Assessing the effect of fire severity on sediment connectivity in central Chile

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

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ABSTRACT

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

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

1. INTRODUCTION

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

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

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

Framing the response of an entire catchment to natural disturbances in terms of variation of sediment supply, routing and deposition is still a controversial issue due to the variety of factors involved (e.g., disturbance properties, sediment characteristics, topography, land cover, hydrological regime). In post-wildfire conditions, if a great amount of sediment is available for sudden mobilization, the awareness of how a catchment facilitates the transfer of sediment between source areas and channel network is vital to predict future scenarios and reduce the associated risk (Mazzorana et al., 2019). To this end, the geomorphic property known as connectivity (Wohl et al., 2019) is gaining interest from the scientific community especially concerning major disturbances. Specifically, sediment connectivity underlies the sediment transfer between the compartments of a geomorphic system and their relationships, which control the sediment cascade and geomorphic response to disturbance events (Bracken and Crooke, 2007; Fryirs, 2013). Several metrics of sediment connectivity have been proposed to overcome the more traditional field measurement and to exploit the high amount of topographic data available nowadays (Heckmann et al., 2018). Following this trend, the topography-based Index of Connectivity (hereinafter IC), proposed by Borselli et al. (2008) and refined by Cavalli et al. (2013) has become a solid and accessible instrument to assess the degree of linkage between sources and sinks of sediment in various contexts. Therefore, many authors grasped the opportunity to map sediment connectivity using the IC in different environments and considering plenty of numerical approaches: Gay et al. (2016) and Kalantari et al. (2017), mapped connectivity in lowlands by integrating catchment infiltration/runoff properties and precipitation-runoff variability, respectively; López-Vicente and Ben-Salem (2019) developed a new aggregated index based on the RUSLE2 equation; Rainato et al. (2018) analyzed the (de)coupling relationships of a small dolomitic catchment.

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

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

i) to investigate interlinked relationship between fire severity and sediment connectivity changes induced by wildfires;

ii) to move towards the standardization of a procedure to apply the IC after major disturbances;

iii) to rely upon open source data so the application of the proposed methodology could be replicated in other contexts.

2. STUDY AREA

The study area is the Rio Toro catchment, located in Chile (Fig. 1a), close to the north-eastern border of the Araucanía Region (IX Región) (Fig. 1b) and affected by two wildfires in 2002 and 2015. The area extends for 18 km^2, entirely inside the Malleco National Reserve, with elevation ranging from 760 to 1810 m a.s.l. and a mean slope of 24°. The climate is classified as temperate warm humid (Fuenzalida, 1965), strongly influenced by the presence of the Andean Cordillera (E) and the Pacific Ocean (W). The average annual precipitation is about 2480 mm (Comiti et al., 2008), with a monthly maximum and minimum of 490 mm and 62 mm in June and January, respectively (average rainfall calculated for the period 2000-2018; source:http://explorador.cr2.cl/). Bedrock layer is primarily composed of pyroclastic rocks generated by the high volcanic activity of the Southern Andes volcanic Zone (SVZ, 33°S – 46°S) and triggered by the Nazca-South America plate convergence (Cembrano and Lara, 2009). The Rio Toro channel network, which features a pluvial/nival hydrological regime (Comiti et al., 2008), develops mainly with south-north direction with a total length of 11 km from the upstream ridges to the downstream Rio Niblinto, where the outlet of the study catchment is established (Fig. 1c). The main channel, receiving water from two branches divided by the central ridge, is classified as a third-order stream featuring a step-pool / cascade bed morphology with a mean channel slope of 0.05 m/m (Comiti et al., 2008; Iroumé et al., 2015; Picco et al., in review). The forest is mainly composed of endemic species of *Araucaria araucana* and *Nothofagus* spp. (southern beech). The two species naturally form mixed forests along the Andes Cordillera in the South-Central Chile and western Argentina (Veblen et al., 1982). The understorey of Araucaria-Nothofagus forests hosts *Chusquea* spp. (*quila*), a fast-growing bamboo plant reaching high densities, especially after major natural disturbances that typically affect this type of landscape (Gunckel et al., 1948; Veblen et al., 1981). Until 2002, when the first wildfire occurred, the Rio Toro catchment was almost completely covered by forests. At lower elevation (below 1200 m.a.s.l.) the main species were *Nothofagus dombeyi and N. nervosa* while *Araucaria araucana* stands dominated the landscape above 1200-1300 m a.s.l. The 2002 fire, occurred in late February, affected both the Malleco National Reserve and the near Tolhuaca National Park, with an overall burned area of about 11660 ha (Assal et al., 2018), greatly contributing to the 20000 ha burned in the region in the summer fire season (González et al., 2005). Besides, during the fire season of 2014-15, which counted 1344 wildfires and almost 46000 ha burned in the Araucanía Region alone (CONAF, 2019), another wildfire affected the same area in late February 2015.

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

FIGURE1

3. MATERIAL AND METHODS

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

FIGURE 2

3.1 Satellite data

The need for multi-temporal images and consistency among the two methodological phases drove the attention towards Landsat missions, which offer long time series and sufficient global coverage at 30 m resolution (Banskota et al., 2014). Two Landsat 7 ETM+ images corresponding to periods pre- and post-2002 wildfire (01/02/2002, 20/02/2003) and two Landsat 8 OLI images corresponding to the pre- and post-2015 wildfire (28/01/2015, 31/01/2016) periods were selected from the U.S. Geological Service free satellite provider EarthExplorer (EarthExplorer, 2019). After the selection, Landsat products were ordered and obtained from the Earth Resources Observation and Science Center (EROS) Science Processing Architecture On Demand Interface (ESPA). The ESPA allows the processing of Landsat data beyond the standard Landsat Level-1 processing level (ESPA, 2018). Therefore, the four images were provided atmospherically corrected at surface reflectance to account for sensor, solar and atmosphere distortion (Young et al., 2017). In addition, we applied transformations to guarantee continuity among the Landsat 7 ETM+ and Landsat 8 OLI bands and avoid misinterpretations in the outcomes (Roy et al. 2016).

The topographic information required for developing the sediment connectivity analysis is represented by the Global Digital Elevation Model (DEM) with a spatial resolution of 12.5 × 12.5 m cell size derived by the ALOS PALSAR satellite imagery system. The data were processed and redistributed by the Alaska Facility Service (ASF, 2019; dataset: ASF DAAC, 2009), which provides Radiometrically Terrain-Corrected (RTC) products. Detailed information about the accuracy of ASF's products can be found in Gesch et al. (2014).

3.2 Field data

During January 2019, multiple field campaigns were carried out in the Rio Toro catchment to collect land cover data. We established a total of 106 square sampling plots of about 400 m^2, in which the percentage of area covered by understorey, bare soil and rocks, grassland, deadwood (standing and/or lying on the ground)and trees was visually determined (Fig. 3). In particular, the understorey was defined as the vegetation layer including bamboo, Araucaria and Nothofagus seedlings and shrubs developing under the trees. The latter category instead, includes only living trees taller than 1.30 m.

In addition, we also evaluated specific ground characteristics on a subset of 46 sampling plots regarding the number of standing dead and living trees and the number of obstructions on the ground (Table S1). The distribution of the plots within the study catchment was highly constrained by the scarce accessibility due to steep slopes, lack of roads and presence of fallen logs. The position of each sampling plot was taken measuring the centroid using a GPS Trimble Juno 5.

FIGURE 3

3.3 Fire severity assessment

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

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

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

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

where, the dNBR is conventionally scaled up by a factor of 1000 to obtain an integer output (Miller et al., 2009) and $dNBR_{offset}$ is obtained by averaging dNBR values calculated outside the wildfires-affected areas in order to avoid reflectance biases given by the natural phenological effect (Parks, et al., 2014; Morresi et al. 2019). Given the occurrence of two wildfires in the Rio Toro catchment, multiple dNBR*s* were calculated as the difference between the years 2003-2002; 2016-2015 and 2016-2002. The latter aims at detecting the spectral changes given by the sum of the two wildfires and it has been considered only as a proxy variable in the function used to classify the severity of the two separate wildfires.

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

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

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

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

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

The final wildfire severity maps were then compared in terms of spatial patterns, with particular focus on the eventual changes or similarities among different severity areas between the two events. Similarity analysis was performed thanks to the Jaccard Index, calculated specifically between areas with the same severity (e.g. unburned 2002 - unburned 2015). On the contrary, the variation was evaluated through the transition matrix (or cross-tabulation matrix), to highlight gains or losses among the classes.

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

3.4 Mapping sediment connectivity

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

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

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

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

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

3.4.1 Weighting factor

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

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

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

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

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

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

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

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

4. RESULTS

4.1 Wildfires severity maps

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

FIGURE 4

FIGURE 5

Despite the major difference in high severity areas, similar patterns can be observed in the two maps: unburned areas near the northern and southern borders; high and moderate areas in the central part. The Jaccard Index, calculated using the intersection and union of the same fire severity areas in % for the two wildfires, demonstrates poor similarity in the overlap for the low and moderate severity classes, with outcomes of 0.06 and 0.12, respectively. The higher similarity was found for the extreme classes with outcomes of 0.30 (High severity) and 0.35 (Unburned). The comparison between the 2002 and 2015 fire severity maps led to the development of the transition matrix (Table 1), which points out the percentage of catchment within each combination of severity classes as well as the total for each period. Diagonal entries show the percentage of severity that did not change throughout the years, suggesting that highly burned (21.4%) and unburned (8.7%) areas are the ones that persisted the most after the events. On the other hand, low (1.1%) and moderate (6.5%) severity areas are the classes that show lower persistence and therefore higher changes. The gain and losses from 2002 to 2015, exhibits that moderate severity class gained the 35.8% of the catchment, whereas high severity class lost the 47.6% of the catchment. Lowest gains were experienced by the low severity class, 9.1% of the landscape, whereas lowest losses were experienced by the unburned class.

TABLE 1

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

TABLE 2

4.2 Sediment connectivity

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

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

FIGURE 6

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

FIGURE 7

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

4.3 Linking fire severity and sediment connectivity

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

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

TABLE 3

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

TABLE 4

Figure 8A shows the DoIC distributions for the period 2003-2002 and Figure 8B the DoIC distributions for the 2016-2015 time window. The medians of DoIC values according to the four severity classes were 0.68, 0.91, 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 the second wildfire the results suggest that higher the fire severity and higher is the increase in IC values, in the 2002 event, the correlation is less clear due to the higher data dispersion. However, in both cases, the distributions of each group were found statistically different among each other (KW test, *p*-value <0.001).

FIGURE 8

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

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

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

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

FIGURE 9

5. DISCUSSION

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

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

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

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

Despite the overall higher increase of IC after the 2002 wildfire, the results demonstrated stronger correlation between fire severity and sediment connectivity after the 2015 event. The first wildfire was characterized by poorer spatial patterns overlap due to the huge extent of the high fire severity class: contrary to DoIC, the fire severity variable was almost saturated by the highest class. In addition, IC values showed higher data dispersion than for the second event. The cause of such different variability of IC values found after the two events may be attributable to the different degree of land cover heterogeneity in the pre-2002 scenarios. While before 2002 the catchment showed high variability of forest structures, hence high ~~fuel~~ vegetation heterogeneity, before the 2015 the vegetation was far more homogeneous. Since the severity of 2002 disturbance was high on the majority of the study area, successional dynamics driving the vegetation recovery started from similar conditions (i.e. complete mortality of canopy trees and consumption of shrub and herb layers) and the short time period between the two disturbances was not enough to differentiate fuel load and structure among different sites. ~~given the passage of the first fire~~

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

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

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

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

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

Finally, it is important to point out that the IC offers only semi-quantitative information of the potential sediment transfers, while for accurately predicting sediment displacement and dynamics, a different analysis considering also other driving factors is indeed required. Notably, in post-wildfire scenarios these factors are associated with the reduction of soil infiltration parameters, changes in soil physicochemical properties and the presence of ashes, which are all responsible of alteration in runoff and sediment transfer (Shakesby, 2011). Considering also these variables would have required dedicated field campaigns and would have moved simple approaches based on geomorphometric indices to more complex and sophisticated models with all the uncertainties related to the different variables estimations. Aware of all the limitations of our approach, in the present work, the aforementioned factors have been overlooked to restrict the variables involved and focus on the topography and land cover based ones. We used land cover changes as the only proxy for sediment impedance. This choice is justified by the lack of multi-temporal DEMs and by the absence of major morphological changes occurred between the two wildfires. In addition, altough our work exploited open-source data, which can be used to replicate and standardize the procedure in different post-disturbance contexts, much attention has been paid to their spatial resolution to consider the most appropriate scale for the results. Sediment connectivity outcomes can cause serious misinterptrations if there is an imbalance between the scale of data and objectives. According to Cantreul et al. (2018), 1 m is the best resolution for the IC application in a crop-managed watershed of 1.24 km^2, while López-Vicente and Álvarez (2018) suggested a 0.20 m resolution to study soil displacement in a 0.274 km^2 area. Different resolutions have been chosen in other contexts. It is our opinion that the choice of the spatial resolution has to consider the objectives of the sediment connectivity analysis and, turning this concept over, the available spatial resolution poses a limit to geomorphometric analysis that could be carried out. High-resolution DEMs are fundamental to investigate fine-scale processes (Cantreul et al., 2018; López-Vicente and Álvarez, 2018; Tarolli et al., 2019) and allows to derive important parameters as local surface roughness to characterize sediment dynamics at these scales Different and simplified approaches can be devised when only coarse DEMs are available and the aim of the study is focused on large scale processes as coarse material sediment transport in large catchments. Accordingly, we found that a Global DEM at a 12.5 m resolutions suitable for detecting major spatial patterns of IC in an Andean catchment. The proposed workflow could be effectively applied to investigatepost-disturbance scenarios in other areas where high-resolution data are not available.

CONCLUSIONS

The interaction between wildfire severity and sediment connectivity has been presented in order to map the ecological and geomorphological effects of multiple wildfires on the Rio Toro catchment (Chile). The proposed method combines field data and open source satellite imagery to identify the spatial patterns of sediment connectivity variations driven by two subsequent wildfires.

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

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

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

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