

An Assessment of Short-medium Term Interventions Using CAESAR-Lisflood in a Post-earthquake Mountainous Area

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Abstract. The 2008 Wenchuan earthquake rapidly triggered local geomorphic changes, shifting abundant material through exogenic processes and creating vast amounts of loose material. The substantial material dynamics increased the risks of geo-hazards (flash floods, landslides, and debris flows) induced by extreme precipitation in the area. Intervention measures such as dams, levees, and vegetation revetments have been constructed in specified sites to reduce sediment transport, thus mitigating the risk of ensuing geo-hazards.

This study assessed the effects of various interventions, incorporated with multiple facilities, on post-earthquake fragile mountains in the short-medium term. Taking the Xingping valley as an example, we used CAESAR-Lisflood software, a two-dimensional landscape evolution model, to simulate three scenarios: unprotected landscapes, present protected landscapes, and enhanced protected landscapes between 2011 and 2013. We defined two indicators to assess the intervention effects of the three scenarios by comparing the geomorphic changes and sediment yields.

The results show that the mitigation facilities are effective, especially engineering efforts cooperating with vegetation revetments in the upstream area. The spatial patterns of erosion and deposition change considerably due to the intervention measures. Additionally, the effectiveness of each intervention scenario shows a gradual decline over time caused directly by the reduction in the reservoir's capacity. The enhanced scenario performs better than the present one, with a smaller downward trend. The simulation results assess the ability and effectiveness of cooperated control measures and will support optimum mitigation strategies.

1 Introduction

Strong earthquakes can trigger co-seismic landslides, discontinuously crack mountains, and thus increase weak structural planes (Huang, 2009) by weathering and erosion. Consequently, material shifted from coseismic landslides and attendant mass failures caused by weakened slopes modify mountain landscapes by various surface processes for days, years, and millennia (Fan et al., 2020). The 2008 Wenchuan Ms 8.0 (the surface-wave magnitude, which is the logarithm of the maximum amplitude of the ground motion of the surface waves with a wave period of 20 seconds) earthquake has been influencing towns and other infrastructure in the affected area. Many studies have mapped the landslides triggered by this devastating earthquake. One study, Gorum et al. (2011), performed an extensive landslide interpretation using a large set of high-resolution optical images and mapped nearly 60,000 individual landslides, all impacting an area of 600 m² or more. Another study, Xu et al. (2014), delineated 197,481 landslides formed by polygons, centroids, and top points compiled from visual image interpretation. To estimate the threat of loose material in subsequent sediment disasters caused by landslides, some research has attempted to measure the volume of deposited material based on field surveys and assumptions. For example, Huang and Fan (2013) estimated that 400 million m³ of material was deposited in heavily affected areas by assuming that the material was deposited on steep slopes with angles larger than 30° and a catchment area of more than 0.1 km². An approximate 2,793 million m³ of

38 sediment was calculated by Chen et al. (2009) using different deposited depth settings in different buffer zones of the Long-
39 menshan central fault. In summary, a tremendous amount of loose material accumulated in the gullies and hillslopes which
40 became available for erosion and other exogenic processes for years to come. As a result, mitigation in the Wenchuan earth-
41 quake-stricken area is still ongoing.

42 Structural mitigation measures have been developed in the affected areas depending on the different site conditions and other
43 technical and economic feasibilities. For example, ecological mitigation, such as vegetation revetments, was conducted to
44 stabilise the source area in hillslopes (Cui and Lin, 2013; Forbes and Broadhead, 2013; Stokes et al., 2014), and check dams
45 were used widely to intercept upriver sediment (Yang et al., 2021; Marchi et al., 2019). And lateral walls and levees which are
46 longitudinal structures (Marchi et al., 2019), can be built to protect infrastructure in mountain watersheds with relatively higher
47 sediment runoff into main streams.

48 Although comprehensive mitigation measures were performed at potentially dangerous sites, disasters still occurred due to
49 rough terrain, vague source material, intensive precipitation, and relatively low-cost mitigation measures (Yu et al., 2010; Cui
50 et al., 2013). Therefore, understanding the effectiveness of intervention measures is crucial for mitigation strategies. Some
51 studies focus on establishing post-evaluation effectiveness index systems that are not supported by sufficient practices (Zhang
52 and Liang, 2005; Wang et al., 2015). Some researchers compare the changes before and after intervention measures by record-
53 ing long-term on-site measurements, which face the challenges of needing a great deal of time, energy and financing (Zhou et
54 al., 2012; Chen et al., 2013). Recent research has compared disaster characteristics before and after mitigation actions, which
55 are quickly obtained from numerical simulations (Cong et al., 2019; He et al., 2022). Nevertheless, these disaster characteristics
56 ignore the long-term effects of earthquakes on geomorphic changes (longer than the duration of a single event). Therefore, the
57 short-medium term (from the duration of a single event to decades after) and spatial geomorphic changes obtained from sim-
58 ulations provide more details to interpret engineering measures in notable locations, even in locations inaccessible to humans.
59 CAESAR-Lisflood (C-L), which is based on the cellular automata (CA) framework (Coulthard et al., 2013), has powerful
60 spatial modelling and computing capabilities to simulate complex dynamic systems (Batty and Xie, 1997; Couclelis, 1997;
61 Coulthard et al., 2002). The model enables the study of many earth system interactions under different geo-environmental.
62 Representation of deposition and erosion within C-L is used widely in rehabilitation planning and soil erosion predictions in
63 post-mining landforms (Saynor et al., 2019; Hancock et al., 2017; J.B.C. Lowry et al., 2019; Thomson and Chandler, 2019;
64 Slingerland et al., 2019) as well as channel evolution and sedimentary budget planning for dam settings (Poepl et al., 2019;
65 Gioia and Schiattarella, 2020; Ramirez et al., 2020, 2022). In addition, there have been a series of studies in mountainous area
66 involving secondary geo-hazard driving factors (Li et al., 2018; Wang et al., 2014b) and vegetation recovery (Zhang et al.,
67 2018). One study, Li et al. (2020) and Xie et al. (2018) used C-L with different rainfall and future climate change scenarios to
68 interpret the landscape evolution after the Wenchuan earthquake. The methods and parameter values used in the above research
69 helped promote this model's application in other study areas.

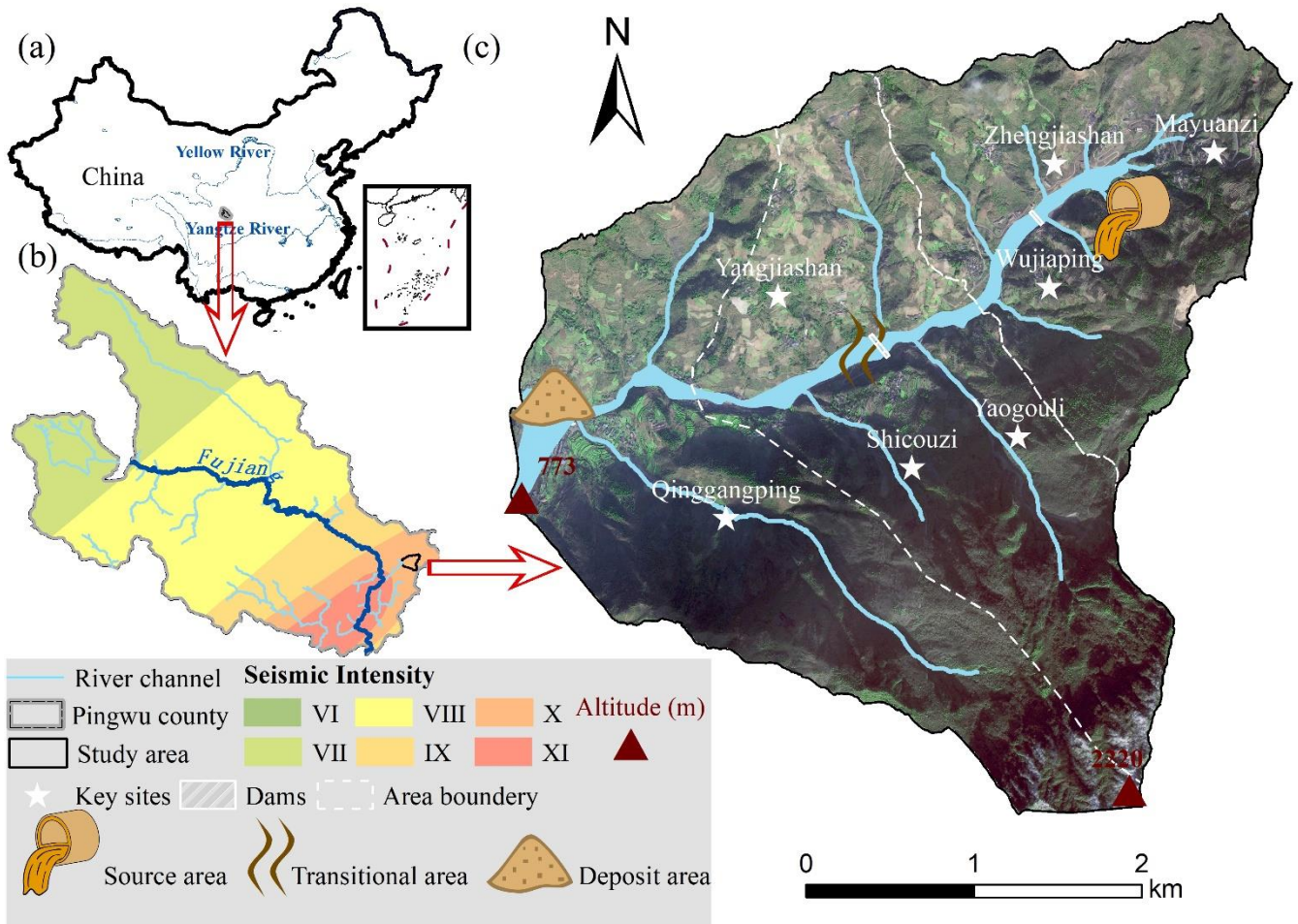
70 In this study, hourly rainfall data over three years were generated by daily downscaling to capture extreme events. Based on
71 the input data, we simulated and compared the geomorphic changes and sediment yield in three scenarios that varied in their
72 mitigation compositions and intensities in the catchment. The objectives were 1) to assess the effectiveness of a set of mitiga-
73 tion facilities to reduce sediment transport, 2) to analyse the role of each facility on geomorphic changes, and 3) to determine
74 the influence of vegetation on catchment erosion.

75 **2 Study area**

76 **2.1 Regional characteristics**

77 The study area was the Xingping valley in north-eastern Sichuan Province, the left branch of the Shikan River (a tributary of
78 the Fu River) (Fig. 1). There are nearly two hundred households scattered among more than five villages in the catchment. The

79 topography of the catchment is rugged, with an elevation between 800 and 3036 m and an area of approximately 14 km². The
 80 catchment is characterised by a high longitudinal gradient (~ 120‰) and more than ten small V-shaped branch gullies. The
 81 length from the northeast to the southwest is 5,770 m, and the width is 4,150 m in the perpendicular direction. The region has
 82 a humid temperate climate with a mean annual temperature of 14.7°C. The mean annual precipitation is 807.6 mm, mainly
 83 between May and September. The steep terrain and short-term heavy rainfall dominate ephemeral streams in this area.
 84 The local basement rocks are mainly metamorphic sandstones, sandy slate, crystalline limestone, and phyllite of the Triassic
 85 Xikang Group (T_{3xk}) and Silurian Maoxian Group (S_{mx}), which are easily worn away by quick weathering in static processes
 86 after disturbs caused from strong earthquakes. Consequently, the Wenchuan earthquake, with a Modified Mercalli Intensity
 87 scale of X, made this area one of the most severely affected locations (Wang et al., 2014a) and produced 10⁶ m³ loose material
 88 by triggering landslides and subsequent weathering in Mayuanzi, Zhengjiashan, and Wujiaping (Fig. 1)(Guo et al., 2018).



89
 90 **Figure 1: An overview of the study area. (a) The location of the study area; (b) A seismic intensity map of the Wenchuan earthquake**
 91 **within Pingwu County; (c) A schematic image of the study area.**

92 **2.2 Historical hazards and intervention measures**

93 Six debris flow-flash flood disaster chain groups have been found in the Xingping valley over the decade after the earthquake.
 94 Based on the published work of SKLGP (State Key Laboratory of Geohazard Prevention and Geoenvironment Protection) and
 95 the local states' geological survey before 2018 and our biannual field surveys since 2012, we catalogued the time of occurrence,
 96 total rainfall of each event, and corresponding disaster details (Table S1). The massive sediment was transported quickly after
 97 the devastating earthquake in 2008 and 2009, and the extreme rainfall in 2013 and 2018 triggered the deposition of extensive
 98 loose material in the channel. Considering the landslide processes, we divided the study area into three regions: the source
 99 area, the transitional area, and the deposit area. The white dashed lines in Fig. 1c, indicate that the loose solid material can
 100 easily be transported from the source area to the deposit area through the transitional zone.

101 An engineering control project was constructed to intercept the upriver material in October 2010. The project included two
 102 check dams, one in the upper source area and the other in the transitional zone (Feng et al., 2017) (Fig. 1c). The upper dam
 103 has a storage capacity of $5.78 \times 10^4 \text{ m}^3$ and a height of 10.0 m. The transitional area dam has a storage capacity of $7.2 \times 10^4 \text{ m}^3$
 104 and a height of 9.0 m. With the reservoirs gradually filling with deposits, the first dredging work was subsequently performed
 105 in 2013. Nearly three years later, the storage capacity behind the upper dam remained at 50% in 2016, while the transitional
 106 area dam could no longer retain sediment.

107 3 Materials and Methods

108 In this study, we examined the intervention effectiveness through the morphological response and sediment yield in the Xing-
 109 ping valley, which was simulated using the C-L model. The research entailed four main steps: 1) setting three scenarios with
 110 different intervention compositions, 2) preprocessing the model input data, including three groups of DEMs, the rainfall data,
 111 and the m value of the C-L, 3) calibration of the hydrological component, and 4) simulating landscape changes and analysing
 112 the intervention effectiveness in 2011-2013.

113 3.1 Scenario settings

114 The abundant source material triggered by landslides should be controlled to prevent the threat of disasters downstream. There-
 115 fore, we designed three scenarios by incorporating engineering and biological measures referenced to current facilities to assess
 116 the effectiveness of intervention measures. Scenario UP: Unprotected landscapes meant the sediment would be transported
 117 without anthropogenic intervention. Scenario PP: Present protected landscapes implied that only the present two check dams
 118 trapped sediment in 2011-2013 without dredging work over the period (see Section 2.2). Scenario EP: Enhanced protected
 119 landscapes emphasised the addition of vegetation revetments in the source area and levees in the deposit area based on the two
 120 check dams in Scenario PP.

121 Figure 1c shows the locations of the existing two check dams in both Scenario PP and Scenario EP. We determined the place-
 122 ments of additional facilities in Scenario EP according to the field survey, which demonstrated that the continuous supply of
 123 sediment was mainly from the source area. Therefore, vegetation revetments such as tree planting would be carried out up-
 124 stream to prevent erosion by stabilising the topsoil and enhancing the soil's infiltration capacity via roots (Lan et al., 2020).

125 Considering the damage caused by flash floods to the residential area downstream, the levees (see Fig. S1 and Section 3.2.2)
 126 are artificial barriers to protect agricultural land and buildings, which help to prevent water and sediment from overflowing
 127 and flooding surrounding areas. Table 1 shows the scenario descriptions, initial model conditions and input rainfall series. The
 128 details about the model input data are introduced below.

129 **Table 1: Scenario settings**

Scenario	Descriptions	Period	DEM (10 m)	Rainfall data
UP	no anthropogenic intervention		UP DEM UP bedDEM	downscaled hourly pre- cipitation over the period
PP	the present two check dams upstream without dredging work additional vegetation revetments in the	2011-2013 (3 years)	PP DEM PP bedDEM	(lumped)
EP	source area and levees in the deposit area based on Scenario PP		EP DEM EP bedDEM	downscaled hourly pre- cipitation over the period (spilt)

130

131 3.2 CAESAR-Lisflood

132 The C-L integrated the Lisflood-FP 2D hydrodynamic flow model (Bates et al., 2010) with the CAESAR landscape evolution
 133 model (LEM) (Coulthard et al., 2002; Van De Wiel et al., 2007), which is described in detail by Coulthard et al. (2013). The

134 catchment mode of C-L was applied in this study, in which the surface digital elevation model (DEM), the bedrock DEM, the
135 grain size distribution, and a rainfall time series are required to simulate the sediment transport and geomorphic changes. There
136 are four primary modules within C-L operated as follows:

137 (1) a hydrological module generates surface runoff from rainfall input using an adaptation of TOPMODEL (topography-based
138 hydrological model) (Beven and Kirkby, 1979),

139 (2) a hydrodynamic flow routing module based on the Lisflood-FP method (Bates et al., 2010) which calculates the flow depths
140 and velocities,

141 (3) an erosion and deposition module uses hydrodynamic results to drive fluvial erosion by either the Einstein (1950) or the
142 Wilcock et al. (2003) equations applied to each sediment fraction over nine different grain sizes,

143 (4) and a slope model of the movement of material from the hillslope to the fluvial system by considering both the mass
144 movement when a critical slope threshold is exceeded and soil creep processes whereby sediment flux is linearly proportional
145 to the surface slope.

146 The C-L model updates variable values stored in square grid cells at intervals, such as DEM, grain size and proportion data,
147 water depth, and velocity. For the three scenarios, the initial conditions, such as DEMs and bedrock DEMs, the rainfall data,
148 and the m values, were preprocessed as follows.

149 **3.2.1 The surface and bedrock digital elevation models**

150 To clearly describe the control process, especially the two dams and levees in the catchment, we unified grid cell scales to 10
151 m for all input data of the C-L. The GlobalDEM product with a 10 m × 10 m resolution and 5 m (absolute) vertical accuracy
152 were used to form three types of initial DEMs (UP DEM, PP DEM, and EP DEM). Before rebuilding the initial DEMs, we
153 filled the sinks of the original GlobalDEM based on the Environmental Systems Research Institute's (ESRI's) ArcMap (ArcGIS,
154 10.8) to eliminate the 'walls' and the 'depressions' in the cells and thus avoided intense erosion or deposition in the early run
155 time. Then, the non-sink DEM was used as the surface DEM in Scenario UP (UP DEM) without any facilities. According to
156 the engineering control project described in Section 3.2.2, the surface DEM of Scenario PP (PP DEM) included the dams by
157 raising the grid cell elevations by 10 m for the dam in the upper stream and 9 m for the dam in the transitional area. Similarly,
158 the surface DEM in Scenario EP (EP DEM) included the dams in the PP DEM. In addition, two levees were produced by
159 raising the grid cell elevation by 2 m, representing at selected locations. For scenario EP, the placement and setting of the
160 vegetation revetments are introduced in Section 3.2.2.

161 The spatial heterogeneity of the source material (Fig. 1c) indicates the discrepancy in the erodible thickness, which equals the
162 difference between the surface DEM (DEM) and the bedrock DEM (bedDEM). We divided the study area into five regions
163 according to the erodible thickness (Fig. S1) by checking the relative elevation of the foundations of buildings, the exposed
164 bedrock, and the deposition depth of landslides to ground level. The average thicknesses of upstream low- and high-altitude
165 areas were set to 10 m and 3 m, respectively, and the thickness of the erodible layer in the downstream area was set to 3 m.
166 For the river channel and outlet, as there would be a large amount of deposition, the thickness of erodible sediment was set to
167 5 m and 4 m, respectively. As the dams in Scenario PP and the levees in Scenario EP were non-erosive concrete, we set the
168 erodible thickness of these features to 0 m. Eventually, the DEM data were formatted to ASCII raster data as required by C-L.
169 The divided regions varied in erodible thickness, the placement of additional levees and vegetable revetments in Scenario EP,
170 and the generation process of DEMs and bedDEMs are shown in Fig. S1.

171 **3.2.2 Vegetation settings**

172 Another parameter required in each scenario simulation was the m value of the hydrological model (TOPMODEL) within C-
173 L, which controls an exponential decline in transmissivity with depth (Beven, 1995, 1997) and influences the peak and duration
174 of the hydrograph in response to rainfall. The m value effectively imitates the effect of vegetation on the movement and storage

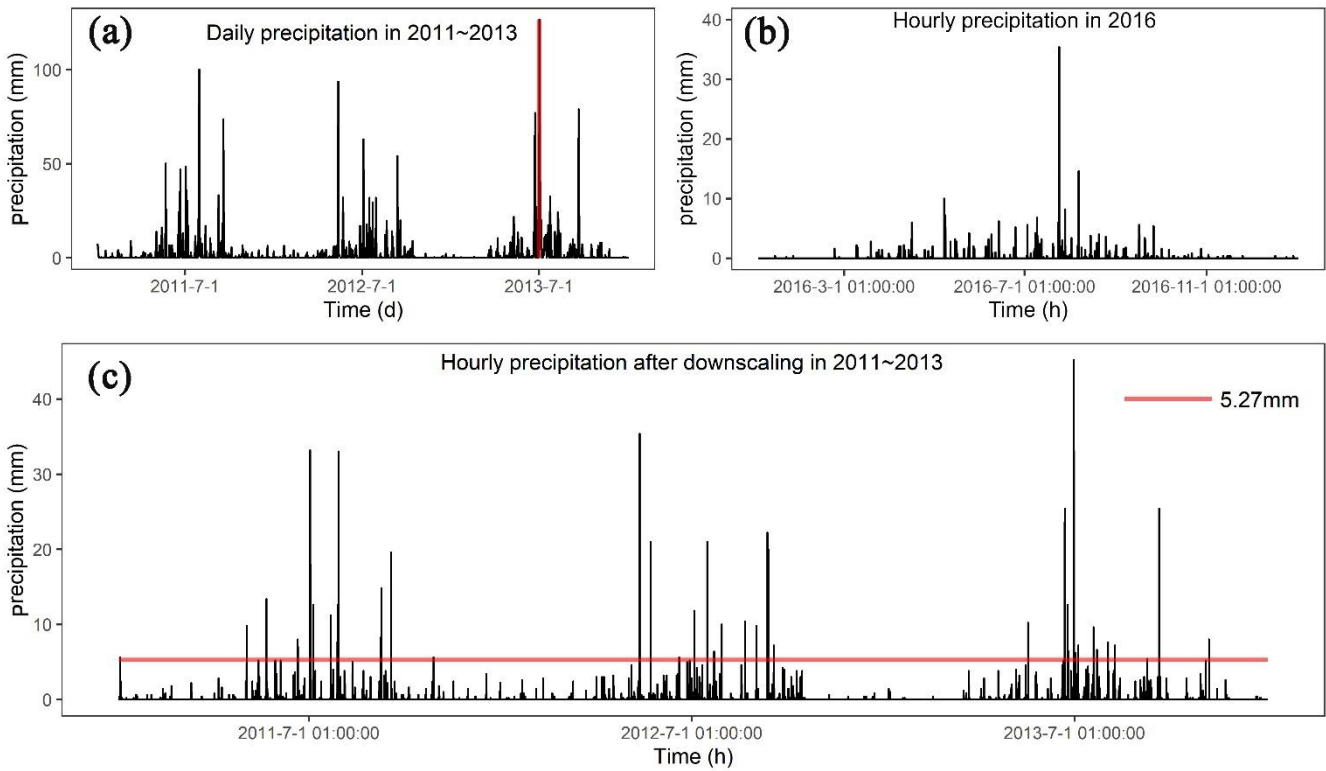
175 of water within the soil. The lower the m value is, the lower the vegetation coverage, and the higher the flash flood peak and
176 the shorter the duration of the flood hydrograph is reflected (Coulthard et al., 2002). The m value is usually determined by the
177 land cover (e.g., 0.02 for forests and 0.005 for grasslands) (Coulthard and Wiel, Van De J., 2017). In our study, we set the m
178 value as 0.008 in our smaller catchment (14 km²) in Scenarios UP and PP, which resembles the m value of farmland covered
179 with lower vegetation coverage in the same catchment studied by Xie et al. (2018) and Li et al. (2018). As mentioned earlier,
180 the upstream-low elevation area covered by the biological measures in the EP scenario was assigned a higher m value of 0.02.
181 This m value was calibrated by the more extensive catchment containing our study area in the flood event of 2013 (Xie et al.,
182 2018).

183 3.2.3 The rainfall data

184 In this research, we compared three scenarios by matching precipitation data between 2011 and 2013, as mentioned in Section
185 3.1. The source data of precipitation in 2011-2013 (Fig. 2a) were obtained from the China Meteorological Administration
186 (<http://data.cma.cn>) with daily temporal resolution. The intensity and frequency of extreme rainfall events affect patterns of
187 erosion and deposition (Coulthard et al., 2012b; Coulthard and Skinner, 2016). Therefore, we used the stochastic downscaling
188 method to generate hourly data to better capture the hydrological events introduced by Li et al. (2020) and Lee and Jeong
189 (2014). The referenced hourly precipitation was observed from the pluviometer located 20 km from the study area in 2016
190 (Fig. 2b), with an annual total precipitation of 684 mm. The observed rainfall in 2016 was characterised by (1) hourly precip-
191 itation between 1.1 mm and 35.4 mm and (2) the maximum and average durations of rainfall events as 24 h and 2.8 h, respec-
192 tively. The main processes of the downscaling method are as follows:

- 193 ● extracting the hourly rainfall of specific days in 2016 closest to the daily rainfall in 2011-2013 through the threshold
194 setting and producing the genetic operators using the extracted hourly rainfall dataset;
- 195 ● mixing the genetic operators by an algorithm (Goldberg, 1989) composed of reproduction, crossover and mutation and
196 repeating until the distance between the sum of hourly rainfall and the actual daily rainfall was less than the set threshold;
- 197 ● normalising the hourly precipitation to keep the daily rainfall value unchanged.

198 Figure 2c shows the downscaled rainfall series between 2011 and 2013. The downscaled hourly rainfall better captured the
199 hydrological events at an hourly scale compared to the hourly mean rain (5.27 mm) on the day with extreme rainfall (126.5
200 mm), which was far from the actual situation. Corresponding to the m value settings, the input of generated hourly precipitation
201 was catchment lumped in Scenario UP and Scenario PP and divided into two separate but identical rainfall events in Scenario
202 EP.



203

204 **Figure 2: (a) Daily precipitation in 2011-2013 (the red vertical line indicates the maximum daily precipitation of 126.5 mm); (b)**
 205 **Hourly precipitation in 2016; (c) Downscaled hourly precipitation in 2011-2013 (the red horizontal line indicates the hourly mean**
 206 **precipitation of 5.27 mm on the day with the maximum precipitation marked in (a)).**

207 3.2.4 Other parameters

208 The C-L model is sensitive to a set of input data introduced by Skinner et al. (2018) for a catchment with a grid cell size of 10
 209 m, such as the sediment transport formula, slope failure threshold, and grain size set. The grain size distribution of sediment
 210 was derived from samplings at 14 representative locations in the same study basin by Xie et al. (2018). Given the grain size
 211 distribution in this study, the Wilcock and Crowe formula was selected as the sediment transport rule, which was developed
 212 from flume experiments using five different sand-gravel mixtures with grain sizes ranging between 0.5 and 64 mm (Wilcock
 213 et al., 2003). Considering the steep slopes on either side of deep gullies, a higher slope failure threshold was determined to
 214 replicate the geomorphic changes between 2011 and 2013. Additionally, we found that the probability of shallow landslides
 215 increased from 20° to 50° in slope gradients between 2011 and 2013 (Li et al., 2018). The slope angle was derived from the
 216 DEM with a 30 m spatial resolution, which caused a lower slope angle than that with a 10 m resolution. As such, we set the
 217 slope angle as 60°, which is lower than the 65° used in a scenario without landslides (Xie et al., 2022) and higher than 50°.
 218 Some parameters were determined by repeated experiments, such as the minimum Q value, and the other input values were
 219 referred to default values recommended by the developers (such as the maximum erosion limit in the erosion/deposition mod-
 220 ule and the vegetation critical shear stress) in <https://sourceforge.net/p/caesar-lisflood/wiki/Home/>. Table S2 in the supple-
 221 mental material presents the model parameters of C-L used in this study.

222 3.2.5 Model calibration

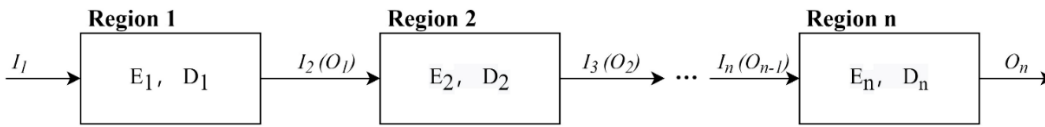
223 Considering the ungauged basins before 2015, we replicated the flash flood event in July 2018 using C-L simulations to cali-
 224 brate the hydrological components. Based on Scenario PP (with two checking dams), we used the two-week hourly precipita-
 225 tion of July 2018 as the input (Fig. S2a), which was recorded by a rain gauge located 2.5 km away from the catchment (Fig.
 226 S2b). The simulation results (Fig. S2c and Fig. S2d) showed an erosion map and a maximum water depth map in Scenario PP
 227 on July 15, 2018. We selected three locations to compare the deposition and inundation in the simulation results with satellite

228 images and photos (Fig. S3). Additionally, the simulated sediment thickness and water depth were close to those measured
 229 from pictures, which indicated that the flash flood event was well replicated by the C-L using the input data.

230 3.3 Output analysis

231 The C-L model outputs of each scenario include hourly water and sediment discharge at the basin outlet and the difference
 232 between DEMs at a specified time and initial DEMs (EleDiffs). We validated the model outputs by comparing the hourly
 233 discharge and EleDiffs reflecting the depth of sediment deposition or erosion (> 0.1 m: deposition, < -0.1 m: erosion) with
 234 field survey materials. The overall temporal and spatial geomorphic changes reflected by EleDiffs under three different sce-
 235 narios were used to assess the geomorphic response to interventions. To explore the geomorphic response to various control
 236 measures, we focused on the notable sites where the checking dams, levees, and vegetation revetments would be located and
 237 recorded the depth of accumulating sediment behind the two dams. To further explore the spatial heterogeneity, we compared
 238 the volumes of deposition and erosion among three divided regions, including the source area, the transitional area, and the
 239 deposit area.

240 Based on the visual analysis and quantitative results, we defined two formulae to assess the effectiveness of the intervention.
 241 The conservation ability (Ca , Eq. (3)) was calculated based on variables in the sediment balance system (Fig. 3). The sediment
 242 volume of deposited sediment (D_n) and input sediment from the upper connected region (I_n) is equal to that of the eroded
 243 material (E_n) and the output sediment to the next part (O_n) over the same period (Eq. (1), Eq. (2)) in the system. A higher value
 244 of Ca in a specific region and scenario indicates a more effective control system.



245
 246 **Figure 3: The sediment balance system in the study area (the Region n indicates the source area, transitional area, and deposit area)**

247

$$I_n = \sum_2^n E_{n-1} - \sum_2^n D_{n-1}, \quad (1)$$

$$I_n + E_n = O_n + D_n, \quad (2)$$

$$Ca = \frac{D_n}{I_n + E_n} \quad (3)$$

248 where n is the region number of the source area (=1), transitional area (=2), and deposit area (=3).

249 Additionally, we designed the relative efficiency (Re , Eq. (4)) to depict the efficiency of intervention measures in Scenario PP
 250 and EP in sediment loss, with the comparison to Scenario UP.

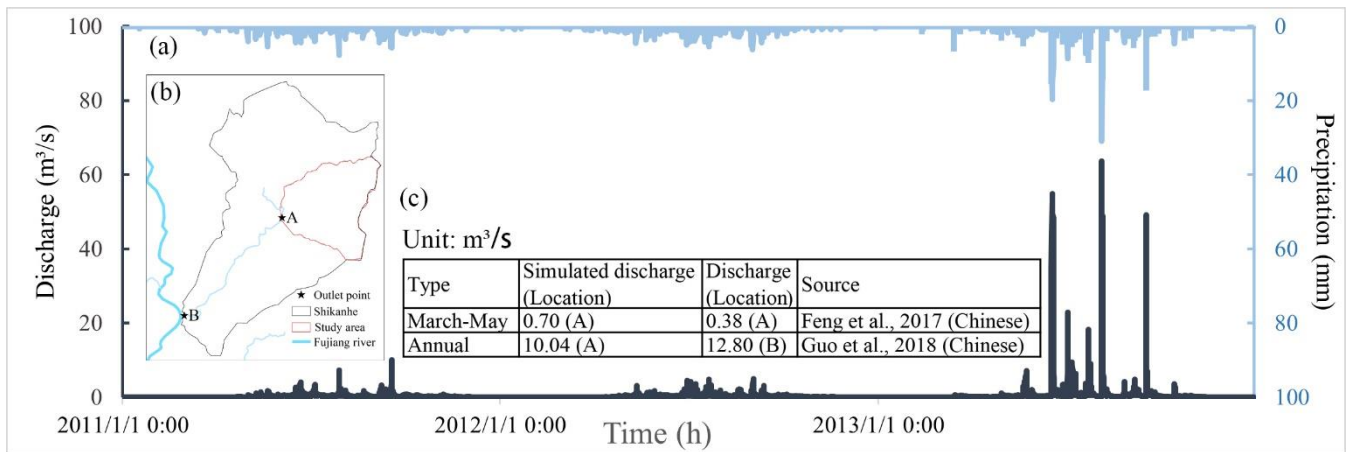
$$Re_{PP/EP,i} = \frac{Q_{UP,i} - Q_{PP/EP,i}}{Q_{UP,i}} \quad (4)$$

251 where i is the sequence of the day; Q_{UP} is the daily sediment yield measured at the catchment outlet in Scenario UP, and $Q_{PP/EP}$
 252 is the same data in Scenario PP or Scenario EP of day i ; and $Re_{PP/EP}$ is the daily relative effectiveness of control measures in
 253 Scenario PP or Scenario EP.

254 **4. Results**

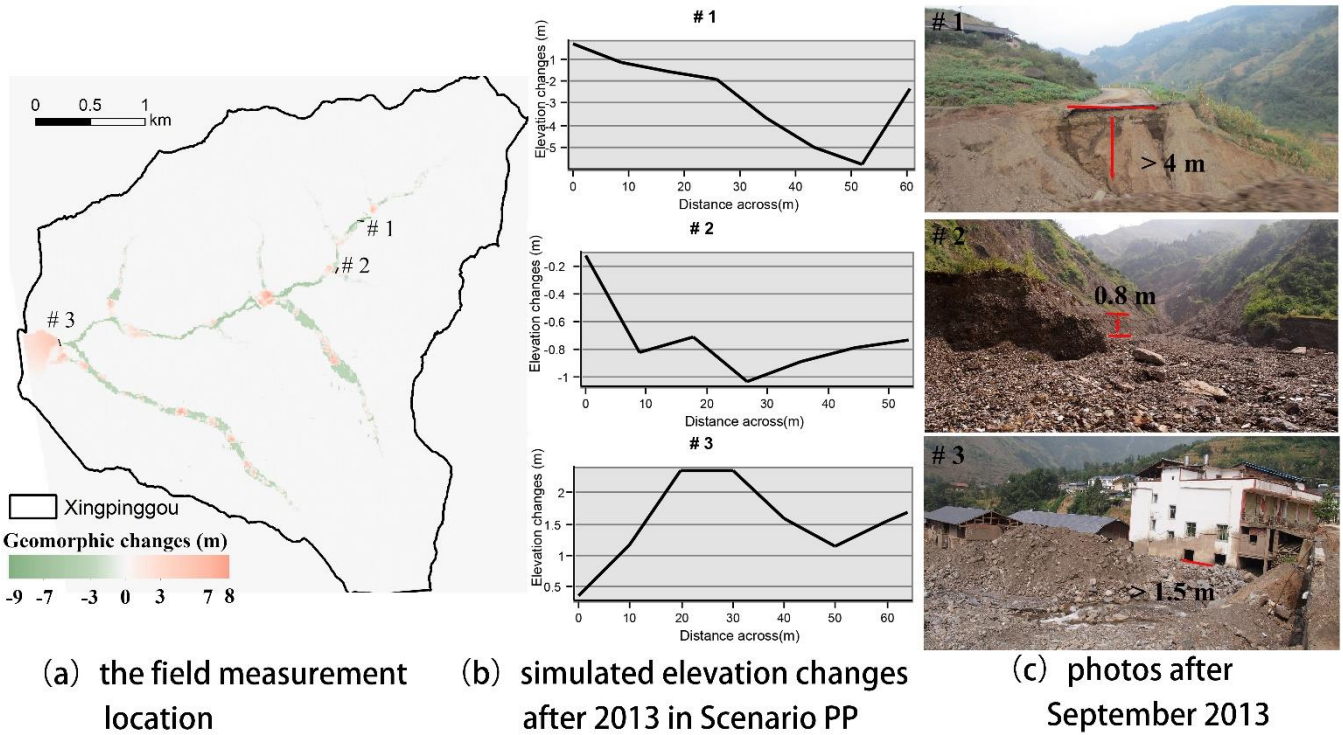
255 **4.1 Model verification**

256 Figure 4 shows the input rainfall data and modelled discharge hydrograph between 2011 and 2013 (Fig. 4a). The comparison
 257 of simulated mean discharge in April through July and the whole year with field survey materials in the two locations are also
 258 presented (Fig. 4b, c). Concerning the discharge hydrograph, the peak discharges (63.7, 54.9, and 50.3 m³/s) correspond well
 259 with the peak rainfall intensities (31, 19.7 and 15 mm). The modelled water discharge from March to May in location A is
 260 slightly larger than the measured value reported by Feng et al. (2017). Additionally, an average annual discharge of 10.04 m³/s
 261 in location A is lower than that of 12.80 m³/s in the catchment outlet (location B), which has an area approximately three times
 262 the size of the study area.



263
 264 **Figure 4: The input and output of the hydrograph. (a) The input hourly precipitation and simulated discharge in 2011-2013 in**
 265 **Scenario PP; (b) The locations of the specified outlet points; (c) A comparison of the simulated average discharge to the recorded**
 266 **discharge.**

267 Typical cross-sections are generated (Fig. 5) based on the replicated landscape changes in Scenario PP. The first site is located
 268 on the upriver road, which is eroded at a depth of 5.7 m according to the simulation results, while the photo shows a depth of
 269 no less than 4.0 m without an apparent eroded base. The cross-section #2 and the site photo of the gully depict that the eroded
 270 depth is approximately 1.0 m. Meanwhile, a clear sediment boundary is found in the building located at the deposited area (#
 271 3), indicating a slightly lower deposition depth than the model predicted.



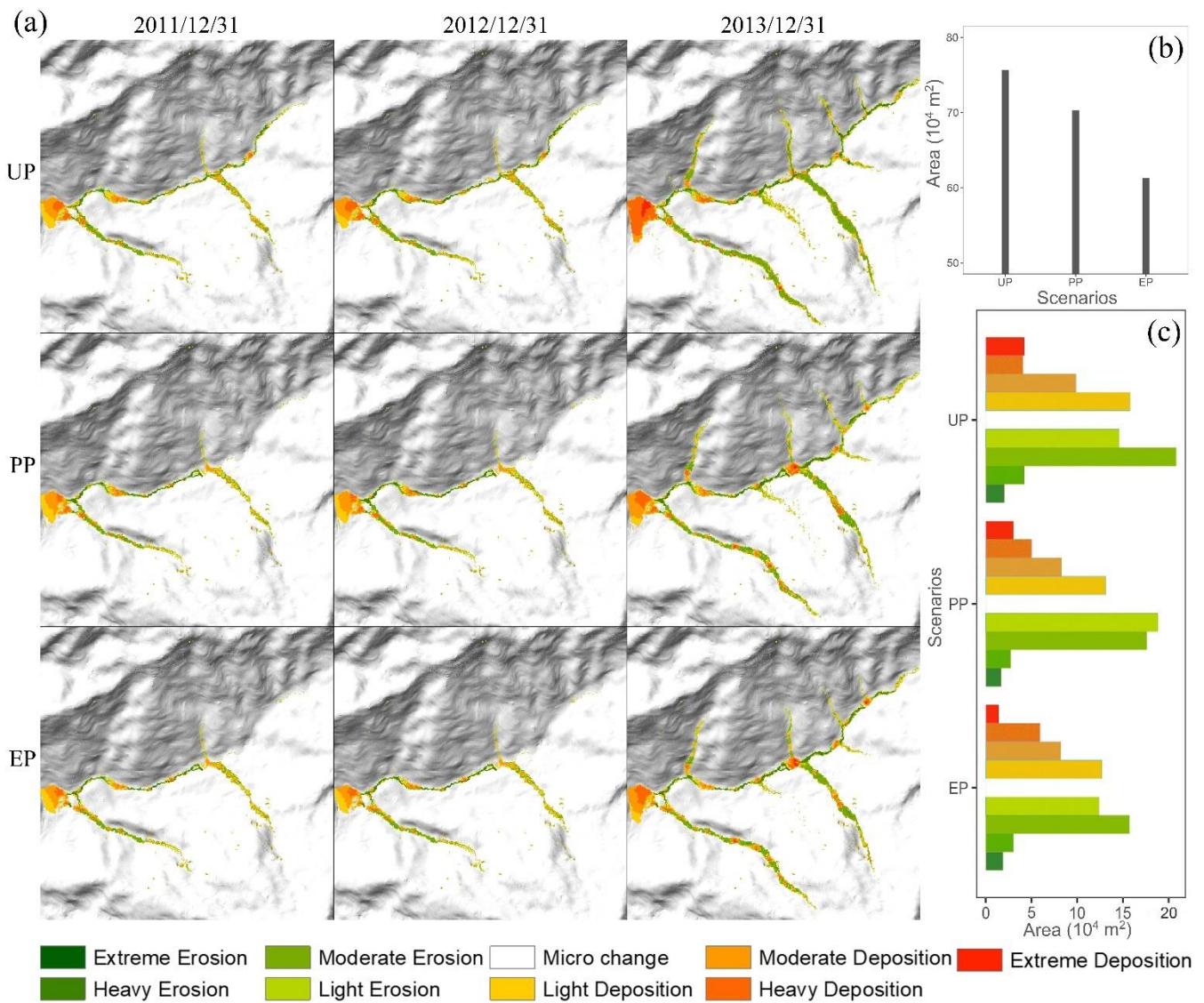
272
273 **Figure 5: The comparison of cross-sections from the simulation results to the field measurements after 2013 in Scenario PP.**

274 **4.2 Overall geomorphic changes**

275 Figure 6a compares the three annual landscape changes in each scenario, which are classified into nine categories by natural
 276 breaks for EleDiffs: extreme erosion (<-7 m), heavy erosion (-7--3 m), moderate erosion (-3--1 m), light erosion (1-0.1 m),
 277 micro change (-0.1-0.1 m), light deposition (0.1-1 m), moderate deposition (1-3 m), heavy deposition (3-7 m), and extreme
 278 deposition (>7 m). A similar spatial pattern of erosion is observed in all three scenarios. More specifically, erosion mainly
 279 emerges in the main channel and the branch valleys, among which the left branches are more pronounced. In contrast, the
 280 depositional zone appears to vary in the three scenarios, especially in the area behind the two dams shown in Scenarios PP and
 281 EP.

282 The total area of affected grid cells representing erosion and deposition for three scenarios are calculated to compare the
 283 damages (Figure 6b). The affected area in Scenario UP is approximately 0.76 km² (5.4% of the total catchment), which is larger
 284 than that in Scenario PP (0.70 km², 5.0% of the whole catchment), and the affected area decreases to 0.61 km² (4.4% of the
 285 total catchment) in Scenario EP. The total area of erosion and deposition decreases gradually with more controlling measures
 286 established in this study.

287 Figure 6c compares the extent of geomorphic changes in three situations using the ranges that varied in depth. The erosion
 288 area of the light one and moderate one is greater than the extreme and heavy erosion area for all three scenarios. The zone of
 289 each erosion degree in UP is more extensive than that in PP, followed by that in EP. In addition, the greater the deposition
 290 depth is, the smaller the deposition covers. In particular, the extreme deposition area is greater than the area of heavy deposition
 291 in the UP scenario. Further analysis shows that extreme, moderate, and light deposition area decrease in the order of UP, PP,
 292 and EP. The heavy deposition area shows the opposite trend, mainly attributed to the checking dams and vegetation revetments.

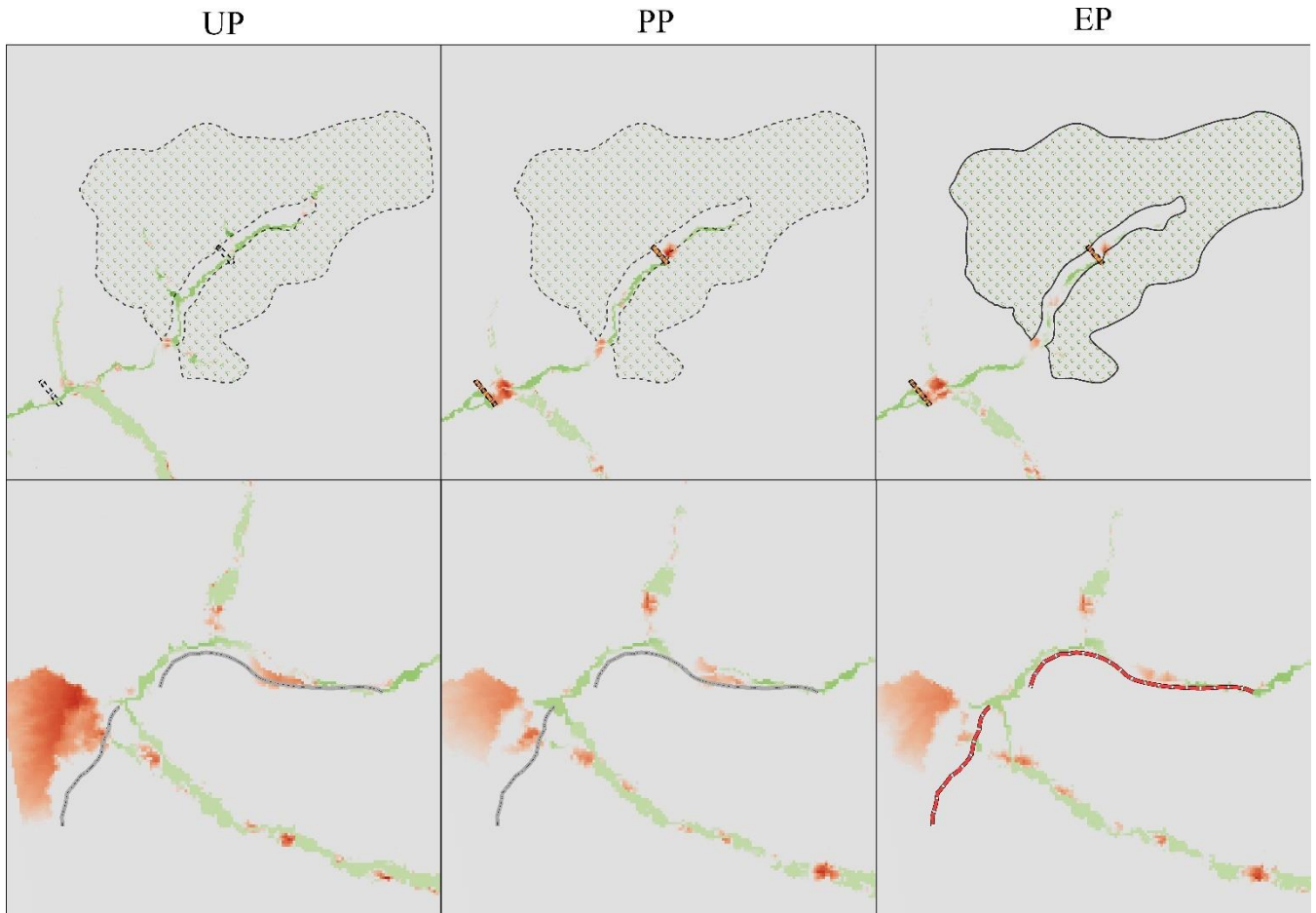


293 **Figure 6: (a) Simulated geomorphic changes over time for the three scenarios; (b) The affected area of deposition and erosion for**
 294 **the three scenarios; (c) The columnar distribution of different erosion and deposition levels.**
 295

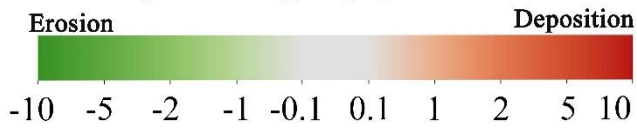
296 4.3 Details of key locations

297 As shown in Fig. 7, the controlling measures and surroundings for the three scenarios are further investigated. Behind the two
 298 dams upriver in Scenarios PP and EP, the evident orange clusters indicate deposition. In contrast, these locations are dominated
 299 by erosion, shown in green in scenario UP. Further analysis of the sediment depth shown in Fig. 8 shows that the deposited
 300 depth behind the dams in Scenario EP is lower than that in Scenario PP. Additionally, in Scenario PP, sediment trapped by dam
 301 1 is less than that of dam 2, but both have deposition thicknesses of more than 10 m, which exceed the dams' heights (dam 1's
 302 height is 10 m, dam 2's height is 9 m). For the simulation results in Scenario EP, the values of deposition depth behind the two
 303 dams are nearly 8 m, which is lower than the dams' heights.

304 The additional biological protection measure alters the material produced from the upriver tributary gullies. A sediment volume
 305 of $14.4 \times 10^4 \text{ m}^3$ is transported from the biological protection area in the EP scenario (solid lines in Fig. 7). A total of 27.1×10^4
 306 m^3 and $16.9 \times 10^4 \text{ m}^3$ of loose material are produced in the same region without biological protection in Scenarios UP and PP,
 307 respectively. The vegetation revetment enhances sediment conservation based on the role of dam 1. Compared with the depo-
 308 sition in UP and PP without levees in the downriver area (shown in the bottom row of Fig. 7), the levees in EP block debris in
 309 the bend of the channel and play an essential role in protecting the residents and cultivated land behind the levees.



Geomorphic changes (m)



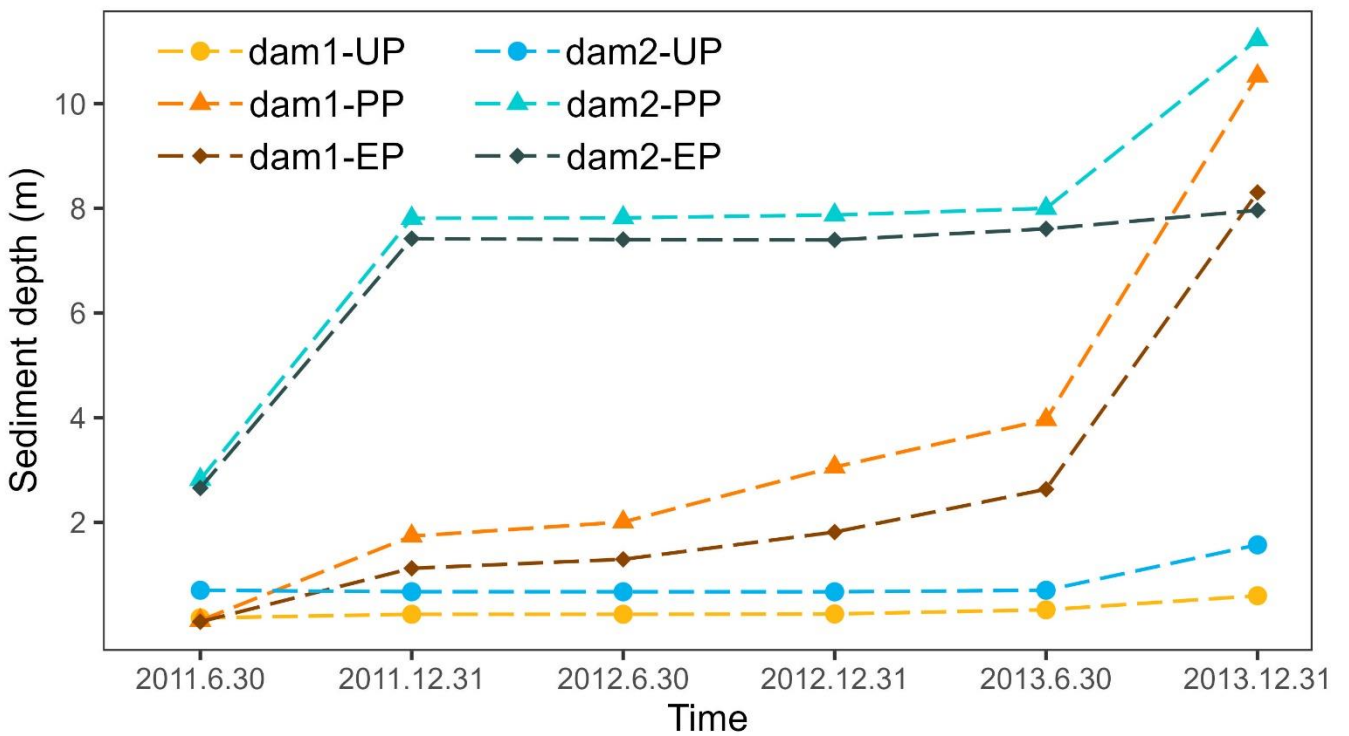
- Unbuilt dam
- Built dam
- No biological protection
- Biological protection
- Built levees
- Unbuilt levees

310

311

312

Figure 7: Geomorphic changes at key locations of the simulation results for the UP, PP, and EP scenarios. The top row is the upriver extent containing dam 1, dam 2 and the vegetation reveget. The bottom row is the downriver extent containing levees.



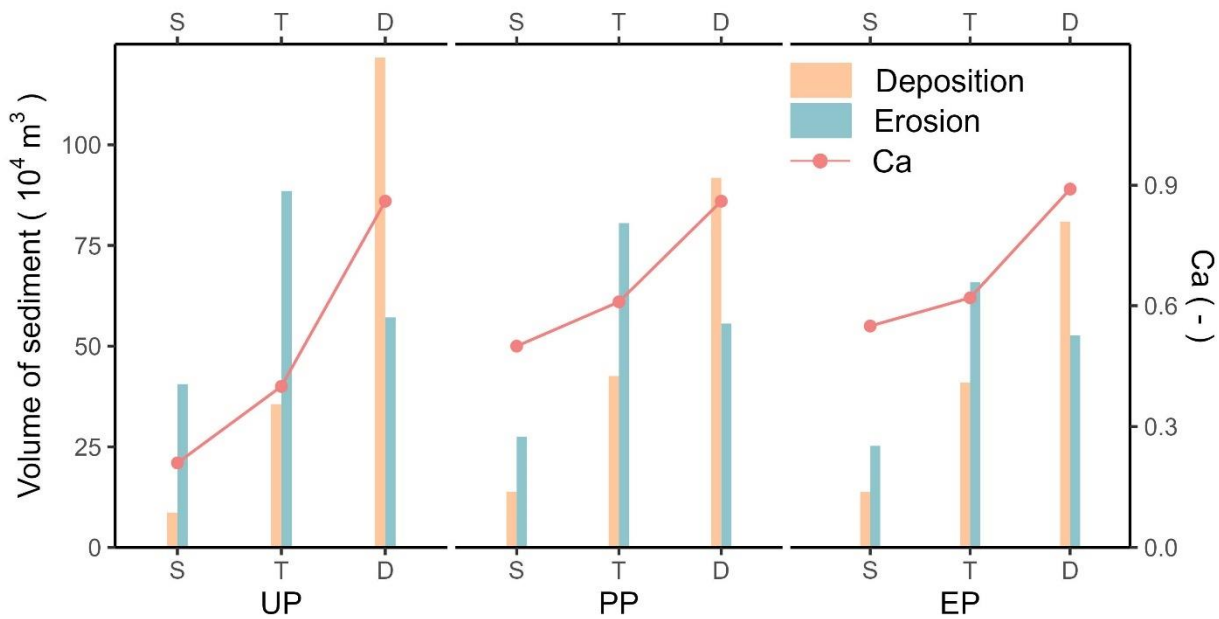
313

314 **Figure 8: The depth of deposited sediment in the dams' placements.**

315 **4.4 Effectiveness assessment of the intervention measures**

316 Figure 9 shows the erosion and deposition volumes in the source, transitional, and deposit areas and compares the conservation
317 ability (Ca) in each scenario. For all three scenarios, the deposition volume in the source area is less than that in the transitional
318 area, and the largest amount of sediment is accumulated in the deposit area. Regarding the eroded sediment, the largest volume
319 is in the transitional area, followed by the transitional area, and the source area presents the lowest volume. Moreover, sediment
320 transport is best controlled in the deposit area and worst contained in the source area under any intervention conditions.

321 Compared with the Ca of the source area in Scenario UP, the value increases by 138.1% in Scenario PP, which is attributed to
322 dam1. Likewise, dam 2 in the transitional area effectively reduces sediment loss, which is reflected by a 52.5% increase in Ca .
323 Furthermore, the mitigation measures in Scenario PP with vegetation revetment and levees in Scenario EP act best. The con-
324 servation ability in the source area increased by 161.9% due to the dam retainment and vegetation revetment, and the levees
325 helped increase the Ca by 3.49% in the deposit area.

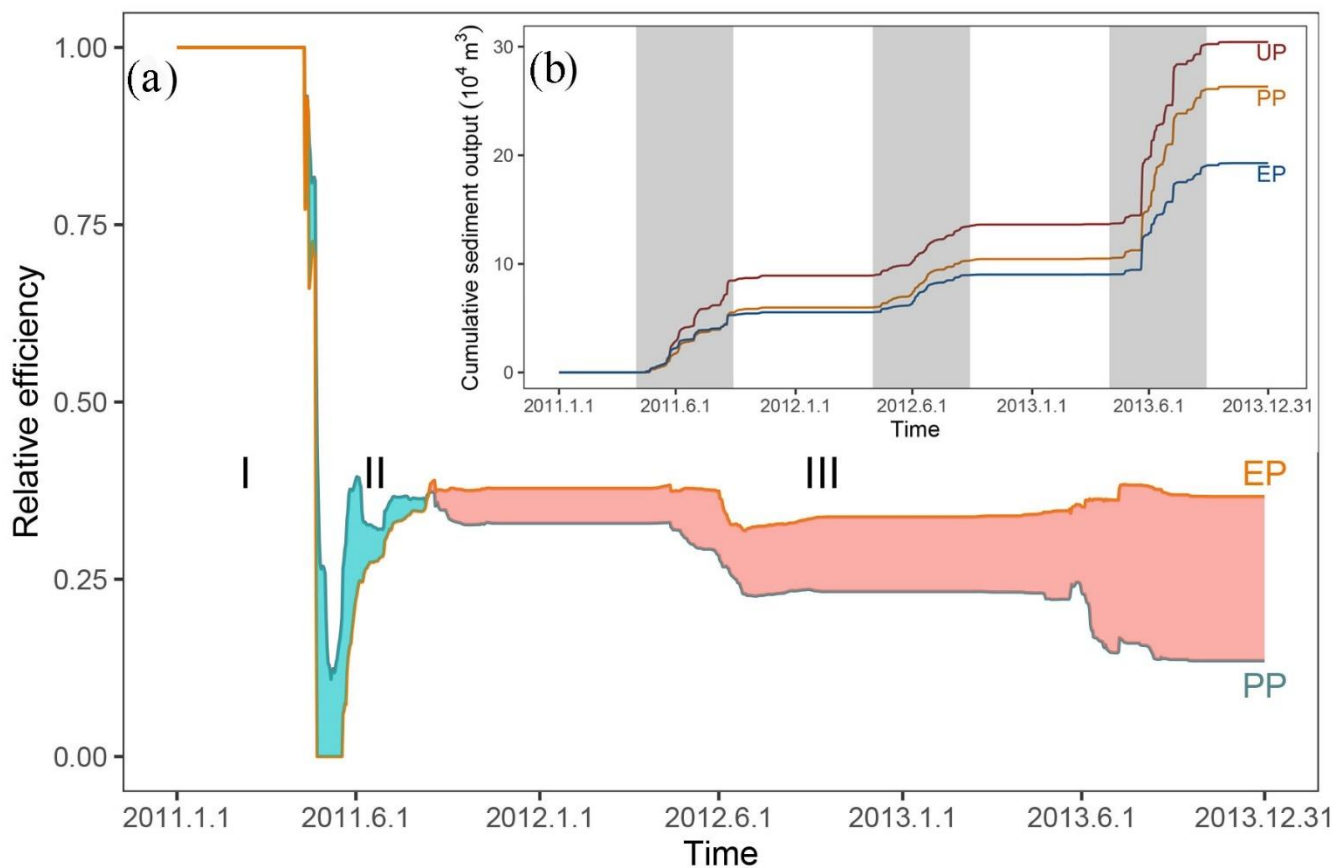


326

327 **Figure 9: The volumes of sediment and the conservation ability (Ca) in the three areas for each scenario (S: source area; T: transi-**
328 **tional area; D: deposit area).**

329 The cumulative sediment yield time series for each scenario and the relative efficiency of scenarios UP and EP are presented
330 in Fig. 10b and Fig. 10a, respectively. The steep curve of the output cumulative sediment indicates a significant increase in the
331 deposition. Three increasing stages are consistent with the rainfall intensity in the three monsoons (May-Sept). The total sedi-
332 ment output in UP is the largest at $\sim 30.4 \times 10^4 m^3$ followed by the sediment yield of PP at $26.3 \times 10^4 m^3$, and EP produced the
333 least material at $19.3 \times 10^4 m^3$.

334 The relative efficiency over the period of controlling measures by human intervention in PP and EP (Fig. 10a) indicates three
335 distinct stages. Stage I shows that the intervention measures in both scenarios completely prevent sediment transport. Later
336 stage II shows a peculiar period when the effect of enhanced protective measures in EP pales in comparison with that in PP
337 through repeated experiments. For stage III, the relative efficiency of the intervention measures in EP is greater than that in
338 UP, which achieves the long-term effect and stable conservation of solid material.



339

340 **Figure 10: (a) Relative efficiency of Scenarios UP and EP compared with the UP (cyan shading represents when PP is more effective**
 341 **than EP and red shading represents the opposite); (b) Cumulative sediment yield over time (grey region highlighting three monsoons).**

342 5. Discussion

343 5.1 Model calibration and uncertainty

344 Calibration and uncertainty are essential issues in the CAESAR-Lisflood (C-L) simulation of the geomorphic response to
 345 intervention measures based on the CA framework (Yeh and Li, 2006). A preliminary calibration was carried out by reproduc-
 346 ing the geomorphic changes and water depth driven by an extreme rainfall event that occurred in 2018. The results (Fig. S3)
 347 demonstrated that the C-L model successfully replicated the flash flood event using the initial conditions and model parameters.
 348 And the calibration of the geomorphic response to the intervention measures was derived from a direct comparison between
 349 the model results and direct measurements (Fig. 4 and Fig. 5). As a result, the simulated water discharge was more than the
 350 measured discharge but with the same order of magnitude. Moreover, the errors of erosion and deposition depth between the
 351 simulation in Scenario PP and photographic evidence at three locations were less than 20%. The results suggest the robustness
 352 of the model settings and parameterisation.

353 The source of uncertainty is mainly from the model parameters and driving factors. Skinner et al. (2018b) provided a detailed
 354 sensitivity analysis of C-L, indicating that the sediment transport formula significantly influences a smaller catchment mod-
 355 elled by 10 m grid cells. The sediment transport law and the Wilcock and Crowe equations (Wilcock et al., 2003) have been
 356 proven suitable in the Xingping valley (Xie et al., 2018, 2022a, b; Li et al., 2020). Nevertheless, the empirical models of
 357 sediment transport overpredict bedload transport rates in steep streams (gradients greater than 3%) (D'Agostino and Lenzi,
 358 1999; Yager et al., 2012). Additionally, the driving factor, the input hourly rainfall data downscaled from the daily sequence,
 359 is an unrealistic situation. Various sediment transport equations and downscaled hourly rainfall data need to be tested in the C-
 360 L model to further decrease uncertainty.

361 5.2 The intervention effects

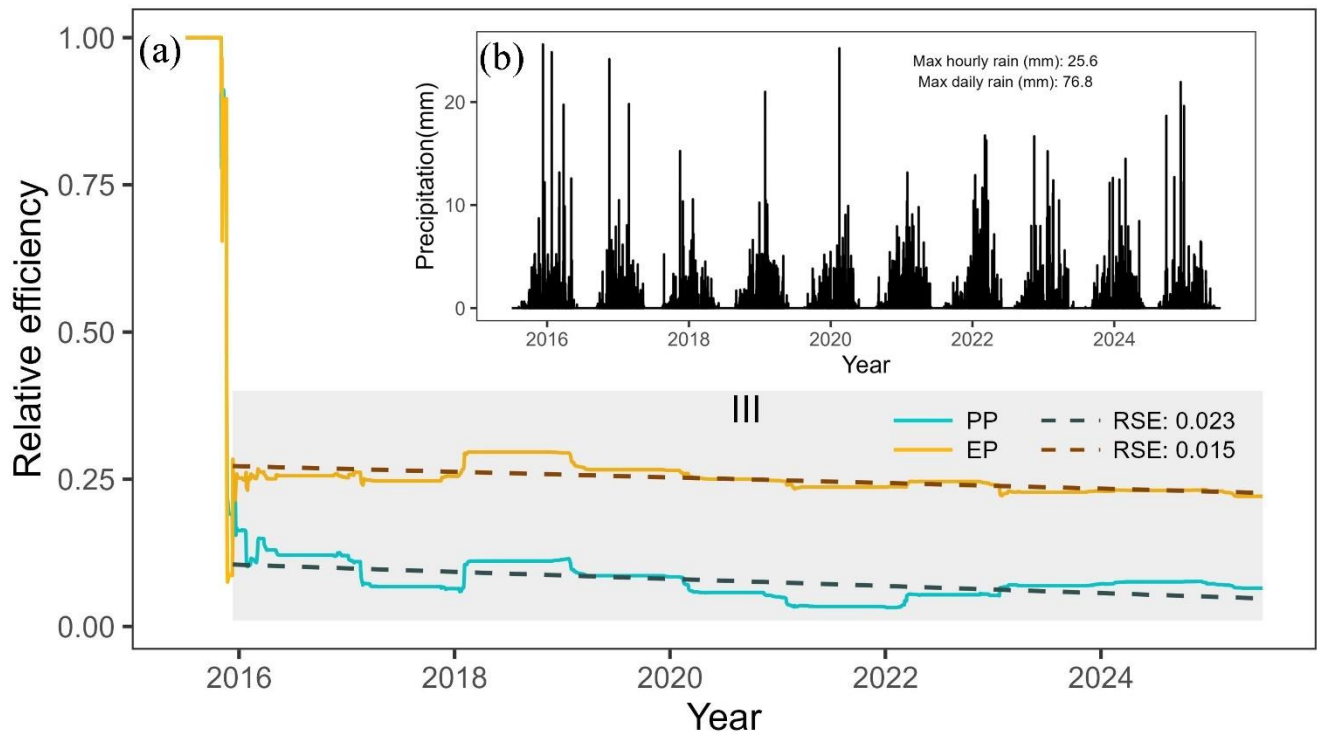
362 In this study, more facilities create more comprehensive intervention systems which aim to control sediment delivery. The C-
363 L model simulated the geomorphic responses to intervention measures and suggested the considerable influence of intervention
364 measures on spatial modifications and sediment yield. The intervention measures lead to fewer total affected areas (7.9%-
365 19.7%) and lower sediment yields (16.7%-36.7%), which are suggested in the overall evidence (see Fig. 6 and Fig. 10). The
366 model's prediction of the overall catchment-scale dynamics due to extreme events is in line with the viewpoints of other authors
367 (Chen et al., 2023; Lan et al., 2020; Chen et al., 2015).

368 The mitigation measures considerably change the soil conservation ability in the three subregions, especially in the source area.
369 We hypothesise that the two main reasons for the decreased erosion in the source area compared to the other two subregions
370 can be inferred from the interactions of loose material and topographic constraints. First, the abundant loose solid material
371 formed by the strong earthquake has stabilised overall since the 2008 debris flow (details in Table S1). Second, the long and
372 deep gullies are mainly located in the transitional area (Yaogouli, Shicouzi, Yangjiashan) and deposit area (Qinggangping),
373 which provide more sediment supply than the source area. As shown in Fig. S4, the movement of the material occurs mainly
374 in the branch valleys in the transitional and deposit zones.

375 Moreover, morphological details and the conservation ability of the three scenarios show the unique role played by different
376 intervention measures. For example, check dams are most effective in blocking sediment, and vegetation revetments strengthen
377 the conservation ability. The synergetic effect of the soil conservation ability increases by more than two-fold due to the com-
378 bination of the check dams and the vegetation coverage. The levees are barriers with a discernable impact on sediment con-
379 servation but with specific object-oriented protection.

380 The effectiveness of mitigation measures decreases over time with a smaller downward trend. We supplemented a ten-year
381 experiment to reveal the declining trend over an extended period. We randomly selected one of the 50 repeated rainfall datasets
382 (year 2016-year 2025) downscaled by Li et al., 2020, which were generated from the NEX-GDDP product (spatial resolution:
383 $0.25^{\circ} \times 0.25^{\circ}$, temporal resolution: daily) under the RCP 4.5 emission scenario. The extracted rainfall sequence was then input
384 into the C-L model to simulate the effectiveness of the three intervention scenarios. The result (Fig. 11) illustrates that stage
385 III (the stable stage that started on the 161st day, in which Scenario EP's intervention measures were more effective) lasted
386 longer than stages I and II. The relative effectiveness in both the PP and EP scenarios decreased gradually, while the curve fell
387 faster in the PP scenario (slope: -1.65×10^{-5}) than in the EP scenario (slope: -1.31×10^{-5}).

388 The storage capacity of the checking dams fades with the sediment accumulated, which necessarily leads to a gradual decrease
389 in intervention effectiveness. Additionally, vegetation revetments remain operationally effective in reducing sediment transport
390 by stabilising topsoil over the period when the role of dam reservoirs gradually fails due to the lack of dredging work. Therefore,
391 the vegetation protection strategy is vital for "green development" to reduce sediment loss but requires further efforts.



392

393 **Figure 11: Rainfall input of ten years and relative efficiency of sediment intervention measures. (a) Relative efficiency changes over**
 394 **ten years (the grey region highlighting stage III, and the dashed lines indicate the linear fitting curves); (b) Rainfall downscaled from**
 395 **NEX-GDDP (NASA Earth Exchange Global Daily Downscaled Projections) product.**

396 5.3 Limitations and applications

397 We built the dams and levees in our simulations by increasing the elevation in the expected location and assuming that it could
 398 not be eroded (see <https://sourceforge.net/projects/caesar-lisflood/>). This method proved experimentally feasible (Poeppl et al.,
 399 2019; Gioia and Schiattarella, 2020). The rigid dam and levee body embedded in the model were not broken or weakened over
 400 time so that the simulation result could underestimate the geohazard risk. Considering the complexity of the geo-hazard mech-
 401 anism, the abovementioned tools cannot simulate the occurrence process of geo-hazard chain links. They ignore the possible
 402 instantaneous damage to the environment and facilities downstream. Some typical geohazard chains have focused on specified
 403 events in the short term and recreated the hazard lifecycle using physical and mechanical models (Fan et al., 2020).

404 The methods applied in the study further demonstrate that the C-L model is an effective tool for understanding short- to med-
 405 ium-term or long-term geomorphological changes (Ramirez et al., 2022; Li et al., 2020; Coulthard et al., 2012a) and observing
 406 the effectiveness of natural hazard intervention measures under different rainfall patterns. Our simulations indicate that the
 407 mitigation facilities in this study are effective, especially engineering efforts incorporating vegetation revetments in the up-
 408 stream area, which would help decision-makers optimise the management strategies to control mountain disasters. Geotech-
 409 nical engineering has disadvantages, even though it is a mature technology that identifies and fixes problems quickly (Cui and
 410 Lin, 2013), such as the need for extensive labour and expense and the difficulty of maintenance. While “green development”,
 411 the planting and maintenance of vegetation cover can effectively prevent erosion by strengthening topsoil and absorbing excess
 412 rainwater via roots (Reichenbach et al., 2014; Stokes et al., 2014; Forbes and Broadhead, 2013; Mickovski et al., 2007). Alter-
 413 natively, these methods can be used to study tree planting patterns on different slopes.

414 6. Conclusions

415 In this study, scenarios involving check dams, biological measures and artificial barriers were simulated using the C-L model
 416 to outline the erosion and deposition area, measure the impacts of blocking sediment, and examine how vegetation revetments
 417 help stabilise slopes. Four key findings are concluded. First, the engineering measures used for controlling sediment transport

418 are efficient, and the performance in protecting the fragile environment can be improved by combining these engineering
419 efforts with other intervention measures, such as vegetation revetments and artificial barriers. Second, the effectiveness of
420 mitigation measures decreases over time. Third, the characteristics of the sediment transport patterns alter considerably due to
421 the intervention measures. The stabilising sediment ability in the source area increased by 161.9% with the additional effect
422 of vegetation revetments. Finally, the present intervention measures need to be revised to reduce erosion and should be com-
423 bined with dredging work.

424 **Declaration of interest statement**

425 The authors declare that they have no known competing financial interests or personal relationships that could have appeared
426 to influence the work reported in this paper.

427 **Author contribution**

428 Di Wang: Conceptualisation, Methodology, Software, Writing-original draft preparation. Ming Wang Kai Liu and Jun Xie:
429 Supervision, Methodology, Writing- Reviewing and Editing, Validation.

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433 the freely available C-L model (<https://sourceforge.net/projects/caesar-lisflood>).

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