



# SAFE-LAND

Mitigating the risk of flooding and  
landslides via artificial intelligence with  
a view to extreme climate events

## Deliverable 6.1: Results of the pilot studies

***MITIGATING THE RISK OF FLOODING AND LANDSLIDES VIA ARTIFICIAL  
INTELLIGENCE WITH A VIEW TO EXTREME CLIMATE EVENTS***



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<b>Abstract</b>	This document is the Deliverable 6.1 of the project “ <i>Mitigating the risk of flooding and landslides via artificial intelligence with a view to extreme climate events (SAFE-LAND)</i> ”. The system developed in the SAFE-LAND project was applied in pilot areas located in Italy, Croatia and Montenegro. The deliverable provides the location of the selected pilot areas, the data collection and the results of testing the tool in pilot areas.
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## 1. INTRODUCTION

This deliverable reports on the implementation and validation of the developed system within the selected pilot areas located in Italy, Croatia, and Montenegro. It provides the geographical identification of the pilot sites, describes the data collection activities undertaken for each area, and presents the results obtained from testing the tool under real operational conditions. The outputs generated by the system are assessed against the results of the hydrogeological and psychological analyses in order to evaluate consistency and reliability.

The document is structured as follows.

Section 2 presents the pilot areas and describes their main geographical and environmental characteristics, together with the data acquisition procedures adopted. It reports the outcomes of the hydrogeological analyses performed on existing slope and river elements, as well as the results of the psychological analyses conducted on the population element. This section establishes the reference baseline for the subsequent validation of the system.

Section 3 illustrates the results obtained from the application of the AI tool to the pilot areas. A comparative assessment is carried out between the web application outputs and the results of the hydrogeological analyses (slope and river elements) and psychological analyses (people element), with the aim of verifying methodological coherence and operational performance under real-case conditions.

Annex 1 is conceived as a technical user manual for the web application. It provides a description of all input parameters required by the system, including a description of their physical interpretation within the implemented models. The parameters are fully aligned with those defined in Deliverables D3.2 and D3.3, ensuring methodological continuity across work packages. Annex 1 therefore serves as a reference framework to support correct system configuration and effective deployment by end users, guaranteeing consistency between the theoretical developments and their practical implementation.

## 2. DESCRIPTION AND ANALYSES OF THE PILOT AREAS

The system was tested in different pilot areas in Italy, Croatia and Montenegro. Different case studies were selected in the three countries to evaluate the landslide and flooding risks. In the following the location of the landslide and flooding risk pilot areas is described. The data collection for each site is also reported in terms of geotechnical, geological, hydrological, and meteorological data.

## 2.1. LANDSLIDE PILOT AREAS

### 2.1.1. Italy

Castel San Vincenzo area extends for 22 km<sup>2</sup> in the Isernia province, Molise region, south Italy (Fig.2.1.1). It is located at coordinates 41°39'N 14°4'E and presents an elevation of 749 m above sea level.

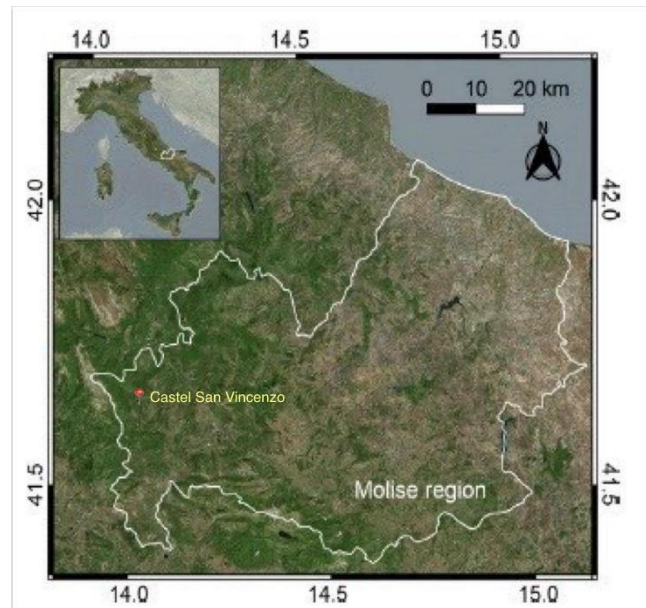


Fig. 2.1.1: Location of the Molise region and in particular Castel San Vincenzo Municipality (red dot).

The digital elevation model (with a 20 m resolution) reveals that the territory is mainly hilly, the slopes that stand on the area have a gradient varying between 10° and 60°, with the highest values in the northern part of the area. The area presents a high landslide susceptibility, typically, the slope failures are triggered chiefly by meteorological events, including intense and prolonged rainfall (Fig. 2.1.2a).

In the context described, the study slope is located in the eastern part of the municipality (orange circle in Fig. 2.1.2b).

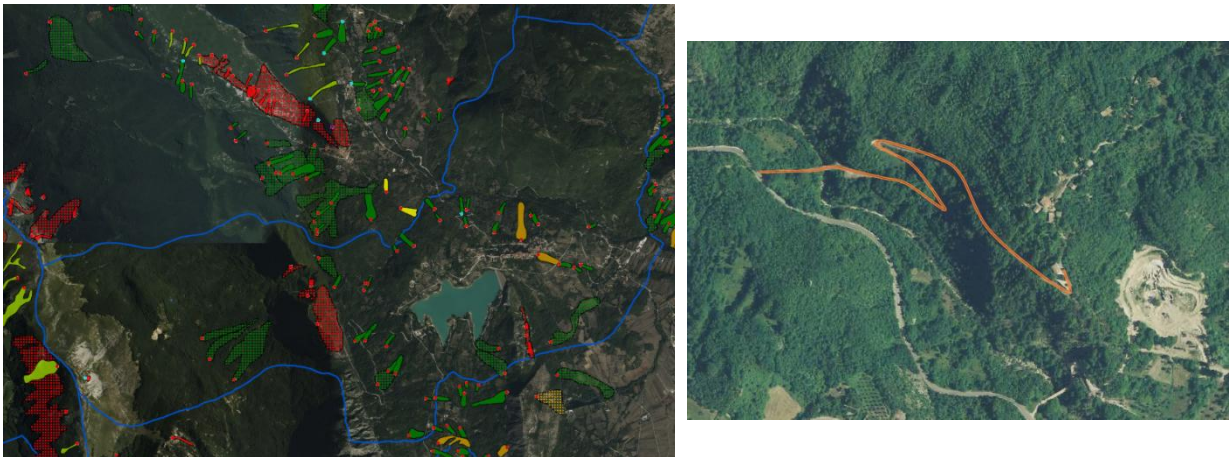


Fig. 2.1.1.2: (a) Spatial distribution of landslides in the Castel San Vincenzo (IFFI database), (b) study case selected.

From a geological perspective, the investigated area is situated within the central Apennines, and it is geosstructurally influenced by tectogenetic phenomena such as the overthrusting of pre-existing paleogeographic units. These units are dated from the Cretaceous to the Pliocene. Thus, the geologic-structural framework of the entire region involved in the project is complex. It spans a chronostratigraphic interval from the Cretaceous to the Pleistocene. In summary, the tectonic units, which were thrust during the orogenic phases starting from the Tortonian, coincide with the opening of the Tyrrhenian Basin (d'Argenio et al., 1973; Mostardini & Merlini, 1986; Patacca et al., 1990; Patacca & Scandone, 2007). These units are distinguished into carbonate platform and slope-basin units, as well as marly-argillaceous-calcareous and siliciclastic basin successions.

More specifically, the geographic area under study is positioned within the geological-structural domain known as Alto Molise. This is located in the transitional sector between the Southern and Central Apennines, connected by tectonic lines such as Ortona-Roccamonfina (Locardi, 1982) or Sangro-Volturno (Ghisetti & Vezzani, 1983).

The bedrock is constituted by carbonate platform facies, while the surface layer is covered by detrital limestones.

The geotechnical investigations consist of MASW (Multichannel Analyses of Surface Waves) and SPT (Standard Penetration Tests), which allowed to define the following two layers from the ground surface downward:

- Layer A: detrital soil with a silty matrix:
- Layer B: calcareous deposits

**INPUT PARAMETERS:**

Table 2.1.1 summarizes the main soil's properties, reporting **mechanical parameters** for drained conditions. It is characterized by the presence of a deformed soil layers that involve a thickness of about 2 m. The **hydraulic parameters** were chosen based on the description of the soil layer, indicating a silty

matrix with a medium permeability. Fig. 2.1.3 shows the geometry for the selected case of study, and in addition, it can be observed the position of the **water table**, where it wasn't found at the depth investigated.

Table 2.1.1: Soil properties of Italian case of study.

Borehole	Depth z (m)	$\gamma$ kN/m <sup>3</sup>	$\phi$ [°]	$c'$ [kPa]	Eed [kg/cmq]	Go [kg/cmq]
1	1.90	19	22.5	0	90	954
1	7.50	20	25.5	2	120	1499
	15	22	36	25	170	

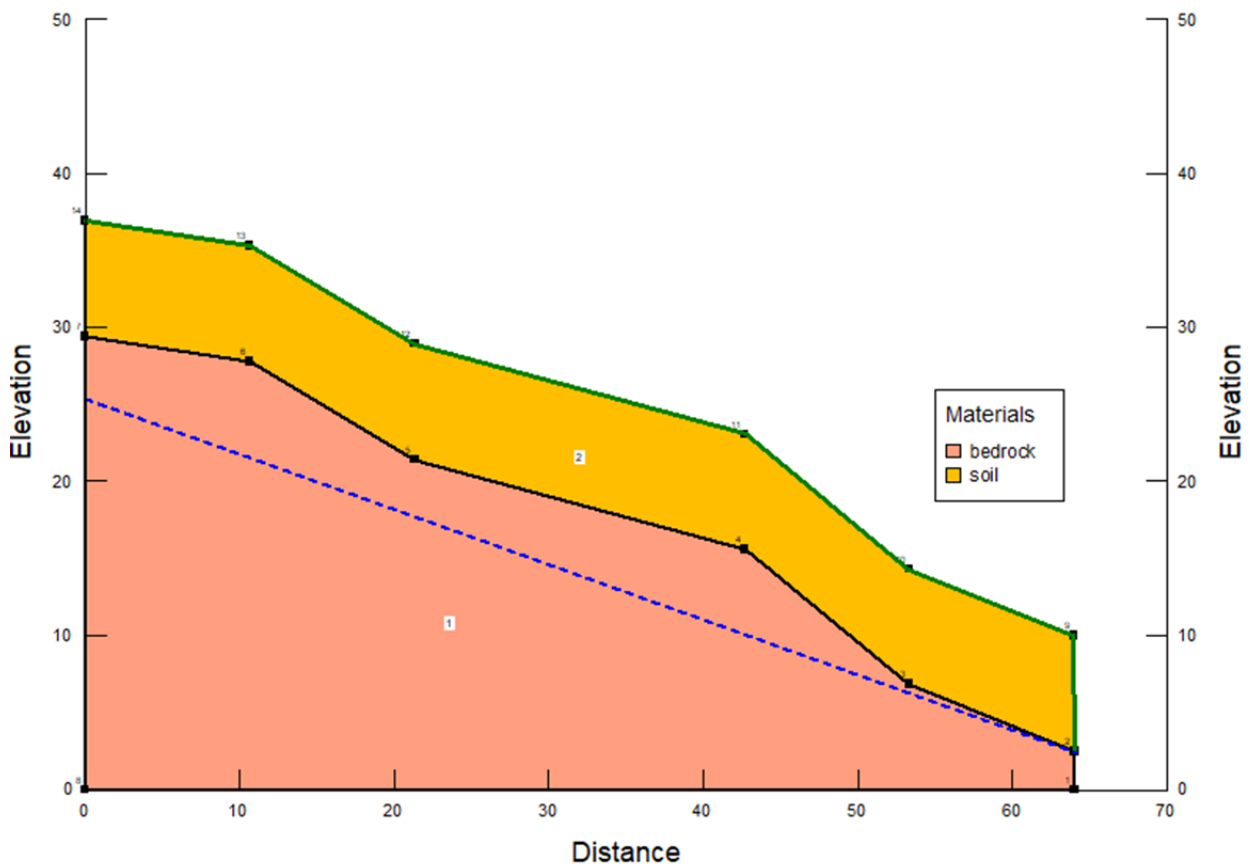


Fig. 2.1.3: Geometry of the Castel Sant'Angelo landslide.

**The rainfalls** selected for the case study in Italy are shown in **Fig. 2.1.4**, where a Chicago hyetograph distribution with a central peak is presented for extreme rainfall events in the Molise Region. The hyetograph represents precipitation events over a 30-hour duration for return periods of 30, 200, and

500 years.

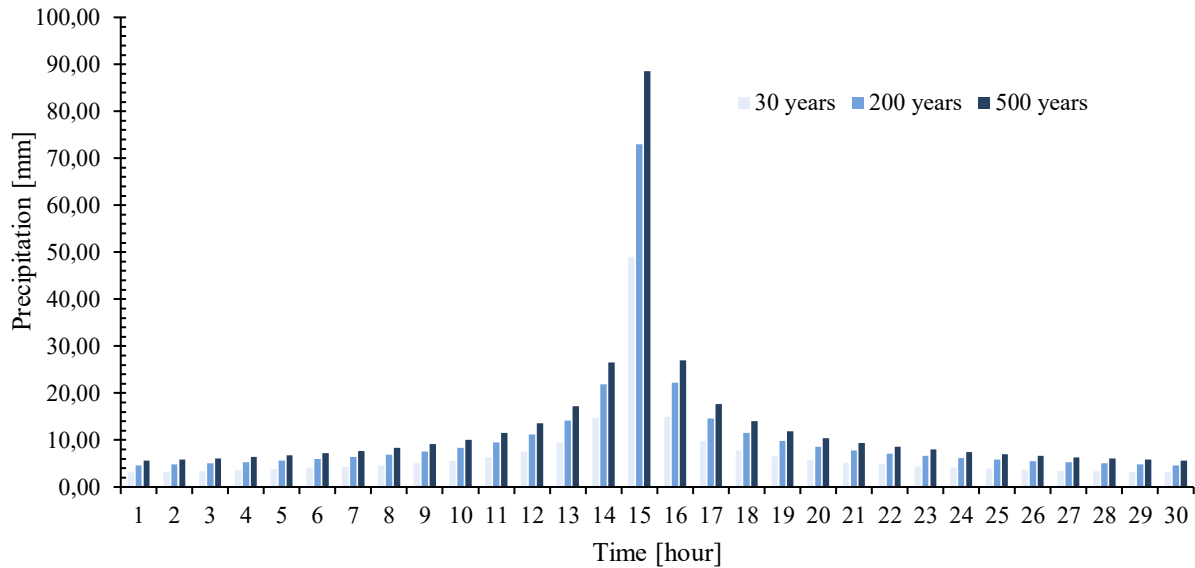
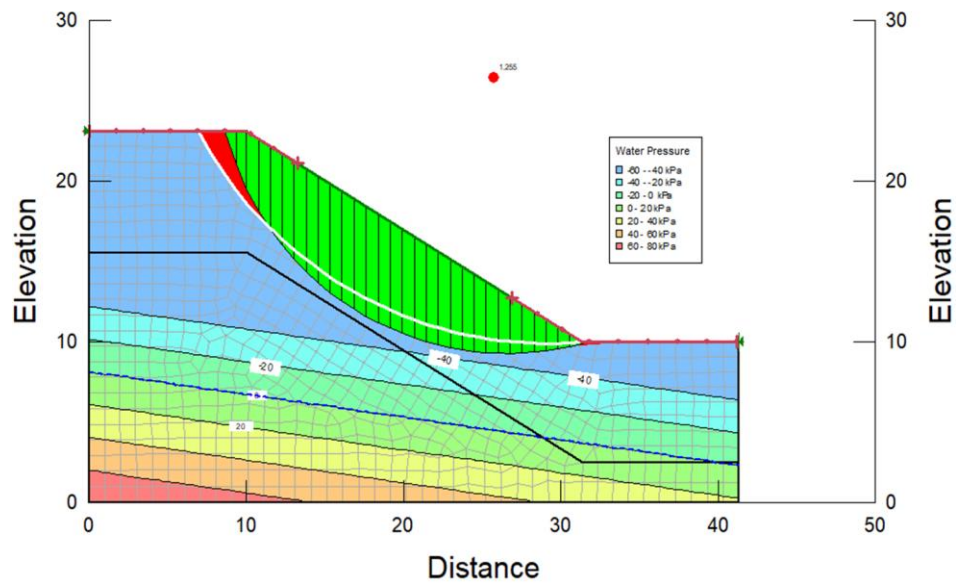


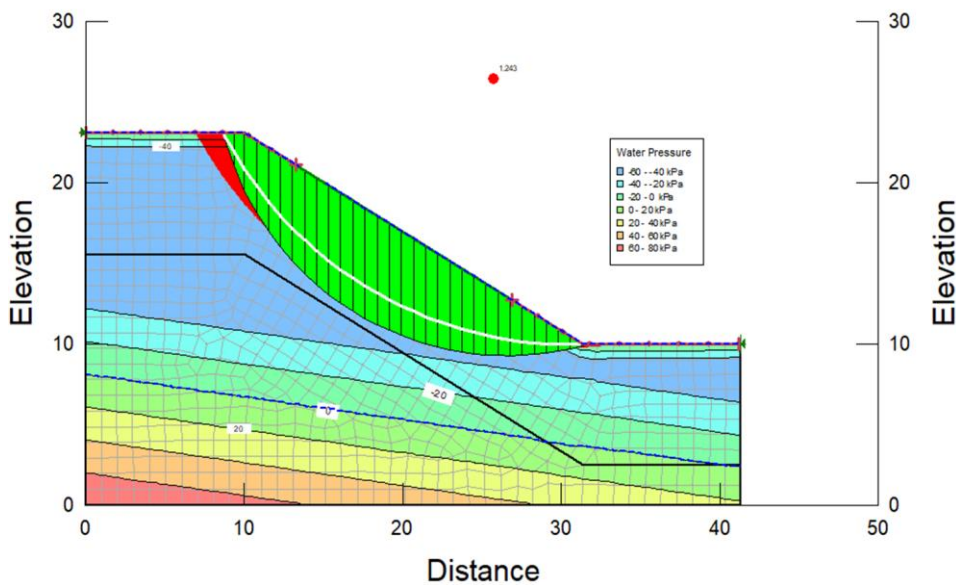
Fig. 2.1.4: Chicago hyetograph for extreme rainfall events in Molise, Italy.

**HYDRO-MECHANICAL MODELING:**

The hydro-mechanical parameters obtained from the pilot area in Molise were used to simulate the response of the slope under the three extreme rainfall events shown in Fig. 2.1.4. A simplified geometry was adopted, by choosing the steeper inclination of the geometry reported in Fig. 2.1.3. As a result of the model, it was obtained the factor of safety (Fos) for the scenario without precipitation (Fig. 2.1.5a) and it can be observed the initial distribution of the water pressure. The response of the slope was analyzed applying the precipitation for the different return periods and in Fig. 2.4b is reported the FoS for a precipitation event with a return period of 500 years. No significant variation of the water table was found since it was located very deep. Table 2.1.2 presents the input parameters used for the base scenario, and after the precipitation event with a return period of 30, 200 and 500 years. As output parameters, the factor of safety, the depth of the sliding surface and the final position of the water table were obtained.



(a)



(b)

Fig. 2.1.5: Output of Geostudio model of the slope in Italy (a) without precipitation (b) precipitation of 30 hours duration with a return period of 500 years

Table 2.1.2: Input and Output parameters of the H-M model in drained conditions (Italy).

Parameters	Unitis	Drained	Drained	Drained	Drained
$\gamma$	kN/m <sup>3</sup>	20	20	20	20
$c'$	kPa	0	0	0	0
$\varphi'$	°	22.5	22.5	22.5	22.5
$C_u$	kPa				
$k_{sat}$	m/s	1E-06	1E-06	1E-06	1E-06
ST	-	2	2	2	2
$\alpha$	°	32	32	32	32
L	m	21.32	21.32	21.32	21.32
B	m	41.23	41.23	41.23	41.23
H	m	13.11	13.11	13.11	13.11
$h_{mi}$	m	23.11	23.11	23.11	23.11
$h_d$	m	10	10	10	10
$h_{Su}$	m	7.57	7.57	7.57	7.57
$h_{Sd}$	m	7.5	7.5	7.5	7.5
$h_{Bu}$	m	15.54	15.54	15.54	15.54
$h_{Bd}$	m	2.5	2.5	2.5	2.5
$z_{wu}^{init}$	m	15	15	15	15
$z_{wd}^{init}$	m	8	8	8	8
$T_r$	Years		30	200	500
$h_w$	mm	0	211.52	315.13	382.04
$t_w$	hr.	0	30	30	30
FoS	-	1.255	1.243	1.243	1.242
$z_s$	m	4.72	4.72	4.72	4.72
$z_{wu}^{final}$	m	15	15	15	15
$z_{wd}^{final}$	m	8	8	8	8

#### RISK ASSESSMENT AND MITIGATION MEASURE:

Landslide risk can be quantified by using the risk matrix reported in deliverable 3.2. To account for the risk is necessary to define the hazard level and the consequences on infrastructure.

1. **Hazard level:** determined based on the scenario without precipitation, and for precipitation with a return period of 30,200 and 500 years (Table 2.1.4 of D.3.2). Adopting the FoS reported in Table 2.1.2, the hazard level was identified as **very low** since all the FoS are greater than 1 (Table 2.1.3).
2. **Evaluation of the consequences on properties:** defined by the position of the structure relative to the landslide body and the significance of the landslide. In this case, the properties are not affected by the landslide body and are therefore classified as OUT. According to the significance level, they are considered not significant, since the sliding surface is shallow ( $z_s = 4.72$  m, as reported in Table 2.1.2). As a result, the **damage level is D1** (Table 2.1.7 D.3.2), implying very low consequences, with a score equal to 0.1.

3. **Risk matrix:** By considering a very low hazard level (0.1) and consequences insignificant (0.1), according to Table 2.18 of D.3.2, the risk level is **very low (VL)**.

Table 2.1.3: Hazard level based on  $FoS_i$  (Molise)

$FoS_0$	$FoS_1$	$FoS_2$	$FoS_3$	Hazard levels	Score Assigned
no rainfall	$T_r=30$ years	$T_r=200$ years	$T_r=500$ years		
1.255	1.243	1.243	1.242	Very Low	0.1

No mitigation measures are suggested for this case since the  $FoS$  is greater than 1.

### 2.1.2 Croatia

The selected case of study in Croatia is located in **Međimurje County**, a region bordered on almost all sides by rivers: the Mura to the north and east, the Drava to the south, and, along part of its western boundary with Slovenia, the Šantavec stream. The dominant characteristic of Međimurje's geological structure is the presence of exclusively sedimentary rocks at the surface (Miletić et al., 1992). These include:

- Pleistocene deposits in the central lowland area known as the Čakovec Plain, as well as in the marginal zones of the Međimurje Hills; and
- Holocene deposits in the lowlands along the Drava and Mura rivers and their tributaries.

In the erosional section formed by the Mura River between Križovec and Podturen, gravel and sand deposits are exposed in several places. Their uppermost horizons rest discordantly on the underlying upper units.

In particular, the documented landslide is located in the **municipality of Strigova-Železna Gora**, whose coordinates are **46° 29' 1.93"N ; 16° 19' 0.84"E (Fig. 2.1.6a)**. The broader manifested instability covers an area larger than 1 hectare and affects the area of agricultural vineyard land, as can be seen in Fig. 2.1.6a. The geotechnical data for the study case was obtained from a geotechnical report, where in-situ and laboratory testing were carried on. The investigation program considered:

1. Exploratory probes drilling borehole.
2. Static cone penetrating cone (CPTu)
3. Dynamic probing with a light dynamic penetrometer (DPL)
4. Geophysical investigation – electrical resistivity tomography (ERT)
5. Laboratory testing



Fig. 2.1.6: (a)location (b) area of the landslide in Medimurje County, Croatia.

The area of analysis is characterized by Sarmatian stage deposits, belonging to the Upper Miocene (2M3<sup>2</sup>), consisting of clastic sediments. Marls, marly limestones, clayey marls, and sands dominate the geology. The terrain is highly dissected, ranging from hilly to mountainous, with deeply incised gullies that are overgrown with shrubs and low vegetation. Outcrops of the bedrock are rare and visible only in low cuts along local roads. Weathered sandy marl is the predominant material.

From the in-situ tests (geoelectrical tomography, CPTu, dynamic probing light), the following **soil profile** was defined:

- **1. High Plasticity Clays (CH)**, located between 0.00 and 1.00 m. The surface part of the cohesive soil at the site consists of fat clays (CH, LL=58-65%), yellow-brown in color, in a stiff plastic consistency state. The soil properties were  $\gamma = 18.5 \text{ kN/m}^3$ ,  $c' = 2 \text{ kPa}$ ,  $\phi' = 18^\circ$ ,  $c_u = 30 - 50 \text{ kPa}$ .
- **2. Overburden clay**, classified as high plasticity clays (CH), located between 1.00 and 3.50 m. Fat clays in the overburden, yellow-brown in color (CH, LL=58%), in a stiff plastic consistency state. The soil properties were  $\gamma = 19.3 \text{ kN/m}^3$ ,  $c' = 8 \text{ kPa}$ ,  $\phi' = 21^\circ$ , and  $c_u = 80 - 100 \text{ kPa}$ .
- **3. Slip surface**, characterized by High Plasticity Clay (CH), located between 3.50 – 3.60 m. In this area, significantly lower values of undrained shear strength were obtained in the slip surface zone. The defined soil properties were  $\gamma = 18.0 \text{ kN/m}^3$ ,  $c' = 1 \text{ kPa}$ ,  $\phi' = 16^\circ$ ,  $c_u = 20 \text{ kPa}$ .
- **4. Base/substrate**, composed by Marls and Marly Clays (CL/ML-CL), located after 3.60 m. Hard marly clays and marls with interbeds of sand, with IP=24%. The soil parameters defined for this material were  $\gamma = 18.8 \text{ kN/m}^3$ ,  $c' = 40 \text{ kPa}$ ,  $\phi' = 28^\circ$ ,  $c_u = 200 \text{ kPa}$ .

**INPUT PARAMETERS:**

Table 2.1.4 summarizes the main soil’s properties, reporting **mechanical parameters** for drained and undrained conditions. The **hydraulic parameters** were chosen based on the description of the soil layer, indicating clayey soils with a low permeability. Fig. 2.1.7 shows the geometry for the selected case of study, and in addition, it can be observed the position of the **water table**, ranging between 1.5 m deep upstream and 0 m deep downstream.

**The rainfalls** selected for the case study in Croatia are shown in Fig. 2.1.8, where a Chicago hyetograph distribution with a central peak is presented for extreme rainfall events in the Čakovec area. The hyetograph represents precipitation events over a 30-hour duration for return periods of 30, 200, and 500 years.

Table 2.1.4: Soil properties of Croatian case of study.

Soil Type	Specific Unit weight, $\gamma$ [kN/m <sup>3</sup> ]	Effective cohesion, $c'$ [kPa]	Effective friction angle, $\phi'$ [°]	Undrain cohesion, $C_u$ [kPa]
1. High Plasticity Clay (CH)	18.5	2	18	30-50
2. Overbunden clay (CH)	19.3	8	21	80-100
3. Slupe surface (CH)	18	1	16	20
4. Base / substrate (CL/ML-CL)	18.8	40	28	200

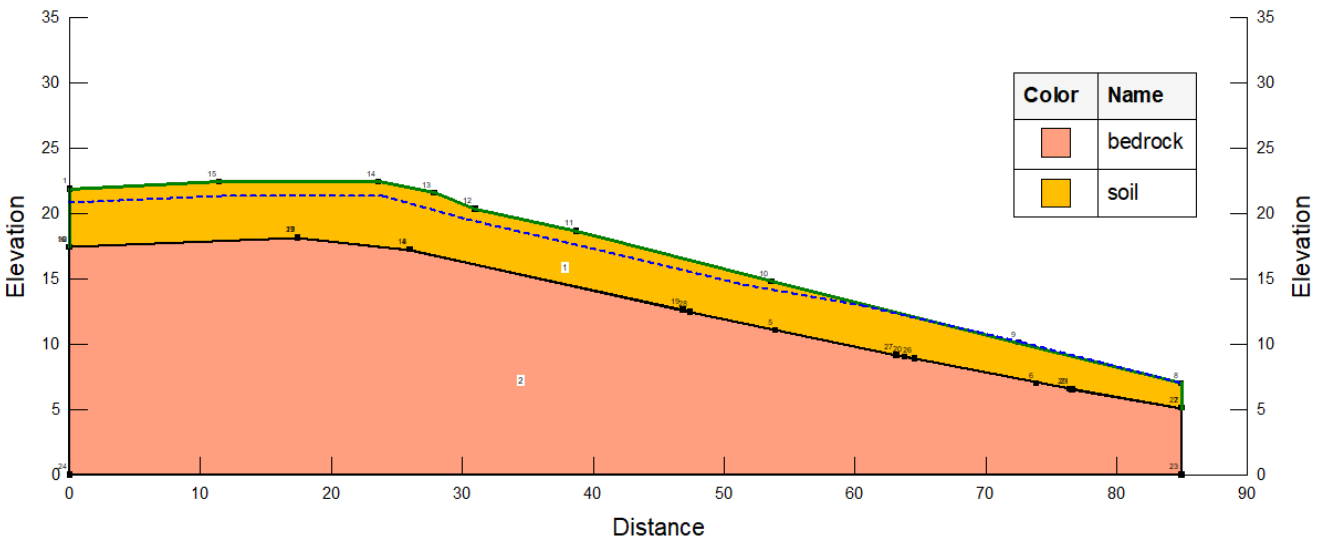


Fig. 2.1.7: Geometry of the Strigova landslide.

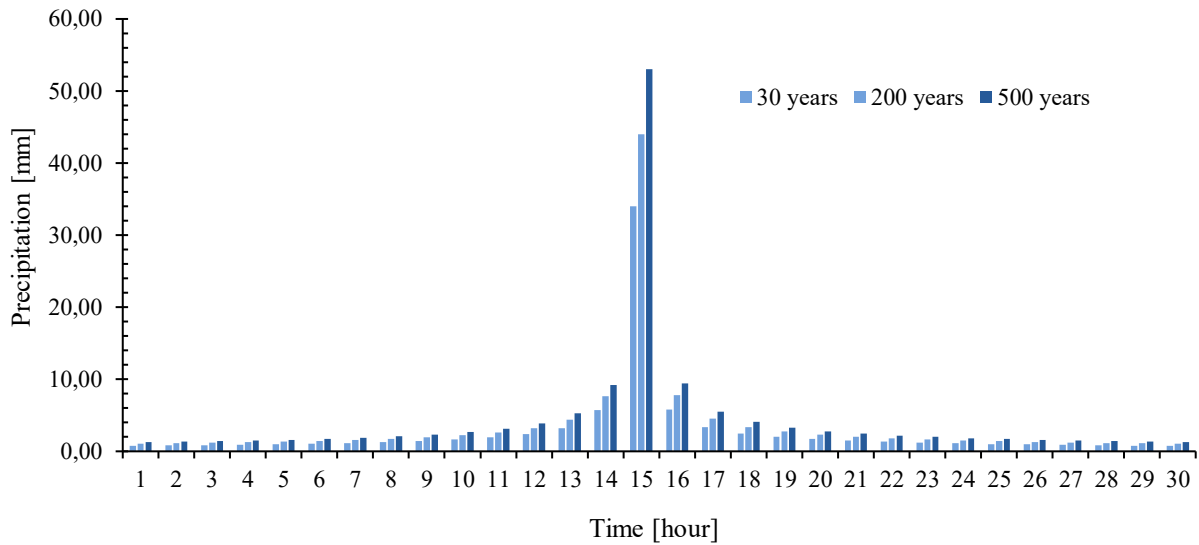
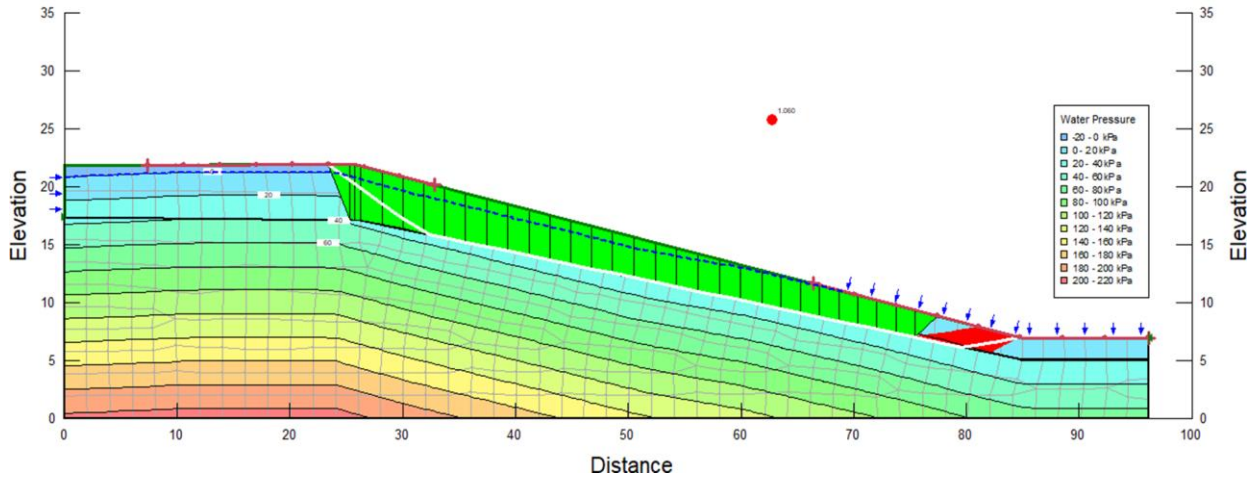


Fig. 2.1.8: Chicago hyetograph for extreme rainfall event in Čakovec area.

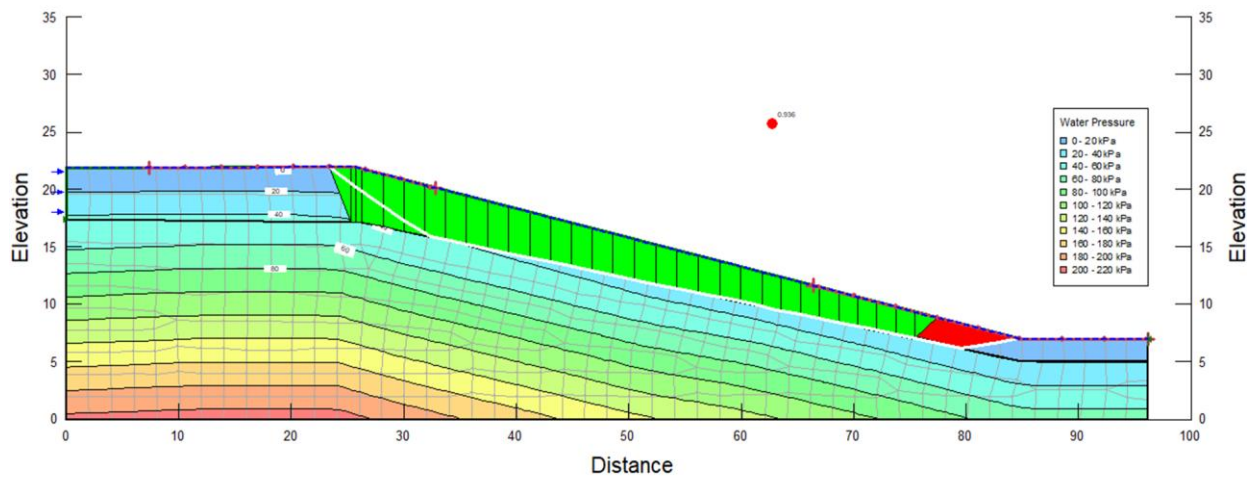
### HYDRO-MECHANICAL MODELING:

The hydro-mechanical parameters compiled from the study case were used to simulate the response of the slope under the extreme rainfall events shown in Fig. 2.3. A simplified geometry was adopted since the input parameters chosen for the AI models training assume a unique slope angle. For the selected case of study in Croatia, it was considered the drained and undrained parameters. For drained conditions, the factor of safety (Fos) was obtained for the base scenario without precipitation (Fig. 2.1.9a), by considering a single soil layer. Additionally, the water pressure distribution can be seen. On the other hand, Fig. 2.1.9b presents the response of the model after the precipitation event with a return period of 500 years. It can be observed the rise of the water table caused by the rainfall, having a final position in coincidence with the water table. Table 2.1.5 presents the input parameters used for the base scenario, and after the precipitation event with a return period of 30, 200 and 500 years. As output parameters, the factor of safety, the depth of the sliding surface and the final position of the water table were obtained.

For undrained conditions, Fig. 2.1.10a and Fig. 2.1.10b show the response of the model without precipitation and after the precipitation event with a return period of 500 years. Table 2.1.6 shows the input and output parameters.



(a)

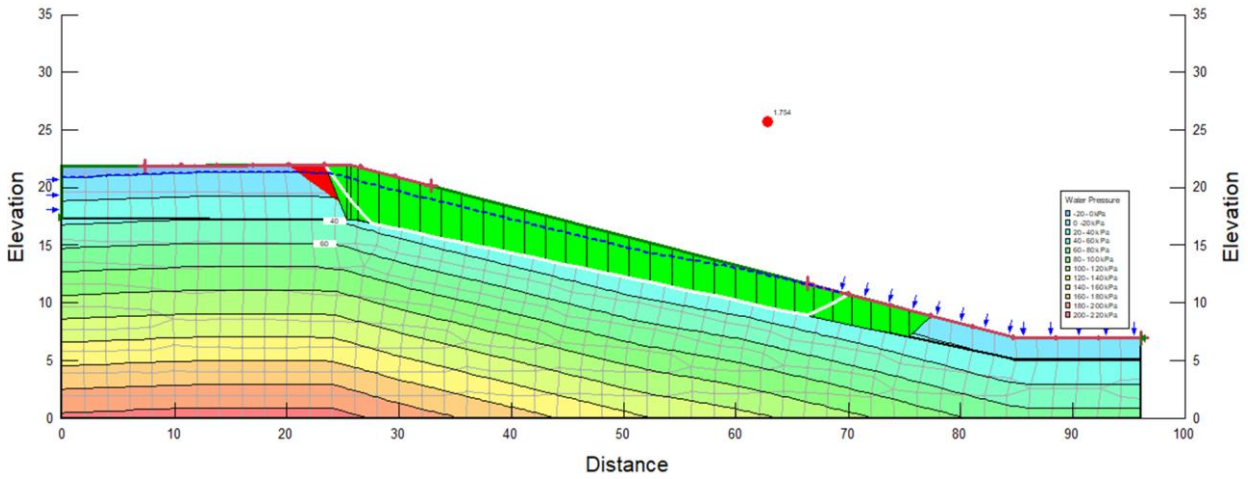


(b)

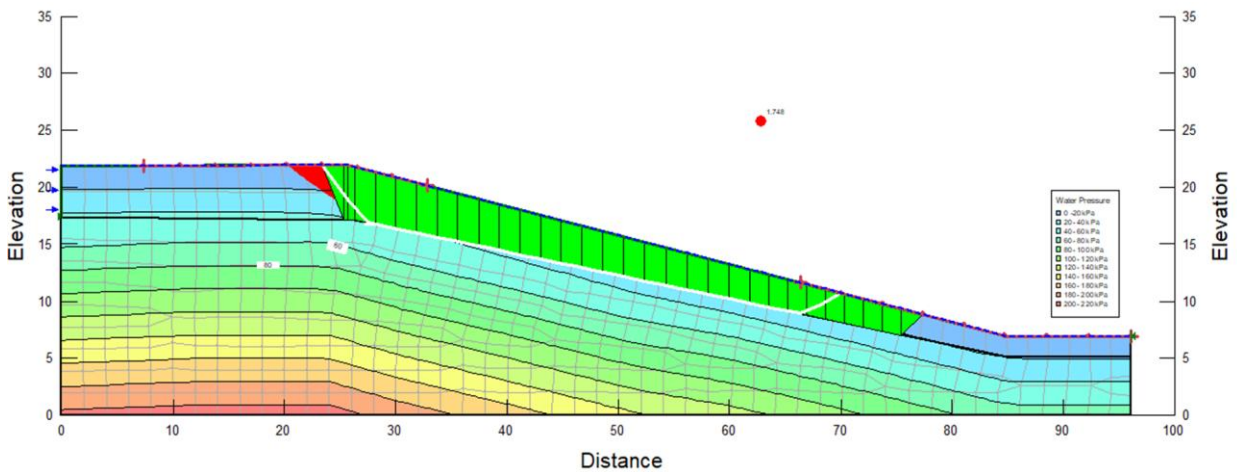
Fig. 2.1.9: Output of Geostudio model of the slope in Croatia in drained conditions (a) without precipitation (b) precipitation of 30 hours duration with a return period of 500 years.

Table 2.1.5: Input and Output parameters of the H-M model in drained conditions (Croatia).

Parameters	Unitis	Drained	Drained	Drained	Drained
$\gamma$	kN/m <sup>3</sup>	18	18	18	18
$c'$	kPa	2	2	2	2
$\varphi'$	°	18	18	18	18
$C_u$	kPa	-	-	-	-
$k_{sat}$	m/s	1E-08	1E-08	1E-08	1E-08
ST	-	3	3	3	3
$\alpha$	°	14	14	14	14
L	m	59.26	59.26	59.26	59.26
B	m	96.12	96.12	96.12	96.12
H	m	15.01	15.01	15.01	15.01
$h_m$	m	21.84	21.84	21.84	21.84
$h_d$	m	6.95	6.95	6.95	6.95
$h_{Su}$	m	4.82	4.82	4.82	4.82
$h_{Sd}$	m	1.87	1.87	1.87	1.87
$h_{Bu}$	m	17.02	17.02	17.02	17.02
$h_{Bd}$	m	5.08	5.08	5.08	5.08
$z_{wu}^{init}$	m	1.5	1.5	1.5	1.5
$z_{wd}^{init}$	m	0	0	0	0
$T_r$	years		30	200	500
$h_w$	mm	0	83.74	111.73	134.59
$t_w$	hr.	0	30	30	30
FoS	-	1.06	0.936	0.936	0.936
$z_s$	m	4.36	4.36	4.36	4.36
$z_{wu}^{final}$	m	0	0	0	0
$z_{wd}^{final}$	m	0	0	0	0



(a)



(b)

Fig. 2.1.10: Output of Geostudio model of the slope in Croatia in undrained conditions (a) without precipitation (b) precipitation of 30 hours duration with a return period of 500 years.

Table 2.1.6: Input and Output parameters of the H-M model in undrained conditions.

Parameters	Units	Undrained	Undrained	Undrained	Undrained
$\gamma$	kN/m <sup>3</sup>	18	18	18	18
$c'$	kPa	-	-	-	-
$\varphi'$	°	-	-	-	-
$C_u$	kPa	20	20	20	20
$k_{sat}$	m/s	1E-08	1E-08	1E-08	1E-08
ST	-	3	3	3	3
$\alpha$	°	14	14	14	14
L	m	59.26	59.26	59.26	59.26
B	m	96.12	96.12	96.12	96.12
H	m	15.01	15.01	15.01	15.01
$h_m$	m	21.84	21.84	21.84	21.84
$h_d$	m	6.95	6.95	6.95	6.95
$h_{Su}$	m	4.82	4.82	4.82	4.82
$h_{Sd}$	m	1.87	1.87	1.87	1.87
$h_{Bu}$	m	17.02	17.02	17.02	17.02
$h_{Bd}$	m	5.08	5.08	5.08	5.08
$z_{wu}^{init}$	m	1.5	1.5	1.5	1.5
$z_{wd}^{init}$	m	0	0	0	0
$T_r$	years		30	200	500
$h_w$	mm	0	83.74	111.73	134.59
$t_w$	hr.	0	30	30	30
FoS	-	1.754	1.748	1.748	1.748
$z_s$	m	4.36	4.36	4.36	4.36
$z_{wu}^{final}$	m	0	0	0	0
$z_{wd}^{final}$	m	0	0	0	0

### RISK ASSESSMENT:

Landslide risk can be quantified by using the risk matrix reported in deliverable 3.2. To account for the risk is necessary to define the hazard level and the consequences on infrastructure.

1. **Hazard level:** determined based on the scenario without precipitation, and for precipitation with a return period of 30,200 and 500 years (Table 2.1.4 of D.3.2). Adopting the FoS reported in Table 2.1.6, the hazard level was identified as **high** (Table 2.1.7).
2. **Evaluation of the consequences on properties:** defined by the position of the structure relative to the landslide body and the significance of the landslide. In this case, the properties are **on**, the property is located on the slope, and according to the significance level, is low significance since the sliding surface is shallow ( $z_s=4.36$  m as reported in Table 2.1.6). As a result the **damage level is D4** (Table 2.1.7 D.3.2), implying **high consequences**, with a score equal to **0.8**.
3. **Risk matrix:** By considering a hazard level **high** (0.8) and **major extensive damage** (0.8), according to Table 2.18 of D.3.2, the **level of risk is high (0.64)**.

Table 2.1.7: Hazard level based on  $FoS_i$  (Croatia)

$FoS_0$ no rainfall	$FoS_1$ $T_r=30$ years	$FoS_2$ $T_r=200$ years	$FoS_3$ $T_r=500$ years	Hazard levels	Score Assigned
1.06	0.936	0.936	0.936	High	0.8

### MITIGATION MEASURE:

The possible mitigation measures based on the depth of the sliding surface ( $z_s$ ) and the final position of the water table ( $z_w^{final}$ ) have been reported in deliverable 3.3, in the annex section. For each mitigation measure an effectiveness matrix was defined, based on those two variables, in which a score was assigned. When the same score is obtained from the effectiveness matrix, the applicability matrix allows to select the better mitigation measure. The values of  $z_s$  and  $z_w^{final}$  are reported in Table 2.1.6, where it can be defined the depth of the sliding surface as medium (3 to 8 m) and the depth of the piezometric surface as high, according to the effectiveness matrix. In Table 2.1.8 are reported the scores for each mitigation measure and the scores for the applicability matrix. For the considered case, the most effective measure is G.2.4, that considers addition of material to guarantee stability.

Table 2.1.8: Scores for mitigation measure (Croatia)

Mitigation measure	Score of Effectiveness Matrix	Score of Applicability Matrix
G.1.1	0	3.5
G.1.2	0	4
G.1.3	0	4
G.1.4	0	3.5
G.1.5	0	4
G.2.1	0.25	3.5
G.2.2	0.5	3.5
G.2.3	0.5	2
<b>G.2.4</b>	<b>1</b>	<b>4</b>
G.3A.1	0.25	4
G.3A.2	0.25	4
G.3A.3	0.25	4
G.3A.4	0.25	4
G.3A.5	0.25	3
G.3.B.1a	0.25	2.5
G.3.B.1b	0.5	2.5
G.3B.2	0.25	2
G.3B.3	0.5	2
G.3B.4	0	1.5
G.4.1	0.5	3
G.4.2	0.25	3
G.4.3	0.25	2
G.4.4	0.25	2
G.5.1	0.25	3.5
G.5.2	0.5	4
G.5.3	0.5	3.5
G.5.4	0.5	3

### 2.1.3. Montenegro

The Povija landslide is located on the left side of the steep slopes of the deep Zeta River valley. It developed on a steep valley flank composed of flysch formations and Quaternary diluvial–eluvial sediments. These materials become saturated due to several groundwater springs emerging at the tectonic contact between carbonate rock masses and impermeable flysch units.

In 1948, the Nikšić–Podgorica railway was constructed across the landslide zone. During the last 25 years, slope movements have required rail realignment approximately twice per year, both horizontally and vertically. The transport of large quantities of bauxite by train generates significant vibration and cyclic loading, which likely contributes to continued instability of the embankment and surrounding terrain. Because the landslide movement is slow, it has been difficult to clearly identify the main direction of

displacement and the exact position of the sliding surface.

The Povija landslide extends for several hundred meters in length, with an approximate width of 200 m along the railway alignment. The first remediation was carried out about 20 years ago and consisted of a surface and deep drainage system. During the first ten years after remediation, movements were significantly reduced, and only occasional minor rail corrections were required. However, in the last decade, landslide activity has reactivated (Tomanovic, 2010).

**The Povija landslide** occurred in 2010 and it is located in a site where the slopes range between 30°-40°, reaching values of 45° in some areas. The material is composed of marls, clay slates, limestones and partially breccias. The landslide of Povija was located at **42° 41' 16.1"N 18° 59' 33.7"E**. Fig. 2.1.11a shows the location of the selected pilot area and Fig.2.1.11b the area where the landslide occurred and consequently a retaining wall was constructed to guarantee the stability of the slope.

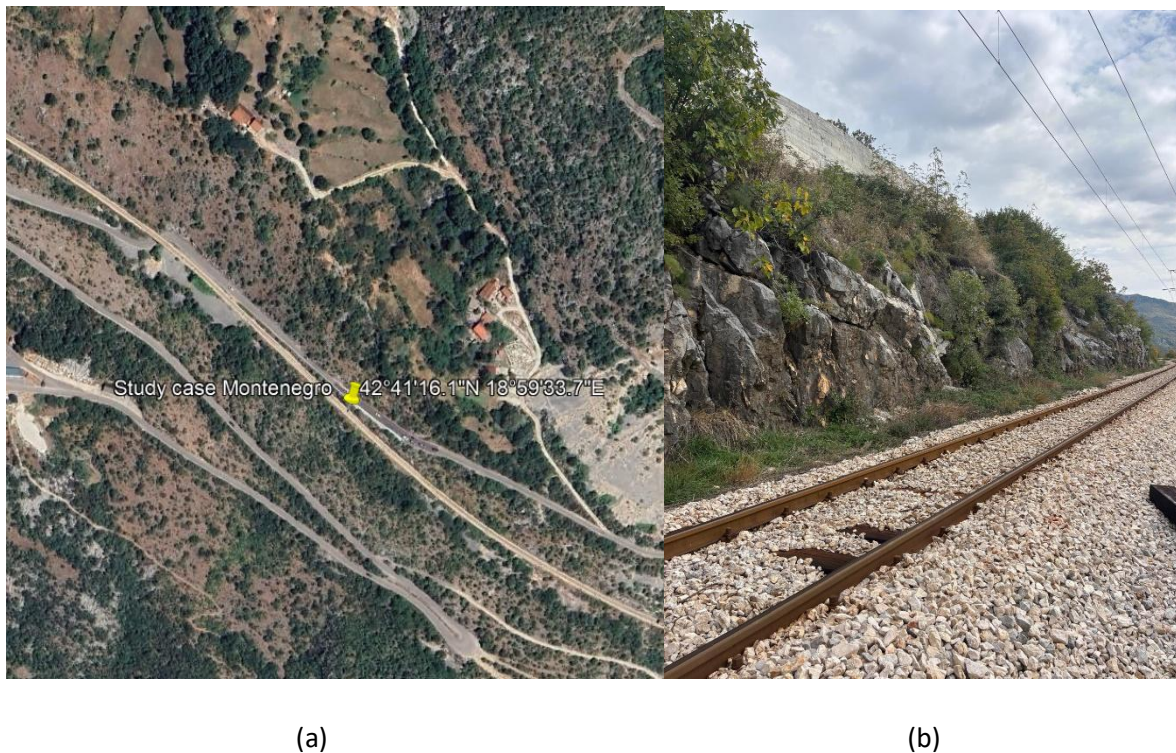


Fig. 2.1.11: (a)location (b) area of the landslide in Montenegro.

**INPUT PARAMETERS:**

Table 2.1.9 summarizes the main soil's properties, reporting **mechanical parameters** for drained conditions. The **hydraulic parameters** were chosen based on the description of the soil layer, indicating high permeability soil. Fig. 2.1.12 shows the geometry for the selected case of study, and in addition, it can be observed the position of the **water table**, located at 4 m deep.

The rainfalls selected for the case study in Montenegro are shown in Fig. 2.1.13, where a Chicago hyetograph distribution with a central peak is presented for extreme rainfall events.. The hyetograph represents precipitation events over a 30-hour duration for return periods of 30, 200, and 500 years.

Table 2.1.9: Soil properties of Montenegrin case of study.

Soil Type	Specific Unit weight, $\gamma$ [kN/m <sup>3</sup> ]	Effective cohesion, $c'$ [kPa]	Effective friction angle, $\phi'$ [°]
Diluvian sediment	18	0	14

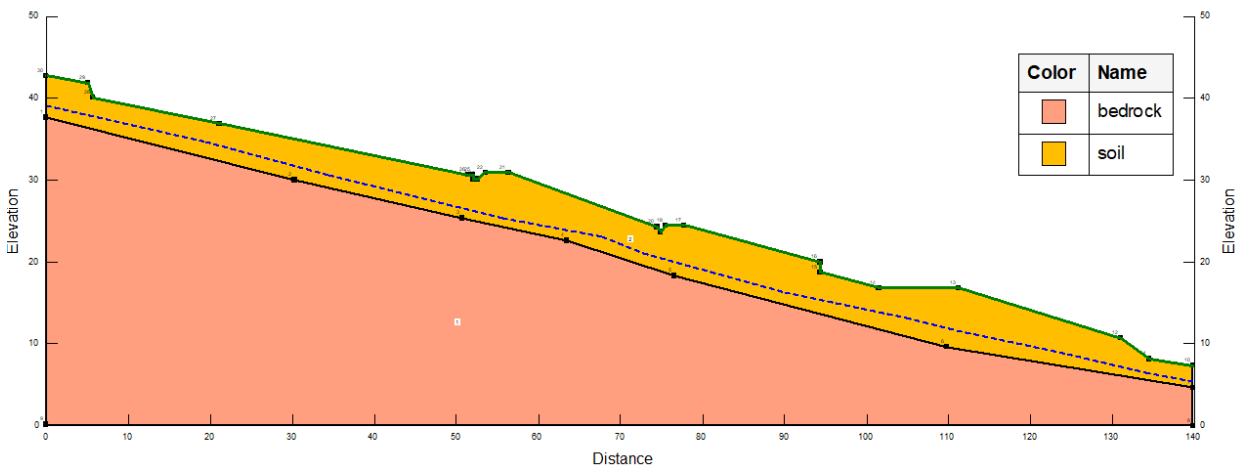


Fig. 2.1.12: Geometry of the Povija landslide.

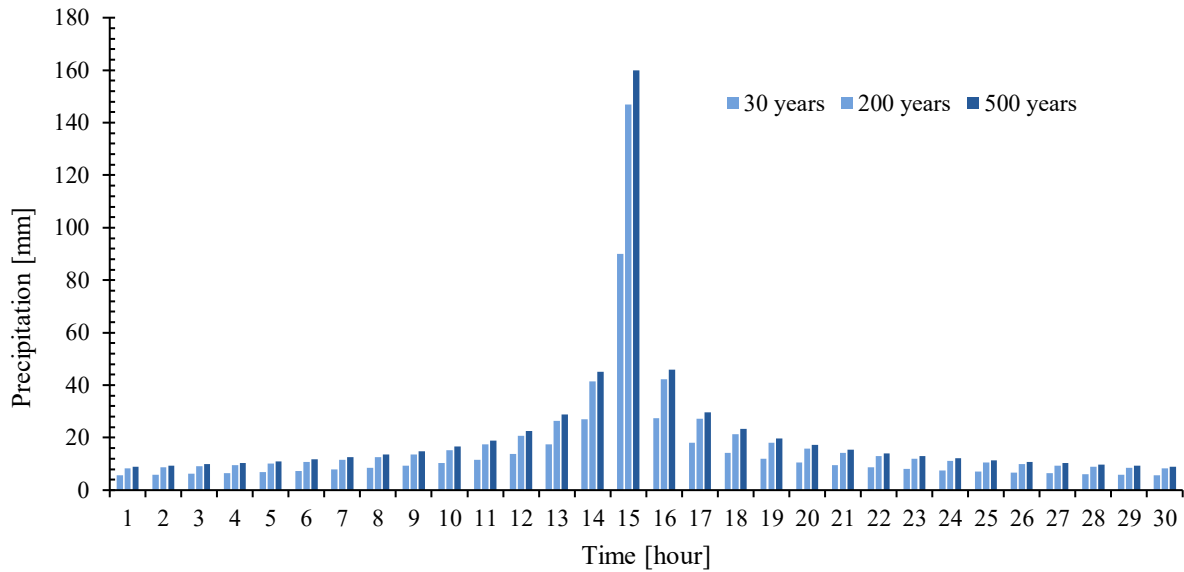
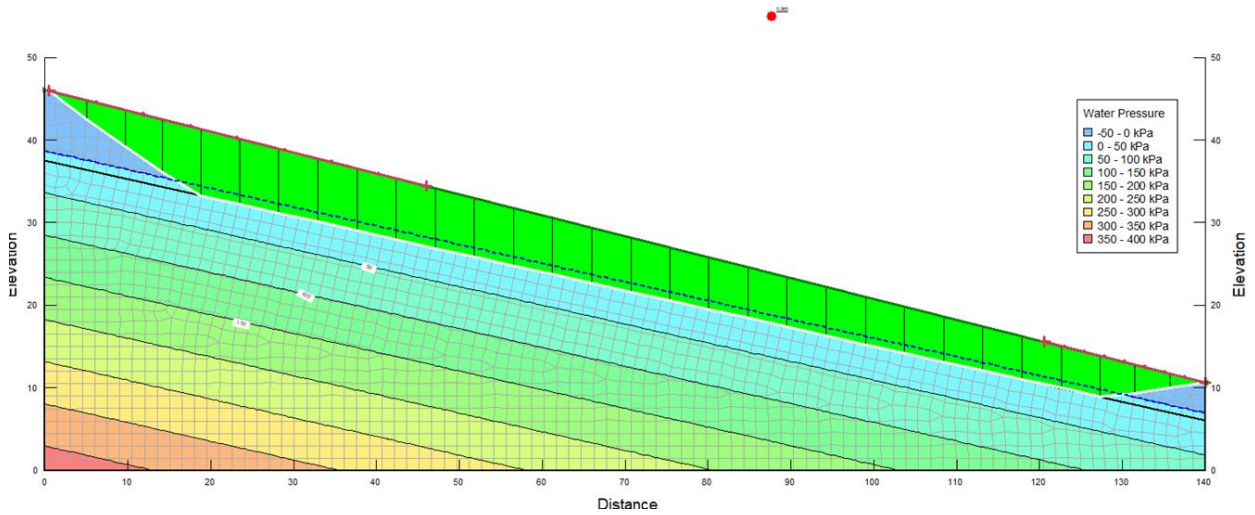


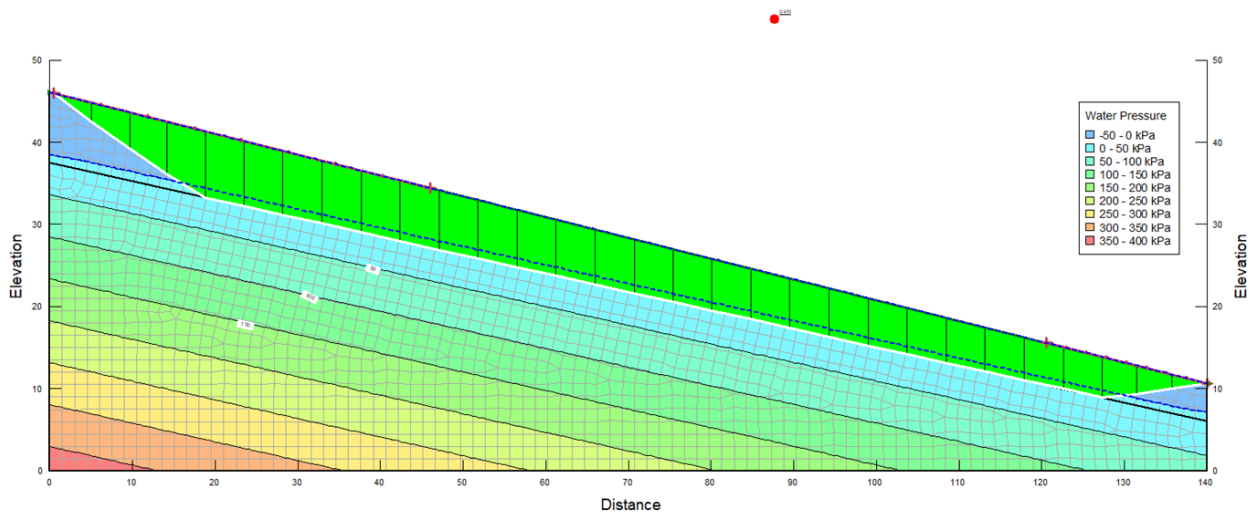
Fig. 2.1.13: Chicago hyetograph for extreme rainfall event for the pilot area in Montenegro.

**HYDRO-MECHANICAL MODELING:**

The hydro-mechanical parameters obtained from the pilot area in Molise were used to simulate the response of the slope under the three extreme rainfall events shown in Fig. 2.1.13. A simplified geometry was adopted, as reported in Fig. 2.1.14. As a result of the model, it was obtained the factor of safety (Fos) for the scenario without precipitation (Fig. 2.1.14a) and it can be observed the initial distribution of the water pressure. The response of the slope was analyzed applying the precipitation for the different return periods and in Fig. 2.1.14b is reported the FoS for a precipitation event with a return period of 500 years. No significant variation of the water table was found from the hydraulic model. Table 2.1.102 presents the input parameters used for the base scenario, and after the precipitation event with a return period of 30, 200 and 500 years. As output parameters, the factor of safety, the depth of the sliding surface and the final position of the water table were obtained.



(a)



(b)

Fig. 2.1.14: Output of Geostudio model of the slope in Montenegro (a) without precipitation (b) precipitation of 30 hours duration with a return period of 500 years.

Table 2.1.10: Input and Output parameters of the H-M model.

Parameters	Unitis	Drained	Drained	Drained	Drained
$\gamma$	kN/m <sup>3</sup>	18	18	18	18
$c'$	kPa	0	0	0	0
$\phi'$	°	14	14	14	14
$C_u$	kPa	-	-	-	-
$k_{sat}$	m/s	1E-04	1E-04	1E-04	1E-04
ST	-	1	1	1	1
$\alpha$	°	14	14	14	14
L	m	76.29	76.29	76.29	76.29
B	m	140	140	140	140
H	m	20.84	20.84	20.84	20.84
$h_m$	m	42.67	42.67	42.67	42.67
$h_d$	m	10.71	10.71	10.71	10.71
$h_{su}$	m	5.16	5.16	5.16	5.16
$h_{sd}$	m	4.61	4.61	4.61	4.61
$h_{su}$	m	37.51	37.51	37.51	37.51
$h_{sd}$	m	6.1	6.1	6.1	6.1
$z_{su}^{init}$	m	4	4	4	4
$z_{sd}^{init}$	m	4	4	4	4
$T_r$	years		30	200	500
$h_w$	mm	0	388.51	592.84	645.27
$t_w$	hr.	0	30	30	30
FoS	-	0.97	0.97	0.97	0.97
$z_s$	m	7.58	7.58	7.58	7.58
$z_{su}^{final}$	m	4	4	4	4
$z_{sd}^{final}$	m	4	4	4	4

### RISK ASSESSMENT:

Landslide risk can be quantified by using the risk matrix reported in deliverable 3.2. To account for the risk it is necessary to define the hazard level and the consequences on infrastructure.

1. **Hazard level:** determined based on the scenario without precipitation, and for precipitation with a return period of 30,200 and 500 years (Table 2.1.4 of D.3.2). Adopting the FoS reported in Table 2.1.10, the hazard level was identified as **very high** (Table 2.1.7), since all the FoS are below 1.
2. **Evaluation of the consequences on properties:** defined by the position of the structure relative to the landslide body and the significance of the landslide. In this case, the infrastructure is **on**, the road and the train rail are in the landslide body, and according to the significance level, is low significance since the sliding surface is intermediate ( $z_s=7.58$  m as reported in Table 2.1.10). As a result the **damage level is D5** (Table 2.1.7 D.3.2), implying **very high consequences**, with a score equal to **0.8**.
3. **Risk matrix:** By considering a hazard level **very high** (1) and **catastrophic consequences** (1), according to Table 2.18 of D.3.2, the **level of risk is very high (1)**.

Table 2.1.11: Hazard level based on  $FoS_i$  (Montenegro)

$FoS_0$	$FoS_1$	$FoS_2$	$FoS_3$	Hazard levels	Score Assigned
no rainfall	$T_r=30$ years	$T_r=200$ years	$T_r=500$ years		
0.97	0.97	0.97	0.97	Very High	1

### MITIGATION MEASURE:

The possible mitigation measures based on the depth of the sliding surface ( $z_s$ ) and the final position of the water table ( $z_w^{final}$ ) have been reported in deliverable 3.3, in the annex section. For each mitigation measure an effectiveness matrix was defined, based on those two variables, in which a score was assigned. When the same score is obtained from the effectiveness matrix, the applicability matrix allows to select the better mitigation measure. The values of  $z_s$  and  $z_w^{final}$  are reported in Table 2.1.10, where it can be defined the depth of the sliding surface as medium (3 to 8 m) and the depth of the piezometric surface as low, according to the effectiveness matrix. In Table 2.1.12 are reported the scores for each mitigation measure and the scores for the applicability matrix. For the considered case, the most effective measures are **G.2.2, G.2.3, G.2.4** and **G.4.1**. For the group G.2, considering the applicability matrix, the most suitable measure is **G.2.4** (addition of material), followed by **G.2.2** (removal of material of driving area). Additionally, for group G4, piles (**G.4.1**) is the most recommended and suitable measure.

Table 2.1.12: Scores for mitigation measure (Croatia)

Mitigation measure	Score of Effectiveness Matrix	Score of Applicability Matrix
G.1.1	0	3.5
G.1.2	0	4
G.1.3	0	4
G.1.4	0	3.5
G.1.5	0	4
G.2.1	0.25	3.5
G.2.2	1	3.5
G.2.3	1	2
G.2.4	1	4
G.3A.1	0.25	4
G.3A.2	0.25	4
G.3A.3	0.25	4
G.3A.4	0.5	4
G.3A.5	0.25	3
G.3.B.1a	0	2.5
G.3.B.1b	0.25	2.5
G.3B.2	0.5	2
G.3B.3	0.25	2
G.3B.4	0	1.5
G.4.1	1	3
G.4.2	0.5	3
G.4.3	0.25	2
G.4.4	0.5	2
G.5.1	0.5	3.5
G.5.2	0.5	4
G.5.3	0.5	3.5
G.5.4	0.5	3

## 2.2. FLOODING PILOT AREAS

### 2.2.1. Italy

The pilot area in Italy is located in the floodplain of the municipality of Pisa. The floodplain of (also known as the Piana di Pisa) is a flat alluvial–coastal lowland located in north-central Tuscany. Its present morphology results from a complex Quaternary geological evolution.

Geologically, the plain developed within a large tectonic depression (a subsiding basin) that was progressively filled with sediments. These deposits consist of alternating marine, lagoonal, and continental layers, forming a multi-layered aquifer system. The subsurface is mainly composed of sands, silts, and clays, with interbedded gravel deposits. The current configuration of the plain was largely shaped during the late Quaternary, especially in the Holocene (from approximately 6000–5000 BCE onward), when sea level stabilized. Sedimentation processes were driven by the combined action of fluvial dynamics and coastal processes. This led to the formation of floodplains, coastal deposits, and extensive marshy environments, particularly north of the Arno River.

From a hydrogeological perspective, the area is characterized by significant groundwater variability and instability. It hosts important artesian aquifers, especially along the foothill belt, while brackish groundwater conditions occur near the coast.

In summary, the floodplain of Pisa is a relatively recent alluvial system formed by the interaction between river sedimentation and shifting coastlines, consisting of a thick sequence of Quaternary deposits resting on an older geological substratum.

In the floodplain, there is the river Arno, one of the main rivers in central Italy. It originates on Mount Falterona in the Apennines and flows westward for about 240 km through Tuscany, passing major cities such as Florence and Pisa before emptying into the Tyrrhenian Sea near Marina di Pisa. The River Arno has historically been prone to flooding, with the most notable event occurring in Florence in 1966. It plays an important role in regional water management, agriculture, ecology, and urban development. In the floodplain, there is also a flood diversion channel (named Scolmatore) designed to reduce peak discharge in the downstream reach of the Arno, particularly near Pisa.

Fig. 2.2.1 shows the location of the floodplain in Italy and a detailed view of the studied area.

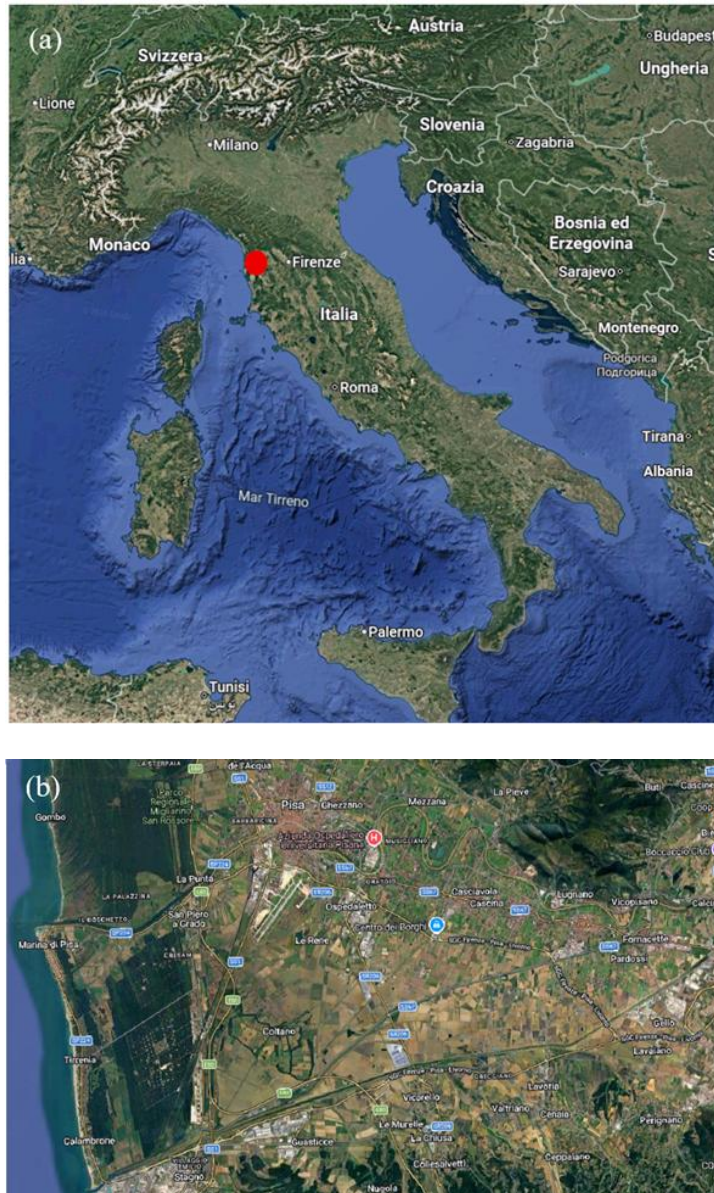


Fig. 2.2.1 (a) Location of the pilot area in Italy. (b) Particular of the selected pilot area.

Data of flood events, including information on the Arno River and the flood diversion channel Scolmatore, and geo-hydrological datasets, were collected from Arno River Basin District Authority.

Based on the methodology established for reference scenarios, we considered the following representative parameters for the pilot area (which are summarized in Table 2.2.1).

- Characteristics of the basin
- Characteristics of the river

- Rainfall for different return periods

As for the characteristics of the basin and river, we adopted the DTM map of the simulated area shown in Fig. 2.2.2.

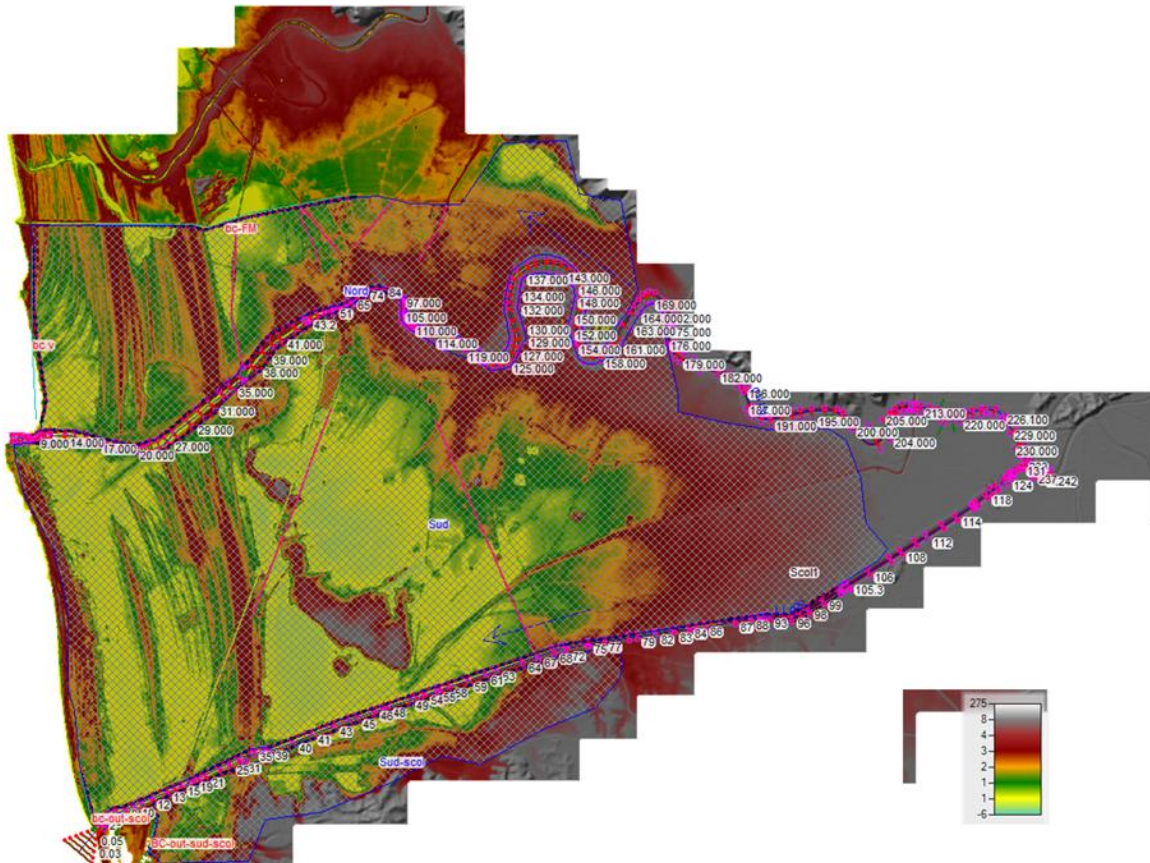


Fig. 2.2.2: DTM map of the case study area adopted in numerical simulations, along with the soil elevation scale in meter.

The rainfalls were elaborated considering data relative to the available pluviometers located in the river basin. The Chicago hyetograph was assumed as the design hyetograph.

Following the methodology adopted for the reference areas (see Deliverable 3.2) we estimated the main parameters adopted in the numerical simulations. For the sake of completeness, we summarize below the main relationships adopted for the estimates.

The peak discharge  $Q_{max}$  accounts for areal effects and is calculated as:

$$Q_{max} = Q_0[-0.116 \ln A + 1.1088] \quad (1)$$

where  $A$  is the drainage basin area [in  $\text{km}^2$ ] and

$$Q_0 = chA/T_c \quad (2)$$

is the discharge calculated using the rational method, with  $c$  indicating the runoff coefficient, and  $h$  representing the rainfall height. Note that the rainfall intensity is  $i=h/T_c$ .

Here  $T_c$  is the concentration time and is evaluated as follows:

$$T_c = [4A^{0.5} + 1.5L]/(0.8H_m^{0.5}) \quad (3)$$

where  $L$  indicates the length of the flow path (in km) and  $H_m$  is the mean elevation of the drainage basin (in m), referred to the elevation of the final (closing) section of the considered river.

Assuming  $t=T_c$ , the rainfall height  $h$  in Eq. (2) is calculated using the depth-duration-frequency relationship pertaining to the analyzed area, i.e.,  $h = at^n$ , with the coefficients  $a$  and  $n$  depending on the return period  $T_r$  (in years). Here  $t$  represents the time (in hours):

Table 2.2.1. Synthesis of the main input parameters and simulations outputs for the case study in Italy.

Location of the case study	River	Runoff coefficient $c$	$a$	$n$	$T_r$	Drainage basin area $A$ ( $\text{km}^2$ )	$L$ (km)	Drainage basin mean slope $I$	Time of concentration $T_c$ [hours]	Rainfall intensity $i$ [mm/h]	Peak discharge $Q_{\max}$ [ $\text{m}^3/\text{s}$ ]	Results of simulations
Italy	Arno	0.4	43.1	0.38	10	8000	126.5	0.1	43.3	4.2	885.1	GeoTIFF maps
			54.9	0.38	30					5.3	1127.1	
			71.6	0.38	100					6.9	1469.0	
			83.4	0.38	200					8.1	1711.0	

By using the HEC-RAS software and considering the DTM map of the study area, different flooding scenarios corresponding to various return periods were simulated.

The results pertaining to each simulated scenario were reported in GeoTIFF files. The simulated scenarios are relative to return periods ranging from 10 to 200 years.

Specifically, in Figures 2.2.3 - 2.2.4, we show the most significant flood maps for  $T_r = 200$  years (Fig. 2.2.3) and  $T_r = 30$  years (Fig. 2.2.4). For  $T_r = 10$  years, no flooding events occur since the watercourse is embanked. The legend in the figures refers to the water depths.

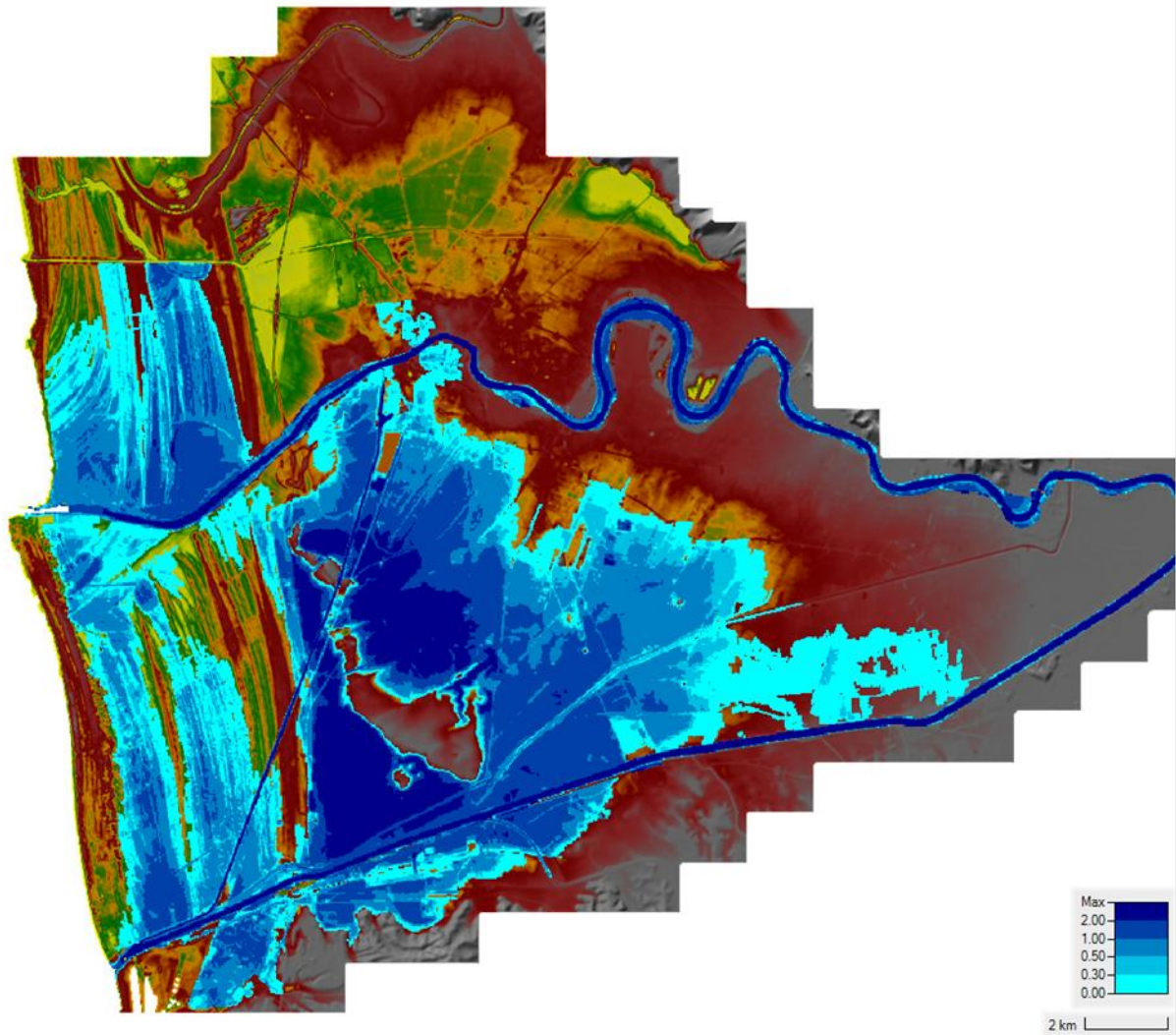


Fig. 2.2.3: Flood envelope map (water depths) in the floodplain of Pisa for a 200-year return period.

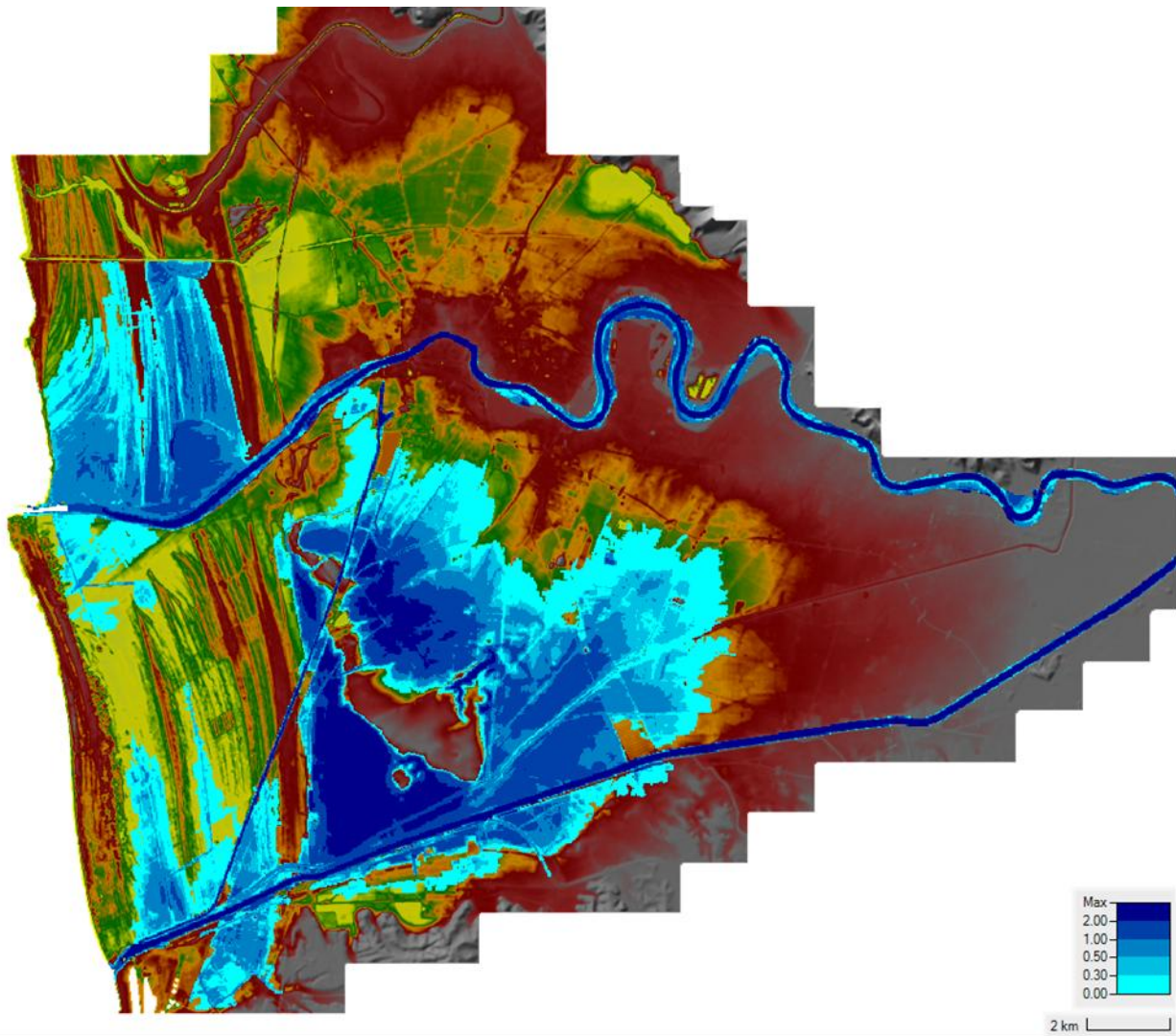


Fig. 2.2.4: Flood envelope map (water depths) in the floodplain of Pisa for a 30-year return period.

As for the hydraulic risk assessment, we adopt the methodology illustrated in the Deliverables 3.2 and 3.3.

Therefore, we should consider:

- The class of damage;
- The hydraulic hazard level.

Tables 2.2.2 and 2.2.3 summarize the identified classes of damage and hydraulic hazard level.

Table 2.2.2. Definition of damage classes.

Code	Class of damage	Description of land use
D1	Low	Woodland area
		Non-buildable agricultural area
		Unbuilt or unbuildable public land
D2	Moderate	Public infrastructure (non-strategic municipal or consortium roads)
		Environmental protection area, buffer zones, private green areas
		Parks, unbuilt public green areas
D3	Medium	Railways
		Lifelines: power lines, pipelines, aqueducts
		General agricultural area (with building potential)
		Area for technological plants, municipal waste landfills; quarry zones
D4	High	Urban centers
		Minor rural centers of particular value
		Completion areas
		Expansion areas
		Artisan, industrial, commercial areas
		Public services mainly with buildings
		Public infrastructures (e.g., main and strategic roads and services)
		Area for disposal of hazardous or special waste
		Hotel area
Area for campsites and tourist villages		

Table 2.2.3. Definition of hydraulic hazard classes.

Code	Class of hydraulic hazard	Description
P3	High	Flood for $Tr \leq 30$ years
P2	Medium	Flood for $30 \text{ years} < Tr \leq 200$ years
P1	Low	Flood for $Tr > 200$ years

For the flood plain of Pisa, we have distinguished between the urban center of Pisa and the surrounding non-urban areas.

### **Urban center of Pisa:**

#### **Class of damage:**

- D4 – High Damage Class

The highest damage class is assigned to urban areas, historical settlements, and strategic or densely built environments. It includes critical infrastructure, residential and commercial zones, public services, hazardous waste areas, and tourism facilities (e.g., hotels and campsites). Here, flood events can lead to major economic damage, human safety risks, and long-term disruptions to key services.

#### **Hydraulic Hazard:**

- P2 – Medium Hazard

This class includes moderate-probability flood events, with a return period between 30 and 200 years ( $30 < Tr \leq 200$  years). These are less frequent than high-hazard events but still present significant risks, especially in populated or economically active areas.

Consequently, considering the hydraulic risk matrix reported in Table 2.2.4. (see also deliverable 3.2), the **hydraulic risk class is:**

- R3 – High Risk:

Significant adverse effects are possible, including threats to public safety, economic productivity, and key infrastructure. Recovery efforts may be substantial.

### **Surrounding non-urban areas:**

#### **Class of damage:**

- D2 – Moderate Damage Class

Areas in this class host non-strategic infrastructure, buffer zones, and green public or private spaces, such as parks or protected landscapes. Although development is limited, flooding can still cause moderate disruption to public amenities, ecosystems, or secondary services.

#### **Hydraulic Hazard:**

- P3 – High Hazard

This level refers to frequent and intense flood events, typically associated with a return period of 30 years or less ( $Tr \leq 30$  years). These floods may occur more than once in a generation and are considered a serious threat to safety, infrastructure, and property.

Consequently, considering the hydraulic risk matrix reported in Table 3.2.1.4. (see also deliverable 3.2), the **hydraulic risk class is:**

- R2 – Medium Risk:

Moderate consequences are expected. Floods may affect economic activities or services, but do not generally pose a threat to life or strategic infrastructure.

Table 2.2.4. Definition of hydraulic hazard classes.

Class of hydraulic risk		Class of hazard		
		P3	P2	P1
Class of damage	D4	R4	R3	R2
	D3	R3	R3	R1
	D2	R2	R2	R1
	D1	R1	R1	R1

As for the usually adopted measures to mitigate the hydraulic risk, we follow the methodology illustrated in Deliverables 3.2 and 3.3.

Based on this methodology, we can identify the hydraulic risk class of the target area, based on the basin characteristics and according to Table 2.2.5, where the acronyms are defined as follows:

- **Structural Measures (SM)**
  - SM1: Routine maintenance of watercourses, clearing and inspection of structures (e.g., culverts, bridges, ditches, drainage canals, etc.)
  - SM2: Retention and Detention Basins
  - SM3: Riverbed and Bank Stabilization
  - SM4: Dikes and Levees construction/reinforcement
  - SM5: Diversion Channels and Floodways

- SM6: Reservoirs and Dams
- **Non-Structural Measures (NSM)**
  - NSM1: Land Use Planning and Zoning
  - NSM2: Flood Forecasting and Early Warning Systems
  - NSM3: Emergency Preparedness and Response Plans
- **Nature-Based Solutions (NBS)**
  - NBS1: Restoration of Floodplains and Wetlands
  - NBS2: Urban Green Infrastructure
  - NBS3: Reforestation and Afforestation in Watersheds

Table 2.2.5. Usually adopted measures (indicated by the corresponding codes) for different classes of hydraulic risk and basin characteristics

<i>Type of basin</i>		<i>Small</i>		<i>Intermediate</i>		<i>Large</i>
<i>Slope class</i>		<i>Low</i>	<i>From moderate to high</i>	<i>Low</i>	<i>Moderate</i>	<i>Low</i>
<b><i>Class of Hydraulic Risk</i></b>	<b>R1</b>	SM1	SM1, NBS3	SM1	SM1, NBS3	SM1, NBS3

	<b>R2</b>	SM1 , NSM1, NSM2, NSM3, NBS1, NBS2	SM1, NSM1, NSM2, NSM3, NBS1, NBS2, NBS3	SM1, SM3, NSM1, NSM2, NSM3, NBS1, NBS2	SM1, SM3, NSM1, NSM2, NSM3, NBS1, NBS2, NBS3	SM1, SM3, NSM1, NSM2, NSM3, NBS1, NBS2, NBS3
	<b>R3</b>	SM1, SM2, SM3, SM4, NSM1, NSM2, NSM3, NBS1, NBS2	SM1, SM2, SM3, SM4, NSM1, NSM2, NSM3, NBS1, NBS2, NBS3	SM1, SM2, SM3, SM4, SM5, NSM1, NSM2, NSM3, NBS1, NBS2	SM1, SM2, SM3, SM4, SM5, NSM1, NSM2, NSM3, NBS1, NBS2, NBS3	SM1, SM2, SM3, SM4, SM5, SM6, NSM1, NSM2, NSM3, NBS1, NBS2, NBS3
	<b>R4</b>	SM1, SM2, SM3, SM4, SM5, NSM1, NSM2, NSM3, NBS1, NBS2	SM1, SM2, SM3, SM4, SM5, NSM1, NSM2, NSM3, NBS1, NBS2, NBS3	SM1, SM2, SM3, SM4, SM5, SM6, NSM1, NSM2, NSM3, NBS1, NBS2	SM1, SM2, SM3, SM4, SM5, SM6, NSM1, NSM2, NSM3, NBS1, NBS2, NBS3	SM1, SM2, SM3, SM4, SM5, SM6, NSM1, NSM2, NSM3, NBS1, NBS2, NBS3

For the **urban center of Pisa**, we have:

- Hydraulic risk: R3.

Consequently, from Table 2.2.5, we obtain that the usually adopted measures are:

SM1, SM2, SM3, SM4, SM5, SM6, NSM1, NSM2, NSM3, NBS1, NBS2, NBS3.

Conversely, for the **surrounding non-urban areas**, we have:

- Hydraulic risk: R2.

Consequently, from Table 2.2.5, we obtain that the usually adopted measures are:

SM1, SM3, NSM1, NSM2, NSM3, NBS1, NBS2, NBS3.

To support and prioritize the selection of the most effective measures listed above, an effectiveness score is assigned to each measure. This score reflects the ability of the specific measure to reduce hydraulic risk, which results from the combination of flood event likelihood (hazard) and the potential severity of its consequences (damage). The score reported in Tables 2.2.6-2.2.8 (see also Deliverable

3.3) ranges from 0.25 to 1, with higher values indicating greater effectiveness.

Table 2.2.6. Effectiveness score of structural measures (identified by their corresponding codes) in reducing hydraulic risk.

Measure	Code	Rationale	Effectiveness score
Routine maintenance of watercourses, clearing and inspection of structures	SM1	Ensures basic hydraulic functionality by preventing blockages and failures in watercourses.	0.6
Retention and Detention Basins	SM2	Stores excess runoff during peak events, thereby reducing flood hazard and protecting downstream areas. Supports risk reduction across both hazard and exposure axes.	0.75
Riverbed and Bank Stabilization	SM3	Controls erosion and stabilizes channels, preserving capacity and minimizing secondary risks (e.g. failure of banks).	0.65
Dikes and Levees construction/reinforcement	SM4	Acts as a primary defense, shielding people, assets, and infrastructure. Highly effective at reducing both flood hazard and vulnerability in protected areas.	1
Diversion Channels and Floodways	SM5	Redirects floodwaters away from at-risk zones, effectively reducing exposure and concentrating flow where impacts are lower. Especially useful in peri-urban regions.	0.85
Reservoirs and Dams	SM6	Allows system-wide flood control through planned storage and release. Effective in lowering hazard levels over large areas, especially in regulated river systems.	0.95

Table 2.2.7. Effectiveness score of non-structural measures (identified by their corresponding codes) in reducing hydraulic risk

Measure	Code	Rationale	Effectiveness score
Land Use Planning and Zoning	NSM1	A correct planning of land use and zoning plays a pivotal role in long-term risk reduction by regulating development in flood-prone areas. It limits exposure by promoting flood-compatible uses.	0.5
Flood Forecasting and Early Warning Systems	NSM2	Uses real-time data and models to anticipate flood events. When paired with outreach and preparedness, it significantly enhances response capacity and reduces fatalities.	0.4
Emergency Preparedness and Response Plans	NSM3	Ensures coordinated action during crises through updated protocols, simulations, and evacuation planning. Critical for reducing impacts during flood events.	0.35

Table 2.2.8. Effectiveness score of nature-based solutions (identified by their corresponding codes) in reducing hydraulic risk

Measure	Code	Rationale	Effectiveness score
Restoration of Floodplains and Wetlands	NBS1	Restores natural flood buffers by allowing controlled overflows into lowlands, reducing peak discharges, recharging groundwater, and enhancing biodiversity.	0.45
Urban Green Infrastructure	NBS2	Implements urban features like green roofs and permeable pavements to manage pluvial flooding by increasing infiltration and delaying runoff in cities.	0.3
Reforestation and Afforestation in Watersheds	NBS3	Enhances soil stability and infiltration, reducing surface runoff and flash flood risks. Especially effective in upland or deforested catchments for hydrological regulation.	0.25

Likewise, based on the total score *S* defined as in Deliverable 3.3 (which is fully consistent with that derived from the effectiveness score alone and is reported, for completeness, in Table 2.2.9), we obtain the following order of prioritization for the mitigation measures:

**Urban center of Pisa:**

1) SM4; 2) SM6; 3) SM5; 4) SM2; 5) SM3; 6) SM1; 7) NSM1; 8) NBS1; 9) NSM2; 10) NSM3; 11) NBS2; 12) NBS3.

**Surrounding non-urban areas:**

1) SM3; 2) SM1; 3) NSM1; 4) NBS1; 5) NSM2; 6) NSM3; 7) NBS2; 8) NBS3.

Note that the mitigation measures are also distinguished between “Highly Recommended” and “Recommended” according to the following criterion for the score *S*.

- $S \geq 1.5$ : Highly recommended (green color in Table 2.2.9)

- S<1.5: Recommended (yellow color in Table 3.2.1.9)

Table 2.2.9. Total score values for each measure

Measure	Code	Score effectiveness	Score applicability	Total score S	Note
Routine maintenance of watercourses, clearing and inspection of structures	SM1	0.6	2.85	1.71	Highly Recommended
Retention and Detention Basins	SM2	0.75	2.3	1.73	Highly Recommended
Riverbed and Bank Stabilization	SM3	0.65	2.65	1.72	Highly Recommended
Dikes and Levees construction/reinforcement	SM4	1	2.25	2.25	Highly Recommended
Diversion Channels and Floodways	SM5	0.85	2.05	1.74	Highly Recommended
Reservoirs and Dams	SM6	0.95	1.85	1.76	Highly Recommended
Land Use Planning and Zoning	NSM1	0.5	2.4	1.20	Recommended
Flood Forecasting and Early Warning Systems	NSM2	0.4	2.2	0.88	Recommended
Emergency Preparedness and Response Plans	NSM3	0.35	2.4	0.84	Recommended
Restoration of Floodplains and Wetlands	NBS1	0.45	2.3	1.04	Recommended
Urban Green Infrastructure	NBS2	0.3	2.5	0.75	Recommended
Reforestation and Afforestation in Watersheds	NBS3	0.25	2.7	0.68	Recommended

## 2.2.2 Croatia

The pilot area in Croatia is situated near the Municipality of Sveti Martin na Muri (coordinates: 46°32'N 16°23'E) in Upper Međimurje, along the border with Slovenia. The municipality spans a total area of 25.24 km<sup>2</sup>. From a geomorphological perspective, it is divided into two distinct zones. The southern section is characterized by gently rolling hills known as the Međimurske Gorice, whereas the northern section forms part of the alluvial plain of the Mura River.

The Mura River effectively separates the municipality into two areas and its floodplain is included within a protected natural area known as the Mura-Drava Regional Park (Fig. 2.2.5). This park lies in the northern part of Međimurje County, at the northernmost edge of Croatia, directly along the Slovenian border, and encompasses the Municipality of Sveti Martin na Muri.

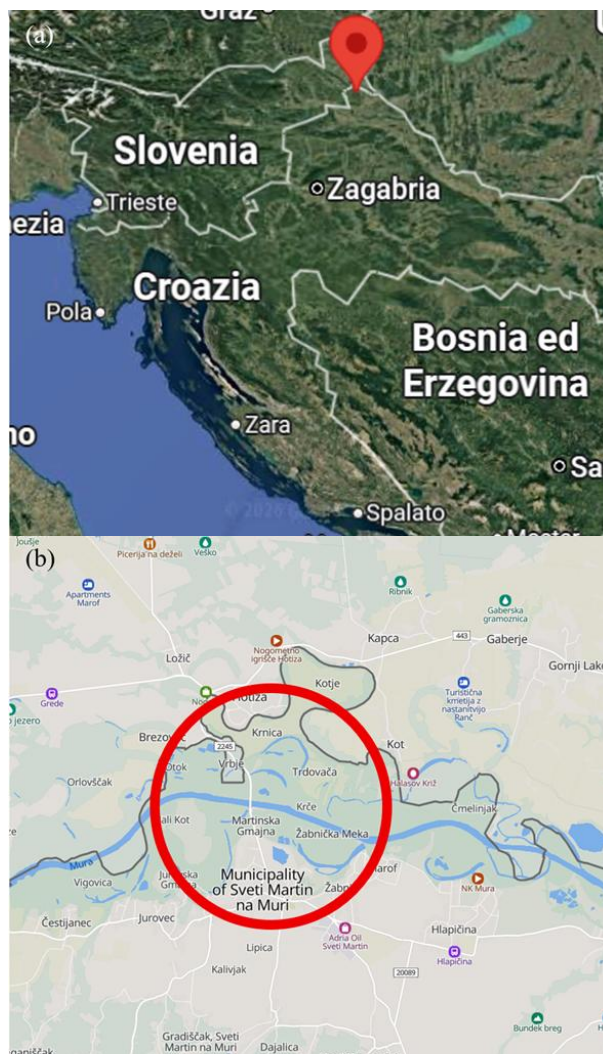


Fig. 2.2.5. (a) Location of the pilot area in Croatia. (b) Particular of the selected pilot area.

Data of flood events, including information on the Mura River and geo-hydrological datasets, were provided by Hrvatske vode, the national public institution responsible for the management of public waters in the Republic of Croatia.

Based on the methodology established for the reference scenarios, we considered the following representative parameters for the pilot area (which are summarized in Table 2.2.10).

- Characteristics of the basin
- Characteristics of the river
- Rainfall for different return periods

As for the characteristics of the basin and river, we adopted the DTM map of the simulated area shown in Fig. 2.2.6.



Fig. 2.2.6. The shaded area represents the simulated pilot area in Croatia.

The rainfalls were elaborated considering data relative to the available pluviometers located in the area of Čakovec. The Chicago hyetograph was assumed as the design hyetograph (see Fig. 2.2.7.). In particular, the hyetograph shown in the following figure represents precipitation events over a 30-hour duration for return periods of 30, 200, and 500 years.

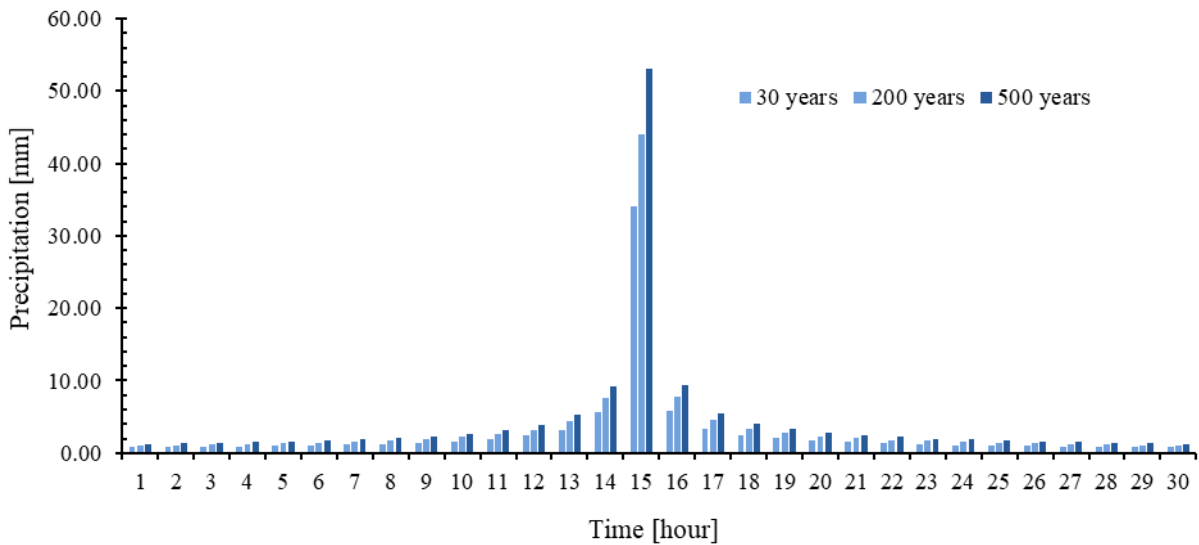


Fig. 2.2.7: Chicago hyetograph for extreme rainfall event adopted for the case study in Croatia.

Following the methodology adopted for the reference areas (see Deliverable 3.2) and synthesized above for the case study in Italy, after estimating the time of concentration  $T_c$  and, consequently, the rainfall intensity pertaining to different scenarios, the peak discharge  $Q_{max}$  was calculated by adopting the rational method and considering a correction factor depending on the extension of the drainage basin area  $A$  (Chow et al., 1988; Bedient et al., 2012; see also Deliverable 3.2). The main input parameters of the basin and the rainfall events considered for this case study are synthesized in Table 2.2.10, along with the main outputs of the simulations.

Table 2.2.10. Synthesis of the main input parameters and simulation outputs for the case study in Croatia.

Location of the case study	River	Runoff coefficient c	a	n	Tr	Drainage basin area A (km <sup>2</sup> )	L (km)	Drainage basin mean slope I	Time of concentration Tc [hours]	Rainfall intensity i [mm/h]	Peak discharge Qmax [m <sup>3</sup> /s]	Results of simulations
Croatia	Mura	0.3	29	0.27	10	13000	161.2	0.1	55.2	1.55	60.3	GeoTIFF maps
			34	0.27	30					1.82	70.7	
			40	0.27	100					2.14	83.2	
			44	0.27	200					2.35	91.5	

By using the HEC-RAS software and considering the DTM map of the basin, different scenarios corresponding to various return periods were simulated.

The results pertaining to each simulated scenario were reported in GeoTIFF files. Specifically, in Figures 2.2.8 – 2.2.11, we show the DTM map adopted in the simulations with the HEC-RAS software and the flood maps for  $T_r = 200$  years (Fig. 2.2.9),  $T_r = 100$  years (Fig. 2.2.10) and  $T_r = 10$  years (Fig. 2.2.11). Note that the soil elevation scale is reported in Fig. 2.2.9, while the water depth scale is shown in Fig. 2.2.10. They are valid for all Figures 2.2.8 – 2.2.11.

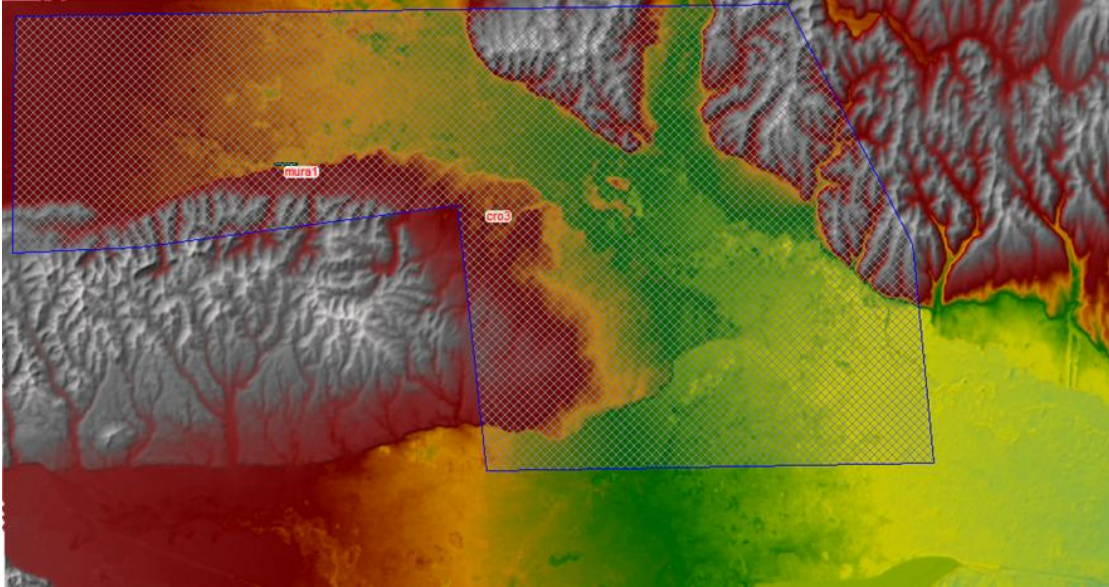


Fig. 2.2.8.: DTM map of the case study area adopted in the numerical simulations

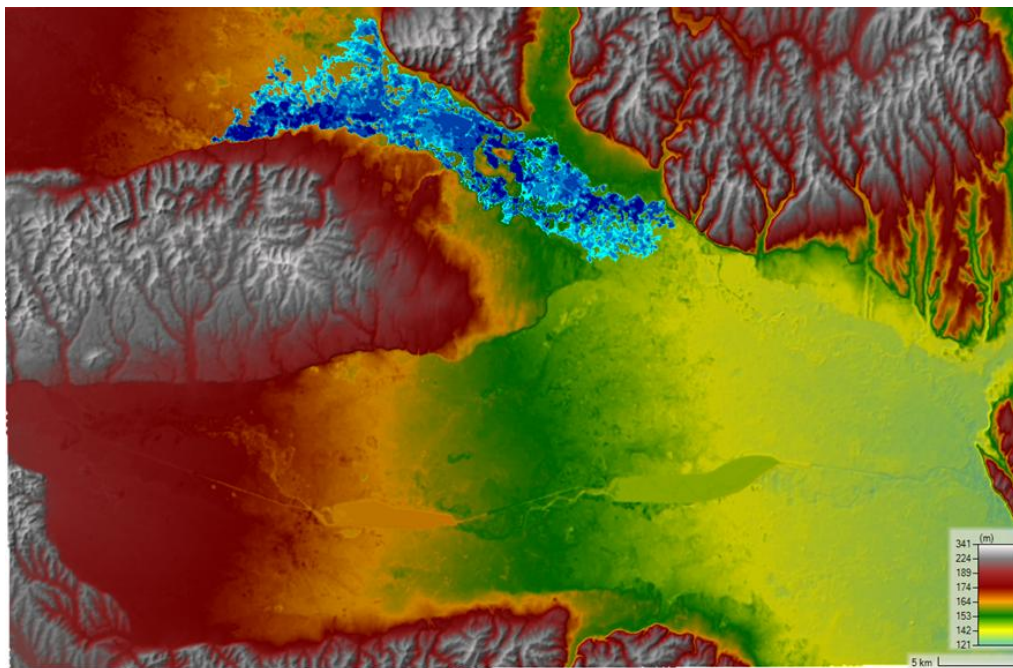


Fig. 2.2.9.: Flood envelope map (water depths) for a 200-year return period.

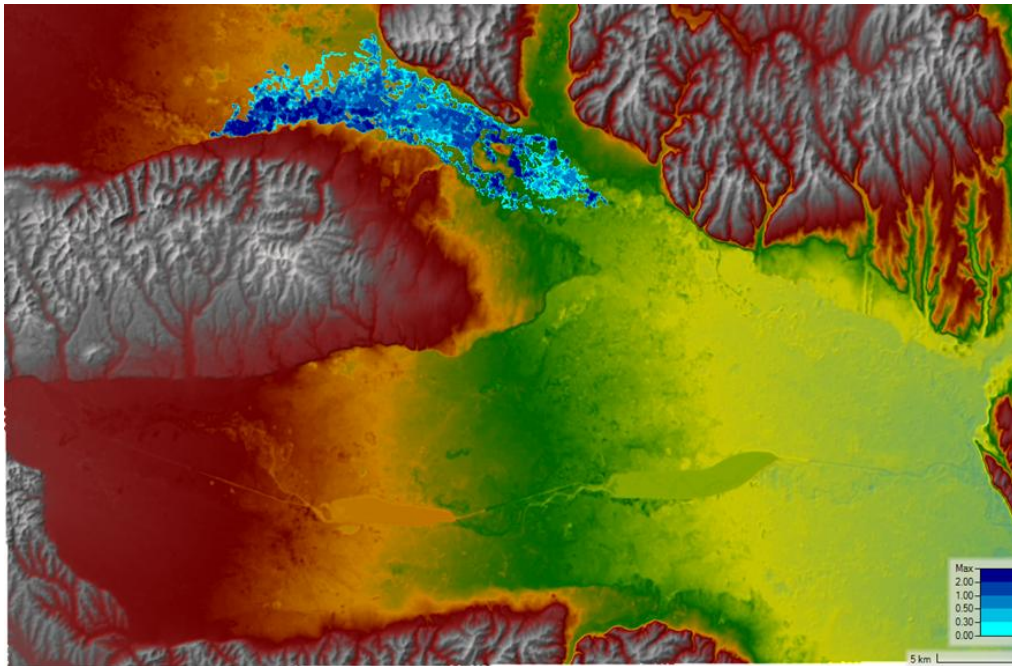


Fig. 2.2.10.: Flood envelope map (water depths) for a 100-year return period.

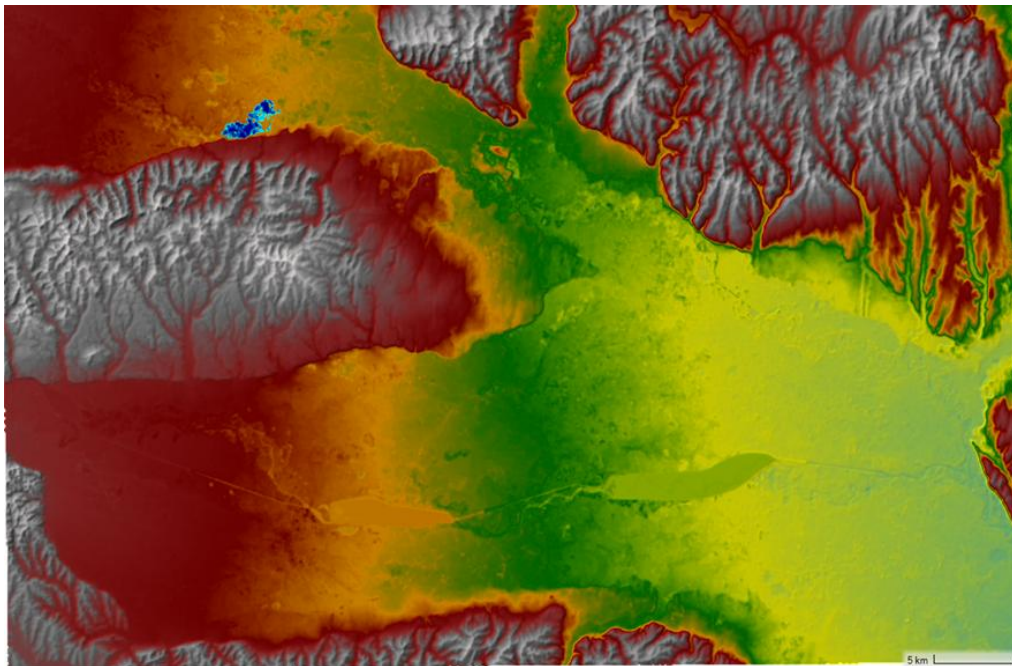


Fig. 2.2.11.: Flood envelope map (water depths) for a 10-year return period.

As for the hydraulic risk assessment, we adopt the same methodology illustrated above and in the Deliverables 3.2 and 3.3.

Therefore, we should consider:

- The class of damage;
- The hydraulic hazard level;

Also in this case, we have distinguished between the urban center (including some present in the area) and the surrounding non-urban areas.

#### **Urban center:**

##### **Class of damage:**

- D4 – High Damage Class

##### **Hydraulic Hazard:**

- P2 – Medium Hazard

Consequently, considering the hydraulic risk matrix reported in Table 2.2.4. (see also deliverable 3.2), the **hydraulic risk class is:**

- R3 – High Risk

#### **Surrounding non-urban areas:**

##### **Class of damage:**

- D2 – Moderate Damage Class

##### **Hydraulic Hazard:**

- P3 – High Hazard

Consequently, considering the hydraulic risk matrix reported in Table 2.2.4. (see also deliverable 3.2), the **hydraulic risk class is:**

- R2 – Medium Risk

As for the usually adopted measures to mitigate the hydraulic risk, we follow the methodology illustrated in Deliverables 3.2 and 3.3.

Based on the hydraulic risk class and the characteristics of the basin of the target area, from Table 2.2.5, we obtain that the usually adopted measures are as follows.

For the **urban center**, we have:

- Hydraulic risk: R3.

Consequently, from Table 2.2.5, we obtain that the usually adopted measures are:

SM1, SM2, SM3, SM4, SM5, SM6, NSM1, NSM2, NSM3, NBS1, NBS2, NBS3.

Conversely, for the **surrounding non-urban areas**, we have:

- Hydraulic risk: R2.

Consequently, from Table 2.2.5, we obtain that the usually adopted measures are:

SM1, SM3, NSM1, NSM2, NSM3, NBS1, NBS2, NBS3.

To support and prioritize the selection of the most effective measures listed above, an effectiveness score is assigned to each measure (see Tables 2.2.6-2.2.8 and Deliverable 3.3).

Likewise, based on the total score  $S$  (defined as in Deliverable 3.3 and reported, for completeness, in Table 2.2.9) we obtain the following order of prioritization for the mitigation measures identified for this case study:

#### **Urban center:**

1) SM4; 2) SM6; 3) SM5; 4) SM2; 5) SM3; 6) SM1; 7) NSM1; 8) NBS1; 9) NSM2; 10) NSM3; 11) NBS2; 12) NBS3.

#### **Surrounding non-urban areas:**

1) SM3; 2) SM1; 3) NSM1; 4) NBS1; 5) NSM2; 6) NSM3; 7) NBS2; 8) NBS3.

### 2.2.3. Montenegro

The pilot area in Montenegro is located in the Municipality of Nikšić (Fig. 2.2.12), in the central and northwestern part of the country, within the expansive Nikšić Field (Nikšićko polje), a karst plain covering approximately 48 km<sup>2</sup> at an elevation of 640 meters above mean sea level (AMSL). The field is surrounded by rugged mountainous terrain typical of western Montenegro, while the town of Nikšić lies at the foot of Trebjesa Hill.

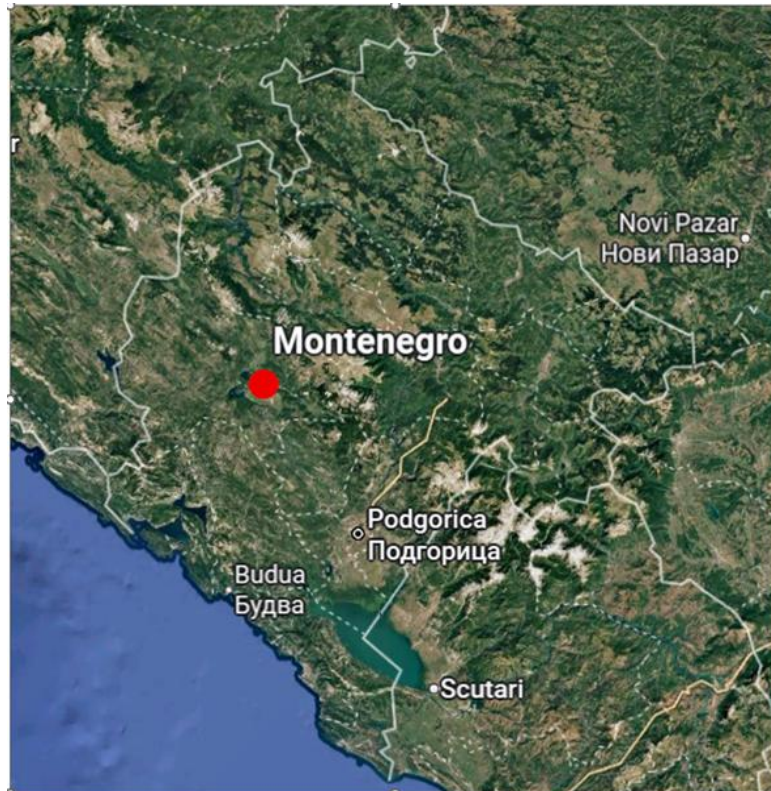


Fig. 2.2.12. Location of the pilot area in Montenegro.

Various rivers/streams/channels and artificial lakes are present in the area of the municipality of Nikšić, i.e., the Zeta, Bistrica, Gračanica and Mrkošnica Rivers.

The Zeta River originates in the field and historically caused frequent flooding, which was significantly reduced after the construction of the Perućica Hydropower Plant in 1960 and the creation of the Krupac, Slano, and Vrtac artificial lakes.

The drainage basin of the Gračanica River occupies an area in central Montenegro between 42°39' and 42°50' north latitude and 19°12' and 19°19' east longitude. It forms part of the complex hydrographic network of the Skadar Basin, which belongs to the Adriatic Sea Basin. The drainage basin includes the southern part of Nikšićko Polje; the northern, northeastern, and eastern slopes of Mount Žirovnica, Prekornica, and Miljevac; and the southern, southwestern, and western slopes of Mount Maganik,

Zurim, and Vojnik.

The Bistrica River is a left-bank tributary of the Zeta River. It originates at the base of Mount Tović.

The Mrkošnica River rises on the southwestern slopes of Mount Trebjesa. Another branch of the same watercourse emerges in the southern part of Nikšić, where its channel has been partially regulated. These two branches converge in Straševina, forming the main course of the Mrkošnica River, which eventually flows into the Zeta River along the southern edge of the plain.

The following Figures show the hydraulic network in the area of the municipality of Nikšić.

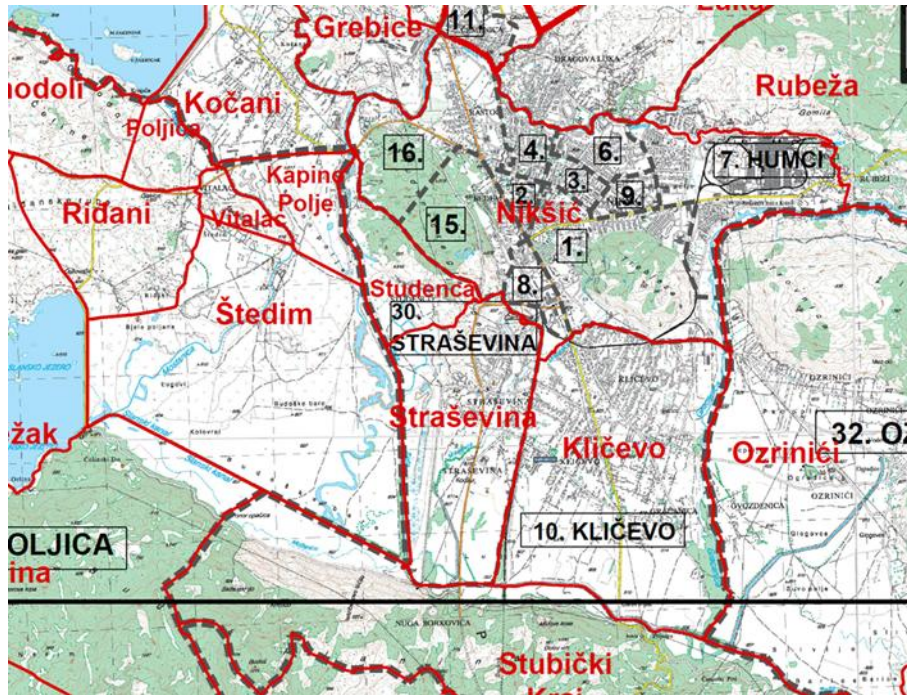


Fig. 2.2.13. Map of the municipality of Nikšić.

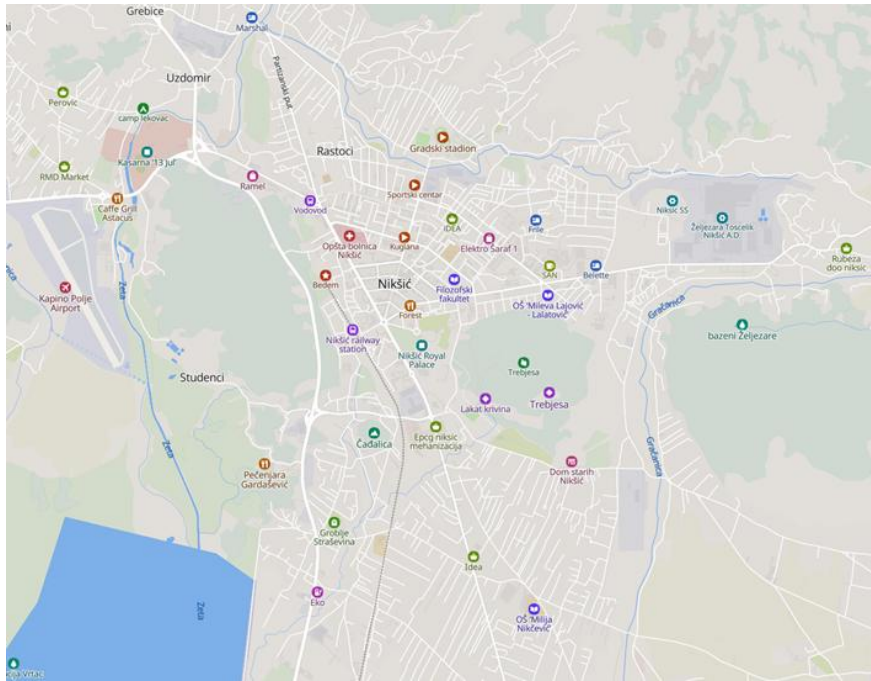


Fig. 2.2.14 Hydraulic network of the northern part of the Municipality of Nikšić.

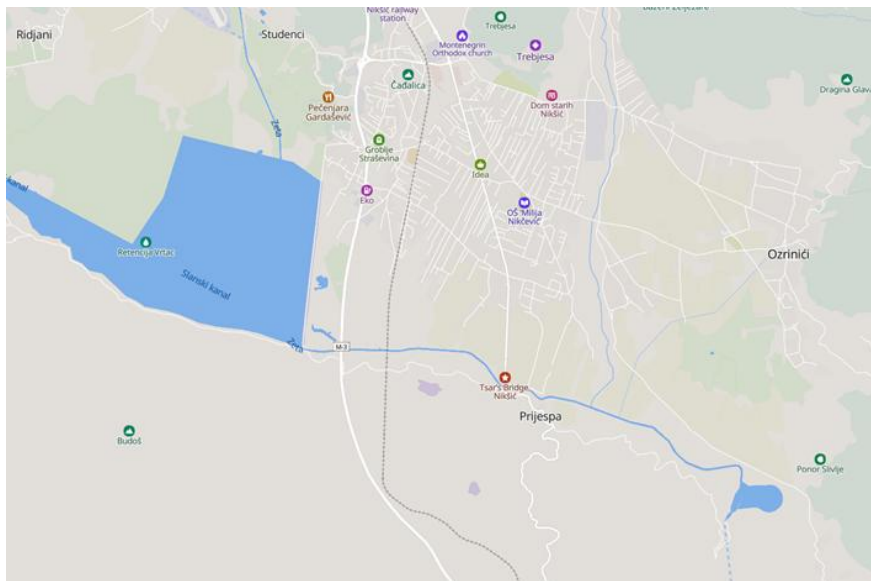


Fig. 2.2.15. Hydraulic network of the southern part of the Municipality of Nikšić.

Based on the methodology established for the reference scenarios, we considered the following representative parameters for the pilot area (which are summarized in Table 2.2.11).

- Characteristics of the basin
- Characteristics of the river
- Rainfall for different return periods

As for the characteristics of the basin and river, we adopted the DTM map of the simulated area shown in Fig. 2.2.16.



Fig. 2.2.16 The shaded area represents the simulated pilot area in Montenegro.

The rainfalls were elaborated considering data relative to the available pluviometers located in the area. The Chicago hyetograph was assumed as the design hyetograph (see Fig. 2.2.17). In particular, the hyetograph shown in the following figure represents precipitation events over a 30-hour duration for return periods of 30, 200, and 500 years.

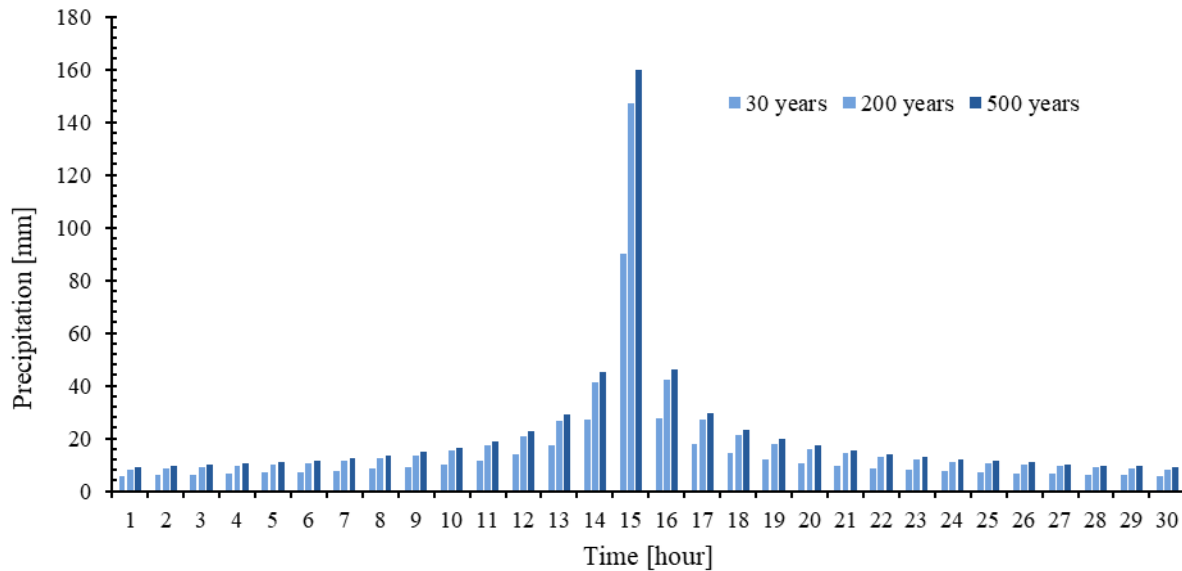


Fig. 2.2.17: Chicago hyetograph for extreme rainfall event adopted for the case study in Montenegro.

Following the methodology adopted for the reference areas (see Deliverable 3.2) and synthesized above for the case study in Italy, after estimating the time of concentration  $T_c$  and, consequently, the rainfall intensity pertaining to different scenarios, the peak discharge  $Q_{max}$  was calculated by adopting the rational method and considering a correction factor depending on the extension of the drainage basin area  $A$  (Chow et al., 1988; Bedient et al., 2012; see also Deliverable 3.2).

The main input parameters of the basin and the rainfall events considered for this case study are synthesized in Table 2.2.11, along with the main outputs of the simulations.

Table 2.2.11. Synthesis of the main input parameters and simulation outputs for the case study in Montenegro.

Location of the case study	River	Runoff coefficient c	a	n	Tr	Drainage basin area A (km <sup>2</sup> )	L (km)	Drainage basin mean slope I	Time of concentration Tc [hours]	Rainfall intensity i [mm/h]	Peak discharge Qmax [m <sup>3</sup> /s]	Results of simulations
Montenegro	Gračanica	0.25	73	0.43	10	312	25.0	0.28	6.8	24.6	848.1	GeoTIFF maps
			90	0.43	30					30.3	1045.6	
			130	0.42	100					42.9	1481.8	
			147	0.41	200					47.6	1643.8	
	Zeta		73	0.43	10	110	14.8	0.08	5.1	28.9	448.2	
			90	0.43	30					35.7	552.6	
			130	0.42	100					50.7	785.3	
			147	0.41	200					56.4	873.7	
	Bistrica		73	0.43	10	20	6.3	0.04	6.2	25.7	97.8	
			90	0.43	30					31.7	120.6	
			130	0.42	100					44.9	171.0	
			147	0.41	200					49.9	189.8	
	Mrkošnica		73	0.43	10	10	4.5	0.04	5.4	27.9	58.7	
			90	0.43	30					34.4	72.3	
			130	0.42	100					48.8	102.7	
			147	0.41	200					54.3	114.2	

By using the HEC-RAS software and considering the DTM map of the area, different scenarios corresponding to various return periods were simulated.

The results pertaining to each simulated scenario were reported in GeoTIFF files.

Specifically, in the following Figures 2.2.18 - 2.2.21, we show the DTM map adopted in the simulations with HEC-RAS software and the flood maps for  $T_r = 200$  years (Fig. 2.2.19),  $T_r = 100$  years (Fig. 2.2.20) and  $T_r = 30$  years (Fig. 2.2.21), along with the water depth scale.

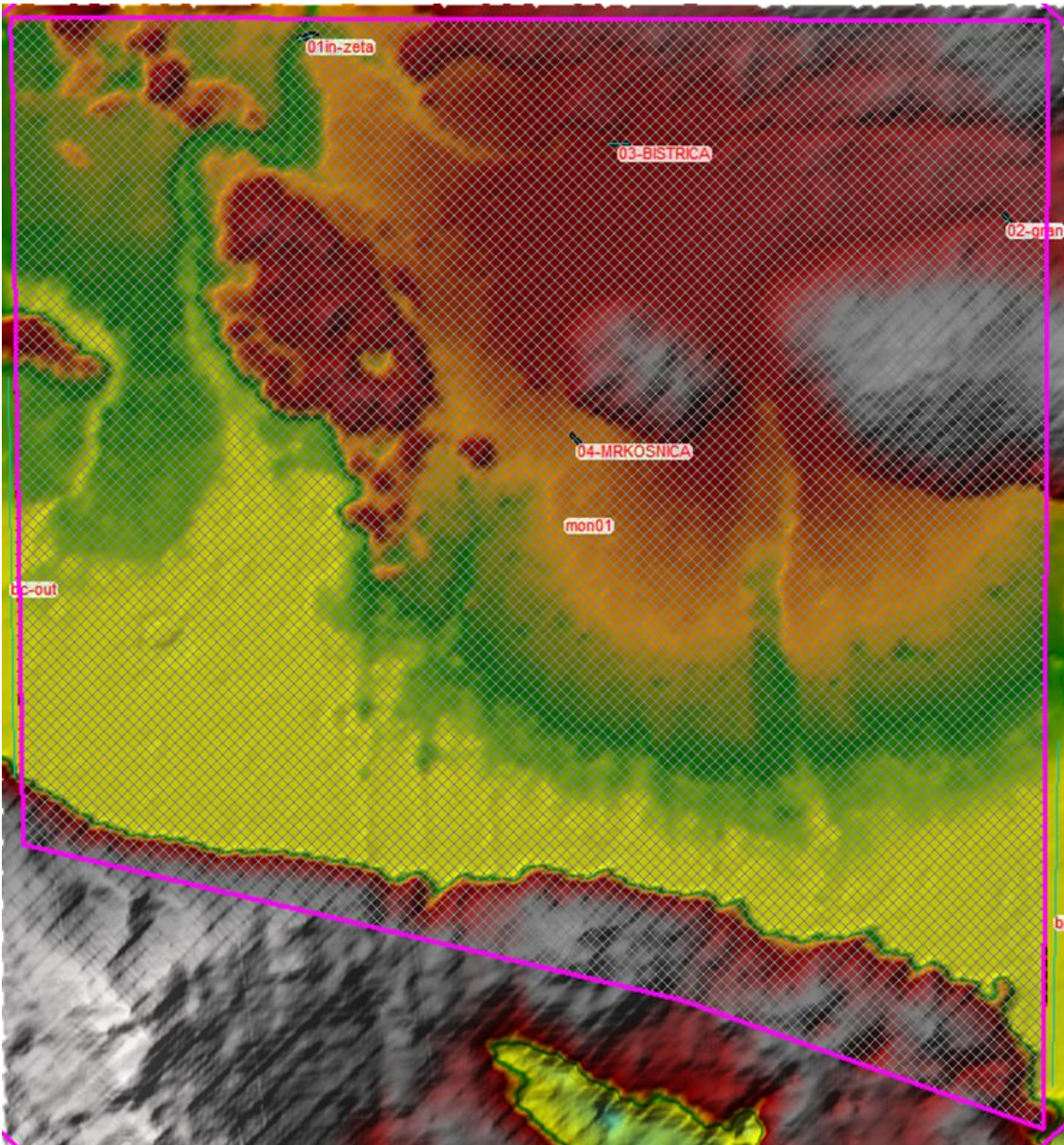


Fig. 2.2.18: DTM map of the case study area adopted in the numerical simulations.

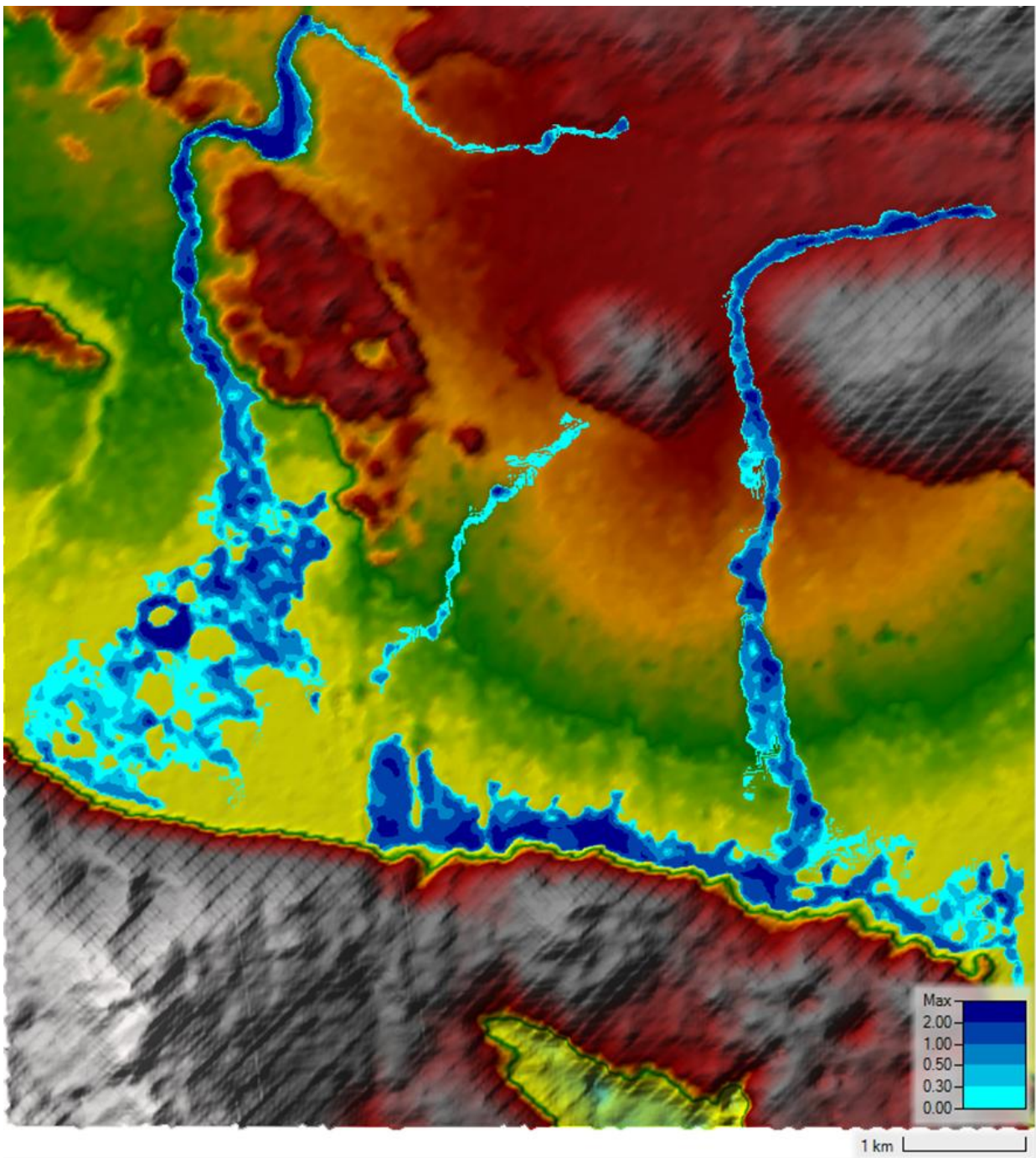


Fig. 2.2.19: Flood envelope map for a 200-year return period.

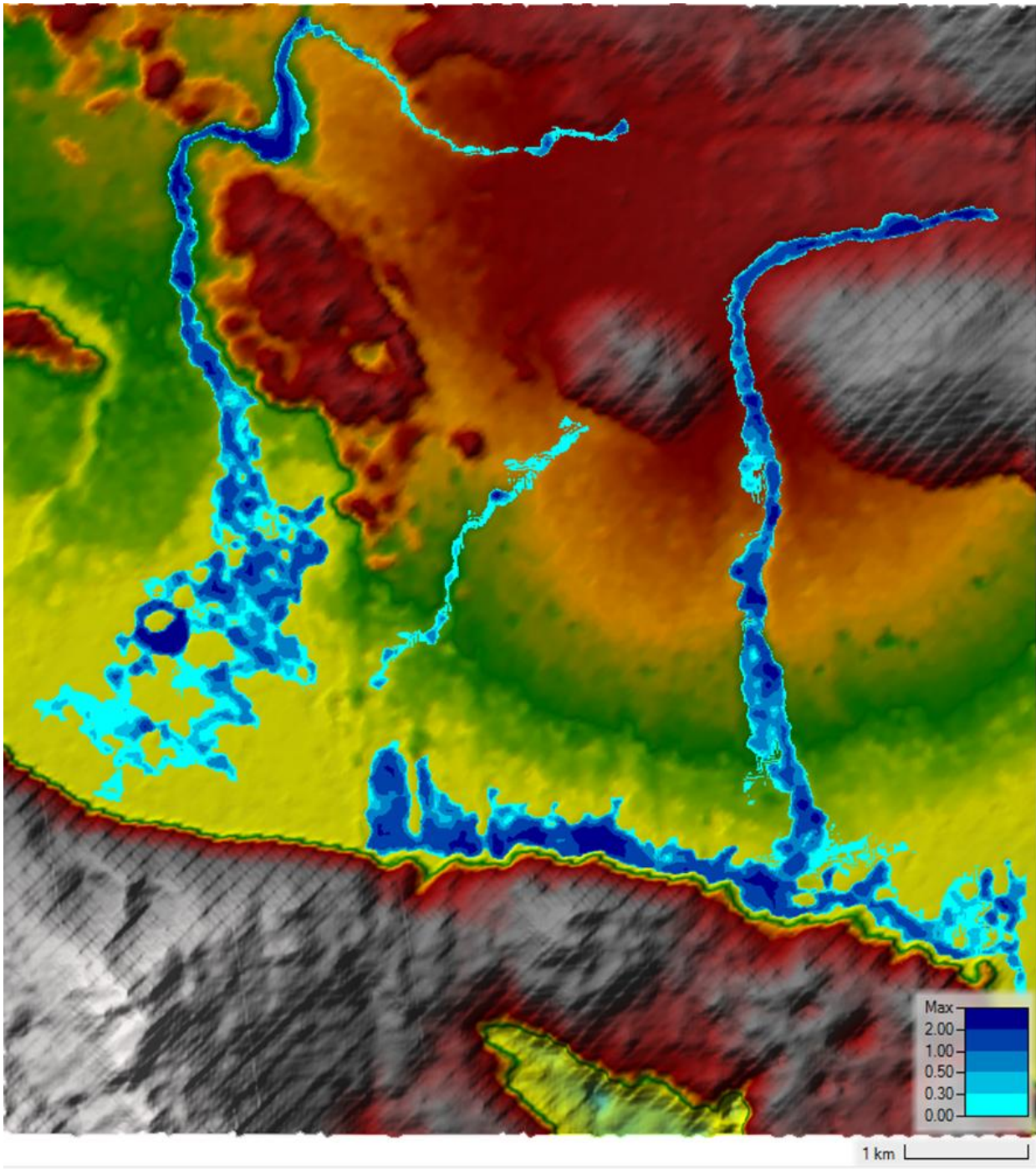


Fig. 2.2.20: Flood envelope map (water depths) for a 100-year return period.

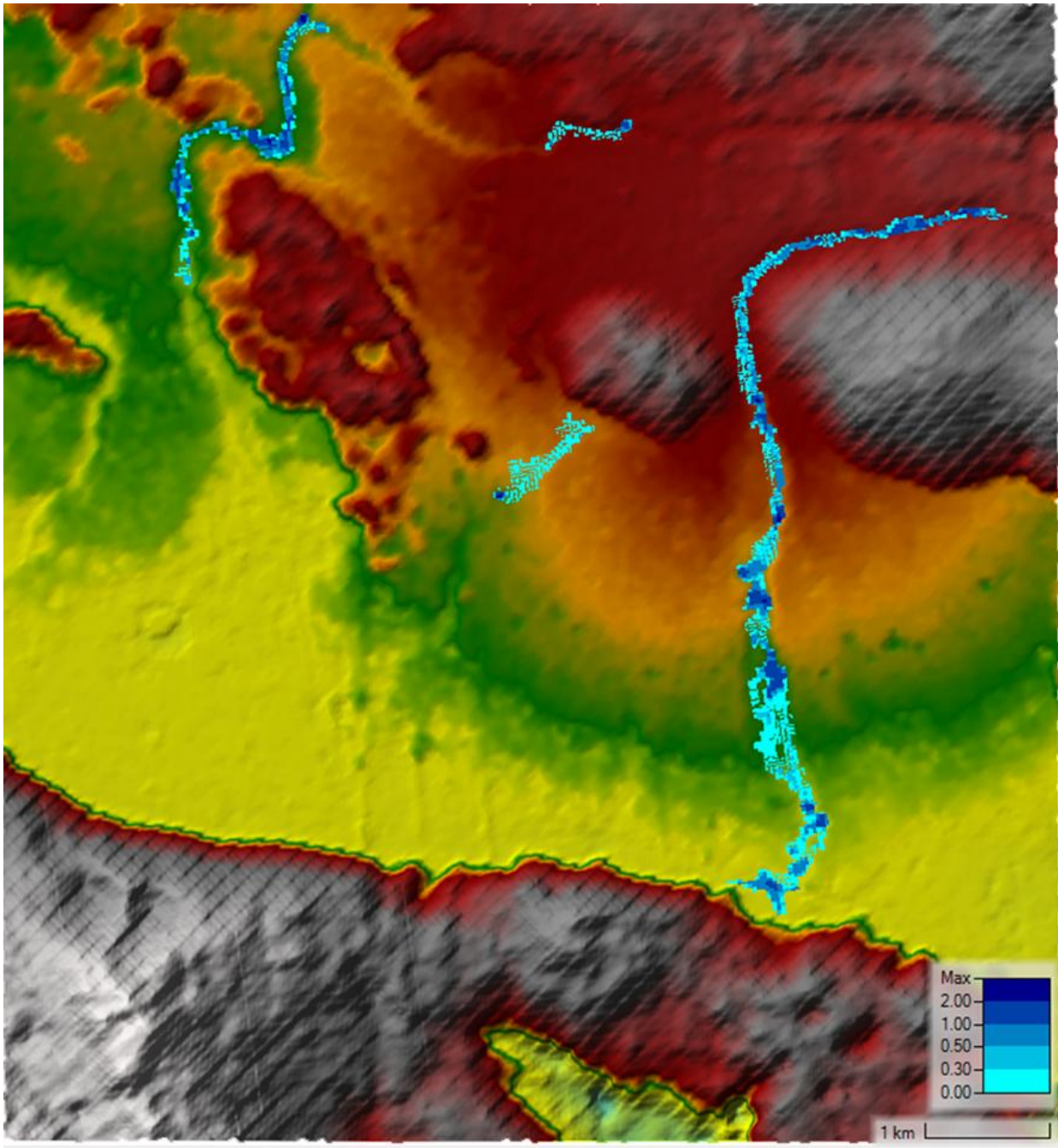


Fig. 2.2.21.: Flood envelope map (water depths) for a 30-year return period.

As for the hydraulic risk assessment, we adopt the same methodology illustrated above and in the Deliverables 3.2 and 3.3.

Therefore, we should consider:

- The class of damage;
- The hydraulic hazard level;

Also in this case, we have distinguished between the urban center and the surrounding areas.

#### **Urban center:**

##### **Class of damage:**

- D4 – High Damage Class

##### **Hydraulic Hazard:**

- P1 – Low Hazard

Consequently, considering the hydraulic risk matrix reported in Table 2.2.4. (see also deliverable 3.2), the **hydraulic risk class is:**

- R2 – Medium Risk

#### **Surrounding non-urban areas:**

##### **Class of damage:**

- D2 – Moderate Damage Class

##### **Hydraulic Hazard:**

- P3 – High Hazard

Consequently, considering the hydraulic risk matrix reported in Table 2.2.4. (see also deliverable 3.2), the **hydraulic risk class is:**

- R2 – Medium Risk

As for the usually adopted measures to mitigate the hydraulic risk, we follow the methodology illustrated in Deliverables 3.2 and 3.3.

Based on the hydraulic risk class (that is the same for the center and surrounding non-urban areas) and the characteristics of the basin of the target area, from Table 2.2.5, we obtain that the usually adopted measures are:

SM1, SM3, NSM1, NSM2, NSM3, NBS1, NBS2, NBS3.

To support and prioritize the selection of the most effective measures listed above, an effectiveness score is assigned to each measure (see Tables 2.2.6-2.2.8 and Deliverable 3.3).

Likewise, based on the total score  $S$  (defined as in Deliverable 3.3 and reported, for completeness, in Table 2.2.9) we obtain the following order of prioritization for the mitigation measures identified for this case study:

1) SM3; 2) SM1; 3) NSM1; 4) NBS1; 5) NSM2; 6) NSM3; 7) NBS2; 8) NBS3.

## 2.3. RISK PERCEPTION IN PILOT AREAS

### 2.3.1. Background, research protocol, and procedures for Psychological Activities

Floods and landslides can have significant **adverse impacts on the mental health** of affected populations, like an increased risk to develop PTSD and anxiety-depression symptomatology (Kumar, 2023; Walinski et al., 2023; Kabunga, 2022; Parel & Balamurugan, 2021; Fernandez et al., 2015). These psychological consequences can negatively affect people's lives, leading to significant difficulties in social and relational skills, work and school performance, reduced quality of life, and physical health issues (APA, 2022). (See Deliverable D3.1). In addition, risk perception influences how individuals behave, affecting preparedness, response, and mitigation to hazards, and consequently personal risk of exposure and vulnerability to hazards (Lechowska, 2022; Bradford et al., 2012). Therefore, it is significant in the context of natural disasters such as floods and landslides, because it influences how people manage hydrogeological emergencies. Specifically, an **adequate people's risk perception** can support effective emergency management and self-efficacy, promoting preparedness through knowledge and awareness of risks and appropriate protection and mitigation behaviors (Marincioni, 2020). Conversely, people's inadequate risk perception, both underestimation and overestimation, can undermine the effectiveness of emergency management (Lechowska, 2018), thereby amplifying personal exposure and vulnerability to hazards (Wachinger et al., 2010). Specifically, **low risk perception** can lead to poor knowledge and awareness of hazards, reckless behaviour, minimisation of hazards/warning signs, and delays in implementing preventive and mitigation measures (Ding et al., 2020). Conversely, a **high-risk perception**, although it may be characterized by a good knowledge of risks and mitigating behaviors (Ding et al., 2020), can lead to greater vulnerability to intense and dysfunctional emotional reactions (Zhao et al., 2023), such as high anxiety and fear, panic, or impulsive behaviors. In emergency situations, such emotional reactions can hinder rational assessment of circumstances and effective decision-making, leading to a state of hyperarousal, hypervigilance, and potentially dangerous impulsive choices. (See Deliverable D3.2). Literature outlined that the quality of risk perception could be affected by some significant factors, such as sociodemographic and personality factors, knowledge, awareness, worry, and the direct experience of a hazard (Biernachki et al., 2009; Lechowska, 2018; Lindell & Hwang, 2008) (see deliverable D3.1).

Therefore, in the context of hydrogeological events, considering psychological risk and the quality of risk perception can be significant for mitigating risks, protecting mental health, and improving communities' response capacity and disaster resilience. More specifically:

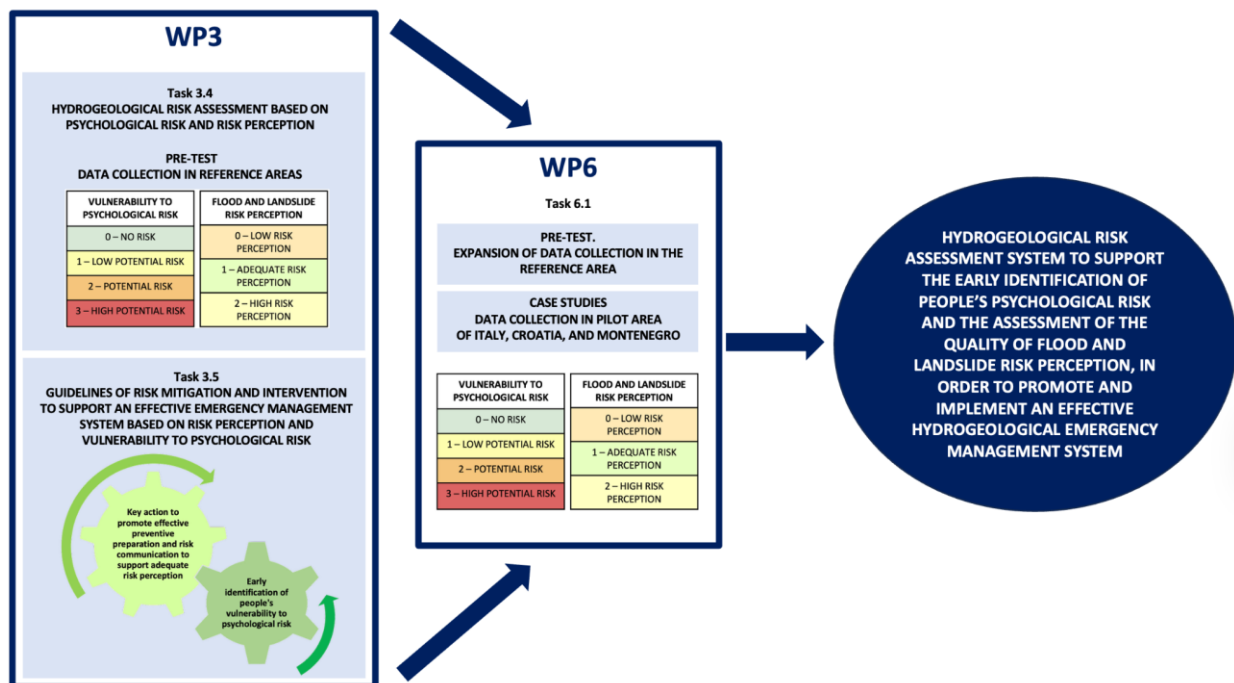
- **Psychological risk assessment** can be an effective preventive measure for identifying the most vulnerable individuals. This is significant because psychological vulnerability may worsen after an emergency, especially in the presence of serious peri- and post-traumatic factors (e.g. injuries, loss of relatives, damage to the home, etc.) (Asnakew et al., 2019; Bei et al., 2010; Dai et al., 2017; Heanoy & Brown, 2024; Mason, Andrews & Upton, 2010; Shabani et al., 2024). Moreover,

psychological vulnerability may also negatively impact risk perception.

- **Adequate risk perception** can support effective emergency response and management by facilitating early recognition of real risks and the timely implementation of appropriate protective behaviors. Conversely, inadequate risk perception (low and high), can interfere with effective emergency response and management, contributing to amplifying personal exposure to hazards.

Therefore, the psychological section of the SAFE-LAND project aims to achieve this objective by proposing a preventive hydrogeological risk assessment system. Specifically, it aims to support the early identification of vulnerability to psychological risk and the assessment of the quality of flood/landslide risk perception, in order to implement an effective hydrogeological emergency management system. To achieve the project's aims, several activities were carried out within WP3 and WP6 (Figure below). The details of these activities and results will be discussed in the following paragraphs.

Psychological Activities in WP3 and WP6



**Procedures:**

The research protocol was approved by the Ethics Committee of e-Campus University (No. 6/2024) and included the self-report questionnaires to collect socio-demographic data and to assess psychological well-being, vulnerability to PTSD, coping strategies, flood/landslide risk perception (knowledge, awareness, worry, previous direct experience and preparedness), and personality traits. The self-report questionnaires were digitized by creating a Qualtrics web survey and was distributed via a QR code/link to collect data in the reference areas for a pre-test (WP3) and in the pilot areas of Italy, Croatia, and Montenegro for the case studies (WP6). Access to the web survey included a description of the research protocol and informed consent, which, upon acceptance, allowed participants to complete the self-

report questionnaires. Participation in the survey was voluntary, and the web survey took approximately 20 minutes to complete. In treating participants, we followed APA guidelines, the 1964 Helsinki Declaration, and its later amendments or comparable ethical standards.

The Research Protocol

RESEARCH PROTOCOL	
1. Socio-demographic Inventory	Socio-demographic data
2. Psychological General Well-being (PGWB, Dupuy, 1984)	Psychological well-being
3. Primary Care PTSD Screen for DSM-5 (PC-PTSD-5, Prins et al., 2016)	Vulnerability to PTSD
4. Brief Cope (Carver, 1997)	Coping strategies
5. Hydrogeological Risk Perception	Flood/landslide risk perception (knowledge, awareness, worry, previous direct experience, and preparedness)
6. Big Five Inventory 10 (BFI-10, Rammstedt & John, 2007)	Personality traits

The psychological risk was assessed using the Psychological General Well-being (PGWB, Dupuy, 1984) and Primary Care PTSD Screen for DSM-5 (PC-PTSD-5, Prins et al., 2016), which allowed for the joint assessment of both psychological well-being and vulnerability to PTSD. A questionnaire was administered to assess hydrogeological risk perception, considering variables such as experience, knowledge, worry, awareness, and preparedness. The table below provides a summary of the variables analysed.

Procedures to Assess Psychological Risk, Hydrogeological Risk Perception and Preparedness

	Variables	Self-report questionnaires	Scoring
PSYCHOLOGICAL RISK	VULNERABILITY TO PTSD	Primary Care PTSD Screen for DSM-5 (PC-PTSD-5, Prins et al., 2016)	PTSD score
	PSYCHOLOGICAL WELL-BEING	Psychological General Well-being (PGWB, Dupuy, 1984)	Psychological well-being score
FLOOD/LANDSLIDE RISK PERCEPTION	EXPERIENCE	Type of past experience with flood or landslide	Score of 0 in case of indirect experience and a score of 1 in case of direct experience
	KNOWLEDGE	Keeping up to date with flood and landslide warnings	Continuous variable
	WORRY	- Emotional response experienced in the past or anticipated in the future if a flood or landslide were to occur - Level of worry in response to a flood or landslide warning for the following day	SUM of the two continuous variables
	AWARENESS	- Awareness of living in a flood/landslide risk area - Awareness of areas in the city most at risk of flooding or landslides	SUM of the two continuous variables
FLOOD/LANDSLIDE PREPAREDNESS	PREPAREDNESS	- Knowledge of response behaviours and emergency management in case of floods or landslides (e.g., protective behaviors, warning systems, risk/safe areas, etc.) - Keeping up to date with flood and landslide warnings - Level of knowledge on how to protect oneself/respond in case of flood/landslide - Keeping up to date with weather warnings	SUM of the continuous variables

## Expansion of data collection in the reference areas and results

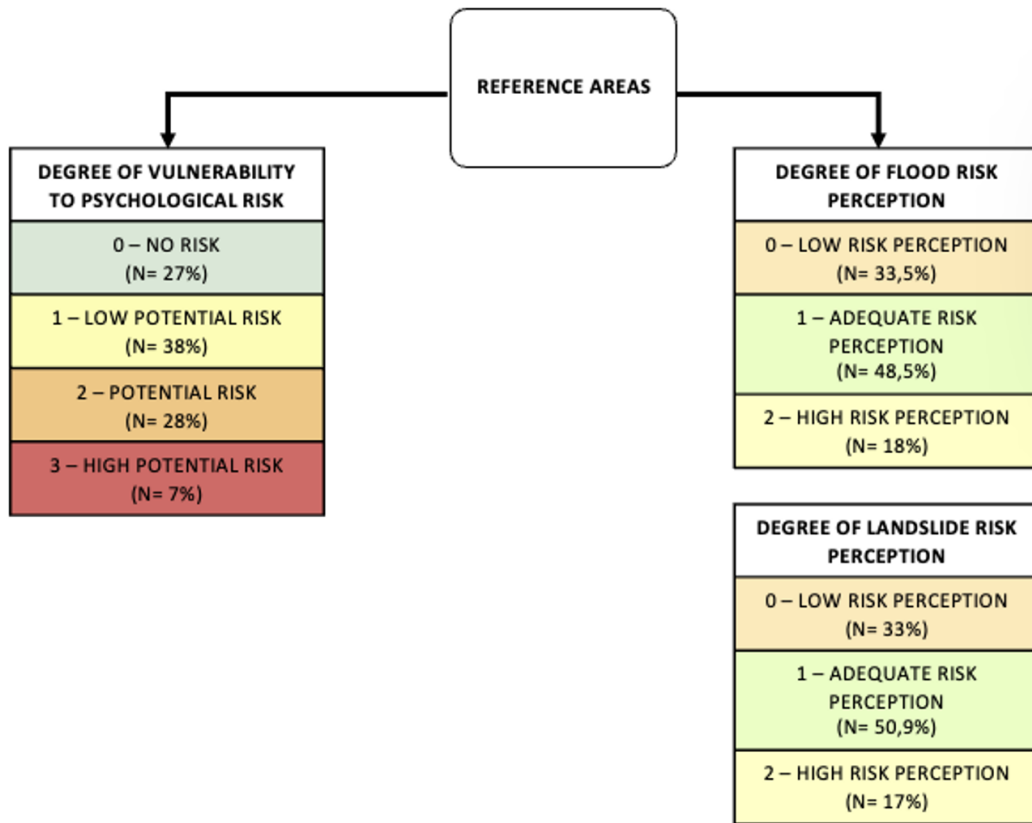
The web survey was distributed to people in the reference area in Italy by sending invitations to participate in the research, along with a QR code/link to access it, via email and social media posts from the research staff. Data collection in the reference areas, which began with an initial sample of 124 Italian participants, was expanded to a total of **823** subjects (72.7% females) aged between 18 to 79 (mean value,  $M = 37.67$ ; standard deviation,  $SD = 13.27$ ). A summary of the participants' demographic characteristics is indicated in the Table below. A significant number of participants were married or cohabiting (46.5%), had a high level of education (47.4% graduated or post-graduated), and had a profession in service and sales occupations (47.4%).

Demographic Characteristics of the Reference Sample

PRE-TEST _ REFERENCE AREAS N= 823			
<b>Age</b>	Mean	37,67	
	Standard deviation	13,27	
	Min	18	
	Max	79	
		<b>N</b>	<b>%</b>
<b>Gender</b>	Male	225	27,3
	Female	598	72,7
<b>Level Of Education</b>	High School Degree Or Less	433	52,6
	Graduated Or Post-Graduated	390	47,4
<b>Income</b>	17,000 Euro Or Less	445	55
	From 17,000 To 35,000 Euro	274	33,3
	More Than 35, 000 Euro	104	12,6
<b>Profession</b>	Students	216	26,3
	Simple Profession, Unemployed	61	7,4
	Skilled Workers	32	3,9
	Service and Sales Occupation	390	47,4
	Professional In Scientific, Tecnical and Human Fields	124	15,1
<b>Marital Status</b>	Single	249	30,3
	Non-Cohabiting Couple	145	17,6
	Married/Cohabiting	383	46,5
	Separated/Divorced	39	4,7
<b>Family Structure</b>	Widowed	7	0,9
	Single	269	32,7
	Childless Couples	218	26,5
	Families With Children	287	34,9
	Single Parents	45	5,5
<b>Personal Special Needs</b>	Widowed	4	0,5
	Absence	703	85,4
	Chronic Disease	36	4,4
	Disability	57	6,9
	Mental Illness	9	1,1
	Combination Of Different Special Needs	18	2,2

Overall, the results for 823 participants indicated that most had low or no potential psychological risk (65%) and adequate flood (48.5%) and landslide (50.9%) risk perception. However, part of the sample showed a potential risk (28%) or high potential risk (7%) of psychological vulnerability and an underestimation (33.5% for flood; 33% for landslide 33%) or overestimation (18% for flood; 17% for landslide) of hydrogeological risk perception (see the Figure below).

Results in the reference area about the Population's Psychological Risk and Quality of Risk Perception.



### Factors Associated with the Distinct Components of Flood Risk Perception and Preparedness

Among participants living in the reference areas (N= 823), a series of correlational analyses was conducted to identify variables associated with the distinct components of flood risk perception and preparedness. Results show that:

- **knowledge** correlates with greater flood risk perception ( $r = .403, p < .01$ ) and preparedness ( $r = .254, p < .01$ );
- **worry** correlates with a greater flood risk perception ( $r = .670, p < .01$ ) but lower preparedness ( $r = -.199, p < .01$ );
- **awareness** correlates with a greater flood risk perception ( $r = .693, p < .01$ ) and preparedness ( $r = .219, p < .01$ );
- **flood experience** correlates with a greater flood risk perception ( $r = .233, p < .01$ ) and preparedness ( $r = .261, p < .01$ );
- **flood risk perception** correlates with greater preparedness ( $r = .073, p < .05$ ).

### Correlation Analyses between Components of Flood Risk Perception and Preparedness.

	1	2	3	4	5	6
1. KNOWLEDGE	1					
2. WORRY	-.083*	1				
3. AWARENESS	.386**	-.015	1			
4. FLOOD EXPERIENCE	.296**	-.112**	.209**	1		
5. FLOOD RISK PERCEPTION	<b>.403**</b>	<b>.670**</b>	<b>.693**</b>	<b>.233**</b>	1	
6. PREPAREDNESS	<b>.254**</b>	<b>-.199**</b>	<b>.219**</b>	<b>.261**</b>	<b>.073*</b>	1

### Factors Associated with the Distinct Components of Landslide Risk Perception and Preparedness

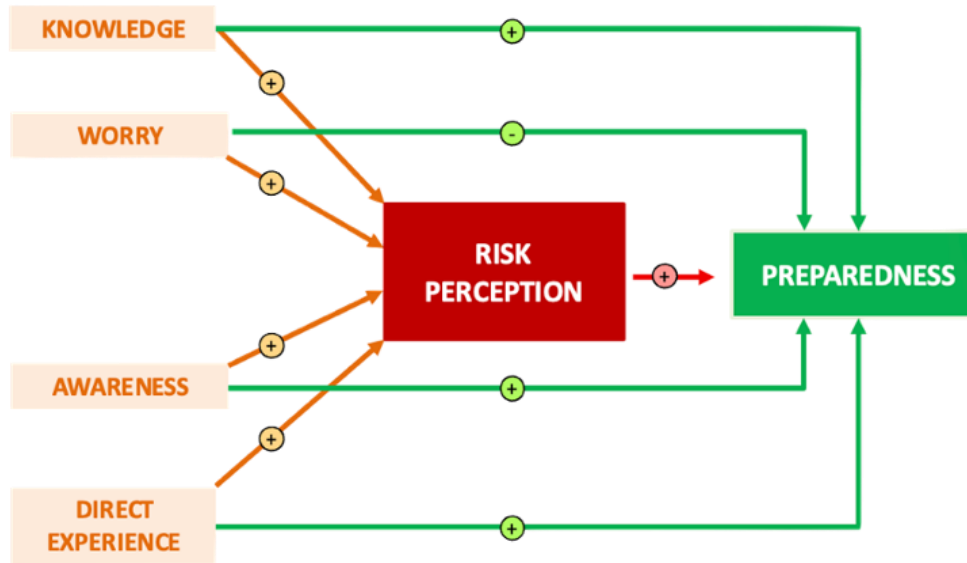
By considering participants living in the reference areas (N= 823), a series of correlational statistical analyses was conducted to identify variables associated with the distinct components of landslide risk perception and preparedness. Results show that:

- **knowledge** correlates with greater landslide risk perception ( $r = .403, p < .01$ ) and preparedness ( $r = .261, p < .01$ );
- **worry** correlates with a greater landslide risk perception ( $r = .694, p < .01$ ) but lower preparedness ( $r = -.174, p < .01$ );
- **awareness** correlates with a greater landslide risk perception ( $r = .660, p < .01$ ) and preparedness ( $r = .273, p < .01$ );
- **landslide experience** correlates with greater landslide risk perception ( $r = .120, p < .01$ ) and preparedness ( $r = .226, p < .01$ );
- **landslide risk perception** correlates with greater preparedness ( $r = .103, p < .01$ ).

### Correlation Analyses between Components of Flood Risk Perception and Preparedness

	1	2	3	4	5	6
1. KNOWLEDGE	1					
2. WORRY	-.075*	1				
3. AWARENESS	.421**	-.044	1			
4. LANDSLIDE EXPERIENCE	.213**	-.116**	.134**	1		
5. LANDSLIDE RISK PERCEPTION	<b>.403**</b>	<b>.694**</b>	<b>.660**</b>	<b>.120**</b>	1	
6. PREPAREDNESS	<b>.261**</b>	<b>-.174**</b>	<b>.273**</b>	<b>.226**</b>	<b>.103**</b>	1

Factors Associated With Distinct Components of Flood/Landslide Risk Perception and Preparedness



**DISCUSSION**

Overall, the study of 823 participants in the reference area reveals a generally positive profile of psychological well-being and adequate hydrogeological risk perception. However, a subgroup of the sample showed potential psychological vulnerability (35%) and risk perception underestimation (33,5% flood; 33% landslide) or overestimation (18% flood; 17% landslide). Therefore, these findings highlight the importance of an integrative approach grounded in psychological and hydrogeological risk perception to mitigate the risks and improve people’s psychological well-being, self-efficacy and disaster resilience. Specifically, it may be important to focus on the psychological state with intervention to support psychological well-being. This is because psychological vulnerability may worsen after an emergency, especially in the presence of serious peri- and post-traumatic factors (e.g. injuries, loss of relatives, damage to the home, etc.) (Asnakew et al., 2019; Bei et al., 2010; Dai et al., 2017; Heanoy & Brown, 2024; Mason, Andrews & Upton, 2010; Shabani et al., 2024). At the same time, an intervention aimed at supporting preventive preparation and risk communication can be important for improving risk perception and preparedness, facilitating early recognition of real risks, and enabling effective and timely emergency responses (see Guidelines, D3.3). In fact, an adequate people’s risk perception can support effective emergency management and self-efficacy, promoting preparedness and appropriate protection and mitigation behaviors (Marincioni, 2020). Conversely, people’s inadequate risk perception, both underestimation and overestimation, can undermine the effectiveness of emergency management (Lechowska, 2018), thereby amplifying personal exposure and vulnerability to hazards (Wachinger et al., 2010).

### 2.3.2. Italy

Case studies were conducted in the pilot areas of Italy, which are characterized by a high risk of floods or landslides. Data collection was conducted through collaboration with SAFE-LAND partners/research staff in the pilot areas, who informed the local population about the opportunity to participate in the study by providing the link/QR code to access it. Overall, **208 subjects** participated in data collection. A summary of the participants' demographic characteristics is in the next Table. More specifically, in the **pilot areas at risk of flooding, 168 subjects** (Tuscany - Pisa) (65.5% females) aged between 18 and 72 (M = 36.95; SD = 12.52) participated. A significant number of participants were married or cohabiting (50%), had a high level of education (42.2% had graduated or post-graduate qualifications), and worked in service or sales occupations (41.6%). Instead, in the **pilot areas at risk of landslides, 40 subjects** (Molise - Castel San Vincenzo) (62.5% females) aged between 20 and 67 (M = 40.93; SD = 14.36) participated. A significant number of participants were married, or cohabiting (50%), had a level of education distributed equally between low and high, and worked in service and sales occupations (37.5%).

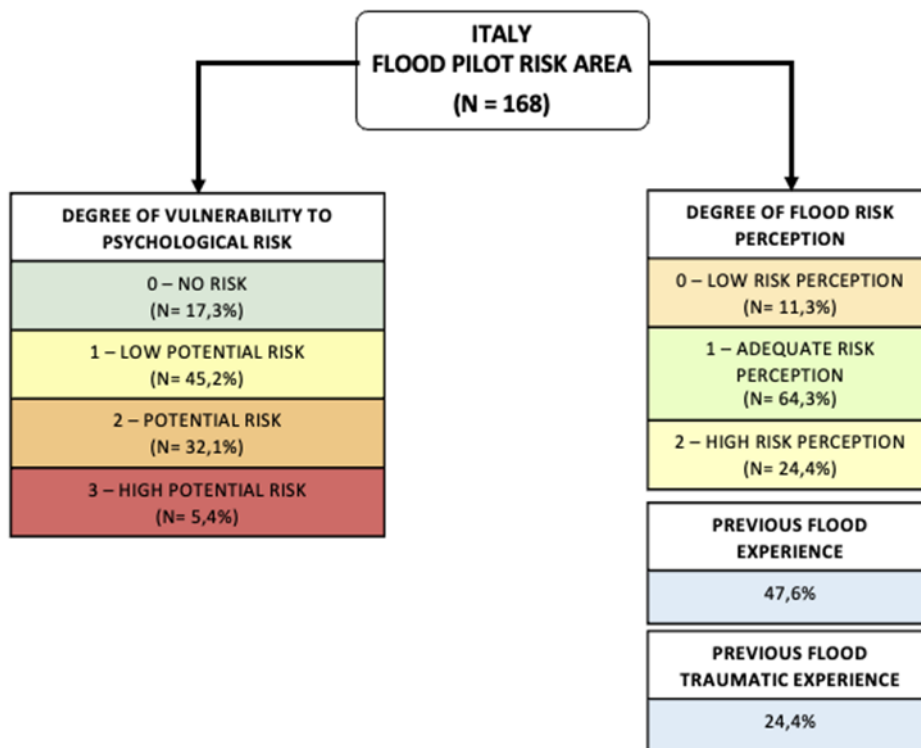
Demographic Characteristics

ITALY _ CASE STUDIES N = 208		ITALY Flood risk pilot area N = 168		ITALY Landslide risk pilot area N = 40	
Age	Mean	36,95		40,93	
	Standard deviation	12,528		14,36	
	Min	18		20	
	Max	72		67	
		N	%	N	%
Gender	Male	58	34,5	15	37,5
	Female	110	65,5	25	62,5
Level of Education	High school degree or less	97	57,7	20	50
	Graduated or post-graduated	71	42,2	20	50
Income	17,000 Euro or less	88	52,3	18	45
	From 17,000 to 35,000 Euro	62	36,9	12	30
	More than 35, 000 Euro	18	10,7	10	25
Profession	Students	48	28,6	7	17,5
	Simple profession, unemployed	9	5,3	1	2,5
	Skilled workers	16	9,5	3	7,5
	Service and sales occupation	70	41,6	15	37,5
	Professional in scientific, technical and human fields	25	14,8	14	35
Marital status	Single	43	25,6	11	27,5
	Non-cohabiting couple	34	20,2	6	15,0
	Married/cohabiting	84	50,0	20	50,0
	Separated/Divorced	7	4,2	3	7,5
	Widowed	-	-	-	-
Family Structure	Single	44	26,2	13	32,5
	Childless couples	58	34,5	9	22,5
	Families with children	57	5,4	16	40,0
	Single parents	9	33,9	2	5,0
	Widowed	-	-	-	-
Personal Special Needs	Absence	143	85,1	36	90,0
	Chronic disease	7	4,2	2	5,0
	Disability	13	7,7	-	-
	Mental illness	2	1,2	-	-
	Combination of different special needs	3	1,7	2	5,0
Flood or landslide experience	No	47	28	18	45
	Flood or landslide experience	80	47,6	16	40
	Flood or landslide traumatic experience	41	24,4	6	15

## Assessment of the Quality of Flood Risk Perception and Psychological Risk

Among participants living in Italian flood-risk pilot areas (N = 168), a descriptive analysis was conducted to assess the quality of flood risk perception and psychological risk. Regarding flood risk perception, results indicate that 11.3% of people had low risk perception, 64.3% had adequate risk perception, and 24.4% had high risk perception. Moreover, 54.2% of people have reported experiencing floods, and 17.9% have reported traumatic flood experiences. Regarding psychological risk, the results indicate that 17.3% of people had no psychological risk, 45.2% had low potential psychological risk, 32.1% had potential psychological risk, and 5.4% had high potential psychological risk.

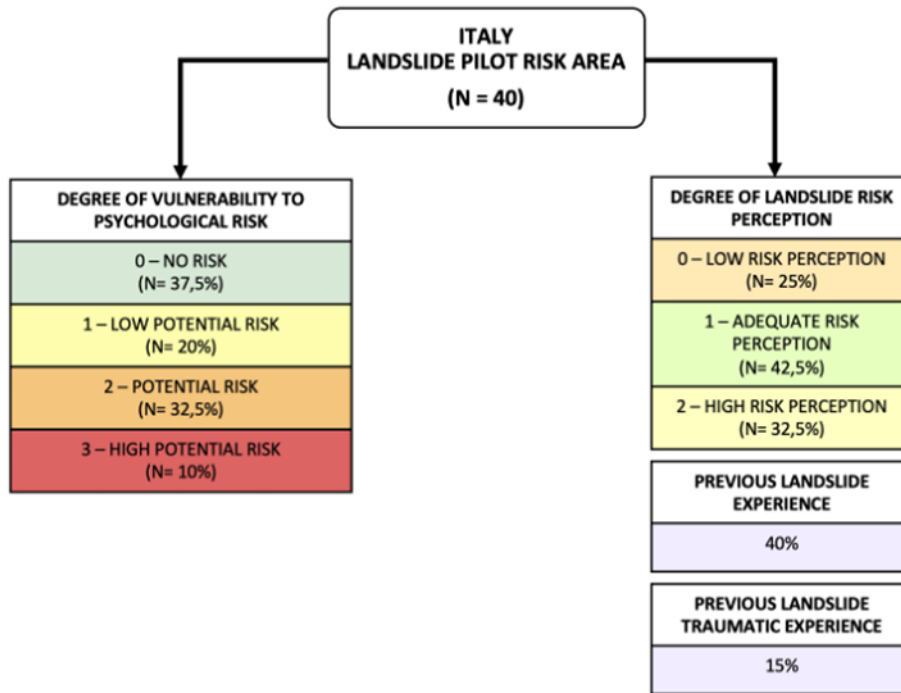
Population's Psychological Risk, and Quality of Flood Risk Perception in Italian Flood Pilot Risk Areas.



## Assessment of the Quality of Landslide Risk Perception and Psychological Risk

Among participants living in Italian landslide-risk pilot areas (N = 40), a descriptive analysis was conducted to assess the quality of landslide risk perception and psychological risk. Regarding landslide risk perception, results indicate that 25% of people had low risk perception, 42.5% had adequate risk perception, and 32.5% had high risk perception. Moreover, 40% of people have reported experiencing a landslide, and 15% have reported a traumatic landslide experience. Regarding psychological risk, the results indicate that 37.5% of people had no psychological risk, 20% had low potential psychological risk, 32.5% had potential risk, and 10% high potential psychological risk.

Population's Psychological Risk, and Quality of Landslide Risk Perception in Landslide Risk Pilot Areas



**Comparison to the results in the Reference Areas**

Overall, the comparison of results in the reference and pilot areas shows similar patterns, with generally positive psychological well-being and adequate hydrogeological risk perception. However, in the Flood Pilot area, a higher percentage of people had an adequate flood risk perception (64.3% flood) than in the reference areas (48.5%). Moreover, in this pilot area, data showed a lower percentage of people who had a low flood risk perception (11.3%) than in the reference areas (33.5%) and a higher percentage of people in the flood pilot areas with high risk perception (24.4%) than in the reference areas (18%). In this area, a subgroup of people (24.4%) also reported a previous traumatic flood experience. In the Landslide pilot area, a lower percentage of people had an adequate (42.5%) and low (25%) landslide risk perception than in the reference areas (50.9% adequate and 33% low). However, a higher percentage of people in the landslide pilot areas reported a higher risk perception (32.5%) than in the reference areas (17%). In this area, a subgroup of people (15%) also reported a previous traumatic landslide experience.

**2.3.3. Croatia**

Case studies were conducted in the pilot areas of Croatia, which are characterized by a high risk of floods or landslides. Data collection was conducted through collaboration with SAFE-LAND partners/research staff in the pilot areas, who informed the local population about the opportunity to participate in the study by providing the link/QR code to access it. Overall, **137** subjects participated in data collection. A

summary of the participants' demographic characteristics is in Table below. More specifically, in the **pilot areas at risk of flooding, 63 subjects** (Sveti Martin na Muri) (60.3% females) aged between 18 and 85 (M = 48.14; SD = 20.62) participated. A significant number of participants were married or cohabiting (54%), had a low level of education (93.65% with a high school degree or less), and worked in service and sales occupations (42.8%). Instead, in the **pilot areas at risk of landslides, 74 subjects** (Štrigova) (70.3% females) aged between 17 to 80 (M = 45.11; SD = 18.97) participated. A significant number of participants were married or cohabiting (58.1%), had a low level of education (77% with a high school degree or less), and worked in service and sales occupations (66.2%).

Demographic Characteristics

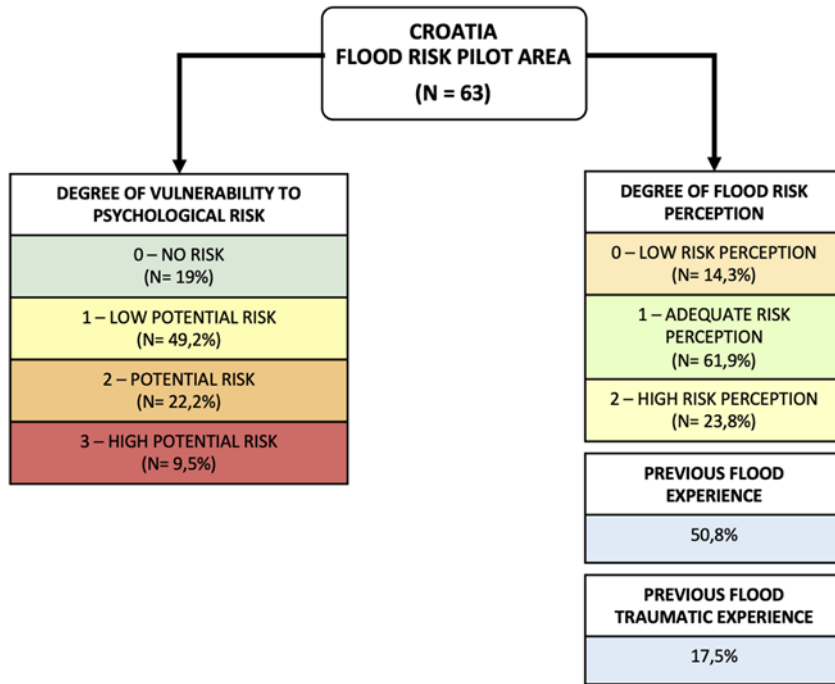
CROATIA_CASE STUDIES N = 137		CROATIA Flood risk pilot area N = 63		CROATIA Landslide risk pilot area N = 74	
Age	Mean	48,14		45,11	
	Standard deviation	20,62		18,97	
	Min	18		17	
	Max	85		80	
		N	%	N	%
Gender	Male	25	39,7	22	29,7
	Female	38	60,3	52	70,3
Level of Education	High school degree or less	59	93,65	57	77
	Graduated or post-graduated	4	6,34	17	22,9
Income	17,000 Euro or less	61	96,8	57	77
	From 17,000 to 35,000 Euro	2	3,2	14	18,9
	More than 35, 000 Euro	-	-	3	4
Profession	Students	-	-	8	10,8
	Simple profession, unemployed	22	34,9	11	14,8
	Skilled workers	6	9,5	4	5,4
	Service and sales occupation	27	42,8	49	66,2
	Professional in scientific, technical and human fields	8	12,6	2	2,7
Marital status	Single	15	23,8	14	18,9
	Non-cohabiting couple	4	6,3	6	8,1
	Married/cohabiting	34	54,0	43	58,1
	Separated/Divorced	1	1,6	6	8,1
	Widowed	9	14,3	5	6,8
Family Structure	Single	16	25,4	14	18,9
	Childless couples	7	11,1	9	12,2
	Families with children	38	60,3	40	54,1
	Single parents	1	1,6	6	8,1
	Widowed	1	1,6	5	6,8
Personal Special Needs	Absence	57	90,5	73	98,6
	Chronic disease	1	1,6	1	1,4
	Disability	-	-	-	-
	Mental illness	-	-	-	-
	Combination of different special needs	5	7,9	-	-
Flood or landslide experience	No	20	31,7	40	54,1
	Flood or landslide experience	32	50,8	32	43,2
	Flood or landslide traumatic experience	11	17,5	2	2,7

## Assessment of the Quality of Flood Risk Perception and Psychological Risk

Among participants living in flood-risk pilot areas (N = 63), a descriptive analysis was conducted to assess the quality of flood risk perception and psychological risk. Regarding flood risk perception, results indicate that 14.3% of people had low risk perception, 61.9% had adequate risk perception, and 23.8% had high risk perception. Moreover, 50.8% of people have reported experiencing floods, and 17.5% have

reported traumatic flood experiences. Regarding psychological risk, results indicate that 19% of people had no psychological risk, 49.2% had low potential psychological risk, 22.2% had potential risk, and 9.5% high potential psychological risk.

Population’s Psychological Risk, and Quality of Flood Risk Perception in Flood Risk Pilot Areas



### Assessment of the Quality of Flood Risk Perception and Psychological Risk

Among participants living in landslide-risk pilot areas (N = 74), a descriptive analysis was conducted to assess the quality of landslide risk perception and psychological risk. Regarding landslide risk perception, results indicate that 23% of people had low risk perception, 47.3% had adequate risk perception, and 29.7% had high risk perception. Moreover, 43.2% of people have reported experiencing a landslide, and 2.7% have reported a traumatic landslide experience. Regarding psychological risk, the results indicate that 29.7% of people had no psychological risk, 48.6% had low potential psychological risk, 21.6% had potential risk, and 0% high potential psychological risk.

Population's Psychological Risk, and Quality of Landslide Risk Perception in Landslide Risk Pilot Areas



**Comparison to the results in the Reference Areas**

Overall, the comparison of results in the reference and pilot areas shows similar patterns, with generally positive psychological well-being and adequate hydrogeological risk perception. However, in the Flood Pilot area, a higher percentage of people had an adequate flood risk perception (61.9%) than in the reference areas (48.5%). Moreover, in this pilot area, data showed a lower percentage of people who had a low flood risk perception (14.3%) than in the reference areas (33.5%) and a higher percentage of people in the flood pilot areas with high risk perception (23.8%) than in the reference areas (18%). In this area, a subgroup of people (17%) also reported a previous traumatic flood experience. In the Landslide pilot area, a lower percentage of people had an adequate (47.3%) and low (23%) landslide risk perception than in the reference areas (50.9% adequate and 33% low). However, a higher percentage of people in the landslide pilot areas with high risk perception (29.7%) than in the reference areas (17%). In this area, a subgroup of people (3%) also reported a previous traumatic landslide experience.

**2.3.4. Montenegro**

Case studies were conducted in the pilot areas of Montenegro, which are characterized by a high risk of floods or landslides. Data collection was conducted through collaboration with SAFE-LAND partners/research staff in the pilot areas, who informed the local population about the opportunity to

participate in the study by providing the link/QR code to access it. Overall, **82** subjects participated in data collection. A summary of the participants' demographic characteristics is indicated in the next Table. More specifically, in the **pilot areas at risk of flooding, 49 subjects** (Ozrinići, Kličevo, Straševina, and Štedim) (59.2% females) aged between 18 to 75 ( $M = 47.23$ ;  $SD = 12.80$ ) participated. A significant number of participants were married or cohabiting (36.7%), had a high level of education (77.5% had graduated or post-graduate qualifications), and worked in service or sales occupations (67.3%). Instead, in the **pilot areas at risk of landslides, 33 subjects** (Povija and Liverovići) (36.4% females) aged between 28 to 75 ( $M = 48.23$ ;  $SD = 11.79$ ) participated. A significant number of participants were married or cohabiting (66.7%), had a high level of education (75.7% had graduated or postgraduate qualifications), and worked in service and sales occupations (75.7%).

Demographic Characteristics

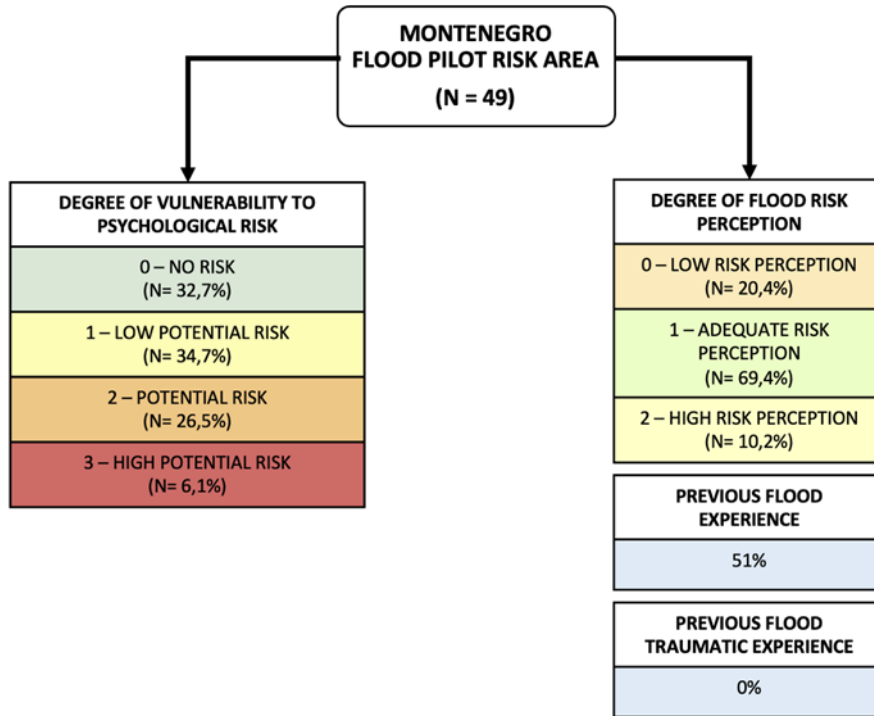
MONTENEGRO_CASE STUDIES N = 82		MONTENEGRO Flood risk pilot area N = 49		MONTENEGRO Landslide risk pilot area N = 33	
Age	Mean	47,23		48,23	
	Standard deviation	12,80		11,79	
	Min	18		28	
	Max	75		75	
		N	%	N	%
Gender	Male	20	40,8	21	63,6
	Female	29	59,2	12	36,4
Level of Education	High school degree or less	11	22,44	8	24,2
	Graduated or post-graduated	38	77,55	25	75,7
Income	17,000 Euro or less	49	100	32	96,6
	From 17,000 to 35,000 Euro	-	-	1	3
	More than 35,000 Euro	-	-	-	-
Profession	Students	1	2	-	-
	Simple profession, unemployed	1	2	-	-
	Skilled workers	8	16,3	4	12
	Service and sales occupation	33	67,3	25	75,7
	Professional in scientific, technical and human fields	6	12,2	4	12
Marital status	Single	14	28,6	7	21,2
	Non-cohabiting couple	10	20,4	1	3,0
	Married/cohabiting	18	36,7	22	66,7
	Separated/Divorced	4	8,2	2	6,1
	Widowed	3	6,1	1	3,0
Family Structure	Single	19	38,8	8	24,2
	Childless couples	4	8,2	4	12,1
	Families with children	20	40,8	19	57,6
	Single parents	3	6,1	1	3,0
	Widowed	3	6,1	1	3,0
Personal Special Needs	Absence	46	93,9	32	97,0
	Chronic disease	-	-	0	0
	Disability	2	4,1	1	3,0
	Mental illness	1	2,0	-	-
	Combination of different special needs	-	-	-	-
Flood or landslide experience	No	24	49	22	66,7
	Flood or landslide experience	25	51	11	33,3
	Flood or landslide traumatic experience	-	-	-	-

## Assessment of the Quality of Flood Risk Perception and Psychological Risk

Among participants living in flood-risk pilot areas ( $N = 49$ ), a descriptive analysis was conducted to assess the quality of flood risk perception and psychological risk. Regarding flood risk perception, results indicate that 20.4% of people had low risk perception, 69.4% had adequate risk perception, and 10.2%

had high risk perception. Moreover, 51% of people have reported experiencing floods, and 0% have reported traumatic flood experiences. Regarding the psychological risk, results indicate that 32.7% of people had no psychological risk, 34.7% had low potential psychological risk, 26.5% had potential psychological risk, and 6.1% high potential psychological risk.

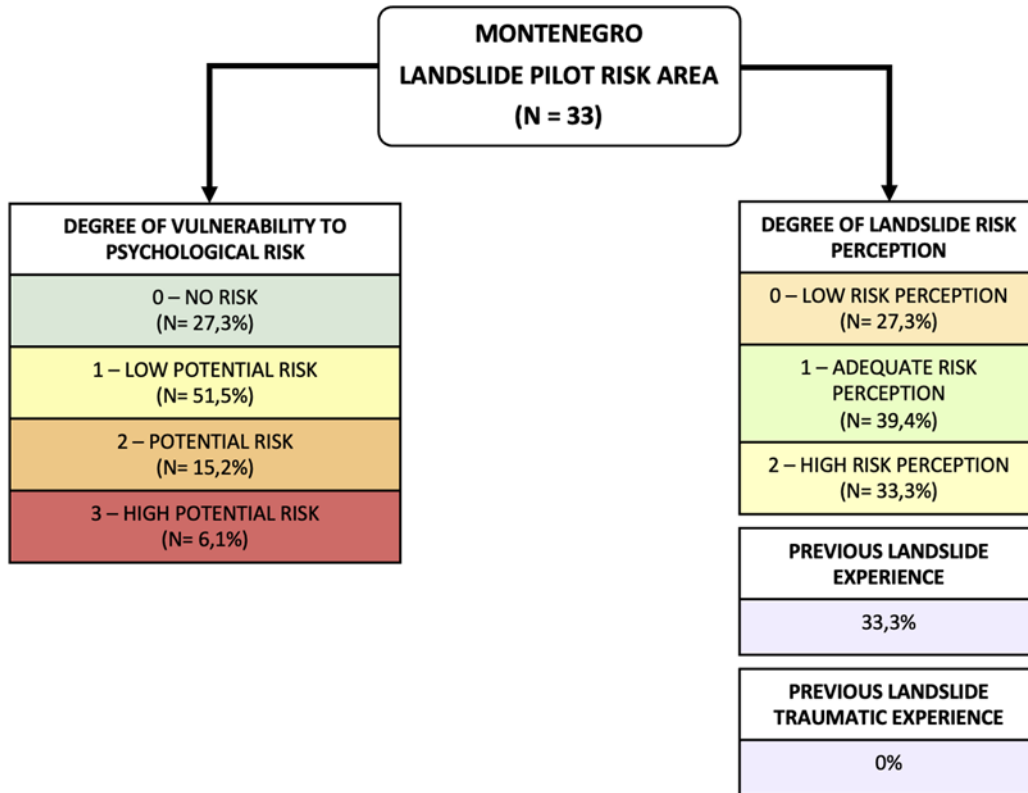
Population’s Psychological Risk, and Quality of Flood Risk Perception in Flood Risk Pilot Areas



### Assessment of the Quality of Flood Risk Perception and Psychological Risk

Among participants living in landslide-risk pilot areas (N = 33), a descriptive analysis was conducted to assess the quality of landslide risk perception and psychological risk. Regarding landslide risk perception, results indicate that 27.3% of people had low risk perception, 39.4% had adequate risk perception, and 33.3% had high risk perception. Moreover, 33.3% of people have reported experiencing a landslide, and 0% have reported a traumatic landslide experience. Regarding psychological risk, the results indicate that 27.3% of people had no psychological risk, 51.5% had low potential psychological risk, 15.2% had potential risk, and 6.1% high potential psychological risk.

Population’s Psychological Risk, and Quality of Flood Risk Perception in Landslide Risk Pilot Areas.



### Comparison to the results in the Reference Areas

Overall, the comparison of results in the reference and pilot areas shows similar patterns, with generally positive psychological well-being and adequate hydrogeological risk perception. In the Flood Pilot area, a higher percentage of people had an adequate flood risk perception (69.4%) than in the reference areas (48.5%). In addition, a lower percentage of people who had a low (20.4%) and high (10.2%) flood risk perception than in the reference areas (33.5% low, 18% high). Unlike in other pilot areas, no participant reported previous traumatic hydrogeological experiences. Instead, in the Landslide pilot area, a lower percentage of people had an adequate (39.4%) and low (27.3%) landslide risk perception than in the reference areas (50.9% adequate and 33% low). However, a higher percentage of people in the landslide pilot areas had a high risk perception (33.3%) than in the reference areas (17%). Unlike in other pilot areas, no participant reported previous traumatic hydrogeological experiences.

### 2.3.5. Flood and Landslide Pilot Areas: Psychological Vulnerability and Risk and Protective Factors for Risk Perception and Preparedness

Case studies were conducted in the pilot areas of Italy, Croatia, and Montenegro, which are characterized by a high risk of floods or landslides. Data collection was conducted through collaboration with SAFE-LAND partners/research staff in the pilot areas, who informed the local population about the opportunity to participate in the study by providing the link/QR code to access it. Overall, **427** subjects participated in data collection across the three pilot nation areas.

Specifically, in the **pilot areas at risk of flooding a total of 280 subjects** participated. A summary of the participants' demographic characteristics is indicated below.

- **168 subjects in Italy** (Tuscany - Livorno, Versilia, Pisa) (65.5% females) aged between 18 to 72 (M = 36.95; SD = 12.52). A significant number of participants were married or cohabiting (50%), had a high level of education (42.2% had graduated or post-graduate qualifications), and worked in service or sales occupations (41.6%).
- **49 subjects in Montenegro** (Ozrinići, Kličevo, Straševina, and Štedim) (59,2% females) aged between 18 to 75 (M = 47.23; SD = 12.80). A significant number of participants were married or cohabiting (36.7%), had a high level of education (77.5% had graduated or post-graduate qualifications), and worked in service or sales occupations (67.3%).
- **63 subjects in Croatia** (Sveti Martin na Muri) (60.3% females) aged between 18 to 85 (M = 48.14; SD = 20.62). A significant number of participants were married or cohabiting (54%), had a low level of education (93.65% with a high school degree or less), and worked in service and sales occupations (42.8%).

In the **pilot areas at risk of landslides a total of 147 subjects** participated. A summary of the participants' demographic characteristics is indicated below.

- **40 subjects in Italy** (Molise - Castel San Vincenzo) (62.5% females) aged between 20 to 67 (M = 40.93; SD = 14.36). A significant number of participants were married, or cohabiting (50%), had a level of education distributed equally between low and high, and worked in service and sales occupations (37.5%).
- **33 subjects in Montenegro** (Povija and Liverovići) (36.4% females) aged between 28 to 75 (M = 48.23; SD = 11.79). A significant number of participants were married or cohabiting (66,7%), had a high level of education (75.7% had graduated or postgraduate qualifications), and worked in service and sales occupations (75.7%).
- **74 subjects in Croatia** (Štrigova) (703% females) aged between 17 to 80 (M = 45.11; SD = 18.97). A significant number of participants were married or cohabiting (58.1%), had a low level of education (77% with a high school degree or less), and worked in service and sales occupations (66.2%).

FLOOD RISK PILOT AREAS _CASE STUDIES N = 280		ITALY N = 168		MONTENEGRO N = 49		CROATIA N = 63	
<b>Age</b>	Mean	36,95		47,23		48,14	
	Standard deviation	12,528		12,80		20,62	
	Min	18		18		18	
	Max	72		75		85	
		N	%	N	%	N	%
<b>Gender</b>	Male	58	34,5	20	40,8	25	39,7
	Female	110	65,5	29	59,2	38	60,3
<b>Level of Education</b>	High school degree or less	97	57,7	11	22,44	59	93,65
	Graduated or post-graduated	71	42,2	38	77,55	4	6,34
<b>Income</b>	17,000 Euro or less	88	52,3	49	100	61	96,8
	From 17,000 to 35,000 Euro	62	36,9	-	-	2	3,2
	More than 35, 000 Euro	18	10,7	-	-	-	-
<b>Profession</b>	Students	48	28,6	1	2	-	-
	Simple profession, unemployed	9	5,3	1	2	22	34,9
	Skilled workers	16	9,5	8	16,3	6	9,5
	Service and sales occupation	70	41,6	33	67,3	27	42,8
	Professional in scientific, technical and human fields	25	14,8	6	12,2	8	12,6
<b>Marital status</b>	Single	43	25,6	14	28,6	15	23,8
	Non-cohabiting couple	34	20,2	10	20,4	4	6,3
	Married/cohabiting	84	50,0	18	36,7	34	54,0
	Separated/Divorced	7	4,2	4	8,2	1	1,6
	Widowed	-	-	3	6,1	9	14,3
<b>Family Structure</b>	Single	44	26,2	19	38,8	16	25,4
	Childless couples	58	34,5	4	8,2	7	11,1
	Families with children	57	5,4	20	40,8	38	60,3
	Single parents	9	33,9	3	6,1	1	1,6
	Widowed	-	-	3	6,1	1	1,6
<b>Personal Special Needs</b>	Absence	143	85,1	46	93,9	57	90,5
	Chronic disease	7	4,2	-	-	1	1,6
	Disability	13	7,7	2	4,1	-	-
	Mental illness	2	1,2	1	2,0	-	-
	Combination of different special needs	3	1,7	-	-	5	7,9
<b>Flood Experience</b>	No	47	28	24	49	20	31,7
	Flood experience	80	47,6	25	51	32	50,8
	Flood traumatic experience	41	24,4	-	-	11	17,5

Demographic Characteristics of the Landslides Risk Pilot Area.

LANDSLIDE RISK PILOT AREAS _ CASE STUDIES N = 147		ITALY N = 40		MONTENEGRO N = 33		CROATIA N = 74	
<b>Age</b>	Mean	40,93		48,23		45,11	
	Standard deviation	14,36		11,79		18,97	
	Min	20		28		17	
	Max	67		75		80	
		N	%	N	%	N	%
<b>Gender</b>	Male	15	37,5	21	63,6	22	29,7
	Female	25	62,5	12	36,4	52	70,3
<b>Level of education</b>	High school degree or less	20	50	8	24,2	57	77
	Graduated or post-graduated	20	50	25	75,7	17	22,9
<b>Income</b>	17,000 Euro or less	18	45	32	96,6	57	77
	From 17,000 to 35,000 Euro	12	30	1	3	14	18,9
	More than 35, 000 Euro	10	25	-	-	3	4
<b>Profession</b>	Students	7	17,5	-	-	8	10,8
	Simple profession, unemployed	1	2,5	-	-	11	14,8
	Skilled workers	3	7,5	4	12	4	5,4
	Service and sales occupation	15	37,5	25	75,7	49	66,2
	Professional in scientific, technical and human fields	14	35	4	12	2	2,7
<b>Marital status</b>	Single	11	27,5	7	21,2	14	18,9
	Non-cohabiting couple	6	15,0	1	3,0	6	8,1
	Married/cohabiting	20	50,0	22	66,7	43	58,1
	Separated/Divorced	3	7,5	2	6,1	6	8,1
	Widowed	-	-	1	3,0	5	6,8
<b>Family structure</b>	Single	13	32,5	8	24,2	14	18,9
	Childless couples	9	22,5	4	12,1	9	12,2
	Families with children	16	40,0	19	57,6	40	54,1
	Single parents	2	5,0	1	3,0	6	8,1
	Widowed	-	-	1	3,0	5	6,8
<b>Personal special needs</b>	Absence	36	90,0	32	97,0	73	98,6
	Chronic disease	2	5,0	0	0	1	1,4
	Disability	-	-	1	3,0	-	-
	Mental illness	-	-	-	-	-	-
	Combination of different special needs	2	5,0	-	-	-	-
<b>Landslide experience</b>	No	18	45	22	66,7	40	54,1
	Landslide experience	16	40	11	33,3	32	43,2
	Landslide traumatic experience	6	15	-	-	2	2,7

### Comparison Among Pilot Areas in Terms of Risk Perception and Psychological Risk

A series of statistical analyses (ANOVAs) was performed to detect significant differences in the mean scores of risk perception and psychological risk. Regarding flood risk perception, participants in Tuscany

and Croatia (flood-prone areas) had the highest risk-perception scores. Regarding Landslide Risk Perception, we did not detect significant differences. Regarding the psychological risk, data showed that Croatian and Montenegrin participants had the highest levels of psychological well-being.

ANOVAs Results to Detect Significant Differences in the Mean Scores of Risk Perception and Psychological Risk

		Mean	SD	F	Sig
<b>Flood Risk Perception</b>	Pre-test Participants (N= 823)	10,8	2,6	13,01	p <.001
	<b>Tuscany (N= 168; Flooding)</b>	<b>12,8</b>	2,7		
	Molise (N=40; Landslides)	11,3	3,1		
	<b>Montenegro (N= 49; Flooding)</b>	<b>11,5</b>	2,4		
	Montenegro (N= 33; Landslides)	11,4	1,8		
	<b>Croatia (N= 63; Flooding)</b>	<b>12,3</b>	3,0		
	Croatia (N= 74; Landslides)	9,7	2,6		
	Total	11,8	2,7		
<b>Landslide Risk Perception</b>				<b>F</b>	<b>Sig</b>
	Pre-test Participants (N= 823)	10,5	2,4	,660	,682
	Tuscany (N= 168; Flooding)	10,7	2,6		
	<b>Molise (N=40; Landslides)</b>	<b>11,0</b>	2,5		
	Montenegro (N= 49; Flooding)	10,5	2,2		
	<b>Montenegro (N= 33; Landslides)</b>	<b>10,8</b>	2,3		
	Croatia (N= 63; Flooding)	10,5	3,4		
	<b>Croatia (N= 74; Landslides)</b>	<b>11,0</b>	2,8		
Total	10,6	2,5			
<b>Symptoms of PTSD (PC-PTSD-5)</b>				<b>F</b>	<b>Sig</b>
	Pre-test Participants (N= 823)	1,1	1,6	14,4	p<.01
	Tuscany (N= 168; Flooding)	1,5	1,6		
	Molise (N=40; Landslides)	1,4	1,8		
	Montenegro (N= 49; Flooding)	0,8	1,3		
	<b>Montenegro (N= 33; Landslides)</b>	<b>0,3</b>	0,8		
	<b>Croatia (N= 63; Flooding)</b>	<b>0,4</b>	1,0		
	<b>Croatia (N= 74; Landslides)</b>	<b>0,4</b>	0,9		
Total	1,3	1,6			
<b>Psychological Well-being (PGWB)</b>				<b>F</b>	<b>Sig</b>
	Pre-test Participants (N= 823)	<b>19,0</b>	5,7	6,049	p<.01
	Tuscany (N= 168; Flooding)	18,9	5,3		
	Molise (N=40; Landslides)	19,5	6,1		
	<b>Montenegro (N= 49; Flooding)</b>	<b>20,3</b>	5,9		
	<b>Montenegro (N= 33; Landslides)</b>	<b>20,7</b>	5,2		
	Croatia (N= 63; Flooding)	18,6	5,8		
	<b>Croatia (N= 74; Landslides)</b>	<b>20,9</b>	3,7		
Total	18,5	5,6			

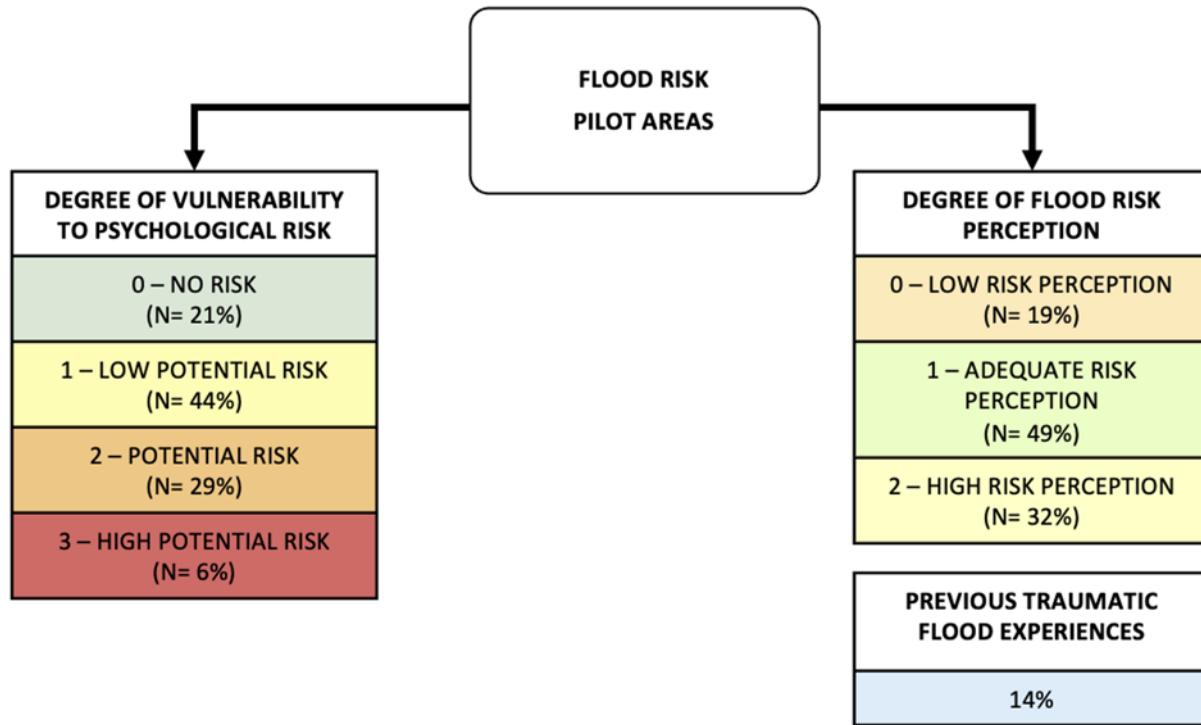
## RESULTS ABOUT FLOOD RISK PILOT AREA

### Assessment of the Quality of Flood Risk Perception and Psychological Risk

Among participants living in flood-risk pilot areas (N = 280), a descriptive analysis was conducted to assess the quality of flood risk perception and psychological risk. Regarding flood risk perception, results indicate that 19% of people had low risk perception, 49% had adequate risk perception, and 32% had high risk perception. Moreover, 14% of people have reported previous traumatic flood experiences. Regarding the psychological risk, results indicate that 21% of people had no psychological risk, 44% had

low potential psychological risk, 29% had potential risk, and 6% high potential psychological risk (see figure below).

Population's Vulnerability to Psychological Risk, and Quality of Floods Risk Perception in the Flood Risk Pilot Areas



### Factors Associated with Distinct Components of Flood Risk Perception and Preparedness

By considering participants living in flood-risk pilot areas (N = 280), a series of statistical analyses were conducted to identify socio-demographic and psychological variables associated with distinct components of risk perception and preparedness. Correlation analyses show that:

- **increasing age** correlates with an increase in knowledge ( $r = .322, p < .01$ ), awareness ( $r = .193, p < .01$ ), flood risk perception ( $r = .214, p < .01$ ) and preparedness ( $r = .402, p < .01$ );
- there are **gender differences**, more specifically, **females** correlate with lower knowledge ( $r = -0.165, p < .01$ ), greater worry ( $r = 0.389, p < .01$ ) and flood risk perception ( $r = 0.279, p < .01$ ), but with lower preparedness ( $r = -.119, p < .05$ );
- the experience of **stressful events** correlates with increased awareness ( $r = .261, p < .01$ ) and flood risk perception ( $r = .251, p < .01$ );
- **increased income** correlates with increased awareness ( $r = .124, p < .05$ ) and preparedness ( $r = .136, p < .05$ );
- **knowledge** correlates with lower worry ( $r = -.130, p < .05$ ) and greater awareness ( $r = .278, p < .01$ ), flood risk perception ( $r = .126, p < .05$ ) and preparedness ( $r = .845, p < .01$ );

- **worry** correlates with a greater flood risk perception ( $r = 0.732$ ,  $p < .01$ ) but lower preparedness ( $r = -0.133$ ,  $p < .05$ );
- **awareness** correlates with a greater flood risk perception ( $r = 0.674$ ,  $p < .01$ ) and preparedness ( $r = 0.361$ ,  $p < .01$ );
- **flood risk perception** correlates with greater preparedness ( $r = 0.185$ ,  $p < .01$ ).

Correlation Analyses in Flood Risk Area between Socio-Demographic/Personal Factors and Components of Flood Risk Perception and Preparedness.

	1	2	3	4	5	6	7	8	9
1. Age	1								
2. Gender	.012	1							
3. Stressful Events	.199**	.178**	1						
4. Income	.146*	-.129*	.093	1					
5. Knowledge	.322**	-.165**	.031	.092	1				
6. Worry	.077	.389**	.063	-.066	-.130*	1			
7. Awareness	.193**	.036	.261**	.124*	.278**	0.039	1		
8. Flood Risk Perception	.214**	.279**	.251**	.075	.126*	.732**	.674**	1	
9. Preparedness	.402**	-.119*	.030	.136*	.845**	-.133*	.361**	.185**	1

Furthermore, correlation analyses indicated that:

- **psychological distress** is correlated with greater worry ( $r = -0.243$ ,  $p < .01$ ) and lower awareness ( $r = -.171$ ,  $p < 0.01$ ), and risk perception ( $r = -.299$ ,  $p < 0.01$ );
- **avoidant coping** is correlated to greater neuroticism ( $r = 0.195$ ,  $p < 0.01$ ) and worry ( $r = 0.150$ ,  $p < .05$ );
- **approach coping** is correlated to greater flood risk perception ( $r = 0.183$ ,  $p < .01$ );
- **conscientiousness** is correlated to greater awareness ( $r = 0.150$ ,  $p < .05$ ) and flood risk perception ( $r = 0.132$ ,  $p < .05$ ).

Correlation Analyses in Flood Risk Area About Psychological Factors and Components of Flood Risk Perception and Preparedness.

	1	2	3	4	5	6	7	8	9	10
1. Psychological Well-being (PGWB)	1									
2. Avoidant Coping	-.190**	1								
3. Approach Coping	.053	.453**	1							
4. Conscientiousness	-.079	.127*	.085	1						
5. Neuroticism	.174**	.195**	.327**	.218**	1					
6. Knowledge	.100	-.076	.032	-.063	-.074	1				
7. Worry	-.243**	.150*	.171**	.030	.005	-.130*	1			

8. Awareness	-.171**	-.004	.062	.150*	.004	.278**	.037	1	
9. Risk Perception	-.299**	.115	.183**	.132*	-.011	.126*	.730**	.674**	1
10. Preparedness	.074	-.036	.084	-.016	-.036	.845**	-.135*	.361**	.185**

The results of the independent samples t-test (see next Table) showed that participants with **special needs**, compared to those without special needs, reported greater levels of worry in case of floods ( $M = 7.4$ ;  $SD = 2.0$ ) ( $t = -2.01$ ,  $p < .05$ ) and greater levels of flood risk perception ( $M = 13.5$ ) ( $t = -2.03$ ,  $p < .05$ ). No statistically significant differences were observed in knowledge, awareness, or preparedness.

Independent-Samples T-Tests Comparing Flood Risk-Related Variables by the Presence of Special Needs.

Presence of Special Needs	N	Mean	SD	t -test	sign
Knowledge	No	246	1.3	1.0	.69
	Yes	34	1.2	0.9	
Awareness	No	246	4.6	1.5	-1.63
	Yes	34	4.9	1.3	
Worry	No	246	6.7	1.9	-2.01
	Yes	34	7.4	2.0	
Flood Risk Perception	No	246	12.3	2.7	-2.03
	Yes	34	13.5		
Preparedness	No	246	4.9	2.3	0.9
	Yes	34	4.5	2.4	

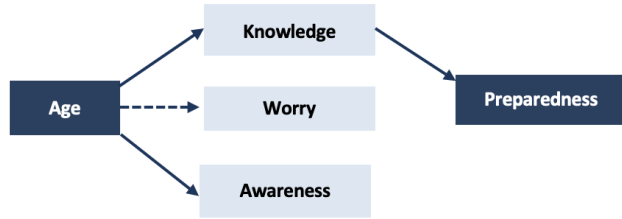
Furthermore, no significant differences in flood risk perception (knowledge, awareness, worry, risk perception, and preparedness) emerged with regard to family structure.

### Linking Mechanism Between Socio-Demographic and Psychological Variables and Preparedness

A series of mediational analyses was conducted to examine the indirect effects of socio-demographic and psychological factors on individual preparedness for a flood. Results have highlighted:

**THE INDIRECT EFFECT OF AGE ON PREPAREDNESS:** The influence of age on preparedness was examined by considering the mediating roles of knowledge, worry, and awareness (specific dimensions of risk perception). Results showed that age affects knowledge and awareness, but not worry. Moreover, results indicated an indirect effect of age on preparedness, mediated by knowledge. In other words, older individuals have greater knowledge of flood risk, which promotes greater preparedness

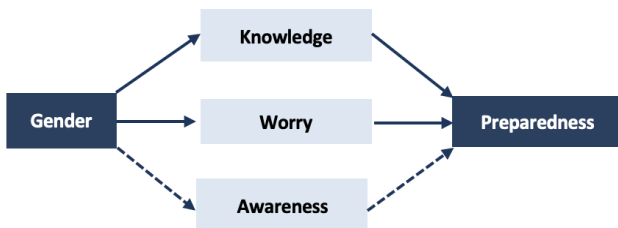
The Indirect Effect Of Age on Preparedness



(Total effect: .05;  $p < .05$ ; Direct Effect: .03;  $p < .05$ ; Indirect effect through knowledge: .02 (BootLLCI: .01; BootULCI: .03).

**THE INDIRECT EFFECT OF GENDER ON PREPAREDNESS:** The influence of gender on preparedness was explored by considering the mediating role of knowledge, worry, and awareness. The results indicated an indirect effect of gender on preparedness, mediated by worry. Males tend to have greater knowledge and less worry. A lower level of worry predicts preparedness and mediates the gender effect on preparedness. In other words, men have more knowledge and less worry, which promotes more preparedness. Conversely, women have more worries and less knowledge, both of which are directly associated with lower preparedness

The Indirect Effect Of Gender on Preparedness.

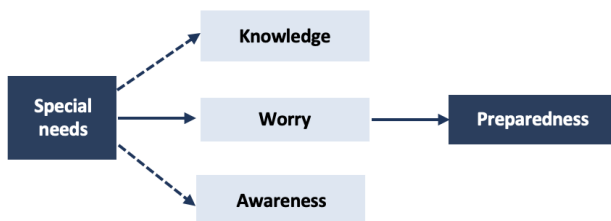


(Total effect: -.56;  $p < .05$ ; Direct Effect: -.40;  $p < .05$ ; Indirect effect through worry: -.14 (BootLLCI: -.3048; BootULCI: -.0120).

**THE INDIRECT EFFECT OF SPECIAL NEEDS ON PREPAREDNESS**

The influence of special needs on preparation was analysed, considering the mediating role of knowledge, worry, and awareness. The results indicated that the presence of special needs tends to increase worry. In turn, worry predicts lower preparation by mediating the effect of special needs. In other words, people with special needs have more worry directly associated with lower preparedness

The Indirect Effect Of Special Needs on Preparedness



(Total effect:  $-.45$ ;  $p > .05$ ; Direct Effect:  $-.13$ ;  $p > .05$ ; Indirect effect through worry:  $-.10$  (BootLLCI:  $-.23$ ; BootULCI:  $-.00$ ).

**THE INDIRECT EFFECT OF CONSCIENTIOUSNESS ON PREPAREDNESS:** The influence of personality in terms of conscientiousness on preparedness was analysed, considering the mediating role of knowledge, worry, and awareness. Conscientiousness is a personality trait characterised by an individual's tendency to be organised, diligent, responsible, and goal-oriented. The results indicated an indirect effect of conscientiousness on preparedness, mediated by awareness. Therefore, conscientiousness is associated with greater awareness, which in turn predicts greater preparedness, thereby mediating the effect of conscientiousness. In other words, people who are highly organized, reliable, and disciplined in their daily lives have more awareness directly associated with preparedness

The Indirect Effect Of Conscientiousness on Preparedness.



(Total effect:  $-.01$ ;  $p > .05$ ; Direct Effect:  $-.07$ ;  $p > .05$ ; Indirect effect through awareness:  $.02$  (BootLLCI:  $.00$ ; BootULCI:  $.05$ ).

## FLOOD TRAUMATIC EXPERIENCE AND ITS EFFECT ON WELL-BEING AND PREPAREDNESS

In this section, the effects of prior flood-related traumatic experiences on risk perception dimensions and preparedness are examined. Individuals exposed to previous floods who reported experiencing high levels of fear, anxiety, and helplessness were classified as having traumatic experiences. In our sample, 14% of the individuals (N = 41) reported previous traumatic flood experiences.

Correlation analyses reveal a series of significant associations

- having experienced a traumatic flood is correlated with greater vulnerability to PTSD ( $r = .144$ ,  $p < .05$ ), lower psychological well-being ( $r = -.194$ ,  $p < .01$ ), greater worry ( $r = -.621$ ,  $p < .01$ ), and awareness ( $r = .223$ ,  $p < .01$ );
- higher vulnerability to PTSD is correlated with lower knowledge ( $r = -.120$ ,  $p < .05$ ), greater worry ( $r = .250$ ,  $p < .01$ ), and lower preparedness ( $r = -0.157$ ,  $p < .01$ );
- psychological well-being is correlated with lower levels of worry ( $r = -.243$ ,  $p < .01$ );
- higher levels of knowledge are correlated with greater awareness ( $r = .365$ ,  $p < .01$ ) and

preparedness ( $r = -0.759, p < .01$ );

- higher levels of worry are correlated with lower preparedness ( $r = -0.135, p < .05$ ).

Correlation Analyses About the Effect of Having Experienced a Traumatic Flood on Psychological Risk and Preparedness.

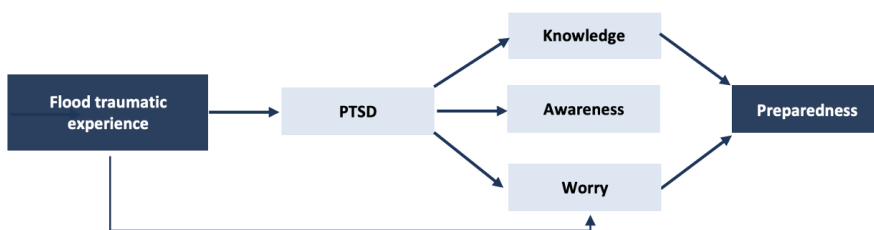
	1	2	3	4	5	6	7
1. Flood Traumatic Experiences	1						
2. PTSD Symptoms	<b>.144*</b>	1					
3. Psychological Wellbeing	<b>-.194**</b>	<b>-.314**</b>	1				
4. Knowledge	.070	<b>-.120*</b>	-.008	1			
5. Worry	<b>.621**</b>	<b>.250**</b>	<b>-.243**</b>	-.042	1		
6. Awareness	<b>.223**</b>	.065	<b>-.171**</b>	<b>.365**</b>	.037	1	
7. Preparedness	.078	<b>-.157**</b>	.074	<b>.759**</b>	<b>-.135*</b>	<b>.361**</b>	1

## THE INDIRECT EFFECT OF PREVIOUS FLOOD TRAUMATIC EXPERIENCES ON PREPAREDNESS

### The serial mediation with PTSD

A series of serial mediation analyses was conducted to examine the mediating mechanisms linking previous flood traumatic experiences to flood preparedness. In the first model, the variables included were: traumatic flood experience as the predictor; PTSD vulnerability as the first mediator; the dimensions of risk perceptions (Knowledge M2, Worry M3, and Awareness M4) as the other mediators; and flood preparedness as the outcome variable. Results showed that a traumatic flood experience affects worry, which in turn reduces preparedness. Moreover, results indicated the other two serial mediations. More precisely, the presence of a traumatic flood experience predicted the PTSD vulnerability, which in turn had effects on higher levels of worry and lower knowledge, directly associated with low preparedness.

Mediating Mechanisms of PTSD Linking Previous Flood Traumatic Experiences to Flood Preparedness



(Total effect: .26;  $p > .05$ ; Direct Effect: .43;  $p < .05$ ; Indirect effect through worry:  $-.36$  (BootLLCI:  $-.54$ ; BootULCI:  $-.16$ ), Indirect effect through PTSD on knowledge:  $-.05$  (BootLLCI:  $-.11$ ; BootULCI:  $-.00$ ); Indirect effect through PTSD on worry:  $-.01$  (BootLLCI:  $-.03$ ; BootULCI:  $-.00$ ).

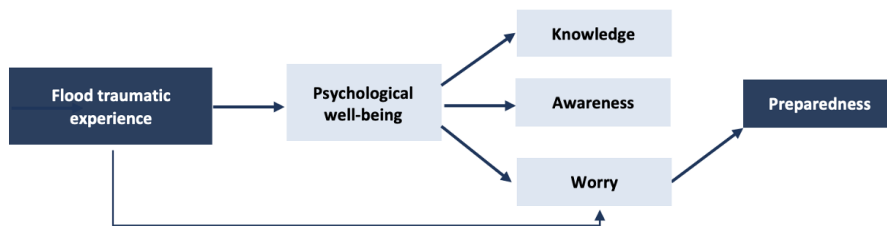
### The serial mediation with Psychological Well-Being

Additional serial mediation analyses were conducted to examine the mediating mechanisms of

psychological well-being linking flood traumatic experiences to flood preparedness. In this second model, the variables included were: the traumatic flood experience as the predictor; psychological well-being as the first mediator; the dimensions of risk perceptions (Knowledge M2, Worry M3, and Awareness M4) as the other mediators; and flood preparedness as the outcome variable.

Results showed that a traumatic flood experience was associated with higher levels of worry, which in turn was directly associated with lower levels of preparedness. Moreover, a traumatic flood experience reduces psychological well-being, which, in turn, increases worry, directly associated with lower preparedness. Therefore, the results indicated an indirect effect of the traumatic flood experience on preparedness, mediated by worry and, in turn, by lower psychological well-being and worry (see Figure below).

Mediating Mechanisms Of Psychological Well-Being Linking Flood Traumatic Experiences To Flood Preparedness.



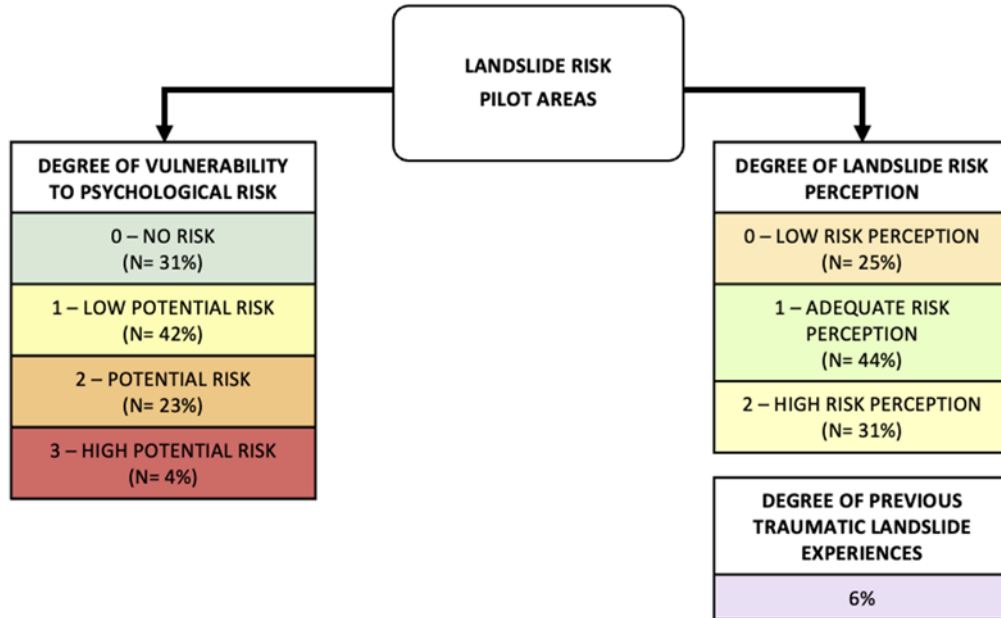
(Total effect: .26;  $p > .05$ ; Direct Effect: .44;  $p < .05$ ; Indirect effect through worry:  $-.35$  (BootLLCI:  $-.53$ ; BootULCI:  $-.16$ ), Indirect effect through PTSD on knowledge:  $-.05$  (BootLLCI:  $-.11$ ; BootULCI:  $-.00$ ); Indirect effect through psychological well-being on worry:  $-.01$  (BootLLCI:  $-.03$ ; BootULCI:  $-.00$ )).

## RESULTS ABOUT LANDSLIDE RISK PILOT AREA

### Assessment of the Quality of Landslide Risk Perception and Psychological Risk

Among participants living in landslide-risk pilot areas ( $N = 147$ ), a descriptive analysis was conducted to assess the quality of flood risk perception and psychological risk. Regarding landslide risk perception, results indicate that 25% of people had low risk perception, 44% had adequate risk perception, and 31% had high risk perception. Moreover, 6% of people have reported previous traumatic landslide experiences. Regarding psychological risk, the results indicate that 31% of people had no psychological risk, 42% had low potential psychological risk, 23% had potential risk, and 4% high potential psychological risk

Results About Population’s Vulnerability to Psychological Risk, and Quality of Landslide Risk Perception in the Landslide Risk Pilot Areas.



### Factors Associated with Distinct Components of Landslide Risk Perception and Preparedness

By considering participants living in landslide-risk pilot areas (N=147), a series of statistical analyses was conducted to identify socio-demographic and psychological variables associated with distinct components of risk perception and preparedness. Correlation analyses show that:

- **increasing age** is correlated with greater knowledge ( $r = .169, p < .05$ ) and preparedness ( $r = .184, p < .05$ )
- there are **gender differences**, more specifically, females are correlated with less knowledge ( $r = -0.249, p < .01$ ), greater worry ( $r = 0.230, p < .01$ ), and with less preparedness ( $r = -0.289, p < .01$ )
- **knowledge** is correlated with greater awareness ( $r = .270, p < .01$ ) and preparedness ( $r = 0.861, p < .01$ )
- **worry** is correlated with greater landslide risk perception ( $r = .646, p < .01$ );
- **awareness** is correlated with greater landslide risk perception ( $r = .744, p < .01$ ) and preparedness ( $r = 0.269, p < .01$ ).
- **landslide risk perception** is correlated with greater preparedness ( $r = 0.183, p < .05$ ).

Correlation Analyses in Flood Risk Area About Socio-Demographic/Personal Factors and Components of Flood Risk Perception and Preparedness

	1	2	3	4	5	6	7	8	9
1. Age	1								
2. Gender	-.209*	1							
3. Stressful Events	-.016	-.072	1						
4. Income	.081	-.089	-.087	1					
5. knowledge	<b>.169*</b>	<b>-.249**</b>	.028	.095	1				
6. Worry	-.103	<b>.230**</b>	-.153	.019	-.052	1			
7. Awareness	-.021	-.063	.106	.110	<b>.270**</b>	.034	1		
8. Landslides Risk Perception	-.042	.099	.019	.139	.198*	<b>.646**</b>	<b>.744**</b>	1	
9. Preparedness	<b>.184*</b>	<b>-.289**</b>	.094	.128	<b>.861**</b>	-.105	<b>.269**</b>	<b>.183*</b>	1

Furthermore, correlation analyses show that:

- The psychological well-being is not correlated with landslide risk perception and preparedness
- The coping strategies are not correlated to landslide risk perception and preparedness
- Conscientiousness is correlated with greater awareness ( $r = .177, p < .05$ )

Correlation Analyses in Landslide Risk Area About Psychological Factors And Components Of Flood Risk Perception And Preparedness

	1	2	3	4	5	6	7	8	9	10
1. Psychological Well-being (PGWB)	1	.000								
2. Avoidant Coping	-.441**	1								
3. Approach Coping	.032	.183*	1							
4. Conscientiousness	.000	.050	-.009	1						
5. Neuroticism	.082	.100	.139	<b>.380**</b>	1					
6. Knowledge	.067	.041	-.115	-.026	-.057	1				
7. Worry	.094	.024	.133	-.093	.098	-.052	1			
8. Awareness	-.026	.047	.032	<b>.177*</b>	.067	<b>.270**</b>	.034	1		
9. Risk Perception	.027	.091	.134	.091	.110	.198*	<b>.646**</b>	<b>.744**</b>	1	
10. Preparedness	-.008	.045	-.077	-.007	-.130	<b>.861**</b>	-.105	<b>.269**</b>	<b>.183*</b>	1

Furthermore, no significant differences in landslide risk perception (knowledge, awareness, worry, risk perception, and preparedness) were observed across family structures. Moreover, unlike the flood-area results, the independent-samples t-test showed no significant differences between participants with and

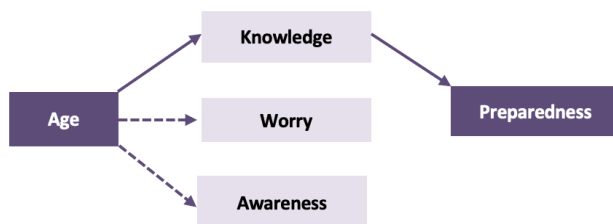
without special needs in risk-perception dimensions or preparedness.

### Linking Mechanism Between Socio-Demographic and Psychological Variables and Preparedness

A series of mediational analyses was conducted to examine the indirect effects of socio-demographic and psychological factors on individual preparedness for a landslide. Results have highlighted:

**THE INDIRECT EFFECT OF AGE ON PREPAREDNESS:** The influence of age on preparedness was analysed, considering the mediating role of knowledge, worry, and awareness. The results indicated an indirect effect of age on preparedness, mediated by knowledge. In other words, older individuals have greater knowledge of landslide risk, which promotes greater preparedness.

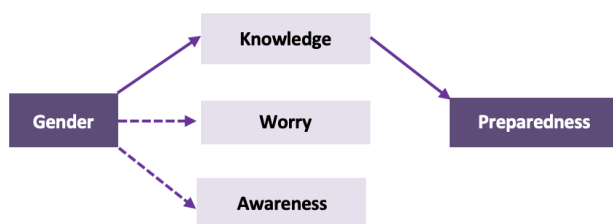
The Indirect Effect Of Age on Preparedness.



(Total effect: .03;  $p < .05$ ; Direct Effect: .00;  $p > .05$ ; Indirect effect through knowledge: .02 (BootLLCI: .00; BootULCI: .05).

**THE INDIRECT EFFECT OF GENDER ON PREPAREDNESS:** The influence of gender on preparedness was analysed, with knowledge, worry, and awareness as mediating variables. The results indicated an indirect effect of gender on preparedness, mediated by knowledge acquisition. Males tend to have greater knowledge, which predicts greater preparedness. In other words, men have more knowledge, which is directly associated with preparedness, while women have less knowledge and lower preparedness.

The Indirect Effect Of Gender on Preparedness



(Total effect: -1.76  $p < .05$ ; Direct Effect: -.41;  $p > .05$ ; Indirect effect through knowledge: -1.26 (BootLLCI: -2.12; BootULCI: -.46).

### LANDSLIDE TRAUMATIC EXPERIENCE AND ITS EFFECT ON WELL-BEING AND PREPAREDNESS

In this section, the effects of prior landslides traumatic experiences on risk perception dimensions and

preparedness were examined. Individuals exposed to previous landslides who reported experiencing high levels of fear, anxiety, and helplessness were classified as having traumatic experiences (6%; N= 10). Subsequently, the effect of having experienced a traumatic landslide on psychological risk and preparedness was explored. Correlation analyses reveal a number of significant associations

- Having experienced a traumatic landslide is correlated with greater vulnerability to PTSD ( $r = .273, p < .01$ )
- PTSD symptoms are correlated with lower preparedness ( $r = -.176, p < .05$ )
- Knowledge is correlated with greater awareness ( $r = .270, p > .01$ ) and preparedness ( $r = .817, p < .01$ )
- Awareness is correlated with greater preparedness ( $r = .275, p < .01$ )

Correlation Analyses About the Effect of Having Experienced a Traumatic Landslide on Psychological Risk and Preparedness.

	1	2	3	4	5	6	7
1. Landslides Traumatic Experiences	1						
2. PTSD Symptoms	<b>.273**</b>	1					
3. Psychological Wellbeing	-.027	-.358**	1				
4. Knowledge	-.057	.004	.067	1			
5. Worry	.471**	.023	.094	-.052	1		
6. Awareness	.071	.087	-.026	<b>.270**</b>	.034	1	
7. Preparedness	-.094	<b>-.176*</b>	.005	<b>.817**</b>	-.103	<b>.275**</b>	1

Mediation analyses indicated that the traumatic experience of a landslide increases vulnerability to PTSD which is directly associated with lower preparedness.

Mediating Mechanisms of PTSD Linking Previous Landslide Traumatic Experiences to Landslide Preparedness



(Total effect:  $-.46, p > .05$ ; Direct Effect:  $-.24, p > .05$ ; Indirect effect through PTSD:  $-.21$  (BootLLCI:  $-.55$ ; BootULCI:  $-.02$ ).

## DISCUSSION

Floods and landslides can have significant long-term adverse impacts on the mental health of survivors. Moreover, people's risk perception influences how individuals behave, affecting preparedness and responses. The use of preventive protection and intervention tools in the event of hydrogeological emergencies can be significant in mitigating risks, protecting mental health, and improving the response capacity and disaster resilience of communities. The psychological section of the European SAFE-LAND project pursues this objective by proposing a preventive hydrogeological risk assessment system. Specifically, it aims to support the early identification of vulnerability to psychological risk and the

assessment of the quality of flood/landslide risk perception, in order to implement an effective hydrogeological emergency management system.

Similarly to the reference areas, overall, the results of 427 participants in the **floods (N=280) and landslide (N=147) pilot areas** reveal a generally positive profile of psychological well-being and adequate hydrogeological risk perception. However, a subgroup of the sample showed potential psychological vulnerability (35% floods, 27% landslide) and risk perception underestimation (19% floods; 25% landslides) or overestimation (32% floods; 31% landslides).

In addition, correlation and mediation analyses were conducted for participants in the **pilot areas**. More specifically, we investigated the impact of some socio-demographic/psychological/emotional/cognitive characteristics on hydrogeological risk perception (knowledge, awareness, and worry) and preparedness. These characteristics can act as both protective and risk factors. Therefore, these factors are significant variables that should be monitored to improve prevention, risk communication, and support interventions during hydrogeological emergencies. In fact, an integrated approach that considers the various dimensions of risk, protection, and people's specific characteristics could enhance people's management and response capabilities, as well as disaster resilience in the event of a hydrogeological emergency. More specifically, our results indicated some significant protective and risk factors:

● **PROTECTIVE FACTORS** are primarily some socio-demographic and psychological factors that include: advanced age, high knowledge, awareness, adequate risk perception, good psychological well-being, and conscientiousness. Overall, these factors can contribute to adaptive modulation of the response to risk, thereby promoting more effective self-efficacy, management, and preparedness of hydrogeological emergencies

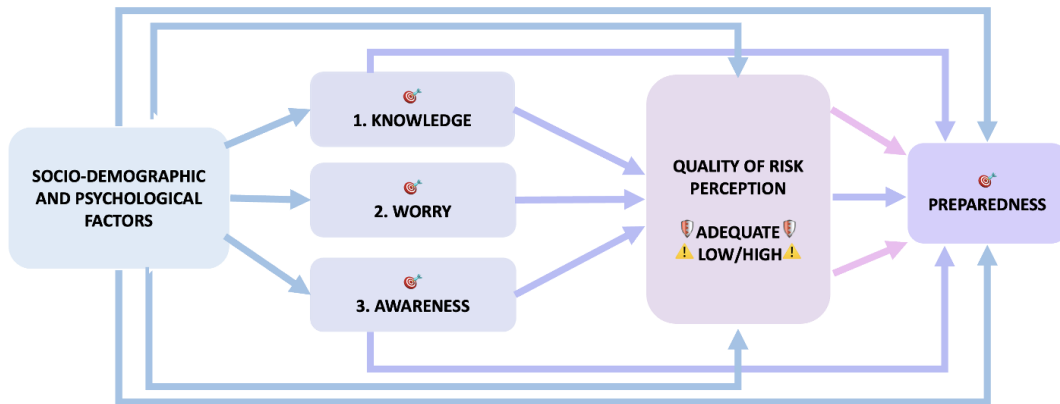
● **RISK FACTORS** include some variables such as younger individuals, women, people with high levels of worry, psychological distress, and special needs. Overall, these groups can exhibit a critical combination of limited cognitive/behavioral resources (knowledge, awareness, risk perception, preparedness) and heightened emotional activation (worry), which can amplify vulnerabilities and hinder effective management of hydrogeological emergencies.

Additionally, a series of mediation analyses highlighted the pathways linking socio-demographic and psychological factors to individual preparedness for floods and landslides.

✔ Overall, the results showed that increasing age and conscientiousness are important protective factors for preparedness through the increase of some protective cognitive/behavioural responses (knowledge and awareness)

▶ Conversely, overall the results showed that female gender and the presence of special needs are significant risk factors for preparedness through the decrease of some emotive and cognitive/behavioural responses (worry and knowledge)

Factors that influence risk perception and preparedness



The main protective/risk factors, the mediational results are presented in the figures below.

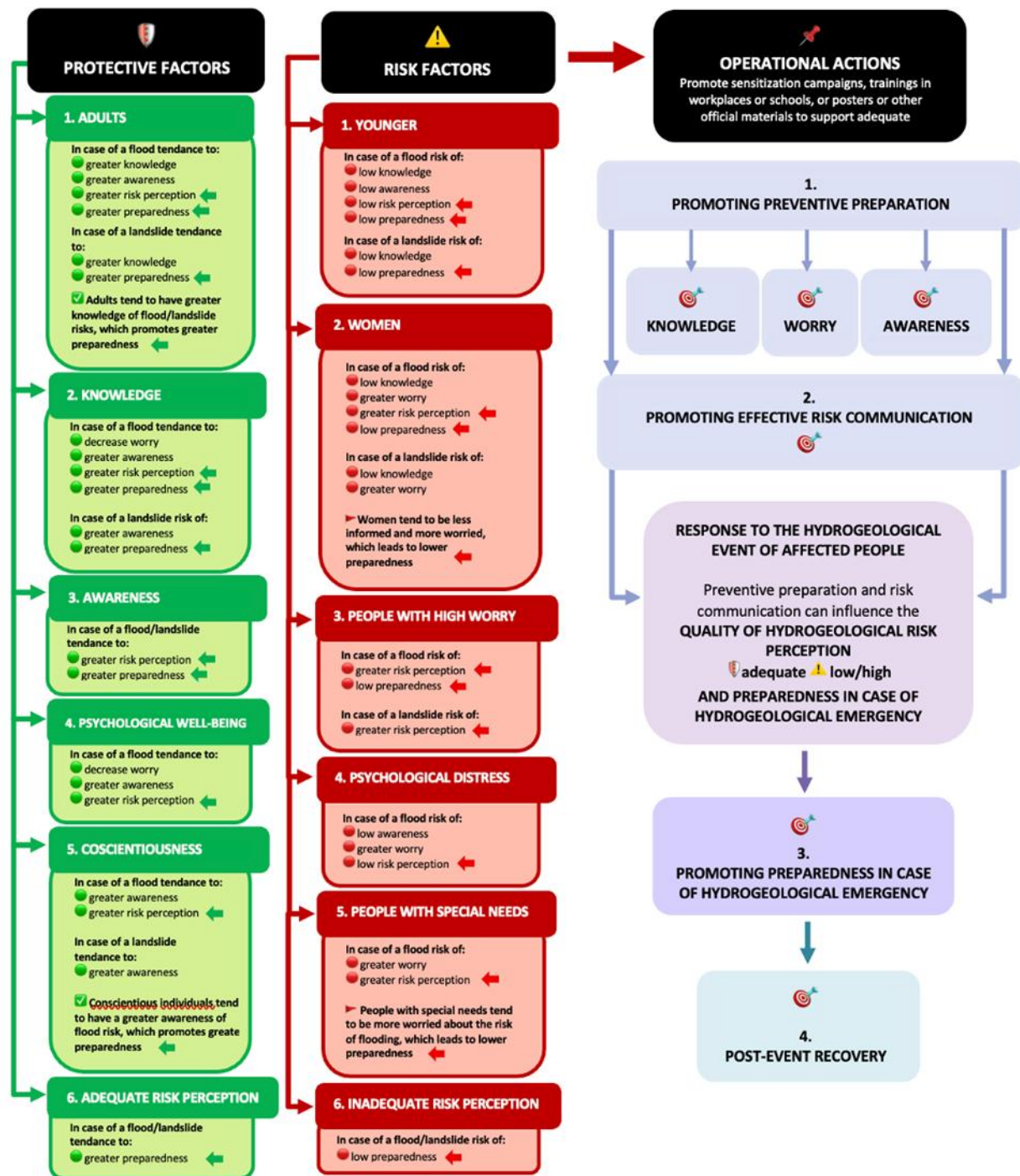
A crucial finding in the context of our research about flood and landslide emergencies is the gender disparity in risk perception and disaster preparedness. Our research indicates that the female gender is a significant determinant of vulnerability during hydrogeological events. Specifically, female participants reported higher levels of subjective worry and risk perception, but lower levels of knowledge and preparedness. The data reveal that for women, the combination of a heightened emotional worry and limited knowledge creates a barrier to proactive behavior and hinders their disaster preparedness. Conversely, men typically exhibit lower worry and higher knowledge, traits that appear to catalyze preparedness. These results are consistent with the existing literature (Brown, Largey & McMullan, 2021; Clayton et al., 2023; Cuesta et al., 2022) that underline how women tend to view disasters as more severe and personally significant. Specifically, studies indicate that women experience more intense "climate anxiety" and worry about natural hazards, not only for their own safety but also for the well-being of their homes and families (Clayton et al., 2023; Cuesta et al., 2022; ADRC, 2022). This emotional burden can lead to poorer mental health outcomes, which inherently reduce the cognitive resources available for emergency planning. In addition, empirical evidence show that, unlike men, who generally report confidence, self-efficacy and preparedness in disaster management, women often perceive themselves as less equipped and with a lower preparedness in case of disaster (Armas & Avram, 2009; Cuesta et al., 2022; Cvetković et al., 2018).

In conclusion, our findings, supported by the scientific literature, highlight how gender is a significant factor in understanding the cognitive and behavioral processes underlying perceptions and reactions to hydrogeological emergencies. These findings extend beyond academic interest and offer practical, gender-sensitive guidance for hydrogeological risk management. In particular, gender differences in risk perception and disaster preparedness can help guide the design of more targeted preventive preparedness programs, support the development of more effective risk communication strategies, and contribute to improving disaster preparedness, with the aim of reducing vulnerability and strengthening the response capacity of the female population in case of a hydrogeological emergency.

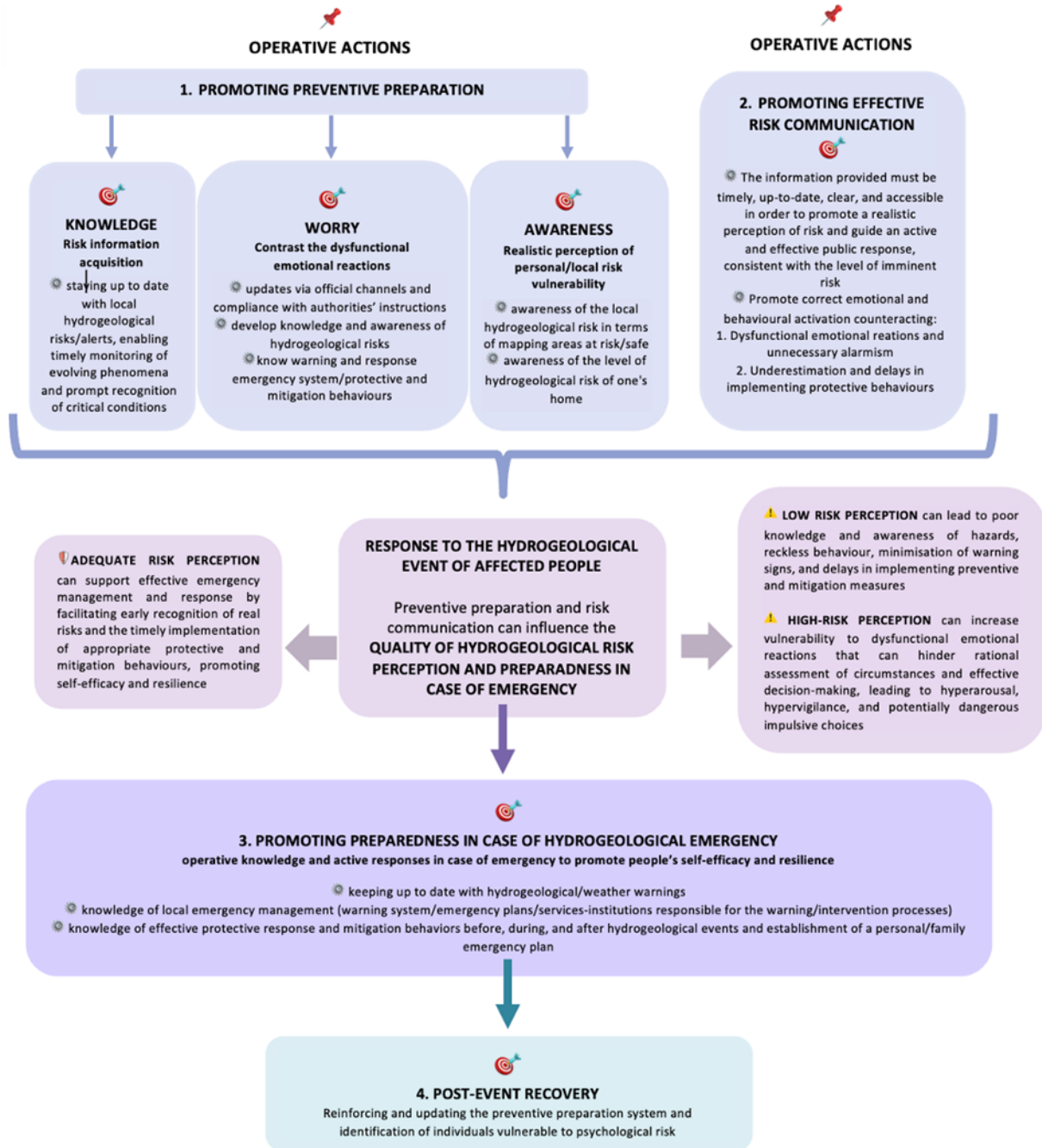
In addition, the exploration of the quality of risk perception and of the risk of psychological vulnerability enabled the use of the operational guidelines to support an effective hydrogeological emergency management system. More specifically, the operational guidelines are based on four main steps:

1. Operational actions to support effective **preventive preparation** by promoting adequate knowledge, worry, and awareness of the flood and landslide risks.
2. Operational actions to support **effective risk communication**.  
=> **Response to the hydrogeological event among affected people: the quality of preventive preparation and risk communication influences risk perception, which, in turn, influences preparedness in the event** of a hydrogeological emergency.
3. Operative action to promote **preparedness**, in terms of operational knowledge and protective and mitigation actions to adopt in case of a hydrogeological emergency, in order to promote people's self-efficacy and disaster resilience.
4. **Post-event recovery**, aimed to promote a culture of risk awareness and strengthening and updating the system of preventive preparation and identification of individuals vulnerable to psychological risk (Deliverable D3.3).

Main Protective/Risk Factors, Mediation and Operational Actions to Support Vulnerabilities and Improve the Management of Hydrogeological Emergencies.



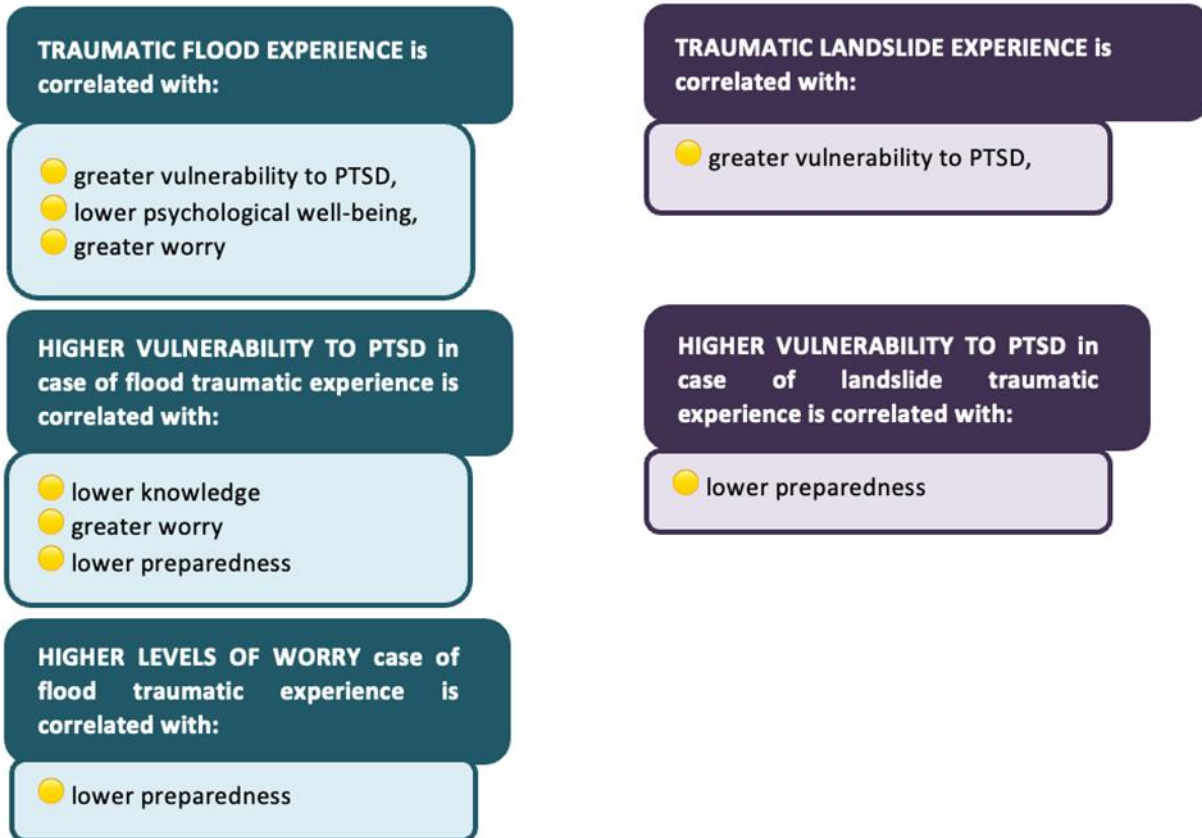
Operative Guidelines to Promote Preventive Preparation, Risk Communication in Order to Support Risk Perception and Preparedness.



## The Significant Role of Previous Traumatic Flood and Landslide Experiences

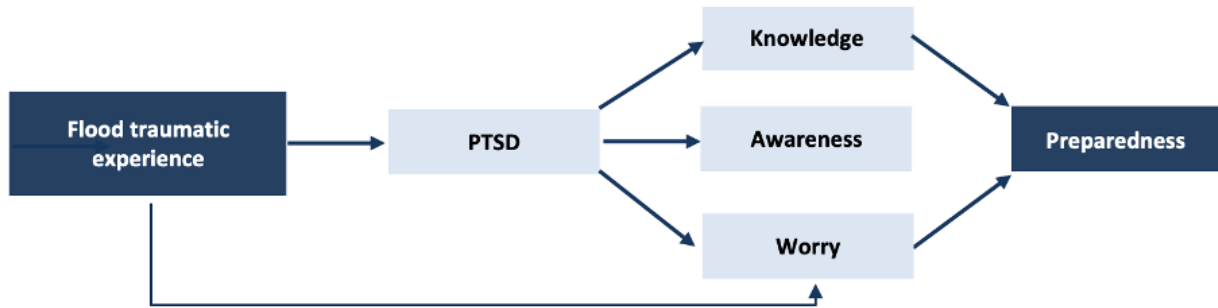
Subsequently, it was explored how a previous experience of a traumatic flood/landslide could be associated with psychological well-being and the dimensions of risk perception and preparedness. The main results evidence the negative effect of traumatic flood experience on people’s well-being and emotional/cognitive/behavioural response processes.

Traumatic Experience Of Flooding And Its Effect On Well-Being And Preparedness



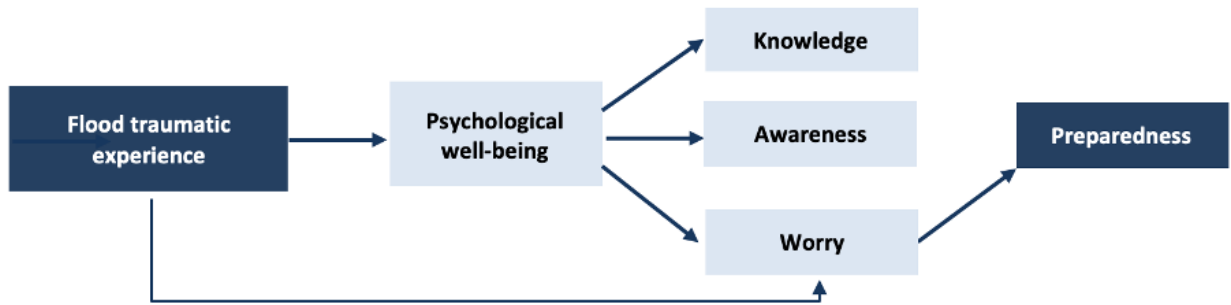
In addition, a series of serial mediational analyses was performed to explore the linking mechanisms between flood/landslide traumatic experiences and preparedness. Results showed that a traumatic flood experience affects worry, which in turn reduces preparedness. Moreover, results indicated that the presence of a traumatic flood experience predicted PTSD vulnerability, which in turn had effects on higher levels of worry and lower knowledge, directly associated with low preparedness.

Mediating Mechanisms of PTSD Linking Flood Traumatic Experiences To Flood Preparedness.



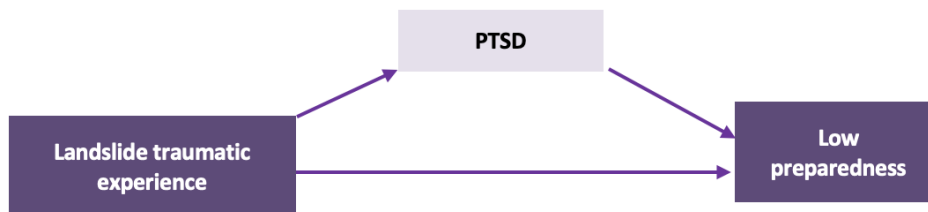
Other results showed that a traumatic flood experience was associated with higher levels of worry, which in turn was directly associated with lower levels of preparedness. Moreover, a traumatic flood experience reduces psychological well-being, which, in turn, increases worry, directly associated with lower preparedness.

Mediating Mechanisms Of Psychological Well-Being Linking Flood Traumatic Experiences To Flood Preparedness.



In addition, other results showed that the traumatic experience of a landslide increases vulnerability to PTSD, which is directly associated with lower preparedness

Mediating Mechanisms of PTSD Linking Previous Landslide Traumatic Experiences to Landslide Preparedness



Overall, these results highlight the significance of prior hydrogeological traumatic experiences in emotional/cognitive response processes and hydrogeological risk preparedness. More specifically, they serve as significant events that negatively influence emotional/cognitive response processes

(knowledge and worry), psychological well-being/vulnerability, and preparedness. It is therefore important to consider the psychological consequences of traumatic experiences of floods and landslides in understanding risk preparedness behaviours, recognising that exposure to traumatic hydrogeological events can compromise individuals' adaptive response capabilities.

## CONCLUSION

In conclusion, the proposed hydrogeological risk assessment can be significant in mitigating risks, protecting mental health, and improving the response capacity and disaster resilience of communities. More specifically, Safe-Land's results showed that psychological risk assessment can be an effective preventive measure because it enables the identification of the most vulnerable individuals. This identification is relevant for two reasons: the first is because psychological vulnerability may worsen after an emergency, especially in the presence of serious peri- and post-traumatic factors (e.g., injuries, loss of relatives, damage to the home, etc.); the second is because psychological vulnerability and distress (PTSD symptoms) can negatively influence risk perception and preparedness. Furthermore, we highlighted that traumatic experiences of floods and landslides can negatively compromise individuals' adaptive responses and self-efficacy, influencing emotional and cognitive responses (knowledge and worry), psychological well-being/vulnerability, and preparedness.

In addition, Safe-Land's results highlighted the importance of assessing hydrogeological risk perception to identify people with inadequate risk perception and high worry, who may be at risk and unable to adopt effective emergency management and responses. More specifically, people with low risk perception can exhibit reckless behaviour, minimise hazards/warning signs, and delay the implementation of preventive and mitigation measures. Conversely, people with high-risk perception and worry could have greater vulnerability to intense and dysfunctional emotional reactions. Moreover, some protective and risk factors could influence emergency management, self-efficacy, and community disaster resilience. More specifically, protective factors (e.g., adults, high knowledge and awareness, good psychological well-being, conscientiousness, and adequate risk perception) can contribute to adaptive modulation of responses to risk, thereby promoting more effective self-efficacy, management, and preparedness for hydrogeological emergencies. Conversely, risk factors (e.g., younger individuals, women, individuals with high levels of worry, individuals with psychological distress, and individuals with special needs) can amplify vulnerabilities and hinder the effective management of hydrogeological emergencies.

Therefore, the proposed Operative Guidelines contain a series of indications to support and promote an adequate risk perception and risk communication, to support an effective emergency response, management, and preparedness by enabling early recognition of real risks and the timely implementation of appropriate protective and mitigation behaviors, improving the response capacity and disaster resilience of communities.

### 3. WEB APPLICATION RESULTS AND COMPARISON

This section presents the results obtained in the pilot areas. Annex 1 provides the user guide of the web application developed, including a description of all input parameters, in line with Deliverables 3.1 - 3.3.

#### 3.1. LANDSLIDE RISK ASSESSMENT AND MITIGATION MEASURES

##### 3.1.1. Pilot area in Italy

Tab. 3.1.1: True and predicted values for drained and undrained slopes in the pilot area in Italy.

Zone	Parameters	Tr	$Fos\ true$	$z_s\ true$	$z_w^{final\ true}$	$Fos\ pred$	$z_s\ pred$	$z_w^{final\ pr}$
Molise	Drained	0	1.255	4.72	15.0	1.334	3.913	14.430
Molise	Drained	30	1.243	4.72	15.0	1.159	3.608	14.309
Molise	Drained	200	1.243	4.72	15.0	1.159	3.608	14.309
Molise	Drained	500	1.242	4.72	15.0	1.155	3.608	14.314

The table above provides a comparative analysis between the true and predicted values of the  $FoS$ ,  $z_s$ , and  $z_w^{final}$  for the Molise area under drained conditions, across different return times  $Tr$ . Overall, the table highlights a consistent behavior of both ground-truth and model-predicted quantities, offering useful insights into the robustness and limitations of the proposed predictive framework.

The true values of  $z_s$  and  $z_w^{final}$  remain perfectly invariant with respect to the return time, fixed at 4.72 and 15.0, respectively. The true  $FoS$  exhibits a very marginal decrease from 1.255 at  $Tr = 0$  to 1.242 at  $Tr = 500$ , indicating that under drained conditions, the adopted geotechnical configuration and hydraulic assumptions largely decouple the slope stability response from transient hydrological forcing.

The predicted results exhibit an initial adjustment followed by a strong stabilization. The predicted  $FoS$  decreases from 1.334 at  $Tr = 0$  to 1.155 at  $Tr = 500$ , with the bulk of the variation occurring before  $Tr = 30$ . Similarly, the predicted value of  $z_s$  shifts from 3.913 to a constant 3.608 for  $Tr \geq 30$ , while the predicted  $z_w^{final}$  is greater than 14 across all return times. This behavior indicates that the predictive model rapidly reaches a steady-state condition, correctly capturing the overall insensitivity of the system to long-term changes in  $Tr$  under drained conditions, suggesting a stable and consistent response of the learned mapping after the initial period. A systematic discrepancy between true and predicted values is observed. In particular, after an initial overestimation at  $Tr = 0$ , the predicted  $FoS$  underestimates the true  $FoS$  by approximately 6% to 7% for subsequent return times. Furthermore, the model consistently underestimates both  $z_s$  (stabilizing at 3.608 predicted versus 4.72 true) and  $z_w^{final}$ . Despite these biases, it is worth noting that the predicted  $FoS$  values remain well above the critical stability threshold ( $FoS = 1$ ) for all scenarios, consistently classifying the slope as stable. From a risk assessment perspective, the underestimation of the  $FoS$  by the model at higher return times yields a more conservative evaluation of slope stability, which provides an implicit safety margin that is generally desirable for hazard screening

and early warning applications.

### 3.1.2 Guidelines for pilot area in Italy

For the Molise study area, the evaluation of mitigation guidelines is omitted for this scenario. As detailed previously, both the ground-truth and model-predicted  $FoS$  values strictly exceed the critical unity threshold ( $FoS > 1$ ) across all considered return periods ( $Tr$ ), with the predicted  $FoS$  maintaining a value greater than 1. Consequently, the slope is consistently classified as stable, demonstrating inherent resilience to the modeled transient hydrological forcing under drained conditions. Given this verified absence of critical instability, the application of stabilization frameworks or intervention guidelines is deemed strictly unnecessary. Therefore, no specific mitigation measures or structural countermeasures are proposed for this configuration, as the baseline hydro-mechanical conditions already satisfy the required safety criteria.

### 3.1.3 Pilot area in Croatia

Tab. 3.1.2: True and predicted values for drained slope in the pilot area in Croatia.

Zone	Parameters	Tr	$Fos\ true$	$z_s\ true$	$z_w^{final}\ true$	$Fos\ pred$	$z_s\ pred$	$z_w^{final}\ pred$
Croatia	Drained	0	1.06	4.36	1.5	0.589	2.140	1.900
Croatia	Drained	30	0.936	4.36	1.5	0.528	2.031	1.876
Croatia	Drained	200	0.936	4.36	1.5	0.528	2.031	1.749
Croatia	Drained	500	0.936	4.36	1.5	0.528	2.031	1.749
Croatia	Undrained	0	1.754	4.36	1.5	1.462	8.159	0.081
Croatia	Undrained	30	1.748	4.36	1.5	1.462	8.159	0.081
Croatia	Undrained	200	1.748	4.36	1.5	1.462	8.159	0.081
Croatia	Undrained	500	1.748	4.36	1.5	1.462	8.159	0.081

The table above provides a comparative analysis between the true and predicted values of the  $FoS$ ,  $z_s$ , and  $z_w^{final}$  for the Croatia area under both drained and undrained conditions, across different return times  $Tr$ . Overall, the table highlights a consistent behavior of both ground-truth and model-predicted quantities, offering useful insights into the robustness and limitations of the proposed predictive framework across varying drainage scenarios.

The true values of  $z_s$  and  $z_w^{final}$  remain invariant with respect to the return time and drainage conditions, at 4.36 and 1.5, respectively. Under drained conditions, the true  $FoS$  exhibits a decrease from 1.06 at  $Tr = 0$  to a constant 0.936 for  $Tr \geq 30$ , crossing the critical stability threshold ( $FoS = 1$ ). Conversely, under undrained conditions, the true  $FoS$  remains significantly higher and more stable, showing a very marginal decrease from 1.754 at  $Tr = 0$  to 1.748 for  $Tr \geq 30$ . This indicates that the adopted geotechnical

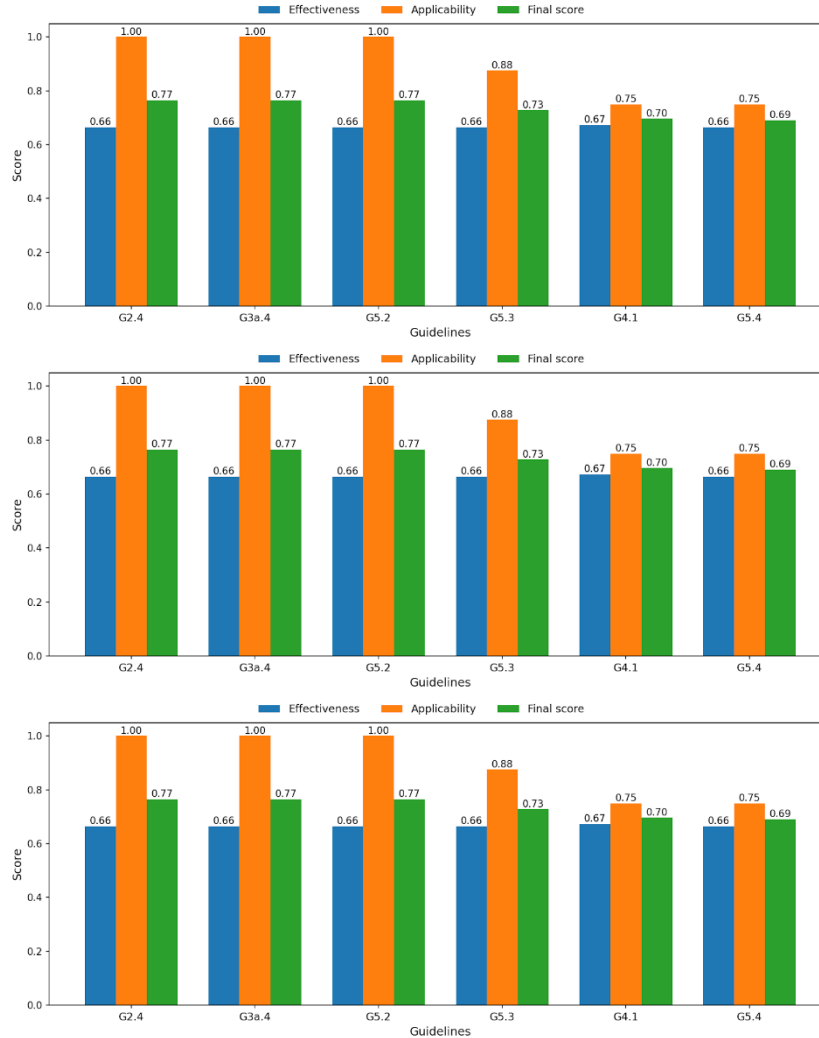
configuration is highly sensitive to the drainage state, with transient hydrological forcing playing a more significant role in stability degradation under drained conditions.

The predicted results exhibit an initial adjustment followed by stabilization under drained conditions, and a strict invariance under undrained conditions. For the drained scenario, the predicted  $FoS$  decreases from 0.589 at  $Tr = 0$  to 0.528 for  $Tr \geq 30$ . Similarly, predicted  $z_s$  and  $z_w^{final}$  show slight initial variations before stabilizing at 2.031 and 1.749 (at  $Tr \geq 200$ ), respectively. For the undrained scenario, the predicted results remain constant across all return times, with  $FoS$  fixed at 1.462,  $z_s$  at 8.159, and  $z_w^{final}$  at 0.081. This behavior indicates that the predictive model rapidly reaches a steady-state condition, correctly capturing the overall insensitivity of the system to long-term changes in  $Tr$  after the initial period.

A systematic discrepancy between true and predicted values is observed across both drainage scenarios. Under drained conditions, the model underestimates the true  $FoS$  (e.g., 0.528 predicted versus 0.936 true at  $Tr \geq 30$ ) and underestimates  $z_s$  (approximately 2.03 predicted versus 4.36 true), while slightly overestimating  $z_w^{final}$ . Conversely, under undrained conditions, the model underestimates the true  $FoS$  (1.462 predicted versus 1.748 true), heavily overestimates  $z_s$  (8.159 predicted versus 4.36 true), and underestimates  $z_w^{final}$  (0.081 predicted versus 1.5 true). Despite these biases, it is worth noting the model's utility from a risk assessment perspective. Under drained conditions, both the true and predicted  $FoS$  values fall below the critical stability threshold ( $FoS = 1$ ) for  $Tr \geq 30$ , meaning the model successfully identifies the onset of instability, even though its underestimation projects a highly pessimistic scenario. Under undrained conditions, the predicted  $FoS$  values remain well above the critical stability threshold, consistently classifying the slope as stable, which perfectly mirrors the ground truth. Overall, the systematic underestimation of the  $FoS$  yields a more conservative evaluation of slope stability, providing an implicit safety margin that is generally desirable for hazard screening and early warning applications.

### 3.1.4 Guidelines for pilot area in Croatia

Fig. 3.1.1: Guidelines for unstable drained slope in the pilot area in Croatia for  $T_r$  equal to 30, 200, and 500



To address the unstable conditions observed under drained configurations for return periods  $T_r \geq 30$  where the true Factor of Safety drops below 1 ( $FoS = 0.936$ ), a quantitative evaluation of potential mitigation guidelines was conducted. As illustrated in the performance distribution charts, guidelines G2.4, G3a.4, and G5.2 emerge as the optimal intervention strategies for unstable slopes, achieving the highest overall final score of 0.77. This superior ranking is predominantly driven by their perfect applicability score (1.00), which maximizes their overall utility alongside a consistent effectiveness score (0.66). In contrast, alternative measures such as G4.1 exhibit a marginally higher effectiveness (0.67) but demonstrate significantly constrained applicability (0.75), thereby limiting their overall utility (final score of 0.70). Guidelines G5.3 and G5.4 show intermediate or lower overall scores (0.73 and 0.69, respectively) due to proportional drops in applicability. Consequently, for critical slope conditions characterized by

$FoS < 1$ , the systematic prioritization of highly applicable frameworks like G2.4, G3a.4, and G5.2 is strongly recommended, as they supply the optimal balance of practical implementation and physical stabilization that theoretically comparable, yet practically limited, interventions fail to deliver.

### 3.1.5. Pilot area in Montenegro

Tab. 3.1.3: True and predicted values for drained slope in the pilot area in Montenegro.

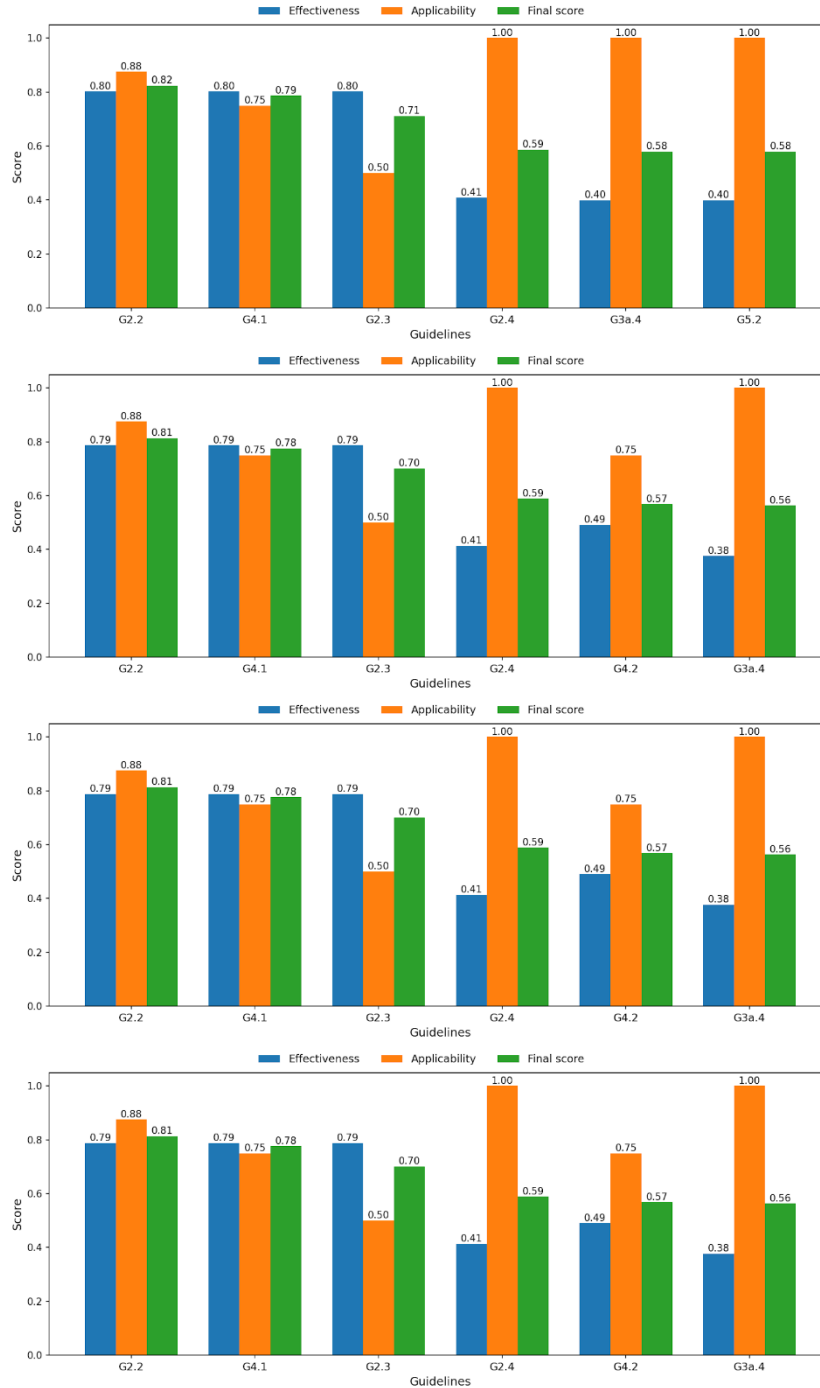
Zone	Parameters	Tr	$FoS\ true$	$z_s\ true$	$z_w^{final}\ true$	$FoS\ pred$	$z_s\ pred$	$z_w^{final}\ pred$
Montenegro	Drained	0	0.97	7.58	4.0	1.183	3.073	1.949
Montenegro	Drained	30	0.97	7.58	4.0	0.927	3.345	1.847
Montenegro	Drained	200	0.97	7.58	4.0	0.922	3.345	1.835
Montenegro	Drained	500	0.97	7.58	4.0	0.922	3.345	1.835

The table above provides a comparative analysis between the true and predicted values of the  $FoS$ ,  $z_s$ , and  $z_w^{final}$  for the Montenegro area under drained conditions, across different return times  $Tr$ . Overall, the table highlights a consistent behavior of both ground-truth and model-predicted quantities, offering useful insights into the robustness and limitations of the proposed predictive framework. The true values of  $z_s$  and  $z_w^{final}$  remain perfectly invariant with respect to the return time, fixed at 7.58 and 4.0, respectively. The true  $FoS$  also exhibits strict invariance, remaining constant at 0.97 across all return times. This indicates that under drained conditions, the adopted geotechnical configuration dictates a baseline state of instability ( $FoS < 1$ ) that is completely insensitive to the transient hydrological forcing associated with varying return periods. The predicted results exhibit an initial adjustment phase followed by strong stabilization. The predicted  $FoS$  decreases sharply from a stable 1.183 at  $Tr = 0$  to an unstable 0.927 at  $Tr = 30$ , eventually settling at 0.922 for  $Tr \geq 200$ . Similarly, the predicted value of  $z_s$  shifts from 3.073 at  $Tr = 0$  to a constant 3.345 for  $Tr \geq 30$ , while the predicted  $z_w^{final}$  shows slight variations before stabilizing at 1.835 at  $Tr \geq 200$ . This behavior indicates that the predictive model rapidly reaches a steady-state condition, correctly capturing the overall insensitivity of the system to long-term changes in  $Tr$  after the initial epoch. A systematic discrepancy between true and predicted values is observed. Most notably, at  $Tr = 0$ , the model overestimates the true  $FoS$  (1.183 predicted versus 0.97 true), erroneously classifying an already unstable slope as stable. However, for  $Tr \geq 30$ , the model corrects this trajectory and slightly underestimates the true  $FoS$  (e.g., 0.922 predicted versus 0.97 true). Furthermore, the model consistently underestimates both  $z_s$  (stabilizing at 3.345 predicted versus 7.58 true) and  $z_w^{final}$  (stabilizing at 1.835 predicted versus 4.0 true). This bias suggests that, although the model is able to reproduce temporal stabilization, it struggles to accurately reconstruct the absolute magnitudes of subsurface-related parameters. Such discrepancies may stem from the limited sensitivity of the input features to depth-related variables, or from the inherent difficulty in inferring subsurface conditions from surface or aggregated descriptors. Despite these biases, the model's performance from a risk assessment perspective presents a critical learning point. The initial overestimation of the  $FoS$  at  $Tr = 0$  represents an unconservative error (false negative for failure), as it fails to identify an existing state of instability. However, for all subsequent return times ( $Tr \geq 30$ ), the predicted  $FoS$  drops below the critical stability threshold ( $FoS = 1$ ), successfully aligning with the ground truth's classification of the slope as unstable. The slight underestimation of the  $FoS$  at higher return times ultimately yields a more conservative

evaluation of slope stability, providing an implicit safety margin that is generally desirable for hazard screening, provided the initial epoch's calibration can be addressed.

### 3.1.6 Guidelines for pilot area in Montenegro

Fig. 3.1.2: Guidelines for unstable drained slope in the pilot area in Montenegro for  $T_r$  equal to 0, 30, 200, and 500.



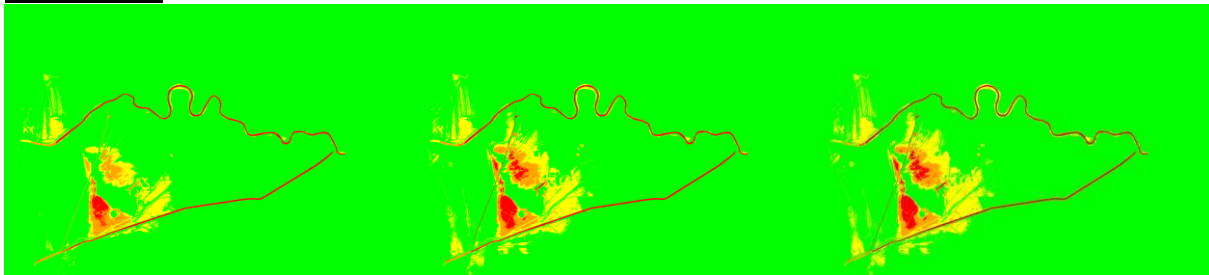
To address the unstable conditions observed under drained configurations across all evaluated return periods ( $Tr = 0, 30, 200, \text{ and } 500$ ), where the true Factor of Safety persistently remains below 1 ( $FoS = 0.97$ ), a quantitative evaluation of potential mitigation guidelines was conducted. As illustrated in the performance distribution charts, guideline G2.2 emerges as the optimal intervention strategy for these unstable slopes, consistently achieving the highest overall final score (0.81–0.82). This superior ranking is predominantly driven by its high effectiveness (0.79–0.80), which provides critical stabilization capability alongside a strong, though not absolute, applicability score (0.88). Following closely is G4.1, which maintains a comparable high effectiveness but suffers a slight reduction in applicability (0.75), yielding a final score of 0.78–0.79. In contrast, alternative measures such as G2.4 and G3a.4 exhibit perfect applicability (1.00) but demonstrate significantly constrained effectiveness (ranging from 0.38 to 0.41), thereby limiting their overall utility (final scores between 0.56 and 0.59). Other guidelines, such as G2.3, show intermediate overall scores (0.70–0.71) primarily due to a concurrent drop in applicability (0.50), while measures like G4.2 exhibit limitations in both dimensions. Consequently, for critical slope conditions characterized by  $FoS < 1$  in the Montenegro area, the systematic prioritization of highly effective and well-balanced frameworks like G2.2 is strongly recommended, as they supply the necessary physical stabilization mechanisms that universally applicable, yet functionally limited, interventions fail to deliver.

## 3.2. FLOOD RISK ASSESSMENT AND MITIGATION MEASURES

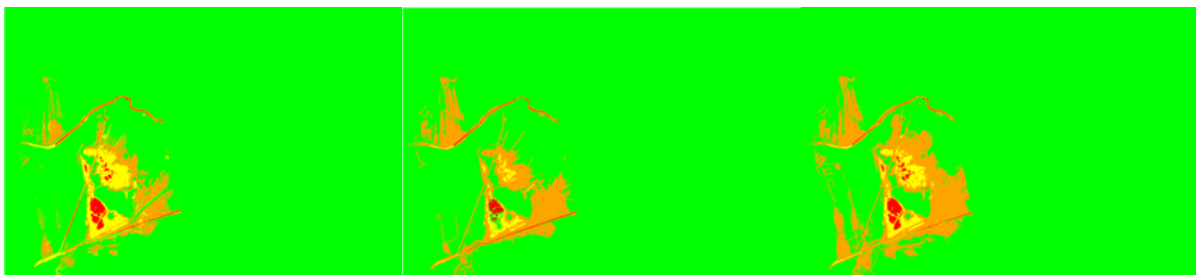
### 3.2.1. Pilot area in Italy

Fig. 3.2.1: Flood extent maps in the pilot area in Italy for  $Tr$  equal to 30, 100, and 200 (first row: true maps, second row: predicted maps).

#### Ground truth



#### Predicted



The figures above illustrate the comparison between ground-truth flood extent maps and the corresponding predictions generated by the proposed web-based application for the Italian pilot area, considering three representative scenarios by varying the return period of the rainfalls. The visual analysis highlights both the strengths and the limitations of the adopted modeling framework in reproducing spatial flood dynamics.

The predicted maps show a good qualitative agreement with the ground truth in terms of the main flooded patterns. In all scenarios, the model correctly identifies the most critical inundated zones, which are consistently located in the same low-lying areas highlighted in the reference maps. This indicates that the proposed approach is able to capture the dominant topographic controls governing flood propagation, which is a crucial requirement for operational flood risk assessment.

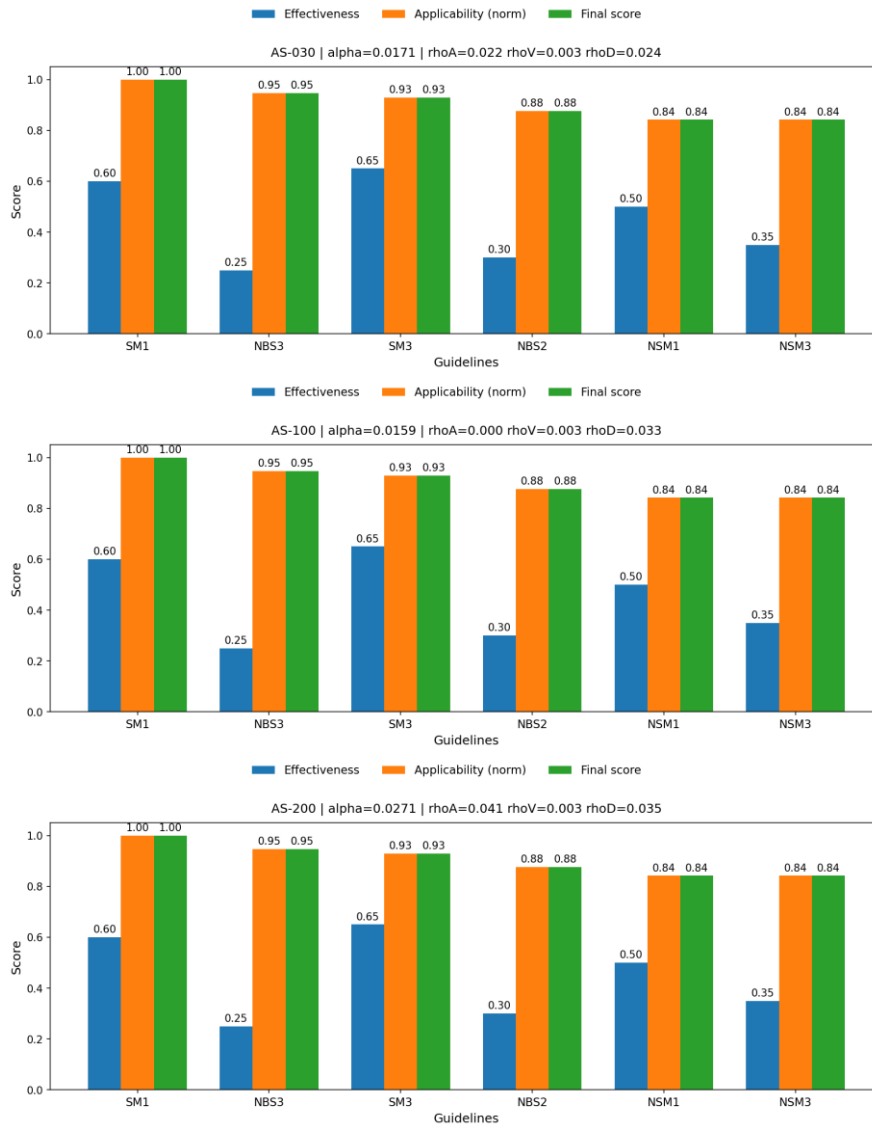
Discrepancies emerge in the extent and intensity of the predicted flooded areas. Compared to the ground truth, the predicted maps tend to exhibit a broader spatial spread of intermediate-risk zones (yellow–orange regions), indicating a systematic overestimation of flood extent. While this behavior increases conservativeness, it may lead to an overprediction of exposed areas, potentially impacting the efficiency of resource allocation for mitigation measures.

Additionally, some localized high-risk clusters visible in the ground-truth maps appear either smoothed or partially displaced in the predicted results. This effect is likely due to spatial averaging introduced by the modeling approach or to limitations in the resolution and representativeness of the input features. Such smoothing reduces the model’s ability to reproduce sharp flood boundaries and small-scale inundation features, which are often controlled by fine-grained topographic or hydraulic elements.

Despite these limitations, the predicted maps consistently avoid false-negative scenarios in which severely flooded areas are classified as safe. This conservative tendency is particularly relevant in the context of flood risk management, where underestimation of hazard can lead to critical failures in preparedness and response. The observed overprediction can therefore be interpreted as a safety-oriented bias, suitable for early warning and large-scale screening applications.

### 3.2.2 Guidelines for pilot area in Italy

Fig. 3.2.2: Guidelines for flood maps in the pilot area in Montenegro for Tr equal to 30, 100, and 200.



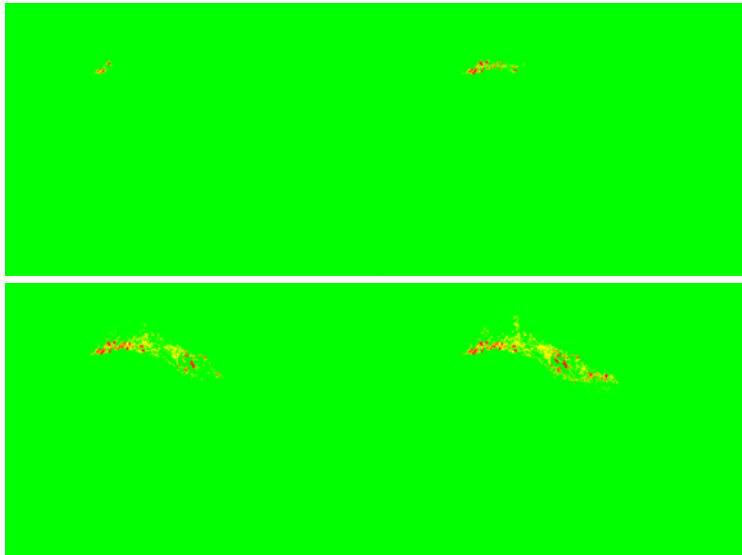
Consistent with the model’s uniform safety-oriented bias, the relative performance of the evaluated countermeasures remains completely invariant across all considered return periods. As illustrated in the performance distribution charts, Structural Measure 1 (**SM1**) consistently emerges as the optimal intervention, achieving a maximum final score of 1.00. Notably, the evaluation framework heavily prioritizes spatial feasibility; the final scores for all measures perfectly mirror their normalized applicability metrics. Consequently, **SM1** ranks highest due to its perfect applicability (1.00) paired with a robust effectiveness of 0.60, making it highly suitable for the broad, intermediate-risk zones predicted by the model. Nature-Based Solution 3 (**NBS3**) follows as the second-highest ranked measure (final score

of 0.95) driven by high applicability, despite exhibiting the lowest overall effectiveness (0.25). Conversely, Structural Measure 3 (**SM3**) provides the highest peak effectiveness (0.65) for localized mitigation but ranks third overall (0.93) due to a slight reduction in applicability. Given the model's tendency to smooth high-risk clusters and overpredict inundation extents, this applicability-driven prioritization provides a pragmatic framework for large-scale resource allocation, favoring widely implementable solutions over highly effective but spatially constrained interventions.

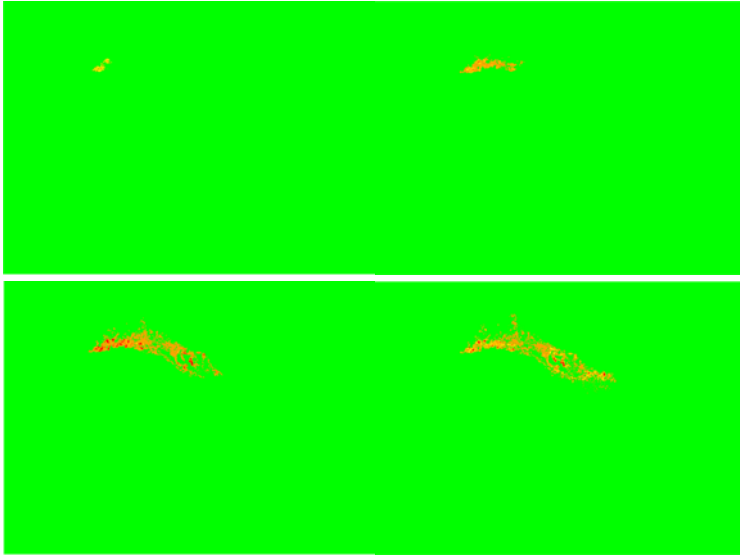
### 3.2.3 Pilot area in Croatia

Fig. 3.2.3: Flood extent maps in the pilot area in Croatia for  $T_r$  equal to 10, 30, 100, and 200 (first row: true maps, second row: predicted maps).

#### Ground truth



## Predicted



The figures above present the comparison between ground-truth flood maps and the corresponding predictions produced by the web-based application for the Croatian pilot area. The analyzed scenarios are characterized by highly localized inundation patterns, which represent a challenging case for flood mapping due to the limited spatial extent of flooded areas relative to the overall domain.

The predicted results show a strong qualitative agreement with the ground truth in terms of spatial localization of flooded zones. In all cases, the model correctly identifies the position and orientation of the inundated clusters, which appear as narrow, elongated features embedded within predominantly non-flooded regions. This indicates that the proposed approach is able to capture subtle topographic or hydraulic controls driving flood concentration, even when the affected areas are small compared to the total map extent.

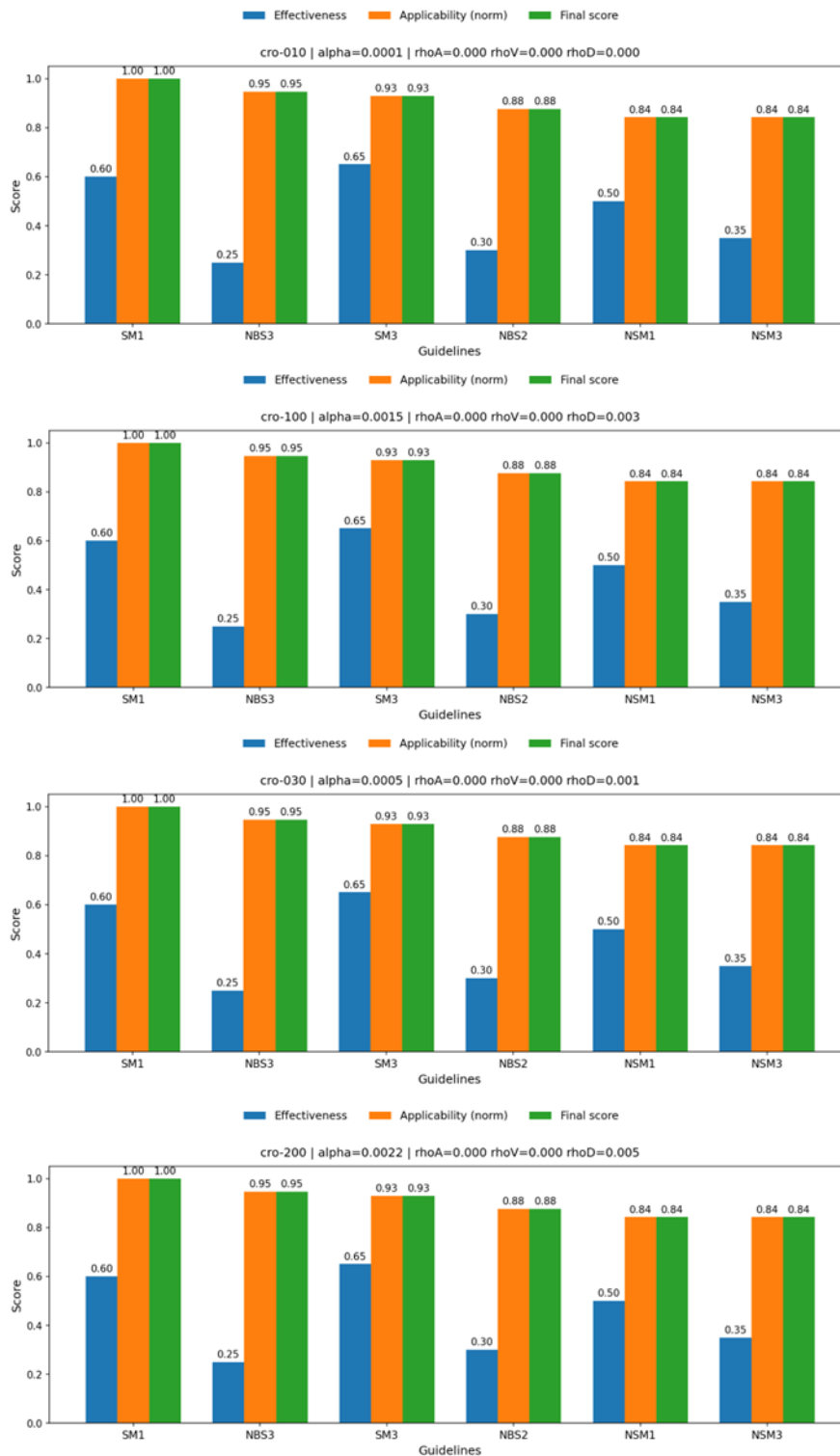
The predicted maps reproduce the general shape and continuity of the flooded regions observed in the ground truth, particularly in the lower panels, where flood extents are more pronounced. The alignment between predicted and observed patterns suggests that the model effectively preserves the underlying flow paths and accumulation zones, which are critical for accurate flood hazard identification in riverine or channel-dominated environments.

Some discrepancies can be observed in the intensity and spatial spread of the predicted flooded areas. In several instances, the predicted maps exhibit a slightly smoother and more diffuse distribution of intermediate-risk zones compared to the ground truth. This behavior points to a tendency toward spatial smoothing, which may reduce the sharpness of flood boundaries and dilute localized peaks of high flood intensity. Such effects are likely related to the resolution of the input data or to aggregation mechanisms inherent in the modeling framework.

Despite these limitations, the predicted results do not introduce significant false-positive flooded areas outside the regions highlighted in the ground truth. This indicates good model specificity and suggests that the approach avoids excessive overestimation of flood extent, which is particularly important in contexts where inundation is sparse and highly localized. At the same time, the absence of major false negatives confirms the model's reliability in detecting critical flooded zones.

### 3.2.4 Guidelines for pilot area in Croatia

Fig. 3.2.4.: Guidelines for flood maps in the pilot area in Croatia for Tr equal to 10, 30, 100, and 200.

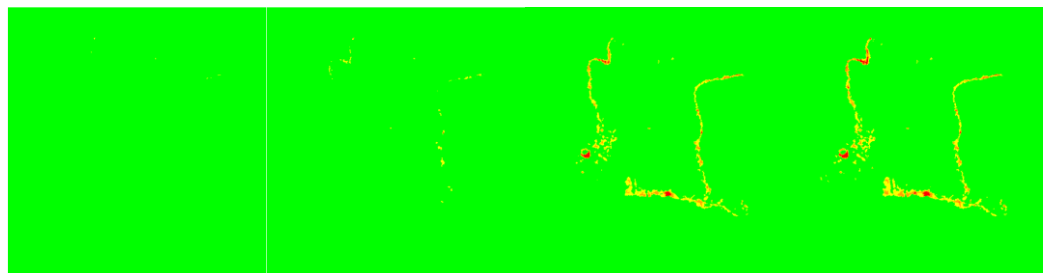


Building on the model’s precise spatial identification of narrow, highly localized inundation patterns in the Croatian pilot area, the evaluation of mitigation guidelines reveals a structural prioritization within the decision framework. As depicted in the performance distribution charts for the simulated return periods (10, 30, 100), the relative rankings and scores of the proposed countermeasures remain strictly invariant across all scenarios, reflecting the model's consistent localization of flooded clusters. Structural Measure 1 (**SM1**) consistently ranks as the optimal intervention, achieving a maximum final score of 1.00. This ranking is entirely driven by the framework's strict alignment of the final score with the normalized applicability metric; **SM1** pairs perfect applicability (1.00) with a robust effectiveness of 0.60. Interestingly, the localized nature of the flooding in this domain—characterized by sparse, elongated features rather than broad inundation—theoretically favors highly targeted interventions. In this regard, Structural Measure 3 (**SM3**) offers the highest peak effectiveness (0.65) among all options but is relegated to the third rank (final score of 0.93) due to a minor reduction in spatial applicability. Conversely, Nature-Based Solution 3 (**NBS3**) secures the second-highest ranking (0.95) almost exclusively through high applicability, despite demonstrating the lowest overall effectiveness (0.25). Consequently, while the predictive model successfully preserves subtle topographic flow paths without introducing significant false positives, the applicability-driven evaluation framework tends to favor broadly implementable solutions (**SM1**, **NBS3**) over highly effective, localized structural measures (**SM3**) that might otherwise be optimally suited for the sparse inundation dynamics of the Croatian site.

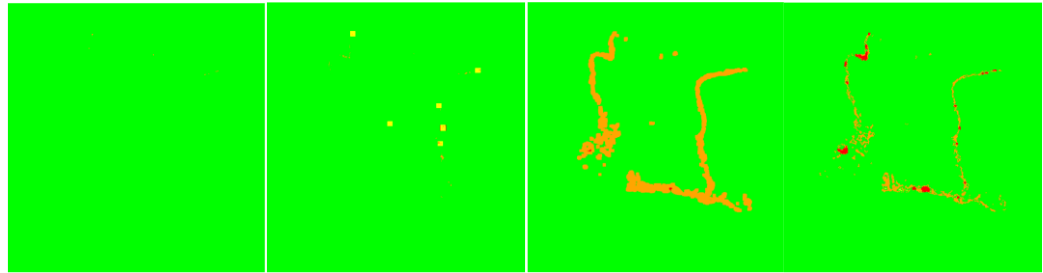
### 3.2.3. Pilot area in Montenegro

Fig. 3.2.5: Flood extent maps in the pilot area in Montenegro for  $T_r$  equal to 10, 30, 100, and 200 (first row: true maps, second row: predicted maps).

#### Ground truth



## Predicted



The figures above present a comparative analysis between ground-truth and predicted flood extent maps across four representative scenarios, illustrating a gradient of increasing spatial complexity and inundation severity. The results provide critical insights into the model's behavior under both highly localized and structurally continuous flood conditions.

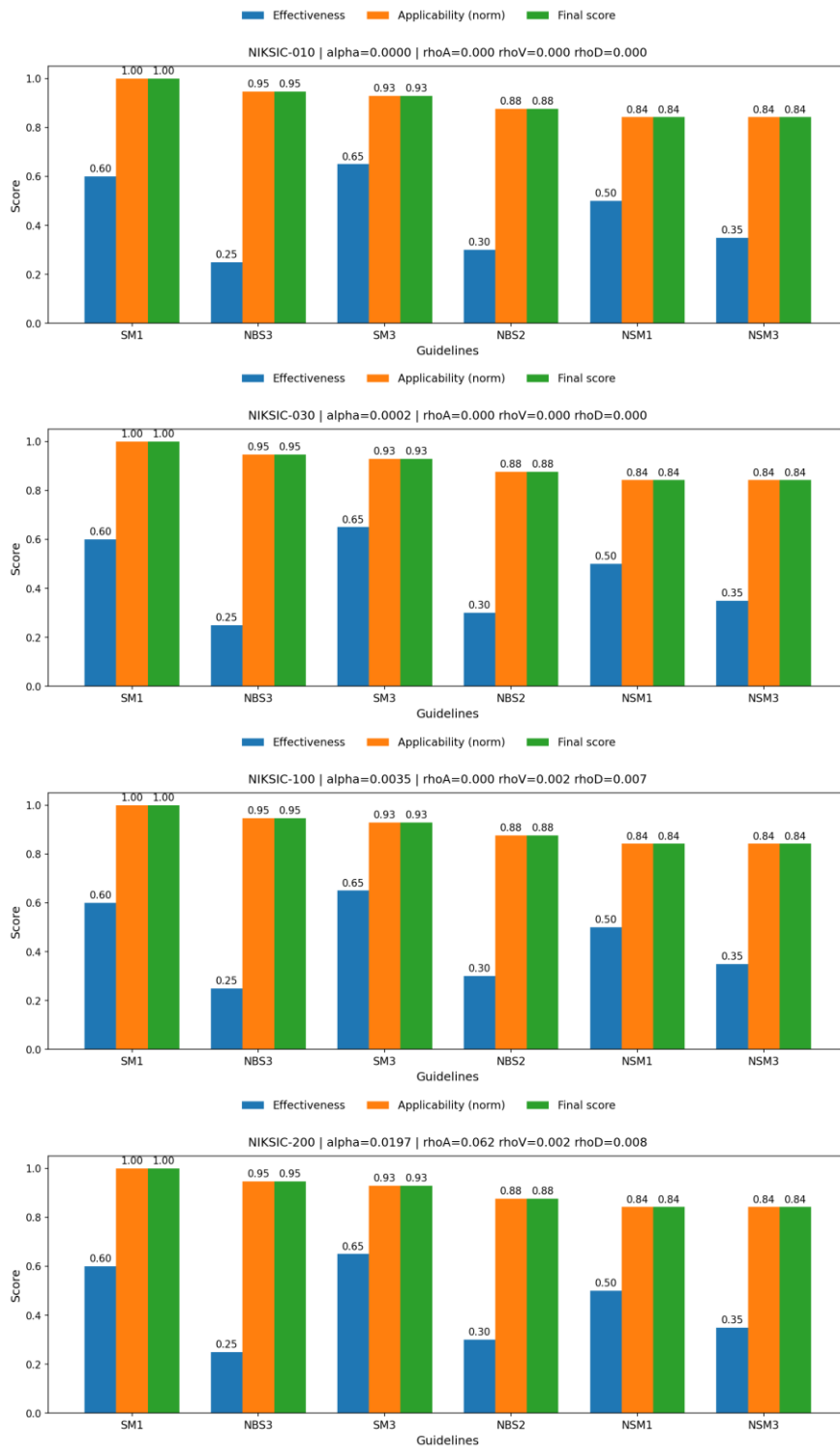
In the first two scenarios (leftmost panels), the ground-truth maps feature extremely sparse, localized flooded pixels with a minimal spatial footprint. While the predictive model successfully recognizes the overall low-hazard nature of these events, subtle structural discrepancies emerge. Specifically, in the second panel, the model approximates the scattered ground-truth signals by generating distinctly blocky, regularized pixel clusters (visible as isolated yellow squares). This behavior indicates a strong spatial regularization effect inherent to the model's architecture; when faced with sub-grid or highly fragmented inundation signals, the model tends to aggregate them into lower-resolution, discrete patches rather than reproducing fine-scale sparsity.

As the inundation severity increases in the third and fourth scenarios (rightmost panels), the flood patterns evolve into clearly defined, continuous flow paths exhibiting a distinct, articulated morphology. The predictive framework successfully reconstructs the global geometry, orientation, and macro-connectivity of these primary flood corridors, demonstrating its capability to capture dominant hydraulic pathways. However, a pronounced tendency toward spatial smoothing is evident. The predicted inundated bands are visibly thicker and more diffuse than the narrowly delineated structures in the ground truth. Furthermore, while the reference maps highlight sharp, localized high-intensity hotspots (indicated by the red clusters), the predicted maps homogenize these regions into broader, intermediate-intensity zones (orange). This suggests that the model prioritizes the overall continuity of the flooded area at the expense of preserving sharp spatial gradients and peak hazard intensities.

Despite the observed regularization artifacts and boundary smoothing, the model demonstrates high reliability in hazard detection. Across all scenarios, no critical false negatives are observed; the primary flooded corridors present in the reference data are consistently detected by the predictive framework. The systematic overprediction of the flood path thickness acts as a conservative, safety-oriented bias. From a risk management perspective, this overestimation ensures that all potentially vulnerable adjacent zones are flagged, which is a desirable feature for large-scale early warning and spatial screening. The proposed predictive framework is effective at identifying macro-scale flood connectivity and preserving the global morphology of hazardous zones, particularly in spatially coherent events.

### 3.2.6 Guidelines for pilot area in Montenegro

Fig. 3.2.6.: Guidelines for flood maps in the pilot area in Montenegro for Tr equal to 10, 30, 100, and 200.



The evaluation of mitigation guidelines reveals a highly stable decision framework that remains insensitive to the progressively increasing spatial complexity of the events. As illustrated in the performance distribution charts for the four scenarios, the relative rankings and scores of the proposed countermeasures are strictly invariant. The framework's output is entirely dominated by the spatial feasibility of the interventions, with the final scores perfectly mirroring the normalized applicability metrics. Consequently, Structural Measure 1 (**SM1**) universally emerges as the optimal mitigation strategy, achieving a maximum final score of 1.00 by pairing perfect applicability (1.00) with a robust effectiveness of 0.60. Nature-Based Solution 3 (**NBS3**) secures the second rank (final score of 0.95) almost exclusively through its high applicability, despite demonstrating the lowest overall effectiveness (0.25) of the evaluated set. In contrast, Structural Measure 3 (**SM3**) offers the highest peak effectiveness (0.65) for localized hazard reduction but is relegated to the third position (0.93) due to its slightly constrained spatial applicability. Given the predictive model's documented tendency to smooth sharp boundaries, enforce spatial regularity, and conservatively overestimate the thickness of flooded zones, this applicability-driven prioritization is highly pragmatic. It inherently favors versatile, widely implementable interventions like **SM1** that can effectively encompass the model's expanded inundation footprints, prioritizing generalized, broad-scale risk coverage over highly targeted—but spatially restricted—structural countermeasures.

### 3.3. RISK AWARENESS

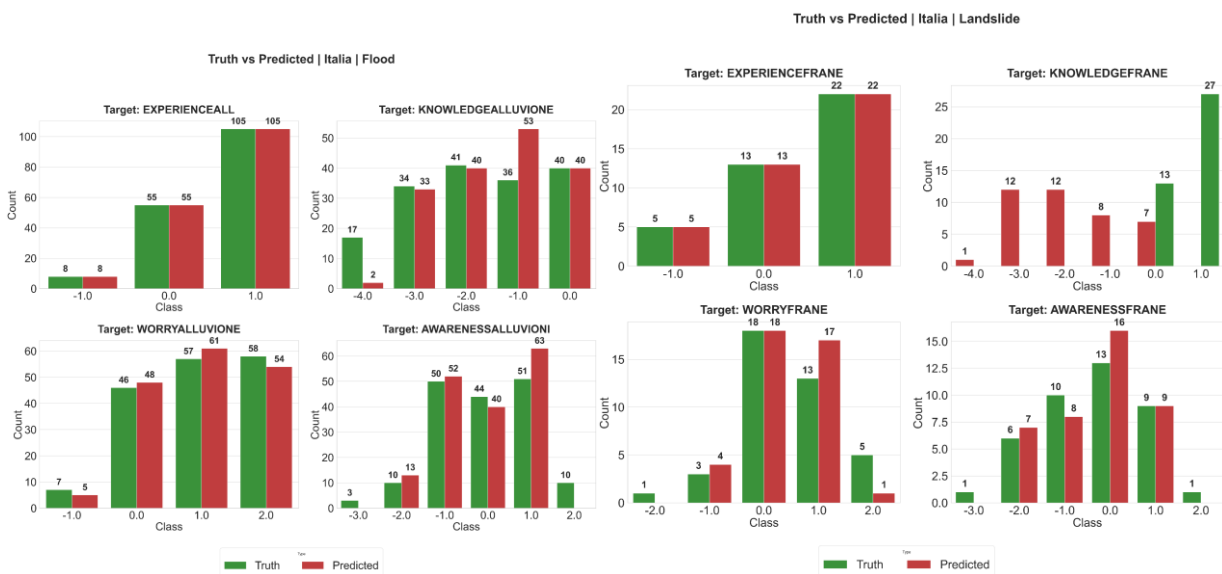
The psychological module of the tool is based on an AI model trained on psychological data collected during the project. During training, the model learned the relations among the main psychological indicators used in the system (experience, knowledge, awareness, and worry). This reduced the amount of information that must be collected when the tool is applied in a new area. For this reason, the competent authorities do not need to repeat a full traditional psychological assessment for every citizen. However, the tool can only operate if at least a reduced set of psychological data has been collected for people living in the selected area of interest and uploaded to the system. If no psychological data are available for that area, the tool does not generate any psychological output.

For each individual record, the system derives the values of experience, knowledge, awareness, and worry. The combination of these values allows the tool to associate the individual to a psychological profile. Profile assignment is similarity-based: each record is associated with the closest learned profile in the feature space defined by these indicators. In the current implementation, similarity is measured through the Euclidean distance in this feature space. Each citizen is thus associated with only one profile. Each profile is linked to a specific set of awareness-raising guidelines. Individuals assigned to the same profile receive the same guidelines, because they show similar values of experience, knowledge, awareness, and worry. Individuals assigned to different profiles receive guidelines adapted to their own profile. This is how the tool moves from individual questionnaires to communal recommendations. The questionnaire is individual, but the recommendations can be used at communal level because the same profiling procedure is applied to a surveyed set of residents in the selected area. Once the surveyed residents have been assigned to profiles, the competent authority can determine how many individuals belong to each profile and calculate the related percentages. This provides an area-level picture of the surveyed population and supports the planning of local awareness actions for the profiles represented in that area. This logic is consistent with Section 2.3, where the pilot areas are already described through percentages of people with different levels of risk perception and psychological vulnerability.

Regarding the relation between people and the selected area of study, no fixed geometric distance is used for the psychological component. The association is dataset-based and area-based. When a slope or basin is selected, the platform does not search for all people within a fixed geometric distance from that element. It retrieves the psychological records linked to the selected area of interest and processes those records based on the learned profiles.

### 3.3.1. Pilot area in Italy

Zone	Hazard	Target	Accuracy	Precision (Weighted)	Recall (Weighted)	F1-Score (Weighted)
Tuscany	Flood	Awareness	0.8988	0.8396	0.8988	0.8646
Tuscany	Flood	Experience	1.0	1.0	1.0	1.0
Tuscany	Flood	Knowledge	0.8988	0.9313	0.8988	0.8731
Tuscany	Flood	Worry	0.9643	0.9663	0.9643	0.9634
Molise	Landslide	Awareness	0.875	0.8426	0.875	0.8521
Molise	Landslide	Experience	1.0	1.0	1.0	1.0
Molise	Landslide	Knowledge	0.6	0.6518	0.6	0.5756
Molise	Landslide	Worry	0.875	0.8798	0.875	0.8376



The Table above summarizes the predictive performance of the model in the two Italian pilot areas: Tuscany for floods and Molise for landslides. It reports the main evaluation metrics (Accuracy, Precision, Recall, and F1-Score) for each psychological and cognitive target related to risk awareness. The results show a stable and coherent behavior of the AI tool in both contexts, confirming the general robustness

of the proposed framework while also revealing some specific limitations.

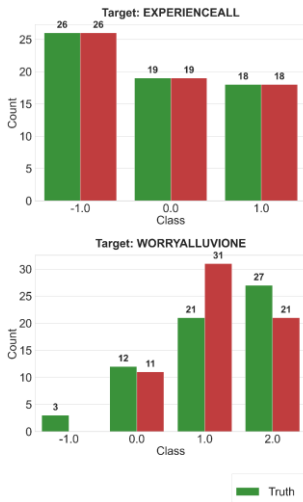
Looking at the individual targets, “Experience” (for both flood and landslide scenarios) is predicted perfectly, with all metrics equal to 1.0. This is likely due to the limited number of input attributes required for this variable, which makes it easier for the model to reconstruct. The targets “Worry” and “Awareness” also show strong performance. In the Tuscany flood case, the F1-Score reaches 0.9634 for Worry and 0.8646 for Awareness, while in the Molise landslide case it is 0.8376 and 0.8521, respectively. These values indicate that the model effectively captures emotional reactions and general levels of awareness, reproducing these subjective dimensions with good reliability.

In contrast, “Knowledge” appears more difficult to predict, especially in the Molise landslide scenario, where the F1-Score decreases to 0.5756 and accuracy to 0.6. This gap suggests that the model has more difficulty estimating the actual level of technical knowledge about landslide response measures. While it can identify general trends in perception and past experience, it struggles to precisely reconstruct more specific and technical aspects. The plots above support these findings: when performance is high, as in the case of “Experience,” prediction errors are concentrated at zero, showing perfect agreement between predicted and real values. For more complex variables such as “Knowledge,” the error distribution is more spread out, clearly showing cases of overestimation and underestimation. Together, the table and the plots provide a transparent view of both the strengths and the critical points of the model.

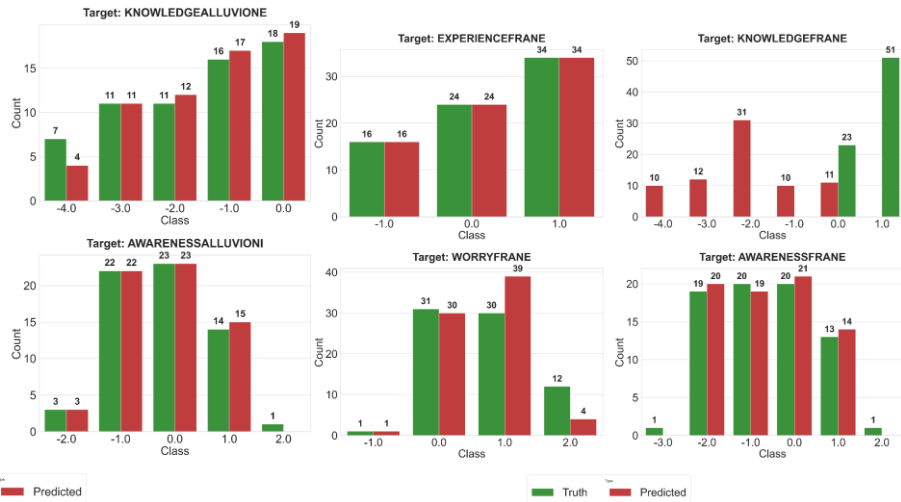
### 3.3.2 Pilot area in Croatia

Zone	Hazard	Target	Accuracy	Precision (Weighted)	Recall (Weighted)	F1-Score (Weighted)
Croatia	Flood	Awareness	0.9841	0.9693	0.9841	0.9765
Croatia	Flood	Experience	1.0	1.0	1.0	1.0
Croatia	Flood	Knowledge	0.9206	0.9256	0.9206	0.9159
Croatia	Flood	Worry	0.7937	0.7929	0.7937	0.7767
Croatia	Landslide	Awareness	0.9595	0.9347	0.9595	0.9464
Croatia	Landslide	Experience	1.0	1.0	1.0	1.0
Croatia	Landslide	Knowledge	0.4595	0.5909	0.4595	0.4736
Croatia	Landslide	Worry	0.8784	0.9064	0.8784	0.8592

Truth vs Predicted | Croazia | Flood



Truth vs Predicted | Croazia | Landslide



The table presents the predictive results for the Croatian study area, focusing on psychological indicators related to both flood and landslide risk. Compared to the Italian cases, the Croatian results show more variability between targets and hazard types, helping to clarify where the model performs reliably and where it faces greater challenges within this specific social and environmental setting.

As observed in Italy, the target “Experience” is classified perfectly for both hazards, with Accuracy and F1-Score equal to 1.0. The model also performs very well in predicting “Awareness,” achieving an F1-Score of 0.9765 for floods and 0.9464 for landslides. These values suggest that the model successfully captures the socio-demographic patterns that shape general risk perception in the Croatian population. Performance is more differentiated for “Worry”: the F1-Score is 0.7767 for floods and increases to 0.8592 for landslides, indicating that emotional responses are not equally predictable across hazard types. The most critical issue emerges for “Knowledge” in the landslide scenario, where Accuracy drops to 0.4595 and the F1-Score to 0.4736. In contrast, flood-related knowledge is reconstructed with high reliability (Accuracy of 0.9206). This clear imbalance confirms the difficulty of estimating detailed cognitive preparedness for landslides based on the available input variables.

The accompanying plots visually reinforce these findings by showing the distribution of prediction errors for each psychological target. For variables such as “Experience” and “Awareness,” the differences between predicted and observed values are concentrated around zero, confirming strong agreement. On the other hand, the graph for landslide-related “Knowledge” displays a much wider spread, highlighting frequent overestimations and underestimations. This dispersion clearly illustrates the model’s uncertainty in capturing specific knowledge levels, complementing the numerical metrics and providing a transparent picture of its predictive boundaries in the Croatian case.

### 3.3.3. Pilot area in Montenegro

Zone	Hazard	Target	Accuracy	Precision (Weighted)	Recall (Weighted)	F1-Score (Weighted)
Montenegro	Flood	Awareness	0.9184	0.9117	0.9184	0.9082
Montenegro	Flood	Experience	1.0	1.0	1.0	1.0
Montenegro	Flood	Knowledge	0.8571	0.8977	0.8571	0.8337
Montenegro	Flood	Worry	0.898	0.9143	0.898	0.8962
Montenegro	Landslide	Awareness	0.9091	0.899	0.9091	0.899
Montenegro	Landslide	Experience	1.0	1.0	1.0	1.0
Montenegro	Landslide	Knowledge	0.9394	0.947	0.9394	0.9377
Montenegro	Landslide	Worry	0.8788	0.9134	0.8788	0.8612

Truth vs Predicted | Montenegro | Flood

Truth vs Predicted | Montenegro | Landslide



The table summarizes the performance of the predictive model for psychological risk and awareness indicators in Montenegro. Unlike the variability observed in Italy and Croatia, the results here show a stable and well-balanced pattern across all targets. Overall, the metrics confirm that the AI tool performs with consistently high reliability in this study area.

As in the other pilot sites, “Experience” is classified perfectly for both hazards, confirming the model’s robustness in identifying past exposure. However, Montenegro stands out for the accuracy achieved in predicting “Knowledge.” The F1-Score reaches 0.8337 for floods and 0.9377 for landslides, indicating that technical preparedness is well captured by the available input features. This suggests a strong and clear relationship between socio-demographic variables and knowledge levels in this context. In addition, both

“Awareness” and “Worry” maintain high and stable F1-Scores, ranging between 0.8612 and 0.9082 for floods and landslides. These results show that the model can reliably identify emotional and cognitive responses without the specific weaknesses previously observed in other regions.

The plots further confirm this balanced performance. Prediction errors are tightly concentrated around zero for all targets, including “Knowledge,” which has shown greater dispersion elsewhere. The absence of wide error spreads indicates very limited overestimation or underestimation. Taken together, the numerical metrics and the graphical analysis demonstrate a strong alignment between predicted and observed values, highlighting the robustness of the model in assessing psychological vulnerability and risk perception in the Montenegrin case.

### 3.3.4 Guidelines

#### Experience

Predicted Class	Strategic Aim	Recommended Key Actions
No/Low Direct Experience(e.g., Class -1)	Build historical memory to counter the illusion of invulnerability	<ul style="list-style-type: none"> <li>• Reconstruct local territorial history of past events via sensitization campaigns .</li> <li>• Distribute materials showing past impacts and recurrence patterns to act as a "proxy" for direct experience</li> </ul>
Moderate-to-High Experience (e.g., Class 0, 1)	Transform past trauma and memory into actionable competence	<ul style="list-style-type: none"> <li>• Promote structured reflection on past responses .</li> <li>• Analyze the effectiveness of past behaviors to identify gaps and refine future mitigation strategies</li> </ul>

Based on the results reported for the three pilot areas the target *Experience* is predicted perfectly in all contexts. For individuals classified as No/Low Direct Experience, the strategic aim is to compensate for the absence of personal exposure by strengthening collective memory. Since the model reliably identifies this group across all pilot areas, decision-makers can confidently implement awareness campaigns focused on reconstructing the local history of past floods or landslides. Actions such as public storytelling, visual materials showing previous impacts, and communication about recurrence patterns can effectively reduce the “illusion of invulnerability.” The robustness of the predictions ensures that these sensitization measures are directed precisely toward the population segments that need them most.

For those classified as Moderate-to-High Experience, the objective shifts from awareness-building to capacity enhancement. Institutions can design targeted initiatives that transform memory into practical competence. Structured reflection activities, such as community debriefings on past emergencies, can help evaluate which behaviors were effective and which revealed weaknesses. This process supports the refinement of mitigation and preparedness strategies, turning past events into learning opportunities rather than unresolved trauma.

In all three national contexts, the perfect classification of *Experience* strengthens the operational value

of these guidelines. The reliability of the predictive tool ensures that interventions aimed at either building historical memory or consolidating experiential knowledge can be implemented with high confidence, making *Experience* a solid foundation for tailored risk communication and preparedness planning.

### Knowledge

Predicted Class	Strategic Aim	Recommended Key Actions
Low Knowledge (e.g., Class -4, -3, -2)	Build a foundational understanding of risks, systems, and behaviors	<ul style="list-style-type: none"> <li>• Distribute official materials on warning systems, municipal emergency plans, and specific protective behaviors</li> <li>• Promote workplace/school sensitization campaigns to enhance self-efficacy</li> </ul>
Correct/High Knowledge (e.g., Class -1, 0)	Maintain readiness and prevent skills decay over time	<ul style="list-style-type: none"> <li>• Organize periodic refresher courses and updates on territorial vulnerability</li> <li>• Encourage continuous monitoring of local warnings through official channels</li> </ul>

Considering the results observed in Tuscany, Molise, Croatia, and Montenegro, the target *Knowledge* shows a more heterogeneous pattern compared to *Experience*. While the model performs very well in several contexts (e.g., floods in Italy and Croatia, and both hazards in Montenegro), it reveals clear weaknesses in predicting landslide-related knowledge in Molise and especially in Croatia. These differences are crucial when interpreting and applying the related guidelines.

For individuals classified as Low Knowledge, the strategic goal is to build a solid and practical understanding of risks and response behaviors. In areas where predictive performance is high, such as Montenegro and flood scenarios in Italy and Croatia, the model can reliably identify population groups lacking essential information. In these cases, authorities can confidently distribute official materials on warning systems, municipal emergency plans, and specific protective actions. School and workplace awareness campaigns become particularly valuable to strengthen self-efficacy and clarify what to do before and during an event. However, in contexts where model accuracy is lower (notably landslides in Molise and Croatia), these interventions should be accompanied by additional local validation, since misclassification may occur.

For those categorized as Correct/High Knowledge, the objective shifts toward maintaining preparedness and preventing the gradual loss of skills. In pilot areas with strong predictive reliability, periodic refresher activities and updates on territorial vulnerability can be effectively targeted. Encouraging continuous monitoring of official warning channels further supports long-term readiness. In contrast, where the model shows uncertainty, policy makers should interpret

high-knowledge classifications with caution, ensuring that overestimations do not lead to neglected training needs.

Overall, the variability in predictive performance across hazards and regions directly affects the operational confidence of these guidelines. Where the model is robust, it can serve as a precise decision-support tool for tailoring educational and preparedness measures. Where performance is weaker, especially for landslide knowledge, complementary assessment strategies are advisable to ensure that interventions accurately address real cognitive gaps.

### Awareness

Predicted Class	Strategic Aim	Recommended Key Actions
Low Awareness (e.g., Class -2, -1)	Align personal perception with objective local risk.	<ul style="list-style-type: none"> <li>• Provide mapping of risk areas versus safe areas</li> <li>• Clarify specific exposure levels for the user's residence or neighborhood</li> <li>• Highlight the objective causes and potential impacts of local hazards</li> </ul>
Correct/High Awareness (e.g., Class 0, 1)	Reinforce vigilance and proactive preparedness	<ul style="list-style-type: none"> <li>• Encourage continuous monitoring of official channels</li> <li>• Reinforce the understanding of hazard causes and impacts</li> </ul>

The target *Awareness* shows generally strong performance, with F1-Scores ranging from good to very high across all hazards. This reliability allows for a confident application of the associated guidelines, although some minor variations between flood and landslide contexts should be considered.

For individuals classified as Low Awareness, the strategic aim is to align personal perception with the actual local risk. In Tuscany, Molise, Croatia, and Montenegro, the model consistently identifies those with limited awareness, enabling targeted interventions. Recommended actions include providing detailed maps of risk versus safe areas, clarifying exposure levels specific to the person's residence or neighborhood, and explaining the causes and potential impacts of local hazards. Since the model's predictions for low-awareness groups are generally reliable, these campaigns can be directed efficiently toward the populations most in need of risk communication.

For those classified as Correct/High Awareness, the goal is to maintain vigilance and promote proactive preparedness. Across all three pilot areas, the model effectively recognizes individuals with adequate awareness, allowing authorities to reinforce their preparedness behaviors. Key actions include encouraging regular monitoring of official channels for alerts and strengthening understanding of hazard causes and potential consequences. The consistent performance for this target ensures that both reinforcement and corrective measures can be applied precisely, supporting long-term risk awareness and fostering a culture of continuous preparedness in each context.

The high predictive accuracy for *Awareness* across the pilot areas provides strong operational confidence. It allows tailored interventions to both improve awareness where it is low and sustain vigilance where it is already high, maximizing the impact of risk communication strategies.

## Worry

Predicted Class	Strategic Aim	Recommended Key Actions
Low Worry(e.g., Class 0, -1)	Contrast underestimation and passivity.	<ul style="list-style-type: none"> <li>• Highlight potential dangers and consequences to trigger proactive behaviors</li> <li>• Involve direct testimonies of past events to stimulate identification and attention to early warning signs</li> </ul>
High Worry(e.g., Class 1, 2)	Prevent panic and dysfunctional emotional reactions	<ul style="list-style-type: none"> <li>• Provide clear, reassuring, and highly operational instructions to channel anxiety into effective decision-making</li> <li>• Offer mental health support and coping guidance</li> <li>• Avoid ambiguous information that fosters unfounded alarmism</li> </ul>

The target *Worry* shows variable but generally strong performance. F1-Scores are slightly lower for floods in Croatia and landslides in Molise compared to other targets, indicating that the model captures emotional responses reasonably well but with some uncertainty in specific hazard-context combinations. This variability is important when applying the related strategic guidelines.

For individuals classified as Low Worry, the goal is to counter underestimation of risk and prevent passive behavior. In pilot areas where the model reliably identifies these groups, interventions can focus on highlighting potential dangers and consequences to stimulate proactive preparedness. Using direct testimonies from past events and emphasizing early warning signs can help increase attention and engagement. In contexts with slightly lower predictive reliability, such as Croatian floods, additional local validation may be needed to ensure that low-worry individuals are correctly targeted.

For those classified as High Worry, the aim shifts to preventing panic or dysfunctional emotional responses. The model's predictions allow targeted communication strategies that provide clear, actionable instructions to channel anxiety toward effective decision-making. Support measures, including mental health guidance and reassurance, can be directed to these groups while avoiding ambiguous information that could trigger unnecessary alarm. The relatively strong accuracy across the pilot areas, particularly in Montenegro, ensures that high-worry populations are effectively identified and managed.

Overall, the predictive results for *Worry* support a nuanced application of the guidelines. Where model reliability is high, interventions can be confidently targeted to either increase cautious attention or

moderate excessive concern. In areas with moderate uncertainty, combining AI predictions with local validation can ensure interventions are appropriately calibrated, maximizing the effectiveness of emotional and behavioral risk management strategies.

## 4. CONCLUSIONS

The SAFE-LAND approach integrates key components—physically-based hydrogeological analyses, psychological assessment of risk awareness, and the derivation of mitigation and awareness-enhancement guidelines—into a unified and coherent framework. These components allowed the development of a structured knowledge base, built on reference elements (slopes, rivers, and people), climate events, and associated damage parameters.

The integration of these components enables the tool to move beyond isolated risk assessment, considering both the physical processes driving landslides and floods and the human dimension related to risk perception. The tool provides concrete support to expert judgement by providing data-driven predictions of hazard, consequences, risk levels, and awareness conditions, together with targeted indications for risk mitigation measures and awareness-raising strategies.

The system does not replace expert evaluation but strengthens it, facilitating more consistent, informed, and timely decision-making, and operates as a screening instrument, allowing users to rapidly identify areas and elements potentially exposed to significant hydrogeological risk. In a practical application scenario, the user is required to input into the tool the technical parameters characterizing real slopes, rivers, and expected climate events. Based on these inputs, the system provides a rapid prediction of landslide and flood risk levels, together with the identification of the most appropriate and effective mitigation measures. At the same time, by entering socio-demographic data related to the exposed population, the tool evaluates the level of risk awareness and provides strategies to enhance it. In this way, the SAFE-LAND system supports a comprehensive assessment that combines physical risk analysis with the human dimension, enabling more informed and context-specific risk management actions.

The approach is directly applicable in real areas, supporting Civil Protection authorities and public bodies in prioritizing interventions. Furthermore, the structured and extensible nature of the knowledge base, together with the adoption of trustworthy AI, ensures that the results are scalable and transferable to other geographical contexts.



**Deliverable 6.1**  
**Annex 1 –Web Application User Manual**

***MITIGATING THE RISK OF FLOODING AND LANDSLIDES VIA ARTIFICIAL  
INTELLIGENCE WITH A VIEW TO EXTREME CLIMATE EVENTS***



Co-funded by the  
European Union

## User Manual

This annex provides a comprehensive user guide describing the structure, functionalities, and operational workflow of the web application developed within the project. The document explains how users can access the system, upload data, simulate hazard scenarios, and interpret the analytical outputs generated by the platform. Particular attention is given to both technical outputs and decision-support elements, ensuring that the tool can be effectively used by domain experts.

### 1 Access control

As shown in Figure 1, the login screen provides secure access to the web application. The IP address and the link for accessing the web application will be published in the final report and on the SAFE-LAND project website under the UCPK Network page. Users authenticate through a standard credential-based procedure using a **username** and **password**. This authentication mechanism ensures that only authorized users can access sensitive data and simulation functionalities. Access control is designed to protect both environmental and psychological data stored within the system.

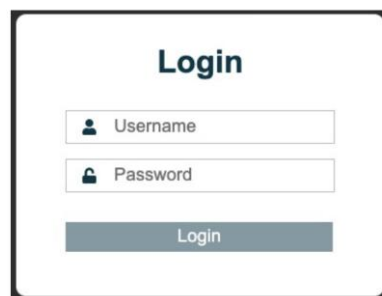


Figure 1: Login interface

### 2 Homepage

After successful authentication, users are redirected to the homepage. The homepage serves as the main landing area of the application and provides an overview of the system's capabilities. From here, users can navigate to all available sections through the main menu located in the header. The homepage is intentionally designed to provide immediate orientation, reducing the cognitive load for users and ensuring that expert operators can quickly access simulation and data management tools.

### 3 Main menu

The Main Menu is a central component of the user interface and is located in the header section,

at the top-right corner of the screen (see Figure 2). It enables intuitive navigation between the primary modules of the platform.

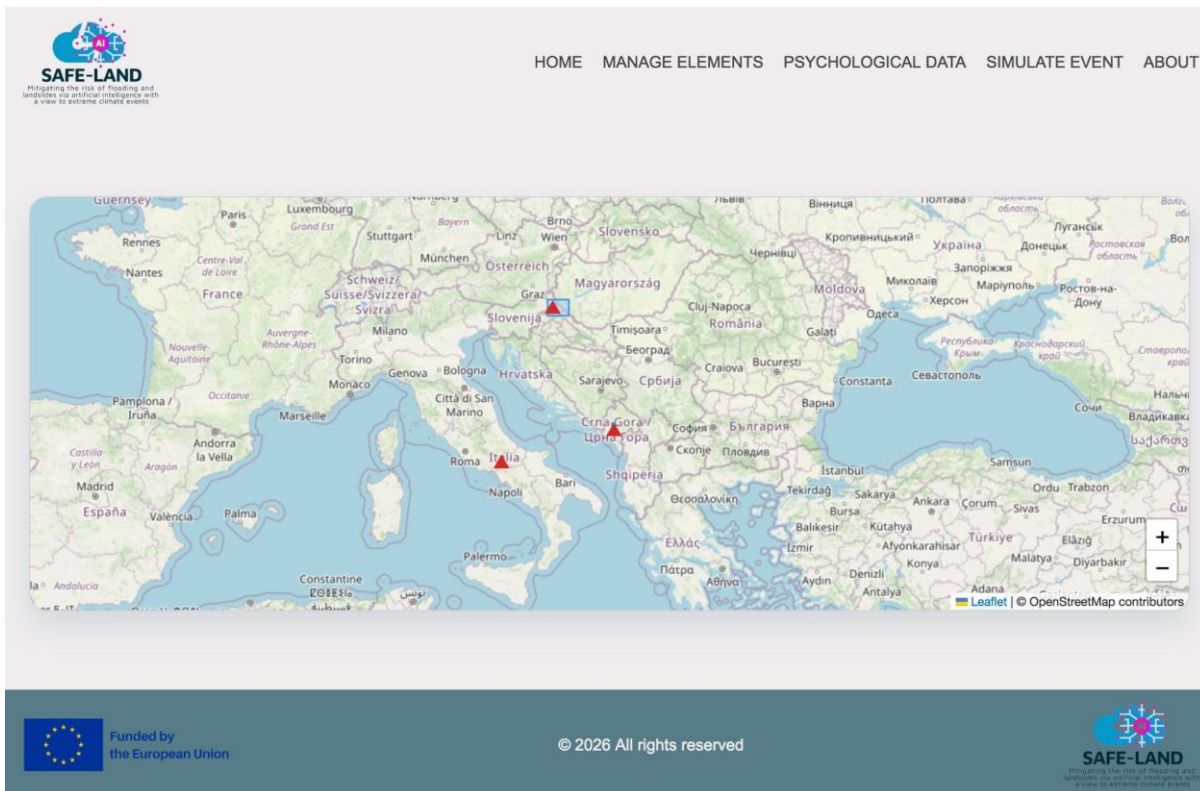


Figure 2: Homepage and main menu (top-right).

In particular, the sections of the main menu are as follows:

- **Home** – Redirects users to the main landing page.
- **Manage Elements** – Opens the section for uploading and managing environmental data.
- **Psychological Data** – Allows access to psychological data related to populations in the areas of interest.
- **Simulate Event** – Provides tools for simulating rainfall events and analyzing their effects.
- **About** – Displays information about the web app and its objectives.

## 4 Manage Elements

The *Manage Elements* section allows users to add new elements (slopes or basins) to the database. The interface for uploading a CSV file is in [Figure 3](#).

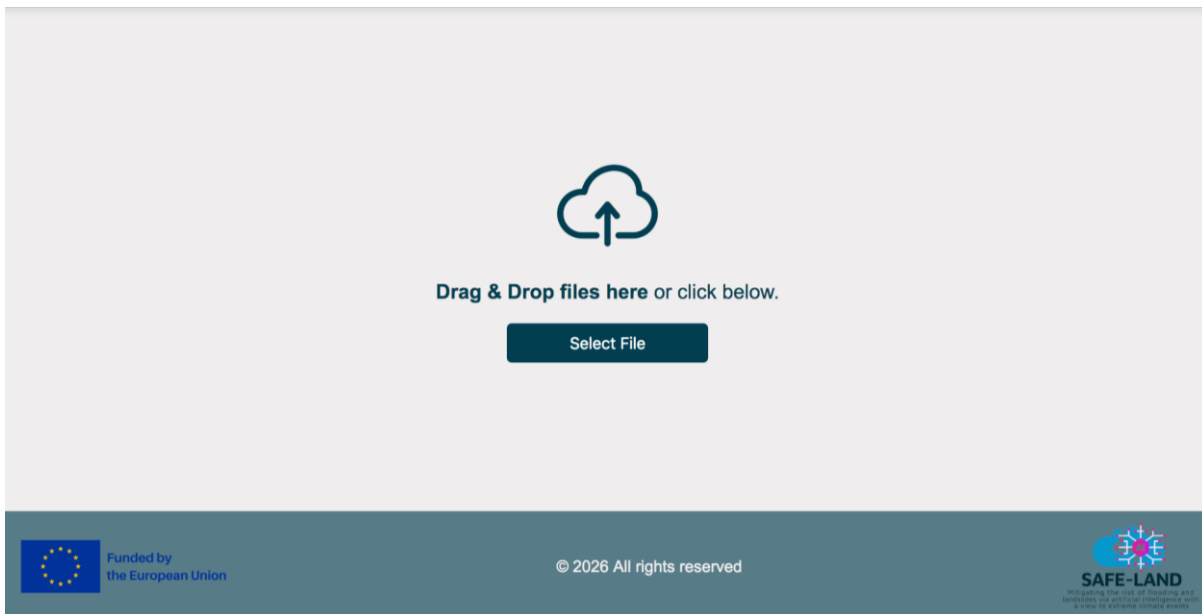


Figure 3: Interface for adding new elements.

Elements are added through a drag-and-drop procedure using a CSV file. Each CSV file may contain one or more elements of a given type (e.g., slopes, basins, or people). This format ensures interoperability with external data sources and facilitates integration with existing geospatial datasets.

Each element type contains a structured set of features describing its physical and geographical characteristics. These features are used by the system to perform analyses. The CSV-based architecture also allows scalability, enabling experts to update datasets without requiring direct intervention in the database structure.

The fields of the CSV files are follows:

## Slope

The input parameters for the slope element are listed in Table 1, and illustrated in Figures 4 and 5.

Table 1. Slope element parameters

	<b>Input parameters</b>	<b>Symbol</b>	<b>Unit</b>
<b>Geometry</b>	Slope angle	$\alpha$	(degrees)
	Slope length	L	[m]
	Slope height	H	[m]
	Total height - upstream	h <sub>u</sub>	[m]
	Total height - downstream	h <sub>d</sub>	[m]
	Soil depth - upstream	h <sub>Su</sub>	[m]
	Soil depth - downstream	h <sub>Sd</sub>	[m]
	Bedrock depth - downstream	h <sub>Bd</sub>	[m]
	Bedrock depth - upstream	h <sub>Bu</sub>	[m]
	Initial piezometric surface depth - upstream	z <sub>wu</sub>	[m]
	Initial piezometric surface depth - downstream	z <sub>wd</sub>	[m]
	Total length	B	[m]
<b>Physical and mechanical soil properties</b>	Soil unit weight	$\gamma$	[kN/m <sup>3</sup> ]
	Water unit weight	$\gamma_w$	[kN/m <sup>3</sup> ]
	Effective cohesion	c'	[kPa]
	Effective friction angle	$\phi'$	[°]
	Undrained strength	c <sub>u</sub>	[kPa]
<b>Hydraulic soil properties</b>	Saturated permeability	k <sub>s</sub>	[m/s]
<b>Rainfall event</b>	Return period	T <sub>r</sub>	[years]
	Accumulated precipitation	rh	[mm]
	Precipitation duration	d	[hrs]
<b>Consequences assessment</b>	Horizontal distance of the property from the crest of the inclined slope section	x	[m]

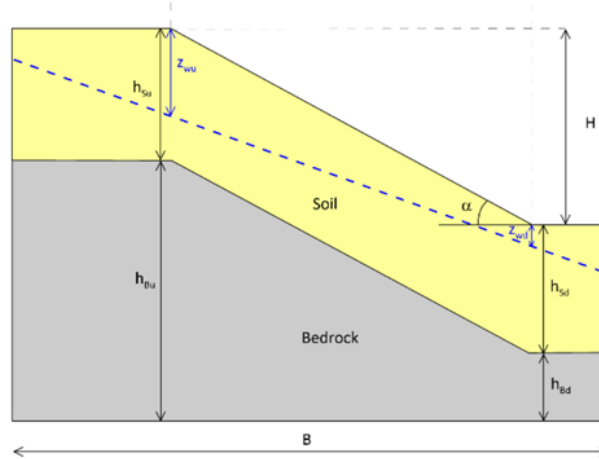


Figure 4. Representation of slope geometry parameters.

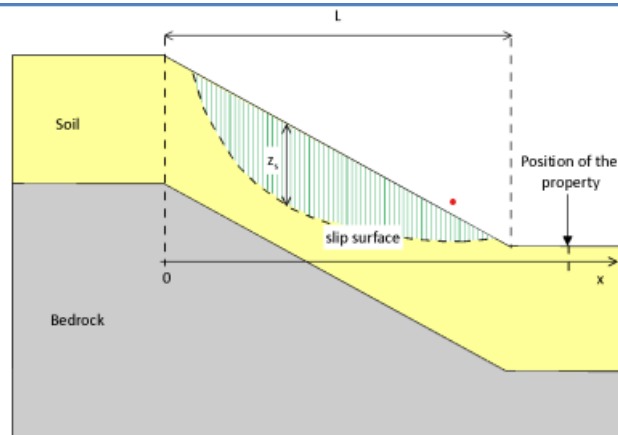


Figure 5. Schematic representation of the position of the properties.

### Basin (river)

The main parameters for the element river are summarized in Table 2, together with the adopted symbols and corresponding units.

Specifically, the main parameters include the basin characteristics, the river parameters, and the main characteristics of the simulated rain event.

Figures 6 and 7 present two example maps showing the floodplain slope and the location of a breakpoint.

Table 2. Main parameters for the element river.

	Parameter	Symbol	Unit
<b>Basin</b>	Inclination of the flood plain	$I$	[-]
	Length of the flow path	$L$	km
	Mean elevation of the drainage basin, referred to the elevation of the final (closing) section of the considered river	$H_m$	m
	Drainage area	$A$	km <sup>2</sup>
<b>River</b>	River slope	$I_R$	[-]
	Peak discharge	$Q_{max}$	m <sup>3</sup> /s
	Flooded volume	$V$	m <sup>3</sup>
	Breakpoint	NA	Location on the DTM map
<b>Rain</b>	Return period	$T_r$	Years
	Rainfall intensity	$i$	mm/hour
	Concentration time	$T_c$	hours

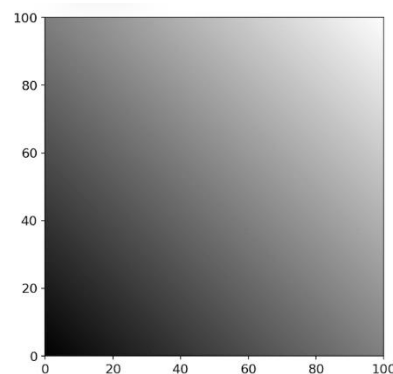


Figure 6. Example of a floodplain inclination (derived from the tabular value of river slope and floodplain slope). The axes indicate the cell number of the discretized floodplain domain, while

the color gradation corresponds to different slope values.

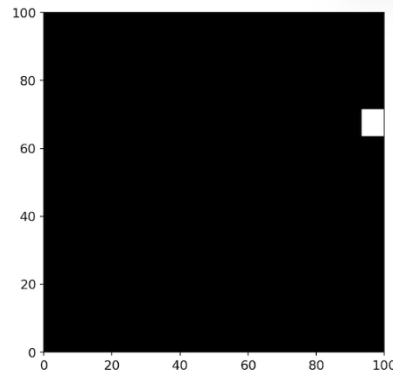


Figure 7. Example of break point location (white rectangle) shown on the floodplain (derived from the tabular value of break point). The axes indicate the cell number of the discretized floodplain domain.

The field names in the CSV file and their unit of measurements must correspond to those indicated in this annex.

### **Psychological data**

The *Psychological Data* section allows users to upload and manage information related to individuals or communities living within the areas of interest. The uploaded dataset defines the individuals analyzed by the system. Each record is assigned a psychological profile used to derive the corresponding awareness guidelines.

The upload interface is identical to that shown in Figure 3 and supports CSV files containing structured psychological indicators.

Table 3. Psychological Data

Feature Code	Description	Scale of Value
@26aCONAPEVOLE ZZARISCHIOCASAall uvione	Awareness of flood risk specifically regarding the respondent's own residence	Is your residence located in the flood risk area?  0= No  1= I don't know  2= Yes

<p>@27aCONSAPEVOL EZZARISCHIOCITTAa lluvione</p>	<p>Perception of which areas of the city are most exposed to flood risk</p>	<p>Do you think there are parts of your town/city more exposed to flood risk than others?</p> <p>0 = I don't know</p> <p>1 = There is no risk in the city</p> <p>2 = Yes, there are parts of the city that are more at risk</p> <p>3 = The city has the same risk everywhere</p>
<p>@28aCONSAPEVOL EZZACAUSEalluvioni</p>	<p>Understanding/knowledge of the underlying causes of floods</p>	<p>Are you informed about the possible causes of floods?</p> <p>0 = Not informed</p> <p>1 = A little informed (1-2 causes)</p> <p>2 = Somewhat informed (3-8 causes)</p> <p>3 = Very well informed (9-12 causes)</p>
<p>@21aESPERIENZAal luzioni</p>	<p>Type of past experience with floods (Direct, Indirect, or None)</p>	<p>Which of the following sentences best indicates your experience with floods?</p> <p>0= No experience</p> <p>1= Indirect experience (e.g. read/seen information in the news or other media, direct experience of a friend/relative</p> <p>2= Direct personal experience</p>
<p>@110BDISASTRINA TURALI</p>	<p>Past experience with other natural disasters beyond the primary hazard</p>	<p>Do you have any previous experience of natural disasters (e.g. earthquakes, floods, landslides, etc.)?</p>

		<p>0= No</p> <p>1= Yes</p>
@22aCONOSCENZA PASSATOalluvioni	Knowledge of previous local flood events in the area	<p>Do you know if in the area where you live there have been floods in the past?</p> <p>0= No</p> <p>1= Yes</p>
@22aCONOSCENZA PASSATOalluvioni	Foundation of knowledge based on awareness of historical local flood events	<p>Do you know if in the area where you live there have been floods in the past?</p> <p>0= No</p> <p>1= Yes</p>
@210bPREPARAZIO NEINBASEALTENERS IINFORMATOalluvioni	Frequency of keeping up to date specifically with flood and landslide warnings	<p>Do you keep abreast of flood warnings?</p> <p>0 = Not informed</p> <p>1= A little informed</p> <p>2 = Somewhat informed</p> <p>3 = Very well informed</p>
@212aAUTOEFFICA CIAalluvione	Self-reported level of knowledge on how to protect oneself/respond to a flood	<p>Do you have enough knowledge to protect yourself/response measures in the event of a flood?</p> <p>0=I have no knowledge</p> <p>1= I have little knowledge</p> <p>2= I have moderate knowledge</p> <p>3=I have a lot of knowledge</p>
@29aPREPARAZION	Knowledge of specific response	Are you informed about the

EINBASEACONOSCE NZEalluvione	behaviors and emergency procedures (warning systems, etc.)	protective behaviors, warning systems, risk/safe areas in the case of a flood?  0= not informed  1= a little informed  2= somewhat informed  3= very well informed
@110aNumerototale eventiT	Quantitative count of total historical events experienced by the respondent	
@21aESPERIENZAal luzioni	Impact of direct past experience on overall theoretical/practical knowledge	Which of the following sentences best indicates your experience with floods?  0= No experience  1= Indirect experience (e.g. read/seen information in the news or other media, direct experience of a friend/relative  2= Direct personal experience
@13b_regione	Geographical feature: The respondent's region of origin	
@11_età	Demographic feature: Age of the respondent	
@13a_città	Geographical feature: The respondent's city of origin	
@24aPREOCCUPAZI ONEALLARMEalluvio ne	Specific level of worry felt in response to an official flood warning	If the news were to report a severe flood warning predicted for tomorrow, how would you feel? Please indicate your level of worry  0= not worried

		<p>1= little worried</p> <p>2= moderately worried</p> <p>3= very worried</p>
@23bEMOZIONEalluvione	Anticipated or past emotional response regarding floods	<p>What emotion did you feel or do you think you would feel if you experienced a flood?</p> <p>1 = Calm</p> <p>2 = Nervousness</p> <p>3 = Worry</p> <p>4= Anxiety</p> <p>5 = Fear</p> <p>6 = Panic</p> <p>7 = Terror</p>
@212aAUTOEFFICACIAalluvione	Self-reported level of knowledge on how to protect oneself/respond to a flood	<p>Do you have enough knowledge to protect yourself/response measures in the event of a flood?</p> <p>0=I have no knowledge</p> <p>1= I have little knowledge</p> <p>2= I have moderate knowledge</p> <p>3=I have a lot of knowledge</p>
@211aMISUREPREVENZAlluvioni	Perception of how adequate local flood prevention measures are in the respondent's city	<p>How adequate are the measures taken to prevent floods that may cause disasters in your city?</p> <p>0 = I don't know</p> <p>1 = Very inadequate</p>

		<p>2 = Fairly adequate</p> <p>3 = Very adequate</p>
RISCHIOCAMBIAMC LIMATICO	General concern or perceived risk regarding climate change	<p>The Climate Change Worry Scale (CCWS; Stewart, 2021)</p> <p>10 items</p> <p>1= Never</p> <p>2= Rarely</p> <p>3= Sometimes</p> <p>4= Often</p> <p>5= Almost always</p>
@210cPREPARAZIO NEINBASEALTENERS IIFORMATOmeteo	Proactive information-seeking through general weather warning updates	<p>Do you keep abreast of weather warnings?</p> <p>0 = Not informed</p> <p>1= A little informed</p> <p>2 = Somewhat informed</p> <p>3 = Very well informed</p>
@213aSICUREZZAall uvione	General perception of personal safety in the event of a flood	<p>How safe would you feel in case of flood?</p> <p>0 = not at all certain</p> <p>1 = somewhat certain</p> <p>2= fairly certain</p> <p>3= very certain</p>
@19a_BisSpec_pers onali	Indicator of specific personal needs or vulnerabilities	<p>Do you consider yourself a person with special needs?</p> <p>0= no</p>

		<p>1= chronic illness</p> <p>2= disability</p> <p>3= mental illness</p> <p>4= chronic + disability</p> <p>5= chronic + mental</p> <p>6= disability + mental</p> <p>7= chronic + disability + mental</p>
@110bMALATTIAGR AVEDIUNFAMILIARE	Personal psychological context: Recent experience with serious illness in a family member	<p>Presence of serious illness of a family member</p> <p>0= No</p> <p>1= Yes</p>
@29aPREPARAZION EINBASEACONOSCE NZEalluvione	Impact of emergency preparedness on the intensity of worry	<p>Are you informed about the protective behaviors, warning systems, risk/safe areas in the case of a flood?</p> <p>0= Not informed</p> <p>1= A little informed</p> <p>2= Somewhat informed</p> <p>3= Very well informed</p>
@26aCONAPEVOLE ZZARISCHIOCASAall uvione	Link between perceiving one's home at risk and heightened worry levels	<p>Is your residence located in the flood risk area?</p> <p>0= No</p> <p>1= I don't know</p> <p>2= Yes</p>
@17_statocivile	Demographic feature: Marital status of the respondent	Marital status

		<p>1= Single</p> <p>2= A couple not cohabiting</p> <p>3= Married/cohabiting</p> <p>4= Separated/divorced</p> <p>5= Widowed</p>
@11_età	Demographic feature: Influence of age on emotional response and hazard worry	
@26bCONSAPEVOL EZZARISCHIOCASAfr ana	Awareness of whether the respondent's residence is located in a landslide risk area	<p>Is your residence located in the landslide risk area?</p> <p>0= No</p> <p>1= I don't know</p> <p>2= Yes</p>
@27bCONSAPEVOL EZZARISCHIOCITTAfr ana	Perception of specific city zones that are more exposed to landslide risk than others	<p>Do you think there are parts of your town/city more exposed to landslides risk than others?</p> <p>0 = I don't know</p> <p>1 = There is no risk in the city</p> <p>2 = Yes, there are parts of the city that are more at risk</p> <p>3 = The city has the same risk everywhere</p>
@28bCONSAPEVOL EZZACAUSEfrane	Understanding of the specific geological or human causes of landslides	<p>Are you informed about the possible causes of landslides?</p> <p>0 = Not informed</p> <p>1 = A little informed (1-2 causes)</p> <p>2 = Somewhat informed (3-8</p>

		causes)  3 = Very well informed (9-12 causes)
RISCHIOCAMBIAMC LIMATICO	Perception of climate change as a driver of landslide events	The Climate Change Worry Scale (CCWS; Stewart, 2021)  10 items  1= Never  2= Rarely  3= Sometimes  4= Often  5= Almost always
@21bESPERIENZAfrane	Past experience with landslides (Direct personal, through friends/family, or media)	Which of the following sentences best indicates your experience with landslides?  0= No experience  1= Indirect experience (e.g. read/seen information in the news or other media, direct experience of a friend/relative  2= Direct personal experience
@22bCONOSCENZA PASSATOfrane	Knowledge of landslide events that have occurred in the respondent's area in the past	Do you know if in the area where you live there have been landslides in the past?  0= No  1= Yes
@22bCONOSCENZA PASSATOfrane	Knowledge of landslide events that have occurred in the respondent's area in the past	Do you know if in the area where you live there have been landslides in the past?

		<p>0= No</p> <p>1= Yes</p>
@210cPREPARAZIONEINBASEALTENERSIINFORMATOmeteo	Proactive information-seeking through general weather warning updates	<p>Do you keep abreast of weather warnings?</p> <p>0 = Not informed</p> <p>1= A little informed</p> <p>2 = Somewhat informed</p> <p>3 = Very well informed</p>
@212bAUTOEFFICACIAfrana	Perceived ability/knowledge to protect oneself during a landslide event	<p>Do you have enough knowledge to protect yourself/response measures in the event of a landslide?</p> <p>0=I have no knowledge</p> <p>1= I have little knowledge</p> <p>2= I have moderate knowledge</p> <p>3=I have a lot of knowledge</p>
@29bPREPARAZIONEINBASEACONOSCE NZEfrana	Specific knowledge regarding landslide response behaviors and procedures	<p>Are you informed about the protective behaviors, warning systems, risk/safe areas in the case of a landslide?</p> <p>0= Not informed</p> <p>1= A little informed</p> <p>2= Somewhat informed</p> <p>3= Very well informed</p>
@11_età	Demographic feature: Age as a factor in accumulated knowledge or perception.	

<p>@210aPREPARAZIONE...INFORMATOfrancese</p>	<p>Proactive monitoring specifically for landslide warnings</p>	<p>Do you keep abreast of landslide warnings?</p> <p>0 = not informed</p> <p>1 = a little informed</p> <p>2 = somewhat informed</p> <p>3 = very well informed</p>
<p>@13a_città</p>	<p>Geographical location: Used to contextualize local hazard knowledge</p>	<p>-</p>
<p>@23aEMOZIONEfrancese</p>	<p>Emotional intelligence/response as a facet of cognitive risk perception</p>	<p>What emotion did you feel or do you think you would feel if you experienced a landslide?</p> <p>1 = Calm</p> <p>2 = Nervousness</p> <p>3 = Worry</p> <p>4 = Anxiety</p> <p>5 = Fear</p> <p>6 = Panic</p> <p>7 = Terror</p>
<p>@13b_regione</p>	<p>Regional context influencing exposure to hazard education or history</p>	
<p>@211bMISUREPREVENZFrancia</p>	<p>Assessment of the adequacy of local landslide prevention measures</p>	<p>How adequate are the measures taken to prevent landslides that may cause disasters in your city?</p> <p>0 = I don't know</p> <p>1 = Very inadequate</p> <p>2 = Fairly adequate</p>

		3 = Very adequate
@16_occupazione	Socio-economic status/employment: A potential indicator of education or exposure	<p>What is your current employment status?</p> <p>0= other</p> <p>1= homemaker, unemployed</p> <p>2= student</p> <p>3= unskilled worker</p> <p>4= skilled worker</p> <p>5= office worker, teacher, shopkeeper, surveyor</p> <p>6= freelancer, executive, manager, middle manager</p>
@23aEMOZIONEfrana	Predominant emotional reaction (e.g., Fear, Anxiety, Calm) toward landslide hazards	<p>What emotion did you feel or do you think you would feel if you experienced a landslide?</p> <p>1 = Calm</p> <p>2 = Nervousness</p> <p>3 = Worry</p> <p>4= Anxiety</p> <p>5 = Fear</p> <p>6 = Panic</p> <p>7 = Terror</p>
@24bPREOCCUPAZIONEALLARMEfrana	Reported level of worry when a landslide warning is issued	<p>If the news were to report a severe landslide warning predicted for tomorrow,</p> <p>how would you feel? Please indicate your level of worry</p>

		<p>0= Not worried</p> <p>1= Little worried</p> <p>2= Moderately worried</p> <p>3= Very worried</p>
BENESSEREWHO	<p>General psychological well-being index (WHO-5) used as a baseline for emotional stability</p>	<p>World Health Organisation-Five Well-Being (WHO-5; World Health Organization)</p> <p>5 items</p> <p>0= Never</p> <p>1= Sometimes</p> <p>2=Less than half the time</p> <p>3= More than half the time</p> <p>4 = Most of the time</p> <p>5= Always</p>

These variables are integrated into the decision-support framework to complement physical risk indicators. By incorporating psychological dimensions, the system can perform a more comprehensive risk assessment that considers both environmental vulnerability and social preparedness. This integration supports informed decision-making, especially in the context of disaster risk management and communication strategies.

## 6 Simulate Event

The *Simulate Event* section enables users to simulate a rainfall event characterized by a selected return period and to evaluate its effects on slopes, river basins, and the resident population. Regarding the psychological component, “resident population” refers to the surveyed individuals represented in the uploaded psychological dataset associated with the selected area of interest. When a slope or basin is selected, the platform retrieves and processes the psychological records of that area. These records are classified individually and the resulting profile distribution supports community-level awareness planning.

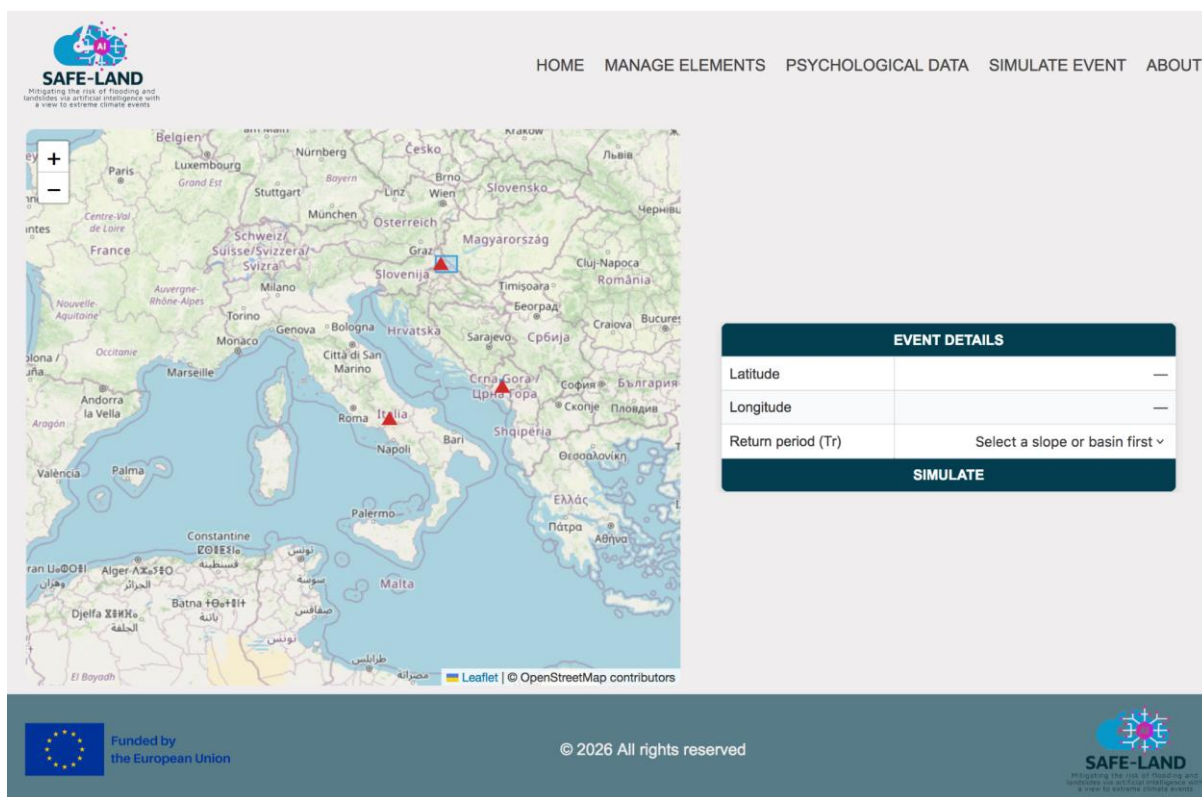


Figure 8: Simulate event interface.

The interface is organized into two main sections:

- On the **left side**, a navigable and zoomable map displays the geographical context.
- On the **right side**, a contextual panel presents interactive controls and analytical outputs.

On the map:

- **Red triangles** represent slopes.
- **Light blue squares** represent basins.

Users must first select a slope or basin directly from the map before proceeding with the analysis.

## 6.1 Slope analysis

As a user clicks on a slope, the interface updates as shown in Figure 9. The right panel shows the geographical coordinates of the selected slope. The user must then select the rainfall return period of interest.

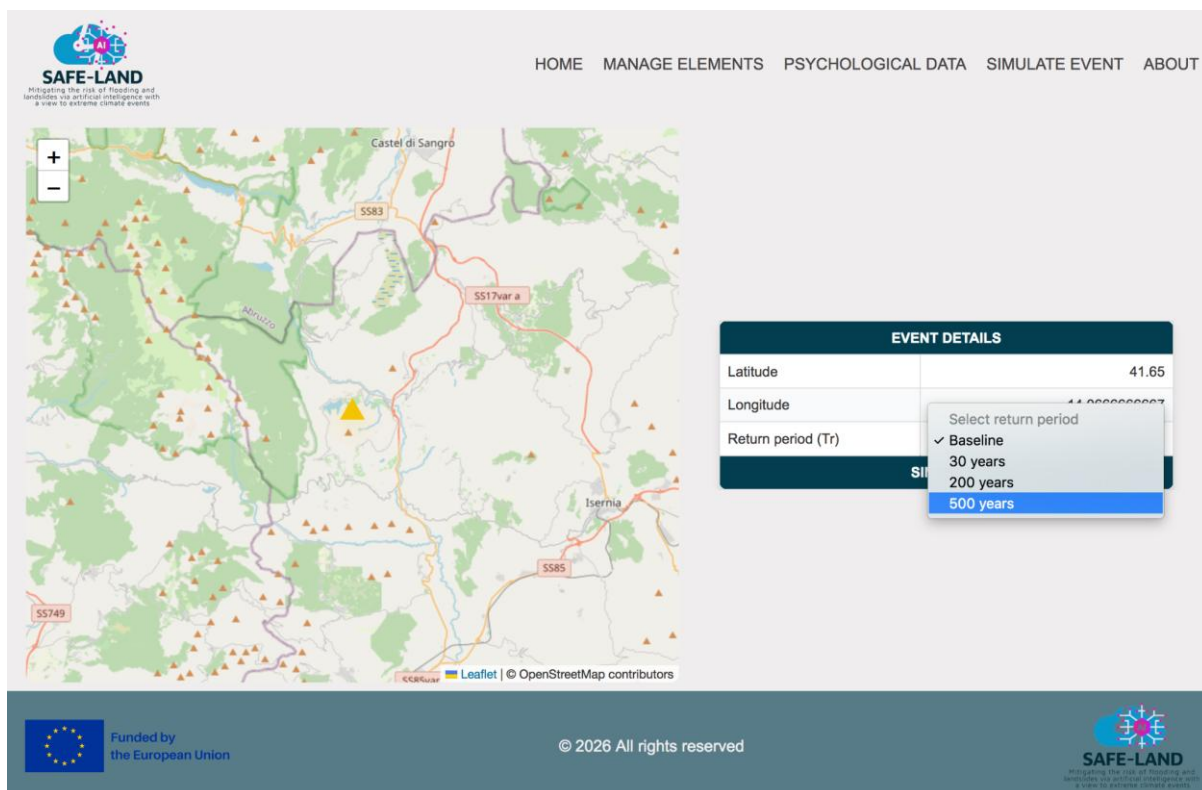


Figure 9: Selection of a slope and a return period for the rainfall event of interest

After clicking the SIMULATE button, the system performs slope stability analysis and updates the interface as shown in Figure 10.

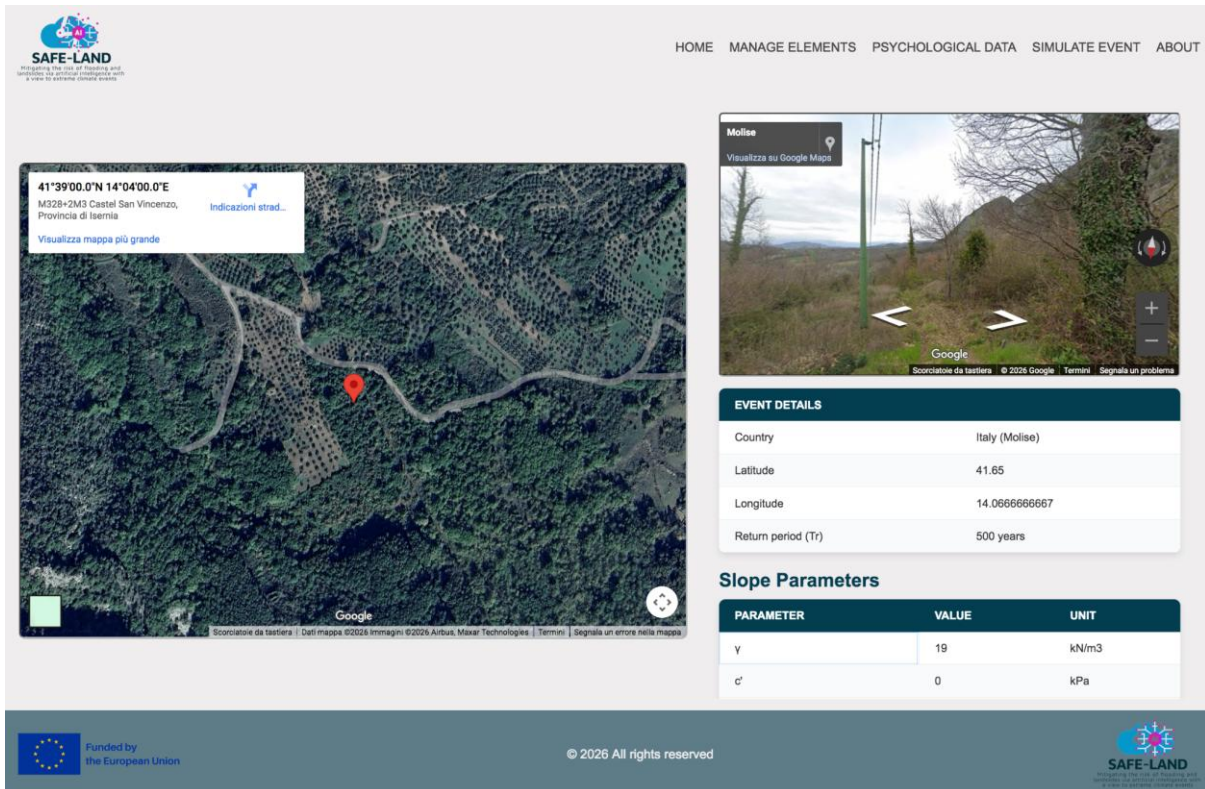


Figure 10: Interface for slope analysis.

The interface provides:

- A georeferenced satellite image of the selected slope (left side).
- A navigable road map (top-right).

The dual-map system enables experts to visually validate simulation outputs. Rather than only relying on numerical indicators, the expert can examine terrain morphology, the presence of infrastructure, buildings, and accessibility conditions. This visual validation strengthens the interpretability and practical applicability of the results.

Scrolling down the right panel, the interface shows the key parameter values for slope stability:

- **Factor of Safety (FoS)**
- **Depth of the slip surface (zs)**
- **Maximum height of the water table (z<sub>w</sub> final)**

Each parameter is presented with its corresponding unit of measurement (see Figure 11).

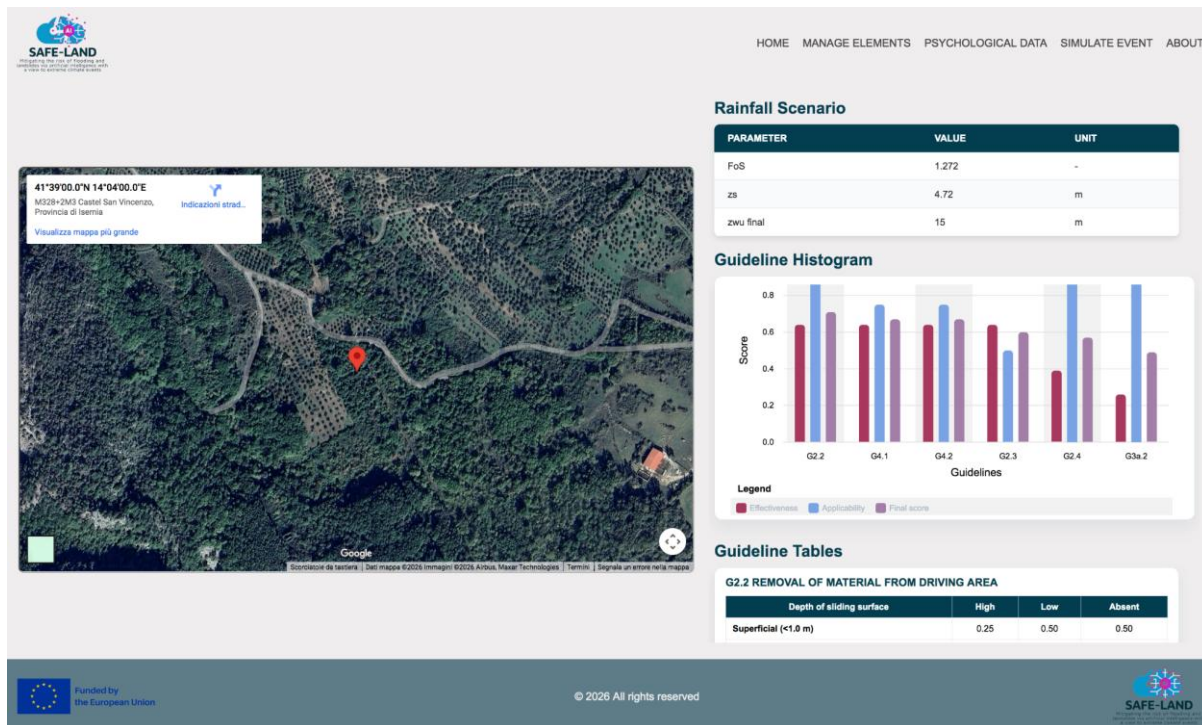


Figure 11: Slope analysis results

The interface then shows the guidelines for slope stabilization (if the slope is unstable) or for securing the slope for the considered rainfall event. The guidelines are presented in a summarized form through a histogram, at the bottom right of Figure 11.

In particular, the histogram consists of three bars colored in red, blue, and purple, which measure three indicators, i.e., effectiveness, applicability, and final score, respectively, on a continuous scale between 0 and 1. The higher the value of a bar in the histogram, the better the corresponding indicator.

The final score is an aggregated value that considers both the effectiveness of slope stabilization and aspects such as implementation cost, required resources, and the time frame needed for implementation. The guidelines are presented in the histogram in decreasing order of final score,

from left to right.

The application shows the details of each guideline below the histogram, as Figure 12 shows.

Guideline Tables				
<b>G2.2 REMOVAL OF MATERIAL FROM DRIVING AREA</b>				
Depth of sliding surface	High	Low	Absent	
Superficial (<1.0 m)	0.25	0.50	0.50	
Shallow (1 to 3 m)	0.25	0.50	0.50	
Medium (3 to 8 m)	0.50	1	1	
Deep (8 to 15 m)	0.25	0.50	0.50	
Very deep (>15 m)	0.25	0.50	0.50	
<b>G2.3 SUBSTITUTION OF MATERIAL WITH LIGHTWEIGHT FILL</b>				
Depth of sliding surface	High	Low	Absent	
Superficial (<1.0 m)	0.25	0.50	0.50	
Shallow (1 to 3 m)	0.25	0.50	0.50	
Medium (3 to 8 m)	0.50	1	1	
Deep (8 to 15 m)	0.25	0.50	0.50	
Very deep (>15 m)	0.25	0.50	0.50	
<b>G4.1 PILES</b>				
Depth of sliding surface	High	Low	Absent	
Superficial (<1.0 m)	0	0	0	
Shallow (1 to 3 m)	0.25	0.50	0.50	
Medium (3 to 8 m)	0.50	1	1	
Deep (8 to 15 m)	0.25	0.50	0.50	
Very deep (>15 m)	0	0	0	
<b>G2.4 ADDITION OF MATERIAL TO MAINTAIN STABILITY</b>				
Depth of sliding surface	High	Low	Absent	
Superficial (<1.0 m)	0.50	0.50	0.50	
Shallow (1 to 3 m)	0.50	0.50	0.50	
Medium (3 to 8 m)	1	1	1	
Deep (8 to 15 m)	0.50	0.50	0.50	
Very deep (>15 m)	0.50	0.50	0.50	
<b>G4.2 DIAPHRAGM WALLS</b>				
Depth of sliding surface	High	Low	Absent	
Superficial (<1.0 m)	0	0	0	
Shallow (1 to 3 m)	0	0	0	
Medium (3 to 8 m)	0.25	0.50	0.50	
Deep (8 to 15 m)	0.50	1	1	
Very deep (>15 m)	0.25	0.50	0.50	
<b>G3a.2 LOCAL REGARDING TO FACILITATE RUN-OFF</b>				
Depth of sliding surface	High	Low	Absent	
Superficial (<1.0 m)	0.50	0.50	0.50	
Shallow (1 to 3 m)	0.50	0.50	0.50	
Medium (3 to 8 m)	0.25	0.25	0.25	
Deep (8 to 15 m)	0.25	0.25	0.25	
Very deep (>15 m)	0	0	0	

Figure 12: Guideline details.

The expert can make decisions based on the scores shown in the histogram and then examine the detailed guidelines to support the effective implementation of the selected stabilization measure on the chosen slope. The histogram thus provides an immediate and synthetic overview of the available options, allowing the expert to quickly compare different alternatives with each other, based on their overall performance. Once a preferred guideline has been identified according to the values of the indicators, the expert can explore its detailed description, technical specifications, and practical considerations in order to assess feasibility and plan the intervention in a structured and informed manner.



Figure 13: Psychological data.

The interface also shows information related to people in the affected area, including indicators such as experience, worry, knowledge, and awareness, depending on the specific type of individuals present in the area (see Figure 13). These indicators provide a qualitative characterization of the local population, helping the expert to better understand the social and psychological context in which the intervention will take place. By integrating technical assessments with human-centered information, the system supports more comprehensive decision-making that considers engineering effectiveness and community preparedness and perception of risk.

Finally, the interface shows the guidelines regarding the risk awareness, and how to increase its level for at-risk profiles. Example guidelines are shown in Figure 14.

<p><b>Psychological Data Guidelines</b></p> <p><b>Risk Profile:</b> High Anxiety (96% Worry), Theoretical Knowledge, but Practical Gaps.</p> <p><b>Floods</b></p> <ul style="list-style-type: none"> <li>• Risk Perception: There is a very high level of concern; 96% of participants reported a worry score above the neutral threshold (&gt;3/10). Females are noticeably more worried (Avg: 7.3) than Males (Avg: 5.8).</li> <li>• Experience vs. Awareness: About 45% of the sample has direct experience with floods. However, awareness scores are moderate (Avg: ~4.8 on a scale up to 7), suggesting that experience does not always translate into high preparedness.</li> <li>• Demographics: Knowledge is high across the board (~82% have knowledge), with no significant gender gap.</li> </ul> <p><b>Strategy:</b> From Anxiety to Action (Operational Checklists)</p> <p><b>Deliverable Reference:</b> Section 3.4.2 (High Worry) states the objective is to "transform high worry into actionable preparedness behaviors" and "promote understanding of official warning and intervention systems to reduce uncertainty".</p> <p><b>Action:</b> Since the population is highly worried, avoid alarmist messaging. Instead, distribute specific "Action Cards" (e.g., "What to do when the siren sounds") to channel anxiety into structured responses.</p>	<p><b>Strategy:</b> Community Drills &amp; Workplace Training</p> <p><b>Deliverable Reference:</b> Section 3.2.1 (Low Knowledge/Gaps) recommends "trainings in workplaces or schools" to enhance "knowledge of effective protective behaviors before, during, and after events".</p> <p><b>Action:</b> Bridge the gap between abstract knowledge and practical application by organizing regular drills, specifically targeting the 45-59 working-age demographic found to be less aware.</p> <p><b>Landslides</b></p> <ul style="list-style-type: none"> <li>• Risk Perception: Concern is slightly lower than for floods but still significant, with 93% expressing worry above neutral. Females again show higher concern (Avg: 5.7) compared to Males (Avg: 5.2).</li> <li>• Awareness Gap: While 50% have experience with landslides, Males show a surprisingly low awareness score (Avg: 3.6) compared to Females (Avg: 4.8), indicating a potential target group for awareness campaigns.</li> <li>• Age Trend: The 60+ age group shows the highest awareness (Avg: 5.0), whereas middle-aged groups (45-59) score the lowest (Avg: 3.7).</li> </ul> <p><b>Strategy:</b> Targeted Engagement for Men</p> <p><b>Deliverable Reference:</b> Section 3.3.1 (Low Awareness) advises promoting "awareness of the causes and potential impacts... at personal and community levels".</p> <p><b>Action:</b> Address the significant awareness gap in the male population (Avg 3.6 vs 4.8 for females) by organizing technical workshops that explain the causes and hydrogeological signs of landslides, moving beyond simple warnings to deep understanding.</p>
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Figure 14: Example guidelines for the selected element.

## 6.2 River

If the user clicks on a basin, the interface updates as shown in Figure 15 and shows the geographic coordinates of the basin centroid in the panel on the right. This allows the user to identify the selected area and verify its spatial location before proceeding with the analysis. Then, the user selects the rainfall return period of interest by using the corresponding drop-down menu on the right-hand side of the interface [Return period (Tr)].

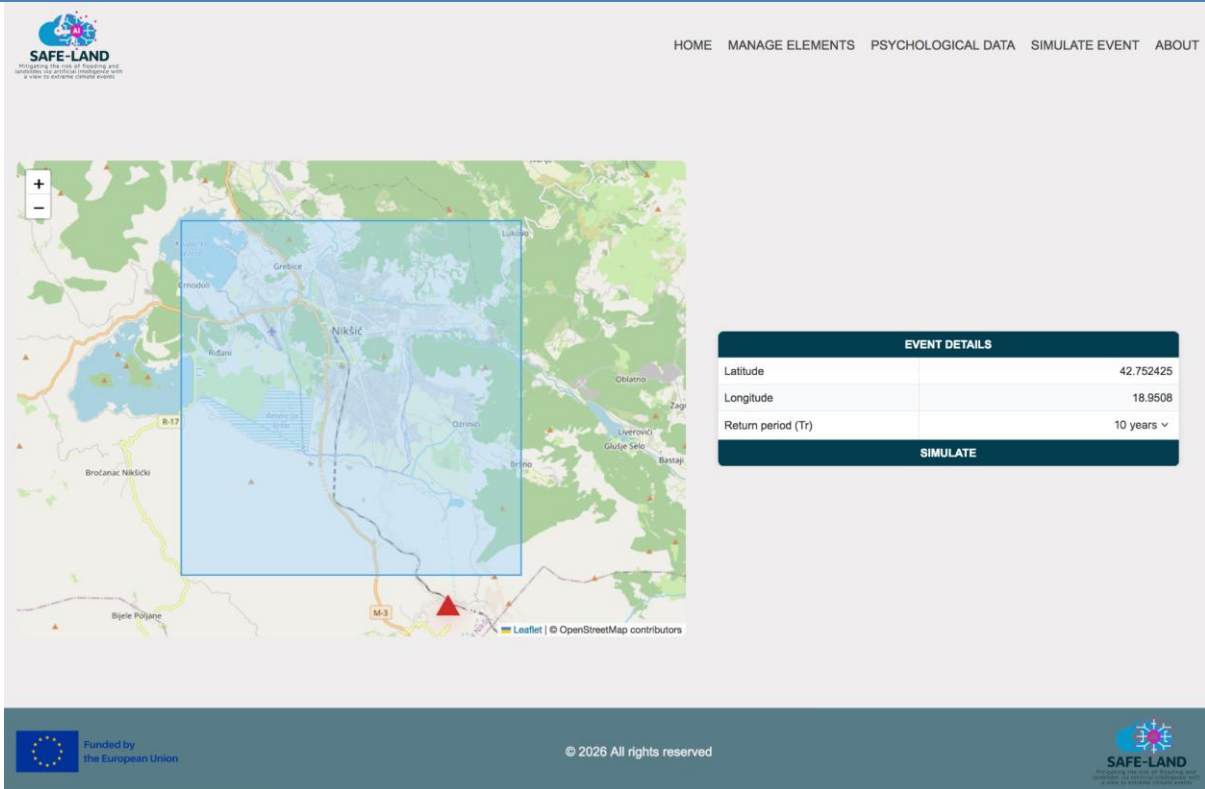


Figure 15: Basin selected by the user.

After selecting the desired return period and clicking on SIMULATE, the system processes the selected scenario and refreshes the visualization, displaying the results of the simulation for the chosen basin and rainfall return period. The interface updates as shown in Figure 16.

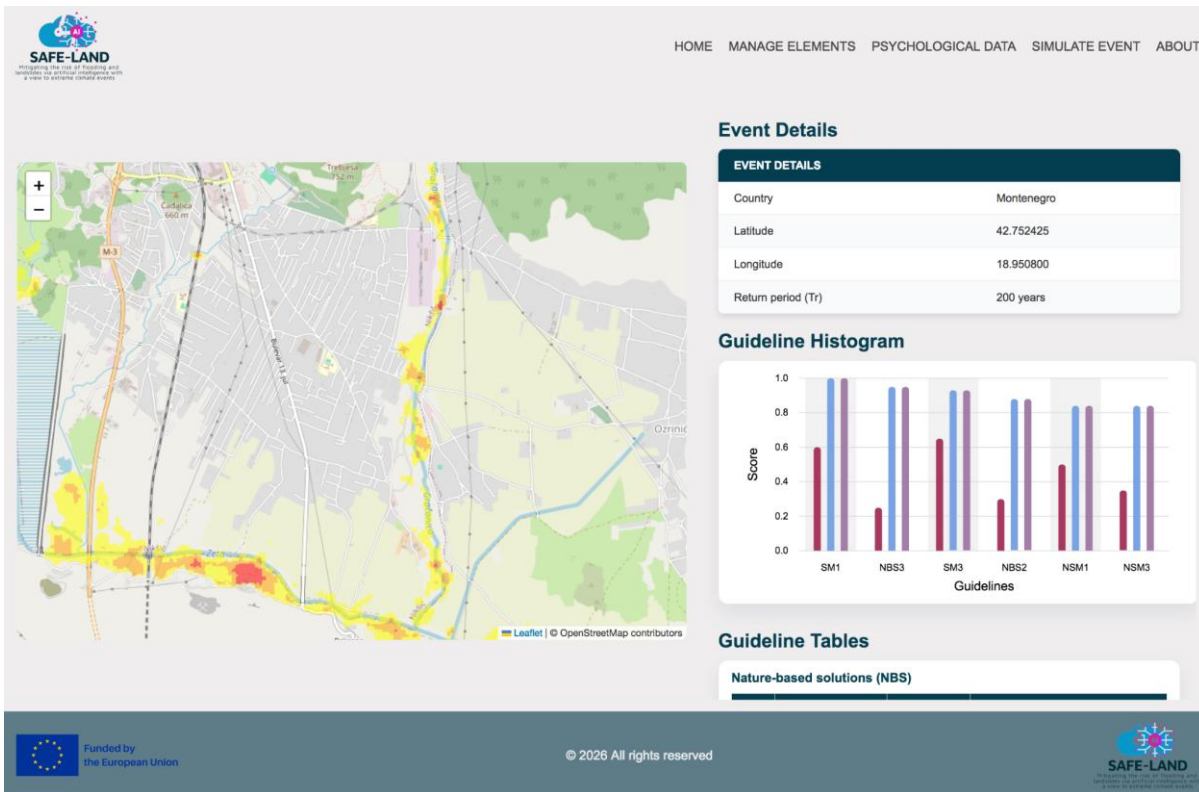


Figure 16: Interface related to the analysis of the rivers within the selected basin, with reference to the rainfall event of interest.

At the end of the processing phase, the system shows, on the left-hand side, an interactive map illustrating the areas potentially flooded as a consequence of the rainfall event characterized by the selected return period. The water level is represented using a yellow-orange-red heatmap color scale. The warmer the color, the higher the level of flooding in the corresponding area.

The map is fully navigable, allowing the expert to zoom in and out and to explore specific zones in detail. This functionality enables a more accurate spatial assessment of the flood-prone areas and supports a better understanding of the spatial distribution and intensity of the predicted inundation.

Figure 17 presents some detailed views of the flooded areas that the expert can examine in order to better contextualize the potential damage to the territory and to the exposed structures resulting from the selected rainfall event. This detailed visualization supports a more informed evaluation of vulnerability and possible impacts at both local and infrastructural levels.



Figure 17: Details of the areas potentially subject to flooding within the basin of interest, with reference to the rainfall event characterized by the selected return period.

As in the case of slopes, the interface presents the guidelines in a histogram on the right-hand side of the screen. For each guideline, three bars indicate, from left to right, effectiveness, applicability, and the final score, which accounts for implementation-related aspects such as the time required, the necessary resources, and the associated costs. The higher the value of each bar, the better the performance of the guideline relative to the corresponding indicator.

Then, the interface presents the detailed description of the guidelines shown in the histogram, summarizing their effectiveness and underlying rationale. This structured presentation supports the expert in understanding the quantitative evaluation of each option and the technical reasoning behind it, thereby facilitating a well-informed selection of the most appropriate mitigation or stabilization measures for the selected basin (see Figure 18).

**Guideline Tables**

Nature-based solutions (NBS)			
Code	Measure	Effectiveness	Rationale
NBS2	Urban Green Infrastructure	0.30	Implements urban features like green roofs and permeable pavements to manage pluvial flooding by increasing infiltration and delaying runoff in cities.
NBS3	Reforestation and Afforestation in Watersheds	0.25	Enhances soil stability and infiltration, reducing surface runoff and flash flood risks. Especially effective in upland or deforested catchments for hydrological regulation.

Non-structural measures (NSM)			
Code	Measure	Effectiveness	Rationale
NSM1	Land Use Planning and Zoning	0.50	A correct planning of land use and zoning plays a pivotal role in long-term risk reduction by regulating development in flood-prone areas. It limits exposure by promoting flood-compatible uses.
NSM3	Emergency Preparedness and Response Plans	0.35	Ensures coordinated action during crises through updated protocols, simulations, and evacuation planning. Critical for reducing impacts during flood events.

Structural measures (SM)			
Code	Measure	Effectiveness	Rationale
SM1	Routine maintenance of watercourses, clearing and inspection of structures	0.60	Ensures basic hydraulic functionality by preventing blockages and failures in watercourses.
SM3	Riverbed and Bank Stabilization	0.65	Controls erosion and stabilizes channels, preserving capacity and minimizing secondary risks (e.g. failure of banks).

Figure 18: Hydraulic mitigation guidelines.

The interface subsequently displays details related to experience, worry, knowledge, and awareness, whose structure is analogous to that described in Section 6.1.

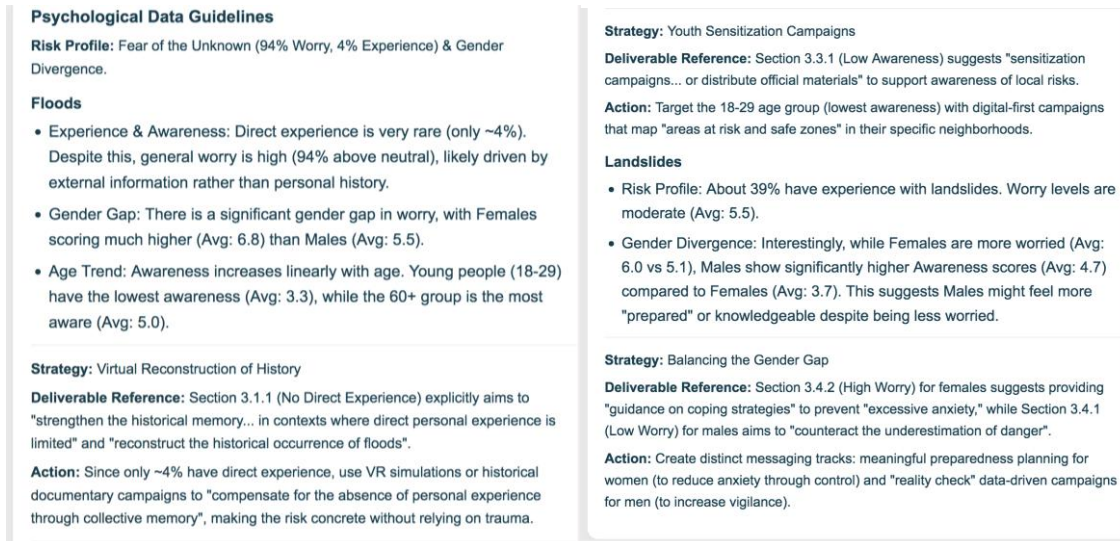


Figure 19: Psychological guidelines.