5): (1) concrete
495 (reinforced); (2) rock piles; (3) gabion meshes; (4) mixed material or (5) natural banks. While
496 rock piles appear to be affected with similar proportions in all damage categories, concrete
497 dominates the category with the heaviest observed damage (Fig. 6). Mixed material channel
498 walls are present in light damage categories (1 and 2) as are gabions. The latter represent a

499 small percentage in damage category 3. When relating the spatial distribution of damaged
500 material types to the location of bridges, as expected, damage occurs preferentially within
501 100m of a bridge. Only natural channel banks and mixed material banks were damaged at
502 greater distances (up to 200m). This observation also confirms that erosion preferentially
503 occurred downstream of bridges rather than upstream.

504

505 **Figure 5 Left: Damage level observed for different material types of retaining walls. Right:**
506 **Material types of retaining walls relative to the proximity of bridges.**

507

508 **Table 4: Damaged channel bank sections represented as the percentage of the total length**
509 **of either the left or right channel side. Sections are attributed to one of six groups (A to F)**
510 **depending on the closest distance to a bridge of either the start or end point of the section.**

511

512 **4.3 Flood impact on buildings**

513 Inundation height could be measured at almost 300 sites and flood marks along building walls
514 indicated minimum heights of 0.2m and maxima of 0.7m. While 611 sampled buildings were
515 not affected by the flood (68%), 287 buildings were inundated, among which 11% were below
516 and 21% above a water level of 0.2m.

517

518 Four damage levels were defined for the building stock (Fig. 6):

519 (1) inundated, without any structural damage; (2) inundated, light damage, building still fit for
520 habitation after cleaning; (3) inundated, significant damage, rooms livable only after
521 refurbishment; (4) inundated, heavy damage, structural refitting required. Among the 287
522 inundated buildings, 144 experienced significant to heavy damage, and 143 buildings were
523 slightly damaged.

524

525 Figure 6: Observed damage levels from left to right (4) inundated, heavy damage, (3)
526 inundated, significant damage; (2) inundated, light damage; and (1) inundated, no structural
527 damage.

528

529 4.4 Linking vulnerability parameters to observed damage

530 Each vulnerability parameter was plotted separately on the basis of the respective contingency
531 table containing the number of levels (Table 1), the number of buildings at each level and their
532 distribution frequency (Fig. 7). Along the channel, 30 randomly selected city blocks of variable
533 size (from 531m² to 10.57ha), and with rather compact and regular shape, were studied. They
534 contained 1103 buildings with footprints ranging from 4 to 2,185m²; the majority of buildings of
535 commercial, industrial or agricultural use were larger than 80 m² and grouped in size categories
536 4 and 5, while primarily residential buildings represented about 45% of all those analyzed.
537 Building density per hectare ranged from 3 to more than 11. However, the majority of the
538 sampled city blocks were characterized by a relatively low building density (< 6 buildings per
539 hectare), which was the result of the relatively large footprints of non-residential buildings.

540

541 Figure 7: Results of univariate analysis summarizing the number of buildings per category.
542 Grayscales from the lowest parameter level 1 (white) to the highest level 5 (dark gray) are
543 the same for all figures.

544

545 In terms of the presence or absence of relationships, the results of the correspondence
546 analysis show that couples incorporating the parameter “Damage” have very strong
547 relationships (Fig. 8). Graphic plots show proximities of parameter levels (Fig. 8, DBR5 and
548 DO4 in the green circle) and oppositions to other levels (Fig. 8, DBR1, DBR2 and DO1 in the
549 blue circle). For the presented example in figure 9, this data projection suggests that buildings
550 more than 50m from a bridge behave in a similar way and are less exposed to experiencing
551 damage than buildings within 5m of a bridge. In our data set, 69.1% of all buildings less than
552 15m and 39.6% between 15 and 30m from a bridge were damaged.

553

554 *Figure 8: Plot of parameter couple "Distance from bridge" and "Damage" at respective levels.*

555 *Note the strong relationship between buildings located close to a bridge (DBR5) and damage*

556 *level 4 (DO4; right side of vertical axis) compared to buildings far from a bridge (DBR1 and 2)*

557 *that have damage level 2 (DO2, left side of vertical axis). Eigenvalues represent 96.54% for*

558 *axis 1, 2.76% for axis 2, and 0.7% for axis 3.*

559

560 While some relationships are expected and strong (e.g. damage versus inundation), others

561 have a weak relationship (damage versus number of storeys or city block shape) or are a direct

562 consequence of the characteristics of the data set (damage versus soil impermeability). Some

563 particularly interesting observations are outlined in the following (Fig. 9):

- 564 • Damage versus distance from channel: inundated buildings without damage dominate at
565 distances beyond 60m of the channel. The closer to the channel, the more intense the
566 damage, e.g. while at distances of 5 to 10m, damage categories 2 to 4 are almost equally
567 present, damage category 4 becomes most important at distances lower than 5 m.
- 568 • Damage versus distance from bridge: similar to the previous observations, inundation
569 without damage occurs preferentially at distances > 90m from bridges. Slight and
570 significant damage also appear at this distance. Heavy damage is significantly less
571 important beyond 90m, but still present. Damage category 4 dominates, however, in
572 distances up to 30m from a bridge.
- 573 • Damage versus structural type: overall, for the data set studied here, damage categories
574 1, 2 and 3 mostly occur with buildings of type 3 (masonry of terra cotta with reinforced
575 concrete roof, 1 or 2 storeys). The heaviest damage is preferentially observed in non-
576 residential buildings.
- 577 • Damage versus inundation height: slight or significant damage is the main consequence
578 at intermediate inundation heights while maximum inundation is related to the highest
579 damage.

- 580 • Damage versus building footprint: generally, damage intensity appears to be independent
581 of building size, i.e. all damage levels have been observed for buildings larger than 20m².
582 Only footprint category 4 (80 – 150m²) experienced more damage than other groups,
583 particularly in the intermediate damage level (2 and 3).
- 584 • Damage versus building density: city blocks of low building density are more likely to suffer
585 damage. That is, at building densities of less than 6 buildings per hectare (category 4 and
586 5), buildings were more often damaged than in city blocks exhibiting high building density.
587 City blocks of higher densities were more often affected by inundation without damage.

588

589 *Figure 9: Results of the bivariate analysis. Damage level is displayed in different gray*
590 *shades, the abscissa (1 to 5) displays the categories of the respective parameter “Distance*
591 *from channel”, “Distance from bridge”, etc.*

592

593 These observations are hypotheses essentially based on graphically plotting the results for all
594 parameter couples of the correspondence analysis (Fig. 8). In order to confirm or reject these
595 hypotheses, it is therefore necessary to further verify using contingency tables and plots from
596 the multiple correspondence analysis (Fig. 9 and 10).

597

598 While simple correspondence analysis examines the relationship between two parameters,
599 multiple correspondence analysis generalizes the comparison by including as many qualitative
600 parameters as available. Scatter plots in this context graphically represent the relationships
601 between the different levels of each parameter (Fig. 10); they enable the comparison between
602 individual buildings, their position among others at certain parameter levels to be determined
603 and finally reveal behavioral tendencies of building groups showing similar characteristics. The
604 position of each parameter level is determined by a bagplot (bivariate boxplot), displaying an
605 ellipse representing 67.5% of buildings within the respective level. Some parameters such as
606 “Inundation height”, “Impermeability of soil” and “Structural building type” display good sorting,
607 i.e. buildings of the same characteristic are well grouped. For other parameters, the sorting is

608 much less evident, dispersion is high and overlapping ellipses representing the weighted
609 center of each parameter group are the result. Hence, one can recognize similarities in the
610 distribution of parameter levels (from 1 to 5, light blue and red, respectively in Fig. 10): buildings
611 of level 4 and 5 are preferentially located to the right side, while levels 1 and 2 remain close to
612 the central axis with a tendency to the left side. Distributions of parameter levels concerning
613 “distance from channel”, “distance from bridge” and “density of buildings” are observed to be
614 very close; the same can be seen for the parameters “damage category” and ‘inundation
615 height”. For these two latter parameters, the scatter plots are very similar. Their relationship is
616 therefore direct as illustrated previously by the bivariate analysis: the higher the inundation
617 height, the higher the damage level. Generally, the scatter plots illustrate that buildings located
618 in the vicinity of the channel and / or a bridge tend to be 1-storey constructions of structural
619 type 3 to 5. They are commonly located in areas of low building density (category 4 or 5). The
620 parameters “shape of city block”, “impermeability of soil” and “building footprint” are not directly
621 related to the previous groups as buildings of varying characteristics, i.e. several parameter
622 levels, are present on the right side of the plot. The distribution pattern of building points follows
623 two general tendencies: firstly, a horse-shoe shape where the distribution of buildings
624 representing a particular parameter level produces an arch pattern spanning from level 1 (light
625 blue; left of vertical axis) to level 5 (red; right of vertical axis); secondly, a random distribution
626 to vertical clustering of all with level 4 and 5 (orange and red, respectively) mostly located in
627 the opposed direction of level 1 to 3 (light blue, dark blue, green; fig. 10).

628

629

630 **Figure 10: Scatter plots representing results of the correspondence analysis. Each point**
631 **represents a building. Ellipses colored from light blue to red represent parameter levels (1 to**
632 **5, respectively) as bagplots (bivariate boxplots). Each bagplot represents 67.5% of the**
633 **buildings defining each level.**

634

635 Plotting all parameter levels along with the number of city blocks enables us to easily relate
636 different levels to each other. As for the scatterplots, the position of the parameter level is
637 defined by the bagplot with 67.5% of the building points defining each level. Again, it becomes
638 clear that buildings that have experienced the highest inundation are localized very close to
639 bridges and have also suffered the most damage; this is particularly within city block n°20 (Fig.
640 11). This group of buildings contrasts with those that did not experience any damage and those
641 that were inundated temporarily without experiencing damage. The latter were located both far
642 away from the channel and any bridge (Fig. 11, city block 3).

643

644 **Figure 11: Projection of parameter levels (color) and city blocks as a result of the bivariate**
645 **analysis. The position of each square is defined by the bagplot representing 67.5% of the**
646 **buildings defining each level. The circles indicate city blocks of similar characteristics and**
647 **thus behavior. City block numbers are plotted to allow comparison but are not included in the**
648 **bivariate analysis. The number of buildings per city block and the respective percentage is**
649 **detailed in the histogram to the right.**

650

651 **Logistic regression**

652 Logistic regression was applied in order to directly analyze the link between the qualitative
653 parameter “Damage” and one or more other parameters and to calculate damage probabilities
654 for all buildings. For this part of the analysis, the parameter “Inundation height” was not
655 considered, as it was the only data measured after the event and hence strongly related to the
656 observed damage, which is the parameter to explain. The eight remaining parameters were:
657 Distance to channel, distance to bridge, shape of city block, impermeability of soil, number of
658 stories, structural type of building, building footprint and building density. Isolating the most
659 significant parameters that determine the damage likelihood progressively reduces the number
660 of vulnerability parameters from 8 to 5. By eliminating non-significant parameters, the
661 contribution of the maintained parameters is constantly recalculated so that the remaining
662 significant ones also reflect the non-significant parameters. Consequently, the “Damage”

663 parameter can be expressed as a function of its relationships with the parameters “Distance
 664 from channel”, “Distance from bridge”, “Shape of city block”, “Structural building type” and
 665 “Building footprint”. To illustrate the different steps of calculation and associated model outputs,
 666 we chose one of 200 scenarios that were realized using different calibration and validation
 667 data sets. Equations (1) and (2) enable us to obtain the respective contributions from the
 668 different parameters (table 5).

669

670 **Table 5: Contributions of each parameter level to damage probability based on the**
 671 **calibration data set (598 buildings).**

672

673 The following example illustrates the way in which the values of table 5 were used to calculate
 674 damage probability for a specific building at a particular damage level.

675 The applied logistic regression model with all remaining significant parameters is presented as
 676 follows:

$$\begin{aligned}
 & \begin{matrix} 1|2 \\ 2|3 \\ 3|4 \end{matrix} S = \begin{matrix} 4.59 \\ 5.99 \\ 7.30 \end{matrix} + \begin{matrix} DC1 \\ DC2 \\ DC3 \\ DC4 \\ DC5 \end{matrix} \begin{matrix} 1.25 \\ 0.57 \\ 0.20 \\ 1.36 \\ 0.27 \end{matrix} + \begin{matrix} DBR1 \\ DBR2 \\ DBR3 \\ DBR4 \\ DBR5 \end{matrix} \begin{matrix} 4.79 \\ 0.03 \\ 1.02 \\ 1.51 \\ 2.22 \end{matrix} + \begin{matrix} SH2 \\ SH3 \\ SH4 \end{matrix} \begin{matrix} 1.03 \\ 1.42 \\ 0.38 \end{matrix} + \begin{matrix} S2 \\ S3 \\ S4 \\ S5 \end{matrix} \begin{matrix} 2.52 \\ 0.08 \\ 1.48 \\ 0.96 \end{matrix} + \begin{matrix} A1 \\ A2 \\ A3 \\ A4 \\ A5 \end{matrix} \begin{matrix} 10.33 \\ 1.99 \\ 2.91 \\ 2.62 \\ 2.82 \end{matrix} \quad (5)
 \end{aligned}$$

678

679 Values in this equation (5) were taken from table 5 and completed following the logistic
 680 regression constraint that the sum of coefficients of each parameter must be equal to zero.

681 That is, parameter “Distance to channel” has been completed by DC1, parameter “Distance to
 682 bridge” by DBR1 and parameter “Building footprint” by A1.

683 We consider for example a building with the following parameter levels: Distance to channel =
 684 4, Distance to bridge = 5, Shape of city block = 4, Structural building type = 5, building footprint
 685 = 5. In order to obtain the probability of experiencing damage (e.g. at level 3) for this building,
 686 we fill in the previous equation using results of table 5 as follows:

687

688 $S = 5.99 - 1.36 - 0.27 + 0.38 - 0.96 - 2.82 = 0.96$ (6)

689

690 The damage probability for this specific building at intensity level lower or equal to 3 can then
691 be calculated using equation (3) and the value obtained for S in equation (6):

692

693 $P(Y \leq 3) = \frac{e^{0.96}}{1 + e^{0.96}}$ (7)

694

695 This particular building therefore has a probability of 72.3% (Eq. 7) of experiencing damage at
696 level 3 (significant damage) or lower in the case of a future flood event of similar intensity to
697 the one of February 2013. In order to calculate the probability for a different damage category,
698 one has to change the intercept constant and proceed in the same way.

699

700 For the 300 buildings in the validation data set for this scenario, the probability to experience
701 damage at different intensity levels was calculated (table 5). With a success rate of 74%, the
702 model performs well predicting for almost three quarters of sampled buildings a damage
703 probability that corresponds to field observations.

704

705 As a result, 27.7% of buildings of the validation data set have a 100% chance of experiencing
706 damage of level 2 (slight damage) or more for an event similar to February 2013. For damage
707 levels 3 and 4, 6.3 and 9% of buildings, respectively, have a 100% chance of being damaged.
708 Various maps could then be drawn representing each building in the data set, whether sampled
709 in the field or not, and their probability of experiencing damage at a certain level (Fig. 12). A
710 comparison of these results with maps illustrating damage levels assessed during field work
711 correlates well: the distribution of the damage probability is overall coherent with field
712 observations of damaged buildings and of the measured flood extent. Results for both
713 calibration and validation data sets are close, not exceeding a difference of 5% for the number
714 of buildings attributed to each damage level. The city block examples presented for the six

715 areas within the study (Fig. 12) enable us to highlight several main points: (1) calculating
716 damage probability by incorporating field data enables expansion of the analysis to buildings
717 not sampled in the field or for which only some of the required parameters were identified; (2)
718 calculated results for the validation data classify a lower number of buildings (c. 15%) in the
719 predicted damage category “2 or more”, which is equivalent to the observed damage level 2,
720 3 and 4, than observed in reality (28%). This is mainly due to the fact that in reality, parameters
721 not considered in our analysis also seem to be important; these include the height of channel
722 retaining walls (Fig. 12, zone 2), the presence of increased surface run-off not coming from
723 the channel (Fig. 12, zone 4), the height and width of bridge openings, the building position
724 upstream or downstream from a bridge, etc.; (3) especially for buildings not affected in 2013
725 (cf. Fig. 12, zone 2, 5 and 6), the calculation of damage probability allows us to identify and
726 visualize graphically areas where mitigation measures such as refitting may be necessary to
727 avoid serious damage during future events; and (4), although rare, some buildings with
728 significant damage observed in the field (Fig. 12, zone 1 and 5) appear to have lower calculated
729 damage probabilities than expected.

730

731 The absence of a logical pattern in the distribution of these damage probabilities reflects the
732 fact that several parameters were considered, each parameter with an individual weight. This
733 considerably improves the damage assessment compared to methods where simple buffer
734 zones along the channel borders are used to determine vulnerability, essentially as a function
735 of distance to the channel.

736

737 **Figure 12: Damage probabilities calculated for damage levels 1,2, 3 and 4 (series A) and all**
738 **observed damage levels (1 to 4) in the field (series B) using calibration and validation data**
739 **sets (898 buildings) of the selected test scenario presented in the manuscript.**

740

741 Finally, concerning the model performance, one scenario with a success rate of 74% was
742 chosen to illustrate the methodology. The model was applied in total 200 times on different

743 calibration and validation data sets in order to examine general performance. Results show
744 that 90% of these tests have a success rate of more than 67%.

745

746 **5. Discussion**

747 A quantitative analysis of the uncertainty of results has been beyond the focus of this study.
748 However, it is important to be aware that both data and applied methods introduce
749 uncertainties. Major sources of uncertainty stem from imprecise or ambiguous measurements
750 (both in the field and from remote acquisition). This may be, for example, a consequence of
751 surveyed data being based on standardized characteristics or deformation due to spatial
752 georeferencing etc. Certain parameters related to the structural behavior of buildings to flow
753 impact, varying impact forces as a function of the impact angle and the grain size of the
754 sediment in the flow, etc. may also not have been assessed in sufficient detail. Another source
755 of uncertainty may stem from the selection of vulnerability parameters taken into account for
756 the mathematical analysis. The fact that we considered a minimum of 5% of the total sample
757 size of buildings needed to be part of a parameter level in order to make it eligible for the
758 statistical analysis was a constraint for data sets where little information was available and
759 adjustments were not possible.

760 For this study however, we could reduce the uncertainty related to the latter aspect to a
761 minimum by limiting the conditions for parameters to the following: (1) contain a minimum
762 number of buildings per parameter level to be significant (5% of total sample number); (2) data
763 either existent from field work or able to be collected from calculation, satellite data or other
764 sources; and (3) represent a single piece of information in order to avoid repetition or
765 overlapping. Parameters that did not account for these conditions were reconsidered. For
766 example, the parameter "Structural type", originally intended to represent different building
767 characteristics such as construction material, the type of roof, and the number of storeys. To
768 make this parameter eligible, "Number of storeys" was extracted as a separate parameter. The
769 "Type of roof" was not identified for enough buildings in order to be considered and was

770 therefore eliminated from the analysis. “Structural type” therefore only represents the
771 construction material in this context.

772 Parameters containing similar information, such as “distance from channel” and “distance from
773 bridge” were voluntarily kept in order to obtain elements of response for particular questions.
774 In reality, a building far from the channel cannot be close to a bridge, while the inverse is
775 possible. Despite a certain interdependency between these parameters, keeping both helps to
776 better estimate the role of bridges in terms of damage probability, which would not be possible
777 if the distance from a bridge was not considered individually.

778
779 Interpretation of the results requires careful comparison of the links between several
780 parameters, particularly if no previous knowledge from real field conditions is available. A few
781 aspects brought to light by scatter plots and logistic regression are pointed in the following.

782

783

784

785

786

787 Scatter plots

- 788 • In this study, building density was calculated as the number of buildings per unit area.
789 High building density in Arequipa generally corresponds to dense habitat where
790 buildings share one or more walls, reducing the space between them and thus reducing
791 the risk of inundation in back rows. Lower building density, in particular for residential
792 buildings, implies gaps between buildings, which creates hydraulic roughness and
793 resistance to flow. This reduces flow velocities on buildings in back rows, but potentially
794 increases them in front rows. This fits to observations from the scatter plots showing
795 that city blocks of lower density exhibit more damaged buildings than those of higher
796 density. However, field observations suggest another reason for increased damage in
797 low-density areas: larger footprints of industrial, commercial and agricultural buildings

798 that, especially for the latter, have more vulnerable structural characteristics than
799 residential buildings. To clarify this possibility may require improvements in how
800 building density is assessed in relation to the structural building type and/or its use.

801 • Comparing building footprint and density of buildings, it appears that the largest
802 buildings (mainly agricultural or industrial, and more rarely commercial) are: (i) more
803 vulnerable than smaller buildings because of their very larger openings, and fewer load-
804 carrying structures such as columns, etc.; and (ii) typically located in city blocks with
805 low building density, which additionally increases the probability of being damaged
806 since the screening effect from adjacent buildings is absent. For footprint categories 1
807 and 2 (small size), the building density per city block frequently remains low enough to
808 potentially put them in damage category 4.

809 • Relating damage level 3 (significant damage) to the structural type of buildings, it
810 becomes obvious that buildings of all types can be damaged, but in this flood event,
811 mostly buildings of category 2 (masonry of terra cotta or ignimbrite with mortar and
812 metal sheet roof, 1 storey) and 3 (masonry of terra cotta with reinforced concrete roof,
813 1 or 2 storeys) were affected; this coincides also with the highest inundation measured
814 and with the smallest distance from the channel and bridges. However, damage
815 categories 2 and 3 group buildings of structural types 6, 7, 8 and 4, 5, respectively.
816 These are all structural types of higher quality, which are estimated to be less
817 vulnerable than structural types 1, 2, 3 grouped in damage category 4. Previous studies
818 regarding physical vulnerability of buildings related to landslide and debris flow hazard
819 in Austria ([Fuchs et al., 2007](#); [Papathoma Köhle et al., 2012](#)), Germany ([Kaynia et al.,](#)
820 [2008](#)), Italy ([Aleotti et al., 2004](#); [Luino, 2005](#); [Galli and Guzzetti, 2007](#)) and the United
821 States ([FEMA: HAZUS-MH, 2010](#)), seem to confirm an increasing vulnerability with
822 decreasing construction quality (either due to construction material or structural
823 characteristics). We therefore deduce for our results that the relationship statistically
824 calculated to be strong between structural type and damage is, in this particular case,

825 the result of the strong influence of the 611 buildings that have not experienced any
826 damage.

827 • “Inundation” versus “number of storeys” shows that buildings of 2 and 3 storeys behave
828 in the same way and have been affected similarly, inundated but less severely
829 damaged than buildings of 1 storey – this is partly due to the fact that the 1-storey-
830 buildings are more frequently close to the channel in the building sample considered
831 for this study. In this context, another parameter has been observed in other studies to
832 be important (Fuchs et al., 2007; Lo et al., 2012; Papathoma Köhle et al., 2012): the
833 presence of windows and other openings that allow material to enter the building may
834 also affect the degree of damage experienced by a building. While for some buildings,
835 such information has been collected in Arequipa, it was not available for enough
836 sampled buildings to be considered for this analysis. Further research should take this
837 aspect into account.

838

839 Logistic regression

840 Logistic regression in addition to the scatter plots, reflects well the issue of an unbalanced data
841 set: buildings without any damage are largely over-represented in our data. In the applied
842 mathematical analysis, this group gains in weight because of their high number leading to
843 calculated damage likelihoods that are greater than those derived from expert judgment. For
844 example, the logistic regression analysis favors buildings without damage as a way to rank
845 buildings of higher quality (structural types 4 to 7) to be more likely to experience damage level
846 3 than buildings supposedly more vulnerable (structural types 1-3). This should improve by
847 incorporating additional damage data from future potential flood events, which will lead to a
848 more balanced data set.

849

850 Scope and limits

851 In the field following the February 2013 event, damage was observed at buildings that were
852 identified in the calculations to have a 10-20% probability of significant damage (intensity 3).

853 On the maps (Fig. 12), this is illustrated by the color code representing the probability to
854 experience a certain damage level for each building. Hence, for buildings colored red, the
855 probability of experiencing heavy damage is higher than 30%, while a dark green building has
856 a more than 30% chance of not experiencing structural damage. This may seem
857 underestimated, however, as when taking damage levels 3 and 4 together, the likelihood to be
858 seriously affected reaches 57%, which is rather considerable. At the same time, 57% of
859 significant to heavy damage implies roughly 43% of slight damage. Since the ultimate goal of
860 risk assessment studies is to avoid the occurrence of future damage, it is therefore important
861 to interpret the damage probabilities with the damage intensity scale in mind. A first
862 interpretation should therefore examine the probability of experiencing structural damage (i.e.
863 damage level 2 to 4) versus no structural damage (damage level 1). And then, in a subsequent
864 step, differentiate the probability of structural damage for informing local risk mitigation
865 strategies. This is all the more important given that this study is considering damage potential
866 for a relatively small flood event. Higher damage probabilities for flood events of larger volumes
867 are therefore to be expected. The comparison of calculated damage probabilities and observed
868 damage emphasizes the potential for using damage probabilities to identify areas with special
869 need for mitigation measures in order to avoid future damage. It also enables us to understand
870 that local parameters, especially those related to channel morphology or topography, such as
871 the height of retaining walls, the direction of the channel course (Fig. 12, zone 2) or local slope,
872 that have not yet been considered in this approach, also influence the damage likelihood.

873

874 **6. Conclusion and perspectives**

875 This study was carried out following a damage survey in the field early after a flash flood event
876 in February 2013. Observed damage intensities were overall low and only few buildings
877 suffered serious damage. Results from the proposed statistical data analysis validate the
878 method as an operational tool to calculate damage probabilities for a flash flood event of similar
879 intensity. However, the lack of damage documentation, in particular for highest damage
880 categories, is at present a constraint to further develop the model for a larger range of hazard

881 types and magnitudes. Ideally, the method will be tested on a database including many case
882 studies. This would allow validation of the methodology not only for small scale, site-specific
883 analysis, but also for broad scale generalized assessment of damage probability for different
884 hazard types and magnitudes.

885 In the close future, several possibilities should be statistically explored:

886 (1) Although an initial analysis of the interactions between parameter couples did not render
887 significant results, parameter interdependency needs further examination in order to be
888 accounted for fully in equations calculating damage probability. This aspect may become more
889 important in the context of a possible extension of the data set in the future. Given additional
890 flood events and new damage data, vulnerability parameters or thresholds of parameter levels
891 may need to be adjusted. This possibly implies an increase in either quantitative or qualitative
892 parameters, in which case the method requires interactions to be accounted for in order to
893 guarantee a similar degree of effectiveness.

894 (2) Analysis of the present data enabled a critical evaluation of parameters considered for
895 vulnerability; however, some of the parameters originally identified were not considered in
896 analysis because of partially missing data and/or an insignificant number of buildings in each
897 parameter level. Other parameters have emerged and should be taken into account, such as
898 the location – upstream or downstream – of the closest bridge, a more detailed series of
899 structural building types for non-residential constructions etc.

900 (3) Given the relatively small size of the event, damage categories were established
901 accordingly in order to ensure a maximum of damage data being recorded; for a larger event,
902 damage categories may need to be defined differently. In order to take into account different
903 event scenarios for the flood, the method needs to evolve towards an additive or cumulative
904 approach. This is important in the case of a building hit by different flood volumes, which
905 implies repetitive measurements of a single data point, an independent analysis of the
906 parameters determining its vulnerability is no longer possible.

907 (4) If the dependent variable is qualitative, the lognormal law may need to be considered
908 instead of the log logistic approach.

909

910 One of the major advantages of the method outlined is that damage probability can be
911 estimated and mapped even for buildings that have not been sampled in the field as long as
912 some of their characteristics are known or are able to be assessed from remote sensing data.
913 Especially in a context where few damage data are available or where access to the field in
914 the aftermath of an event is difficult, this technique helps to assess and project damage
915 potential to non-sampled areas. This is as useful for both loss estimation and risk prevention,
916 by contributing to the planning of mitigation measures such as refitting or risk management, or
917 by evacuation planning in the case of disaster.

918

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925

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1157 **Table caption**

1158 Table 1: Vulnerability parameters concerning building characteristics, building environment
1159 and flood hazard with their respective levels as defined for this study.

1160 Table 2: Material types characterizing channel banks along the left and right riverside of the
1161 Avenida Venezuela channel. Numbers indicate the frequency distribution of channel
1162 sections in each material category and their respective distance to a bridge. The total
1163 number of sections located at a certain distance from a bridge is illustrated in bold
1164 with, to its right, the corresponding percentage of total channel bank length.

1165 Table 3: Section lengths of channel banks as a function of construction material and location
1166 on left and right riverside.

1167 Table 4: Damaged channel bank sections represented as the percentage of the total length
1168 of either the left or right channel side. Sections are attributed to one of six groups (A
1169 to F) depending on the closest distance to a bridge of either the start or end point of
1170 the section.

1171 Table 5: Contributions of each parameter level to damage probability based on the
1172 calibration data set (598 buildings).

1173

1174 **Figure caption (black and white reproduction in print is intended)**

1175 Figure 1A: Geographical setting and location of Arequipa city, Peru. B: The study area
1176 Avenida Venezuela channel and six zones that will serve to illustrate observations in
1177 the following.

1178 Figure 2: Longitudinal channel profile (black line) with channel width (green dots), and
1179 sections in which erosion occurred (orange bars). The gray scale bar represents
1180 channel bed type, i.e. natural gravel, sand (dark gray), natural with occasional
1181 concrete steps (white) and concrete (medium gray); the channel wall material is
1182 represented by concrete (red), mixed material (concrete, brick, boulders; yellow) and
1183 natural (blue). For complementary information see also table 2 to 4.

1184 Figure 3: Field-survey-based mapping of inundation extent resulting from overbank flow
1185 along the Avenida Venezuela channel.

1186 Figure 4: Three examples of particular channel courses and resulting damage.

1187 Figure 5 Left: Damage level observed for different material types of retaining walls. Right:
1188 Material types of retaining walls relative to the proximity of bridges.

1189 Figure 6: Observed damage levels from left to right (4) inundated, heavy damage, (3)
1190 inundated, significant damage; (2) inundated, light damage; and (1) inundated, no
1191 structural damage.

1192 Figure 7: Results of univariate analysis summarizing the number of buildings per category.
1193 Grayscales from the lowest parameter level 1 (white) to the highest level 5 (dark gray)
1194 are the same for all figures.

1195 Figure 8: Plot of parameter couple *“Distance from bridge”* and *“Damage”* at respective levels.
1196 Note the strong relationship between buildings located close to a bridge (DBR5) and
1197 damage level 4 (DO4; right side of vertical axis) compared to buildings far from a
1198 bridge (DBR1 and 2) that have damage level 2 (DO2, left side of vertical axis).
1199 Eigenvalues represent 96.54% for axis 1, 2.76% for axis 2, and 0.7% for axis 3.

1200 Figure 9: Results of the bivariate analysis. Damage level is displayed in different gray
1201 shades, the abscissa (1 to 5) displays the categories of the respective parameter
1202 *“Distance from channel”, “Distance from bridge”, etc.*

1203 Figure 10: Scatter plots representing results of the correspondence analysis. Each point
1204 represents a building. Ellipses colored from light blue to red represent parameter
1205 levels (1 to 5, respectively) as bagplots (bivariate boxplots). Each bagplot represents
1206 67.5% of the buildings defining each level.

1207 Figure 11: Projection of parameter levels (color) and city blocks as a result of the bivariate
1208 analysis. The position of each square is defined by the bagplot representing 67.5% of
1209 the buildings defining each level. The circles indicate city blocks of similar
1210 characteristics and thus behavior. City block numbers are plotted to allow comparison

1211 but are not included in the bivariate analysis. The number of buildings per city block
1212 and the respective percentage is detailed in the histogram to the right.

1213 Figure 12: Damage probabilities calculated for damage levels 1,2, 3 and 4 (series A) and all
1214 observed damage levels (1 to 4) in the field (series B) using calibration and validation
1215 data sets (898 buildings) of the selected test scenario presented in the manuscript.

1216

1217 **APPENDIX caption**

1218 Appendix A and B: Survey forms for the damage assessment of buildings, conceived for
1219 masonry (A) and reinforced concrete (B) structures following experiences from
1220 previous studies concerning natural hazard impact (Zuccaro et al., 2008; Zuccaro and
1221 De Gregorio, 2013; Jenkins et al., 2014).

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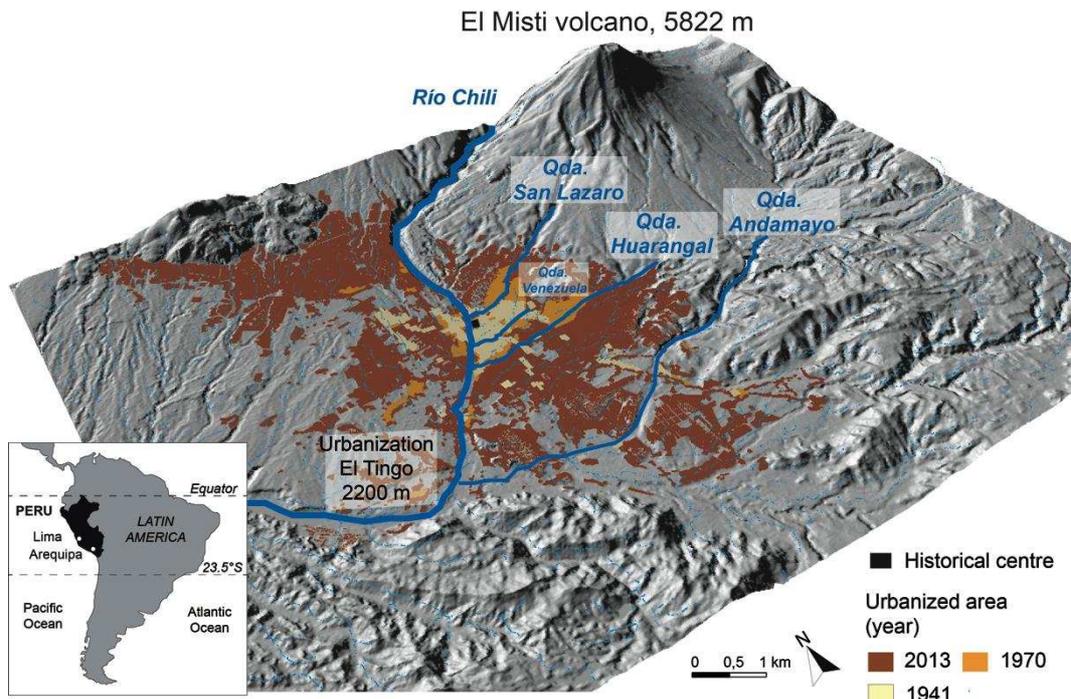
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Figure 1: Geographical setting and location of Arequipa city, Peru

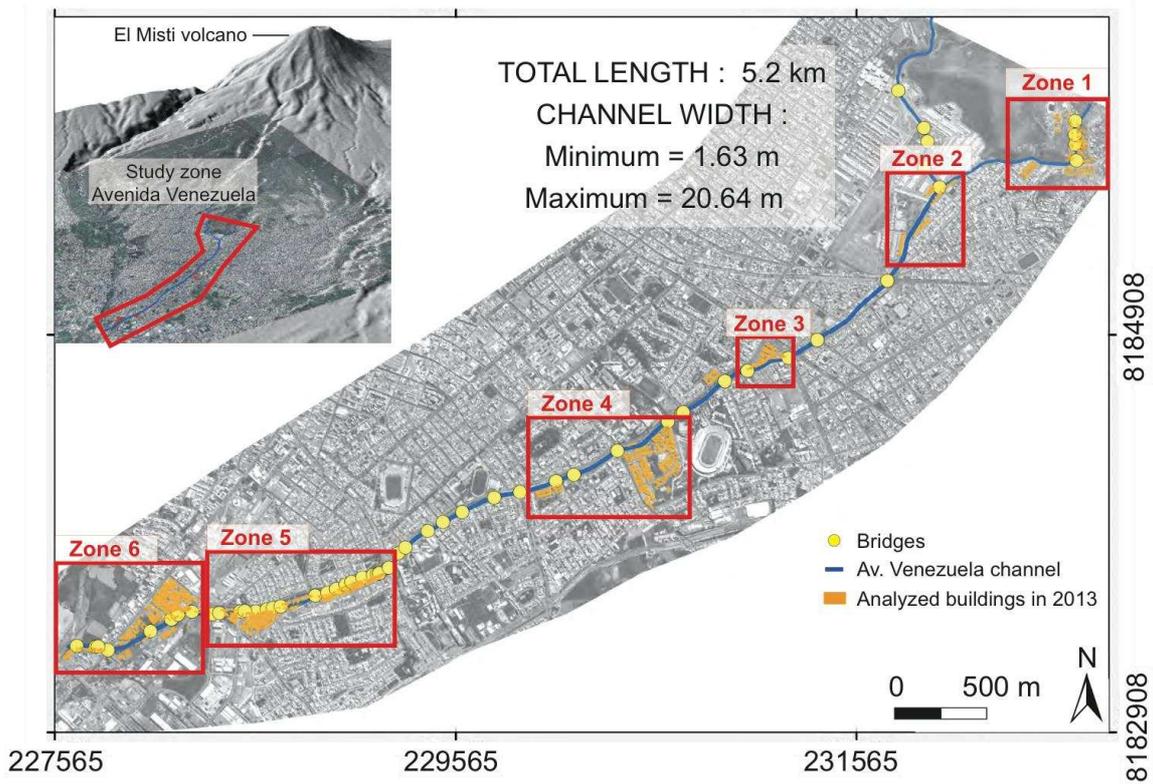


Figure 2: The study area Avenida Venezuela channel and six zones that will serve to illustrate observations in the following.

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Building vulnerability parameter							
	Parameter Abbreviation	Unit	Parameter level				
			5	4	3	2	1
Distance from channel	DC	Meter	≤ 5]5;10]]10;25]]25;60]	>60
Distance from bridge	DBR	Meter	≤ 15]15;30]]30;50]]50;90]	>90
Shape of city block	SH	/	Complex	Irregular	Regular	Compact	Perfect
Impermeability of soil	IS	/	Permeable	/	/	/	Impermeable
Structural type of building	S	/	1,2,3	9,10,11,12	4,5	6,7,8	/
Number of storeys	NS	/	1	2	3	4 and more	/
Inundation	I	Meter	/	> 0.4	0.2-0.4	< 0.2	0
Building footprint	A	Square meter	> 150]80-150]]50-80]]10-50]	≤10
Building density per city block	DE	Number per hectare]0-40]]40-60]]60-80]]80-110]	≥110
Damage parameter							
Observed damage (see fig. 7)	DO	/	Heavy	Moderate	Slight	Temporary inundation without damage	No damage

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Figure 3: Building vulnerability parameters and their levels as defined for this study.

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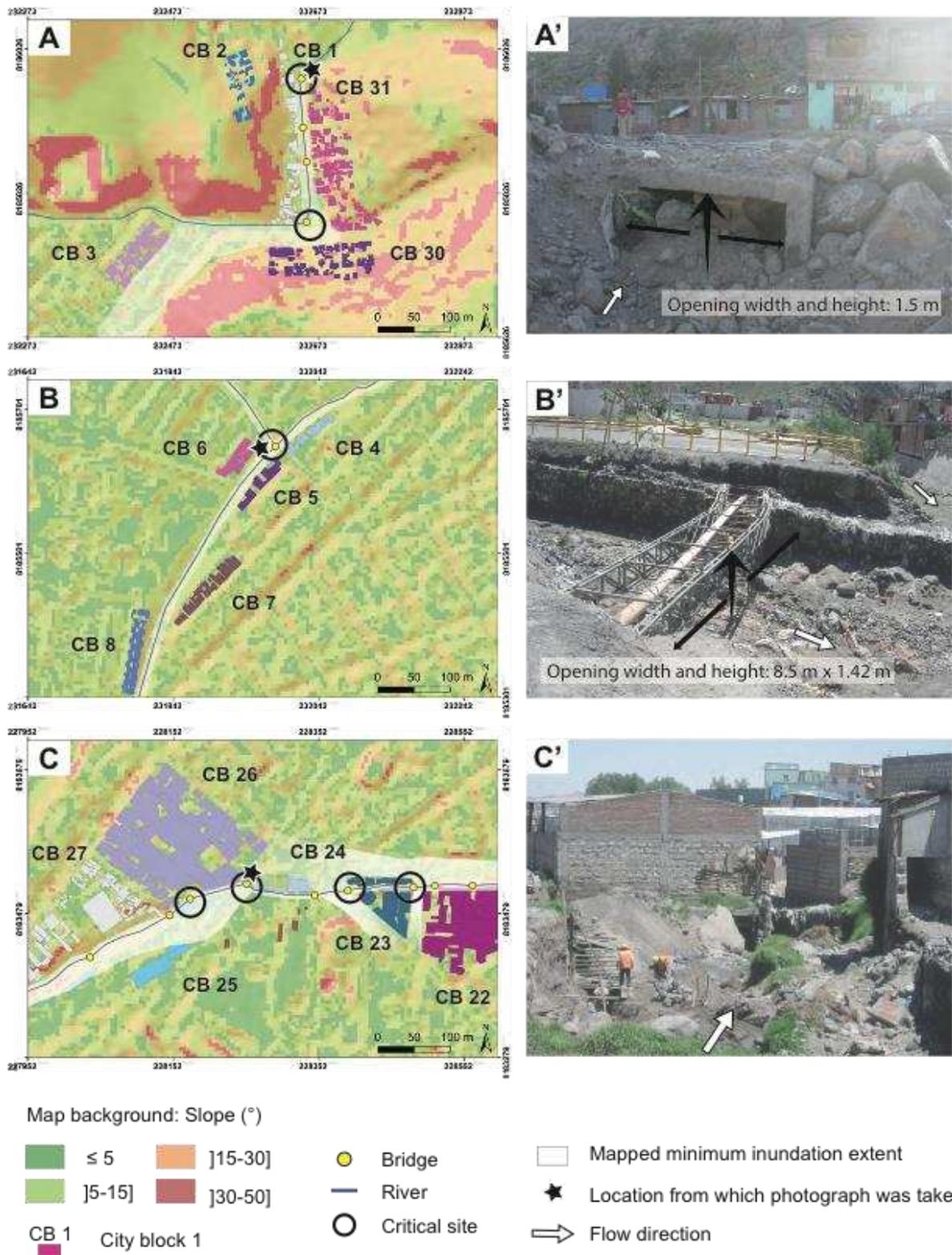
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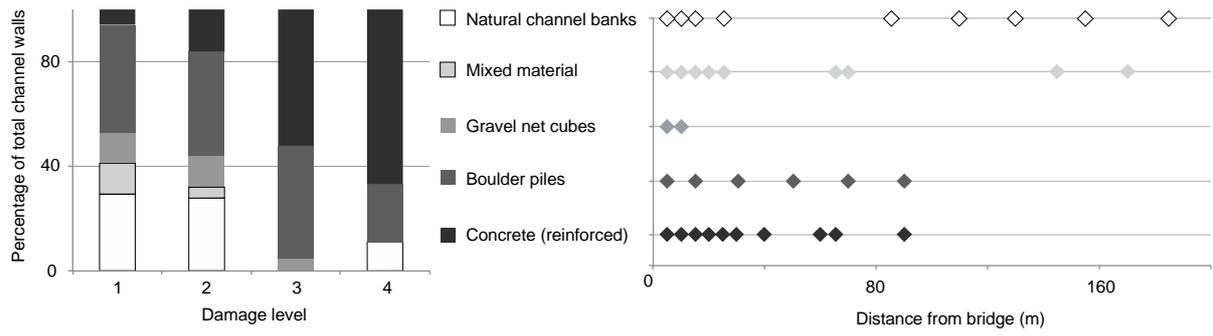
Figure 4: Longitudinal channel profile (blue line) with channel width (green dots), and sections in which erosion occurred (orange bars). The gray scale bar below represents channel bed type, i.e. natural gravel, sand (dark gray), natural with occasional concrete steps (light gray) and concrete (medium gray); the channel wall material is represented by concrete (dark brown), mixed material (concrete, brick, boulders; light brown) and natural (medium brown).



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Figure 5: Three examples for particular channel courses and occurred damage.

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Figure 6 Left: Damage level observed for different material types of contention walls. Right: Material types of contention walls relative to the proximity to bridges.

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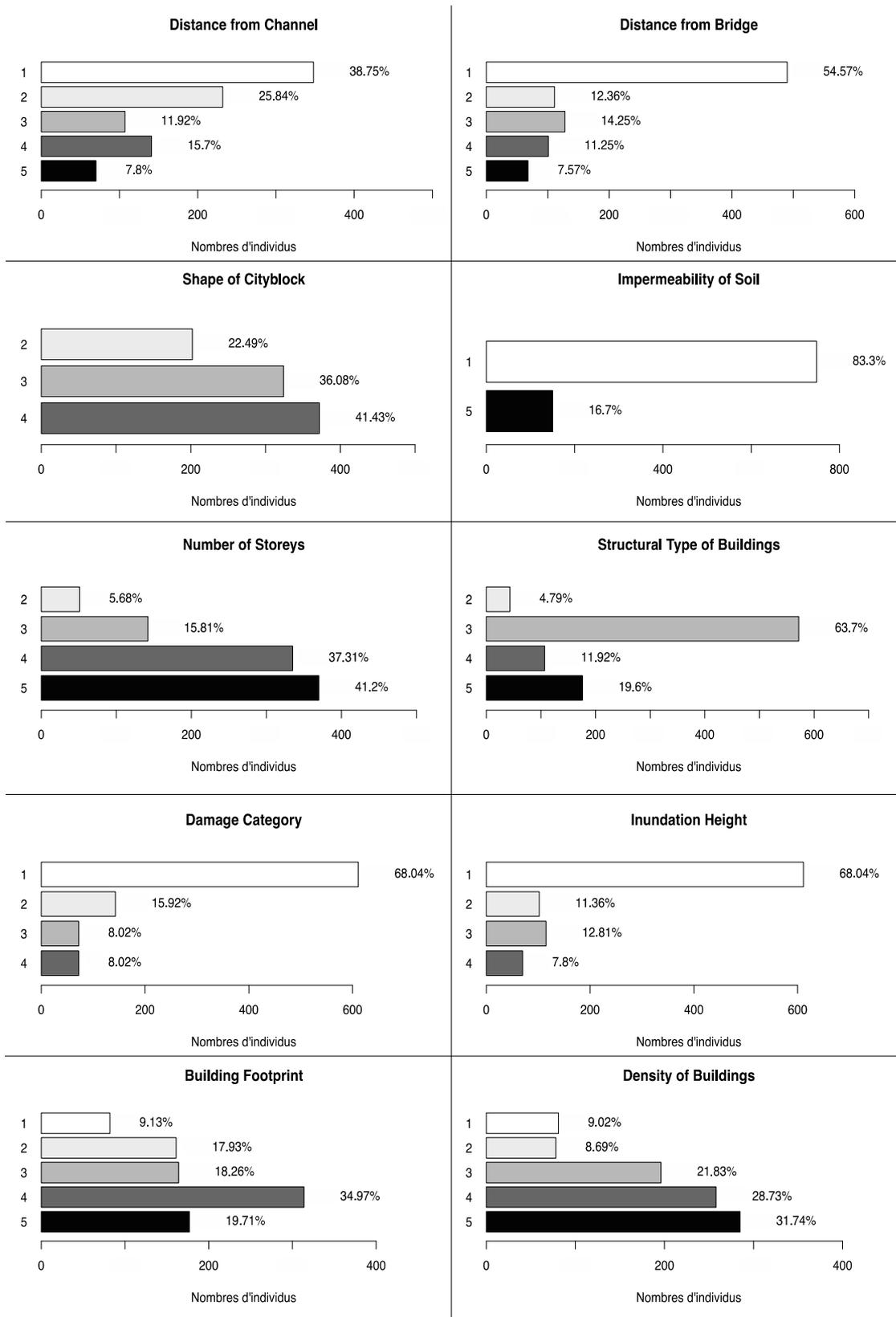
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Figure 7: Observed damage levels from left to right (4) inundated, heavy damage, (3) inundated, important damage; (2) inundated, light damage; and (1) inundated, without damage.



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Figure 8: Results of univariate analysis summarizing the number of buildings per level. Grayscales from the lowest level 1 (white) to the highest level 5 (dark gray) are the same for all figures and represent the parameter levels (refer to fig. 3 for details on level characteristics).

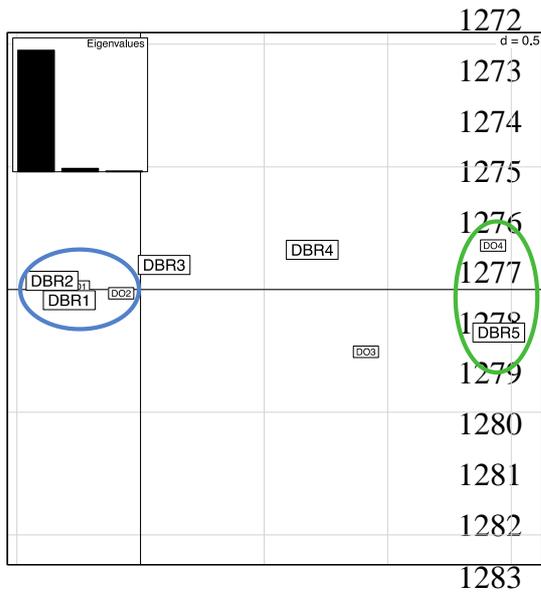
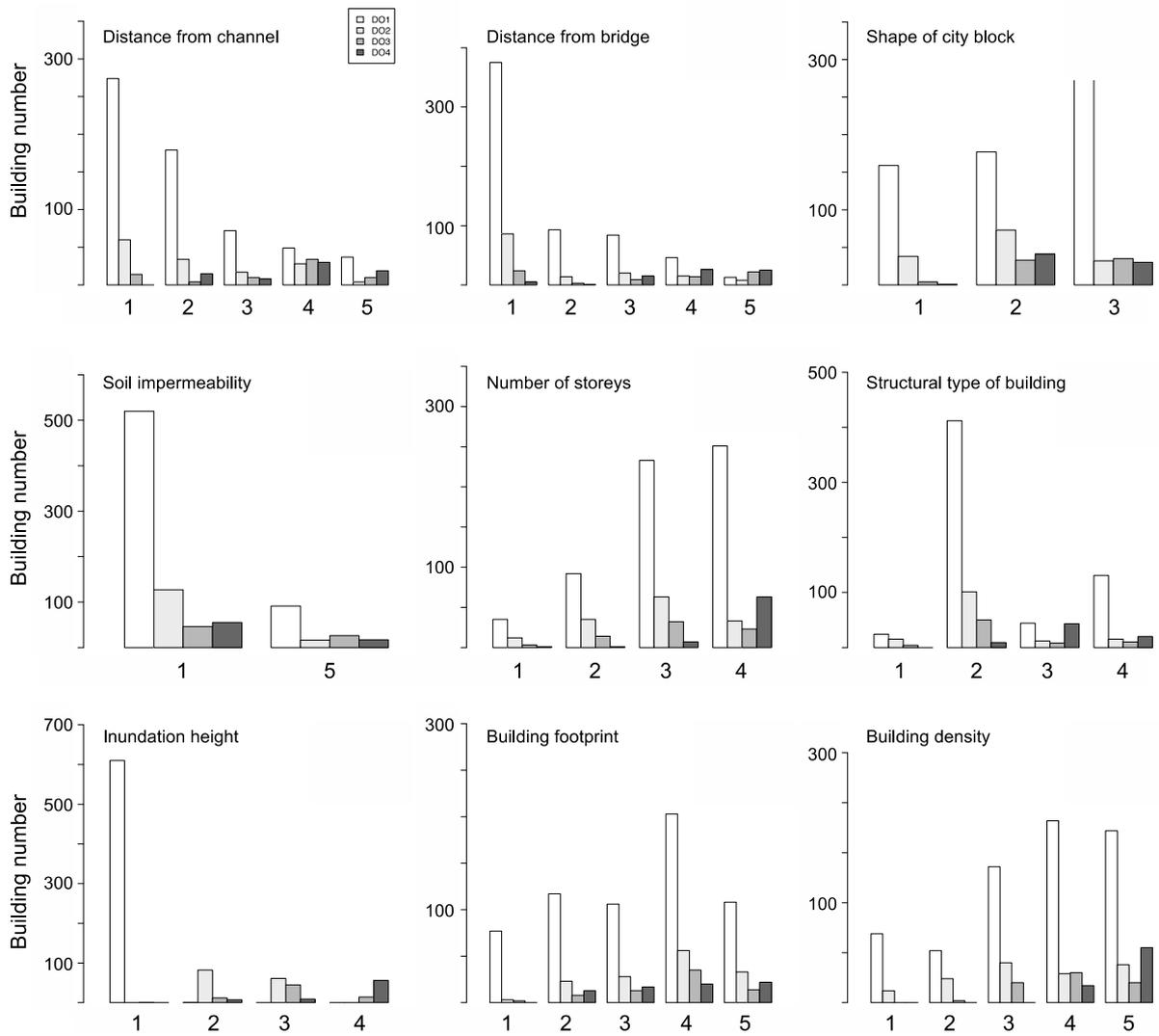


Figure 9: Plot of parameter couple “Distance from bridge” and “Damage” with respective levels. Note the strong relationship between buildings located close to a bridge (DBR5) and damage level 4 (DO4; right side of vertical axis) opposed to buildings far from a bridge (DBR1 and 2) that have damage level 2 (DO2, left side of vertical axis).



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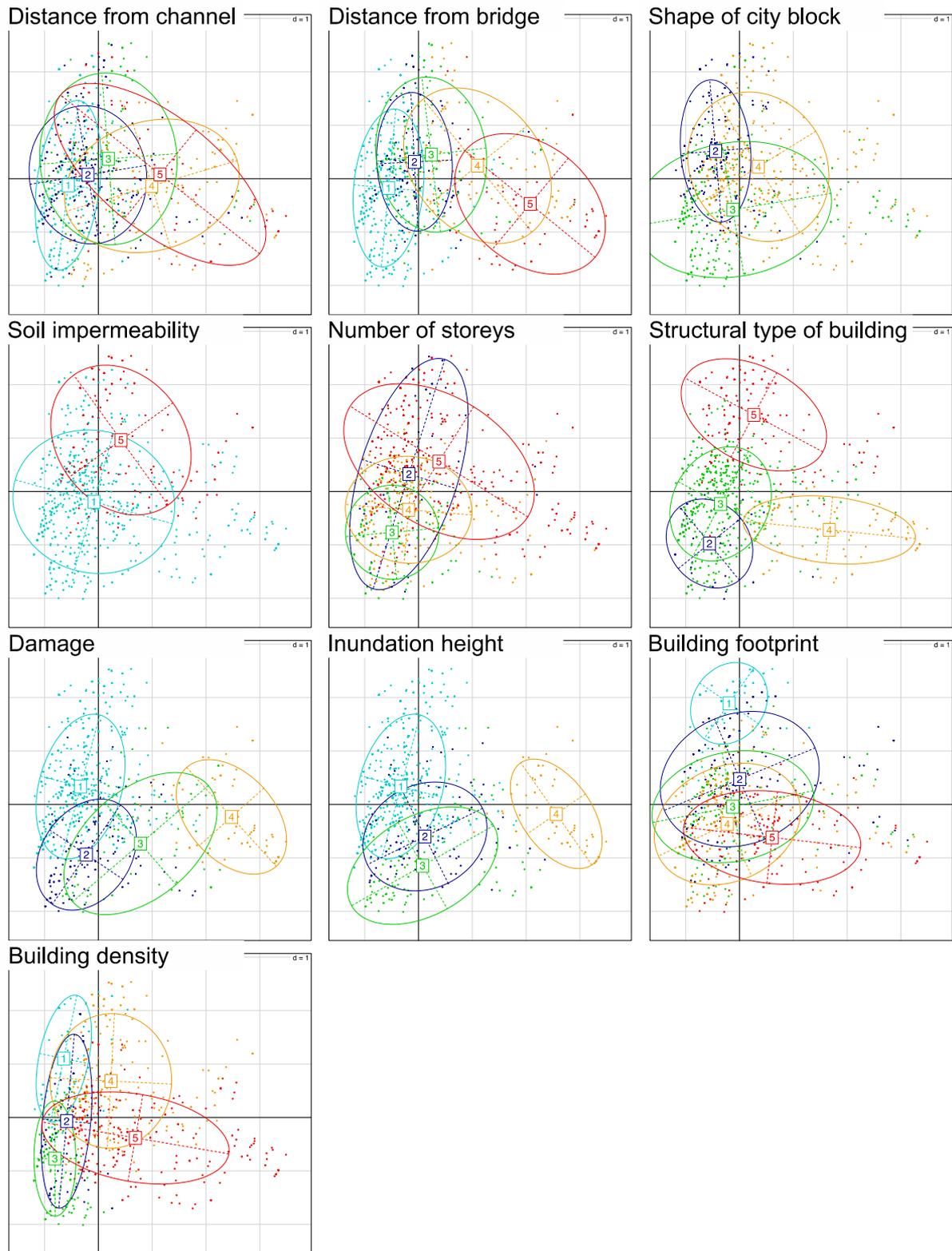
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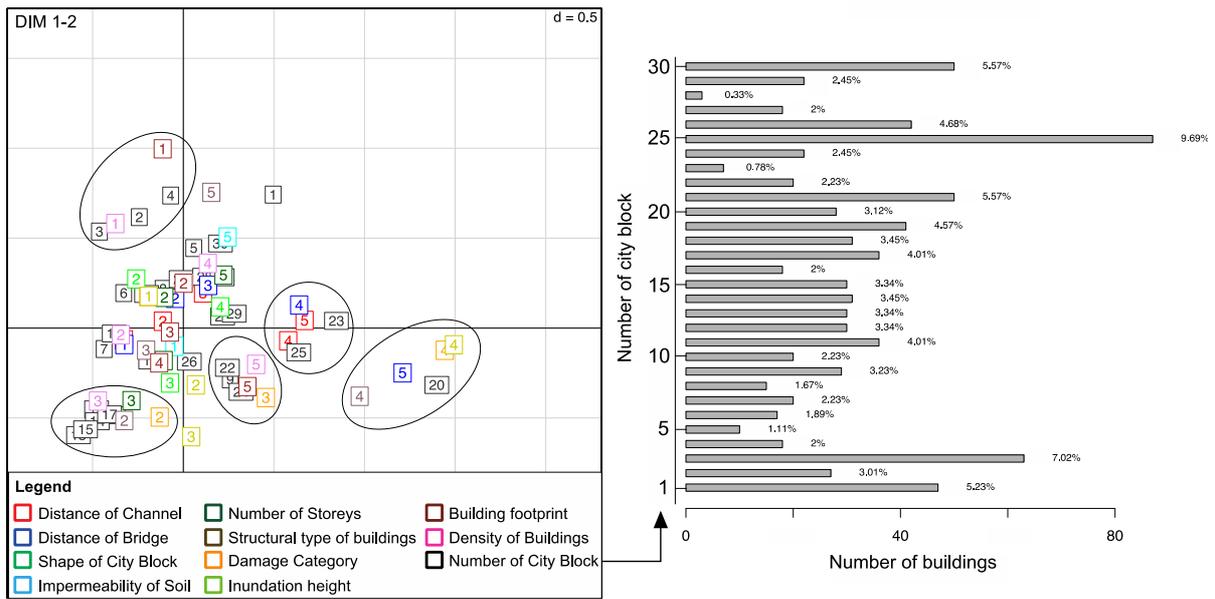
Figure 10: Results of the bivariate analysis. Damage level is displayed in different gray shades, the abscissa (1 to 5) displays the categories of the respective parameter “Distance from channel”, “Distance from bridge”, etc.



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Figure 11: Scatter plots representing results of the bivariate analysis. Colors from blue to red represent parameter levels (1 to 5). The barycenter of the ellipse represents 67.5 % of the buildings defining each level.

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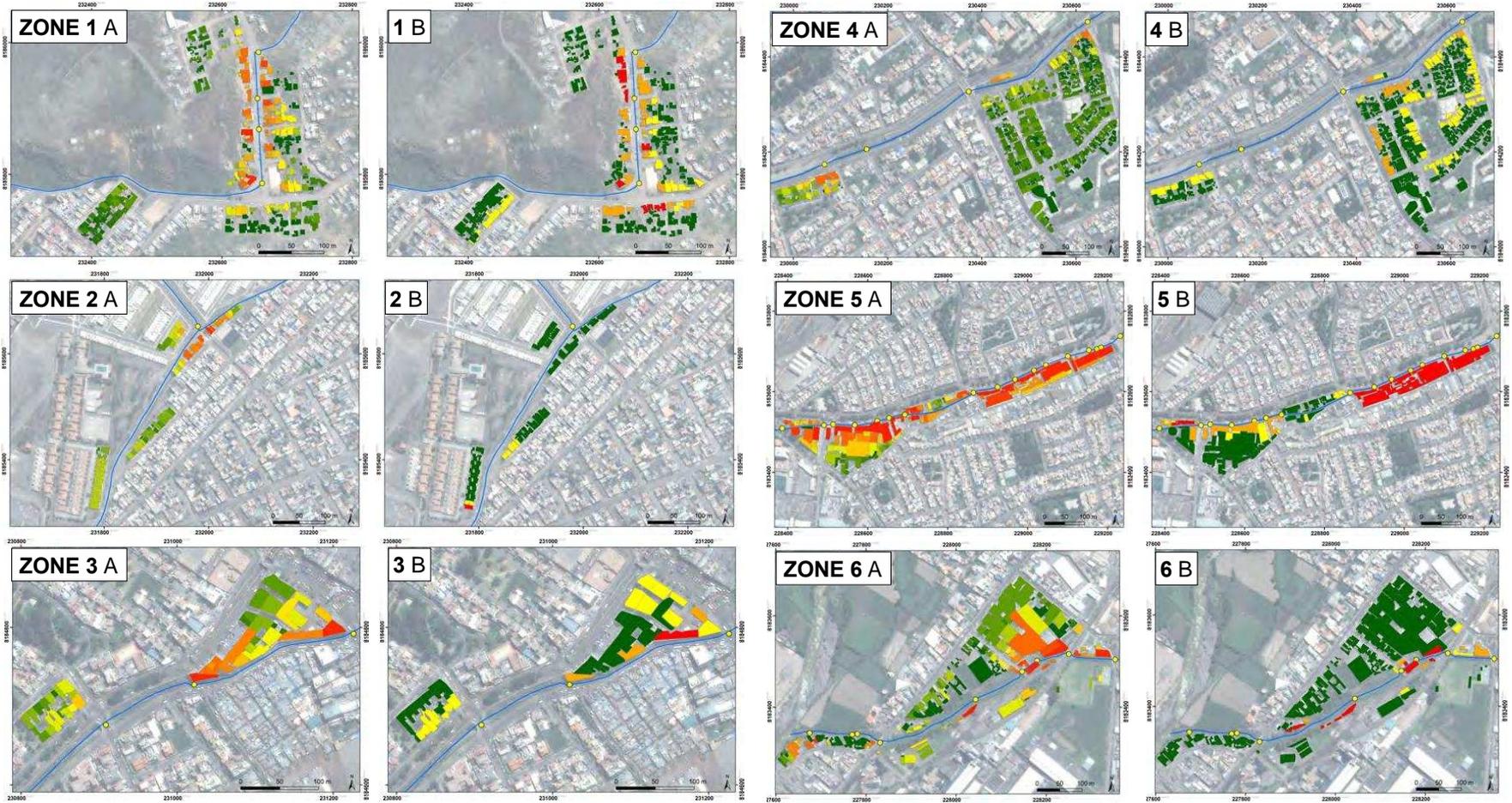
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Figure 12: Projection of parameter levels (color) and city blocks as a result of the bivariate analysis. The position of each square is defined by the barycenter of the ellipse representing 67.5 % of the buildings defining each level. The circles indicate city blocks of similar characteristics and thus behavior. City block numbers are plotted to allow comparison but are not included in the bivariate analysis. The number of buildings per city block and the respective percentage is detailed in the histogram to the right.



Damage level

Series A - Calculated damage likelihood (%)



Series B - Observed damage level in the field



1304 Figure 13: Damage probabilities calculated for damage level 3 and 4 (series A) and all
1305 observed damage levels (1 to 4) in the field (series B).
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