



HAL
open science

Terrain analysis, erosion simulations and sediment fingerprinting: a case study assessing the erosion sensitivity of agricultural catchments in the border of the volcanic plateau of Southern Brazil

Alice Dambroz, Jean Minella, Tales Tiecher, Jean Moura-Bueno, Olivier Evrard, Fabricio Pedron, Ricardo Dalmolin, Felipe Bernardi, Fabio Schneider, Olivier Cerdan

► **To cite this version:**

Alice Dambroz, Jean Minella, Tales Tiecher, Jean Moura-Bueno, Olivier Evrard, et al.. Terrain analysis, erosion simulations and sediment fingerprinting: a case study assessing the erosion sensitivity of agricultural catchments in the border of the volcanic plateau of Southern Brazil. *Journal of Soils and Sediments*, 2022, 22, pp.1023-1040. 10.1007/s11368-022-03139-6 . cea-03528031

HAL Id: cea-03528031

<https://cea.hal.science/cea-03528031v1>

Submitted on 17 Jan 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Copyright

1 **Terrain analysis, erosion simulations and sediment fingerprinting: a case study**
2 **assessing the erosion sensitivity of agricultural catchments in the border of the**
3 **volcanic plateau of Southern Brazil**

4

5 Alice P. B. Dambroz¹, Jean P. G. Minella¹, Tales Tiecher², Jean M. Moura-Bueno¹,
6 Olivier Evrard³, Fabricio A. Pedron¹, Ricardo S. D. Dalmolin¹, Felipe Bernardi¹, Fabio J.
7 A. Schneider¹, Olivier Cerdan⁴

8

9 ¹ Federal University of Santa Maria, Soil Department, Santa Maria, RS, Brazil

10 ² Federal University of Rio Grande do Sul, Soil Department, Porto Alegre, RS, Brazil

11 ³ Laboratoire des Sciences du Climat et de l'Environnement (LSCE – IPSL), Unité Mixte
12 de Recherche 8212 (CEA/CNRS/UVSQ), Université Paris-Saclay, Gif-sur-Yvette,
13 France

14 ⁴ Bureau de Recherches Géologique et Minières (BRGM), Orléans, France

15 Corresponding Author: Alice P. B. Dambroz, e-mail: alice_pbd@outlook.com

16 ORCID: Alice P. B. Dambroz (<https://orcid.org/0000-0003-0921-1034>), Jean P. G.
17 Minella (0000-0001-9918-2622), Tales Tiecher (0000-0001-5612-2849), Jean. M.
18 Moura-Bueno (0000-0002-7240-3728), Olivier Evrard (0000-0002-3503-6543), Fabricio
19 A. Pedron (0000-0002-5756-0688), Ricardo S. D. Dalmolin (0000-0002-8834-9869),
20 Felipe Bernardi (0000-0002-7964-6474), Fabio J. A. Schneider (0000-0001-8406-6661),
21 Olivier Cerdan (0000-0003-1395-3102)

22

23 **Abstract**

24 **Purpose**

25 Erosion and its spatial distribution in three agricultural headwater catchments were
26 assessed in the border of the volcanic plateau in Southern Brazil. We analyzed terrain,
27 hydrological processes and land use influence to provide a comprehensive assessment of
28 the catchments' sensitivity to erosion.

29 **Methods**

30 Topographic attributes were acquired from a digital elevation map, WaterSed model was
31 parametrized to simulate runoff, diffuse erosion and sediment yield, and sediment source
32 contributions were estimated using sediment fingerprinting based on near-infrared
33 spectroscopy.

34 **Results**

35 According to the modeled results, areas covered by crop fields, grasslands and those
36 adjacent to the drainage network are the most sensitive to erosion. Short distances from
37 the source to the river network and the occurrence of high magnitude rainfall events (80
38 mm) promoted increases in connectivity for runoff/sediment transfer. Erosion simulations
39 show that areas of low infiltration, as unpaved roads, were important runoff generators
40 during lower volume rainfall events (25 mm). Sediment fingerprinting provided
41 satisfactory results to quantify the contributions of unpaved roads to sediment (~39%).
42 Topsoil and stream channels were also significant sediment sources for the set of analyzed
43 samples, corresponding to average contributions of 38 and 23%, respectively.

44 Conclusion

45 Areas sharing geomorphological similarities did not lead to similar sediment
46 contributions. Vegetation cover controlled erosion in topographically sensitive areas.
47 Unpaved roads provide a significant sediment source, followed by topsoil and stream
48 channels. The complementary results provide useful insights to better coordinate planning
49 environmental conservation strategies in these fragile landscapes.

50

51 **Key-words** Erosion sensitivity; Topographic attributes; GIS; WaterSed; Sediment
52 fingerprinting; source to sink.

53

54 **1 Introduction**

55

56 Soil erosion is responsible for economic, social, and environmental damages
57 occurring both on- and off-site (Boardman et al. 2019). There is an interest in
58 understanding erosion processes to propose better management practices. These studies
59 require long term monitoring data (Silva et al. 2021), which can be costly to acquire. Yet,
60 there are tools to rapidly analyze an environment's fragility. Topographic attributes'
61 analysis is a quick and useful tool for spatial representation of erosion susceptibility and
62 zones prone to material loss and deposition (Moore et al. 1991; Wilson and Gallant 2000;
63 Gruber and Peckham 2009; Vijith and Dodge-Wan 2019) for large areas with complex
64 terrain. Advances in remote sensing (Karydas et al. 2014) and its data availability made
65 it common to use models to estimate or predict soil erosion, providing a first look on the
66 dynamic processes of soil degradation, runoff and erosion in an area of interest (Mitasova
67 et al. 1996; Alewell et al. 2019; Teng et al. 2019). These approaches can be combined

68 with rapid monitoring techniques, such as fingerprinting (Martínez-Carreras et al. 2010),
69 to quickly reflect the panorama of the spatial distribution of soil degradation.

70 The analysis of topographic attributes aims to address the natural variabilities of
71 a landscape and can be used to propose the most appropriate practices for soil and water
72 conservation, by reducing environmental impacts of agriculture. Its applicability to
73 catchment scales has a main role to identifying risk areas and maintaining natural
74 resources and environmental sustainability (Berry et al. 2005). Slope and the Stream
75 Power Index are topographic attributes widely used in hydrology to characterize the
76 spatial patterns of soil erosion (Mitasova et al. 1996; Ahmad 2018). This terrain analysis
77 has been used for determining erosion susceptibility (Vijith and Dodge-Wan 2019) and
78 identifying erosion hotspots (Mhired et al. 2018). Although they may characterize both
79 simple and complex terrain features, they do not reflect land use, climate and soil
80 management practices' effects on catchment hydrology.

81 Since the erosive process is dynamic in time and space and dependent of other
82 controlling factors, a more detailed analysis of an environment's fragility to erosion
83 should be considered. Besides topography, rainfall characteristics, soil type, land use and
84 management are also controlling factors of soil erosion, suggesting that – at the catchment
85 scale – there is a need for a more complex analysis. For this reason, mathematical models
86 combine a series of parameters (Merritt et al. 2003) to describe and to predict the
87 occurrence of surface runoff and erosion according to changes in soil properties, rainfall
88 patterns, and land use and management (Nearing et al. 2005). Empirical models (e.g.,
89 RUSLE) have been used for assessing erosion risk (Bezak et al. 2021) as they require
90 relatively fewer input parameters, making the numeric solution objective, yet with a
91 limited process description. Accordingly, physically-based distributed models provide an
92 alternative tool for evaluating the spatial variability of erosion within a catchment,
93 through the identification of erosion hotspots (Lemma et al. 2019).

94 Although the erosion processes occurring within a catchment reflect on sediment
95 yield, material transfer from hillslopes to river systems also depends on landscape
96 connectivity and depositional processes (Wohl et al. 2019). The complexity of processes
97 and parameters that affect hillslope and bank erosion makes it difficult to quantify
98 sediment supply from a catchment to a river channel (Julien 1995). To address this, the
99 sediment fingerprinting technique (Haddadchi et al. 2013; Walling 2013; Collins et al.
100 2020) couples traditional sediment monitoring programs with tracing techniques to
101 estimate sediment sources across the landscape (Evrard et al. 2011; Owens et al. 2016).

102 This approach provides a quantification of source contributions to sediment through the
103 analysis of conservative bio-physico-chemical properties in potential source and target
104 material. For this purpose, cost- and time-intensive conventional tracing properties (e.g.,
105 radionuclides, elemental and isotopic geochemistry), or simple and alternative methods
106 as those relying on near-infrared spectroscopy coupled to statistical modelling were
107 shown to be efficient in estimating land use source contributions to sediment yield
108 (Verheyen et al. 2014; Tiecher et al. 2021).

109 Still, all the hydrological and erosion processes occurring within a catchment are
110 not assured to be incorporated in a holistic approach or model that comprehends the series
111 of phenomena occurring on variable and continuous ranges of scales (Gentine et al. 2012).
112 For instance, to improve the understanding of erosion processes occurring from the source
113 to the outlet of a catchment, sediment fingerprinting has been coupled to erosion modeling
114 in target catchments (Palazón et al. 2016; Battista et al. 2020; Uber et al. 2021).
115 Integrating techniques to provide multiple lines of evidence may increase the robustness
116 of the erosion processes' assessment.

117 Therefore, a more accurate process representation should address the variabilities
118 by coupling the analysis of these dynamic systems (Gentine et al. 2012). While hillslope
119 processes may be addressed by terrain analysis and erosion modelling, sediment
120 fingerprinting could enlighten the connection between them and the drainage network.
121 To this end, the purpose of this study is to use complementary tools to evaluate the
122 sensitivity to erosion and its spatial distribution in three environmentally fragile
123 headwater catchments, nested within a heterogeneous catchment located along the border
124 of the volcanic plateau in Southern Brazil, characterized by an intensive agricultural use
125 and without continuous hydro sedimentological monitoring. Three approaches were
126 analyzed including i) terrain analysis, ii) erosion modeling as a dynamic erosion index
127 and iii) sediment fingerprinting to provide a comprehensive assessment of the sensitivity
128 of these landscapes to erosion.

129

130 **2 Materials and methods**

131

132 2.1 Study area characterization

133

134 Guarda Mor catchment (Fig. 1), in Southern Brazil, is characterized by different
135 land uses, soil types and lithology, and a complex terrain morphology. The average annual

136 rainfall is 1,940 mm, according to data collected from 2011 to 2020 at station number
137 2953008 (ANA 2021). The mean annual temperature is 19°C and climate is subtropical,
138 type Cfa 2, according to Köppen's classification (Alvares et al. 2013).

139 **Fig. 1** Location of Guarda Mor catchment, Júlio de Castilhos' rainfall-runoff
140 monitoring station and ANA's weather station number 2953008 within the state of Rio
141 Grande do Sul. In detail, soil and sediment sampling sites at Guarda Mor catchment.

142 Guarda Mor's main river monitoring station (GMex) drains a surface area of
143 approximately 18.5 km², with elevation ranging from 194 to 511 meters (Fig. 2). A nearly
144 levelled to very undulating relief is observed in its upper and lower segments, while its
145 middle third is characterized by a basaltic escarpment. This catchment comprises three
146 nested sub catchments with respective drainage areas of 2.1, 4.2 and 1.4 km², referred to
147 as S1, S2 and S3 hereafter.

148 Located in a transition zone between the Meridional Plateau and the Central
149 Depression of Rio Grande do Sul, GMex is characterised by a diverse geology (Wildner
150 et al. 2008), as observed in Fig. 2. The Southern Plateau, in its upper segment, is underlain
151 by volcanic rocks from the Serra Geral Group (Rossetti et al. 2018), including rocks from
152 the Caxias sub-group (rhyodacite) and the Torres and Vale do Sol Formations (basalt). In
153 the Central Depression (sedimentary basin), sandstones from the Botucatu and Caturrita
154 Formations are found (Fig. 2).

155 **Fig. 2** Guarda Mor catchment. **a** Digital elevation map. **b** Pedological and **c**
156 geological maps. **d** Land use classification map.

157 This geological diversity led to the formation of several soil types (Fig. 2), which
158 were mapped by Pedron et al. (2021). They include, according to the WRB classification
159 System (IUSS Working Group WRB 2015), Leptosols, Nitisols, Cambisols, Gleysols,
160 Regosols and Acrisols.

161 To create an annual land use map, the Difference Vegetation Index, Enhanced
162 Vegetation Index, Normalized Difference Vegetation, Normalized Ratio Vegetation
163 Index and soil adjusted vegetation index were derived from LANDSAT-8 satellite
164 images. Field observation and Random Forest modeling (Breiman 2001) were used for
165 building the map. The selected images were taken in April, September and December in
166 2019, so that seasonal changes in vegetation cover were well captured. Later, the main
167 road segments were digitized manually using both satellite images and field observations.

168 According to the land use classification map (Fig. 2), forests occupy 44% of this
169 catchment's area, followed by crop fields (39%), grasslands (11%), urban or pavement

170 areas (2%), unpaved roads (1%) and water bodies (1%). Forests are mostly located in the
171 steepest portion of this catchment. In the upper segment of the headwater catchments,
172 land use mainly consists of crop fields, where a succession of soybeans monoculture in
173 summer and wheat or oats during winter are cultivated in a no-till system. Grasslands are
174 areas under permanent pasture, without soil tillage nor sowing of seasonal crops.

175 Crop fields cover 60 and 63% of the area of S2 and S3, respectively. Forests
176 occupy 21 and 20% of the area in each sub catchment, grasslands occupy 11 and 12% of
177 the area and unpaved roads 2 and 1%. In S2 and S3, 1-2% of the area is covered by urban
178 or paved areas, mainly farmhouses. In S1, crop fields are also the main land use (43%),
179 forests occupy 33%, grasslands 16%, while paved/urban areas and unpaved roads occupy
180 each 3% of its area. In S1 and S2 (Fig. 1), there are two crossing points between the
181 drainage network and the roads, which have a total length close to 4500 and 5000 meters,
182 respectively. In S3, the total road extension is less than 900 meters long and no crossing
183 point is observed with the river drainage network.

184

185 2.2 Terrain analysis

186

187 Topographic attributes data were acquired for GMex, S1, S2 and S3 to spatially
188 identify the main hotspots where erosion processes are strongly relief-influenced. Using
189 a zonal statistics tool on QGIS v. 3.8.3 (QGIS Development Team 2020), data from the
190 topographic attributes under each land use were extracted for every sub catchment, for its
191 comparison and analysis.

192 An ALOS PALSAR Digital Elevation Model (DEM) (ASF DAAC 2010) was
193 obtained with a spatial resolution of 12.5 m. It was downscaled to a resolution of 10 m
194 for this study (Fig. 2), to avoid truncation errors during GIS' processes and overestimation
195 of roads and stream channel's areas in the land use map. All maps were processed and
196 obtained using the System for Automated Geoscientific Analyses (SAGA GIS v. 2.3.2)
197 and QGIS v. 3.8.3 was used for organizing and preparing the final maps.

198 From the DEM, the following primary topographic attributes were obtained: a)
199 slope, profile and plan curvatures calculated by the method of the 9th parameter 2nd order
200 polynom (Zevenbergen and Thorne 1987); and b) catchment area using a recursive
201 function. Zero value for profile or plan curvature indicates the occurrence of linear or
202 planar surfaces, respectively. Negative profile curvatures represent convex surfaces and
203 positive values, concave areas. Plan curvatures represent surfaces of convergent (negative

204 values) or divergent (positive values) flow. Slope and catchment area were used as input
205 data for calculating the secondary topographic attributes: a) Topographic Wetness Index
206 (TWI), following Beven and Kirkby's (1979) TOPMODEL; b) LS Factor, based on
207 Moore et al. (1991) method; c) and Stream Power Index (SPI), also based on Moore et al.
208 (1991). Frequency histograms using these data were organized for each sub catchment.

209

210 2.3 Soil erosion modeling

211

212 The goal of this approach was to parameterize an erosion model, that considers
213 soil surface and land use characteristics, to provide a dynamic indicative of the
214 catchments' erosion sensitivity in response to a storm rainfall event. Therefore, we chose
215 the raster-based, spatially distributed and event-based WaterSed model (Patault et al.
216 2020; Grangeon et al. 2021). It was developed to model the spatial distribution of runoff
217 and erosion from field to catchment scale. WaterSed is an upgrade of the STREAM
218 model, which was designed to avoid over-parameterization and uncertainties in modelling
219 (Cerdan et al. 2002). Spatially-distributed modelling approaches are adequate for
220 understanding sediment transport, since every sediment source is characterized by
221 different travel times (Merritt et al. 2003). Considering potential difficulties in
222 representing processes or interpreting physical phenomena with equations and parameters
223 without overloading model parametrization, WaterSed model represents an interesting
224 compromise that permits to take into account the main erosion processes (infiltration,
225 saturation, detachment by raindrop, detachment by runoff, deposition) with an adapted
226 parameterization that is easily obtained (see Chabert (2019) for full explanation or
227 Grangeon et al. (submitted)).

228

229 WaterSed's consistent conceptual structure includes a hydrologic and a sediment
230 module, details on its equations are in Landemaine (2016). WaterSed presents a simple
231 and efficient strategy for incorporating land use and management's effects on erosion and
232 hydrological processes. Furthermore, it allows the incorporation of runoff's re-infiltration
233 process, an important feature considering the study catchment. Runoff and sediment that
234 reach the permanent river network are directly delivered to the lowest point downstream.
235 The model results were used to analyze diffuse erosion processes occurring under each
236 land use through the calculation of zonal statistics. The model does not allow the
237 simulations of channel bank erosion and sediment storage within the channel; besides, in
238 these sub catchments, channels run over bedrock with boulders and have stable margins.

238 The model is run using SAGA GIS and the input data is composed of decision
239 tables and raster maps. The maps correspond to: DEM; stream network and channel
240 width; soil type and land use. Each land use is then associated to soil surface
241 characteristics based on decision tables, which allowed the parametrization approach used
242 in this study. The tables (Cerdan et al. 2002a, 2002b) are built based on expert knowledge
243 and adjusted to local conditions, according to each land use, to associate soil properties
244 observed in the field to infiltration rates. They include Manning's roughness coefficient,
245 a potential value for suspended sediment concentration (SSC), soil erodibility, infiltration
246 rate and antecedent moisture content.

247 Although we do not have data from hydro-sedimentary monitoring in the study
248 catchment to calibrate and validate WaterSed, we chose to parameterize it for modeling
249 runoff volume, sediment yield and diffuse erosion in the three sub catchments. The data
250 that was used in this parametrization was obtained from a runoff and SSC dataset we had
251 access to. The data was monitored on hillslopes and zero-order catchments, where
252 WaterSed was calibrated based on a robust database of water and sediment discharges.
253 The site is a nearby field-scale, rainfall-runoff monitoring station in Júlio de Castilhos
254 (Fig. 1). Detailed information on the site's characteristics and direct measurements'
255 obtention can be found in Londero et al. (2021a, 2021b) and Schneider (2021). Further
256 information is presented in Tables 1 and 2 in the supplementary material.

257 These parameters were used since both study areas are exposed to similar
258 environmental conditions, considered to be representative of those occurring in Guarda
259 Mor's headwater sub catchments. Values for Manning's roughness coefficient were
260 defined based on Engman (1986). Default scale effect correction and recession time, flow
261 width, critical runoff peak for rill erosion and sediment settling parameter coefficients
262 were applied.

263 The model also requires information on rainfall depth and duration. The rainfall
264 events we chose to simulate are based on events that generated significant runoff and
265 were monitored in the nearby Júlio de Castilhos station (29°13'39"S, 53°40'38"W)
266 (Londero et al. 2017; Londero et al. 2021a), their characteristics are described in Table 1.

267

268 2.4 Fine sediment fingerprinting

269

270 The origin of riverbed sediment was determined by a fingerprinting method based
271 on NIR spectroscopy (Verheyen et al. 2014; Tiecher et al. 2016; Tiecher et al. 2021) and

272 modeling with Support Vector Machine (SVM) to build spectroscopic models of
273 sediment estimation (Tiecher et al. 2021). Two source groupings (by land use and by sub
274 catchment) were considered as potential end-members to analyze the spatial variability
275 and the main erosion processes to explain the sediment yield observed at the outlets.

276 The first approach was based on spatial sources and the three headwater sub
277 catchments were considered as end-members. The objective of this so-called tributary
278 approach was to indicate which sub catchment contributed with greater amounts of
279 sediment that reached the GMex's outlet. The second approach considered land use
280 source types (including topsoil, forest, unpaved roads, and stream channel) within each
281 sub catchment, with the objective to outline which land uses or landscape components
282 were contributing with more sediment to S1, S2 and S3's outlets. Therefore, sediment
283 samples were both, alternatively, used as sources and target material, whether they were
284 considered in the first or second approach, respectively.

285

286 2.4.1 Soil and sediment sampling and analysis

287

288 Potential sediment sources were sampled based on visual field evidence of erosion
289 or soil degradation and connectivity to the drainage network, in each sub catchment. The
290 soil samples were collected from crop fields, grasslands, stream channels, forests, and
291 unpaved roads. Due to sample similarities that led to low discrimination of sources,
292 samples from crop fields and grasslands were grouped as topsoil source, such as
293 Poulenard et al. (2009) and Verheyen et al. (2014) also did. Each sample was composed
294 by five sub-samples that were mixed and homogenized to compose a representative
295 sample (Table 2). They were collected on the soil surface (0–2 cm depth), due to the
296 higher likelihood of surface material to be mobilized by water erosion.

297 Sediment deposited on the riverbed were sampled along the river channels at the
298 outlets of S1, S2, S3 and at GMex, between January and June in 2019. Care was taken
299 during the sediment sample collection process to avoid losing fine material.

300 All samples were oven-dried with forced air circulation and at a temperature
301 between 40 and 50°C. Then, samples were gently disaggregated and sieved at 63 μm , to
302 minimize particle size differences between samples (Lacey et al. 2017), and between
303 potential sources and sediment material. Afterwards, all samples were analyzed by near-
304 infrared spectroscopy. The spectra range from 12,000 to 4,000 cm^{-1} was scanned, using
305 the Bruker MPA FT-NIR (Fourier transform near-infrared) spectrometer, at a resolution

306 of 2 cm⁻¹. Samples were carefully placed in a Petri dish prior to scanning and background
307 readings were regularly performed.

308

309 2.4.2 Building spectroscopic models to estimate sediment source contributions

310

311 To calibrate the prediction models and test the analyzed properties' additive
312 behavior, artificial mixtures (Poulenard et al. 2009) were prepared in the lab using source
313 samples. The set of mixtures was designed to account for spectral diversity, and it was
314 used for calculating the model's confidence statistics by testing its performance. First,
315 samples of each potential source were mixed in equal weight proportions to compose one
316 reference sample. Then, from these, other mixtures were created by mixing them in
317 different proportions to build the statistical model. For the tributary approach, 37 artificial
318 mixtures were created with the sediment samples collected from each sub catchment.
319 Their distribution can be visualized in a ternary diagram (Fig. 1 in the supplementary
320 material). For the land use approach, 72 artificial mixtures were created covering a range
321 from 0 to 100% of each potential source sample (Table 3 in the supplementary material).

322 The spectra dataset was transformed by a smoothing and data derivative
323 algorithm, Savitzky-Golay derivative, first-order polynomial (11 window points)
324 (Savitzky and Golay 1964). By calculating the first derivative, this pre-processing
325 calculates the change rate between absorbance and wavelength, highlighting the
326 occurrence of bands. This was performed using the R package "prospectr" (Stevens and
327 Ramirez-Lopez 2013).

328 Then, for establishing a relationship between spectral data (x variable) and the
329 contribution of a given source (y variable), SVM models (package e1071 – Meyer et al.
330 2019) were adjusted. The SVM is a non-parametric model and was run with the kernel
331 function, which separates the calibration data into hyperplanes and seeks to establish
332 correlations between the dependent and independent variables when these have non-linear
333 behavior (Ivanciuc 2007). The kernel function seeks to establish correlations between the
334 reflectance value and the target variable, in which the model seeks to identify a
335 interpolation function between the variables and creates support vectors, a robust
336 procedure in statistical learning models (Ivanciuc 2007). This type of model was selected
337 due to the occurrence of non-linear correlations between the organo-mineral components
338 of soils/sediments and the spectral variables (Viscarra Rossel and Behrens 2010) and
339 given the acquisition of more accurate estimates using this model in comparison, for

340 example, to parametric models Partial Least Square Regression (PLSR), by Tiecher et al.
341 (2021).

342 Data from the artificial samples was randomly separated among calibration and
343 validation sets. Each model was calibrated with 70% of the samples ($n = 26$ and 51 ,
344 tributary and land use approaches) and validated with the remaining 30% of the samples
345 ($n = 11$ and 21 , tributary and land use approaches). A total of 15 SVM regression models
346 were independently calibrated, one for each sediment source. No boundary conditions to
347 avoid results lower than 0 or higher than 100% were set for the models. The models were
348 used for predicting the contribution of each potential source to the individual sediment
349 samples.

350 To evaluate model accuracy, the following parameters were calculated: coefficient
351 of determination (R^2), mean error (ME) and mean square root of the prediction error
352 (RMSE). The spectral wavelengths of the sediment samples collected at the four outlets
353 were submitted to a principal component analysis (PCA) and hierarchical clustering on
354 principal components (package Factoshiny – Vaissie et al. 2020) for visualizing the
355 differences in samples used in the tributary approach.

356

357 **3 Results and discussion**

358

359 **3.1 Terrain analysis**

360

361 The spatial distribution of the TWI, SPI and LS Factor is found on Fig. 3. Results
362 of the terrain analysis are presented by subdividing potential erosion zones in different
363 sensitivity value classes and according to the different land uses.

364 **Fig. 3** Maps of Topographic Wetness Index (TWI), Stream Power Index (SPI) and
365 LS Factor.

366 In S1, 40% of the area has slopes between 8 and 20% (Fig. 4). S2 is the gentlest
367 sub catchment, around 60% of its area has low-levelled slopes (0 to 8%). Flat slopes
368 occupy less than 10% of S3's area and 40% of the hillslopes range from 8 to 20%. Steeper
369 slopes are located closer to the streams in both S1 and S3. Forests are found in steep areas
370 of S1 and S3, as well as grasslands and crop fields, although in different proportions.

371 **Fig. 4** Frequency histograms for Topographic Wetness Index (TWI), LS Factor,
372 Stream Power Index (SPI) and Slope of sub catchments and GMex.

373 Flat profile curvatures occupy 45, 47 and 44% of the area of S1, S2 and S3,
374 respectively. Convex and concave surfaces correspond each to around 27% of their areas.
375 Regarding plan curvatures, 96% of the area of S1 and S2, and 94% of S3's, are occupied
376 by planar surfaces. Divergent curvatures correspond to 1% of the sub catchments' areas.
377 Convergent curvatures correspond to 3% of S1 and S2's surfaces and 4% in S3. In all sub
378 catchments, crop fields are the land use with the most convergent surfaces (Fig. 5), except
379 for unpaved roads in S2. The most divergent surfaces are forests in S1 and S3, followed
380 by grasslands. In S3, the most divergent surfaces are over crop fields and grasslands.

381 **Fig. 5** Boxplots of zonal statistics analysis for topographic attributes (LS Factor,
382 Slope, Stream Power Index – SPI, Topographic Wetness Index – TWI and Plan
383 Curvature) and land uses in sub catchments 1, 2 and 3.

384 TWI ranged from around 5.5 to 21 in the sub catchments (Fig. 4). S1 and S3 have
385 similar TWI range distribution, and S2 has a larger area of higher TWI. Stream channels
386 have the highest median TWI values. Overall, TWI distribution among land uses is similar
387 (Fig. 5).

388 SPI ranged from 0 to around 290,000 in S1, to 340,000 in S2 and to 170,000 in
389 S3. Nearly 99% of the sub catchments' areas have values corresponding to less than
390 10,000. Therefore, greater differences are observed in the remaining area, for which data
391 were separated into five classes (Fig. 4) in each sub catchment and GMex. S1 shows a
392 tendency to increased soil erosion per area, given its greater percentage of higher SPI
393 values. In S1, the highest SPI values are found in crop fields followed by forests,
394 grasslands and stream channels (Fig. 5). As S2 has a greater drainage area, it reaches
395 higher SPI values. Grasslands reach the highest SPI values in S2, followed by forests and
396 crop fields. Unpaved roads also reach the highest value in S2. While in S3, the crop fields
397 and stream channels reach the highest values, followed by forests.

398 LS factor ranged from 0 to 27 in S1, 0 to 18 in S2 and 0 to 19 in S3 (Fig. 5). Higher
399 values were found closer to the drainage network. S1 and S3 show dense areas with higher
400 values due to the combination of high steepness and slope length in these zones,
401 explaining their high potential for erosion and material transport. Stream channels,
402 grasslands and forests in S1 are land uses that showed some of the highest LS Factor
403 values (Fig. 5). In S2, forests reach the highest value for this attribute. Given the LS factor
404 range, crop fields in S3 are likely more sensitive to erosion than in S1 and S2.

405 Most of the areas with steeper slopes in these sub catchments are occupied by
406 forests. Dense vegetation covers, such as those observed in forests, can intercept part of

407 the precipitation (Sari et al. 2016). This can delay the time for soil infiltration to be
408 exceeded and limit runoff rates. Slope analysis results show that S2 tends to have a lower
409 punctual erosive capacity than S1 and S3. S1 and S3 share some similarities in the ranges
410 of these indexes. Besides having a general tendency to increases in flow speed, given its
411 steeper slopes (Wilson and Gallant 2000), the presence of shallow soils (Fig. 2) may also
412 lead to greater surface runoff (Brosens et al. 2020).

413 A few larger zones of planar and linear curvature, which coincide with segments
414 of lower SPI values and high TWI values (Fig. 3), underline the occurrence of zones
415 where runoff and sediment may accumulate. Although higher TWI values may be
416 representative of overland flow connectivity in a catchment, isolated areas of higher TWI
417 are also indicative of hydrological sinks and disconnectivity or discontinuity in sediment
418 and runoff transfer, favoring sediment deposition (Jancewicz et al. 2019). S2 has larger
419 area of higher TWI values than the other two sub catchments (Fig. 4). Yet, SPI differences
420 among the sub catchments indicate that S2 has a higher runoff energy.

421 On hillslopes, higher TWI values can also indicate that these areas are more prone
422 to concentrated forms of erosion. For instance, Momm et al. (2012) used TWI to identify
423 the location of ephemeral gullies, Mihret et al. (2018) also found TWI to be successful in
424 predicting gully formation, along with SPI. In addition, Vijith et al. (2019) determined
425 that slope, SPI and the LS factor were some of the most crucial variables to predict erosion
426 susceptibility in a catchment. Mapping these variables provides a prerequisite to
427 implementing precision conservation, for soil and water conservation (Berry et al. 2005).
428 In Fig. 6 TWI and SPI maps over satellite images of crop fields of GMex show
429 concentrated forms of erosion corresponding to higher values of these indexes.

430 **Fig. 6** Comparison between higher TWI (a and b) and SPI (c and d) values and
431 satellite images in crop fields of sub catchment 1.

432 By this analysis, the most fragile zones are associated with crop fields, grasslands
433 and near the drainage network (Fig. 3). High index values were observed at upper
434 catchment locations on unpaved roads, a landscape component known to be prone to
435 runoff generation (Ziegler et al. 2000), such as crop fields are (Londero et al. 2017).

436

437 3.2 Erosion modeling

438

439 For each event (Table 1), only precipitation volume, rainfall duration and
440 imbibition were altered. Increases in volume and magnitude enhanced modeling outputs'

441 visualization in terms of runoff and sediment production's spatial distribution (Fig. 7).
442 Since we did not calibrate nor validate the model and used this analysis as a runoff/erosion
443 sensitivity index, results should be carefully interpreted as erosion estimates.

444 **Fig. 7** WaterSed output maps for runoff and erosion in the three sub catchments,
445 for events 1, 2, 3 and 4.

446 The values for surface runoff (m³) and sediment yield (kg) simulated at the outlet
447 of each sub catchment, and the maximum values for diffuse erosion (kg) observed within
448 each sub catchment are found in Table 4 in the supplementary material. Simulated runoff
449 and sediment yield of S2 were systematically the highest. S1 and S3 had, respectively,
450 the overall second highest and lowest amounts of runoff and sediment yield at their
451 outlets. The maximum erosion was observed in S2, followed by S1 and S3.

452 The spatial distribution of runoff increases the connectivity from upper segments
453 occurring in these catchments. The simulation of event 4 (Fig. 7), a lower volume rainfall,
454 shows lower runoff volumes. Flow on hillslopes was less connected to streams, but
455 unpaved roads provided significant zones of runoff generation. On the contrary, greatest
456 volume and magnitude from event 2 reflected on an enhanced connectivity.

457 Greater rainfall volumes led to increased sediment yield. The highest amounts
458 were obtained for S2. Despite the event's magnitude, the highest sediment yield for S1
459 and S3 were not observed at their outlets, but at upper catchment locations. S1 reached
460 higher values than S3, except for event 2. Higher values observed far from S1 and S3's
461 outlets can be attributed to runoff re-infiltration or sediment deposition calculated by the
462 model (Landemaine 2016). Considering the simulated values at the outlets, results
463 indicate S2's greater fragility, due to higher sediment yield, runoff and sediment
464 connectivity.

465 As for diffuse erosion, greater rainfall volumes led to greater amounts of erosion.
466 The zonal statistics analysis (Fig. 8) showed that crop fields are the most erodible land
467 use in all sub catchments, especially in S2 and S3. In S1, both forests and grasslands were
468 also prone to erosion. Paved areas and unpaved roads showed higher erosion proportions
469 in S1 than in S2 and S3. The opposite result was observed for stream channels.

470 **Fig. 8** Zonal statistics for diffuse erosion estimates and land uses in sub
471 catchments 1, 2 and 3.

472 With greater catchment area, S2 showed the greatest potential for runoff, sediment
473 yield and diffuse erosion. The maps (Fig. 7) indicate that unpaved roads can rapidly
474 generate runoff, even during low-intensity events. For greater rainfall volumes, the most

475 sensitive areas are located near the headwaters, in the vicinity of the drainage network
476 and steepest areas, similarly to the observations from terrain analysis.

477

478 3.3 Sediment fingerprinting

479

480 Calibration results and the associated statistical metrics showed a good
481 performance of the different models, although validation results showed large variations
482 in model performance. These results are shown in Table 3. Models for unpaved roads and
483 forests were the best in every sub catchment, with R^2 between 0.99 and 1.00 for
484 calibration, and between 0.71 and 0.93 for validation, indicating their good discrimination
485 of these sources. For all models, summed predictions reached totals slightly greater than
486 100%, in line with the overestimation observed by Poulenard et al. (2009) and attributed
487 to differences in soil and sediment material used for model calibration and prediction.

488 Since NIR range of soil spectra is influenced by different soil organic and mineral
489 constituents (Viscarra Rossel et al. 2006), forest models could have presented better
490 results due to highest organic matter content among the potential sources, resulting in
491 better distinction and model performance (Brosinsky et al. 2014). Low organic matter
492 content on unpaved roads may be responsible for their good discrimination, as observed
493 by Tiecher et al. (2016, 2021).

494 In contrast, model validation for topsoils showed R^2 results ranging from 0.28 to
495 0.36. This may be due to great variability in the sample material or insufficient sampling
496 to represent this source. Regarding stream channel contributions, Tiecher et al. (2016)
497 associated this source's good discrimination to the fact that soils located near the drainage
498 network are subject to biogeochemical alterations due to oxi-reduction reactions, leading
499 to a different mineral composition and, therefore, different spectral features.

500 Regarding sediment source contributions in S1, topsoil, unpaved roads and forest
501 showed variable sediment supply throughout time (Fig. 9). Stream channels displayed the
502 lowest variations in their contributions. A single sample presented 50% of the sediment
503 contribution originating from unpaved roads. This source supplies a mean contribution of
504 41%. Stream channels showed almost constant contributions to sediment, with an average
505 28% contribution. Finally, forests had the lowest sediment contribution (mean: 8%).

506 **Fig. 9** Boxplots for sediment source contribution in Fingerprinting 1 (**a**) and
507 Fingerprinting 2 (**b** = S1, **c** = S2, **d** = S3).

508 S2 had the lowest average forest contribution to sediment (mean: 1%). Unpaved
509 roads were the highest sediment source in S2, with an average of 50% and a maximum
510 contribution of 60% in an individual sample. Average agricultural topsoil contribution
511 was 27%. Stream channel sediment contribution varied from 15 to 38%, averaging 23%.

512 Unlike the previous sub catchments, the main sediment source for S3 was topsoil
513 (mean: 59%), followed by unpaved roads (mean: 24%). Stream channel had the lowest
514 contribution to sediment (mean: 18%) compared to the other sub catchments, varying
515 between 5 and 20%. Average forest contributions were lower than 7%.

516 There is a variation among the main sediment sources in the three sub catchments
517 and a significantly high contribution from unpaved roads in all of them (Fig. 9), especially
518 in S2. Stream channels also supplied a similar contribution (~ 23%) to sediment in all
519 catchments, although in lower proportions (18%) in S3 where the topsoil contribution
520 was higher (59%) than in S1 and S2.

521 Given S1's lower topsoil contribution, crop fields might not have contributed with
522 much sediment due to soil management based on no-till. As demonstrated by Londero et
523 al. (2017) and Deuschle et al. (2019), no-till's permanent biomass over the soil surface
524 protects it against erosion, decreasing sediment yield from agricultural plots. Although
525 vegetation cover may decrease sediment yield from crop fields, runoff may have
526 concentrated along hillslopes, leading to greater contributions from downstream
527 landscape components from the crop fields and grasslands, such as stream channels.

528 The lowest contribution from unpaved roads in S3 could be due to fewer road
529 segments within its drainage area, compared to S1 and S2, and to their location in the
530 upper portion of the sub catchment (Fig. 1).

531 Regarding tributary sediment contributions at GMex station (Fig. 9), on average,
532 almost 90% of sediment originated from S1 with a low contribution from S3. Contribution
533 from S2 ranged from 10 to 29%. Negative results found for S3 and its poor validation
534 results outline the need for analysing more powerful tracers to achieve a better
535 discrimination between sub catchments in the future. These contrasted results may also
536 be attributed to the large differences in geology and soil types found downstream from
537 the sub catchment's outlets and the characteristics of significant sources that could not be
538 sampled in the current research. This variation in geology and soil contributes to
539 increasing the variation in spectral data used to develop the estimation models. In
540 addition, the spectral data of the present study represents only the near-infrared region,
541 which is also a factor that results in less accurate estimates of sediment sources (Tiecher

542 et al. 2021). In the future, a denser sampling should be performed for better characterizing
543 sources drained by tributaries. Associated with this, spectral data in the visible and mid-
544 infrared regions should be used to improve the characterization of the organic and mineral
545 constituents of the sediment sources.

546 According to the PCA, sediment samples from S1, S2 and S3 are located close to
547 each other in the first dimension, in which the percentage of explained variance in the
548 dataset reaches 87.27%. Samples from S2 separate well from S1 and S3 in the second
549 dimension, explaining 9.94% of the variance. However, the samples from GMex were
550 also well separated from those of the sub catchments in both dimensions (Fig. 10), which
551 means that other sub catchments may be contributing to the sediment load at GMex.

552 **Fig. 10** Individuals factor map from Principal Components Analysis for sediment
553 samples for the outlets of sub catchments 1, 2 and 3, and GMex.

554 A hierarchical cluster analysis separated the samples from GMex in a first cluster,
555 and from S1, S2 and S3 in a second one. This shows there is a significant difference
556 between sediment samples collected at GMex and at the upstream catchments. Again, this
557 highlights the need to monitor unsampled regions within GMex, where the contribution
558 of additional sources may dilute that of the three sub catchments considered here.

559

560 3.4 The complementarity of tools to understand the erosive process

561

562 Terrain analysis and erosion modeling simulations' distribution of erosion-prone
563 areas in the sub catchments demonstrates that they are mainly located in crop fields and
564 near the streams, especially under grasslands and forests. Sediment fingerprinting results
565 further increased the knowledge on these catchment's terrain and erosion modeling
566 analysis, as it provided additional information on the significant contribution of unpaved
567 roads on sediment contribution.

568 The most fragile areas to erosion are those located near the drainage network,
569 similarly to what Capoane (2019) observed when assessing the erosion susceptibility of
570 a Brazilian catchment. There appears to be some disconnectivity between landscape
571 components and the drainage network among the sub catchments. Hotspots located near
572 the drainage channels can accumulate upstream runoff and run-on and connect them to
573 the river channel (Bracken and Croke 2007). Hydrological connectivity is most likely to
574 exist where distances from hillslope to channel are shorter (Bracken and Croke 2007).
575 Those spots can also be associated with the formation of rill and gully erosion, which act

576 as pathways for runoff to concentrate and be delivered with high transport and erosive
577 energy to the drainage network.

578 Forests are found in areas with steep slopes and higher values for LS Factor and
579 SPI, and they could be considered as very fragile. Erosion modeling outputs showed that
580 forests in S1 were slightly more erodible. Yet, according to modelling, forests have a
581 lower erosion potential and sediment fingerprinting showed that this land use provided
582 very low sediment contributions in all sub catchments. This demonstrates the role of
583 vegetation control on catchment degrading processes (Qiu et al. 2014).

584 Sediment fingerprinting results, such as those obtained by Tiecher et al. (2018) in
585 an agricultural catchment of Southern Brazil, showed high sediment contributions from
586 topsoil and stream channels. Topsoil contribution was the highest in suspended sediment
587 samples (Tiecher et al. 2018), so future studies in this catchment should also collect and
588 analyze samples in the water column taken in the rivers during flow events.

589 Sediment contribution from stream channels could be due to runoff leaving crop
590 fields and grasslands with sufficient energy to erode riverbanks and to transport sediment
591 from these sources. As this source was not simulated by WaterSed, it is difficult to directly
592 compare results obtained with the different methods, which leads to uncertainty. Other
593 uncertainties are related to the unsampled area between the sub catchments' and GMex's
594 outlets, which would incorporate the different soils found within this catchment.

595 S1 is likely the sub catchment with the most sensitive zones to erosion, according
596 to terrain analysis. According to erosion modeling, it had the second greatest simulated
597 sediment yield and runoff, whereas tributary sediment fingerprinting results showed it
598 supplied the highest sediment contribution to GMex. Regarding S3's sediment
599 fingerprinting, the greater contributions originated from topsoil, as higher SPI and LS
600 Factor values were observed in its crop fields. This is a major distinction compared to
601 observations in S1 and S2, where the greatest sediment contribution was from unpaved
602 roads. So, for S3, it can be concluded that terrain analysis provided a good representation
603 of the erosion processes caused by overland flow across topographically fragile areas.

604 Based on these attributes, S1 and S3 showed a somewhat similar
605 geomorphological organization, with the same dominant soil classes. Sediment samples
606 collected at their outlets were also grouped together by the PCA, demonstrating a similar
607 data variance. Yet, they behave differently when considering erosion modeling and
608 sediment fingerprinting results, with S1 sharing more similarities with S2 than S3,
609 demonstrating the impact of land use to control the sensitivity to erosion. Although S2

610 apparently had the highest disconnectivity caused by sinks, evidenced by terrain analysis,
611 erosion modeling showed that this sub catchment had the greatest potential for runoff
612 exported at the outlet. And the highest simulated sediment yield values were observed at
613 its outlet, in contrast to the observation of maximum sediment yield at upper locations in
614 S1 and S3, where significant sediment deposition occurred before reaching the outlet.

615 In S1 and S2, sediment contributions from topsoil and stream channels were found
616 to be high, although a great proportion of sediment originated from unpaved roads. This
617 confirms previous results obtained when calculating the sediment budget in a small
618 catchment of Southern Brazil, where, despite occupying a minor proportion of the surface
619 area, roads provided a significant sediment source contribution, supplying around 36% of
620 the sediment to the river system (Minella et al. 2014). Also in Southern Brazil, Thomaz
621 and Peretto (2016) found unpaved roads to have contributed with 70 to 87% of SSC in a
622 headwater catchment. Unpaved roads have great potential for generating deleterious
623 environmental impacts (Silva et al. 2021), such as increased runoff generation (Ziegler et
624 al. 2000) and SSC in rivers, especially in small order streams (Thomaz et al. 2013).

625 From terrain analysis, we can interpret erosion sensitivity from a topographic
626 point of view, but this is not the only erosion controlling factor in these catchments.
627 Therefore, we benefit from combining approaches as we add information on more
628 controlling factors to increase our understanding of complex natural phenomena.
629 Modelling incorporates the climate, soil and land use influence over erosion, as well as
630 its spatial distribution. In S1, for instance, there are steep slopes and high LS Factor and
631 SPI values near the drainage network and the erosion modelling results corroborate with
632 them, showing greater diffuse erosion in grasslands and forests, which occupy that area.
633 Yet, although terrain analysis would not reflect a great erosion sensitivity from unpaved
634 roads, modelling does show their importance as areas of limited infiltration that generate
635 runoff even during low magnitude rainfall events, promoting constant runoff and
636 sediment mobilization.

637 Still, there is great complexity regarding the connection between hillslope and
638 river channel in terms of sedimentation (Walling 1983). The greatest diffuse erosion in
639 S3 was from crop fields, as topsoil was the main sediment source of that catchment. Yet,
640 while modeling outputs for stream channel and unpaved roads were not as significant,
641 they are important sediment sources in S1 and S2, for instance. Sediment fingerprinting
642 reflects the integration of all erosion processes occurring in a catchment and, although

643 modelling added insights to the understanding of soil erosion, it may not be sufficient to
644 reflect the connectivity of a catchment (Wohl et al. 2019, Uber et al. 2021).

645 These complementary methodologies led to results with contrasted levels of
646 information, including basic and advanced techniques. They address different individual
647 erosion processes, from local to landscape observations and from the dynamic response
648 of hydrological and erosion processes during individual rainfall events to their integration
649 controlling the sediment yield at the catchment outlet. Despite the results model outputs,
650 the consistence and the added value of their insights provides evidence that there is
651 potential for validating the sediment fingerprinting results once erosion model outputs are
652 validated based on continuous river flow and sediment monitoring data.

653

654 **5 Conclusions**

655

656 Combining terrain, erosion modelling and sediment fingerprinting analyses
657 provided complementary insights into sediment dynamics in the region along the border
658 of the Southern Brazilian basaltic plateau. Terrain analysis and erosion modelling
659 outlined the specific fragility of crop fields, grasslands and areas located near the drainage
660 network, characterized by high connectivity to the river system, increasing
661 material/sediment transfer. When modeling greater rainfall intensity events, these areas
662 appeared to expand. Geomorphological similarities in sub catchments did not lead to
663 similar sediment contributions. This demonstrated the impact of vegetation cover to
664 control erosion in topographically sensitive areas. Unpaved roads supply important
665 sediment sources, followed by topsoil and stream channels, while forests showed
666 negligible contribution. Combining different environmental diagnosis techniques was
667 effective to outline the fragility of those areas where overland flow may accumulate and
668 lead to accelerated processes of soil degradation. Despite its limitations, sediment
669 fingerprinting provided very useful results that were confronted with those obtained from
670 the more classical terrain analysis and erosion simulations through the quantification of
671 sediment contributions from contrasted tributaries. The obtained information should be
672 useful to the public managers to guide the implementation of effective soil erosion control
673 measures across the landscapes of this environmentally fragile region of South America.

674

675 **Acknowledgments** The authors would like to thank the financial support from the
676 National Council for Scientific and Technological Development – CNPq, Project No.

677 437523/2018-7. The authors are grateful to the Laboratório Federal de Defesa
678 Agropecuária (LFDA Porto Alegre, RS) for allowing the NIR spectral readings.

679

680 **Declarations**

681 **Funding** This study was financially supported by the National Council for Scientific and
682 Technological Development – CNPq (grant number 437525/2018-7).

683 **Conflicts of interest/Competing interests** The authors declare that they have no conflict
684 of interest that are relevant to the content of this article.

685 **Availability of data and material** Data and material will be made available on
686 reasonable request.

687 **Code availability** Code will be made available on reasonable request.

688

689 **References**

690

691 Agência Nacional de Águas (ANA) (2021) Hidroweb.

692 <https://www.snirh.gov.br/hidroweb/serieshistoricas>

693 Ahmad I (2018) Digital elevation model (DEM) coupled with geographic information
694 system (GIS): an approach towards erosion modeling of Gumara watershed,

695 Ethiopia. *Environ Monit Assess* 190(10):568 <https://doi.org/10.1007/s10661-018-6888->

696 8

697 Alewell C, Borrelli P, Meusburger K, Panagos P (2019) Using the USLE: Chances,
698 challenges and limitations of soil erosion modelling. *Int Soil Water Conserv Res*

699 7(3):203-225 <https://doi.org/10.1016/j.iswcr.2019.05.004>

700 Alvares CA, Stape JL, Sentelhas PC, de Moraes Gonçalves JL, Sparovek G (2013)

701 Köppen's climate classification map for Brazil. *Meteorol Z* 22(6):711-728

702 <https://doi.org/2010.1127/0941-2948/2013/0507>

703 ASF DAAC (2010) Hi-Res Terrain Corrected; Includes Material © JAXA/METI 2010.

704 Accessed through ASF DAAC 2019. <https://doi.org/10.5067/Z97HFCNKR6VA>

705 Battista G, Schlunegger F, Burlando P, Molnar P (2020) Modelling localized sources of
706 sediment in mountain catchments for provenance studies. *Earth Surf Process Landf*

707 45(14):3475-3487 <https://doi.org/10.1002/esp.4979>

708 Berry JK, Delgado JA, Pierce FJ, Khosla R (2005) Applying spatial analysis for

709 precision conservation across the landscape. *J Soil Water Conserv* 60(6):363-370

- 710 Beven KJ, Kirkby MJ (1979) A physically based, variable contributing area model of
711 basin hydrology/Un modèle à base physique de zone d'appel variable de l'hydrologie du
712 bassin versant. *Hydrol Sci J* 24(1):43-69 <https://doi.org/10.1080/02626667909491834>
- 713 Bezak N, Mikoš M, Borrelli P et al (2021) Soil erosion modelling: A bibliometric
714 analysis. *Environ Res* 197:111087 <https://doi.org/10.1016/j.envres.2021.111087>
- 715 Boardman J, Vandaele K, Evans R, Foster ID (2019) Off- site impacts of soil erosion
716 and runoff: Why connectivity is more important than erosion rates. *Soil Use*
717 *Manag* 35(2):245-256 <https://doi.org/10.1111/sum.12496>
- 718 Boudreault M, Koiter AJ, Lobb DA, Liu K, Benoy G, Owens PN, Danielescu S, Li S
719 (2018) Using colour, shape and radionuclide fingerprints to identify sources of sediment
720 in an agricultural watershed in Atlantic Canada. *Can Water Resour J* 43(3) :347-365
721 <https://doi.org/10.1080/07011784.2018.1451781>
- 722 Bracken LJ, Croke J (2007) The concept of hydrological connectivity and its
723 contribution to understanding runoff- dominated geomorphic systems. *Hydrol Process:*
724 *Int J* 21(13):1749-1763 <https://doi.org/10.1002/hyp.6313>
- 725 Breiman L (2001) Random Forests. *Mach Learn* 45:5-32
726 <https://doi.org/10.1023/A:1010933404324>
- 727 Brosinsky A, Foerster S, Segl K, Kaufmann H (2014) Spectral fingerprinting: sediment
728 source discrimination and contribution modelling of artificial mixtures based on VNIR-
729 SWIR spectral properties. *J Soils Sediments* 14(12):1949-1964
730 <https://doi.org/10.1007/s11368-014-0925-1>
- 731 Brosens L, Campforts B, Robinet J, Vanacker V, Opfergelt S, Ameijeiras- Mariño Y,
732 Minella J, Govers G (2020) Slope gradient controls soil thickness and chemical
733 weathering in subtropical Brazil: understanding rates and timescales of regional
734 soilscape evolution through a combination of field data and modeling. *J Geophys Res*
735 *Earth Surf* 125(6) <https://doi.org/10.1029/2019JF005321>
- 736 Capoane V (2019) Susceptibilidade a erosão na bacia hidrográfica do córrego
737 Guariroba, Campo Grande, Mato Grosso do Sul. *Acta Bras* 3(2):49-55
738 <https://doi.org/10.22571/2526-4338180>
- 739 Cerdan O, Le Bissonais Y, Couturier A, Saby N (2002a) Modelling interrill erosion in
740 small cultivated catchments. *Hydrol Process* 16(16):3215-3226
741 <https://doi.org/10.1002/hyp.1098>
- 742 Cerdan O, Souchère V, Lecomte V, Couturier A, Le Bissonais Y (2002b)
743 Incorporating soil surface crusting processes in an expert-based runoff model: sealing

- 744 and transfer by runoff and erosion related to agricultural management. *Catena* 46(2-
745 3):189-205 [https://doi.org/10.1016/S0341-8162\(01\)00166-7](https://doi.org/10.1016/S0341-8162(01)00166-7)
- 746 Chabert C (2019) Modélisation distribuée de l'aléa érosif dans le bassin versant de la
747 Loire et nouvelles perspectives de validation. Thesis, Université Paris-Saclay
- 748 Collins AL, Blackwell M, Boeckx P et al (2020) Sediment source fingerprinting:
749 benchmarking recent outputs, remaining challenges and emerging themes. *J Soils*
750 *Sediments* 20(12):4160-4193 <https://doi.org/10.1007/s11368-020-02755-4>
- 751 Deuschle D, Minella JPG, Hörbe TAN, Londero AL, Schneider FJA (2019) Erosion and
752 hydrological response in no-tillage subjected to crop rotation intensification in southern
753 Brazil. *Geoderma* 340:157–163 <https://doi.org/10.1016/j.geoderma.2019.01.010>
- 754 Engman ET (1986) Roughness coefficients for routing surface runoff. *J Irrig Drain*
755 *Eng* 112(1):39-53 [https://doi.org/10.1061/\(ASCE\)0733-9437\(1986\)112:1\(39\)](https://doi.org/10.1061/(ASCE)0733-9437(1986)112:1(39))
- 756 Evrard O, Navratil O, Ayrault S, Ahmadi M, Némery J, Legout C, Lefèvre I, Poirel A,
757 Bonté P, Esteve M (2011) Combining suspended sediment monitoring and
758 fingerprinting to determine the spatial origin of fine sediment in a mountainous river
759 catchment. *Earth Surf Process Landf* 36(8):1072-1089 <https://doi.org/10.1002/esp.2133>
- 760 Gentine P, Troy TJ, Lintner BR, Findell KL (2012) Scaling in surface hydrology:
761 Progress and challenges. *J Contemp Water Res Educ* 147(1):28-40
762 <https://doi.org/10.1111/j.1936-704X.2012.03105.x>
- 763 Grangeon T, Vandromme R, Cerdan O, De Girolamo AM, Lo Porto A (2021)
764 Modelling forest fire and firebreak scenarios in a Mediterranean mountainous
765 catchment: Impacts on sediment loads. *J Environ Manag* 289:112497
766 <https://doi.org/10.1016/j.jenvman.2021.112497>
- 767 Grangeon T, Vandromme R, Pak LT, Martin P, Cerdan O, Richet JB, Evrard O,
768 Souchère V, Auzet AV, Ludwig B, Ouvry JF. Dynamic parameterization of soil surface
769 characteristics for hydrological models in agricultural catchments. Submitted to *Catena*
- 770 Gruber S, Peckham S (2009) Land-surface parameters and objects in hydrology. In:
771 Hengl T, Reuter HI (eds) *Geomorphometry: Concepts, Software, Applications*. Elsevier,
772 Amsterdam, pp 171-194
- 773 Haddadchi A, Ryder DS, Evrard O, Olley J (2013) Sediment fingerprinting in fluvial
774 systems: review of tracers, sediment sources and mixing models. *Int J Sediment*
775 *Res* 28(4):560-578 [https://doi.org/10.1016/S1001-6279\(14\)60013-5](https://doi.org/10.1016/S1001-6279(14)60013-5)

- 776 IUSS Working Group WRB (2015) World reference base for soil resources 2014,
777 update 2015: International soil classification system for naming soils and creating
778 legends for soil maps. *World Soil Resour Rep* 106:192
- 779 Ivanciuc O (2007) Applications of support vector machines in chemistry. *Rev Comput*
780 *Chem* 23:291 <https://doi.org/10.1002/9780470116449.ch6>
- 781 Jancewicz K, Migoń P, Kasprzak M (2019) Connectivity patterns in contrasting types of
782 tableland sandstone relief revealed by Topographic Wetness Index. *Sci Total*
783 *Environ* 656:1046-1062 <https://doi.org/10.1016/j.scitotenv.2018.11.467>
- 784 Julien PY (1995) *Erosion and sedimentation*. Cambridge University Press
- 785 Karydas C, Panagos P, Gitas IZ (2014) A classification of water erosion models
786 according to their geospatial characteristics. *Int J Digit Earth* 7(3):229-250
787 <https://doi.org/10.1080/17538947.2012.671380>
- 788 Laceby JP, Evrard O, Smith HG, Blake WH, Olley JM, Minella JP, Owens PN (2017)
789 The challenges and opportunities of addressing particle size effects in sediment source
790 fingerprinting: a review. *Earth-Sci Rev* 169:85-103
791 <https://doi.org/10.1016/j.earscirev.2017.04.009>
- 792 Landemaine V (2016) *Érosion des sols et transferts sédimentaires sur les bassins*
793 *versants de l'Ouest du Bassin de Paris: analyse, quantification et modélisation à*
794 *l'échelle pluriannuelle*. Thesis, Normandie Université
- 795 Lemma H, Frankl A, Griensven A, Poesen J, Adgo E, Nyssen J (2019) Identifying
796 erosion hotspots in Lake Tana Basin from a multisite Soil and Water Assessment Tool
797 validation: Opportunity for land managers. *Land Degrad Dev* 30:1449–1467
798 <https://doi.org/10.1002/ldr.3332>
- 799 Londero AL, Minella JPG, Deuschle D, Schneider FJA, Boeni M, Merten GH (2017)
800 Impact of broad-based terraces on water and sediment losses in no-till (paired zero-
801 order) catchments in southern Brazil. *J Soils Sediments* 18(3):1159-1175
802 <https://doi.org/10.1007/s11368-017-1894-y>
- 803 Londero AL, Minella JPG, Schneider FJA, Deuschle D, Menezes D, Evrard O, Boeni
804 M, Merten GH (2021a) Quantifying the impact of no-till on runoff in southern Brazil at
805 hillslope and catchment scales. *Hydrol Process* 35(3):e14094
806 <https://doi.org/10.1002/hyp.14094>
- 807 Londero AL, Minella JPG, Schneider FJA, Deuschle D, Merten GH, Evrard O, Boeni M
808 (2021b) Quantifying the impact of no-till on sediment yield in southern Brazil at

809 hillslope and catchment scales. *Hydrol Process* 35(7):e14286
810 <https://doi.org/10.1002/hyp.14286>

811 Martínez-Carreras N, Krein A, Udelhoven T, Gallart F, Iffly JF, Hoffmann L, Pfister L,
812 Walling DE (2010) A rapid spectral-reflectance-based fingerprinting approach for
813 documenting suspended sediment sources during storm runoff events. *J Soils Sediments*
814 10:400-413 <https://doi.org/10.1007/s11368-009-0162-1>

815 Merritt WS, Letcher RA, Jakeman AJ (2003) A review of erosion and sediment
816 transport models. *Environ Model Softw* 18(8-9):761-799 <https://doi.org/10.1016/S1364->
817 [8152\(03\)00078-1](https://doi.org/10.1016/S1364-8152(03)00078-1)

818 Meyer D, Dimitriadou E, Hornik K, Weingessel A, Leisch F, Chang CC, Lin CC (2014)
819 e1071: Misc functions of the Department of Statistics (e1071), TU Wien. R package
820 version 1(3)

821 Mhired DA, Dagneu DC, Assefa TT, Tilahun SA, Zaitchik BF, Steenhuis TS (2019)
822 Erosion hotspot identification in the sub-humid Ethiopian highlands. *Ecohydrol*
823 *Hydrobiol* 19(1):146-154 <https://doi.org/10.1016/j.ecohyd.2018.08.004>

824 Minella JP, Walling DE, Merten GH (2014) Establishing a sediment budget for a small
825 agricultural catchment in southern Brazil, to support the development of effective
826 sediment management strategies. *J Hydrol* 519:2189-2201
827 <https://doi.org/10.1016/j.jhydrol.2014.10.013>

828 Mitsova H, Hofierka J, Zlocha M, Iverson LR (1996) Modelling topographic potential
829 for erosion and deposition using GIS. *Int J Geogr Inf Syst* 10(5):629-641
830 <https://doi.org/10.1080/02693799608902101>

831 Momm HG, Bingner RL, Wells RR, Wilcox D (2012) AGNPS GIS-based tool for
832 watershed-scale identification and mapping of cropland potential ephemeral
833 gullies. *Appl Eng Agri* 28(1):17-29 <https://doi.org/10.13031/2013.41282>

834 Moore ID, Grayson RB, Ladson AR (1991) Digital Terrain Modelling: a review of
835 hydrological, geomorphological, and biological applications. *Hydrol Process* 5:3-30
836 <https://doi.org/10.1002/hyp.3360050103>

837 Nearing MA, Jetten V, Baffaut C, Cerdan O, Couturier A, Hernandez M, Le Bissonnais
838 Y, Nichols MH, Nunes JP, Renschler CS, Souchère V (2005) Modeling response of
839 soil erosion and runoff to changes in precipitation and cover. *Catena* 61(2-3):131-154

840 Owens PN, Blake WH, Gaspar L, Gateuille D, Koiter AJ, Lobb DA, Petticrew EL,
841 Reiffarth D, Smith HG, Woodward JC (2016) Fingerprinting and tracing the sources of
842 soils and sediments: earth and ocean science, geoarchaeological, forensic, and human

- 843 health applications. *Earth-Sci Rev* 162:1-23
844 <https://doi.org/10.1016/j.earscirev.2016.08.012>
- 845 Palazón L, Latorre B, Gaspar L, Blake WH, Smith HG, Navas A (2016) Combining
846 catchment modelling and sediment fingerprinting to assess sediment dynamics in a
847 Spanish Pyrenean river system. *Sci Total Environ* 569:1136-1148
848 <https://doi.org/10.1016/j.scitotenv.2016.06.189>
- 849 Patault E, Landemaine V, Ledun J, Soullignac A, Fournier M, Ouvry JF, Cerdan O,
850 Laignel B (2020) Predicting Sediment Discharge at Water Treatment Plant Under
851 Different Land Use Scenarios Coupling Expert-Based GIS Model and Deep Neural
852 Network. *Hydrol Earth Syst Sci Discuss* 1-26 <https://doi.org/10.5194/hess-2020-363>
- 853 Pedron FA, Dalmolin RSD, Moura-Bueno JM, Schenato RB, Soligo MF, Nalin RS,
854 Freitas HM (2021) Levantamento detalhado de solo da bacia do arroio Guarda Mor.
855 MSRS, Santa Maria
- 856 Poulénard J, Perrette Y, Fanget B, Quetin P, Trevisan D, Dorioz JM (2009) Infrared
857 spectroscopy tracing of sediment sources in a small rural watershed (French Alps). *Sci*
858 *Total Environ* 407:2808-2819 <https://doi.org/10.1016/j.scitotenv.2008.12.049>
- 859 QGIS Development Team (2020) QGIS Geographic Information System. Open Source
860 Geospatial Foundation Project <https://qgis.org>
- 861 Qiu Z, Hall C, Drewes D, Messinger G, Prato T, Hale K, Van Abs D (2014)
862 Hydrologically sensitive areas, land use controls, and protection of healthy
863 watersheds. *J Water Resour Plan Manag* 140(7):04014011
864 [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000376](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000376)
- 865 Rossetti L, Lima EF, Waichel BL, Hole MJ, Simões MS, Scherer CM (2018)
866 Lithostratigraphy and volcanology of the Serra Geral Group, Paraná-Etendeka Igneous
867 Province in southern Brazil: Towards a formal stratigraphical framework. *J Volcanol*
868 *Geotherm Res* 355:98-114 <https://doi.org/10.1016/j.jvolgeores.2017.05.008>
- 869 Sari V, Paiva EMCDD, Paiva JBDD (2016) Intercepção da chuva em diferentes
870 formações florestais na região sul do Brasil. *Rev Bras Recur Hidr* 21(1):65-79
871 <https://doi.org/10.21168/rbrh.v21n1.p65-79>
- 872 Savitzky A, Golay MJE (1964) Smoothing and differentiation of data by simplified least
873 squares procedures. *Anal Chem* 36:1627-1639 <https://doi.org/10.1021/ac60214a047>
- 874 Schneider FJA (2021) Modeling sediment yield on hillslopes under no-till farming.
875 Thesis, Universidade Federal de Santa Maria

- 876 Silva CC, Minella JPG, Schlesner A, Merten GH, Barros CAP, Tassi R, Dambroz APB
877 (2021) Unpaved road conservation planning at the catchment scale. *Environ Monit*
878 *Assess* 193(9):1-23 <https://doi.org/10.1007/s10661-021-09398-z>
- 879 Stevens A, Ramirez-Lopez L (2013) An introduction to the prospectr package. R
880 package Vignette R package version 0.1.3
- 881 Teng HF, Hu J, Zhou Y, Zhou LQ, Shi Z (2019) Modelling and mapping soil erosion
882 potential in China. *J Integr Agric* 18(2):251-264 [https://doi.org/10.1016/S2095-](https://doi.org/10.1016/S2095-3119(18)62045-3)
883 [3119\(18\)62045-3](https://doi.org/10.1016/S2095-3119(18)62045-3)
- 884 Thomaz EL, Peretto GT (2016) Hydrogeomorphic connectivity on roads crossing in
885 rural headwaters and its effect on stream dynamics. *Sci Total Environ* 550:547-555
886 <https://doi.org/10.1016/j.scitotenv.2016.01.100>
- 887 Thomaz EL, Vestena LR, Ramos Scharrón CE (2014) The effects of unpaved roads on
888 suspended sediment concentration at varying spatial scales—a case study from Southern
889 Brazil. *Water Environ J* 28(4):547-555 <https://doi.org/10.1111/wej.12070>
- 890 Tiecher T, Caner L, Minella JPG, Bender MA, Santos DR (2016) Tracing sediment
891 sources in a subtropical rural catchment of southern Brazil by using geochemical tracers
892 and near-infrared spectroscopy. *Soil Tillage Res* 156:478-491
893 <https://doi.org/10.1016/j.still.2015.03.001>
- 894 Tiecher T, Minella JPG, Evrard O, Caner L, Merten GH, Capoane V, Didoné EJ, Santos
895 DR (2018) Fingerprinting sediment sources in a large agricultural catchment under no-
896 tillage in Southern Brazil (Conceição River). *Land Degrad Dev* 29(4):939-951
897 <https://doi.org/10.1002/ldr.2917>
- 898 Tiecher T, Moura-Bueno JM, Caner L, Minella JP, Evrard O, Ramon R, Naibo G,
899 Barros CA, Silva YJ, Amorim FF, Rheinheimer DS (2021) Improving the quantification
900 of sediment source contributions using different mathematical models and spectral
901 preprocessing techniques for individual or combined spectra of ultraviolet–visible, near-
902 and middle-infrared spectroscopy. *Geoderma* 384:114815
903 <https://doi.org/10.1016/j.geoderma.2020.114815>
- 904 Uber M, Nord G, Legout C, Cea L (2021) How do modeling choices and erosion zone
905 locations impact the representation of connectivity and the dynamics of suspended
906 sediments in a multi-source soil erosion model?. *Earth Surface Dynamics* 9(1):123-44
907 <https://doi.org/10.5194/esurf-9-123-2021>
- 908 Vaissie P, Monge A, Husson F (2020) Perform Factorial Analysis from ‘FactoMineR’
909 with a Shiny Application. Package ‘Factoshiny’ version 2.2

- 910 Verheyen D, Diels J, Kissi E, Poesen J (2014) The use of visible and near-infrared
911 reflectance measurements for identifying the source of suspended sediment in rivers and
912 comparison with geochemical fingerprinting. *J Soils Sediments* 14(11):1869-1885
913 <https://doi.org/10.1007/s11368-014-0938-9>
- 914 Vijith H, Dodge-Wan D (2019) Modelling terrain erosion susceptibility of logged and
915 regenerated forested region in northern Borneo through the Analytical Hierarchy
916 Process (AHP) and GIS techniques. *Geoenvironmental Disasters* 6(1):8
917 <https://doi.org/10.1186/s40677-019-0124-x>
- 918 Viscarra Rossel RA, Behrens T (2010) Using data mining to model and interpret soil
919 diffuse reflectance spectra. *Geoderma* 158(1-2):46-54
920 <https://doi.org/10.1016/j.geoderma.2009.12.025>
- 921 Viscarra Rossel RA, Walvoort DJJ, McBratney AB, Janik LJ, Skjemstad JO (2006)
922 Visible, near infrared, mid infrared or combined diffuse reflectance spectroscopy for
923 simultaneous assessment of various soil properties. *Geoderma* 131(1-2):59-75
924 <https://doi.org/10.1016/j.geoderma.2005.03.007>
- 925 Walling DE (2013) The evolution of sediment source fingerprinting investigations in
926 fluvial systems. *J Soils Sediments* 13:1658-1675 [https://doi.org/10.1007/s11368-013-](https://doi.org/10.1007/s11368-013-0767-2)
927 [0767-2](https://doi.org/10.1007/s11368-013-0767-2)
- 928 Walling DE (1983) The sediment delivery problem. *J Hydrol* 65(1-3):209-237
929 [https://doi.org/10.1016/0022-1694\(83\)90217-2](https://doi.org/10.1016/0022-1694(83)90217-2)
- 930 Wildner W, Ramgrab GE, Lopes RC, Iglesias CMF (2008) Mapa Geológico do Estado
931 do Rio Grande do Sul (1:750,000) Porto Alegre: Serviço Geológico do Brasil
- 932 Wilson JP, Gallant JC (2000) Digital terrain analysis. *Terrain analysis: Principles and*
933 *applications* 6(12):1-27
- 934 Wohl E, Brierley G, Cadol D et al (2019) Connectivity as an emergent property of
935 geomorphic systems. *Earth Surf Process Landf* 44(1):4-26
936 <https://doi.org/10.1002/esp.4434>
- 937 Zevenbergen LW, Thorne CR (1987) Quantitative analysis of land surface
938 topography. *Earth Surf Process Landf* 12(1):47-56
939 <https://doi.org/10.1002/esp.3290120107>
- 940 Ziegler AD, Sutherland RA, Giambelluca TW (2000) Runoff generation and sediment
941 production on unpaved roads, footpaths and agricultural land surfaces in northern
942 Thailand. *Earth Surf Process Landf* 25(5):519-534 [https://doi.org/10.1002/\(SICI\)1096-](https://doi.org/10.1002/(SICI)1096-9837(200005)25:5<519::AID-ESP80>3.0.CO;2-T)
943 [9837\(200005\)25:5<519::AID-ESP80>3.0.CO;2-T](https://doi.org/10.1002/(SICI)1096-9837(200005)25:5<519::AID-ESP80>3.0.CO;2-T)

944

945 **Tables**

946

947 Table 1. Rainfall events characteristics.

948

	Rainfall event	Rainfall (mm)	Duration time (minutes)	Previous rainfall (48 hours)
1	08 October 2015	35	84	43.68
2	19 November 2015	80	222	14.07
3	14 December 2015	36	522	46.62
4	29 December 2015	25	168	16.8

949

950 Table 2. Number of potential sediment source samples and sediment samples.

951

Catchment/ Sources	Source samples						Sediment samples
	Crop fields	Unpaved Road	Stream Channel	Grassland	Forest	Total	Riverbed sediment
S1	8	9	9	7	6	39	7
S2	14	9	6	6	6	41	6
S3	6	6	6	6	6	30	6
GMex	-	-	-	-	-	-	6
Total	28	24	21	19	18	110	15

952

953 Table 3. Support Vector Machine models calibration and validation performance for
954 measured and predicted artificial mixtures composition.

955

	Sources	Performance indicator	Calibration	Validation
GMex	S1	R ²	1	0.58
		RMSE	2.75	25.46
		ME	0.34	-8.28
	S2	R ²	1	0.93
		RMSE	3.11	12.63
		ME	0.59	7.65
	S3	R ²	1	0.37
		RMSE	2.95	26.59
		ME	0.52	2.38
S1	Topsoil	R ²	1	0.36
		RMSE	3.31	20.01
		ME	0.19	3.43
	Stream channel	R ²	1	0.37
		RMSE	2.66	20.5

		ME	1.32	0.52
	Unpaved roads	R ²	1	0.92
		RMSE	2.58	6.52
		ME	0.84	2.76
	Forest	R ²	0.99	0.9
		RMSE	2.38	15.65
		ME	0.57	-3.5
S2	Topsoil	R ²	1	0.32
		RMSE	3.42	21.54
		ME	0.45	3.23
	Stream channel	R ²	1	0.37
		RMSE	2.6	19.63
		ME	0.95	1.4
	Unpaved roads	R ²	0.99	0.8
		RMSE	2.66	9.03
		ME	0.58	4.4
	Forest	R ²	0.99	0.29
		RMSE	2.57	24.76
		ME	0.7	-5.92
S3	Topsoil	R ²	1	0.28
		RMSE	3.38	22.06
		ME	0.22	7.68
	Stream channel	R ²	1	0.39
		RMSE	2.63	18.76
		ME	0.96	-0.1
	Unpaved roads	R ²	1	0.93
		RMSE	2.53	5.04
		ME	0.05	0.92
	Forest	R ²	0.99	0.71
		RMSE	2.74	23.23
		ME	0.91	-6

956

957 **Figure Captions**

958

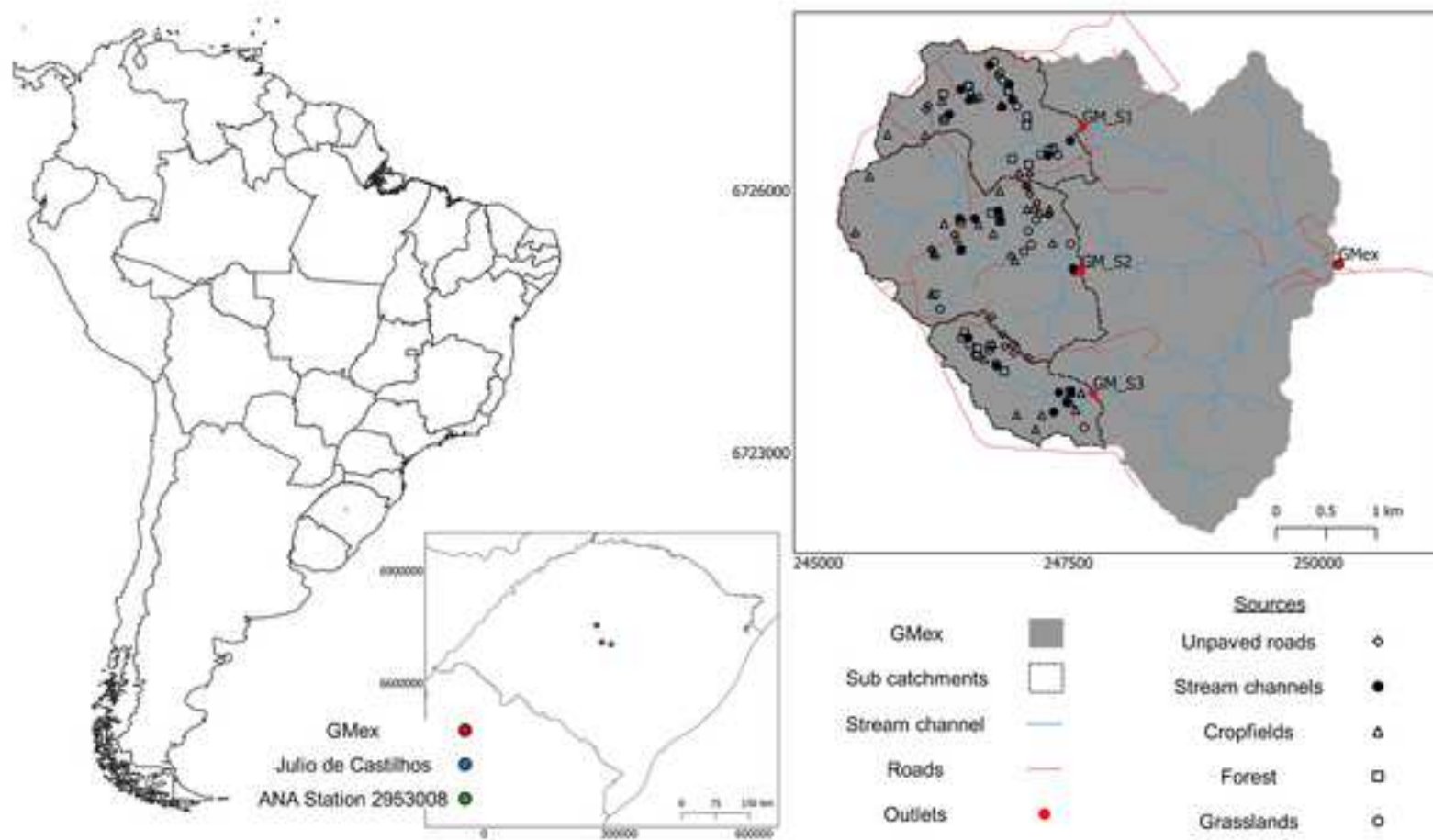
959 **Fig. 1** Location of Guarda Mor catchment, Júlio de Castilhos' rainfall-runoff monitoring
 960 station and ANA's weather station number 2953008 within the state of Rio Grande do
 961 Sul. In detail, soil and sediment sampling sites at Guarda Mor catchment

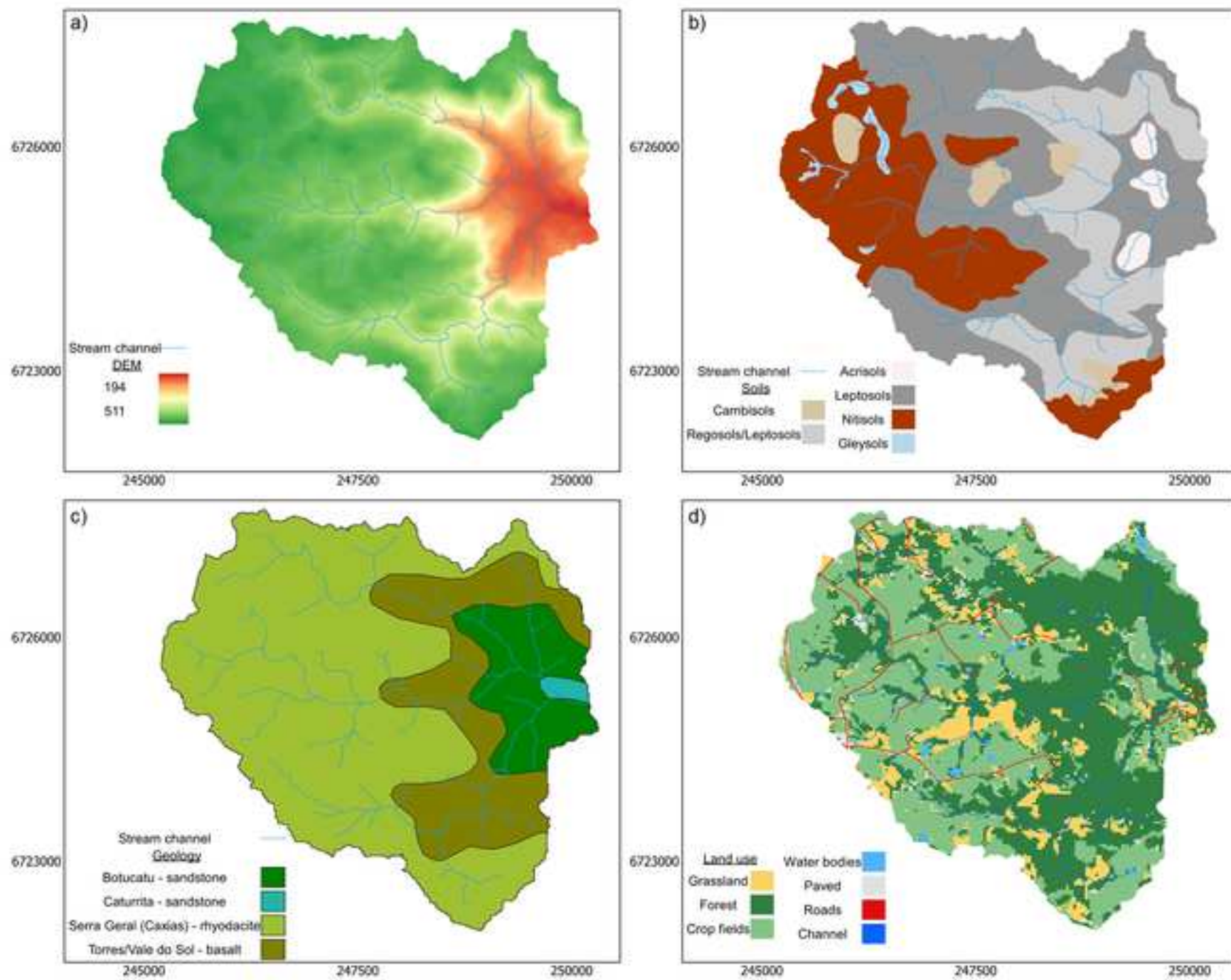
962 **Fig. 2** Guarda Mor catchment. **a** Digital elevation map. **b** Pedological and **c** geological
 963 maps. **d** Land use classification map

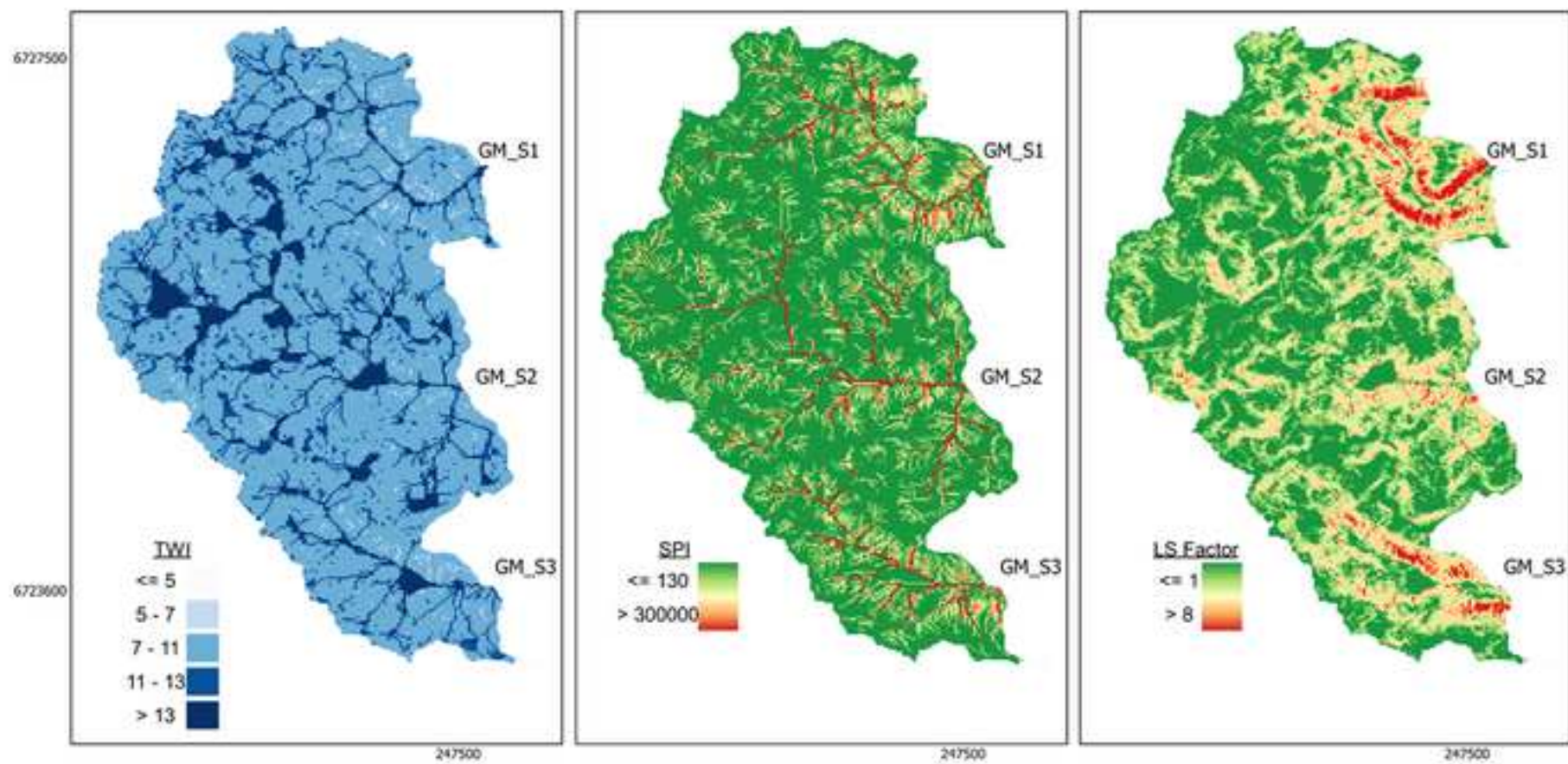
964 **Fig. 3** Maps of Topographic Wetness Index (TWI), Stream Power Index (SPI) and LS
 965 Factor

966 **Fig. 4** Frequency histograms for Topographic Wetness Index (TWI), LS Factor, Stream
 967 Power Index (SPI) and Slope of sub catchments and GMex

- 968 **Fig. 5** Boxplots of zonal statistics analysis for topographic attributes (LS Factor, Slope,
969 Stream Power Index – SPI, Topographic Wetness Index – TWI and Plan Curvature) and
970 land uses in sub catchments 1, 2 and 3
- 971 **Fig. 6** Comparison between higher TWI (**a** and **b**) and SPI (**c** and **d**) values and satellite
972 images in crop fields of sub catchment 1.
- 973 **Fig. 7** WaterSed output maps for runoff and erosion in the three sub catchments, for
974 events 1, 2, 3 and 4
- 975 **Fig. 8** Zonal statistics for diffuse erosion estimates and land uses in sub catchments 1, 2
976 and 3
- 977 **Fig. 9** Boxplots for sediment source contribution in Fingerprinting 1 (**a**) and
978 Fingerprinting 2 (**b** = S1, **c** = S2, **d** = S3)
- 979 **Fig. 10** Individuals factor map from Principal Components Analysis for sediment
980 samples for the outlets of sub catchments 1, 2 and 3, and GMex







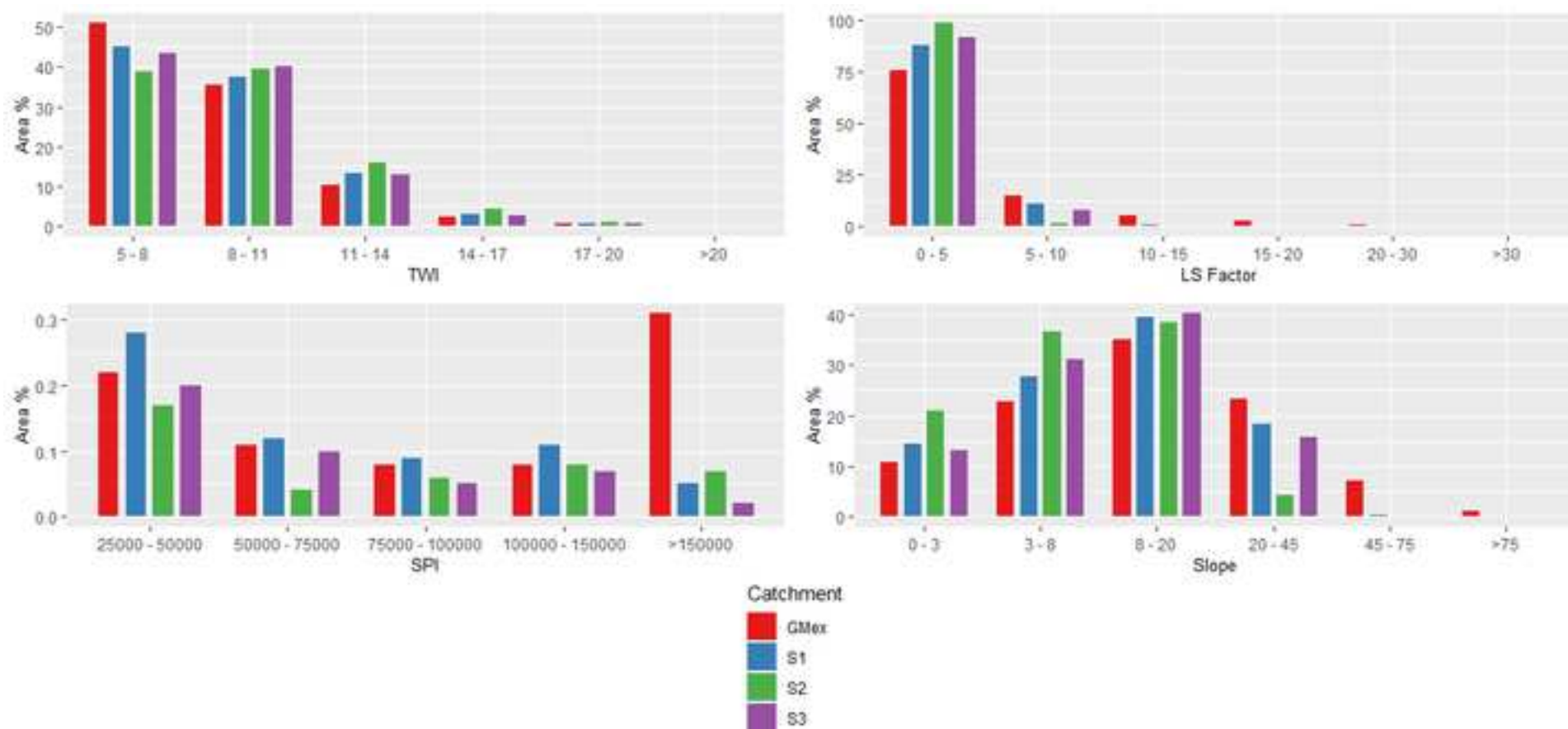
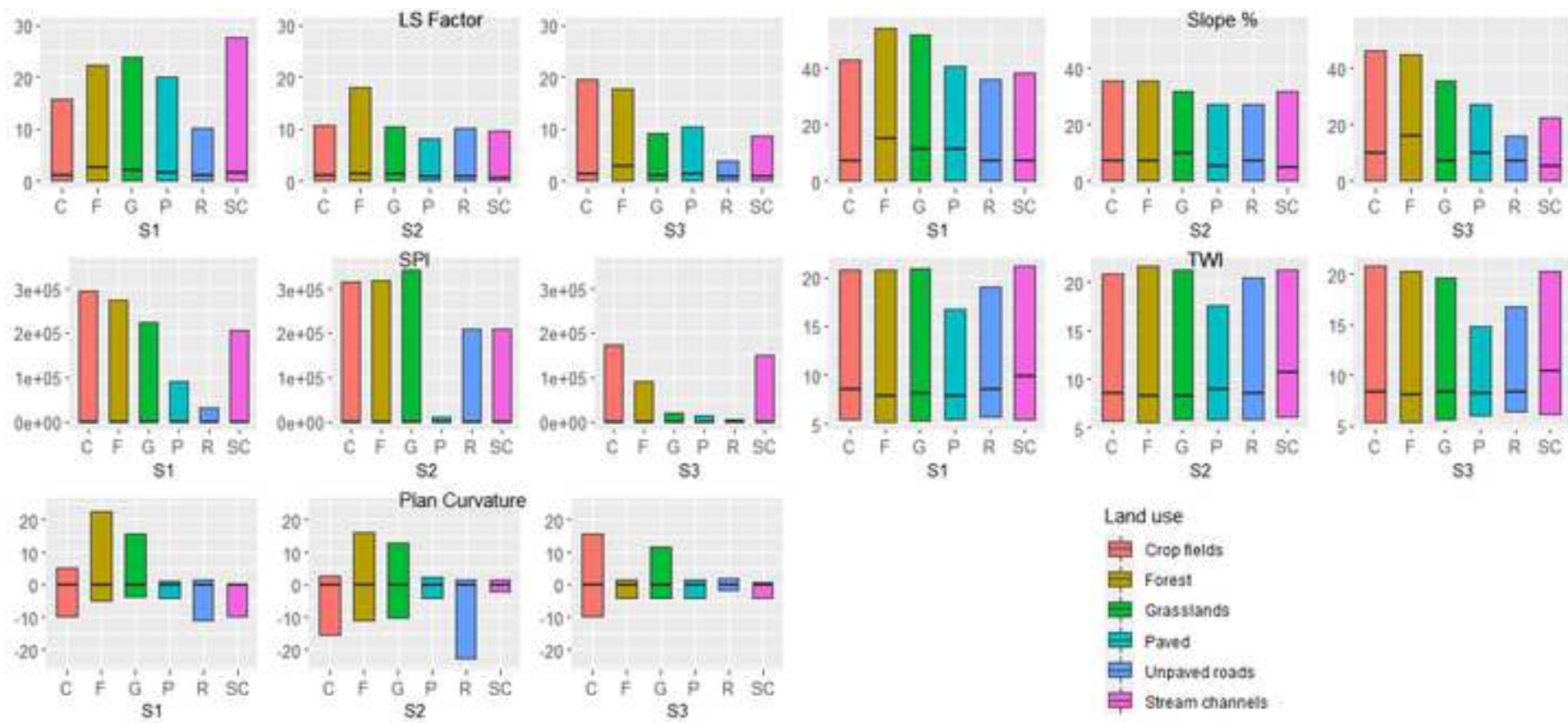


Fig. 5



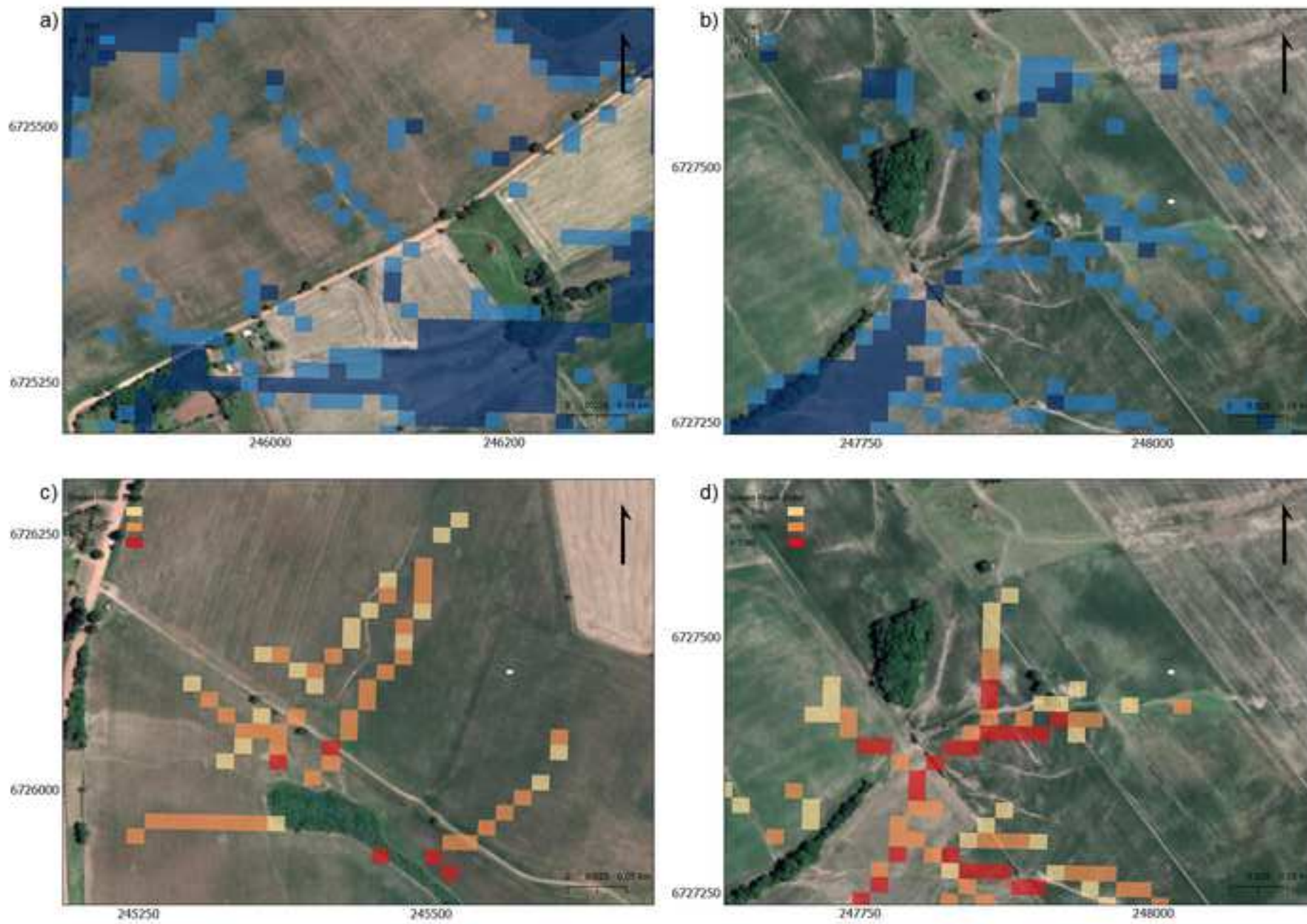


Fig. 7

