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Assessing the effect of fire severity on sediment connectivity at the catchment scale

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1 Keywords: sediment connectivity, wildfire, fire severity, natural disturbance, Rio Toro, Chile.

2 ABSTRACT

3
4 Chilean territory is permanently affected by severe wildfires, which drastically reduce the forest cover and
5 promote water runoff, soil erosion, sediment yields and slope instabilities. To understand how the geomorphic
6 system responds to wildfires in terms of sediment dynamics, the assessment of sediment connectivity, i.e.
7 the property describing the relationships between compartments of a geomorphic system, is crucial. This
8 study aims to quantify the spatial linkages between fire severity and sediment connectivity to identify common
9 patterns and driving factors. The compound use of field data and open-source satellite imagery helped to
10 apply the Relative differenced Normalized Burn Ratio (RdNBR) and the Index of Connectivity (IC) in the
11 context of two consecutive wildfires (occurred in 2002 and 2015) in the Rio Toro catchment (Chile).-The fire
12 severity assessment showed that the 2002 event affected 90% of the catchment, with high severity areas
13 representing around 70%. The 2015 wildfire instead, affected 76% of the catchment with moderate severity
14 around 42%. Accordingly, the IC increased after both wildfires, as a result of the sudden reduction in forest
15 cover in severely affected areas. However, only for the second disturbance, it was possible to observe a

16 clear relationship between the RdNBR and the IC variations. The different degree of vegetation cover
17 heterogeneity between the two pre-wildfire scenarios contributed to different fire severity and IC variability
18 between the two disturbances. The use of open-source data and the development of a weighting factor (W),
19 to be used in IC, able to capture the land cover change driven by the wildfires, could make it straightforward
20 the application of this approach promoting its reproducibility in other catchments for land management and
21 risk mitigation purposes.

22 1. INTRODUCTION

23

24 Landscape configuration is determined by the interaction of natural disturbances, geomorphic processes and
25 landforms expressed at multiple spatial and temporal scales. Wildfires are recognized as major agents of
26 land and soil degradation (Shakesby, 2011) and geomorphological changes in densely vegetated landscapes
27 (Neary et al., 2005). In burned catchments, the interaction among vegetation, fire severity and hydro-
28 geomorphic components needs to be deeply investigated to understand the variety of observed responses.
29 The high amount of burned material (e.g., charcoal and ashes) deposited on the soil surface can modify soil
30 properties by increasing or reducing soil infiltration capacity depending on the time since fire (Woods and
31 Balfour, 2008; Shakesby, 2011) (Swanson, 1981; Certini, 2005; Shakesby and Doerr, 2006; Larsen et al.,
32 2009). Therefore, the alteration of soil properties often leads to the increase of water runoff, exacerbation of
33 soil erosion and, eventually, higher production of sediment yield, which can be detected even at a long-term
34 scale (Benavides-Solorio and MacDonald, 2001; Neary et al., 2005). Furthermore, the fire effects are different
35 in terms of hydrological (e.g. overland flow generation) and erosional (e.g. sediment loss) responses. As
36 stated by Vieira et al. (2015) in fact, the latter is more evident because of the role played by the changes in
37 soil aggregate stability and organic matter content, which indirectly favors erosive capacity of the runoff.
38 Direct effects on river systems have been documented concerning the increase of in-channel wood
39 recruitment (Benda and Sias, 2003), the alteration of channel stability (e.g. channel aggradation, DeBano et
40 al., 1998), the speed of vegetation recovery and the rapid relocation of the channel heads along the hillslopes
41 (Wohl and Scott, 2017). Indirect effects mainly concern the alteration of annual water yields (Hallema et al.,
42 2019) and hillslope instabilities given the higher occurrence of landslides and debris flows (Neary, 2005).

43 Many classification systems and change detection methods of multispectral data, ~~based on satellite imagery,~~
44 such the Relative differenced Normalized Burn Ratio (Miller and Thode, 2007), have been adopted to map
45 and measure the overall effect of fire on vegetation and surficial soil, i.e. burn severity (DeBano et al., 1998).
46 It is widely recognized that this overall effect strongly depends on the fire intensity, duration and pre-fire
47 disturbance history, which determines variable sensitivity across the landscape and over time (Brogan et al.,
48 2019). Further intrinsic factors such as the area, topography, vegetation, geology and climate, affect the
49 magnitude of changes caused by the natural disturbance (Swanson, 1981). Notably, topography shows
50 strong relationships with fire severity because it influences biophysical gradients (e.g., moisture, solar
51 radiation) and characteristics of the fuel. For instance, upper slope positions ~~locations~~ and steep slopes are
52 typically increasing the pre-heat of fuels, whereas different orientations cause high variability in fuel's drying
53 out (Iniguez et al., 2008; Carmo et al., 2011).

54 In this context, the assessment of fire severity, which often encompasses the properties of intensity and
55 duration, is essential to quantify the fire-related impact. The determination of fire severity and related impacts
56 would help to: i) protect sensitive ecosystems from reduction of soil organic matter, modification of population
57 dynamics and roots failure; ii) to safeguard local forest and water users from the reduction of forest
58 productivity and touristic value, and from the sudden release of chemicals into the stream network; iii) to
59 prevent economic losses for downstream areas caused by mass failure and floods (Neary et al., 2005).

60 Framing the response of an entire catchment to natural disturbances in terms of variation of sediment supply,
61 routing and deposition is still a controversial issue due to the variety of factors involved (e.g., disturbance
62 properties, sediment characteristics, topography, land cover, hydrological regime). In post-wildfire conditions,
63 if a great amount of sediment is available for sudden mobilization, the awareness of how a catchment
64 facilitates the transfer of sediment between source areas and channel network is vital to predict future
65 scenarios and reduce the associated risk (Mazzorana et al., 2019). To this end, the geomorphic property
66 known as connectivity (Wohl et al., 2019) is gaining interest from the scientific community especially
67 concerning major disturbances. Specifically, sediment connectivity underlies the sediment transfer between
68 the compartments of a geomorphic system and their relationships, which control the sediment cascade and
69 geomorphic response to disturbance events (Bracken and Croke, 2007; Fryirs, 2013). Several metrics of
70 sediment connectivity have been proposed to overcome the more traditional field measurement and to exploit

71 the high amount of topographic data available nowadays (Heckmann et al., 2018). Following this trend, the
72 topography-based Index of Connectivity (hereinafter IC), proposed by Borselli et al. (2008) and refined by
73 Cavalli et al. (2013) has become a solid and accessible instrument to assess the degree of linkage between
74 sources and sinks of sediment in various contexts. Therefore, many authors grasped the opportunity to map
75 sediment connectivity using the IC in different environments and considering plenty of numerical approaches:
76 Gay et al. (2016) and Kalantari et al. (2017), mapped connectivity in lowlands by integrating catchment
77 infiltration/runoff properties and precipitation-runoff variability, respectively; López-Vicente and Ben-Salem
78 (2019) developed a new aggregated index based on the RUSLE2 equation; Rainato et al. (2018) analyzed
79 the (de)coupling relationships of a small dolomitic catchment.

80 Mapping the IC with respect to major natural disturbances is becoming paramount to understand the variation
81 of sediment connectivity's spatial patterns, their evolution and to predict downstream adjustments (Cavalli et
82 al., 2019). In post-disturbance scenarios, sensitivity is defined as the rate of response to the change, so that
83 highly connected systems tend to respond faster than less-connected ones (Brunsdon and Thornes, 1979).
84 Geomorphic systems affected by volcanic eruptions (Martini et al., 2019), land-use change (Persichillo et al.,
85 2018; Llana et al., 2019), typhoons and monsoons (Chartin et al., 2017; Singh and Sinha, 2019), and wildfires
86 (Williams et al., 2016; Estrany et al., 2019; Ortíz-Rodríguez et al., 2019) are closely monitored for their
87 sensitivity in terms of sediment connectivity. However, still strong efforts need to be made to standardize a
88 process to consider the land cover change and its effect on the IC to make such an accessible tool fully
89 applicable. In other terms, is it possible to convey the essential information about land cover changes into a
90 single parameter, such as the Index of Connectivity, to explain or predict catchment-scale responses to
91 natural disturbances? To address this question, multi-disciplinary approaches are indeed required to consider
92 different phenomena from different standpoints and to support useful catchment management decisions.

93 Accordingly, the present study aims at defining how multiple wildfires interact with catchment-scale sediment
94 connectivity by analysing fire severity and sediment connectivity spatial patterns and by identifying common
95 driving factors and interlinked relations in an Andean catchment. The general objectives of the work are to
96 improve awareness about the fire-related impacts from a multidisciplinary perspective, by linking the
97 ecological and geomorphic response and to provide a methodological approach to prioritize areas of hillslope
98 instabilities in wildfire-affected river basins. The specific objectives are:

- 99 i) to investigate interlinked relationship between fire severity and sediment connectivity changes induced by
100 wildfires;
- 101 ii) to move towards the standardization of a procedure to apply the IC after major disturbances;
- 102 iii) to rely upon open source data so the application of the proposed methodology could be replicated in other
103 contexts.

104

105 2. STUDY AREA

106

107 The study area is the Rio Toro catchment, located in Chile (Fig. 1a), close to the north-eastern border of the
108 Araucanía Region (IX Región) (Fig. 1b) and affected by two wildfires in 2002 and 2015. The area extends for
109 18 km², entirely inside the Malleco National Reserve, with elevation ranging from 760 to 1810 m a.s.l. and a
110 mean slope of 24°. The climate is classified as temperate warm humid (Fuenzalida, 1965), strongly influenced
111 by the presence of the Andean Cordillera (E) and the Pacific Ocean (W). The average annual precipitation
112 is about 2480 mm (Comiti et al., 2008), with a monthly maximum and minimum of 490 mm and 62 mm in
113 June and January, respectively (average rainfall calculated for the period 2000-2018;
114 source:<http://explorador.cr2.cl/>). Bedrock layer is primarily composed of pyroclastic rocks generated by the
115 high volcanic activity of the Southern Andes volcanic Zone (SVZ, 33°S – 46°S) and triggered by the Nazca-
116 South America plate convergence (Cembrano and Lara, 2009). The Rio Toro channel network, which
117 features a pluvial/nival hydrological regime (Comiti et al., 2008), develops mainly with south-north direction
118 with a total length of 11 km from the upstream ridges to the downstream Rio Niblinto, where the outlet of the
119 study catchment is established (Fig. 1c). The main channel, receiving water from two branches divided by
120 the central ridge, is classified as a third-order stream featuring a step-pool / cascade bed morphology with a
121 mean channel slope of 0.05 m/m (Comiti et al., 2008; Iroumé et al., 2015; Picco et al., in review). The forest
122 is mainly composed of endemic species of *Araucaria araucana* and *Nothofagus* spp. (southern beech). The
123 two species naturally form mixed forests along the Andes Cordillera in the South-Central Chile and western
124 Argentina (Veblen et al., 1982). The understorey of *Araucaria-Nothofagus* forests hosts *Chusquea* spp.
125 (*quila*), a fast-growing bamboo plant reaching high densities, especially after major natural disturbances that

126 typically affect this type of landscape (Gunckel et al., 1948; Veblen et al., 1981). Until 2002, when the first
127 wildfire occurred, the Rio Toro catchment was almost completely covered by forests. At lower elevation
128 (below 1200 m.a.s.l.) the main species were *Nothofagus dombeyi* and *N. nervosa* while *Araucaria araucana*
129 stands dominated the landscape above 1200-1300 m a.s.l. The 2002 fire, occurred in late February, affected
130 both the Malleco National Reserve and the near Tolhuaca National Park, with an overall burned area of about
131 11660 ha (Assal et al., 2018), greatly contributing to the 20000 ha burned in the region in the summer fire
132 season (González et al., 2005). Besides, during the fire season of 2014-15, which counted 1344 wildfires
133 and almost 46000 ha burned in the Araucanía Region alone (CONAF, 2019), another wildfire affected the
134 same area in late February 2015.

135 In central Chile, land use practices and extreme climatic conditions are exacerbating wildfires effects
136 (Bowman et al., 2019). For this reason, there is growing interest in monitoring future developments for this
137 and similar areas, where slope instabilities could be expected. Even though no instabilities were reported
138 ~~recorded~~ by other studies after the 2002 wildfire (Comiti et al., 2008; Iroumé et al., 2015), the re-occurrence
139 of the 2015 event may have increased their likelihood.

140

141

FIGURE1

142 3. MATERIAL AND METHODS

143

144 The present study was carried out following a methodological workflow with two parallel phases regarding (i)
145 the assessment of severity of the two wildfires occurred in 2002 and 2015, and (ii) the mapping of sediment
146 connectivity changes following the aforementioned events (Fig. 2). The development of both activities relies
147 upon field data, acquired during field campaigns carried out in 2019, and freely available satellite Landsat
148 data provided by open-source websites.

149

150

151

FIGURE 2

152 3.1 Satellite data

153

154 The need for multi-temporal images and consistency among the two methodological phases drove the
155 attention towards Landsat missions, which offer long time series and sufficient global coverage at 30 m
156 resolution (Banskota et al., 2014). Two Landsat 7 ETM+ images corresponding to periods pre- and post-
157 2002 wildfire (01/02/2002, 20/02/2003) and two Landsat 8 OLI images corresponding to the pre- and post-
158 2015 wildfire (28/01/2015, 31/01/2016) periods were selected from the U.S. Geological Service free satellite
159 provider EarthExplorer (EarthExplorer, 2019). After the selection, Landsat products were ordered and
160 obtained from the Earth Resources Observation and Science Center (EROS) Science Processing
161 Architecture On Demand Interface (ESPA). The ESPA allows the processing of Landsat data beyond the
162 standard Landsat Level-1 processing level (ESPA, 2018). Therefore, the four images were provided
163 atmospherically corrected at surface reflectance to account for sensor, solar and atmosphere distortion
164 (Young et al., 2017). In addition, we applied transformations to guarantee continuity among the Landsat 7
165 ETM+ and Landsat 8 OLI bands and avoid misinterpretations in the outcomes (Roy et al. 2016).
166 The topographic information required for developing the sediment connectivity analysis is represented by the
167 Global Digital Elevation Model (DEM) with a spatial resolution of 12.5×12.5 m cell size derived by the ALOS
168 PALSAR satellite imagery system. The data were processed and redistributed by the Alaska Facility Service
169 (ASF, 2019; dataset: ASF DAAC, 2009), which provides Radiometrically Terrain-Corrected (RTC) products.
170 Detailed information about the accuracy of ASF's products can be found in Gesch et al. (2014).

171 172 3.2 Field data

173
174 During January 2019, multiple field campaigns were carried out in the Rio Toro catchment to collect land
175 cover data. We established a total of 106 square sampling plots of about 400 m², in which the percentage of
176 area covered by understorey, bare soil and rocks, grassland, deadwood (standing and/or lying on the
177 ground)and trees was visually determined (Fig. 3). In particular, the understorey was defined as the
178 vegetation layer including bamboo, Araucaria and Nothofagus seedlings and shrubs developing under the
179 trees. The latter category instead, includes only living trees taller than 1.30 m.
180 In addition, we also evaluated specific ground characteristics on a subset of 46 sampling plots regarding the
181 number of standing dead and living trees and the number of obstructions on the ground (Table S1). The

182 distribution of the plots within the study catchment was highly constrained by the scarce accessibility due to
183 steep slopes, lack of roads and presence of fallen logs. The position of each sampling plot was taken
184 measuring the centroid using a GPS Trimble Juno 5.

185

186

187

FIGURE 3

188

189

190 3.3 Fire severity assessment

191

192 Using the multispectral satellite data described in the section 3.1, we first calculated the Normalized Burn
193 Ratio (NBR) for each pre- and post-wildfire year (2002, 2003; 2015, 2016) according to the following formula:

194

195

$$NBR = \frac{NIR - SWIR2}{NIR + SWIR2} \quad (1)$$

196

197 where, *NIR* is the Near InfraRed band and *SWIR2* is the ShortWave InfraRed band, which are the two
198 wavelengths most sensitive to wildfires (Key and Benson, 2006). In order to provide a quantitative measure
199 of change, the NBR calculated after the fire was subtracted from the NBR calculated before the fire. The
200 resulting delta NBR (dNBR) was calculated as follows:

201

$$dNBR = \left((NBR_{prefire} - NBR_{postfire}) * 1000 \right) - dNBR_{offset} \quad (2)$$

203

204 where, the dNBR is conventionally scaled up by a factor of 1000 to obtain an integer output (Miller et al.,
205 2009) and $dNBR_{offset}$ is obtained by averaging dNBR values calculated outside the wildfires-affected areas in
206 order to avoid reflectance biases given by the natural phenological effect (Parks, et al., 2014; Morresi et al.
207 2019). Given the occurrence of two wildfires in the Rio Toro catchment, multiple dNBRs were calculated as

208 the difference between the years 2003-2002; 2016-2015 and 2016-2002. The latter aims at detecting the
209 spectral changes given by the sum of the two wildfires and it has been considered only as a proxy variable
210 in the function used to classify the severity of the two separate wildfires.

211 Furthermore, to improve the accuracy of wildfire severity assessment we calculated the Relative dNBR
212 (RdNBR), following equation 3:

213

214

$$RdNBR = \frac{dNBR}{\sqrt{|NBR_{prefire}|}} \quad (3)$$

215

216 where the absolute sign in the denominator avoids unreal numbers as results.

217 Choosing the relative ratio (RdNBR) instead of the absolute one (dNBR) permits to ~~increase~~ enhance the
218 classification accuracy for high severity categories especially in more heterogeneous environments and to
219 compare fires across time and spatial scales (Miller and Thode, 2007). The resulting three RdNBR maps
220 (2002-2003, 2015-2016 and 2002-2016) were then classified using field data.

221 From the sampling plots, we tested the combination of field metrics that best fitted with RdNBR values
222 corresponding to the period 2002-2016, which summarizes all the changes in reflectance caused by both
223 wildfires. The ratio between areas of bare ground and bare ground plus tree cover area (hereinafter defined
224 as Severity Factor, SF) reported the strongest relationship with RdNBR values, according to a second-order
225 polynomial function ($R^2 = 0.65$). Using the natural breaks algorithm, the SF was grouped into four classes
226 corresponding to unburned (or negligible severity), low, moderate and high severity. Using the polynomial
227 function it was possible to carry out the four RdNBR classes' thresholds, which determine the classification
228 scheme used in the wildfire severity maps 2002-2003 and 2015-2016 (Fig. S1). The classification accuracy
229 calculated between measured and predicted severity of sampling plots was 62% with a Cohen's Kappa
230 coefficient (κ) of 0.45, indicating moderate agreement between the raters.

231 The final wildfire severity maps were then compared in terms of spatial patterns, with particular focus on the
232 eventual changes or similarities among different severity areas between the two events. Similarity analysis
233 was performed thanks to the Jaccard Index, calculated specifically between areas with the same severity

234 (e.g. unburned 2002 - unburned 2015). On the contrary, the variation was evaluated through the transition
235 matrix (or cross-tabulation matrix), to highlight gains or losses among the classes.

236 To improve awareness on how the topographic features of the Rio Toro affected the fire severity in the two
237 events, two Generalized Linear Models (GLMs) were carried out. The effect of slope, elevation (continuous),
238 slope position (Guisan et al., 1999), aspect (categorical) were tested on the RdNBR. We applied simple
239 random sampling with a 95% confidence interval to select the most appropriate number of samples to be
240 used in the GLMs.

241

242 3.4 Mapping sediment connectivity

243

244 The analysis of sediment connectivity was performed through the Index of Connectivity, applied to four
245 periods corresponding to 2002, 2003, 2015 and 2016. The IC in the Rio Toro catchment was computed using
246 the open-source, stand-alone software SedInConnect 2.3 (Crema and Cavalli, 2018), which operates using
247 TauDEM tool for hydrological functions (Tarboton, 1997). Following the original formula by Borselli et al.
248 (2008), the IC relies upon two components that describe the linking relationships between sediment sources
249 and downstream areas, so:

250

251

$$IC = \log_{10} \left(\frac{D_{up}}{D_{dn}} \right) = \log_{10} \left(\frac{\bar{W} \bar{S} \sqrt{A}}{\sum_i \frac{d_i}{S_i W_i}} \right) (4)$$

252

253 where, D_{up} is the upslope component representing the potential for downward routing of the sediment
254 according to the catchment's upslope area features. Hence, \bar{W} and \bar{S} are the average value of the impedance
255 to sediment fluxes and the average slope (m/m) in the upslope catchment, is respectively and A is the
256 contributing area (m^2) of the specific point under investigation. On the denominator, D_{dn} is the downslope
257 component including the characteristics that could affect the transfer of sediment: d_i is the length (m) of the
258 flow path along the i^{th} cell, W_i is the weighting factor and S_i the slope gradient of the i^{th} cell.

259 In the present study, we made use of a unique DEM as the main source of topographic information for the
260 computation of the IC for the four wildfire scenarios. This choice was constrained by the lack of representative
261 DEMs for the two events and by the assumption that no major morphological changes, detectable at 12.5 m
262 resolution, occurred during the period between the two wildfires. On the contrary, an adaptive weighting factor
263 has been developed to represents the differences of impedance to sediment fluxes likely to be caused by
264 the large variability in land cover due to the wildfires.

265 Finally, to highlight the linkages between hillslopes and the Rio Toro (i.e. lateral connectivity of the system),
266 we set the whole stream network as target of the IC computation.

267

268 3.4.1 Weighting factor

269

270 To derive the weighting factor for the IC, the Manning's n for the overland flow was selected original USLE
271 C-factor (Wischmeier and Smith, 1978) and its variants (see Chartin et al., 2017; Lizaga et al., 2017; López-
272 Vicente and Ben-Salem, 2019) since we consider it a better proxy of sediment impedance in natural
273 catchments. Following the additive method provided by Arcement and Schneider (1989), an ad-hoc
274 Manning's coefficient was computed for each of the 46 sub-sampling plots according to the ground
275 characteristics collected during field campaigns and described in the section 3.2.

276 From the plot-derived Manning's n , a new approach has been adopted, based on the abrupt land cover
277 changes at the pixel scale, in order to produce four catchment-scale weighting factor maps. The four W factor
278 maps (hereinafter W factor maps) were generated starting from the correlation between the Manning's n and
279 the spectral vegetation index known as Integrated Forest Z-score (IFZ) calculated from the four Landsat
280 images (eq. 5). The IFZ is a threshold-based index aiming at identifying the likelihood of a pixel to be not
281 forested so that it represents a strong index to track vegetation changes and recovery after wildfires (Huang
282 et al., 2010; Morresi et al., 2019)

283

$$284 \quad IFZ = \sqrt{\frac{1}{NB} \sum_{i=1}^N \left(\frac{b_i - \bar{b}_i}{SD_i} \right)^2} \quad (5)$$

285

286 Where, NB is the number of spectral bands employed (in this work SWIR and SWIR2) b_i is the spectral value
287 of the pixel of band i , \bar{b}_i and SD_i are respectively the mean and standard deviation of random pixel samples
288 of the band i . Hence, the IFZ and Manning's n are inversely related: higher is the chance for a pixel to be not
289 forested and lower is the impedance to sediment fluxes. More information about the fitting model IFZ-
290 Manning's n are present in the supplementary material (Fig. S2).

291 Although similar approaches, combining land use-based roughness and spectral indexes, have been
292 proposed in the field of connectivity (e.g. Mishra et al., 2019), they mainly focused on the use of Normalized
293 Difference Vegetation Index (NDVI) that is less sensitive to the sudden changes in reflectance than the IFZ
294 (Huang et al., 2010; Chu, et al., 2016; Morresi et al., 2019). Once the Manning's n was extended for the
295 whole catchment and the four periods, the final weighting factor maps (W) were generated following the
296 normalization equation originally proposed by Trevisani and Cavalli (2016) for the topographic roughness:

297

$$298 \quad W = 1 - \frac{\ln(n) - \ln(n_{min})}{\ln(n_{max}) - \ln(n_{min})} \quad (6)$$

299

300 where n_{min} and n_{max} are the minimum and maximum Manning's coefficients included within the range 0.001 -
301 1 and converted in the logarithmic form. The main advantages of this operation are: i) to preserve the
302 adimensionality of IC, as also stressed by Zanandrea et al. (2020), ii) to offer a wider range of W factor
303 values, otherwise constrained by the additive method of Arcement and Schneider (1989), and allowing an
304 enhancement of the spatial variability in the final IC maps and iii) to move towards the full standardization of
305 land use-based W factor.

306 In the present work, differences among datasets were analysed for their statistical significance using the non-
307 parametric Kruskal-Wallis (KW) test; the comparisons were considered statistically significant if $P < 0.001$
308 (given the high statistical power from the high number of pixels). All statistical procedures were carried out
309 with the support of Rstudio version 1.2.5019 (Rstudio Team, 2016) and Statgraphics 18.

310

311 4. RESULTS

312

313 4.1 Wildfires severity maps

314

315 Two severity maps based on RdNBR classification for 2002 (Fig. 4) and 2015 (Fig. 5) wildfires in the Rio
316 Toro catchment are presented. After the 2002 event, significant burned areas covered 1657 ha, which
317 corresponds to the 90.9% of the whole study catchment basin. Particularly, high severity represents the most
318 widespread class, occupying 68.9%, whereas moderate and low severity classes characterize 14.7% and
319 7.3% of the study area, respectively. On the contrary, the area classified as unburned covers 9.1% of the
320 catchment area and it is mainly located in the further upstream and downstream positions. The 2015 fire
321 severity map shows 1384 ha of burned areas (75.8%), with the prevalence of moderate severity areas,
322 covering the 42.2% of the total study catchment. Less represented are the high and low severity patches,
323 which covers 23.4% and 10.2% of the total area, respectively. The map shows a major presence of high
324 severity areas, mainly located on the left slopes facing North-East and, conversely, moderate and low severity
325 spread along the right slope, facing South-West. Still, the areas unaffected by the fire can be found at lower
326 and upper elevations as well as in the higher and steeper ridges on the right slope. However, unburned areas
327 are the second most represented class with 24.1%.

328

329 ### FIGURE 4 ###

330 ### FIGURE 5 ###

331

332 Despite the major difference in high severity areas, similar patterns can be observed in the two maps:
333 unburned areas near the northern and southern borders; high and moderate areas in the central part. The
334 Jaccard Index, calculated using the intersection and union of the same fire severity areas in % for the two
335 wildfires, demonstrates poor similarity in the overlap for the low and moderate severity classes, with
336 outcomes of 0.06 and 0.12, respectively. The higher similarity was found for the extreme classes with
337 outcomes of 0.30 (High severity) and 0.35 (Unburned). The comparison between the 2002 and 2015 fire
338 severity maps led to the development of the transition matrix (Table 1), which points out the percentage of
339 catchment within each combination of severity classes as well as the total for each period. Diagonal entries

340 show the percentage of severity that did not change throughout the years, suggesting that highly burned
341 (21.4%) and unburned (8.7%) areas are the ones that persisted the most after the events. On the other hand,
342 low (1.1%) and moderate (6.5%) severity areas are the classes that show lower persistence and therefore
343 higher changes. The gain and losses from 2002 to 2015, exhibits that moderate severity class gained the
344 35.8% of the catchment, whereas high severity class lost the 47.6% of the catchment. Lowest gains were
345 experienced by the low severity class, 9.1% of the landscape, whereas lowest losses were experienced by
346 the unburned class.

347

348 ### TABLE 1 ###

349

350 The results of the GLMs showed that RdNBR values are statistically related to slope, aspect (p -value < 0.001)
351 and slope position (p -value < 0.05) variables in both wildfires. On the contrary, elevation did not show
352 statistical correlation with fire severity (p -value > 0.05) in the first wildfire, whereas in the second one did
353 (Table 2). Since slope position is derived from the combination of slope and elevation, it showed a weaker
354 but still significant correlation with fire severity in both cases. Besides, the analysis regarding the combined
355 effect of the two categorical variables (slope position and aspect) gave negative results due to non-
356 significance (p -value > 0.05).

357

358 ### TABLE 2 ###

359

360 4.2 Sediment connectivity

361

362 Peculiar spatial patterns can be observed in the IC maps (Fig. 6). In 2002, high IC areas were located mainly
363 on the left slopes and stream banks, whereas low IC values characterize the small sub-catchment close to
364 the outlet, as well as the high and flat areas along the southern border (Fig. 6A). Following the 2002 wildfire,
365 the IC maps show high values of the index also near the channel heads of the two main branches of the Rio
366 Toro (Fig. 6B). Apparently, the IC remained constant also for 2015 (Fig. 6C) and 2016 (Fig. 6D) maps.

367 Although the multi-temporal assessment points out similar patterns of high and low IC in all the scenarios,
368 the degree of linkage between slopes and channel network, enhanced in post-wildfire scenarios.

369

FIGURE 6

370
371 To emphasize the IC changes, the difference of IC (DoIC) between post-wildfire and pre-wildfire scenarios
372 was computed for the two events. The DoIC maps are presented in Figure 7, where darker the colour, higher
373 the increase in IC after the wildfire. It is important to mention that the classification of the two maps varies
374 according to the value range of each map, except for the decrease class, since this class consistently refers
375 to negative values. The 2003-2002 DoIC map (Fig. 7A) shows a clear upward trend, with a mean value of
376 $1.07(\pm 0.38)$ and observed minimum and maximum variation of -1.56 and 2.88 respectively. Low, moderate
377 and high increase of IC values cover 24.1%, 51.8% and 23.4% of the whole catchment, with mean values of
378 0.57, 1.11, 1.52. Notably, high positive DoIC values are detectable near the junction of the two main streams
379 and in the proximity of areas of convergence of flows and channel heads. On the contrary, areas showing
380 decreasing IC values are covering the 0.7% of the catchment (mean -0.28).

381

FIGURE 7

382

383
384 After the second wildfire, the 2016-2015 DoIC map (Fig. 7B) shows again an upward trend but with a lower
385 mean values than the first event for the overall catchment (0.53 ± 0.22) and DoIC classes (-0.11, 0.20, 0.51,
386 0.75). Nonetheless, the representativeness of each DoIC class is: decrease areas are 1.3%; low increase
387 areas are 20.7%; moderate increase areas are 40% and high increase 38%. The spatial arrangement of the
388 classes shows high increase IC areas close to the stream network and they are mainly located in the central
389 part of the basin rather than at the channel heads. Decreasing IC areas are instead confined to small spots
390 near the outlet and on the high and flat areas along the southern border, already characterized by low IC in
391 the pre-wildfire scenario (Fig. 6C).

392

393 4.3 Linking fire severity and sediment connectivity

394

395 The comparison between fire severity and sediment connectivity can help to shed light on the effect of how
396 a wildfire can affect sediment connectivity. As expected, from a first qualitative assessment of the maps, the
397 spatial patterns are very similar. Areas of lower DoIC (decrease and low increase) located where the fire
398 severity is lower (unburned and low severity) and areas of higher DoIC (moderate and high increase) where
399 the fire severity is higher (moderate and high severity).

400 Quantitatively, the overlap between the connectivity and severity component is expressed as the area (%) of
401 DoIC class that partly covers the corresponding fire severity class (Table 3). Particular attention was given
402 to the diagonal values, representing the overlap of counterparts. After the first wildfire, the 84.7% overlap
403 confirms what previously observed between the two maps: high DoIC spatial patterns extensively
404 corresponds to high fire severity.

405

406 ### TABLE 3 ###

407

408 On the contrary, the correspondence between decrease IC areas and unburned areas is only the 24.9%.
409 Indubitably, the huge extent of high severity class causes most of the DoIC areas to be greatly overlapped
410 by it. Even the decrease IC areas, in fact, are constituted by high severity areas for the 40.8%. After the
411 second wildfire, the highest correspondence is between decrease IC areas and unburned areas (Table 4),
412 with an overlap of 94.5%, which confirms what can be seen in the maps. Still, high overlap is visible among
413 higher classes, i.e. moderate-moderate, high-high, with a 54.3% and 43.4% respectively.

414

415 ### TABLE 4 ###

416

417 Figure 8A shows the DoIC distributions for the period 2003-2002 and Figure 8B the DoIC distributions for the
418 2016-2015 time window. The medians of DoIC values according to the four severity classes were 0.68, 0.91,
419 1.05, 1.19 for the first event and 0.22, 0.49, 0.62 and 0.70 for the second one, respectively. While considering
420 the second wildfire the results suggest that higher the fire severity and higher is the increase in IC values, in
421 the 2002 event, the correlation is less clear due to the higher data dispersion. However, in both cases, the
422 distributions of each group were found statistically different among each other (KW test, p -value <0.001).

423

424

FIGURE 8

425

426 The distribution of DoIC values, fire severity and topography is presented in Figure 9, where the three most
427 significant topographic variables (Table 2) are used.

428 Generally, among all fire severity classes, the higher DoIC values correspond to high severities but, again,
429 the DoIC values for the first event show higher data dispersion than the second. After the 2002 wildfire, the
430 higher DoIC values are found in areas facing North, whereas the lowest values in areas facing West, with
431 both statistically different (KW test, p -value <0.001) from the others (Fig.9A). The DoIC values for the 2015
432 wildfire instead do not show a clear pattern among the aspects and there is no statistical difference (KW test,
433 p -value >0.001) between North and West for the high fire severity classes (9B). The interaction with slope
434 position for the first event (Fig.9C) shows that the highest and lowest DoIC interquartile ranges are observed
435 for the lower slope positions, in which the DoIC distributions are also the only statistically different from the
436 others.

437 This result suggests that, when a fire occurs, slope positions at intermediate elevation characterized by low
438 slopes greatly enhanced fire severity and consequently the increase in IC. On the other hand, without any
439 disturbance, this type of position promotes vegetation development. In the second case, again unburned
440 areas located on lower slopes show the lowest DoIC values but the highest increase characterizes the areas
441 of high severity on upper slopes (Fig. 9D).

442 Finally, the variation of DoIC as function of slope indicates that a higher increase in IC values is detected at
443 minor slope degrees in the first event (Fig. 9E) but, the opposite trend, in the second event (Fig. 9F).

444

445

FIGURE 9

446 5. DISCUSSION

447

448 In the Rio Toro catchment, two major wildfires occurred in 13 years, causing severe changes to the land
449 cover and vegetation structures. The assessment of fire severity showed that most of the catchment was hit

450 by wildfire of moderate and high severity. Indeed the first wildfire strongly affected the vegetation community
451 of the catchment and surrounding territory, as observed by other authors (Comiti et al., 2008; Iroumè et al.,
452 2015; Assal et al., 2018; Mazzorana et al., 2019; Picco et al., in review). On the other hand, the second
453 wildfire showed lower severity values but similar spatial patterns, for instance, demonstrated by the
454 persistence of unburned areas at the northern and southern borders. The result of lower severity after
455 previous high severity events is in contrast with some studies developed in the south-west of the US (Holden
456 et al., 2010; Parks et al., 2014) but shared by Stevens-Rumann et al. (2016), who found this divergence as
457 caused by slower vegetation recover ~~response~~ after the prior disturbance. In our study area, in fact, the first
458 fire had much more fuel's availability compared to the second one, which occurred just after 13 years. In the
459 assessment of the ~~2015~~second event, the use of a relative vegetation index, such the RdNBR, helped to
460 avoid the bias of the low amount of 2015 pre-fire vegetation caused by the first wildfire. However, the
461 difference between the two fire severity maps could be caused by the classification procedure, which relies
462 upon field surveys carried out four years after the second wildfire, or by the RdNBR values used in the
463 polynomial function and associated to total changes after both wildfires (RdNBR 2016-2002, see section 3.3).
464 The resulting 62% of classification accuracy, obtained from the measured and predicted severity, can affect
465 model outcomes. In the end, the choice of an appropriate spectral index for fire severity assessment is
466 fundamental. We selected the SWIR-based NBR, for its higher sensitivity to fire damages and post-
467 disturbance forest structure recovery (Pickell et al., 2016). Although Ortíz-Rodríguez et al. (2019) found good
468 classification agreement using the NDVI for fire severity assessment, the peculiar condition of fire recurrence
469 in the Rio Toro catchment led us to avoid indexes with lower disturbance response, such as the NDVI, which
470 proved to overestimate recovery rates (Schroeder et al., 2011; Morresi et al., 2019).

471 As proved in several case studies (Iniguez et al., 2008; Oliveras et al., 2009; Estes et al., 2017), topography
472 plays a fundamental role in the distribution patterns of burned areas. In the Rio Toro catchment, slope more
473 than other variables showed correlation to fire severity. Nonetheless, other fire drivers like wind, temperature
474 and fuel's characteristics must not be neglected for their growing importance in the context of climate change
475 and particularly in south-central Chile, where a strong decrease in precipitation is expected in the next years
476 (CONAMA, 2006; Úbeda and Sarricolea, 2016).

477 The analysis of sediment connectivity highlighted a general increase of IC values after the wildfires, with high
478 IC increase mainly located in the headwaters in 2002 and the central part of the catchment in 2015. This
479 suggests that, after the second wildfire, potential loose sediment could have higher chances to enter the
480 channel network and being transported downstream thanks to their proximity to the outlet.

481 Moreover, the DoIC average values observed for the two wildfires, reflected the difference in fire severity:
482 higher overall increase of IC values after the first wildfire than the second one (i.e. higher DoIC values for the
483 2002 disturbance). However, the lower increase observed in the second scenario could be associated with
484 the estimation of the Manning's n , which primarily drives the IC in our study case. While for the fire severity
485 assessment we made use of a relative index for burn detection, the IC calculation was based on the IFZ,
486 which enhances the detection of forest recovery and thereby higher impedance to sediment fluxes. Hence,
487 the difference in the DoIC between the two events can be associated to: i) lower severity of the 2015 wildfire,
488 ii) IFZ overestimation of the 2015 pre-fire vegetation cover iii) actual fast recovering rate in the Araucaria-
489 Nothofagus forest after the first wildfire. The last hypothesis is also supported by field evidence. Just four
490 years after the 2015 wildfire, shrubs species such the endemic *Chusquea* spp. re-occupied large patches of
491 the study area and blocking many pathways. Therefore, in our study area, shrubs might represent the
492 conjunction between the ecological and geomorphological response, since their encroachment can enhance
493 rapidly the storage capacity and reduce sediment connectivity.

494 Despite the overall higher increase of IC after the 2002 wildfire, the results demonstrated stronger correlation
495 between fire severity and sediment connectivity after the 2015 event. The first wildfire was characterized by
496 poorer spatial patterns overlap due to the huge extent of the high fire severity class: contrary to DoIC, the fire
497 severity variable was almost saturated by the highest class. In addition, IC values showed higher data
498 dispersion than for the second event. The cause of such different variability of IC values found after the two
499 events may be attributable to the different degree of land cover heterogeneity in the pre-2002 scenarios.
500 While before 2002 the catchment showed high variability of forest structures, hence high ~~fuel~~ vegetation
501 heterogeneity, before the 2015 the vegetation was far more homogeneous. Since the severity of 2002
502 disturbance was high on the majority of the study area, successional dynamics driving the vegetation
503 recovery started from similar conditions (i.e. complete mortality of canopy trees and consumption of shrub

504 and herb layers) and the short time period between the two disturbances was not enough to differentiate fuel
505 load and structure among different sites. ~~given the passage of the first fire~~

506 The application of the IC permitted to capture the main changes in possible sediment sources, routes and
507 deposits at the catchment scale. In post-disturbance scenarios the IC has been used to summarize the
508 sediment dynamic changes but, according to the characteristics of the disturbance and environment, different
509 *W* factors would have been used. In forested mountain catchments, neither the standard Roughness Index
510 (Cavalli et al., 2013) nor the C-factor are suggested since they are more focused on applications to high
511 altitude headwater catchments characterized by lack of forest cover and agricultural catchments where the
512 role of crop management systems in terms of soil loss is pivotal. On the contrary, Manning's *n* is becoming
513 much more used (e.g. Persichillo et al., 2018; Llana et al., 2019), especially with high land-use heterogeneity.
514 Nonetheless, the Manning's *n* causes low distribution in *W* factor values and requires tabled data. We tried
515 to overcome the first issue, which has been proved to impact negatively the IC (Zanandrea et al., 2020), by
516 normalizing the *W* factor. To avoid the mere use of tabled data, we implemented a methodology that exploits
517 field observations and remote sensing data in order to adapt the *W* factor to specific post-disturbance
518 conditions without yielding too much subjectivity. Zanandrea et al. (2020), offered an alternative *W* factor that
519 properly preserved adimensionality and emphasized the role of forests but without the chance to adjust the
520 methodology to dynamic environments. Therefore, with this work we tried to progress toward the
521 standardization of the *W* factor without neglecting the importance of field data and considering the role of
522 regeneration in post-wildfire scenarios by using the IFZ over the NDVI.

523 The choice of the appropriate *W* factor also depends on the data availability as well as temporal and spatial
524 scales. For instance, Mishra et al. (2019) calculated the impedance according to a simple remote assessment
525 of vegetation, based on the C-factor and NDVI, to study major sediment connectivity patterns in a large basin;
526 Estrany et al. (2019), used the traditional Roughness Index to study plot-scale vegetation-sediment structures
527 in micro-catchments; Kalantari et al. (2017), proposed a *W* factor based on runoff generation potential, having
528 different land use and group of soil types within the lowland study area.

529 The compound analysis of fire severity and sediment connectivity highlighted the main areas of interest,
530 where presumably the land cover changes were exacerbated and so characterized by high severity and high
531 increase in IC. It is worth mentioning that the increase of IC at the pixel scale is not the mere result of the

532 adopted weighting factor but it is also the outcome of the propagation of changes due to land cover variations
533 in the catchment. Considering also the intrinsic characteristics of the catchment, it was possible to identify
534 where the IC increased the most for each fire severity class. Therefore, it appeared that during the first
535 wildfire, lower slope positions and on gentle slopes facing North promoted fire severity; hence the IC. These
536 results can be seen partially in contradiction with literature data. In fact, while on northern aspects, in the
537 southern hemisphere, temperature and fuel conditions are usually suitable for increasing wildfire occurrence
538 and severity, lower slope positions on gentle slopes are not (Carmo et al., 2011; Estes et al., 2017). These
539 areas were actually covered by *Nothofagus spp.*, species that do not present resistance traits and can be
540 deeply affected even at intermediate fire intensity (Gonzalez et al., 2005). On upper slope positions the
541 *Araucaria* stands were greatly damaged when high-intensity crown fires affected the stand, while with lower
542 intensity the severity was lesser due to the resistance traits of the species, such as thick bark and a crown
543 displaced several meters above the ground in mature trees (Burns 1993; Gonzalez et al., 2010).

544 To provide useful information for management decisions, the results of the present study should be
545 considered as a whole. Hence, the prioritization of catchment areas after wildfires would rely on: i) the fire
546 severity maps, describing where overland flow, soil erosion and sediment yields could be suddenly boosted,
547 ii) the most recent IC map, showing where there is higher degree of connectivity to sensitive targets, and iii)
548 the DoIC map, demonstrating where the connectivity suddenly increased.

549 However, in post-fire scenarios falling dynamics of damaged and standing dead trees can last for decades
550 and, depending on species and snag size (Marzano et al., 2012; Molinas et al., 2017), they can either provide
551 elements able to enhance microsite for regeneration on the slopes (Marzano et al., 2013) or be recruited as
552 large wood in river systems. (Benda and Sias, 2003).

553 Finally, it is important to point out that the IC offers only semi-quantitative information of the potential sediment
554 transfers, while for accurately predicting sediment displacement and dynamics, a different analysis
555 considering also other driving factors is indeed required. Notably, in post-wildfire scenarios these factors are
556 associated with the reduction of soil infiltration parameters, changes in soil physicochemical properties and
557 the presence of ashes, which are all responsible of alteration in runoff and sediment transfer (Shakesby,
558 2011). Considering also these variables would have required dedicated field campaigns and would have
559 moved simple approaches based on geomorphometric indices to more complex and sophisticated models

560 with all the uncertainties related to the different variables estimations. Aware of all the limitations of our
561 approach, in the present work, the aforementioned factors have been overlooked to restrict the variables
562 involved and focus on the topography and land cover based ones. We used land cover changes as the only
563 proxy for sediment impedance. This choice is justified by the lack of multi-temporal DEMs and by the absence
564 of major morphological changes occurred between the two wildfires. In addition, although our work exploited
565 open-source data, which can be used to replicate and standardize the procedure in different post-disturbance
566 contexts, much attention has been paid to their spatial resolution to consider the most appropriate scale for
567 the results. Sediment connectivity outcomes can cause serious misinterpretations if there is an imbalance
568 between the scale of data and objectives. According to Cantreul et al. (2018), 1 m is the best resolution for
569 the IC application in a crop-managed watershed of 1.24 km², while López-Vicente and Álvarez (2018)
570 suggested a 0.20 m resolution to study soil displacement in a 0.274 km² area. Different resolutions have
571 been chosen in other contexts. It is our opinion that the choice of the spatial resolution has to consider the
572 objectives of the sediment connectivity analysis and, turning this concept over, the available spatial resolution
573 poses a limit to geomorphometric analysis that could be carried out. High-resolution DEMs are fundamental
574 to investigate fine-scale processes (Cantreul et al., 2018; López-Vicente and Álvarez, 2018; Tarolli et al.,
575 2019) and allows to derive important parameters as local surface roughness to characterize sediment
576 dynamics at these scales. Different and simplified approaches can be devised when only coarse DEMs are
577 available and the aim of the study is focused on large scale processes as coarse material sediment transport
578 in large catchments. Accordingly, we found that a Global DEM at a 12.5 m resolutions suitable for detecting
579 major spatial patterns of IC in an Andean catchment. The proposed workflow could be effectively applied to
580 investigate post-disturbance scenarios in other areas where high-resolution data are not available.

581

582 CONCLUSIONS

583

584 The interaction between wildfire severity and sediment connectivity has been presented in order to map the
585 ecological and geomorphological effects of multiple wildfires on the Rio Toro catchment (Chile). The

586 proposed method combines field data and open source satellite imagery to identify the spatial patterns of
587 sediment connectivity variations driven by two subsequent wildfires.

588 In the study catchment, the wildfire severity assessment pointed out the different severity patterns between
589 the two events. The 2002 wildfire affected the 91% of the catchment, of which almost 70% was classified as
590 high severity, while the 2015 wildfire significantly affected the 76%, of which only the 23% was classified as
591 high severity. These results are mainly ascribed to the different fuel's availability and land cover heterogeneity
592 between the two pre-fire scenarios. The sediment connectivity maps showed large areas of high IC increase
593 located at the headwaters, after the first wildfire, and in the central part of the catchment after the second
594 wildfire. The IC values varied according to the difference in fire severity: catchment's average increase of
595 1.07 after the first wildfire, 0.53 after the second one. However, the response of IC to fire severity was less
596 evident in the first event, being the overlap between fire severity and DoIC spatial patterns leveled off by the
597 vastity of high severity areas. Therefore, the relationship between wildfire severity and sediment connectivity
598 was weaker when the severity classification approached saturation.

599 The methodology proposed represents a good compromise between the reliability of the results and the
600 limited availability of high resolution data in inaccessible areas. The integration between geomorphometric
601 analysis based on open-source satellite products and field work can definitely promote sediment connectivity
602 spatial patterns characterization and the study of its relationship with wildfire severity, although more efforts
603 can be made to improve the classification accuracy. In addition, the computation of a normalized W factor
604 helped to better capture the main effects of the wildfires on the IC thanks to appropriate land cover change
605 detection indices.

606 Finally, we suggest that further research in this field may consider also the integration of soil properties in the
607 analysis, which be source of significant alterations of the sediment impedance, as well as the use of multiple
608 topographic surveys if available.

609

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611

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