



Politecnico
di Bari

Repository Istituzionale dei Prodotti della Ricerca del Politecnico di Bari

Flood-prone areas assessment using linear binary classifiers based on flood maps obtained from 1D and 2D hydraulic models

This is a post print of the following article

Original Citation:

Flood-prone areas assessment using linear binary classifiers based on flood maps obtained from 1D and 2D hydraulic models / Manfreda, Salvatore; Samela, Caterina; Gioia, Andrea; Consoli, Giuseppe Gerardo; Iacobellis, Vito; Giuzio, Luciana; Cantisani, Andrea; Sole, Aurelia. - In: NATURAL HAZARDS. - ISSN 0921-030X. - 79:2(2015), pp. 735-754. [10.1007/s11069-015-1869-5]

Availability:

This version is available at <http://hdl.handle.net/11589/55904> since: 2021-03-13

Published version

DOI:10.1007/s11069-015-1869-5

Terms of use:

(Article begins on next page)

Flood-Prone Areas Assessment Using Linear Binary Classifiers based on Flood Maps obtained from 1D and 2D Hydraulic Models

Salvatore Manfreda¹, Caterina Samela¹, Andrea Gioia², Giuseppe Gerardo Consoli¹,
Vito Iacobellis², Luciana Giuzio¹, Andrea Cantisani¹ and Aurelia Sole¹

¹ Università degli Studi della Basilicata, Via dell'Ateneo Lucano 10, Potenza, Italy.

email: salvatore.manfreda@unibas.it,

² Politecnico di Bari, Via E. Orabona 4, Bari, Italy.

(Last modified 10/04/2015)

ABSTRACT

The identification of flood-prone areas is a critical issue becoming everyday more pressing for our society. A preliminary delineation can be carried out by DEM-based procedures that rely on basin geomorphologic features. In the present paper, we investigated the dominant topographic controls for the flood exposure using techniques of pattern classification through linear binary classifiers based on DEM-derived morphologic features. Our findings may help the definition of new strategies for the delineation of flood-prone areas with DEM-based procedures. With this aim, local features - which are generally used to describe the hydrological characteristics of a basin - and composite morphological indices are taken into account in order to identify the most significant one. Analyses are carried out on two different datasets: one based on flood simulations obtained with a 1-D hydraulic model, and the second one obtained with a 2-D hydraulic model. The analyses highlight the potential of each

morphological descriptor for the identification of the extent of flood-prone areas and, in particular, the ability of one geomorphologic index to represent flood inundated areas at different scales of application.

Keywords: flood hazard, DEM, terrain analysis, geomorphic approaches, ungauged basins.

1 ***1 INTRODUCTION***

2 Floods, which are becoming more frequent in urban areas, are one of the natural
3 phenomena more difficult to prevent and to deal with, especially in developing
4 countries (Douglas et al., 2012). The remarkable number of inundations that caused,
5 in the last decades, thousands of deaths and huge economic losses, testifies the
6 vulnerability of many Countries to the flood hazard. On one hand, the exposure of
7 human activities is increasing with the expansion of cities, leading to the reduction of
8 the natural water retention capacity of the soil (e.g., Cannon, 1994; Ceola et al.,
9 2014); on the other hand, there is a motivated suspect that the frequency of great
10 floods is increasing with time (e.g., Milly et al., 2002; Prudhomme, 2002). The
11 current situation is pushing the international community to find new strategies to cope
12 with flood hazards.

13 The European legislation has introduced new policies for the assessment and
14 management of flood risk for territory protection with the Floods Directive
15 2007/60/EC. This Directive requires Member States to assess the flood risk, mapping
16 the flood extent over their territories, in order to evaluate assets and humans at risk,

17 and to take adequate and coordinated measures to reduce this risk for a sustainable
18 hydraulic protection of the territory. The European case is just an example of context
19 where the flood risk is felt as a critical issue that should be faced, in terms of
20 planning, at a large scale. For this reason, the definition of procedures able to provide
21 extended description of the flood-prone areas is a growing need in Europe and several
22 other countries. Therefore, much effort is going into the identification of flood-prone
23 areas through the use of time-consuming hydrological/hydraulic simulations.

24 The patterns of flood inundations are also critical for the ecology of floodplains
25 (Townsend et al., 1998). In fact, the temporal and spatial dynamics of floods may
26 alter the distribution of vegetation and biodiversity of wetlands (Sharitz and Mitsch;
27 1993). Therefore, the accurate representation of inundation extents, as well as of
28 surface water bodies, is crucial for the management and conservation of wetland
29 ecosystems (Nei et al., 2009; Bridgham et al., 2013).

30 In this framework, the research has recently shown that the delineation of flood-prone
31 areas can be carried out using simplified methods that rely on basin geomorphologic
32 features (e.g., Nardi et al., 2006; Manfreda et al., 2011; Degiorgis et al., 2012;
33 Manfreda et al., 2014a; Jalayer et al., 2014; De Risi et al., 2014; Papaioannou et al.,
34 2014). Such innovative procedures may provide a preliminary delineation of the
35 flood-prone areas useful for the planning of numerical analyses, and for insurance
36 companies that have a growing interest toward the identification of the assets and
37 population at risk.

38 This kind of approach may be extremely beneficial in the definition of new
39 procedures for the identification of flooded areas from remote sensing techniques,
40 where the topographic information may be used as external constraint in the adopted

41 algorithms, that generally rely only on the local slope or the distance to the channel
42 (e.g., Brivio et al., 2002). For instance, Fluet-Chouinard et al. (2014) used the
43 topographic information to generate inundation probability maps for downscaling
44 course-scale remote sensing data.

45 In particular, Degiorgis et al. (2012) introduced the use of linear binary classifiers to
46 investigate the relationships between several morphological features and the flooding
47 hazard at the catchment scale. In the present work, we extend the number of
48 morphological features investigated, using single local features as well as composite
49 indices (built with the specific aim to represent a metric of flood hazard) derived from
50 Digital Elevation Models (DEMs).

51 The performances of the selected morphological features on the Bradano River
52 (Southern Italy) are evaluated at different scales of application, using two reference
53 flood inundation maps: one obtained applying a mono-dimensional approach over the
54 entire basin (basin scale) and one obtained using a two-dimensional approach at the
55 basin outlet (local scale). This last represents an extremely interesting study case that
56 has never been considered for geomorphic applications. In fact, most of the
57 applications made since now have only compared morphological features with mono-
58 dimensional simulations over mountainous areas, but it is well known that the most
59 challenging problem for hydraulic studies is represented by flat areas. Hence, the
60 main motivation for this study is the identification of a metric suitable for both
61 mountainous and flat areas.

62 In recent studies, the best-performing local features, among those adopted, were the
63 difference in elevation between the considered point and the source of risk (H), and
64 the distance from the nearest stream (D). These features have been also applied in the

65 present study case with a number of additional morphological indices. Results
66 highlighted remarkable differences in the performances of indices and features
67 applied in different contexts. The study allowed to better address the sensitivity of
68 each index with the change of scale, spatial resolution, etc.

69

70 **2 STUDY AREA**

71 The Bradano River is one of the major rivers of the Basilicata Region (southern
72 Italy), with a drainage area of about 2,765km². The climate is characterized by a dry-
73 sub humid regime with scarce rains and zero base flow during the summer period (see
74 Fiorentino et al., 2007). More than the 77% of the total surface is covered by
75 agricultural areas, and only the 23% by woodlands and semi-natural areas (this
76 information is provided by the CORINE-Land Cover map of the European
77 Environmental Agency). The upper basin is characterized by a marked topography;
78 by contrast, the terminal portion of the basin, close to the outlet, is extremely flat.

79 This river basin is one of the most critical in terms of flooding for both the Basilicata
80 and the contiguous Puglia Region. It produced several floods, causing significant
81 damages especially in the portion of the basin close to the river outlet to the Ionian
82 Sea. The first documented flood of the Bradano River refers to the 1827, when two
83 bridges were destroyed interrupting the connection from the South to the City of
84 Matera (this historical event is documented in the archives of the Kingdom of the
85 Two Sicilies under Ferdinando II). Later on, a dramatic event occurred in 1959 when
86 the cities near the coast were significantly damaged and several buildings were
87 destroyed. More recently, flooding also occurred in 1972, 2004 and 2011 (see Figure
88 1), producing inundations in the outlet portion of the river basin, which is

89 characterised by gentle slopes and flat surfaces. Some additional information on the
90 damages produced by most of these events can be found on <http://www.evalmet.it/>.

91

92 **3 METHODS AND DATASETS**

93 **3.1 Flood Maps**

94 The extent of the inundated areas was studied by the River Basin Authority of
95 Basilicata (RBAB), that mapped all the rivers of this region. The complex
96 morphological characteristics of the basin forced the RBAB to use both one-
97 dimensional (1D) and two-dimensional (2D) hydraulic models for flood mapping.
98 The first was used for flood propagation along the main river, while the 2D model
99 application was limited to a smaller portion of the river basin nearby the outlet (about
100 80km²) characterised by extremely flat surfaces, in order to reduce the computational
101 efforts.

102 Two-dimensional models allow studying flood propagation in the areas where it is not
103 possible to recognize a prevailing direction of the water flow. Nevertheless, these
104 models are computationally intensive and for this reason their application is generally
105 limited to a portion of a river basin, while 1D models allow providing a more
106 extensive description of the flood extent at the basin scale. In fact, in the present case
107 the evaluation of the flood-prone areas for a given return period for the main river
108 was carried out by the use of the HEC-RAS model (HEC-RAS, 2010), which is less
109 reliable when dealing with the flat portion of the river basin. Therefore, the basin
110 outlet was investigated by using a 2D approach. Both maps were obtained using a
111 synthetic hydrograph derived from regional analyses assuming a return period of 30
112 years. The flood peak was calculated using the VAPI methodology (Claps et al.,

113 1999), while the synthetic hydrograph was obtained exploiting the synthetic flow
114 hydrograph proposed by NERC (1975) and modified by Fiorentino & Margiotta
115 (1999).

116 It is necessary to remark that the RBAB's studies are limited to a portion of the basin
117 that includes the main River, but several tributaries are not analyzed. Therefore, it is
118 highly desirable to have a tool able to provide an extensive characterization of the
119 flood hazard over the entire river network. With this aim, we explored the use of
120 binary classifiers exploiting the two flood maps that refer to the same basin, but differ
121 for reference scale, DEM resolution and methodology adopted for flood mapping.

122 In order to clarify the procedure used by the RBAB to delineate flood maps, it is
123 useful to provide some additional information about the models adopted. One model
124 is HEC-RAS that probably does not require further descriptions, being a widely used
125 software well documented on the web page of US army Corps of Engineers
126 (<http://www.hec.usace.army.mil>). On the contrary, it seems appropriate to provide
127 additional information about the 2D hydraulic model named FLORA-2D (FLOOD and
128 Roughness Analysis) recently introduced by Cantisani et al. (2012, 2014).

129

130 **3.2 FLORA-2D**

131 FLORA-2D was developed recently within a collaboration between the University of
132 Basilicata and the company "Research on Energy System" (RSE spa). It has been
133 developed with the aim to simulate flood propagation in flat areas taking into
134 consideration the dynamic effect of vegetation. In fact, flow resistance due to
135 vegetation can be a dominant factor in the inundation process for relatively shallow
136 inundation (<1 m).

137 FLORA-2D has the capability to simulate the inundations considering the spatial and
138 temporal variation of the resistance due to vegetation. Each node of the
139 computational matrix has a roughness coefficient depending on the type of
140 vegetation, flow depth and velocity. In particular, the Manning coefficient n is
141 calculated according to Petryk and Bosmajian (1975) when the vegetation is rigid,
142 and Freeman et al. (2000) in the case of flexible vegetation. The general algorithm
143 governing the flood propagation is based on the “shallow water equations” simplified
144 by neglecting the convective terms.

145 The model has been validated over the Bradano river using flood maps obtained from
146 satellite data. This kind of procedure is becoming more common with the increased
147 potentials of remote sensing products (see e.g., Frappart et al., 2005; Iacobellis et al.,
148 2013, Domeneghetti et al., 2014). An example of a remote sensed image for the flood
149 event of March 2011 is given in Figure 1.A, which has been used by Cantisani et al.
150 (2014). Model reliability has been further investigated using for comparison the
151 model Mike21 HD by the Danish Hydraulic Institute, FLO-2D by O'Brien (2007),
152 FLATModel by Medina et al. (2007). In all cases, the results were comparable in
153 terms of flood extent, but with the great advantage of a significant reduction of the
154 computational costs.

155 In the present application, the computational domain was defined by a square grid
156 with resolution of 10m, while the time step was set to 2sec. This resolution provides a
157 good compromise between simulation time and data accuracy for a correct
158 representation of the process (Sole et al., 2011). It was also observed that the time
159 step of 2s ensures the model stability.

160 The above-mentioned hydrograph was assigned as upstream boundary condition,

161 while a constant water level equal to 0.5 m a.s.l. was considered as downstream
162 boundary condition (the sea level is assumed slightly above the ordinary conditions).
163 Finally, the spatial distribution of the flow resistance was derived from LiDAR data,
164 used to generate maps of vegetation height (Cobby et al., 2001).

165 **3.3 Digital Elevation Models**

166 Digital Elevation Models (DEMs) contain a significant amount of information that
167 may be helpful for the delineation of flood-prone areas (see e.g., Manfreda et al.,
168 2014).

169 In the present case, we used, for the entire river basin, the USGS HydroSHEDS
170 (Hydrological data and maps based on SHuttle Elevation Derivatives at multiple
171 Scales-hydrosheds.cr.usgs.gov/index.php) elevation data, available for the entire
172 globe at a fairly good resolution; instead for the portion of the basin outlet we
173 adopted a high resolution LIDAR-derived DEM.

174 Figure 2 provides a graphical description of the investigated area; in particular,
175 Figure 2.A describes the digital elevation model of the Bradano river basin (called
176 SRTM DEM), extracted from HydroSHEDS (hydrosheds.cr.usgs.gov/index.php) and
177 Figure 2B shows the digital elevation model at the outlet (called LiDAR DEM) of the
178 same basin, extracted from a LiDAR high-resolution DEM and resampled to a 10m x
179 10m grid.

180 HydroSHEDS DEMs are derived from remote sensed elevation data of the NASA
181 Shuttle Radar Topography Mission (SRTM). The original SRTM data have been
182 conditioned using a sequence of automated procedures: a DEM-VOID has been
183 released, where the no-data voids have been filled and the main elevation
184 inconsistencies removed. Furthermore, a DEM-CON is also available for

185 hydrological applications; it has been further conditioned in order to accurately
186 reproduce the actual river network. The conditioning process alters the original
187 elevation data and this limits the use of the DEM–CON to drainage network
188 identification procedures. Both the mentioned DEMs have been used for the Bradano
189 River, with a resolution of 3 arc-second that corresponds, for the current study area,
190 to a square grid size of about 90m.

191 The LiDAR high-resolution DEM, instead, was obtained combining airborne LiDAR
192 survey and field measurements that were carried out specifically for the RBAB,
193 paying particular attention to position and elevation of levees. The laser scanning
194 survey was carried out with a density of point equal to 0.7 points/m².

195 Figure 3 provides a representation of the standard flood maps used as reference for
196 the application of the linear binary classification. In particular, Figure 3.A shows a
197 flood map derived using a one-dimensional approach over the entire Bradano River,
198 instead Figure 3.B provides a representation of the flooded areas identified by the
199 application of the FLORA-2D model at the outlet of the Bradano basin.

200 **3.4 LINEAR BINARY CLASSIFIERS AND ROC ANALYSIS**

201 Techniques of pattern classification are used to compare DEM-derived quantitative
202 morphologic features and existing flood hazard maps. The linear binary classifiers
203 represent a useful tool for the scope, allowing a quantitative comparison between two
204 binary maps (see Degiorgis et al., 2012). In particular, the flooded areas are easily
205 converted into a binary map assigning a code 1 for flooded areas and a code 0 for
206 marginal hazard areas. The marginal hazard areas are introduced in order to identify
207 the portion of the river basin where a clear distinction between flooded and non-
208 flooded areas is possible. The comparison with morphological features is possible

209 imposing a threshold value to distinguish between the two possible values of the map.
210 In this scheme, the threshold value becomes a parameter that may be changed in
211 order to optimize the performance of each feature.

212 Binary classifiers need to be trained. For this reason, areas predicted as flooded by the
213 use of hydraulic models (one-dimensional over the entire Bradano basin and two-
214 dimensional at the outlet) are used to calibrate the optimal threshold that allows to
215 distinguish flood-prone areas for each selected feature.

216 Single and composite morphologic features are scaled in normalized features lying
217 between -1 and 1. Different normalized thresholds are applied to each normalized
218 features obtaining a binary map of 0 and 1. Comparing this map with the flood map
219 obtained by the hydraulic model, there are four possible conditions in each point of
220 the map: if the threshold detects a flooded area when this condition is present, the
221 point is counted as a true positive; otherwise, if it classifies a point as non-flooded
222 (negative), it is counted as a false negative. If the site is defined non-flooded by the
223 inundation map and it is classified as negative, it is counted as a true negative;
224 otherwise, if it is classified as positive, it is counted as a false positive.

225 The quality of each binary classifier is evaluated using the Receiver Operating
226 Characteristic (ROC) curves that represent a good measure of performance. The ROC
227 graphs are obtained by varying the threshold of the classifier and are defined as the
228 set of pairs of true positive rate (plotted on the Y axis) and false positive rate (plotted
229 on the X axis). ROC curves are also used to select a suitable threshold value (see
230 Fawcett, 2006).

231 We recall that the true positive rate (also called hit rate) is estimated as:
232

233
$$r_{tp} \approx \frac{\text{Positives correctly classified}}{\text{Total positives}} \quad [1]$$

234

235 The false positive rate (also called false alarm rate) of the classifier is:

236

237
$$r_{fp} \approx \frac{\text{Negatives incorrectly classified}}{\text{Total negatives}} \quad [2]$$

238

239 The diagonal line $y = x$ represents the strategy of randomly guessing a class. Any
240 classifier that appears in the higher left triangle performs better than random
241 selection. The best value of the normalized threshold is obtained by minimizing the
242 sum of the false positive rate and the false negative rate $r_{fp} + (1 - r_{tp})$ assigning equal
243 weights to the two rates.

244 In order to compare different kinds of binary classifiers, a common method to reduce
245 ROC performance to a single scalar value is to calculate the Area Under the ROC
246 Curve, abbreviated AUC. The value of the AUC ranges from 0.5 (completely random
247 classifier) to 1.0 (perfectly discriminating classifier).

248

249 **3.4.1 SINGLE FEATURES**

250 In the present section, we provide a synthetic description of the DEM-derived
251 morphologic features adopted in the present study. Among all possible features, we
252 considered the same list adopted by Degiorgis et al. (2012):

- 253 1. the upslope contributing area, A_s [m^2];
254 2. the surface curvature, $\nabla^2 H$ [-], defined as the Laplacian of the elevation;

- 255 3. the local slope, S [-], estimated as the maximum slope among the eight possible
256 flow directions that connect the cell under exam to the adjacent cells;
- 257 4. the distance from the nearest stream, D [m], defined as the length of the path that
258 hydrologically connects the location under exam to the nearest element of the
259 reference drainage network;
- 260 5. the elevation to the nearest stream, H [m], computed as the difference between the
261 elevation of the cell under exam and the elevation of the final point of the above-
262 identified path.

263 A description of these features computed for the Bradano River Basin is given in
264 Figure 4, where one can observe the plots obtained using the DEM at 90m of
265 resolution in Figure 4.A (for the entire basin), while the features obtained for the
266 basin outlet with a DEM at 10m of resolution are given in Figure 4.B. It is necessary
267 to specify that in this last case features like the contributing area have been corrected
268 in order to avoid border effects assigning to the channel cells on the border values
269 derived from the larger DEM.

270

271 **3.4.2 COMPOSITE INDICES**

272 In addition to the mentioned features, a number of composite indices have been also
273 used. Some of these indices are taken from the literature and others have been defined
274 with the aim to describe the relative distance between the water surface during a flood
275 and the local elevation (see Manfreda et al., 2014b). In particular, we adopted the
276 following indices:

277

278 ▪ The modified topographic index, TI_m , first introduced by Kirkby (1975), has
 279 proven to be a good indicator for the delineation of areas exposed to flood
 280 inundation (Manfreda et al., 2011). This index takes the form:

$$281 \quad TI_m = \ln\left(\frac{A_d^n}{\tan(\beta)}\right), \quad [3]$$

282 where A_d [m] is the drained area per unit contour length, $\tan(\beta)$ is the local gradient,
 283 n is an exponent <1 .

284

285 ▪ The downslope index, DW_i , proposed by Hjerdt et al. (2004) represents a new way
 286 of estimating the hydraulic gradient. The method does not use the exit point at the
 287 stream as reference; instead, it calculates how far (L_d [m]) a parcel of water has to
 288 travel along its flow path to lose a certain amount of potential energy (d [m]). This
 289 index is defined as:

$$290 \quad \tan(\alpha_d) = \frac{d}{L_d}, \quad [4]$$

291 where d was set equal 5m in the present case.

292

293 ▪ H/D : it is obtained by calculating the ratio between the flow distance D and
 294 elevation difference H .

295

296 ▪ $\ln[h(A_s)/H]$: this index aims to compare in each point a variable water depth h with
 297 the elevation difference H , where h is calculated for each basin cell assuming a
 298 scaling relationship with the contributing area (A_s) by using an hydraulic scaling
 299 relation:

$$300 \quad h(A_s) \approx A_s^n, \quad [5]$$

301 where h is the water depth [m], A_s is the upslope contributing area at the point of
302 interest [m^2], n is the exponent (dimensionless) set equal to 0.3 (see e.g. Nardi et
303 al., 2006).

304

305 ▪ $\ln[h(A_r)/H]$: this index is similar to the previous one, but in this case h is
306 computed as a function of the contributing area A_r in the section of the drainage
307 network hydrologically connected to the point under exam (see figure 4).

308

309

310 ▪ $[h(A_r) - H] / \tan(\alpha_d)$: this index aims to describe, in each point of the
311 investigated basin, the change between water depth $h(A_r)$ and the elevation
312 difference H divided by a surrogate of the hydraulic gradient represented by the
313 downslope index.

314

315 ▪ $[h(A_r) - H] / D$: this index aims to describe, in each point of the investigated basin,
316 the change between water depth $h(A_r)$ and the elevation difference H divided by
317 the distance D .

318 All the indices and features are standardized in order to assume a value included in
319 the range -1 and 1.

320 Figure 6 provides a visual description of the introduced indices computed for the
321 entire Bradano River basin (A) and the Bradano outlet (B). It is necessary to state that
322 the present list of indices was developed by the authors with the specific aim of
323 identifying an hydraulic metric able to account for the main features affecting flood

324 diffusion on the landscape. These indices have been tested also on the Tiber River in
325 Manfreda et al. (2014b).

326

327 **4 RESULTS AND DISCUSSION**

328 All suggested features and composite indices have been used to explore their
329 individual ability to describe flood hazard in the Bradano River basin. Given the
330 strong morphological differences existing between the main river and its terminal
331 part, it is extremely interesting to compare the performances of indices applied over
332 the two areas.

333 Figures 7 and 8 show respectively the ROC curves obtained by separately
334 thresholding each feature on the proposed study area for the two datasets previously
335 introduced. In Figures 7, ROC curves are obtained by comparing the proposed
336 features with the flood map of the Bradano basin obtained by using a 1-D hydraulic
337 model, while in Figure 8 by comparing the proposed features with the flood map of
338 the outlet of Bradano basin evaluated using a 2-D hydraulic model. Generally, the
339 best performing parameters are those that minimize the area above the curve or
340 maximize the area under the curve.

341 The visual comparison of all ROCs highlights the potential of each feature or index in
342 delineating the flood-prone areas in different contexts. The inter-comparison of the
343 four panels presented in Figure 7 and 8 allow stating that:

- 344 i. Among all single features considered the difference in elevation between the
345 considered point and the source of risk (H), and the distance from the nearest
346 stream (D) generally perform better. In fact, the ROC curve of such features
347 has a very large AUC in the first area (Figure 7A).

- 348 ii. The behaviour of single features is different in the two considered study cases.
349 In particular, they lower significantly their performances when applied to the
350 flat area of the basin outlet (see Figure 8A).
- 351 iii. Among the composite indices, the best performing ones are the $\ln(h(A_s)/H)$
352 and the $\ln[h(A_r)/H]$ indices for the main river (application of 1-D hydraulic
353 model over the entire Bradano river) and $\ln[h(A_r)/H]$ and $[h(A_r) - H]/D$
354 indices for the basin outlet (see Figure 7B and 8B).
- 355 iv. The composite index, $\ln[h(A_r)/H]$, provides similar performances in the two
356 study areas considered herein, and therefore seems the most promising metric
357 among those considered since now.

358 It is interesting to underline that the single features become less sensitive when
359 dealing with a flat landscape and even features like H and D , that generally are well
360 suited for flood mapping in several context, here seem to fail. The reason is certainly
361 due to the specific morphological complexity of the area that probably cannot be
362 characterized by this simple metric. On the other hand, the composite index,
363 $\ln[h(A_r)/H]$, is able to reproduce closely the flood map derived both in the flat area
364 and also over the entire river basin.

365 In order to provide a quantitative description of the quality of each classifier, we
366 summarize in Tables 1 and 2 the performance of each feature computed for an
367 optimal threshold value, considering the basin scale and the local scale of application,
368 respectively investigated through the one-dimensional and two-dimensional
369 approach. The optimal threshold values were identified by minimizing the sum of the
370 false positive rate and the false negative rate $r_{fp} + (1 - r_{tp})$. In particular, Tables (1 and
371 2) provide the following information: the relative values of the optimal normalized

372 threshold τ , the false positive rate r_{fp} , the true positive rate r_{tp} , the sum $r_{fp} + (1-r_{tp})$
373 and the area under the curve AUC for each of the presented features for the Bradano
374 River basin.

375 Results show that the index $\ln[h(A_r)/H]$ is consistently one of the best performing
376 indices in both cases. Furthermore, it is really remarkable that the thresholds
377 identified for this index are similar in the two cases considered herein, while other
378 features or indices show a larger variability of the performances and of the threshold
379 values calibrated in the two considered cases. This result is particularly significant
380 considering the change of scale of the two DEMs and also the reference hydraulic
381 models adopted. This result may be somehow due to the fact that this index try to
382 resample a physical property of flooding that is independent from the scale and the
383 morphological characteristics of the study area. All this should be explored in
384 additional study cases, but it is extremely stimulating if confirmed, because it would
385 demonstrate the great advantage of this methodology, that could allow to extend the
386 flood mapping over large areas starting from the study of a small portion of the basin
387 and using any kind of hydraulic model for the calibration of the method.

388 An example of application of the procedure over the Bradano River basin is given in
389 Figure 9A and B, where we identified the portion of the basin that have a value of the
390 $\ln[h(A_r)/H]$ index above the calibrated threshold. The maps obtained using the
391 $\ln[h(A_r)/H]$ index provided good performance in both the analysed contexts. After the
392 calibration of the optimal thresholds of this index, the flood hazard has been extended
393 over all tributaries, obtaining a realistic description of the flood prone areas that may
394 be extremely useful for the local River Basin Authority to extend their knowledge
395 about flood hazard.

396

397 **5 CONCLUSION**

398 The present study investigates the role of different morphological descriptors in the
399 identification of flood-prone areas over the Bradano River basin. In particular, the
400 performances of the proposed features are evaluated using a linear binary classifier
401 and ROC analysis at two different scales of application: at the entire basin scale,
402 using for comparison a flood map derived by a one-dimensional simulation, and in a
403 flat zone of the river basin, exploiting a flood map derived by a two-dimensional
404 model (FLORA-2D). Among the local features, the best performing ones are the
405 difference in elevation between the considered point and the source of risk (H), and
406 the distance from the nearest stream, D ; instead, among the composite indices the
407 ones performing better are the $\ln[h(A_s)/H]$ and $\ln[h(A_r)/H]$. In particular, this last
408 seems to be more consistent and less sensitive to the change of resolution in the
409 adopted DEM, the reference hydraulic map used for calibration, and the different
410 topography of the training area. It also provides a reliable representation of the flood-
411 prone areas even in the case of flat areas, where other indices or features become less
412 and less sensitive. The outcomes of the present study are particularly promising,
413 especially considering the number of artificial modifications that characterize the
414 Bradano River.

415

416 **Acknowledgements:** We would like to acknowledge the valuable contribution of the
417 two anonymous reviewers. This research was carried out within the framework of
418 activities of the CINID under the research agreement with the Civil Protection of the
419 Basilicata Region.

420 **REFERENCES**

- 421
422 Bridgham SD, Cadillo-Quiroz H, Keller JK, & Zhuang Q (2013) Methane emissions
423 from wetlands: Biogeochemical, microbial, and modeling perspectives from local to
424 global scales. *Global Change Biology*, 19(5), 1325–1346.
- 425 Brivio PA, Colombo R, Maggi M & Tomasoni R (2002) Integration of remote sensing
426 data and GIS for accurate mapping of flooded areas, *International Journal of Remote*
427 *Sensing*, 23:3, 429-441, DOI: 10.1080/01431160010014729.
- 428 Cannon T (1994) Vulnerability analysis and the explanation of "natural" disasters, in
429 A. Varley (ed.) *Disasters, development and the environment*, Chichester: John Wiley.
- 430 Cantisani A (2012). Monitoraggio e modellazione per la protezione dal rischio
431 idraulico in aree pianeggianti mediante lo sviluppo e l'applicazione di modelli
432 bidimensionali e l'utilizzo di strumenti GIS Open Source (Università della
433 Basilicata).
- 434 Cantisani A, Giosa L, Mancusi L, Sole A, (2014) FLORA-2D: A New Model to
435 Simulate the Inundation in Areas Covered by Flexible and Rigid Vegetation.
436 *International Journal of Engineering and Innovative Technology*, vol. 3, Issue 8, p.
437 179-186, ISSN: 2277-3754.
- 438 Ceola S, Laio F, Montanari A, (2014) Satellite nighttime
438 lights reveal increasing human exposure to floods worldwide, *Geophysical Research*
439 *Letters*, Volume 41, Issue 20, pages 7184–7190, 28 October 2014.
- 440 Claps P, Fiorentino M., *Rapporto di sintesi sulla valutazione delle piene in Italia –*
441 *Guida Operativa all'applicazione dei rapporti regionali sulla valutazione delle piene*
442 *in Italia, 1999, Linea 1 Previsione e Prevenzione degli eventi idrologici estremi. CNR*
443 *– GNDCI Roma.*

444 Cobby DM, Mason DC, Davenport IJ, (2001) Image processing of air born scanning
445 laser altimetry for improved river flood modelling, *ISPRS Journal of*
446 *Photogrammetry and Remote Sensing*, 56(2): 121-138.

447 De Risi R., Jalayer F., De Paola F. and Giugni M. (2014) Probabilistic delineation of
448 flood-prone areas based on a digital elevation model and the extent of historical
449 flooding: the case of Ouagadougou. *Boletín Geológico y Minero*, 125 (3): 329-340
450 ISSN: 0366-0176.

451 Degiorgis M, Gnecco G, Gorni S, Roth G, Sanguineti M, Taramasso AC (2012)
452 Classifiers for the detection of flood-prone areas using remote sensed elevation data.
453 *J. Hydrol.*, 470-471, 302–315.

454 Domeneghetti A, Tarpanelli A, Brocca L, Barbetta S, Moramarco T, Castellarin A,
455 Brath A (2014). The use of remote sensing-derived water surface data for hydraulic
456 model calibration. *Remote Sensing of Environment* 149, (2014), 130–141.

457 Douglas I, Alam K, Maghenda M, Mcdonnell Y, Mclean L and Campbell J, (2008)
458 Unjust waters: climate change, flooding and the urban poor in Africa, *Environment*
459 *and Urbanization* 20: 187, DOI: 10.1177/0956247808089156.

460 Fawcett T (2006) An introduction to ROC analysis. *Pattern Recognit. Lett.* 27, 861–
461 874.

462 Fiorentino M, Manfreda S, Iacobellis V (2007) Peak Runoff Contributing Area as
463 Hydrological Signature of the Probability Distribution of Floods. *Adv. Water Resour.*,
464 30(10), 2123-2134.

465 Fiorentino M, Margiotta MR (1999) La valutazione dei volumi di piena ed il calcolo
466 semplificato dell'effetto di laminazione di grandi invasi, *Atti del 19° corso di*

467 aggiornamento su "Tecniche per la difesa dall'inquinamento, G. Frega (a cura di),
468 Editoriale Bios, Cosenza, 203-222.

469 Fluet-Chouinard E, Lehner B, Rebelo L-M, Papa F, and Hamilton SK, (2014)
470 Development of a global inundation map at high spatial resolution from topographic
471 downscaling of coarse-scale remote sensing data, *Remote Sensing of Environment*,
472 <http://dx.doi.org/10.1016/j.rse.2014.10.015>

473 Frappart F, Seyler F, Martinez J-M, León J G, Cazenave A, (2005) Floodplain water
474 storage in the Negro River basin estimated from microwave remote sensing of
475 inundation area and water levels, *Remote Sensing of Environment*, 99(4), 387--399
476 <http://dx.doi.org/10.1016/j.rse.2005.08.016>.

477 Freeman GE, Rahmeyer W, Copeland R R (2000) Determination of Resistance Due to
478 Shrubs and Woody Vegetation, Coastal and Hydraulics Laboratory, ERDC/CHL TR-
479 00-25, U.S. Army Engineer.

480 HEC-RAS 4.1: online available at: http://www.hec.usace.army.mil/software/hecras/documentation/HEC-RAS_4.1_Reference_Manual.pdf.

482 Hjerdt KN, McDonnell JJ, Seibert J, Rodhe A (2004). A new topographic index to
483 quantify downslope controls on local drainage. *Water Resour. Res.*, 40, W05602.

484 Iacobellis V, Gioia A, Milella P, Satalino G, Balenzano A and Mattia F (2013) Inter-
485 comparison of hydrological model simulations with time series of SAR-derived soil
486 moisture maps. *European Journal of Remote Sensing*- 46: 739-757; doi:
487 10.5721/EuJRS20134644.

488 Jalayer F, De Risi R, De Paola F, et al. (2014) Probabilistic GIS-based method for
489 delineation of urban flooding risk hotspots, *Natural Hazards*, ISSN: 0921030X, DOI:
490 10.1007/s11069-014-1119-2.

491 Kirkby MJ (1975) *Hydrograph modelling strategies*, Progress Phys. Hum. Geogr.,
492 69–90.

493 Manfreda S, Di Leo M, Sole A (2011) Detection of Flood Prone Areas using Digital
494 Elevation Models. *J. Hydrol. Eng.*, 16(10), 781-790.

495 Manfreda S, Nardi F, Samela C, Grimaldi S, Taramasso AC, Roth G and Sole A,
496 (2014a) Investigation on the Use of Geomorphic Approaches for the Delineation of
497 Flood Prone Areas, *J. Hydrol.*, 517, 863-876.

498 Manfreda S, Samela C, Sole A, and Fiorentino M (2014b) Flood-Prone Areas
499 Assessment Using Linear Binary Classifiers based on Morphological Indices.
500 Vulnerability, Uncertainty, and Risk: pp. 2002-2011. doi:
501 10.1061/9780784413609.201.

502 Medina V, Hurlimann M, Bateman A, Application of FLATModel, a 2D finite
503 volume code, to debris flows in the northeastern part of Iberian Peninsula,
504 Landslides, Springer Verlag Editor, 2007.

505 Milly PCD, Wetherald RT, Dunne KA, Delworth TL (2002) Increasing risk of great
506 floods in a changing climate. *Nature*, 415, 514-517.

507 Nardi F, Vivoni ER, Grimaldi S (2006) Investigating a floodplain scaling relation
508 using a hydrogeomorphic delineation method. *Water Resour. Res.*, 42, W09409.

509 Nel JL, Roux DJ, Abell R, Ashton PJ, Cowling RM, Higgins JV, Thieme M, Viers JH
510 (2009) Progress and challenges in freshwater conservation planning. *Aquatic
511 Conservation: Marine and Fresh water Ecosystems*, 19(4), 474–485.

512 O'Brien J, FLO-2D User Manual. Version2007.06.

513 Papaioannou G, Vasiliades L, Loukas A (2014) Multi-Criteria Analysis Framework
514 for Potential Flood Prone Areas Mapping, J Water Resources Management, Springer
515 Netherlands, <http://dx.doi.org/10.1007/s11269-014-0817-6>.

516 Petryk S, Bosmajian G B (1975) Analysis of flow through vegetation, Journal of the
517 Hydraulics Division, ASCE, 101(7): 871-884.

518 Prudhomme C, Reynard N and Crooks S (2002) Downscaling of global climate
519 models for flood frequency analysis: where are we now?, Hydrol. Process. 16, 1137–
520 1150.

521 Sharitz RR, Mitsch WJ (1993) Southern hardwood forests. In: Martin, W.H., Boyce,
522 S.G., Ehtemacht, A.C. (Eds.), Biodiversity of the Southeastern United States:
523 Lowland Terrestrial Communities. Wiley, New York, pp. 311-372.

524 Sole A, Giosa L, Cantisani A, Statuto D, Nolè L (2011) Analisi di sensibilità nella
525 modellazione delle inondazioni di aree pianeggianti - Sensitivity analysis in flood
526 modeling of flat areas, Italian Journal of Engineering Geology and Environment,
527 Special Issue, pp. 157-167, DOI: 10.4408/IERGE. 2011-01.S-12.

528 Townsend PA, Walsh SJ, (1998) Modeling floodplain inundation using an integrated
529 GIS with radar and optical remote sensing, *Geomorphology*, Volume 21, Issues 3–4,
530 January 1998, Pages 295-312, ISSN 0169-555X, <http://dx.doi.org/10.1016/S0169->
531 [555X\(97\)00069-X](http://dx.doi.org/10.1016/S0169-555X(97)00069-X).

532
533

534

EntireBradanoBasin - 1D Hydraulic Model					
Single features	τ	r_{fp}	r_{tp}	$r_{fp}+(1-r_{tp})$	AUC
A_s	-0.999	0.021	0.186	0.834	0.584
D	-0.928	0.178	0.784	0.395	0.882
ΔH	0.051	0.627	0.897	0.730	0.578
H	-0.960	0.113	0.963	0.150	0.964
S	-0.956	0.286	0.898	0.388	0.870

Indices	τ	r_{fp}	r_{tp}	$r_{fp}+(1-r_{tp})$	AUC
Tim	-0.235	0.286	0.899	0.387	0.869
DW_i	-0.980	0.142	0.883	0.259	0.919
H/D	-0.974	0.272	0.812	0.460	0.841
$\ln[h(A_r)/H]$	-0.422	0.143	0.939	0.204	0.950
$\ln[h(A_s)/H]$	-0.612	0.134	0.953	0.182	0.953
$[h(A_r)-H]/DW_i$	-0.991	0.790	0.992	0.799	0.654
$[h(A_r)-H]/D$	0.818	0.133	0.874	0.259	0.933

535 Table 1. Results of the linear binary classifiers for the Bradano River basin: the optimal
536 normalized threshold, τ , the false positive rate, r_{fp} , the true positive rate, r_{tp} , the sum $r_{fp} +$
537 $(1 - r_{tp})$, and the area under the curve (AUC) for each descriptor. The best performing features
538 are highlighted using bold characters.

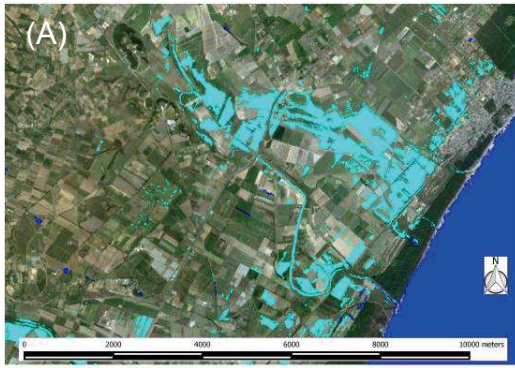
539

Bradano Outlet - 2D Hydraulic Model					
Single features	τ	r_{fp}	r_{tp}	$r_{fp}+(1-r_{tp})$	AUC
As	-0.991	0.000	0.015	0.985	0.507
D	-0.842	0.247	0.458	0.789	0.625
ΔH	0.330	0.421	0.458	0.963	0.527
H	-0.574	0.768	0.990	0.778	0.609
S	-0.986	0.644	0.719	0.926	0.548

Indices	τ	r_{fp}	r_{tp}	$r_{fp}+(1-r_{tp})$	AUC
TIm	-0.139	0.453	0.531	0.922	0.555
DW _i	0.000	0.142	0.441	0.701	0.609
H/D	-0.755	0.911	0.992	0.919	0.505
ln[h(A_r)/H]	-0.423	0.267	0.811	0.456	0.791
ln[h(A _s)/H]	-0.809	0.759	0.956	0.803	0.623
[h(A _r)-H]/DW _i	-0.068	0.558	0.886	0.672	0.659
[h(A_r)-H]/D	0.471	0.221	0.734	0.487	0.798

540 Table 2. Results of the linear binary classifier for the outlet of Bradano River basin: the optimal
541 normalized threshold value τ , the false positive rate r_{fp} , the true positive rate r_{tp} , the sum of
542 $r_{fp}+(1-r_{tp})$ and the area under the curve (AUC) for each descriptor. The best performing features
543 are highlighted using bold characters.

544

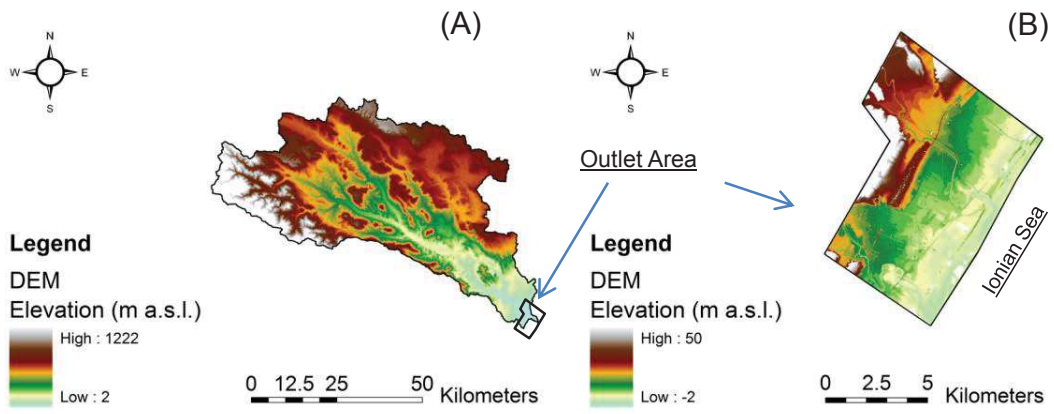


545

546 **Figure 10. A) Inundated areas during the flood event of March 2011 obtained by processing**
547 **remote sensed images. B) The Ancient Temple of “Tavole Palatine” flooded by the event of**
548 **March 2011.**

549

550



551

552

553

Figure 1. SRTM DEM of the entire Bradano River basin (A). LiDAR DEM of the basin outlet of Bradano River (B).

554

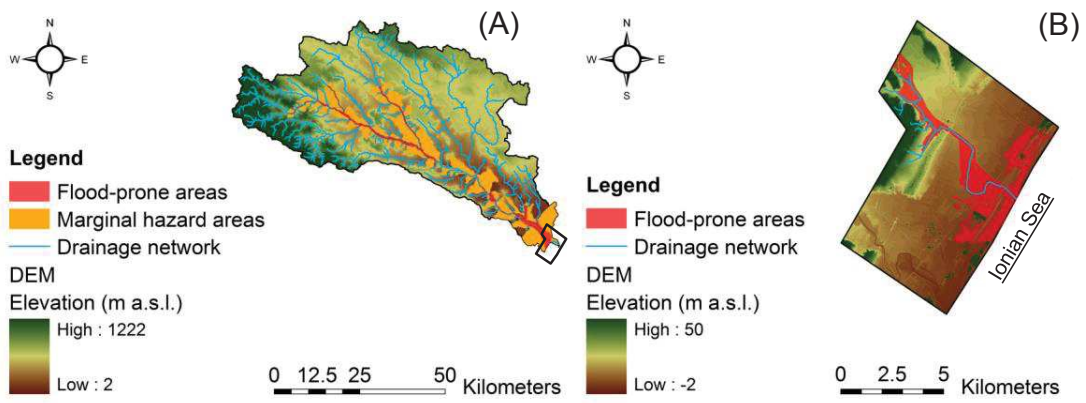
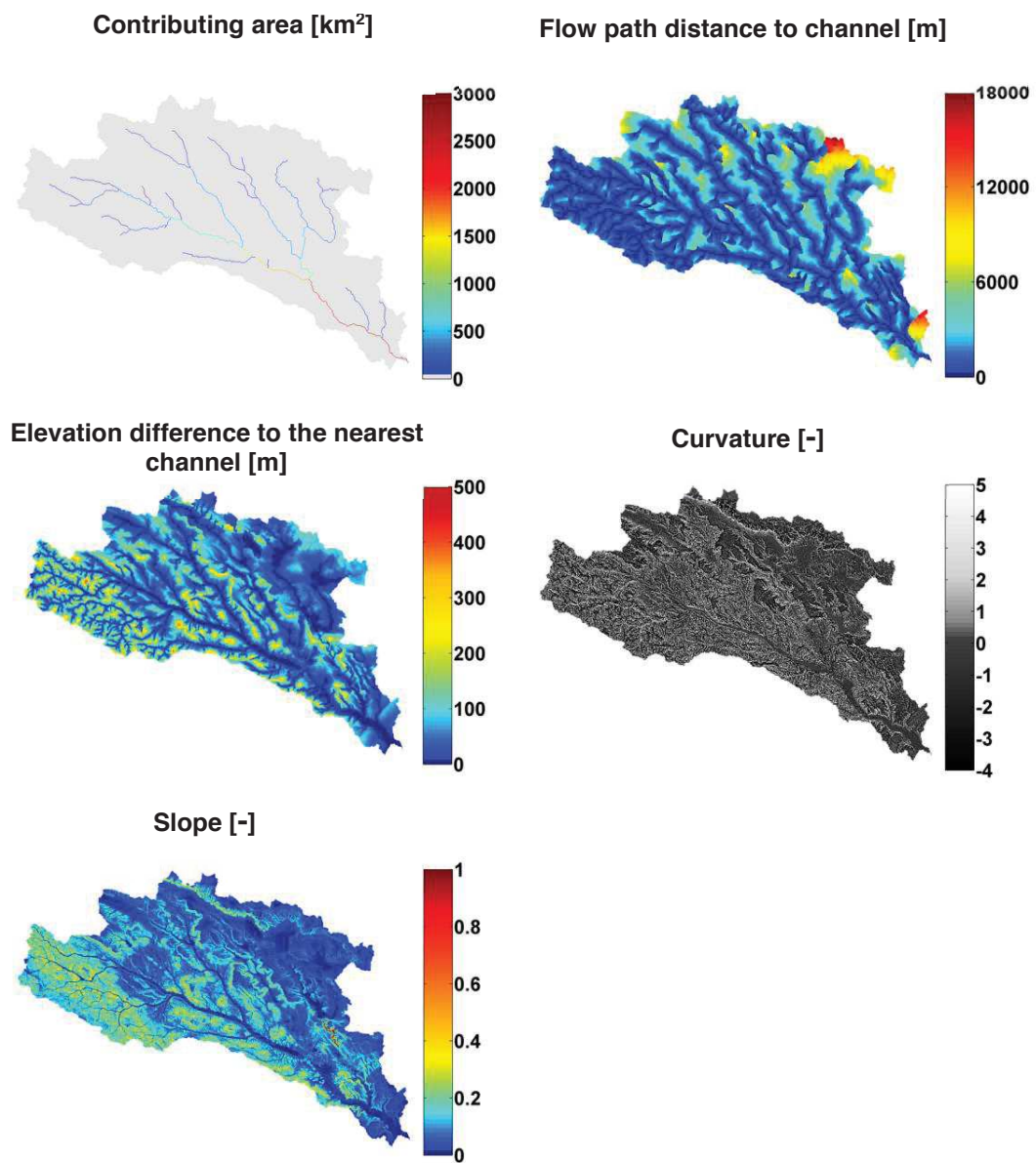


Figure 2. Flood map derived by using a one-dimensional approach over the entire basin of Bradano (A). Flood map derived by using a two-dimensional approach at the outlet of Bradano River basin (B).

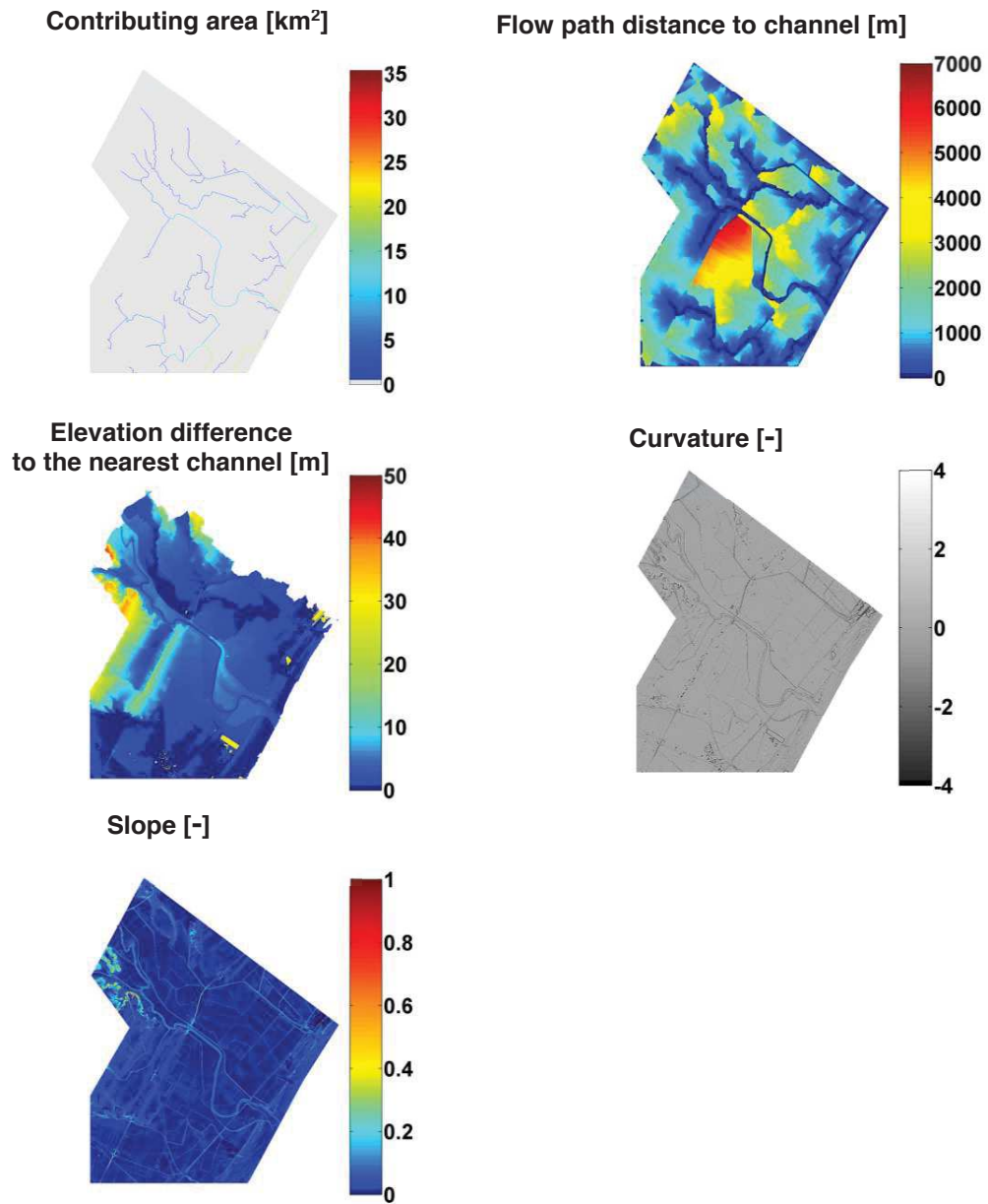


560

561

562

Figure 3A. Local morphological features estimated for the entire Bradano river basin using the SRTM DEM with 90 m of resolution.



563

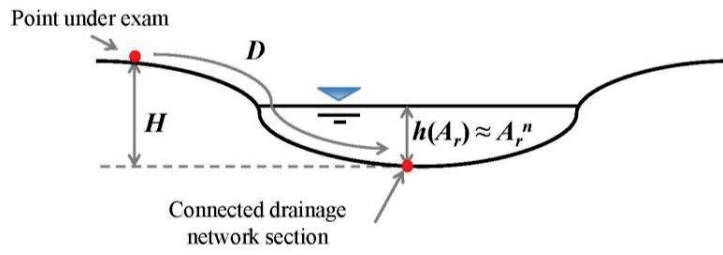
564

565

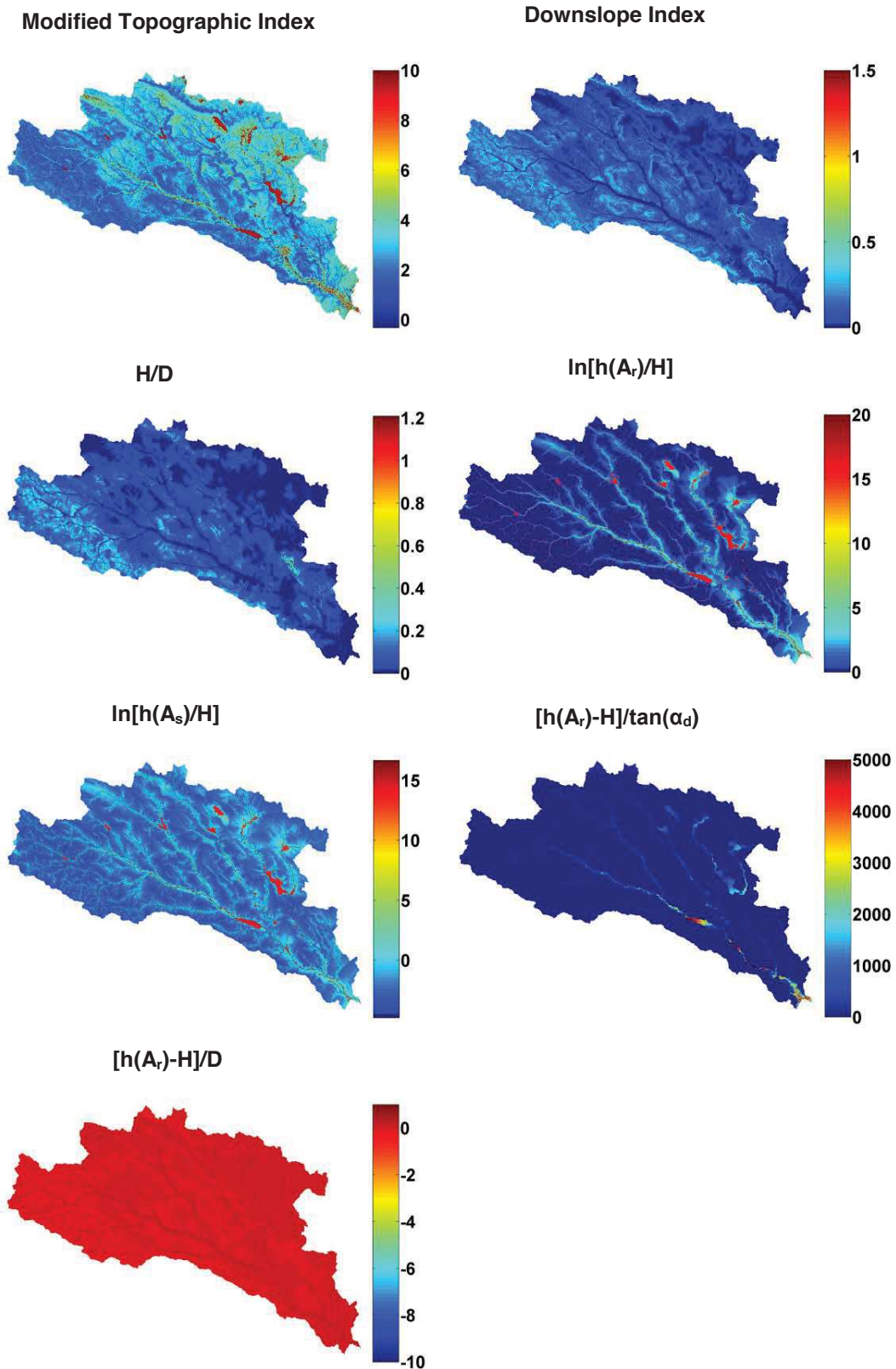
Figure 3B. Local morphological features calculated at the outlet of the Bradano basin estimated using the LiDAR DEM with 10 m of resolution.

566

567
568



569
570 **Figure 4. Example of a hydraulic cross-section with the description of the parameters H and h .**
571



572

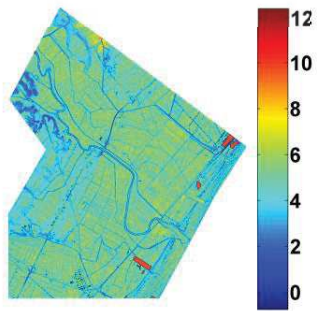
573

574

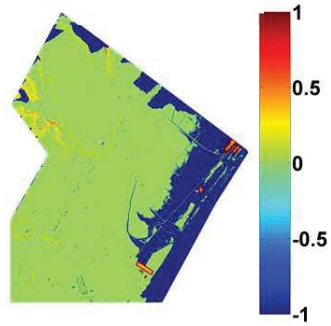
Figure 5A. Composite morphological indices estimated for the entire Bradano river basin using the SRTM DEM with 90 m of resolution.

575

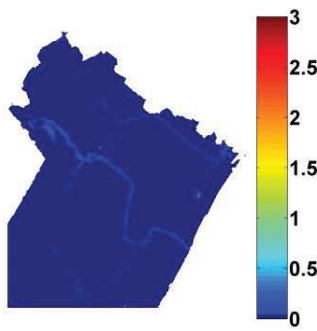
Modified Topographic Index



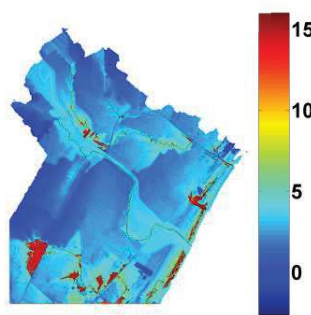
Downslope Index



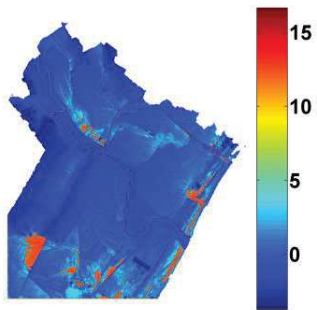
H/D



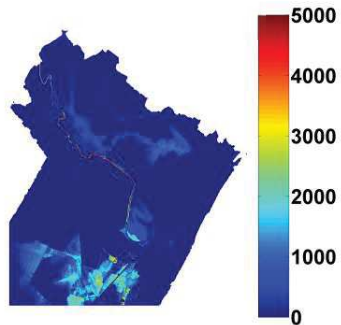
$\ln[h(A_r)/H]$



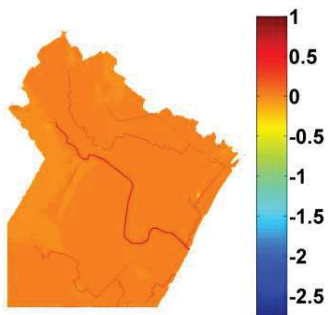
$\ln[h(A_s)/H]$



$[h(A_r)-H]/\tan(\alpha_d)$



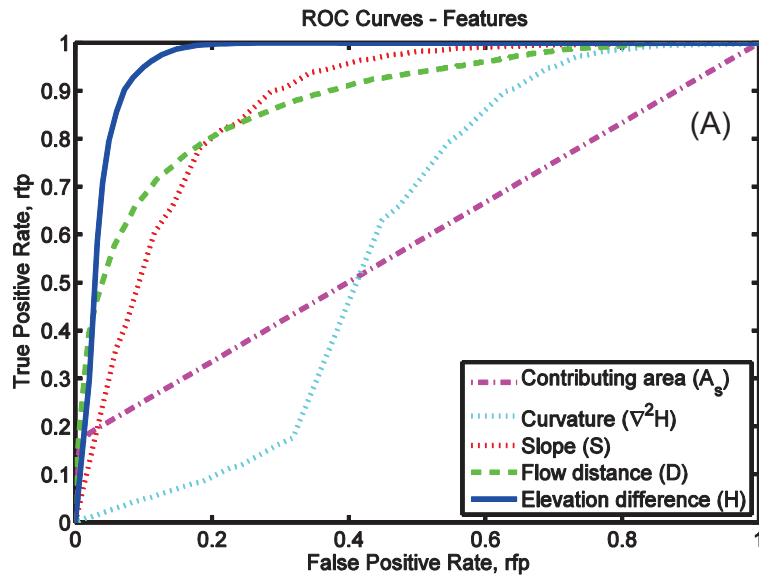
$[h(A_r)-H]/D$



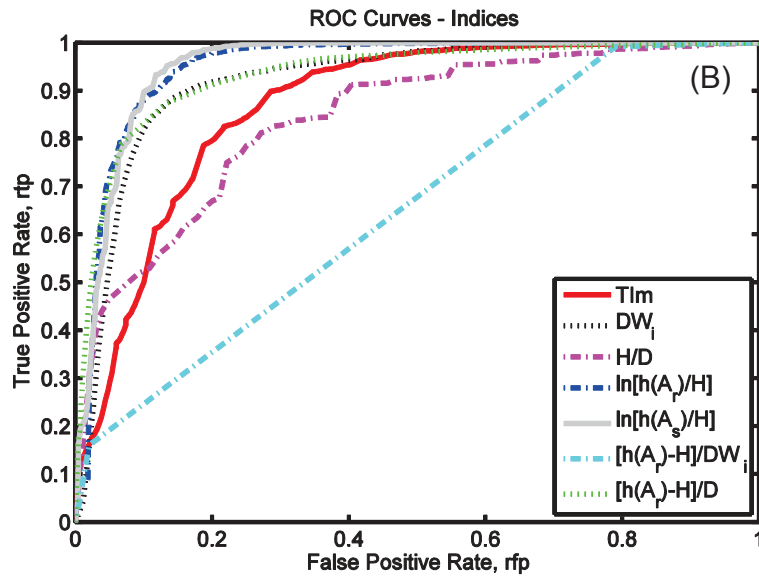
576

577
578

Figure 5B. Composite morphological indices computed at the outlet of the Bradano river basin estimated using the LIDAR DEM with 10 m of resolution.



579

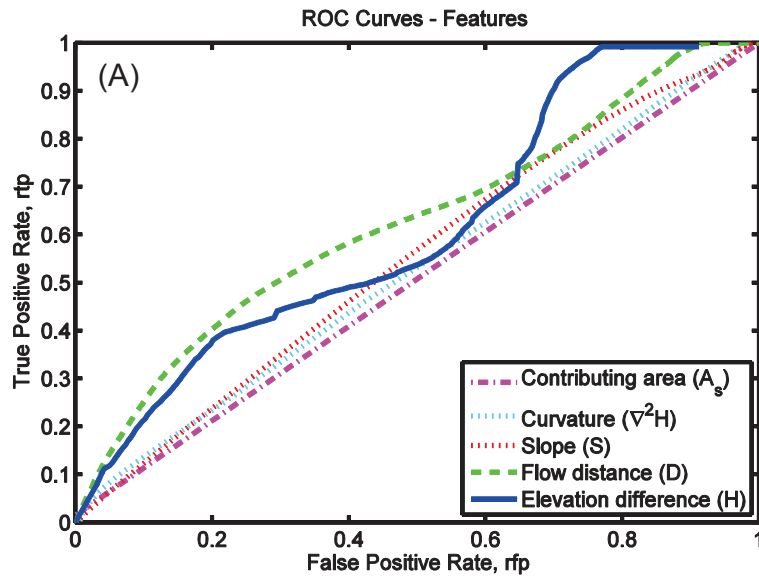


580

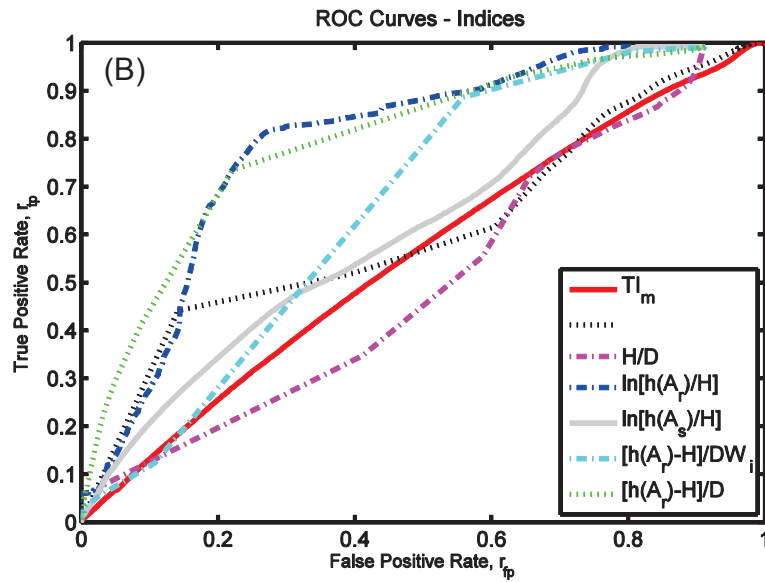
581

582 Figure 6. ROC curves obtained for local features (A) and composite indices (B) obtained by
 583 comparing the proposed features with the flood map of the Bradano basin obtained using the 1-
 584 D hydraulic model.

585



586



587

588

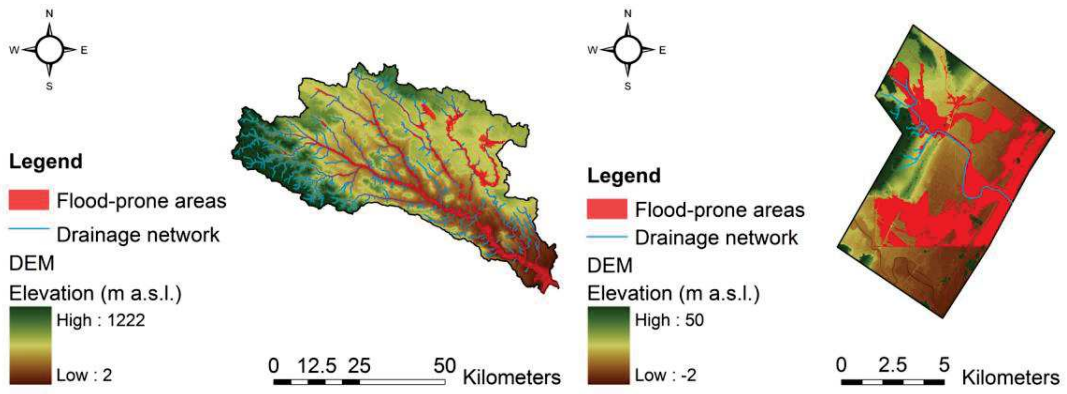
589

590

591

Figure 7. ROC curves obtained for local features (A) and composite indices (B) obtained by comparing the proposed features with the flood map of the outlet of Bradano basin evaluated using the 2-D hydraulic model.

592



593

594

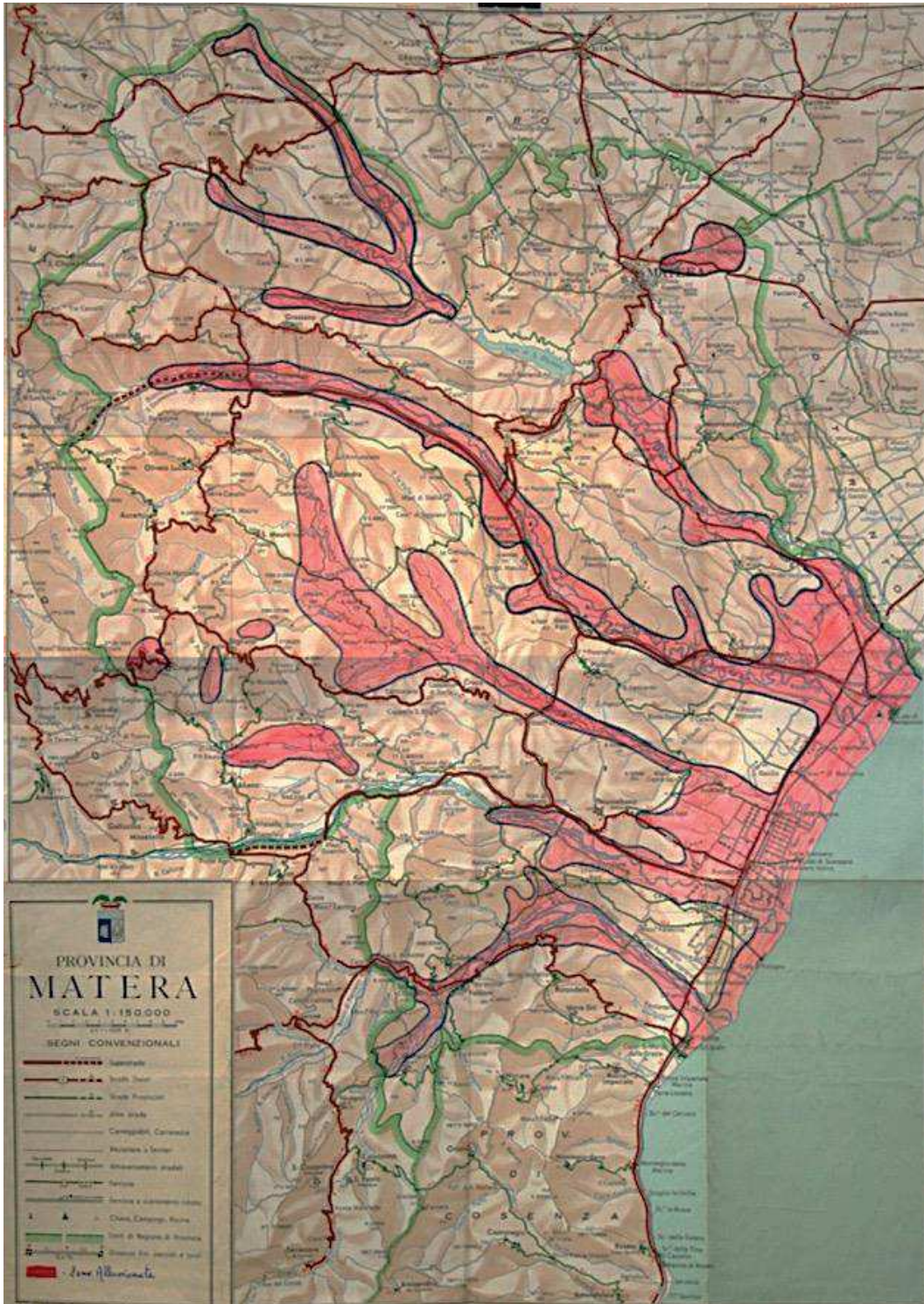
595

596

Figure 8. Flood maps of the Bradano River basin obtained using the linear binary classifier based on the index $\ln(h(A)/H)$ applied on the entire basin (A) and the basin outlet (B).

597
598

Additional Material for Editor and Reviewers



599
600
601

Figure 9. Inundated areas during the flood event of January 1972 edited by the Province of Matera.