

1 **EVALUATION OF CONNECTIVITY INDICES APPLIED TO A MEDITERRANEAN AGRICULTURAL**
2 **CATCHMENT**

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12

13 **Abstract**

14 Connectivity analysis has proved a very valuable approach in understanding runoff and sediment
15 fluxes in catchments. Many analyses use Connectivity Indices to model the patterns, but various
16 versions of the Index have been developed. This paper tests the effects of these variants of the
17 Index as applied to an agricultural-terraced catchment in the semi-arid Mediterranean region where
18 occurrence of connectivity is relatively well documented to validate the modelling. This paper
19 compares three versions of the Connectivity Index that use vegetation/land use (C), topography (RI)
20 and roughness (n) as the weighting factors. Two different slope algorithms are also tested. The
21 weightings are derived from a UAV (drone) survey, with simultaneous ground field mapping. The
22 UAV imagery is found to provide a good, high resolution basis for determining detailed topography
23 and vegetation cover. The slope limit present in some modelling is found to be unsuitable in this

24 landscape where steep terrace embankments that are vegetated in places, and also partially
25 vegetated uplands, occur. Subsequent modelling removed the slope limit. The major patterns of
26 flow produced are similar between the models and are largely related to the overall topography and
27 major drainage lines but considerably modified by the terracing. The model outcomes differ in
28 detail, with the C factor model, incorporating vegetation, coming nearer to the field situation. The
29 main deficiency in all the indices is the weakness in modelling ponding and sedimentation created by
30 the terraces, and therefore the disconnectivity in the landscape. Comparison with field data
31 confirms the variable connectivity in rainstorms, the effects of features such as tracks, and the effect
32 of management actions. Evidence from field mapping during the last two decades indicates that the
33 models probably represent the maximum possible functional connectivity.

34

35 Key words: Connectivity Index; vegetation; soil erosion; sedimentation; drylands; disconnectivity

36

37 **1. Introduction**

38 The concept of connectivity has received increasing attention in hydrology and geomorphology since
39 the late 1990s and is now widely accepted as a major paradigm and framework for analysis of runoff
40 and sediment flux in catchments and the effects of various characteristics. It has been shown to be of
41 value in assessing sources of sediments, soil erosion distribution, sediment delivery and sediment yield
42 and has been applied in catchment and river channel management (Brierley et al., 2006; Fryirs et al.,
43 2007b; Wohl et al., 2019). The main conceptual developments, building on the original ideas and
44 applications by Brierley and Fryirs and associates (Brierley and Fryirs, 1999; Fryirs and Brierley, 1999),
45 refined ideas on controls of connectivity and identification of connected and non-connected or
46 disconnected areas (Bracken and Croke, 2007; Bracken et al., 2013; Lexartza-Artza and Wainwright,
47 2009; Wohl, 2017). States of structural and functional connectivity were differentiated and different

48 types of connection of longitudinal (downslope, down channels, hillslope- channel coupling), lateral
49 (channel- floodplain) and vertical (within soil layers and water bodies) were identified (Lexartza-Artza
50 and Wainwright, 2009; Wohl, 2017) . The importance and types of disconnectivity have been
51 recognised (Fryirs et al., 2007a; Hooke, 2003; Hooke and Sandercock, 2017; Recondes, 2017a;
52 Sandercock and Hooke, 2006).

53 The idea that not all sediment eroded in a catchment is delivered downstream has long been
54 recognised in the concept of Sediment Delivery Ratio (Walling, 1983), in the jerky conveyor belt
55 concept that included storage (Ferguson, 1981; Newson, 1997) and was demonstrated in sediment
56 budgets produced by Trimble (1983). Connectivity was distinctive in concentrating on the pathways
57 and the extent of links between potential sources and sinks all the way through the flow and sediment
58 routes, rather than lumping catchment characteristics and quantifying outcomes from areas. Various
59 approaches to quantification of connectivity have been developed but the breakthrough came with
60 the Index of Connectivity (IC) developed by Borselli, et al (2008), which has formed the basis for much
61 subsequent modelling. The IC was further elaborated by Cavalli and associates, using some different
62 factors and weightings (Cavalli et al., 2013). Transformation of the calculation of Index of Connectivity
63 (IC) for areas into an accessible software package opened up application by the research community
64 (Crema and Cavalli, 2018). Alternative approaches to quantification include use of graph theory and
65 network parameters (e.g., Fressard and Cossart, 2019; Heckmann and Schwanghart, 2013). Increasing
66 availability and resolution of remote sensing imagery and techniques of spatial data acquisition have
67 facilitated the development and application of connectivity concepts and quantification (Cantreul et
68 al., 2018; Cavalli et al., 2019). Many of the applications and analyses of the Borselli/Cavalli Indices of
69 Connectivity have been in either mountainous environments, with emphasis on rocky hillslopes and
70 zones prone to debris flows and landslides (e.g., Bordoni et al., 2018; Persichillo et al., 2018; Schopper
71 et al., 2019; Scorpio et al., 2018; Zanandrea et al., 2019) or in Mediterranean agricultural environments
72 where agricultural terraces and land use influence patterns of connectivity (e.g., Calsamiglia et al.,
73 2017; Calsamiglia et al., 2018a; Lizaga et al., 2018; López-Vicente and Alvarez, 2018), though

74 applications are rapidly expanding to a wider range of climatic, topographic and land use
75 environments.

76 The connectivity indices developed by Borselli and Cavalli use characteristics of each pixel of a
77 catchment or study area to calculate the potential for flow connection and cumulate this in the
78 downslope direction, producing maps of the values of the index for every pixel. The Connectivity
79 Indices are increasingly used to test the effects of various factors and changes such as in land cover
80 or presence of structures (Cucchiaro et al., 2019; Kumar et al., 2014; López-Vicente et al., 2017).
81 Various researchers have experimented with introducing additional factors and weightings to
82 calculate the index and have suggested modifications, especially for lowland and more vegetated
83 environments (e.g. Gay et al., 2016; Zingaro et al., 2019). However, here the three main models of
84 Borselli (C factor), and Cavalli (n and RI versions) will be tested since they are in widespread use but
85 still require greater evaluation, especially against field observations. All the indices aim to model the
86 pathways of flow that will occur given the conditions of each pixel and to quantify the cumulated
87 amount of flow and sediment but use weighting factors to assess the influence on sediment transfer.
88 Factors that contribute to the index are flow surface controls, such as topography elements and
89 surface roughness, represented by land cover (Borselli et al., 2008; Cavalli et al., 2013; Surian et al.,
90 2016). The models have differing emphases, through different factor weightings, on the topographic
91 and vegetation elements, reflecting the environments for which they were developed. Borselli's was
92 developed for Mediterranean upland agricultural environments, including specifically partly in the
93 present study catchment (Recondes, 2007b). Cavalli's indices were developed for steep rocky terrain
94 as found in the Alps.

95

96 Deficiencies in the connectivity indices have been recognised (e.g., Heckmann et al., 2018; Wohl et al.,
97 2019) and several researchers emphasise the importance of field mapping for validation and for
98 verifying actual existence of pathways (Cossart et al., 2018; Messenzehl et al., 2014; Nicoll and
99 Brierley, 2017). Recent research is assessing the effectiveness of use of drones for validation and/or

100 DEM creation and is testing effects of DEM resolution (Cantreul et al., 2018; Estrany et al., 2019; López-
101 Vicente and Álvarez, 2018; Tarolli et al., 2019).

102 The main purpose of this paper is to assess the suitability of connectivity indices to characterise
103 patterns of flow and sediment connectivity in Mediterranean, agricultural terraced landscapes,
104 validating this approach on a previously mapped area where much is known on patterns of
105 connectivity. The aim is to assess the extent to which connectivity indices allow modelling both of
106 flow and sediment fluxes and connectivity adequately and to evaluate the influence of factors that
107 are under-represented or underestimated. This will lead to suggestions of strategies for
108 improvement and applicability of IC models. A secondary aim is to assess the efficacy of use of
109 drone imagery for mapping connectivity and calculating indices. The paper also highlights the
110 challenges of validation, the effects of changes over time, and the high degree of human influence in
111 such a landscape.

112

113

114 **2. Methods**

115 **2.1 Study area characteristics**

116 The area used for this testing and evaluation of connectivity indices and drone deployment is a sub-
117 catchment of the Cárcavo catchment in SE Spain (Fig.1), which was the location for most of the work
118 on development of connectivity assessment and effects of vegetation undertaken in the EU
119 RECONDES project (Hooke and Sandercock, 2017, 2012; Marchamalo et al., 2016; Recondes, 2007b;
120 Sandercock and Hooke, 2006), including research by Borselli and colleagues on development of their
121 index. The area has an average rainfall of c.300 mm/year and the whole catchment is mainly
122 underlain by Miocene marl. The selected sub-catchment has an area of 14ha and the main drainage
123 is in the northeasterly direction (Fig. 1), with a total relief of 46 m. It is an area of mainly terraced
124 almond and olive groves but contains some abandoned land and areas of rock outcrops with semi-

125 natural vegetation and of afforestation on the margins (Fig. 2). It has one main track crossing it and
126 the remains of another old, abandoned track, and also ramps for access to fields between terraces.
127 The relief or banks between terraces are of the order of 0.5-1.5m in height, with varying degrees of
128 vegetation cover (Fig.2). The fields with almonds and olives are ploughed frequently, usually about
129 three times a year. Some fresh planting of trees in terraces has taken place over the past 10 years,
130 mainly for replacing dead trees. Vegetation on embankments and in the semi-natural areas is not
131 highly seasonal, comprising mostly perennial shrubs that withstand drought and alter very little year
132 to year or seasonally. Ground cover of herbs can appear after wet periods but is mostly soon
133 removed by ploughing. The area has been monitored by field mapping since 2004, with frequent
134 mapping in the period 2004-7 (a dry period) and sparse surveys, mostly annually in January, since
135 then. The major connectivity patterns and their relation to rainfall have already been analysed for
136 the early period (Marchamalo et al., 2016).

137

138 *Fig. 1 - Cárcavo location, relief and land use*

139

140 The major characteristics of the connectivity pattern revealed by the mapping 2004-7 (Marchamalo
141 et al., 2016), and confirmed in subsequent mapping, are summarised here (Fig. 3). The main
142 drainage lines correspond to the overall original topography of the catchment, with central flow to
143 the north-east down the centre of the area but modified by the terracing and management actions.
144 Mapping after rainfall events, varying in magnitude but mostly low magnitude and at differing times
145 after management actions such as ploughing (but mostly in the same season of January), shows that
146 a major feature of the drainage and connectivity is the occurrence of relatively short pathways in
147 storms, that are erosive, producing rills, but that most of these usually terminate in areas of ponding
148 and sedimentation upstream of the terrace embankments (Fig. 2c). Breaches in the embankments or
149 overflow/ throughflow have occurred in high rainfall events, though rarely (Fig. 2c). Management
150 actions have directly altered the configurations in some locations, with the main natural drainage

151 being slightly shifted into a constructed ditch in the lower section (Fig. 2a), a minor track crossing put
152 in at the head of the main gully at the downstream end, and some large soil piping (tunnelling) in
153 fields upstream of the main gully/channel (Hooke, 2006; Hooke and Sandercock, 2012; Marchamalo
154 et al., 2016), in existence until 2011 then filled in (Fig 2a). The previous analysis had shown that the
155 main track crossing the area in the upper part is highly influential in generating runoff Fig. 2c), as is
156 also an abandoned former agricultural area of low vegetation cover (Fig. 2a) (Hooke, 2006; Hooke
157 and Sandercock, 2012; Marchamalo et al., 2016). Regular maintenance actions include mending of
158 breaches, frequent ploughing and weed control, and replacement and replanting of trees in some
159 fields.

160

161 ***2.2 UAV survey, and DEM construction***

162 A DJI Phantom 3 was used to take aerial photographs of the sub-catchment, in January 2019; the
163 flight was operated at 60 metres high, 75% of frontal and lateral overlapping, and it took 265 photos.
164 All images had UAV natural 3D georeferenced information. Nevertheless, 13 ground control points
165 were established at different altitudes around the watershed, with the markers surveyed using a
166 Topcon GPS RTK HiperPro instrument with <20 mm error. The UAV data were processed in Agisoft
167 Metashape Professional, including the spatial adjustments based on the ground control points and a
168 two-step, no ground points filtering, to remove vegetation and man-made structures. It was possible
169 to create DEMs with different resolution but in this analysis only the 0.2 m spatial resolution DEM
170 was used, following conclusions by López-Vicente and Álvarez (2018), working in a Spanish
171 Mediterranean agricultural terraced area similar to the present field area, in which they specifically
172 tested different DEM resolution from drone images. They concluded that 0.2m DEM provided the
173 best IC result, vertically and horizontally, including good results to identify the small erosion lines,
174 that are around 0.2m wide, like those found in the Cárcavo area. Our preliminary tests of different
175 resolutions confirmed these findings. Ground photographs and field mapping were undertaken at

176 the time of the drone photography. In addition, an orthophotomosaic with 0.03 m spatial resolution
 177 was created, and together these allowed connectivity ground truthing.

178

179 **2.3 Calculations of indices and series of tests**

180 One of the frameworks that allows quantification of the connectivity is the Index of Connectivity (IC)
 181 (Borselli et al., 2008), that calculates the continuous potential connectivity between different points
 182 on the surface. The IC uses a GIS model approach to define the potential connectivity on a pixel/cell
 183 scale. It combines a downslope component and an upslope component (Equation 1). The downslope
 184 component (D_{dn}) is related to the distance and impediments between a point and the nearest sink.
 185 These downslope impediments are defined by the cell slope angle (S) and the cell surface roughness,
 186 defined by vegetation and land use characteristics (Borselli et al., 2008; Sougnez et al., 2011),
 187 classified as the Weight factor (W). The W value ranges between 0 and 1, higher values representing
 188 less roughness and consequently higher connectivity. The upslope component (D_{up}) is based on
 189 potential runoff/discharge, calculated by discharge area (A), and on sediment yield potential,
 190 controlled by upslope average slope angle (S) and upslope average surface roughness (W). It is
 191 expressed by:

$$IC_k = \log_{10} \left(\frac{D_{up,k}}{D_{dn,k}} \right) = \log_{10} \left(\frac{\bar{W}_k \bar{S}_k \sqrt{A_k}}{\sum_{i=k,n_k} \frac{d_i}{W_i^2 S_i}} \right) \quad (\text{Equation 1})$$

192
 193 In the Borselli et al. (2008) model the W is related to the C-factor used in USLE/MUSLE models; this
 194 parameter reflects soil protection and soil loss (Table 1). Also, it is possible to include several
 195 sediment sinks, such as streams, roads, urban areas (Borselli et al., 2008) or the watershed outlet
 196 (Cavalli et al., 2013). In this paper, to understand the whole watershed connectivity pattern, the
 197 lowest downstream point of the main drainage area studied was defined as the outlet and used as
 198 the sink target.

199

200 *Table 1*

201

202 Cavalli et al (2013), made three relevant changes to Borselli's IC in their original model, termed the
 203 RI model because it incorporates a roughness factor model: flow direction algorithm changed from
 204 D8 to D-infinity to allow for divergent flow paths; created a slope angle limit; and changed the C-
 205 factor to a topographic roughness index (RI). The authors made clear that changes were necessary
 206 due to the specific mountainous rocky surface they were analysing and to the possibility to use high
 207 resolution digital terrain models (HR-DTM). The D-infinity algorithm enables identification of
 208 divergent flow dynamics and, as a result of DTM cell size, it could identify more accurately the flow
 209 width than the D8 algorithm, which identifies only one flow direction, neglecting divergent flow
 210 patterns and the flow width (standardised as the pixel width). The slope gradient limit was set as 1
 211 m/m in the Cavalli model, justified by the local characteristics in their analysed area, where areas
 212 with gradient over this limit show no or very little sediment availability, such as rocky cliffs, very
 213 steep slopes and bedrock channels. The third, and critical change, was the replacement of the C-
 214 factor by RI derived from the HR-DTM, using a 2.5 m DTM. The reason for this modification is the
 215 lack of vegetation and land use in the mountainous/Alpine area, where the surface roughness is
 216 controlled by surface morphology of rock outcrops and debris cover. The RI parameter (Cavalli et al.,
 217 2013) is the standard deviation of the residual topography $(x_i - x_m)$ (Equation 2) and it is defined as
 218 the Weighting factor (Equation 3) following the expressions:

219

$$RI = \sqrt{\frac{\sum_{i=1}^{25} (x_i - x_m)^2}{25}}$$

220

(Equation 2)

$$W = 1 - \left(\frac{RI}{RI_{MAX}} \right)$$

221

(Equation 3)

222 Additionally, the authors indicate that this allows the model to run with only one input data, the
223 residual topography, turning this IC-RI model into the most commonly used (Calsamiglia et al.,
224 2018b; Cantreul et al., 2018; Marchi et al., 2019; Messenzehl et al., 2014; Nicoll and Brierley, 2017;
225 Schopper et al., 2019), especially after the release of a free open-source tool – SedInConnect
226 (Crema and Cavalli, 2018). Subsequently, vegetation and land cover data were re-introduced as W,
227 based on Manning’s n roughness coefficient (Bordoni et al., 2018; Persichillo et al., 2018; Surian et
228 al., 2016), following the idea to use RI for unvegetated areas and Manning’s n roughness coefficient
229 for vegetated areas (Table 1). There are several other approaches to calculate the connectivity index
230 at cell scale using different Weighting factors, such as NDVI vegetation index or other environmental
231 parameters (Cislighi and Bischetti, 2019; de Walque et al., 2017; Gay et al., 2016; Ortíz-Rodríguez et
232 al., 2017; Zingaro et al., 2019).

233

234 Initial models were run in the present research to test the difference between the index calculation
235 using no slope restriction, as in Borselli et al. (2008) (subsequently denoted here as Bor_IC) and
236 using the restriction in the Cavalli model of a slope limit of 1m/1m (denoted as Cav_IC). In the
237 Cárcavo environment, there are steep slopes that are not rocky, mainly embankments with varying
238 degrees of vegetation. At the same time, the three main weighting factors were used – C factor (C),
239 Manning Roughness Coefficient (n), and Topographic Roughness Index (RI) to test the differences
240 produced by those factors. The land cover map was created using the UAV orthophotomosaic and
241 field data, identifying the vegetation cover and land use and soil management. The C-factor values
242 and Manning coefficient values applied (Table 1) were based on well-known values in the literature
243 (Panagos et al., 2015; Papaioannou et al., 2018; Persichillo et al., 2018). The RI was calculated using
244 the 0.2 m UAV DEM in the SedInConnect tool (Crema and Cavalli, 2018). The D-infinity algorithm,
245 proposed by Cavalli et al. (2013) was used, because it is widely regarded as a better algorithm than
246 D8 (Lana-Renault et al., 2018; López-Vicente and Álvarez, 2018; Messenzehl et al., 2014; Nicoll and
247 Brierley, 2017; Ortíz-Rodríguez et al., 2017; Persichillo et al., 2018; Schopper et al., 2019).

248

249 It is essential to understand the complexity of comparing the different versions of IC models, mainly
250 changes in W parameters (e.g. C/n from land use and RI from topographical information). These W
251 values do not show a similar histogram value distribution (Fig. 4), leading to unequal values that are
252 not directly comparable. Because of this characteristic, using absolute thresholds to compare
253 different unnormalised models creates misinterpretations. As a result, IC model comparisons use
254 different statistic distribution analysis methodologies, such as stretch distribution (Chen et al., 2013;
255 Estrany et al., 2019; Zhao et al., 2020; Zingaro et al., 2019); data clustering visualisation (López-
256 Vicente and Ben-Salem, 2019); and percentile thresholds (Calsamiglia et al., 2018b; Calsamiglia et al.,
257 2020). The results here were classified using Jenks natural breaks (Persichillo et al., 2018; Tiranti et
258 al., 2018) in 10 classes. This data clustering method aims to find the optimal arrangement of classes
259 by minimizing the average deviance from each class mean in distributions that do not show obvious
260 natural/fixed breaks (Chen et al., 2013). These classes were grouped into three divisions of Low
261 connectivity (classes 1 to 3), Moderate connectivity (classes 4 to 7), and High connectivity (classes 8
262 to 10) for spatial visualisation of the IC maps.

263

264 ***2.4 Field mapping methods and dates.***

265 Field mapping of connectivity was undertaken by ground walk-over surveys, observing and
266 measuring signs of flow lines, erosion and deposition, and marking them on a base map,
267 supplemented by GPS points and photography to record features (Marchamalo et al., 2016).
268 Connectivity pathways are followed and interpreted in the field at the time. The base map used
269 was a 1/5000 map produced from orthophotos by Murcia Region (1995). The field mapping was
270 undertaken using the protocol developed in the RECONDES project (Cammeraat, 2005), applied by
271 Borselli et al. (2008) in developing and testing their index, and applied in the Cárcavo catchment in
272 studies by Lesschen et al. (2009), Marchamalo et al. (2016) and Meerkerk et al. (2009). Since 2007, it
273 has only been possible to map the area occasionally and not necessarily after heavy rainstorms. It

274 did include mapping after the heavy rainfall and flood events of September 28th, 2012 in SE Spain
275 (Hooke, 2016, 2019) but rainfall was not extreme in the Cárcavo catchment. Subsequent to the
276 drone photography, mapping also took place in January 2020 after very heavy rain of >200mm in
277 September 2019. Frequency of repeat flow lines has been assessed (Fig. 3). The compilation for the
278 period 2008-20 only shows the main rills, for clarity. Rill lines that are not continuous usually
279 terminate in small fans or very shallow sedimentation zones (Fig. 2c). The field mapping is also
280 complemented by ground photography and field notes, including evidence of management actions
281 and alterations, major ones of which are indicated in Fig.2a.

282

283 *Fig. 2*

284

285 **3. Results**

286 **3.1 Effects of slope restriction**

287 Six models were processed – Bor_C, Bor_RI, Bor_N, Cav_C, Cav_RI, Cav_n – where “Bor” represents
288 the models without slope limit, “Cav” the models with 1 m/m slope limit; C is C-factor as W, RI is
289 Topographic Roughness index, and n is Manning’s Roughness Coefficient. The effects of using the
290 Cavalli algorithm that has a slope limit of 1 m/m (45 °) were compared with the results after removal
291 of the slope limit. Steep slopes (angle over 45° - 1 m/m) represent 1.1% of the watershed, mainly
292 terrace embankments and natural hilly areas. Firstly, to identify the slope limit effects on IC models
293 (Table 2), these steep areas were separately analysed. The comparison results in the expected
294 increase in proportion of high connectivity areas in the models without slope limit (“Bor” models),
295 proportionally increasing by 0.7% (C-factor), 4.0% (Manning's roughness coefficient), and 3.4%
296 (Roughness index) for the three versions of the IC. Consequently, the different slope sensitivity of
297 the IC models is evident, where the land use parameter can decrease the influence of the slope
298 angle, notably in the C-factor model. In this case, this happens because the steep slopes are
299 concentrated on the terrace embankments and around the hills, which are predominately covered

300 by denser vegetation, like trees and bushes. Likewise, the roughness index will increase with the
301 topographic variation, compensating the slope sensitivity. On the other hand, the increase of 18.6%
302 (from 18.2 to 21.6) in the Manning coefficient is controlled by the small amplitude of the values in
303 different land cover types (0.6 to 0.95), showing low sensitivity to the land cover parameter and
304 enhancing the slope importance. Although slopes of $> 45^\circ$ represent only 1.1% of the total area, the
305 results (Fig. 5) show clearly there is an impact on the connectivity at the embankments. The slope
306 limit can mask high connectivity areas on the embankment, that can generate erosion and
307 embankment failure and alter connectivity pathways significantly (Fig. 2c). The justification given by
308 Cavalli et al. (2013) for this limit (that when there is more than 45° there is only rock exposure)
309 cannot be applied to this area, therefore the subsequent analyses are carried out with the models
310 without slope limit.

311

312 *Fig. 5*

313

314 **3.2 Comparison between connectivity models and with field evidence**

315 Subsequent IC modelling has been carried out for the three versions of the indices, Borselli C factor
316 (IC_C), Cavalli Manning n (IC_n) and Cavalli Roughness Index (IC_RI), all without slope restriction.
317 They have been applied to the whole catchment and to five sub-areas that represent different types
318 of terrain and land use as follow (Fig. 6):

319 1. Whole catchment

320 2. Runoff from upland, area of abandoned land leading to a culvert under track and into terraced
321 almond groves

322 3. Part of rocky, steep, semi-natural area with scrubby vegetation

323 4. Main cultivation area with division into strips, terraced with vegetated embankments

324 5. Main strip field areas, separated by embankments, different types and conditions of trees.

325 6. Zone of high relief agricultural terracing in former central main drainage line.

326

327 For each area, a comprehensive analysis has been carried out, integrating the drone imagery, the
328 slope values, the IC outcomes using the C, n and RI factors, and vectorial features mapped from
329 drone imagery (Figs. 6-10). The patterns of flow predicted by the indices are also compared with the
330 longer-term field mapping records, both from 2004-7 (Marchamalo et al., 2016) and 2008-2020 (Fig.
331 3), and the 2019 field mapping at the time of the acquisition of imagery, and with all field notes and
332 ground photography of every date. The comparative statistics for proportions of area in each
333 grouped connectivity class for each model version for the whole catchment and the selected sub-
334 areas are presented in Table 3. The results, comparing the models and also comparing with field
335 evidence, for each of these areas are summarised in the following sections:

336

- 337 1. **Whole sub-catchment (Fig. 6).** Large differences emerge using the Borselli index C-factor
338 compared with n and RI. In the C model, zones of low connectivity are all the fields and
339 most slopes. High connectivity areas are the edge of the upland in the south and the gully
340 head and main channel at the downstream end (North end of image). RI and n produce
341 much more extensive areas of high connectivity. The high connectivity areas (implying
342 major sources) are mostly the bare areas but also low vegetation areas at the base of the
343 uplands and the steeper areas near the main gully/ drainage head, though vegetation cover
344 is high in parts of that. Threads of channels show up on all sets but are much more obvious
345 on n/ RI versions. They do show some flows through/ over embankments. The main
346 drainage lines, influenced by topography, do emerge strongly in all models. Uplands
347 themselves emerge as low connectivity on C maps but higher in n and RI models. Lateral
348 flow in terraced fields is present to a limited extent but does not emerge as a strong
349 element. In relation to field mapping over the longer term, almost all fans mapped in the
350 field are omitted and flow is shown as more continuous than actually occurs on most
occasions.

351 *Fig. 6 Whole catchment model.*

352

353 2. **Artificial pipe (culvert) and track area (Fig. 7).** For all three versions, the IC outputs show
354 some major drainage lines present, with similar pattern and replicating the culverted flow
355 under the track. The prominent patterns are of two main drainage lines crossing the track
356 and one ancillary flow from the SE. The main flow from upstream of the track, which is from
357 the bare area of abandoned land above that does actually occur frequently, is correctly
358 predicted and corresponds to where the culvert now leads flow under the track. Relatively
359 high generation from the track is correctly simulated by the C model but much lower
360 connectivity is shown in this zone on the n and Ri models. The more southerly flow line has
361 not been observed to cross the track but flow is often generated from the track. The main
362 flow downstream of the track in all the models replicates the long existing and highly
363 frequent rill present there after most storms (Fig. 3). The SE flow appears from the
364 photographs and in the field to be highly influenced by the plough lines at the time of drone
365 imagery, which is a recurrent situation in the field. The flow lines are conditioned by this pre-
366 existing topography, including the persistent rills, and the presence of the culvert. Overall,
367 the modelling picks up some of main lines but some of the links differ in detail from the field
368 mapping. The C-weighted model differs from the n and RI in degree of connectivity of the
369 low gradient, bare ploughed fields downstream of the track. The statistical distribution of IC
370 values for each version indicates that the area has a generally low proportion of high
371 connectivity, but it is much higher for the C model than n and RI models. The large
372 differences are in medium connectivity, rather than low connectivity.

373 *Fig. 7*

374 3. **Natural area and main track (Fig.8).** Very large differences in degree of connectivity and
375 intensity of flowlines northwards off the upland are apparent between the models. The

376 connectivity is low for the C factor model, but that model shows high connectivity at the
377 base of the upland to the north, which is an area of abandoned land with little vegetation
378 and a resistant surface. All three factors indicate the exit of the flow in the same location
379 which is a pre-existing breach (X). All three versions produce a small distinct drainage in the
380 SE corner, which did actually occur as a major flow down an old, minor track in 2020 after
381 the heavy rain of September 2019, and with large deposits formed at the end of the old
382 track onto the main track. Only minor flows and rills were visible prior to that. All model
383 versions show a slight flow off the downslope side of the main track which has occurred
384 occasionally. Overall, the connectivity pattern mostly comprises short paths in the field,
385 which are picked up to some extent by the models, but some extra pathlines, never
386 observed, are modelled. The statistics indicate much higher connectivity for RI than C and n
387 models. The upland area is steep and rocky with relatively dense vegetation cover; it is not
388 very erodible and supplies little sediment.

389 *Fig. 8*

390 4. **Terrace lines (Fig. 9).** The main drainage lines are similar between the three models but
391 vary in intensity. All show the main drainage line flowing east near the W-E field boundary
392 which has always been a major flowline and was converted into a major ditch in late 2011.
393 The Index maps do not detect the exact position of that correctly but do show the natural rill
394 that frequently develops down the ramp and was the former main drainage (Y) (Fig. 9). All
395 three models show zones of high connectivity and potential source areas just downstream of
396 the N-S embankments, influenced by the steep slopes, although to differing degrees
397 between the two main zones. These are not obvious source areas in the field and are
398 influenced by the blockage effect of the embankments. All models show a flow through the
399 easterly embankment which is a pre-existing breach (Z) but the soil piping leading to it was
400 filled at the time of the ditching in 2011. They also show the flow diagonally across the NE
401 field which was a line of deep soil piping (Hooke, 2006; Fig. 2) until filled by the farmer in

402 2015, though it partially reopened in the very big storm of September 2019. This is the line
403 of natural drainage influenced by the overall topography. Some minor parallel rills in the
404 southernmost field are picked up by the models. The statistics reveal that the proportion of
405 low connectivity is markedly less in the C factor model, that shows the vegetation
406 connectivity buffering effect in the fields. The proportions of high connectivity are similar for
407 all three outputs, but the contributions of these source zones are different between the
408 three models.

409 *Fig. 9*

410 5. **Terrace area (Fig. 10).** All model versions pick out differences between the different fields
411 which are due to varying cover and recentness of ploughing, but this is much more distinct
412 on C factor model maps. All pick out the drainage lines parallel to the field boundaries and
413 the lines of ploughing. In this area, the terraces are levelled up by embankments but the
414 overall slope is to the north. A few breaches by northerly flow in the southerly embankment
415 are indicated on the n and RI maps, which are rarely present in the landscape. A bank failure
416 on the northerly embankment is not influencing the flow lines, nor has it in field mapped
417 activity. The vegetated embankments themselves are zones of low connectivity on all
418 models. The whole area is modelled as of low connectivity and field mapping also detected
419 little activity throughout the period (Fig.3). It was only in the 2006 event and to some extent
420 the 2020 event that longer rills and extensive sedimentation were visible, parallel to the
421 embankments. The statistics confirm the high proportion of low and medium connectivity
422 areas for all versions. However, the distribution between low and medium is very different
423 for C from n and RI models, with the former having much greater medium connectivity,
424 reflecting the influence of the differing vegetation covers.

425 *Fig. 10*

426 6. **Central drainage area (Fig. 11).** This is a complicated area in the main topographic drainage
427 zone, but with two sets of highly vegetated steep embankments influencing the flow lines.

428 All three index maps show two main flow lines, one from the southern field flowing east of
429 the central vegetated bank and the other flowing from the westerly field through the gap in
430 the embankment then round the vegetated zone. Both these flow lines have occurred in the
431 field, though the former was only detected in 2019 and 2020, becoming much more active in
432 recent years. The index maps fail to show the flows linking up to some extent and they fail
433 to show the sedimentation area. Indeed, on the n and RI model maps what was observed to
434 be a sedimentation zone and fan area in the field is marked as a high connectivity, source
435 zone. This area was heavily influenced by tractor wheelings in 2019 so some rills that must
436 have produced the sedimentation had been flattened or are not clearly visible on the drone
437 imagery. The flow over the W-E bank in the centre is picked up by all three models. All three
438 outputs showed similar proportions of high connectivity areas, but the medium connectivity
439 area proportion is much higher for the C model and lower for low connectivity than in the n
440 and RI models. Overall, the models are replicating well the complicated patterns of flow in
441 this zone, but they are determined to some extent by the rills and flow lines detected by the
442 drone photography and DEM and so are reproducing these patterns. The C model
443 represents better the low connectivity on vegetated embankments, while the n and RI
444 models over-estimate these areas, showing high connectivity on the conserved
445 embankments.

446 *Fig 11*

447 Overall, the modelling does not pick up major lines of flow parallel to field boundaries adequately,
448 nor the position of all breaches that have occurred at times of high runoff. The models in general do
449 not detect fans and major areas of ponding and sedimentation that occur in many events and thus
450 zones of disconnection, at least for sediment. All the models reproduce most of the major drainage
451 lines.

452

453 **4. Discussion**

454 Conclusive results were obtained on the effect of removing the slope limit for this type of
455 Mediterranean terraced landscape, that was introduced in the Cavalli versions of the model. The tests
456 showed clearly the impact of the slope limit on the connectivity at the embankments. The slope limit
457 can mask high connectivity areas on the embankment, that can generate erosion and embankment
458 failure, as observed in the 2006 flow event (Marchamalo et al., 2016). It may also be why, for example,
459 Calsamiglia et al. (2018a) identified that 27% of their terrace embankment failures happened on
460 medium and low connectivity points, with no clear signal of flow lines.

461 Comparison of the outcomes of the three different versions of the IC model, using the same input
462 data of the DEM and at a resolution of 0.20 m and using no slope limit, predict largely the same
463 overall major drainage lines and the statistical results indicate similar proportions of areas in
464 different connectivity classes (Table 2). A relatively low proportion of the total area shows high
465 connectivity but the values provided by the models vary from 9.5 % (n) to 14.6% (C factor). The
466 differences in connectivity proportions are largest in area 2, draining some low-gradient, abandoned
467 land and the main track, with the C-model giving a higher proportion of high connectivity. In the
468 other areas (areas 4, 5 and 6) which are mainly agricultural terraces, the C factor model tends to
469 distribute more of the area into the medium connectivity category than low connectivity compared
470 to the n and RI models, but proportions of high connectivity are similar. In the upland zone (Area 3),
471 which is steep but vegetated, the RI index gives much more high connectivity, and the C factor
472 model produces more low connectivity area.

473

474 Thus, some of the most notable differences between the models are in areas where the RI and n
475 models are not detecting the effects of dense vegetation, e.g. on embankments, or cover in fields
476 and on the rocky slopes. In the indices, RI and n only have a limited range of values, mainly related to
477 topographic influences, whereas weighting using the crop factor provides a much greater range of

478 values (Table 1) and allows for different cover modelling and is thus more sensitive. Experiments
479 were undertaken with using absolute values and the same class thresholds for all models but this
480 misrepresents the modelling. It is also unknown which model to standardise onto unless field
481 validation is undertaken. Therefore, we have used relative classes. Other researchers have compared
482 different scenarios using absolute values in a specific model but not comparison between models.
483 The present models produce a high density of flow lines, probably representing maximum potential
484 connectivity under prevailing conditions and structures. The grouping of the 10 connectivity classes
485 into three clusters (low, medium and high connectivity) helps to clarify the patterns and identify
486 main pathways more easily.

487

488 Vegetation cover on the embankments has been identified from the field mapping as limiting
489 connectivity. On the other hand, vegetated banks have steep slopes, enhancing connectivity. The
490 degree of vegetation cover and nature of the embankment is important and not well modelled by
491 the n and RI models. Vegetation effects do include a roughness influence, which decreases velocity
492 and thus erosion, but vegetation also increases resistance to erosion and increases infiltration, so
493 decreasing runoff (Hooke and Sandercock, 2012; Sandercock and Hooke, 2011). It has been shown
494 in this catchment and in other locations in SE Spain and similar landscapes that embankment
495 breaches are often the initiation point of gullying in abandoned lands, where embankments are not
496 maintained, (Faulkner, 2008; Hooke and Sandercock, 2012; Lesschen et al., 2008, 2009). It was a
497 recommendation made in the RECONDES study on use of vegetation to combat land degradation
498 (Hooke and Sandercock, 2017, 2012; Recondes 2007a, 2007b) that embankments and ramps
499 between terraces should be vegetated to reduce connectivity. Hooke and Sandercock (2012, Fig. 9)
500 used the present study area to illustrate how strategies of use of vegetation to minimise connectivity
501 and reduce soil erosion could be applied. This also has important implications for conservation
502 agriculture and restoration in degraded lands of the world, where vegetated bunds can be highly
503 effective in reducing runoff and erosion.

504

505 The other major deficiency in all the tested connectivity indices is that they do not work well in flat
506 land and, very importantly, they do not adequately map areas of ponding, infiltration and sediment
507 deposition, or some flow lines parallel to field boundaries found in these terraced landscapes (López-
508 Vicente et al., 2013; Calsamiglia et al., 2018a; Moreno-de-las-Heras et al., 2019). On many of the
509 terraces in the field maps, it can be seen that flow and sediment go into sink areas as small fans at
510 the end of the terrace, and flow paths do not cross into the next terrace, or only do so on rare
511 occasions of high rainfall amount (Fig. 12). Some of the fan/ deposition areas are shown as major
512 source areas in the modelling, rather than stores/ sinks, implying that they overflow, which is not
513 always the case. That could result from the DEM 0.2m resolution that identifies even tiny rills,
514 overestimating the connectivity process generated by these features, creating non-existent source
515 areas. Field observations confirm that these flat sedimentation areas act as disconnectors for most
516 frequent storms and very few connect up even in the larger storms (Marchamalo et al., 2016),
517 including the 200mm storm of September 2019 (Fig.3b), so it is difficult to identify thresholds for
518 overflow. The formation of terraces has a major aim of creating ponding, increasing soil moisture
519 retention and decreasing soil loss, which can be seen in several studies (Calsamiglia et al., 2018a;
520 Calsamiglia et al., 2018b; López-Vicente et al., 2013; Moreno-de-las-Heras et al., 2019). They have a
521 major effect on connectivity, which is not being adequately predicted by the models. This is partly
522 because the algorithms in the IC models use conditioned hydrological DEMs to create flow
523 accumulation and downstream length parameters. They remove spurious sinks and wipe out natural
524 depression and structural disconnection on erosion/drainage lines. On the other hand, they may be
525 representing the maximum possible potential of connectivity. Cantreul et al. (2018) show that small
526 feature responses are directly affected by pixel size, larger pixel sizes hiding the connectivity effect.
527 At the same time, several studies do identify structures such as roads and tracks as decoupling
528 elements (Calsamiglia et al., 2018a; Kumar et al., 2014), and the original model used roads and
529 paths as disconnectivity structural element (Bordoni et al., 2018; Borselli et al., 2008). It is possible

530 to produce temporary sinks by inserting depressions and disconnectivity elements in the models as
531 polygonal "zero" values but this has mostly been done for the large features and structures such as
532 roads, lakes and check dams. (Bordoni et al., 2018; Borselli et al., 2008; Franco and Souza, 2019; Gay
533 et al., 2016; López-Vicente et al., 2020). The software for the calculation of the Cavalli index does
534 now have an option to input sinks into the DEM/ surface conditions
535 (https://github.com/HydrogeomorphologyTools/SedInConnect_2.3/) but these are pre-determined
536 by the user and therefore it does not independently predict where storage will occur. Pre-entering
537 where sinks are located from field evidence negates the value of use of the IC modelling as a
538 predictor.

539

540 The adequacy of the models to predict soil erosion and sediment flux at this scale is debatable.
541 Although the models demonstrate a sensitivity to micro-topography, which has been shown to be
542 highly influential in several studies from field observations (Sampson et al., 2012), IC models do not
543 adequately model the differing nature and erodibility of the surfaces, particularly infiltration
544 capacity and surface resistance, Thus, the effects of harder surfaces such as tracks are
545 underestimated. Tracks have been shown to be very high generators of runoff in many landscapes
546 (e.g. Croke et al., 2005). The IC maps are displaying the potential runoff pathways, but they do not
547 indicate which are erosive and therefore the formation of rills and gullies and potential removal of
548 soil and transfer downslope. It is assumed in the modelling that erosion and sediment fluxes are
549 proportional to the connectivity index value. Comparison of the field and drone mapping (e.g. in Fig.
550 11.6) with the model maps (Fig. 11.3-5) indicates that the main rills do correspond with high
551 connectivity lines mapped but not all lines in the model are erosional and rills. The upland areas,
552 although with steep slopes and relatively sparse vegetation, produce relatively little sediment
553 because of their resistance, whereas the bare soil areas are very prone to rilling and gullyng. It is
554 therefore difficult to establish thresholds for sediment flux without ancillary information. The
555 modelled high connectivity pathways probably do indicate the potential positions of erosion or

556 supply, but the erodibility of the surfaces needs to be incorporated. Developments are taking place
557 that incorporate such factors (e.g. Chartin et al., 2017; Gay et al., 2016; López-Vicente and Ben-
558 Salem, 2019; Zingaro et al., 2019), but they require adequate data on surface material properties.

559

560 The state of the ground in 2019 obviously became the basis for the calculation of the connectivity
561 from the drone imagery, so the modelling is controlled by pre-existing features, even to the scale of
562 rills and plough lines. The influence of minor variations in topography and morphology emerges
563 clearly here and has been shown previously from field evidence to have a profound influence on
564 pathways, for example, small breaches, low points on tracks or embankments (Hooke and
565 Sandercock, 2012, Fig. 2c; Marchamalo et al., 2016). Here, the modelling replicates some effects but
566 not all subtle effects and exact locations. The extent to which temporary or ephemeral features such
567 as plough lines should influence the modelling will depend on the purpose and whether such
568 structural controls are likely to persist.

569

570 Comparisons with field mapping from less intense events, documented in Marchamalo et al. (2016)
571 and in subsequent field mapping (Fig. 3), indicate that discrepancies associated with the IC modelling
572 are not simply that the latter represents very high flows or, indeed, only detects lesser flows.
573 Marchamalo et al. (2016) have already shown that antecedent soil moisture and vegetation cover
574 conditions, as well as degree of ploughing, make a significant difference in flow and sediment
575 processes measured in the field. Major storms in September 2012 (61.3 mm in 24hr) and September
576 2019 (162 mm in 24 hr) did not, however, produce major changes or new features as expected. The
577 major exception of a new feature detected in January 2020 was a major flow and deposit from an
578 old track fringing the southern side of the upland, which was present in the models (Fig. 8) In
579 addition, the former line of large soil piping at the downstream end of the major drainage, which
580 had been filled in, was partially opened up again, which was correctly modelled, in spite of a lack of

581 topographic features in 2019 and on the DEM. The modelling therefore could provide a useful
582 indication of where deliberate modification is unlikely to be effective in high magnitude events;
583 models may show the tendency for the connectivity patterns to revert to natural drainage lines,
584 influenced by the macro-topography.

585

586 Field validation is also complicated by changes due to management. For example, over the 16-year
587 period of monitoring, connectivity has decreased in southern fields in Area 3 (Fig. 2a, Fig. 3), mainly
588 due to less maintenance and ploughing, so increased ground vegetation cover has grown in wet
589 periods, reinforcing the influence and effectiveness of vegetation cover in reducing runoff. Other
590 management actions in the monitored period include the track construction, infilling of the major
591 soil piping, and the construction of the new ditch. Tractor wheelings, ploughing intensity and
592 direction, and replanting of some trees, involving creation of pits and extra watering, have had some
593 localised effects. These are the kinds of activities common in these agricultural terraces. Overall,
594 the main lines of activity and connection have persisted, influenced by the structures, and certain
595 rills have been repeatedly reactivated.

596

597 Several researchers have used UAV imagery as the basis for connectivity modelling and detection
598 (Calsamiglia et al., 2020; Cantreul et al., 2018; Estrany et al., 2019). It has been shown here that it
599 can detect even tiny rills and plough lines so is highly effective in mapping large areas. However,
600 these will be built into high resolution DEMs derived from the imagery and the basis for the
601 modelling and therefore are bound to control flow patterns. They are not an independent validation
602 of predictive connectivity in the landscape that would take place without these ephemeral features
603 unless separate data or a lower resolution DEM is used for generation of IC. On the other hand, the
604 sensitivity of the modelling means that it could be used to detect changes produced by events or
605 management actions by altering the DEM and ground cover (Cantreul et al., 2018; Koci et al., 2020;

606 Lizaga et al., 2018; Llena et al., 2019; López-Vicente and Álvarez, 2018). Drone detection of ponding
607 and sedimentation is challenging because differences in elevation can be very small, but the
608 smoothness of the surface can be different from other areas (Fig.11, so this could be complemented
609 by spectral techniques (Asadi et al., 2019; Foerster et al., 2014; Ortíz-Rodríguez et al., 2019; Singh
610 and Sinha, 2019). However, overall, this high-resolution photography can be used for mapping of
611 features over the whole area, which is challenging to achieve in ground validation.

612

613 **5. Conclusions**

614 Comparisons between the three main versions of the connectivity index, using C, n and RI factors,
615 for this sub-catchment in a dry Mediterranean landscape with agricultural terraces, indicate that
616 that the weight given to vegetation cover, topography and roughness effects can make a significant
617 difference to the details of the degree of connectivity, though not so much to the overall patterns
618 and location of occurrence of features. The roughness type indices (Cavalli, et al., 2013) using n and
619 RI factors underestimate the effects of vegetation, which, though sparse, can be highly influential on
620 connectivity in this type of landscape. The effects of the steepness of embankments can also be
621 underestimated if the slope limit, introduced in the Cavalli models, is imposed. Where vegetation is
622 a significant influence on runoff and erosion, the Borselli C- weighting algorithm represents the
623 connectivity more realistically than the Cavalli n and RI models. The IC indices reflect the type of
624 areas for which they were developed, but care needs to be taken in applying them to different areas.
625 Use of the C index for weighting and not using a slope limit are recommended for vegetated
626 landscapes and those with small, steep structural features.

627 Comparison with 16 years of field mapping in the area as well as the drone imagery used to create
628 the model simulations indicates that the major missing element in all the model outcomes, however,
629 is the occurrence of ponding and sedimentation on terraces and the discontinuities in pathways
630 between terraces. Modelling without considering infiltration capacity and surface erodibility

631 hinders the capacity of modelling the occurrence of erosional and depositional features, although
632 vegetation does influence those factors. The models are not dealing adequately with disconnectivity,
633 especially for sediment fluxes. Overall, the ICs are indicating flow paths and potential flow
634 connectivity, but not sediment connectivity as such, though they may show the potential for that
635 from the flow index.

636 The field mapping indicates that the modelling probably represents the maximum potential runoff
637 and all possible pathways. Grouping of connectivity classes into maps helps identification of major
638 pathways. The long-term monitoring has also demonstrated that actual responses vary between
639 rainstorms even of comparable amount, but also to more complex conditions. Some of the major
640 features created in some of the largest events are simulated by the models, although others are
641 absent. Management actions also have direct and indirect effects on the pathways in this landscape,
642 complicating the conditions and responses. Comparison of the modelling and the mapping combined
643 with effects of management actions indicate that flow is likely to revert to natural pathways dictated
644 by macro-topography in the largest runoff events.

645 The drone photography can be used for mapping major flow and erosion features but field mapping
646 on the ground is still needed. The drone imagery used for the modelling dictates the pathways
647 modelled, so presence of ephemeral features like pre-existing rills will condition the patterns.
648 However, the drone imagery also demonstrates its efficacy in providing the basis for accurate
649 modelling that detects micro-topographical variations, such as on trackways, which make a
650 difference to prediction of the location of pathways.

651 Overall, this analysis implies that the modelling cannot be used as an exact predictor, but as a more
652 general indicator of degree of flow connectivity and main pathways. It has been shown that the
653 weighting of factors in the different versions of the IC models makes a significant difference to the
654 model outcomes especially for vegetated areas. The main drawback of IC models is that
655 disconnectivities and sediment flux are not adequately modelled.

656

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668

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913 **Figures**

914 Fig.1 Maps of a) the location, b) relief, and c) land use, of the study sub-catchment

915 Fig. 2 a) Orthophoto mosaic from drone imagery, and locations of key features , - the blue arrow
916 indicates the position and direction of the image in b) ; b) panoramic photography of the study area;
917 c) photographs of typical erosional and deposition features: clockwise: 1. Flow off track, 2. rill in
918 field, 3.old breach, 4. flow through and downstream of embankment, 5. upstream of the
919 embankment, 6. sedimentation in flow pathway, 7. pathways and sedimentation in terraces, 8. rill
920 from track

921 Fig. 3 Field mapping: a) compilation of sources, pathways and sinks, 2004-2008 (after Marchamalo
922 et al., 2016; Hooke and Sandercock, 2017); b) Major rills mapped on 10 dates, 2008-2020.

923 Fig.4 IC histogram curve of Connectivity Index values for Cárcavo watershed generated by three
924 models with differing weighting factors: Red-RI; Green - n; Blue - C factor.

925 Fig. 5: Examples of IC models showing the differences produced by the two slope algorithms on very
926 steep embankments – slope angle over 1 m/m. Top: Model without slope limit. Bottom: Model with
927 slope limit of 1 m/m.

928 Fig. 6 Whole catchment compilation in the drone mosaic and showing the sub-areas in Figs 6-10. 1:
929 Slope angle. 2/3/4: IC models with different Weighting factors. “C” – C-factor. “n” – manning
930 roughness coefficient. “RI” – Roughness index.

931 Fig. 7 Area2 – Artificial pipe (culvert) and track area

932 Fig. 8 Area 3 – Natural upland area and main track

933 Fig. 9 Area 4 – Terraced area in main drainage line. Y indicates the position of the former main
934 drainage line; Z is the position of a pre-existing embankment breach.

935

936 Fig. 10 Area 5 – Terraced area with varying types and density of crop trees and degree of ploughing

937 Fig. 11 Area 6 – Central drainage area with complex embankments

938 Fig. 12 Sedimentation areas in February 2019; a) Drone photograph, b) ground photograph.

939 Features have been influenced by some management actions.

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943 Table 1: Values of C-factor (based on Panagos et al., 2015) and of Manning's n roughness coefficient
 944 (based on Persichillo et al., 2018; Zanandrea et al., 2019) parameters

Land Use classes	W – C Factor	W - Mannings n Roughness Values
Tillage	0.9	0.95
Road	0.85	0.95
Bare soil	0.8	0.95
Olive	0.241	0.8
Almond	0.296	0.8
Grass	0.25	0.75
Bushes	0.04	0.65
Trees	0.006	0.6

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948 Table 2: Connectivity classes on very steep slope areas (over 1 m/m); Bor – Borselli 2008-
 949 without slope limit, Cav – Cavalli 2013 –slope limit of 1 m/m; “C” – C-factor, “n” – manning
 950 roughness coefficient. “RI” – Roughness index (Cavalli 2013).

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		MODELS						
		Bor_C	Cav_C	Bor_RI	Cav_RI	Bor_n	Cav_n	
CONNECTIVITY CLASSES	1	0.1%	0.2%	0.0%	0.0%	0.0%	0.0%	
	2	14.3%	20.5%	0.0%	0.0%	0.0%	0.0%	
	3	10.2%	5.7%	0.0%	0.0%	0.0%	0.0%	
	4	12.0%	14.5%	0.0%	0.0%	0.1%	0.1%	
	5	22.4%	21.0%	0.0%	0.1%	1.8%	4.9%	
	6	13.5%	12.7%	0.9%	1.2%	36.5%	47.2%	
	7	11.1%	9.8%	17.4%	21.1%	40.0%	29.6%	
	8	8.5%	8.6%	47.2%	52.5%	17.6%	15.6%	
	9	7.1%	6.7%	30.1%	23.8%	4.0%	2.6%	
	10	0.8%	0.4%	4.4%	1.3%	0.0%	0.0%	
	MODELS WITH GROUPED CLASSES							
			Bor_C	Cav_C	Bor_RI	Cav_RI	Bor_n	Cav_n
		Low (1-3)	24.5%	26.4%	0.0%	0.0%	0.0%	0.0%
		Medium (4-7)	59.1%	57.9%	18.3%	22.3%	78.4%	81.7%
		High (8-10)	16.4%	15.7%	81.7%	77.7%	21.6%	18.2%

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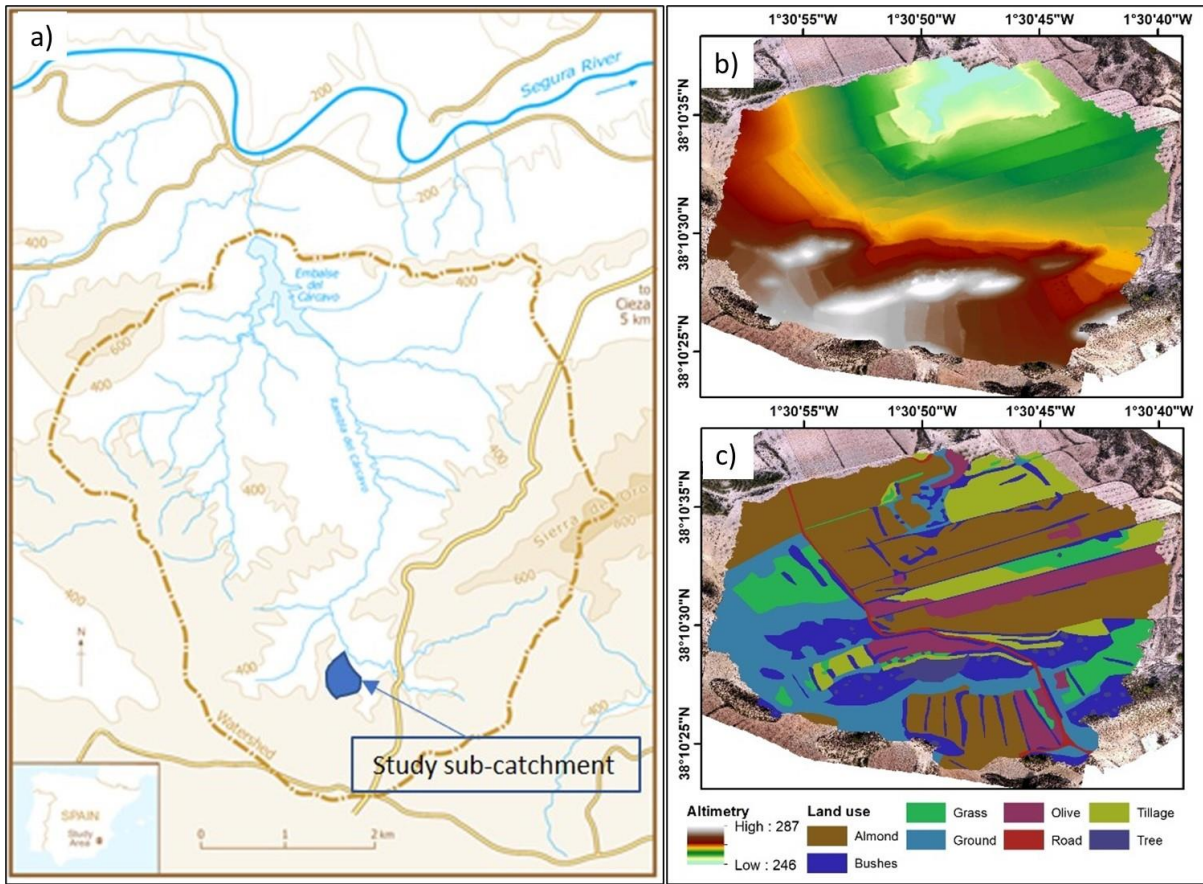
955 Table 3: Summary table of statistical differences of grouped connectivity classes between
 956 the indices for the whole study catchment (1) and each sub-area (2-6).

957

	MODELS																	
	1_C	1_n	1_RI	2_C	2_n	2_RI	3_C	3_n	3_RI	4_C	4_n	4_RI	5_C	5_n	5_RI	6_C	6_n	6_RI
low	21.2%	29.6%	34.7%	24.2%	22.0%	25.7%	17.8%	10.9%	11.4%	8.8%	18.8%	25.7%	23.3%	49.1%	58.2%	13.0%	25.9%	32.5%
medium	64.8%	61.6%	53.2%	58.3%	71.9%	69.0%	68.9%	76.6%	60.5%	74.9%	67.0%	57.9%	69.4%	45.4%	35.9%	80.2%	67.5%	58.3%
high	14.0%	8.8%	12.1%	17.5%	6.1%	5.3%	13.3%	12.5%	28.1%	16.3%	14.3%	16.4%	7.3%	5.5%	6.0%	6.8%	6.6%	9.3%

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959 Fig.1 Maps of a) the location, b) relief, and c) land use, of the study sub-catchment



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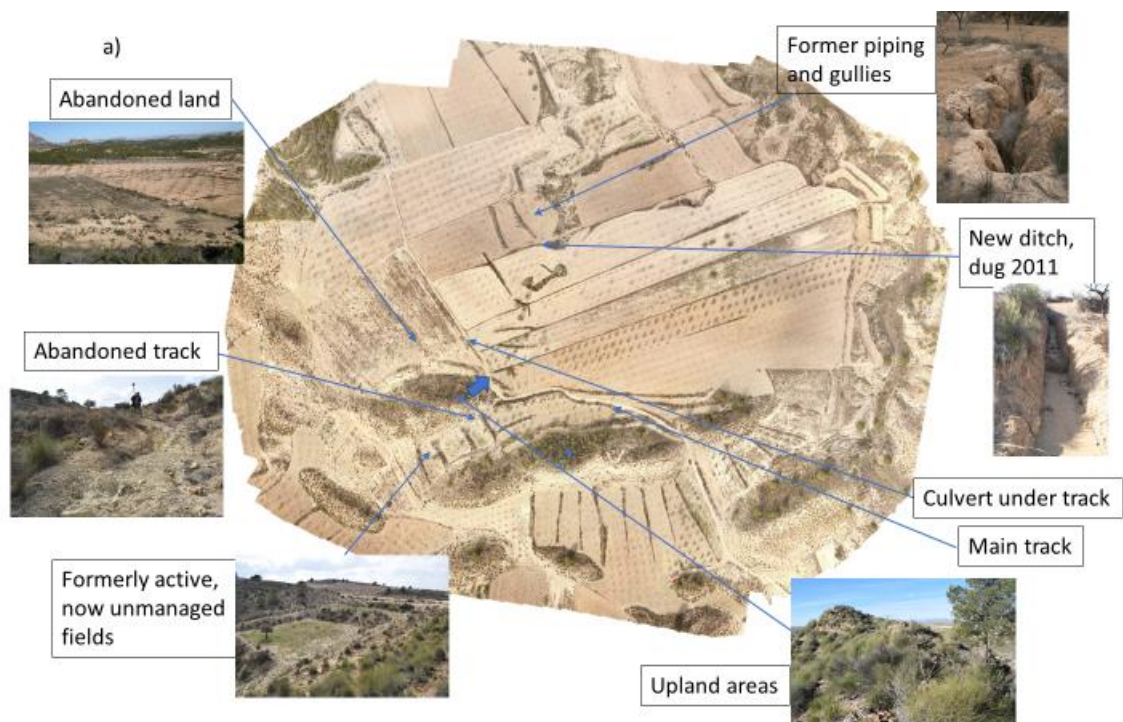
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965 Fig. 2 a) Orthophoto from drone imagery and locations of key features - the blue arrow indicates
 966 the position and direction of the image in b) ; b) panoramic photography of the study area; c)
 967 photographs of typical erosional and deposition features; clockwise: 1. Flow off track, 2. rill in field,
 968 3. old breach, 4. flow through and downstream of embankment, 5. upstream of the embankment, 6.
 969 sedimentation in flow pathway, 7. pathways and sedimentation in terraces, 8. rill from track

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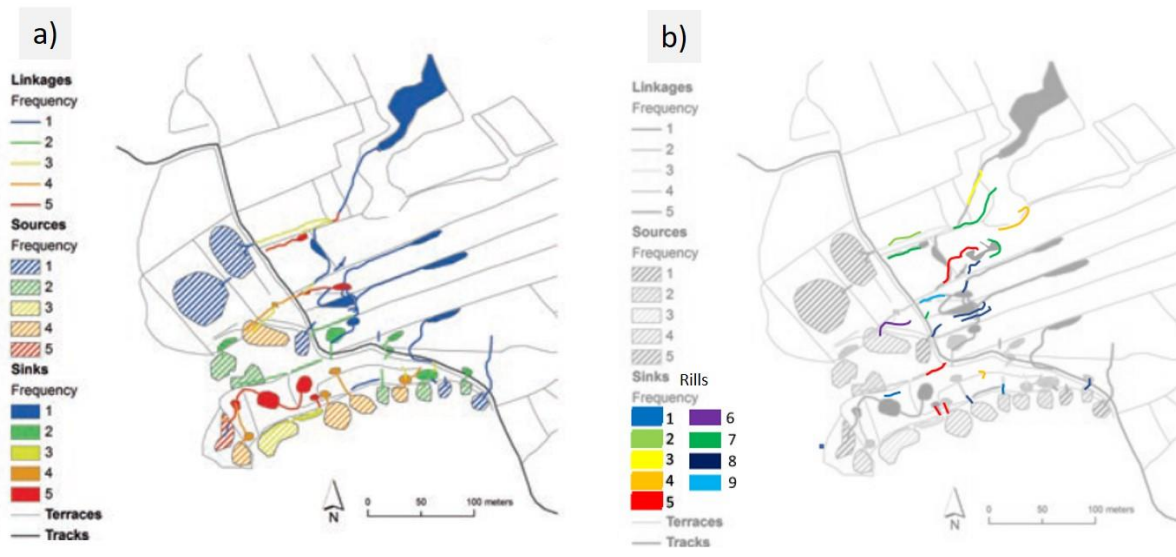


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975 Fig.3 Field mapping: a) compilation of sources, pathways and sinks, 2004-2008 (after Marchamalo et
 976 al, 2016; Hooke and Sandercock, 2017); b) Major rills mapped on 10 dates, 2008-2020.



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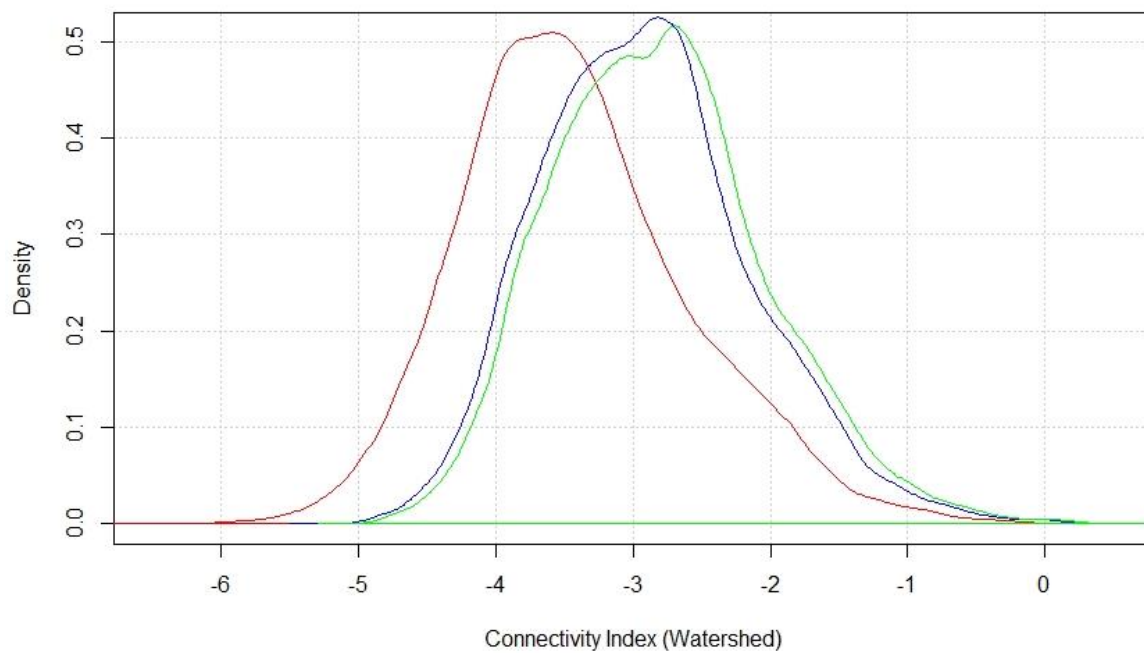
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986 Fig.4 IC histogram curve of Connectivity Index values for Cárcavo watershed generated by three
987 models with differing weighting factors: Red - RI; Green - n; Blue - C factor.



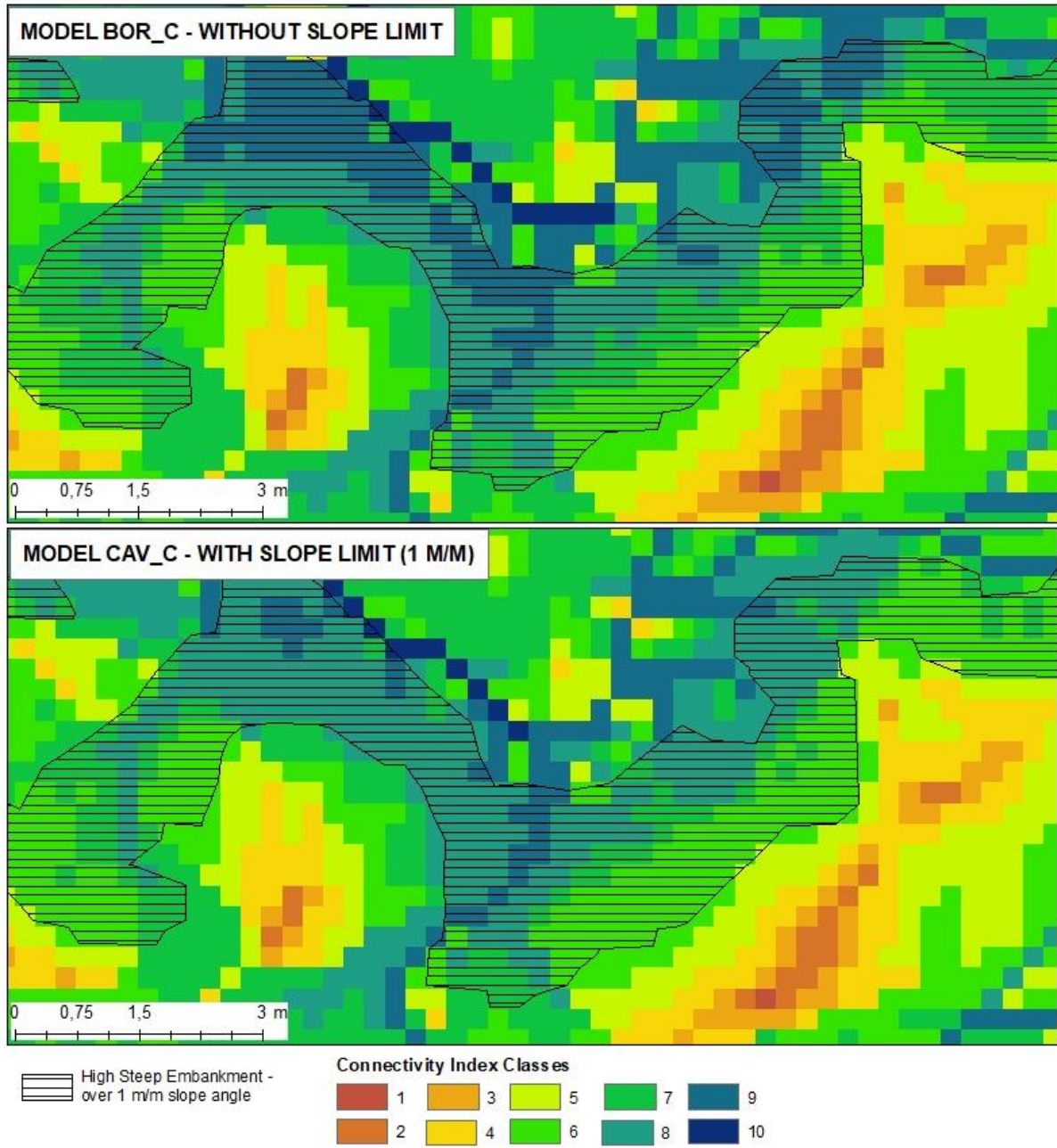
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991 Fig. 5: IC models focusing on very steep embankments – slope angle over 1 m/m. Top: Model
 992 without slope limit. Bottom: Model with slope limit of 1 m/m.

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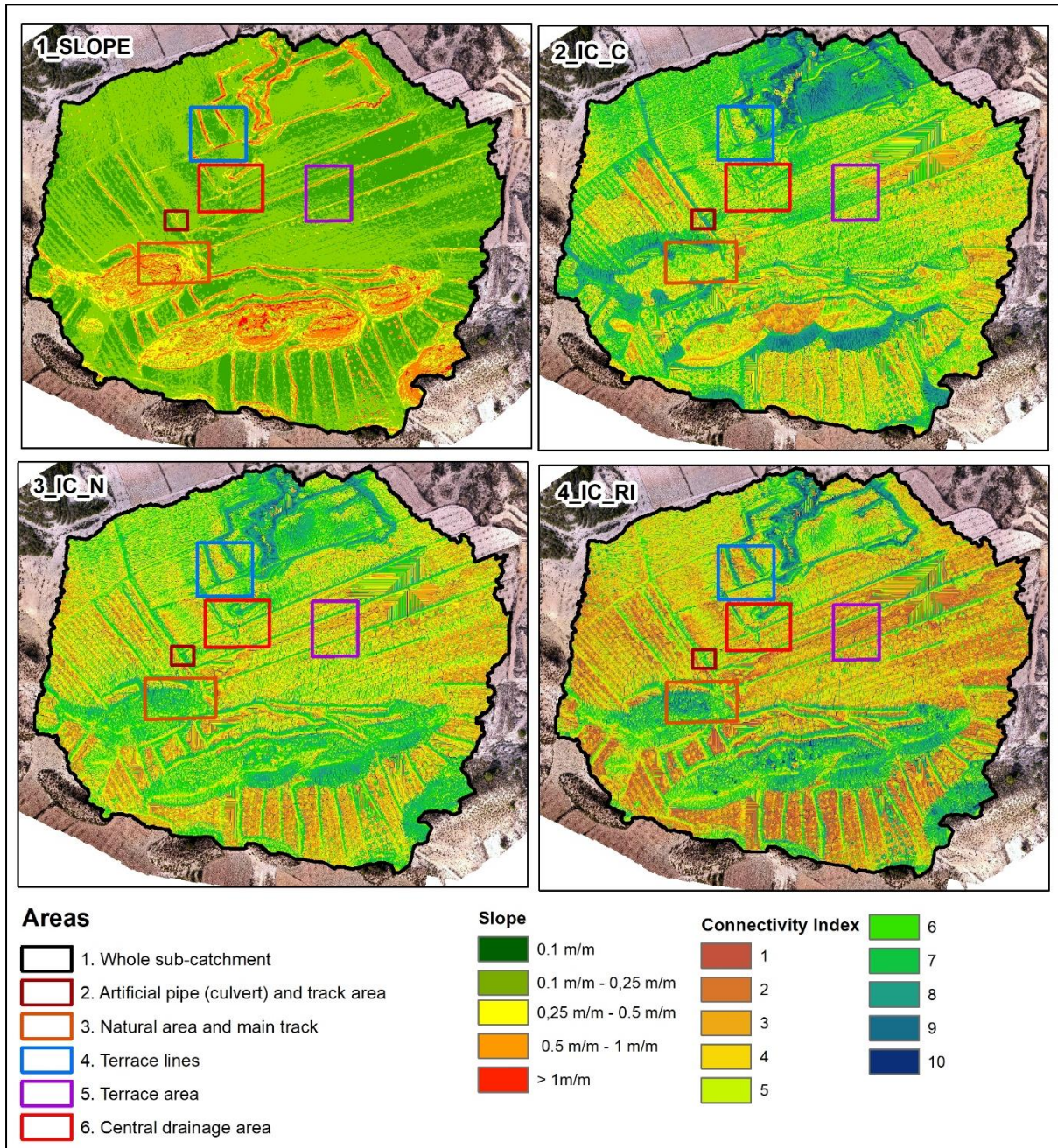
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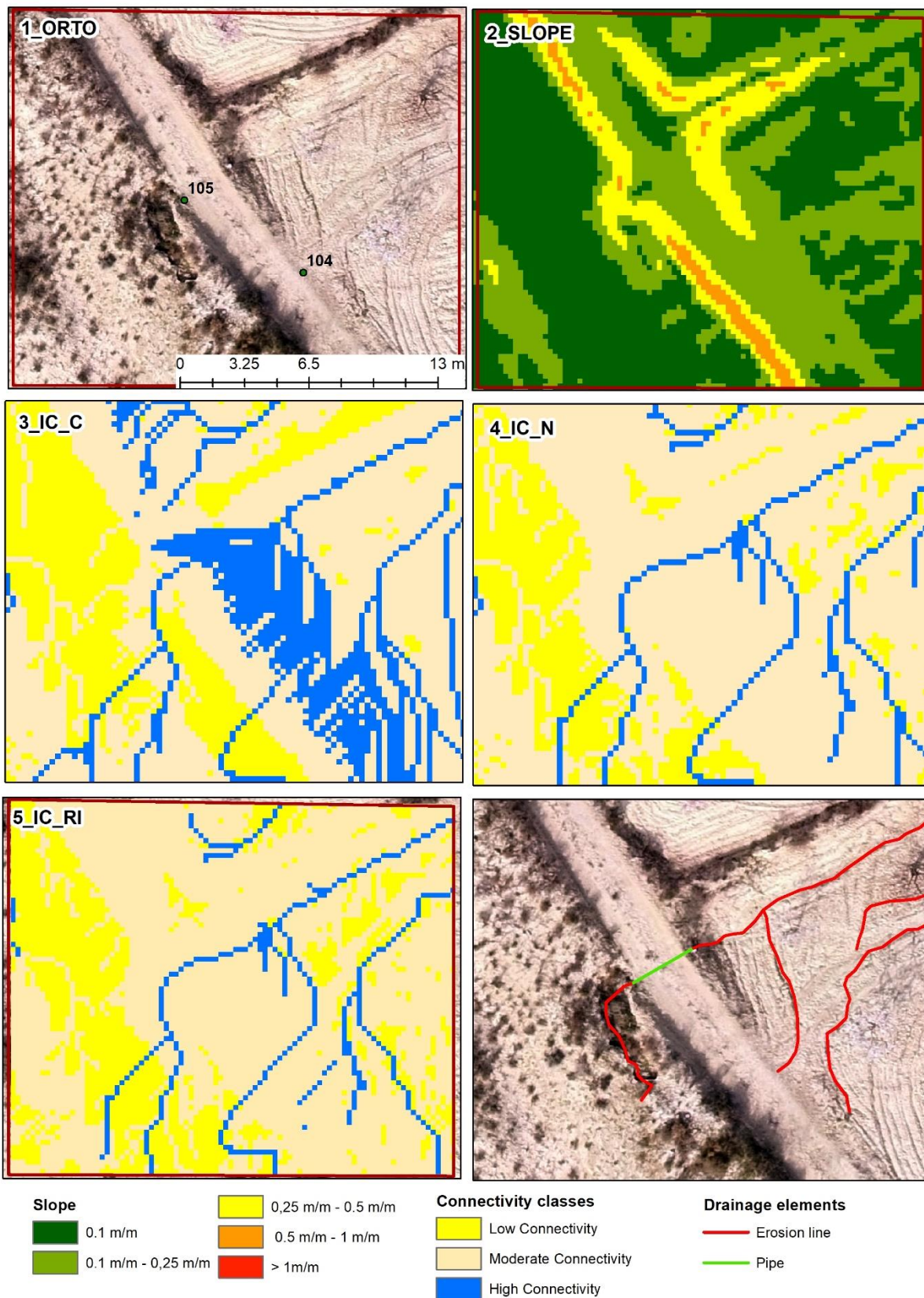
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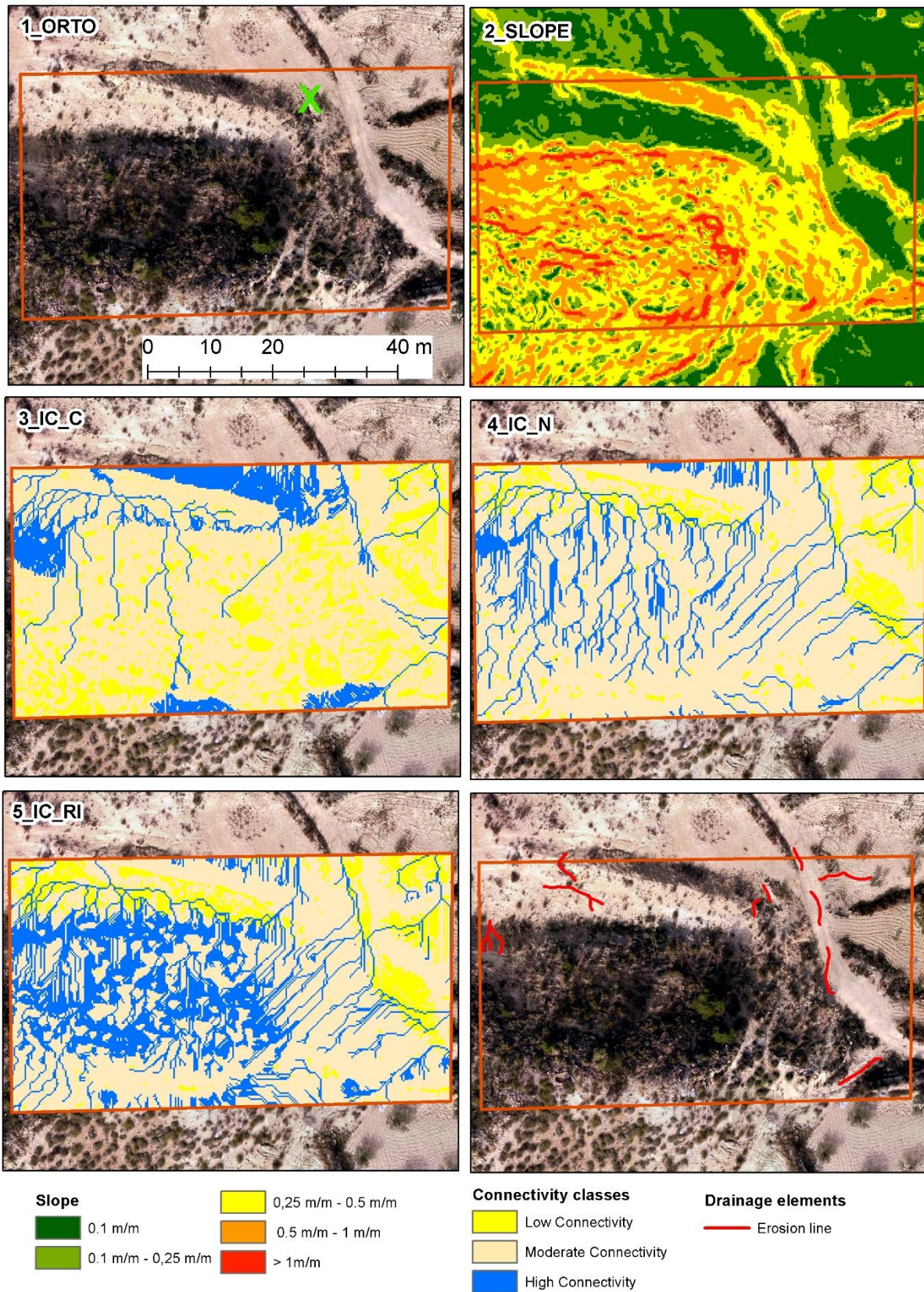
998 Fig. 6 Whole catchment compilation but also showing the sub-areas on the drone mosaic. 1: Slope
 999 angle. 2/3/4: IC models with different Weighting factors. "C" – C-factor. "n" – manning roughness
 1000 coefficient. "RI" – Roughness index.



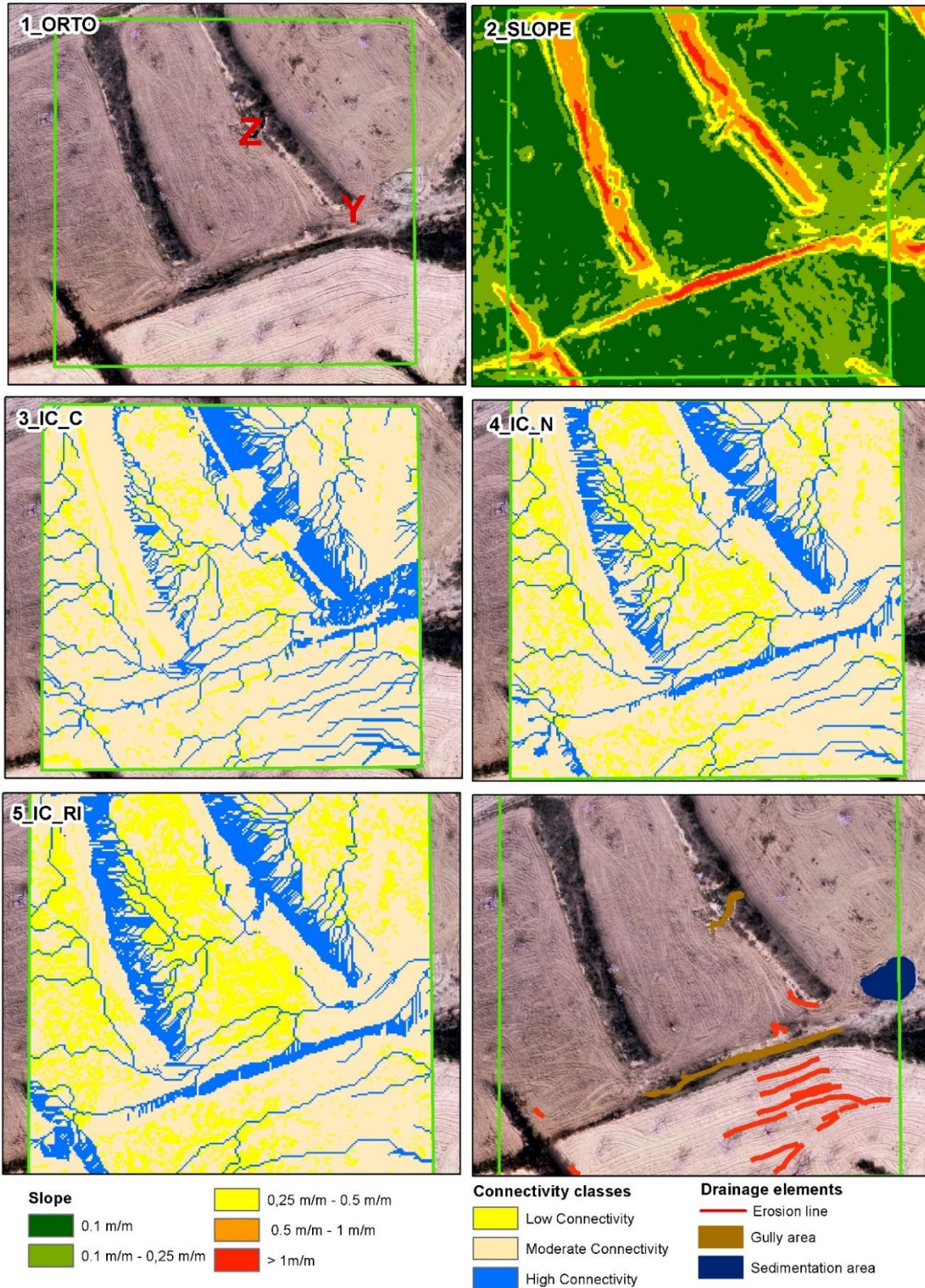
1002 Fig. 7 Area 2 – Artificial pipe (culvert) and track area



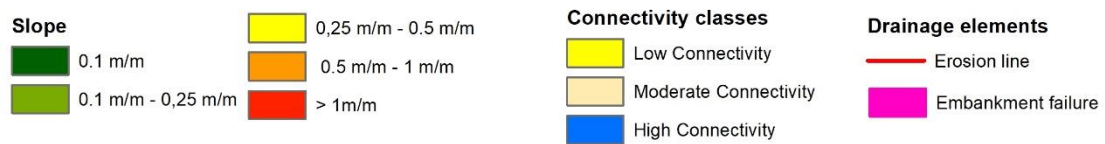
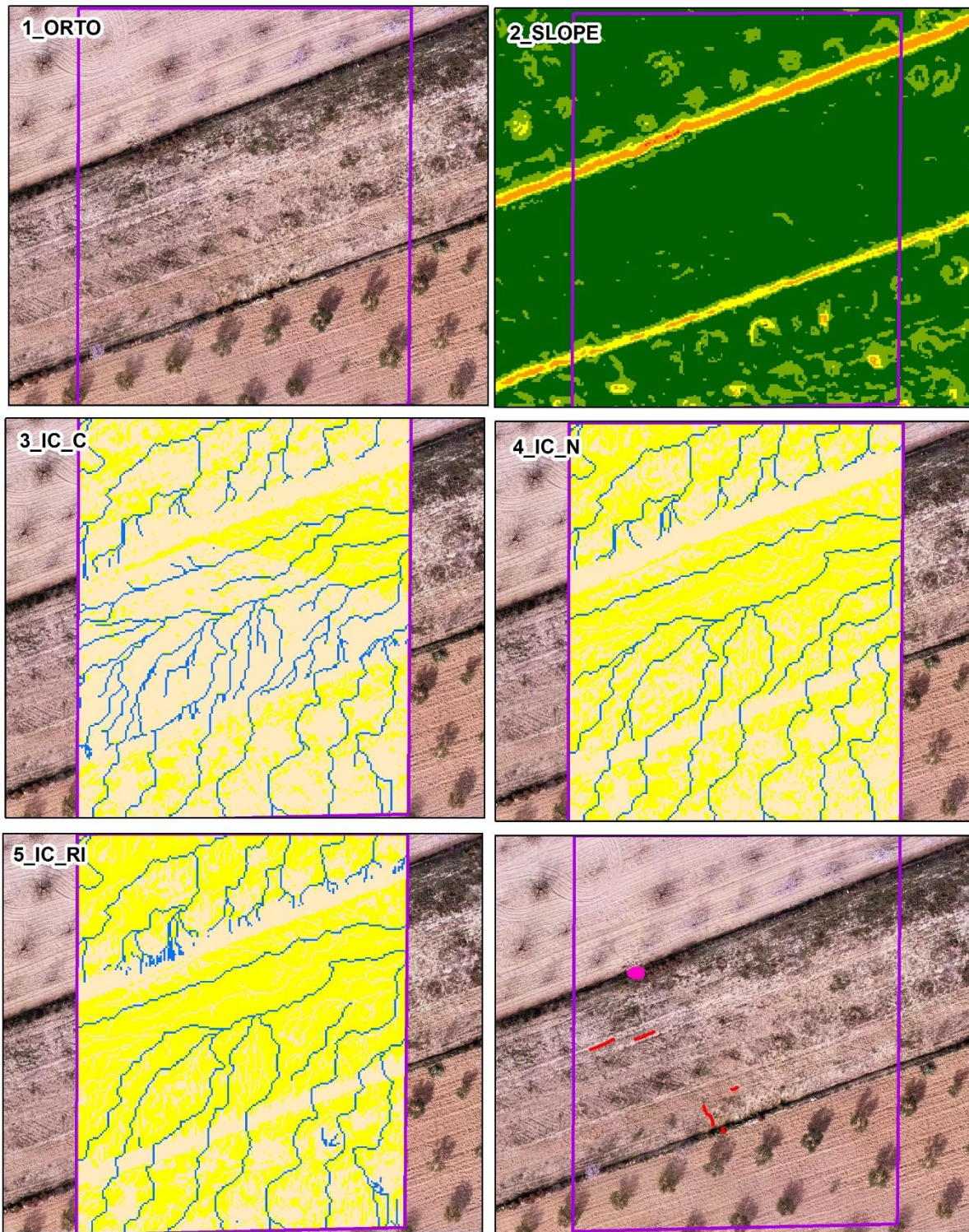
1004 Fig. 8 Area 3 – Natural upland area and main track



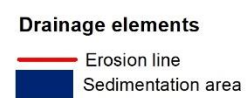
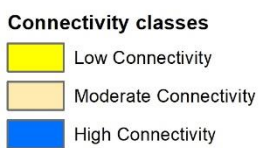
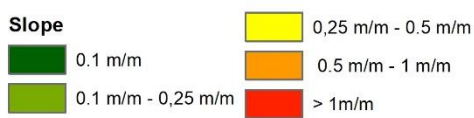
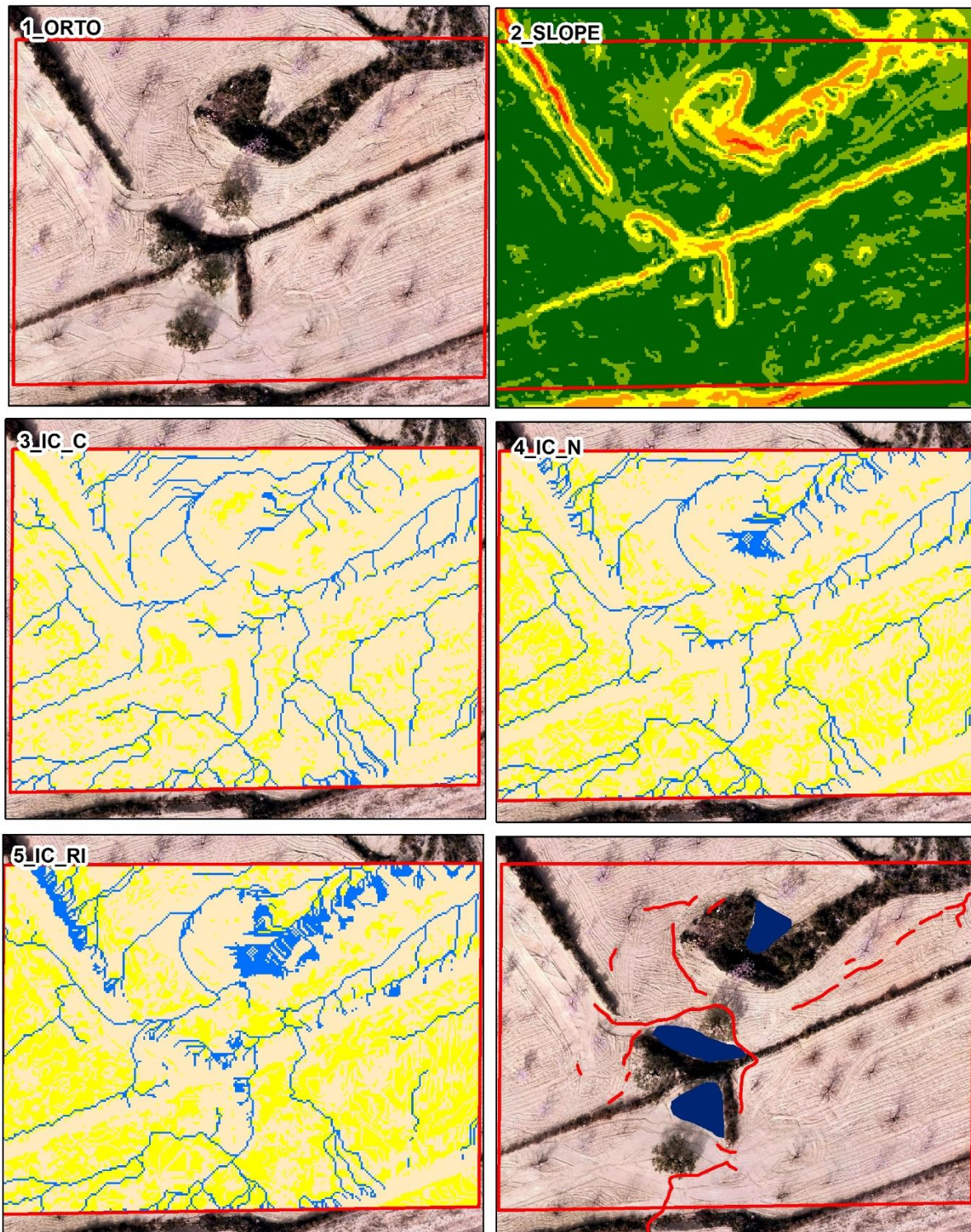
1006 Fig. 9 Area 4 – Terraced area in main drainage line. Y indicates the position of the former main
 1007 drainage line; Z is the position of a pre-existing embankment breach.



1009 Fig. 10 Area 5 – Terraced area with varying types and density of crop trees and degree of ploughing



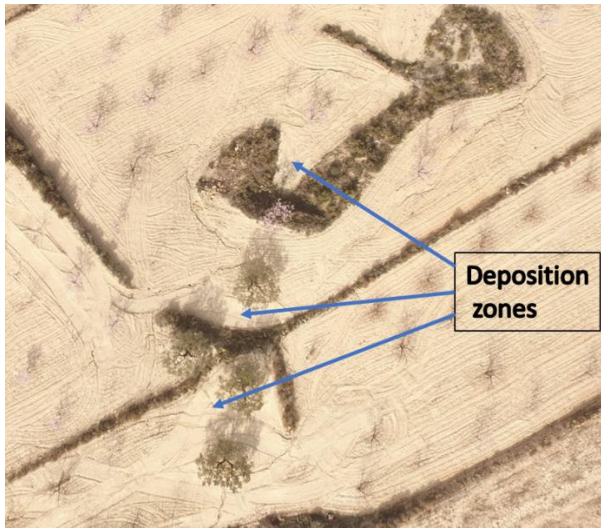
1011 Fig. 11 Area 6 – Central drainage area with complex embankments



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1014 Fig. 12 Sedimentation areas in February 2019; a) Drone photograph, b) ground photograph.

1015 Features have been influenced by some management actions.



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