

1 **Towards Flash Flood Modeling Using Gradient Resolving**
2 **Representative Hillslopes**

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29 **Key Points**

- 30 • Physically based representative hillslope models resolve the main gradients
31 controlling overland flow, a key requirement for modelling flash floods in small,
32 data-scarce and rural catchments.
- 33 • Climate reanalysis data enable the initialization of a process-based model,
34 establishing plausible initial conditions for event-based flash flood modelling that
35 can guide the design of retention basins in small to medium sized catchments.
- 36 • Transfer of model parameters from past experiments to data-scarce catchments
37 within the same hydrological landscape is feasible and water level measurements
38 at flood defense reservoir can be used for model building and testing.

39 **Abstract**

40 It is increasingly acknowledged that the acceleration of the global water cycle, largely
41 driven by anthropogenic climate change, has a disproportionate impact on sub-daily and
42 small-scale hydrological extreme events such as flash floods. These events occur thereby
43 at local scales within minutes to hours, typically in response to high-intensity rainfall
44 events associated with convective storms. Despite their local scale and rapid onset, the
45 effects of flash floods can be devastating, making their prediction and mitigation of critical
46 importance. However, the modeling and analysis of such events in data-scarce regions
47 present a unique set of challenges. In the present work, we show that by employing
48 physically based representative hillslope models that resolve the main gradients
49 controlling overland flow hydrology and hydraulics, we can get reliable simulations of
50 flash flood response in small data-scarce catchments. To this end, we use climate
51 reanalysis products and transfer soil parameters previously obtained for hydrological
52 predictions in an experimental catchment in the same landscape. The inverted mass
53 balance of flood reservoirs downstream is employed to derive a target data set for model
54 evaluation in these nearly ungauged basins. We show that our approach using
55 representative hillslopes and climate datasets can provide reasonable uncalibrated
56 estimates of the overland runoff response (flood magnitude, storm volume, and event
57 runoff coefficients) in three of the four catchments considered. Given that flash floods
58 typically occur at scales of a few km² and in ungauged places, our results have
59 implications for operational flash flood forecasting and the design of small and medium
60 flood retention basins around the world.

61 **Plain Language Summary**

62 Flash floods have become increasingly common worldwide, with catastrophic damages
63 to both human life and the economy. While the extent of global warming and climate
64 change impacting these events is still under much debate, it is almost certain now that we
65 need to be better equipped to understand and model these extremes to prevent and
66 mitigate the possible risk to human life and infrastructure in a warming climate. To test,
67 if we can use first principles derived from thermodynamic conservation laws and process
68 based hydrological models for the same, we modelled flash flood response in four
69 headwater catchments over Southern Germany using the concept of ‘representative
70 hillslope’. Since the regions considered in our work are nearly ungauged, we made use of
71 global climate reanalysis products and parameter transfer from past experiments. The
72 encouraging results obtained in predicting the flood magnitude and volume speak to the
73 overall applicability of our approach. We are able to get decent uncalibrated predictions
74 in three out of the four catchments considered with minimum computational effort.
75 However, as the results in one of the catchments show, further research and modelling
76 experiments are required to advance the applied methodology for the design of flood
77 mitigation measures and operational flash flood forecasting. Understanding and
78 managing the adverse impacts of such extreme hydroclimatic events remains one of the
79 crucial hurdles facing humanity towards the sustainable development goals (SDG17) in
80 this decade.

81 ***Keywords – flash floods, ungauged basins, physically based models, parameter transfer,***
82 ***representative hillslopes.***

83 **1 Introduction**

84 As early as 2008, the Organisation for Economic Co-operation and Development (OECD)
85 highlighted climate change and hydro-meteorological extremes as some of the most
86 pressing challenges facing humanity. Flood events, a key component of these extremes,
87 manifest at varying spatial and temporal scales, each driven by distinct meteorological
88 conditions. Flash floods, for instance, occur on local scales within a span of minutes to
89 hours. These events are triggered by high-intensity rainfall from convective storms,
90 resulting in infiltration excess and significant overland flow (Bronstert et al., 2018;
91 Marchi et al., 2016, 2010; Meyer et al., 2022; Ruiz-Villanueva et al., 2012). While these
92 floods pose immediate risks, such as loss of human life, their consequences extend to
93 long-term impacts like soil erosion, sediment transport, and subsequent deterioration of
94 water quality and soil fertility, particularly in agricultural settings. On the other end of
95 the spectrum are large-scale riverine floods, which occur due to synoptic scale low-
96 pressure systems characterized by widespread and sustained precipitation. Unlike flash
97 floods, these events are governed by capacity-controlled runoff formation processes like
98 saturation excess, known as Dunne overland flow (Dunne and Kirkby, 1978), and
99 subsurface storm flow. Additionally, flood routing in channel networks and snowmelt
100 contributions, play crucial roles (Blöschl et al., 2007). This stands in contrast to the
101 Hortonian overland flow (Horton, 1933) typically observed in flash floods driven by
102 convective storms.

103 Flood forecasting and risk management have to cope with both types of flood events, and
104 both are naturally highly sensitive to climate change (IPCC, 2021). The largest observed
105 floods in many European rivers have occurred in the last three decades, which count
106 among the most flood-rich periods in the past 500 years (Blöschl et al., 2020). With
107 respect to local flash floods, the situation seems not better. For instance, 22 flash floods
108 in southwest Germany occurring in the past 20 years, had estimated design return
109 periods exceeding 500 years (Göppert, 2018). This is in line with the recent accumulation
110 of flash floods in Europe (Meyer et al., 2022), which likely reflects the already ongoing
111 acceleration of the hydrological cycle, with expected increasing frequencies of more
112 intense convective rainstorms and flash floods due to Clausius-Clapeyron scaling (Pall et
113 al., 2007). This is alarming, as the flash flood series in the summer of 2016 alone caused
114 about €2.5 bn of damage in Germany (Munich Re, 2016). All this recent evidence calls for

115 improving the current standards in a) flood predictions and b) methods for deriving
116 hydrological extreme values for design.

117 Considerable progress has been made in alert systems for riverine floods (Borga et al.,
118 2011; Thielen et al., 2009). These systems rely on ensemble numerical weather
119 predictions and conceptual hydrological models such as LARSIM (Bremicker, 1998), HBV
120 (Hundecha and Bardossy, 2004) or LISFLOOD (van der Knijff et al., 2010). Conceptual
121 hydrological models simulate rainfall-runoff generation using linear reservoir concepts
122 characterised by effective fluxes, states, and effective parameters (Hrachowitz and Clark,
123 2017). Despite their simplicity, countless studies have shown that they capture capacity-
124 controlled runoff generation processes quite well (Berkowitz and Zehe, 2020). Today it
125 is known that conceptual models provide reliable predictions of streamflow for
126 catchments larger than 200 km² (Zehe et al., 2014), explaining their widespread and
127 successful operational use.

128 Despite their success, conceptual models, like every model, also have limitations. They
129 usually give lumped integral responses and do not provide detailed information on how
130 each principal component within the model interacts (Fatichi et al., 2016). Predictions
131 are also subject to model structural uncertainty as several parameter sets may reproduce
132 the target discharge data within the learning phase in an acceptable manner (Beven and
133 Binley, 1992). While multi-response calibration is generally well suited to reduce
134 parameter uncertainty, this venture is not straightforward in the case of conceptual
135 models, as their parameters and states cannot be measured directly (Berkowitz and Zehe,
136 2020; Hrachowitz and Clark, 2017). This has crucial implications for the transfer of such
137 models to ungauged regions. In most cases, they do not perform well in regions outside
138 their calibrated range. In the context of flash flooding this is of key importance, as these
139 events are rare, typically impacting small catchments or even specific hillslopes which
140 are often ungauged. They are thus tricky and challenging to observe with conventional
141 rain and discharge measurement networks (Borga et al., 2008), which implies that the
142 sample for model learning and testing is small. Hence they are strongly related to the
143 classical ‘predictions in ungauged basins - PUB problem’ (Hrachowitz et al., 2013;
144 Sivapalan et al., 2003), which implies the estimation of either the occurrence frequency
145 or forecasting the hydrological response using current/future climate and topographic
146 inputs without the benefit of past observational time series for direct model calibration.

147 Here, we propose that gradient resolving, physically based hydrological models (Fatichi
148 et al., 2016; Paniconi and Putti, 2015) are well suited to address the challenges of flash
149 flood predictions in such data scarce regions. By solving coupled partial differential
150 equations (PDEs) that represent infiltration, soil moisture dynamics, runoff, streamflow
151 and evaporation in space and time, such models allow for spatially distributed
152 simulations of extreme flash floods (Pérez et al., 2011; Steinbrich et al., 2016; Zehe et al.,
153 2001).

154 Our primary aim is to evaluate the efficacy of gradient-resolving, physically based
155 hydrological models for predicting flash floods triggered by convective rainstorms in
156 data-scarce regions. Further, we aim to explore the feasibility of operationalizing these
157 models for the design of small and medium reservoirs in such regions. One of the primary
158 challenges in employing physically based models lies in their 'data greed,' requiring
159 extensive input data, as well as the computational expense involved in running the
160 models. To mitigate the data requirement challenge, we propose to leverage existing
161 information from well-studied past catchments within the same hydrological landscape.
162 Specifically, we suggest utilizing these well-instrumented catchments as 'donor
163 catchments' to transfer model structures and parameters to target catchments that are
164 poorly instrumented but share similar hydrological characteristics (Figures 1 & 2T).
165 Specifically, we explore:

- 166 1. Is it feasible to transfer model parameters from a past monitored experimental
167 catchment to data-scarce catchments for uncalibrated flash flood predictions in
168 response to increased convective storm activity?
- 169 2. To overcome the computational expense challenge, we explore whether *the*
170 *representative hillslope* concept (Loritz. et al. 2017; see section 3.1) is an effective
171 way to reduce computation burden, while maintaining a balance between model
172 complexity and data requirements?

173 As study areas, we selected several headwaters upstream of flood defence reservoirs in
174 South West Germany, operated by the Elsenz-Schwarzbach Water Board (Zweckverband
175 Hochwasserschutz Elsenz-Schwarzbach, 2016). In June 2016, several of these flood
176 reservoirs were overtopped in response to a convective rainstorm. While these
177 catchments are in the same hydrological landscape as the previously monitored
178 Weiherbach experimental headwater shed (Zehe et al., 2001), they are, despite the

179 available water level gauges in the reservoirs, completely unmonitored with respect to
180 rainfall, streamflow and soil moisture. To overcome the related challenges, we
181 investigate:

- 182 3. Can climate reanalysis data initialize process-based hydrological models and
183 transition to higher-resolution radar precipitation data without requiring
184 recalibration during flood simulations?
- 185 4. Is reservoir mass balance inversion a reliable method for estimating storm
186 hydrographs during flash flood events and how does the inherent uncertainty of
187 such floods affect design considerations?

188 **2 Venue and Model**

189 **2.1 Study Area**

190 The four headwater catchments (in this study referred to as W22, W32, W39 and W44)
191 belong to the Elsenz-Schwarzbach catchment in the State of Baden Württemberg,
192 Southern Germany (Figure 1 & Figure B1 in Appendix B). The catchment is located within
193 the eastern “Kraichgau”, west of Bad Rappenau and around 50 km from the nearest cities
194 - Heidelberg and Karlsruhe. Due to a series of catastrophic flooding episodes in 1993-94,
195 a comprehensive flood protection concept for the entire region was envisaged, which led
196 to the development of local flood retention basins throughout the catchment area. The
197 size of the catchments varies from 1-6 km²; they all drain into the Krebsbach, which joins
198 into the Schwarzbach near Waibstadt (the nearest gauging station – Eschelbronn
199 Schwarzbach, being more than 12km from our study area). The Elsenz-Schwarzbach
200 finally merges into the Neckar, one of the Rhine's largest tributaries. From Figure 1, it is
201 clear that even though the catchments are primarily agricultural in nature (major crops
202 being – cereals, maize, sugar beets and potatoes), they are situated upstream of the
203 population centres of the region. As flooding could have catastrophic impacts on human
204 life and establishment, these settlements have been protected by regulated flood defence
205 reservoirs.

206 During the end of May to early June 2016, several strong convective rainfall events
207 clustered in Germany because of persistent atmospheric conditions (Bronstert et al.,
208 2018; Meyer et al., 2022; Piper et al., 2016). Rain totals exceeding 100 mm were reported
209 in a day, triggering flash floods in many small catchments over Southern Germany. The
210 impacts in the Elsenz-Schwarzbach were also severe, with several of the flood control

211 reservoirs being overtopped. To investigate the feasibility of our approach (Figure 2) and
212 of the CAFLOW model to simulate such events, we focus our attention on the severe event
213 of 08 June 2016 in the region (Appendix -B). Since no streamflow gauges are available for
214 the four headwater catchments, we use the water level measurements in the flood control
215 reservoirs to estimate the runoff response based on the reconstructed reservoir inflow
216 (W22, W32, W39 and W44). The storm runoff response is calculated based on inverting
217 the reservoir mass balance with the knowledge of the reservoir geometry and stage-
218 outflow relationship (Appendix-C). Related uncertainties are accounted for by using a
219 relative percentage error value (5%) in the stage level measurements.

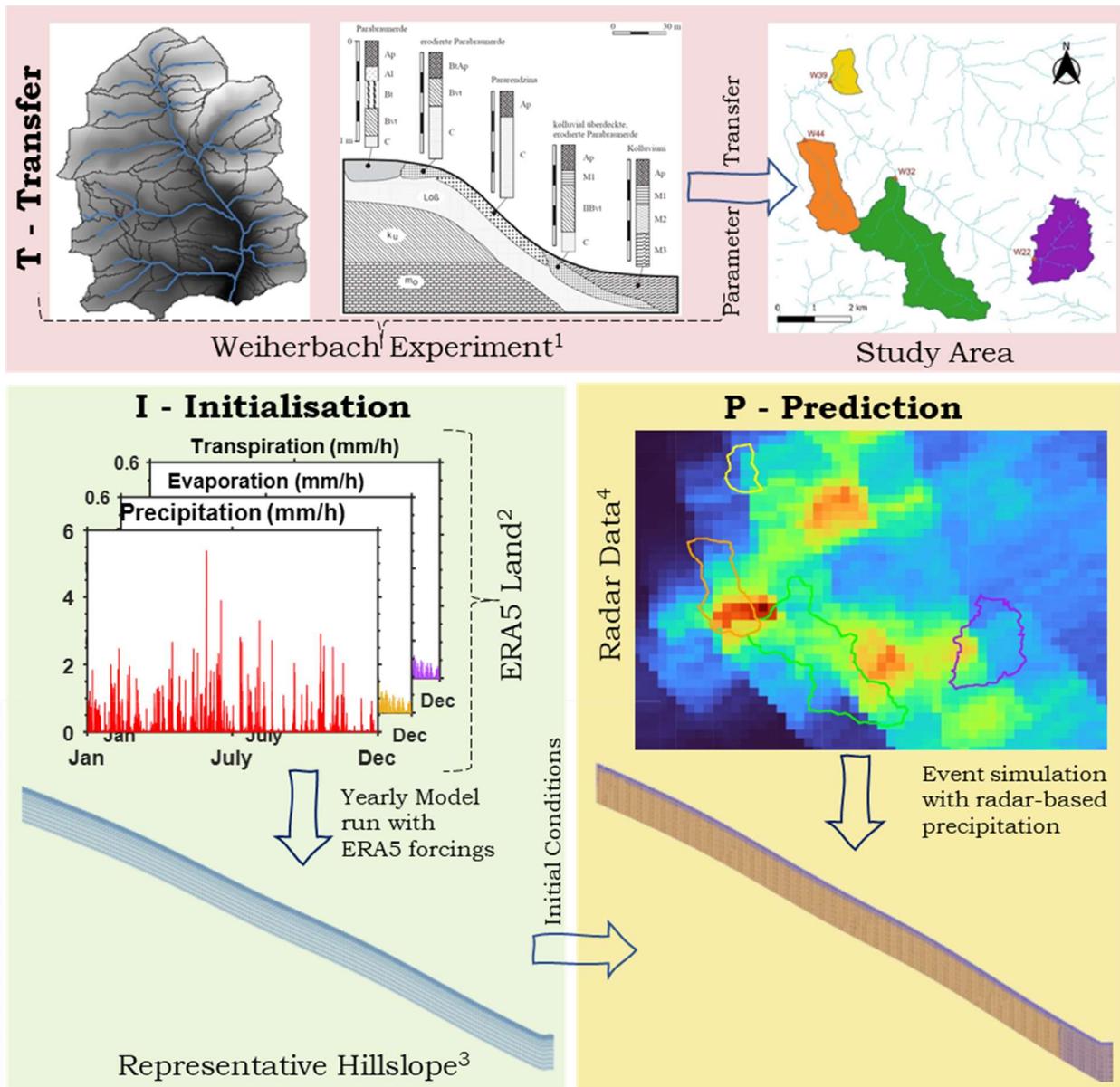


220 Figure 1 Overview of the location of the four headwater catchments considered in the study. Also,
221 shown in the figure are the downstream flood control reservoirs, which afford protection to the
222 towns in the region. The overlay layer depicts a Sentinel-2 (Drusch et al., 2012) multispectral true
223 colour composite image showing the major land use patterns during May-June 2016. Figure B1 in
224 Appendix B shows the stream network of Krebsbach and Schwarzbach and also the total
225 accumulated precipitation during the event.

226 **2.2 CATFLOW in a Nutshell**

227 The quest for accurately identifying and modelling the governing processes of water
228 balance and reactive pesticide transport in rural catchments motivated both the setup of
229 the Weiherbach experimental catchment in the 90's (Plate and Zehe, 2008; Zehe et al.,
230 2001) and the development of the process-based model CATFLOW (Zehe et al., 2001).
231 The model relies on the subdivision of a catchment into several 2D hillslopes and an
232 interconnected drainage (optional) and river network. However, each hillslope is
233 modeled separately and hence this provides the opportunity to run each hillslope
234 individually without the associated stream network. Hillslopes are discretised along a
235 two- dimensional cross section using terrain following curvilinear orthogonal
236 coordinates. Soil water dynamics within the hillslopes are characterized using the
237 potential based form of the 2D Darcy–Richards equation, solved by a mass conservative
238 Picard solver using adaptive time stepping (Celia and Bouloutas, 1990). Soil hydraulic
239 properties can be parameterised according to van Genuchten (1980) and Mualem (1976),
240 Tang and Skaggs (1977) or the recently proposed PDI model (Peters et al., 2021)

241 Overland flow is simulated using the diffusion wave approximation of the Saint-Venant
242 equation and explicit upstreaming, in combination with the Gauckler-Manning-Strickler
243 formula. The model can optionally account for rills (Schroers et al., 2022), sediment
244 transport (Schroers et al., 2023) and reactive transport of solutes (Klaus and Zehe, 2010).
245 Evaporation and transpiration are usually simulated using a SVAT (Surface Vegetation –
246 Atmosphere Transfer) module based on the Penman–Monteith equation, accounting for
247 annual cycles of plant phenology, albedo, and roughness using tabulated data. Stomatal
248 conductance is characterized after Jarvis (1976), or via the inversion of sap flow data
249 (Loritz et al., 2022). CATFLOW has been used in numerous landscapes to explore
250 watershed functioning, the predictability of (flash) flooding (Villinger et al., 2022; Zehe
251 et al., 2005; Zehe and Blöschl, 2004) the role of subsurface storm flow for runoff
252 generation (Loritz et al., 2017; Wienhofer and Zehe, 2014) or the value of distributed
253 precipitation for improving stream flow predictions (Loritz et al., 2021; Zehe et al., 2005).



254 Figure 2 Illustration of our methodological approach– Transfer (T), Initialisation (I) and
 255 Prediction (P). In Transfer (T), we transfer our knowledge of hillslope properties and soil
 256 parameters from the Weiherbach to our study area in Krebsbach. The Initialisation (I) phase
 257 involves deriving the representative hillslope (detailed in Figure 3) for the catchments and using
 258 the ERA5 Land forcings to run the hillslope model for an entire year. In the prediction phase, (P),
 259 the same model is run with the fine-resolution radar forcing and initial conditions from
 260 Initialisation (I) for predicting the flash flood discharge. (1 -Zehe et al. (2001), 2 - Muñoz-Sabater
 261 et al., (2021), 3 - Figure 3 & Loritz et al. (2017), 4 -Kachelmannwetter, n.d (Radar Data.)

262 **3 Methodology**

263 Setting up a process based model of any hydrological system mainly requires two types
264 of information (Remson et al., 1971). The first one concerns the fundamental laws
265 governing the dynamics of system state variables and fluxes and related process
266 parametrizations (e.g., preferential macropore flow) related to the chosen model. The
267 second involves the data representing the “landscape” in the equation set. A proper
268 identification of these properties is crucial for reliable model performance, and they can
269 be divided into a) system geometry, b) system parameters and c) initial and boundary
270 (forcing) conditions. The current section details the steps required for setting up the
271 model in this respect. We firstly explain the concept of the representative hillslope and
272 its derivation from digital topographical data, then elaborate on the transfer of soil and
273 land use parameters from the Weiherbach. Finally, we explain the spin up of the model
274 using ERA5 Land and the radar-based precipitation product used during the event
275 simulation.

276 **3.1 The representative hillslope concept**

277 Physically based hydrological models are renowned for their substantial computational
278 demands, often impeding their broader application (Paniconi and Putti, 2015). As a
279 result, catchment hydrology research has pivoted towards simplifying these models,
280 ensuring they retain their physical underpinnings. Notable models that exemplify this
281 approach include the hillslope storage Boussinesq model by Troch et al. (2003) and the
282 representative elementary watershed model proposed by Reggiani et al. (1998). In this
283 study, we adopt a gradient-based simplification termed 'representative hillslopes', as
284 introduced by Loritz et al. (2017). Their work demonstrated that the water balance and
285 streamflow generation in the Colpach catchment (19 km²) could be accurately simulated
286 using a single representative hillslope, negating the need for an associated river network.
287 Here we provide a concise explanation on why this approach works. The concept behind
288 a *representative hillslope* is that both surface and subsurface water fluxes are propelled
289 by differences in potential energy (Loritz et al., 2017; Zehe et al., 2013). These differences
290 emerge from rainfall distribution over varied topography. In the context of intense
291 convective rainstorms, our focus narrows to the energy balance of overland flow. Here,
292 the driving potential energy difference hinges on the relative elevation between a
293 location and its corresponding flow outlet. It's crucial to recognize that only a minute
294 portion of this potential energy is converted into overland flow kinetic energy, with the

295 majority being dissipated, primarily influenced by factors such as Manning’s roughness
296 (Schroers et al., 2022).

297 Preserving this energy dynamic implies that the topography of the representative
298 hillslope should be structured to maintain average topographic gradients along the flow
299 path to the nearest drainage point. A viable method involves segmenting geo-potential
300 energy by proximity to the river and averaging within each segment. Specifically, we
301 consider the distribution of flow profile lines shown in Figure 3B for catchment W22. For
302 any distance class (also shown in Figure A1: Appendix – A), the total flow potential is the
303 sum of all the potential of the cells within the class, which is proportional to the relative
304 elevation difference of the cells. For the catena profile, we require a representative value
305 for this class so that the total energy remains conserved. We use the Linear Average
306 Representative Slope Profile concept from Francke et al. (2008) for the same. The method
307 involves a weighting factor based on the relative occurrence of each cell in a flow path
308 (characterised by the flow accumulation values). Therefore, the value of the mean
309 elevation (h_i) for a class at distance i :

$$h_i = \frac{\sum_{j=1}^n h_j \sqrt{f_j}}{\sum_{j=1}^n \sqrt{f_j}} \quad (3.1)$$

310 where h_j & f_j are the relative elevation and flow accumulation values for each cell in the
311 class at a distance i and $j: 1 \text{ to } n$ be the total number of cells in the class. The
312 representative value for any other attribute (say width) can also be calculated similarly.

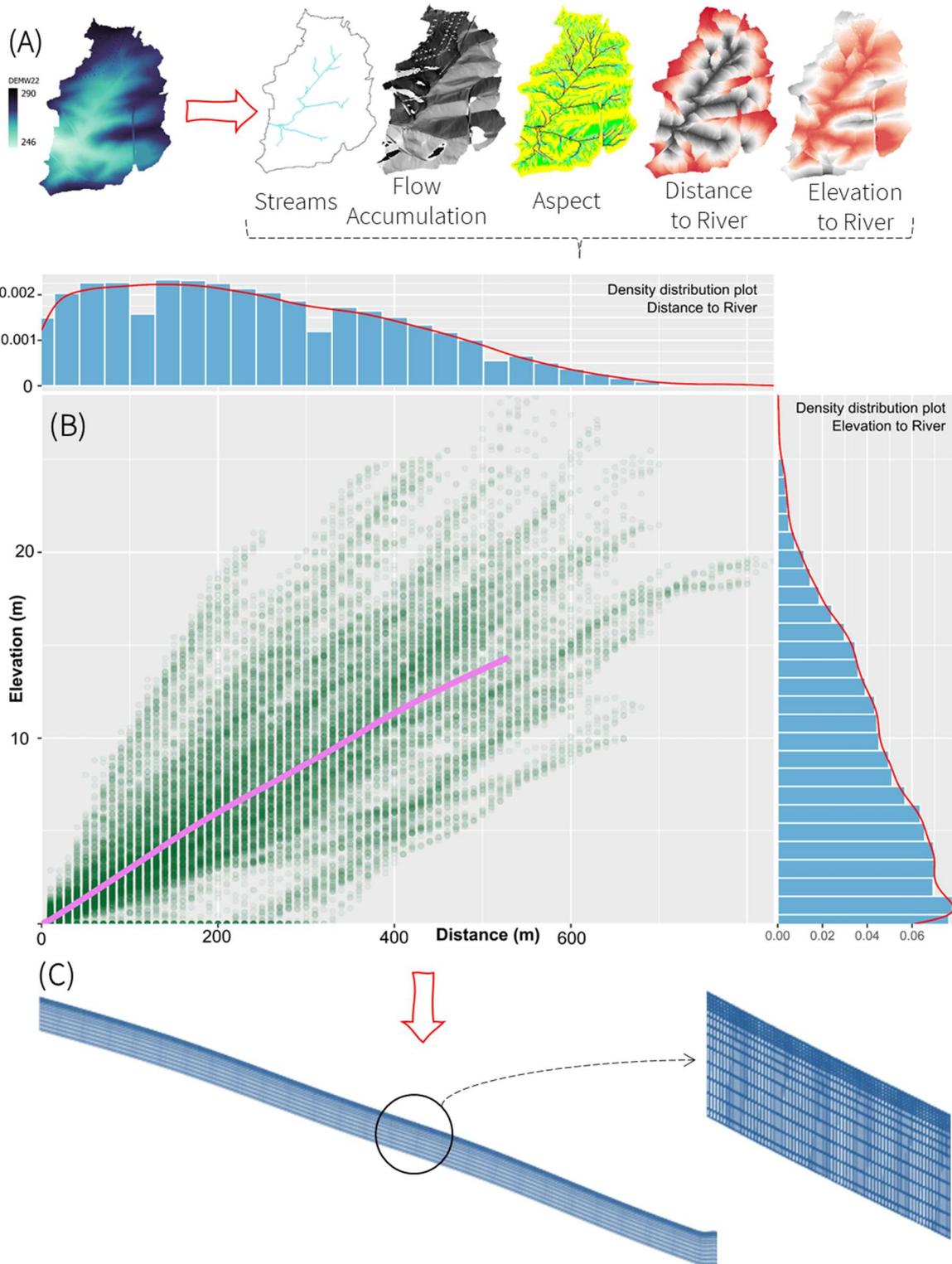
313 **3.2 System Geometry (Deriving the hillslope profile)**

314 The representative hillslope topography is derived for each of the four catchments (Fig
315 1) as illustrated for the catchment W22 in Fig 3. Firstly, the digital elevation model (DEM)
316 is pre-processed to fill all depressions and sinks. We then derive the flow accumulation,
317 aspect, and stream rasters from this filled DEM. The distance to the river and elevation to
318 river rasters (which indicates the relative horizontal and vertical distance from a cell to
319 the nearest river segment, respectively) are then extracted.

320 The distance from the nearest river segment and the corresponding relative elevation
321 difference is plotted for all the cells within the catchment of interest (Fig 3B). In Fig 3B,
322 each green dot denotes a $10 \times 10 \text{ m}^2$ cell in the catchment. The representative hillslope
323 catena is then derived based on the methodology explained in Section 3.1. The potential
324 energy conservation along the direction of the flow profile by means of the weighted

325 mean elevation values is validated using four different distance classes (100m, 200m,
326 300m & 400m: Fig A1) in Appendix – A. The representative hillslope profile obtained for
327 W22 is shown as a pink overlay in Fig 3B. The catena length is chosen intuitively based
328 on the relative elevation and distance from stream distribution plots (Fig 3B). The
329 representative hillslope is then transferred to CATFLOW (Fig 3C) for simulating the
330 catchment water balance.

331 For numerical simulation, the hillslope W22 was discretised into 531 (1 node for every 1
332 m) horizontal and 15 vertical elements. The total hillslope depth was set to 2 m, based on
333 the transfer of knowledge from Weiherbach (see section 3.3). The vertical grid resolution
334 varied from 0.05 m near the surface to 0.25 m towards the bottom node (Fig 3C). For ease
335 of numerical simulation, we choose a uniform width (area of catchment/representative
336 hillslope length) for all hillslope elements. Boundary conditions were set to the
337 atmospheric boundary at the top and the no flow boundary at the left margin. Towards
338 the lower boundary, a gravitational flow condition was established.



339 Figure 3 Workflow diagram illustrating the major steps involved in deriving the representative
 340 hillslope catena for the catchment W22. Derivation of raster maps (streams, flow accumulation,
 341 aspect, distance, elevation to river from the filled digital elevation model (DEM) (A). Selection and
 342 binning of every distance and corresponding elevation to the nearest river segment (B).
 343 Calculation of mean distance using flow accumulation weights (see also Appendix – A). Final
 344 derived representative hillslope (pink overlay line in panel B) in panel C.

345 **3.3 Transfer of System Parameters from Weiherbach**

346 Since our present study area in the Elsenz-Schwarzbach consists mainly of agricultural
347 loess catchments with similar geological and pedological characteristics of the previously
348 monitored Weiherbach catchment (Zehe et al., 2001) and have the same major crops, we
349 attempted a transfer of the soil and land use parameters from the previous field
350 experiments (Fig 2-T).

351 A typical hillslope soil catena in the Weiherbach (Fig 2T: Zehe et al., 2001) consists of
352 Calcaric Regosol (FAO/UNESCO, 1988; *Pararendzina*) or Luvisol (FAO/UNESCO, 1988;
353 *Parabraunerde*) on top and mid slope sectors and Coluvisol (FAO/UNESCO, 1988;
354 *Kolluvium*) in the hillslope foot. Hence, the representative hillslopes were assumed to
355 have a similar distribution of soils along the downstream profile (Calcaric Regosol /
356 Luvisol along 90% of the length of the hillslope and Coluvisol on the remaining 10%). The
357 soil hydraulic functions based on the parameters of Mualem (1976) and van Genuchten
358 (1980) were determined by Schäfer (1999) and Delbrück (1997) for the typical soils in
359 the Weiherbach using both field and laboratory experiments (See Table 3 in Zehe et al.
360 2001). The same was utilized to set up the soil properties in the present study.

361 Estimates of surface roughness after the Manning-Strickler coefficient, K_{st} , for different
362 crop types and maturity stages were obtained from more than 60 irrigation experiments
363 conducted in the Weiherbach. (Throughout the remainder of this work, we use both
364 Manning's roughness and Strickler values interchangeably to refer to the roughness
365 coefficient (k) in the Gauckler-Manning-Strickler formula. Interested readers are referred
366 to (Hager, 2015) for a historical anecdote). However, previous studies (Lumbroso and
367 Gaume, 2012) have shown that the traditional estimates of the Manning's coefficient do
368 not adequately represent flash flood conditions. Specifically, due to overbank flow during
369 such extreme events, changes in the associated roughness properties are invariable.
370 Hence, due to the high uncertainties involved in such calculations and the non-linear
371 changes (e.g., overbank flow) typically seen during flash floods, we use an ensemble
372 approach for the surface roughness. In principle, instead of running the model for one
373 pre-selected Manning's roughness, we run the simulations for the range of Strickler
374 values within the reported experiments in the Weiherbach (6-12 $m^{1/3}/s$) and report the
375 mean and spread of the ensemble predictions.

376 As stated, CATFLOW also includes an advanced evapotranspiration subroutine, which
377 enables time continuous simulations for a model spin up. However, use of this module
378 requires detailed information about the relative fraction of each crop, which is not
379 available for the summer of 2016, as well as detailed ground based data on radiation,
380 wind speed, air humidity and temperature, which are neither at hand for our study area
381 nor for most regions in the world. Hence, we decided not to use the inbuilt
382 evapotranspiration module, but ran the model using globally available climate data sets
383 for the model spin up. Specifically, we coupled the hillslope model with the climate
384 reanalysis product ERA5 Land (Muñoz-Sabater et al., 2021), using precipitation and
385 evapotranspiration during the event simulation and for model spin up as detailed in the
386 next sections.

387 **3.4 Initial and Boundary Conditions**

388 The problem of inferring the initial conditions is a key challenge in all event-based
389 modelling strategies (Beauchamp et al., 2013; Zeimet et al., 2018). The challenge is
390 usually not estimating the “actual” soil moisture state but establishing an initial state
391 coherent with the land atmosphere interactions and parameterisations within the model
392 (Koster et al., 2009). In essence, we seek an initialisation identical to the dynamics being
393 captured by our model.

394 In the present work, we use the ERA5 Land hourly precipitation and evapotranspiration
395 reanalysis data for initializing our representative hillslope model (Fig 2I) within a spin-
396 up period of a year. The model was run using the mean catchment values of forcing data
397 from ERA5 Land until the event of interest (8.06.2016 00:00 UTC); the corresponding soil
398 moisture pattern was saved and then used as initial conditions for the event simulation
399 with a radar based precipitation estimate (temporal resolution of 5 min) without
400 recalibration.

401 During the event of 08 June 2016 (Appendix – B), there were no operational rainfall
402 gauges that we know of, within the catchment area of Krebsbach. The nearest gauge
403 operated by the Baden-Württemberg State Institute for the Environment, Survey and
404 Nature Conservation (Landesanstalt für Umwelt, Messungen und Naturschutz Baden-
405 Württemberg - LUBW) lay towards the southeast of catchment W22 in Bad Rappenau -
406 Bonfeld (LUBW Station ID – 76730: Fig B1 in Appendix B). The gauge recorded a total
407 precipitation sum of around 28 mm on 08 June. The German Weather Services (Deutscher

408 Wetterdienst -DWD) operates a nearby gauge in Waibstadt (DWD Station ID – 13674),
409 west of catchment W44. The DWD gauge reported a total daily precipitation of 11 mm.
410 Considering the mismatch between the two gauges and the need for a finer
411 spatiotemporal estimate of the convective storm activity, we opt for a radar product
412 (temporal resolution – 5 min) provided by Kachelmannwetter (Kachelmannwetter, n.d.)
413 as the forcing boundary condition for the model. Appendix – B depicts radar images of
414 the storm on 08.06.2016 over our study region. Overall, it can be seen that the storm
415 activity is captured quite well by the fine resolution radar product. The direction of the
416 storm also agrees with the smaller magnitude of total precipitation reported by the DWD
417 gauge compared to the LUBW gauge (which seems to be nearer to the storm centre: Fig
418 B1 in Appendix B).

419 **4 Results**

420 In the following section, we first showcase the initialisation using ERA5 Land and
421 evaluate the performance of the hillslope models in describing the soil moisture changes
422 at the annual scale (4.1). We then detail the event based flash flood simulations using the
423 same representative hillslope models and radar based precipitation forcing in 4.2. Finally
424 (4.3), we discuss the shape and LULC of the four catchments, and shed light on the
425 potential to include spatially variable precipitation forcings for flash flood simulation
426 using the representative hillslope approach.

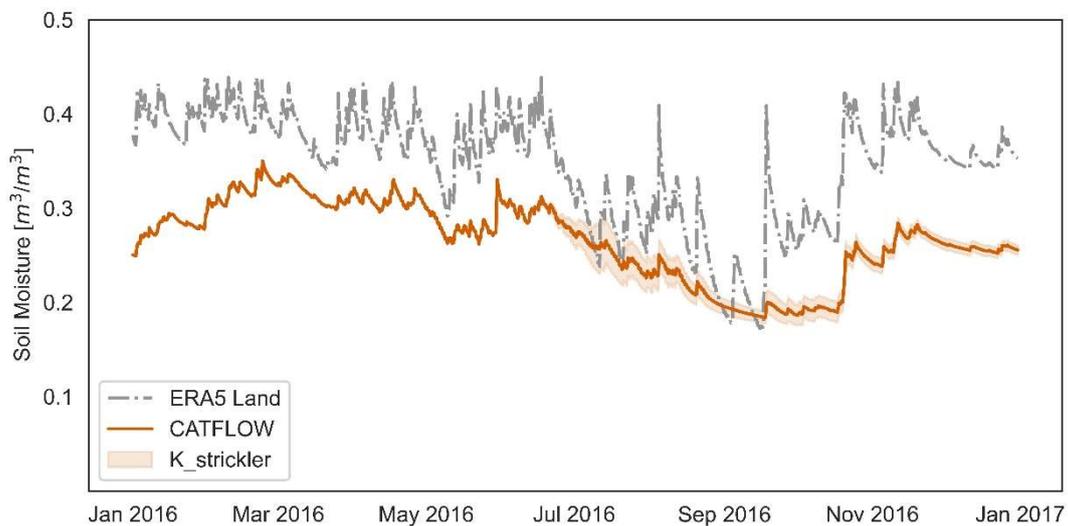
427 **4.1 Model Initialisation with ERA5 Land**

428 Figure 4 shows the top soil (0-5 cm) water content simulated with the representative
429 hillslope that was forced by ERA5 Land precipitation and evapotranspiration for
430 catchment W22. Variations of Manning Strickler, K_{st} ($m^{1/3}/s$) leads to a variation in soil
431 water content during the summer period. To characterize the coherence of these soil
432 moisture simulation with the gridded ERA5 reanalysis product, we calculated the Kling-
433 Gupta Efficiency (KGE) (Gupta et al., 2009) between the CATFLOW top layer soil moisture
434 ensemble predictions with the spatially averaged ERA5 Land surface soil moisture (0-7
435 cm) (Fig 4 and Table 1).

436 While this revealed high KGE values, CATFLOW simulations were consistently drier than
437 the ERA5 Land reanalysis product and the yearly CATFLOW runs (Figure 4). This
438 mismatch likely reflects the different soil parameterizations and scale disparities in the
439 two models. It is important to note that we do not expect perfect fit between the two

440 modeled soil moisture products, our interest is in capturing the overall local dynamics in
 441 soil moisture changes for such ungauged regions.

442 To better understand the relative role of such a bias in the overall KGE calculations, we
 443 also calculated the three components of the modified KGE (Pearson correlation, r and bias
 444 ratio, beta and variability ratio, gamma in Table 1) as per (Kling et al., 2012). As expected,
 445 we obtained high pearson correlation values (around 0.80) for all the different runs
 446 (varying K_{st} values). The high correlation shows that our approach reproduces the yearly
 447 dynamics of soil moisture changes in the region (using the coarse resolution globally
 448 available ERA5 Land data as a benchmark). The values of beta and gamma indicate the
 449 overall bias and variability of the modeled values compared to the ERA5 Land data.



450 Figure 4: Time series of ERA5 Land surface soil moisture (0-7 cm) averaged over the entire
 451 catchment (grey) and the soil moisture simulations with CATFLOW (0-5 cm), red represents the
 452 ensemble mean, shaded regions depict the uncertainties (\pm the standard deviation)
 453 corresponding to different values of the Strickler coefficient ($K_{st} = 6-12$).

454 Table 1 Goodness of fit measures between the modeled soil moisture values of different
 455 CATFLOW runs (varying Manning Strickler coefficient K_{st}) with ERA5 Land surface soil moisture
 456 for catchment W22.

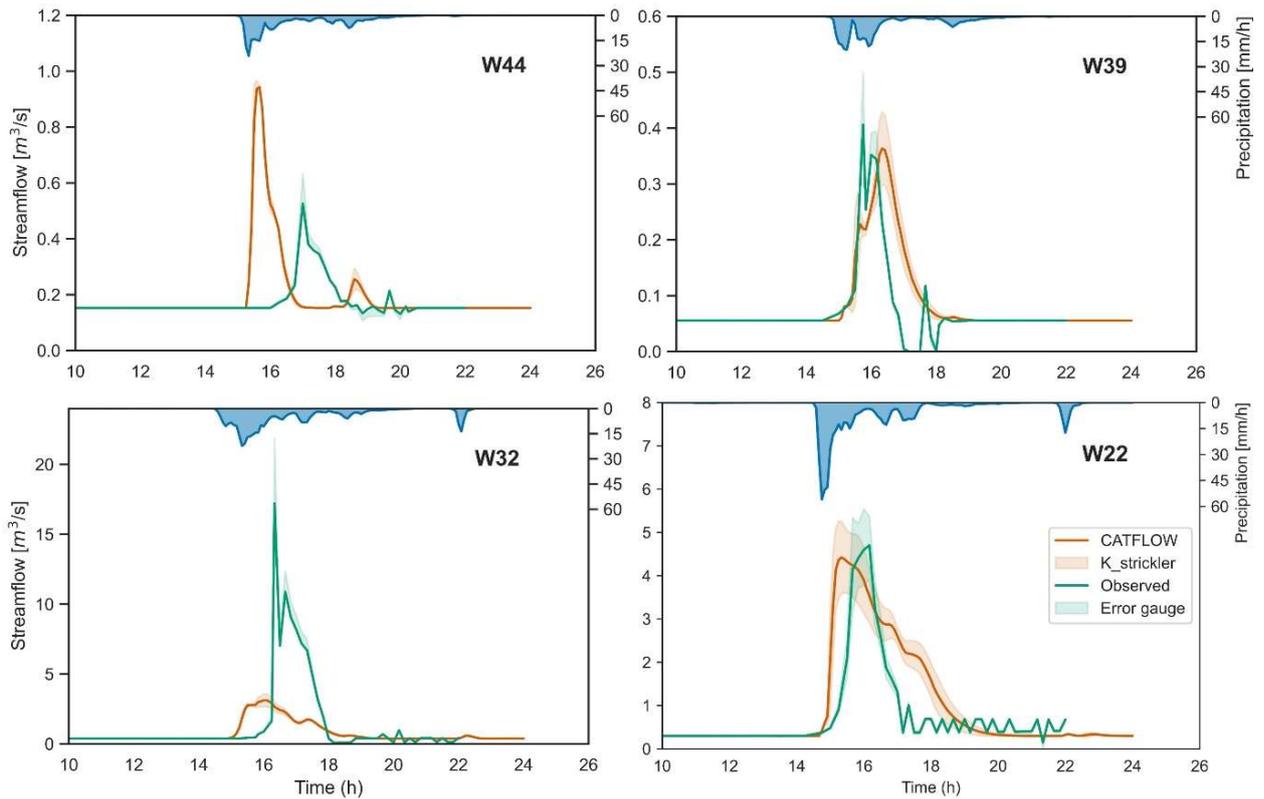
K_{st} ($m^{1/3}/s$)	KGE	r	Gamma	Beta
6	0.651	0.798	0.812	0.786
7	0.654	0.797	0.821	0.784
8	0.662	0.800	0.836	0.782
9	0.691	0.822	1.050	0.752

10	0.690	0.822	1.051	0.751
11	0.671	0.800	0.861	0.779
12	0.699	0.824	1.019	0.756

457 As we used ERA5 Land forcing variables (precipitation and evapotranspiration) to run
458 the CATFLOW model, and then again ERA5 Land soil moisture states to evaluate the
459 model performance, it remains to be seen whether the correlation is not only due to
460 inherent, modeled dependencies within the reanalysis product. To shed light on this
461 question, we again compared the CAFLOW simulations to another estimate of soil
462 moisture for the same region, the in situ Soil Moisture Active Passive (Derksen et al.,
463 2017) remote sensing product and obtained a decent (albeit lower) correlation value of
464 $r=0.61$.

465 **4.2 Flash flood modeling using representative hillslopes.**

466 The representative hillslope models were then used to simulate the runoff response for
467 the convective storm event on 08.06.2016 in the four catchments in the study area using
468 the dynamical initial conditions obtained from the yearly scale runs using ERA5 Land. It
469 is worth mentioning here that our approach of initializing the models using the reanalysis
470 datasets helps in avoiding a random guess of the initial states and in complimenting
471 parsimony principles. The approach also has implications for operationalization of the
472 model (by changing the reanalysis product to a suitable nowcast product). Figure 5
473 displays the simulated catchment response modelled using a uniform precipitation series
474 - the spatially averaged radar precipitation over each catchment (Appendix - B). The
475 model performance in the four catchments is evaluated against the reconstructed inflow
476 hydrograph obtained from the reservoir mass balance (Appendix - C) assuming relative
477 measurement error measures for peak flow, volume, and time to peak as given in Table
478 2.



479 Figure 5: Rainfall - Runoff hydrographs for the flash flood event on 08.06.2016 at the four
 480 headwater catchments (W22, W32, W39 and W44). Green curve indicates the reconstructed
 481 inflow to the flood defence reservoir (Appendix - C), assuming measurement uncertainties of 5%.
 482 Red curve indicates the mean values (\pm SD) of the predicted flood discharge by the CATFLOW
 483 model ensemble (varying Strickler coefficient values). All simulation times are in UTC time zone.

484 Table 2: Characteristics of simulated and reconstructed storm hydrographs. The error values are
 485 calculated between the mean values of the ensemble CATFLOW predictions and the inverted
 486 flood hydrograph for each catchment. Area of each catchment is indicated in brackets.

Flood Characteristics	W22 (2.91 km ²)		W32 (5.6 km ²)		W39 (0.73 km ²)		W44 (2.44 km ²)	
	Obs	Sim	Obs	Sim	Obs	Sim	Obs	Sim
Storm Precipitation (mm)	49	-	35	-	26	-	24	-
Peak Discharge, Q (m ³ /s)	4.703	4.421	17.212	3.123	0.406	0.363	0.527	0.943
Time of Peak, t (s)	58200	55200	58800	57900	56700	58800	61200	56400
Flood Volume, V (m ³)	45637	57978	72209	49868	5189	5959	13466	14537
Flood Volume, V (mm)	15.7	19.9	12.9	8.9	7.1	8.2	5.5	5.9
Runoff Coefficient, R	0.32	0.41	0.37	0.25	0.27	0.31	0.23	0.25

Percentage Error in Peak Discharge, P_Q (%)	-	6	-	82	-	11	-	-79
Error in time to Peak, P_t (s)	-	3000	-	900	-	-2100	-	4800
Percentage Error in Flood Volume, P_V (%)	-	-27	-	31	-	-15	-	-8

487 The model captures the steep ascent of the rising limb of the flood hydrograph, albeit with
488 a time lag, and matches the magnitude of peak discharge values in at least two out of the
489 four catchments (W22 and W39). Visually, the uncertainties in the simulated response
490 due to changes in surface roughness are almost identical to the possible observational
491 errors in the gauge level measurements (5%) that propagated into the estimated storm
492 hydrograph.

493 More specifically, the peak flow errors (Table 1) in W22 (6%) and W39 (11%) are within
494 the expected ranges considering the high uncertainties involved in local flash flood
495 predictions. It is also interesting to note that the hillslope approach underestimates the
496 peak flow magnitude but overestimates the flow volume for both the catchments. Also,
497 the peak flow is delayed in W39 (happens later than observed) while it occurs earlier in
498 W22.

499 On the contrary, in catchment W32, the hillslope model severely underestimates the
500 storm response, while in W44 it slightly over predicts the discharge values. To better
501 understand the apparent deviation in performance for catchments W32 and W44
502 compared to W22 and W39, we closely examined the storm pattern and then the relative
503 shape, LULC and orientation of the catchments w.r.t the storm activity.

504 **4.3 Role of LULC and distributed rainfall forcing**

505 From Fig 1, we can observe that the catchments W32 and W44 appear to be more
506 elongated and fan-shaped in contrast to the broader shaped catchments W22 and W39.
507 Additionally, based on Fig 2P and details provided in Appendix B, the storm's direction
508 suggests that our initial assumption of uniform precipitation across the representative
509 hillslopes might not apply as neatly to the elongated catchments (W32 & W44).

510 However, the quite sharp discharge response of W32 (around 15 m³/s within 15 minutes)
511 seems unreasonably high when compared with the overall precipitation input and
512 response in other catchments. One possible explanation could be an obstruction in the
513 flow path perhaps due to debris like wood or sediment from the agricultural upstream
514 areas of W32, which, as indicated by Fig B1 in Appendix B, was closer to the storm center.

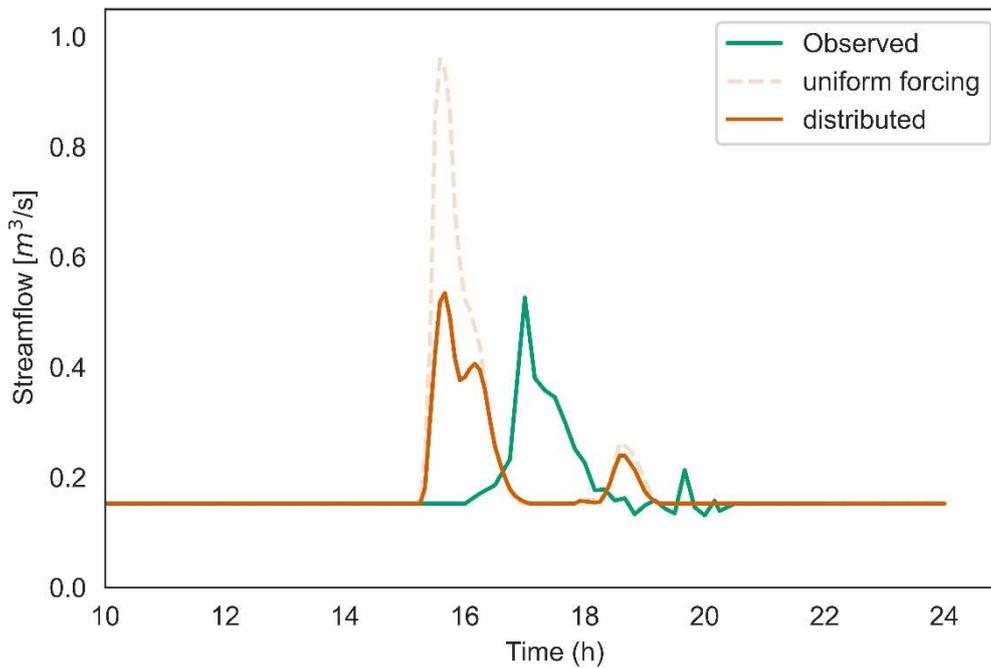
515 This might have inadvertently created a temporary retention area, which then burst after
516 a certain point, mimicking the effects of a dam break and resulting in a sudden inflow to
517 the reservoir. Magnitude amplification due to such debris flows and driftwood blockages
518 during flash floods have been reported in regions around the world (Chen et al., 2021;
519 Schalko et al., 2018; Spreitzer et al., 2019).

520 The total event runoff coefficients calculated for each catchment (Table 2) also shows that
521 while the approach slightly overestimates the response in all the other three catchments
522 (W22, W39 and W44), it underrepresents the runoff response by around 12% in
523 Catchment W32. One possible reason for the apparent stronger runoff production, might
524 be the presence of larger fraction of impervious sealed built-up surface in W32. From
525 Figure 1, it is seen that the small town of Haselbach lies within the catchment area, this
526 contrasts to the other three catchments which are mostly only of agricultural or forest
527 type (which also imposes limitations on the parameter transfer from the agricultural
528 rural Weiherbach catchment). Another interesting point is that there is a well defined
529 distribution of agricultural and forested areas along the stream profile in W32 (crops at
530 the upstream plateaus and forest along the tributaries or near the outlet). These regions
531 could hence behave like sub catchments having distinct concentration times.

532 However, it is worthwhile to note that out of all the four catchments the timing of the
533 peak is most accurately captured in W32, which also has relevant implications for flood
534 warning systems.

535 To investigate whether a distributed forcing input could help in better characterization
536 of response in such elongated catchments, we again ran the simulations for catchments
537 W32 and W44 using different rainfall time series along the representative hillslopes.
538 Intuitively, we divided the catchment as having two different precipitation forcings over
539 the upstream and downstream regions, to better reflect the storm pattern over the region
540 (Appendix-B). Since this didn't lead to major changes for catchment W32 (apart from a
541 minor increase in the peak flood), we only show the results for W44 in Fig 6. The
542 predicted discharge values for catchment W44 are now remarkably close to the observed
543 ones, relative peak errors reduce from around 80% to just 2% (Table 3). The relative
544 volume error decreases to 2% from the earlier 8%, while the time to peak error remains
545 nearly constant. This might be due to the longer stream network and the inability of the

546 hillslope approach to mimic the stream routing in such elongated hillslopes with more
 547 stream structures.



548 Figure 6 Flood hydrographs for catchment W44. Green curve indicates the reconstructed
 549 reservoir inflow, dotted red curve stands for model run using uniform precipitation forcing for
 550 the entire representative hillslope, solid red line denotes the model run with distributed forcing.
 551 All simulation times are in UTC time zone.

552 Table 3: Goodness of fit measures for the representative hillslope modelled discharges ($K_{st} = 9$)
 553 with the reservoir stage inverted streamflow measures for distributed forcings over catchment
 554 W44.

Flood Characteristics	W44 (2.44 km ²)		
	Observed	Uniform forcing	Distributed forcing
Peak Discharge, Q (m ³ /s)	0.527	0.959	0.535
Time of Peak, t (s)	64800	56100	56400
Flood Volume, V (m ³)	13465.92	14567.44	13714.541
Runoff Coefficient, R	0.23	0.25	0.25
Percentage Error in Peak Discharge, P _Q (%)	-	-82.19	-1.52
Error in time to Peak, P _t (s)	-	53.13	50
Percentage Error in Flood Volume, P _V (%)	-	-8.18	-1.8

555 **5 Discussion**

556 In this study, we aimed to predict flash flood responses in data-scarce, small (<6 km²)
557 headwater catchments subjected to convective storm events. We utilized the
558 representative hillslope concept and transferred parameters from a previous
559 experimental catchment to establish process-based models for the four catchments
560 under consideration. Given the absence of a comprehensive observational network in the
561 area, we dynamically initialized initial conditions using climate reanalysis data.
562 Furthermore, compared our event based simulations with reservoir streamflow inverted
563 hydrographs. This comparison allowed us to quantify the relative simulation error
564 values. Our endeavor to model and understand flood dynamics in these specific regions,
565 despite the data limitations, gave crucial insights which presents a step forward in
566 mitigation and preparation for such extreme events.

567 **5.1 Towards short term predictability in ungauged basins**

568 The Predictions in Ungauged Basin Initiative (IAHS PUB Initiative: Hrachowitz et al.,
569 2013) attempted to bridge the gap in hydrologic predictions over ungauged basins by the
570 concept of regionalization i.e to undertake a transfer of hydrological understanding from
571 gauged to ungauged environments. Spatial proximity is one of the most widely used and
572 simple regionalization techniques. The successful transfer of the previously obtained soil
573 hydraulic parameters and the catena from the Weiherbach to the four Elsenz-
574 Schwarzbach catchments, suggests that both could be valid in the entire hydrological
575 landscape, the Kraichgau. The same applies to the crop specific Manning-Stricker
576 parameters. In consequence, hydrological observatories like the Weiherbach (Zehe et al.,
577 2001), the HOAL (Blöschl et al., 2016) or the Attert experimental basin (Pfister et al.,
578 2017) could serve as donors for soil and vegetation parameters and behavioral hillslope
579 setups within the same hydrological landscape.

580 Flash floods usually come as (bad) surprises, often impacting regions when and where
581 we least expect them (Borga et al., 2008). Hence, strategies that provide robust warnings
582 are essential. However, since they are also quite rare in nature, there lacks a coherent
583 motivational starting point to invest time and resources into them (Montz and Grunfest,
584 2002). In this study, we derived representative hillslope catenas for four head water
585 catchments preserving their geopotential energy differences along the mean distance to
586 the stream. Since, these representative catenas are thermodynamically consistent (based

587 on relative elevation differences and flow accumulation weighted mean values as
588 discussed in Section 3.1 & Appendix -A) to the flow profiles in the catchment, we
589 postulated that the representative hillslope should be able to provide reasonable
590 estimates for rainfall-runoff prediction without the need for any manual event
591 calibration.

592 While our approach provided near uncalibrated predictions for surface runoff in two out
593 of the four catchments (W22 & W39), in the third catchment (W44), we had to release the
594 assumption of uniform precipitation forcing over the hillslope and go for a distributed
595 approach. The method was not able to capture the abrupt response in Catchment W32.
596 However, as discussed in the text, the different landuse patterns within such elongated
597 catchments implies that we may have to go for an approach involving different hillslopes
598 for the different LULC classes and then add a suitable flow routing component to avoid
599 the mismatch. In case they are not at hand, the soil hydraulic parameters (transferred
600 from the experimental Weiherbach catchment in the current study: Table 3 in Zehe et al
601 2001) can be estimated using soil maps and textural data based on pedo-transfer
602 functions (Rosetta: Schaap, 1999) for catchments of interest. The ensemble approach of
603 using a range of roughness values helps overcome uncertainties involved in such
604 parameters during extreme event simulations. This could be a first step in
605 operationalization of such a flash flood event modeling system for small to lower
606 mesoscale catchments with data gaps and scarcity issues.

607 **5.2 Tackling data scarcity**

608 Continuous simulations, for estimating initial conditions for the event simulations, were
609 conducted using globally available climate reanalysis products (ERA5 Land). The
610 importance of such antecedent soil moisture conditions in constraining the flood
611 response cannot be overemphasized (Manoj J et al., 2023, 2022;), as has been shown for
612 many catchments across Europe (Berghuijs et al., 2019; Blöschl et al., 2019, 2017). Global
613 climate models have delivered commendable outcomes when it comes to capturing
614 climate and weather extremes on regional scales. However, their potential in estimating
615 the impacts of smaller scale hydrological events remains largely unexplored (IPCC, 2021;
616 Poschlod, 2022). The representative hillslope approach which marries the beneficial
617 components of lumped conceptual models with hydrological process based paradigms

618 could be a way forward to implement the vast knowledge of climate model simulations
619 to smaller event scales.

620 Marchi et al. (2010) analysed around 25 major flash floods over Europe and showed that
621 proper observational records didn't exist for more than half of the investigated events.
622 During such intense flash floods, direct current meter measurements are often not
623 possible due to safety and technical considerations. Furthermore, these events usually
624 occur in remote ungauged regions with limited accessibility (Borga et al., 2008). It is
625 important to stress here that even in cases with flow measurement gauges, prediction of
626 discharge values during such convective events usually involves lot of uncertainties due
627 to faulty devices, dynamical riverbed changes and floating debris in the stream
628 (Lumbroso and Gaume, 2012). As is common in such poorly gauged catchments
629 (Bronstert et al., 2018), we didn't have a streamflow gauge to compare our model
630 performance, and hence we made use of the reservoir geometry and downstream flood
631 retention reservoirs to obtain a crude estimate of the storm characteristics. This strategy
632 creates a win-win situation, because local water resource managers are natural end users
633 of such a warning system, and we tremendously increase the sample of historical test
634 cases and complement the small sample that is available from the few gauging stations
635 that observe catchments $< 10 \text{ km}^2$.

636 **5.3 Implications for Design Considerations**

637 Natural streamflow variability has been altered by both climate change and
638 anthropogenic water resources management policies (Pérez Ciria et al., 2019) over the
639 last decades. Hence, it becomes imperative to consider multiple hydrological scenarios
640 and a broader range of climatic forcings for the design of reservoirs and other flood
641 control measures.

642 The evaluation and design of such hydraulic structures are generally based on univariate
643 extreme values statistics, in Germany usually inferred from gridded KOSTRA rainfall
644 extremes (Junghänel et al., 2017). These serve as input for event-based rainfall-runoff
645 simulations using rather simple concepts such as the unit hydrograph hydrological
646 models and in combinations with conceptual methods like the SCS-Curve number or
647 rational method. This approach is essentially linear, which implies that the return period
648 of the precipitation event determines the return period of flood runoff. Formation of flash

649 flood runoff is essentially non-linear, a 200-year precipitation event can cause a 10000
650 year flood, as observed for instance in the Weiherbach (Villinger et al., 2022).

651 Similarly, the flood reservoir W22 has been designed for a 100 year flood, though the
652 precipitation event in 2016 had a return period (based on total precipitation) between
653 10 -20 years (Zehe et al, 2023) it still resulted in overflowing of the reservoir. In a
654 different study we tested whether the event in 2016 could be reproduced using the
655 simple FGM model (Ihringer, 1994 : the model uses the Unit Hydrograph method), that
656 was used for designing the flood retention reservoir W22. This worked – but only after
657 doubling the precipitation amount, which changes the return period from 20y to 200 -
658 500y. Thus underpinning, that standard estimators for runoff coefficients have
659 deficiencies to cope with Hortonian overland flow and its strong dependence on
660 precipitation intensity. This has crucial implications for the design and management of
661 water resource infrastructure in a warming climate. Spatially distributed, process-based
662 approaches that conserve both mass and momentum principles can incorporate multiple
663 processes and complex feedbacks during the event. Ultimately, this helps to account for
664 non-linear system responses and tipping points (L.Pimm, 1985).

665 Throughout Europe, record breaking summer heatwaves and droughts have been
666 reported in recent years (Tripathy and Mishra, 2023: 2022 Compound Drought and Heat
667 Wave). The occurrence of convective storm driven floods during summers have
668 compounding effect on reservoir water management policies as water resources
669 planners and reservoir operators face the daunting task of balancing the need for
670 agricultural and irrigation water demand with the challenge of tackling flood risk.
671 Efficient modeling and forecasting of flash floods could help mitigate the risk of such
672 interconnected hazard cascades. Vegetative plant barriers (Richet et al., 2017) and other
673 ecosystem based flood defence solutions (Temmerman et al., 2013) have also come up as
674 a more sustainable and environmental friendly alternative to conventional manmade
675 flood defense measures. The hillslope scale again emerges as an interesting sub-unit
676 within a catchment (*virtual laboratories*: Fatichi et al., 2016) for testing the impact of such
677 bio geomorphological measures on runoff response and sediment yield.

678 **5.4 Limitations and Outlook**

679 The perils of applying continuum-based models at scales for which the governing
680 equations were not developed is well reviewed in literature (Hrachowitz and Clark,

681 2017). Such distributed, process-based approaches are also criticized for their
682 complexity and larger data requirement compared to simple conceptual models.
683 Conceptual (scaled-down) approaches on the other hand do not perform well in regions
684 and scenarios which deviates from their well calibrated range of conditions (Fatichi et
685 al., 2016; Hrachowitz and Clark, 2017). Hence, on balance, we believe that, under the
686 threat of a non-stationary climate (Milly et al., 2008) and unprecedented flow regime
687 changes, strategies which involve a convergence of different modelling philosophies are
688 called for.

689 The representative hillslope approach for flash flood modelling is a venture in this regard.
690 However, limitations remain that need to be properly understood and accounted for. The
691 2D effective representative hillslope used to represent the catchments implies the
692 assumption of symmetry where the runoff production is controlled by hillslope parallel
693 and vertical fluxes and their driving gradients (Loritz et al., 2017). The derived effective
694 catena profile depicts our best guess based on the available topographical data (DEM).
695 Any uncertainties and errors in the terrain representation will invariably propagate to
696 our model geometry. Another point is the sensitivity to different DEM resolutions, raster
697 filling and flow direction algorithms (Loritz et al., 2019).

698 So far, the flood simulations were essentially event based with no separate baseflow
699 component (a constant baseflow was considered from start till end). Moreover, in our
700 case, we do not attempt to fit the model response to the discharge curve obtained from
701 the reservoir level measurements. Our main aim is to mimic the catchment response
702 during such high intensity events in a simple, parsimonious manner. We also endeavored
703 to consider the uncertainties in our modelled response (by varying the surface
704 roughness) and the observational benchmark (relative error in gauge measurements). It
705 is indeed true that the choice of process based model implies that we deal with a much
706 larger number of system parameters and boundary conditions, compared to conceptual
707 models. The strength is that these parameters are observable and, as shown in this study,
708 transferable.

709 The forcings and soil moisture simulated by any land surface model (ERA5 Land, in our
710 case) is highly model-dependent and direct transfer of one model product to another can
711 lead to inconsistencies due to deviations in formulations (Koster et al., 2009). Attempting
712 such a switch of forcing from a coarse gridded reanalysis product (ERA5 Land) to a fine

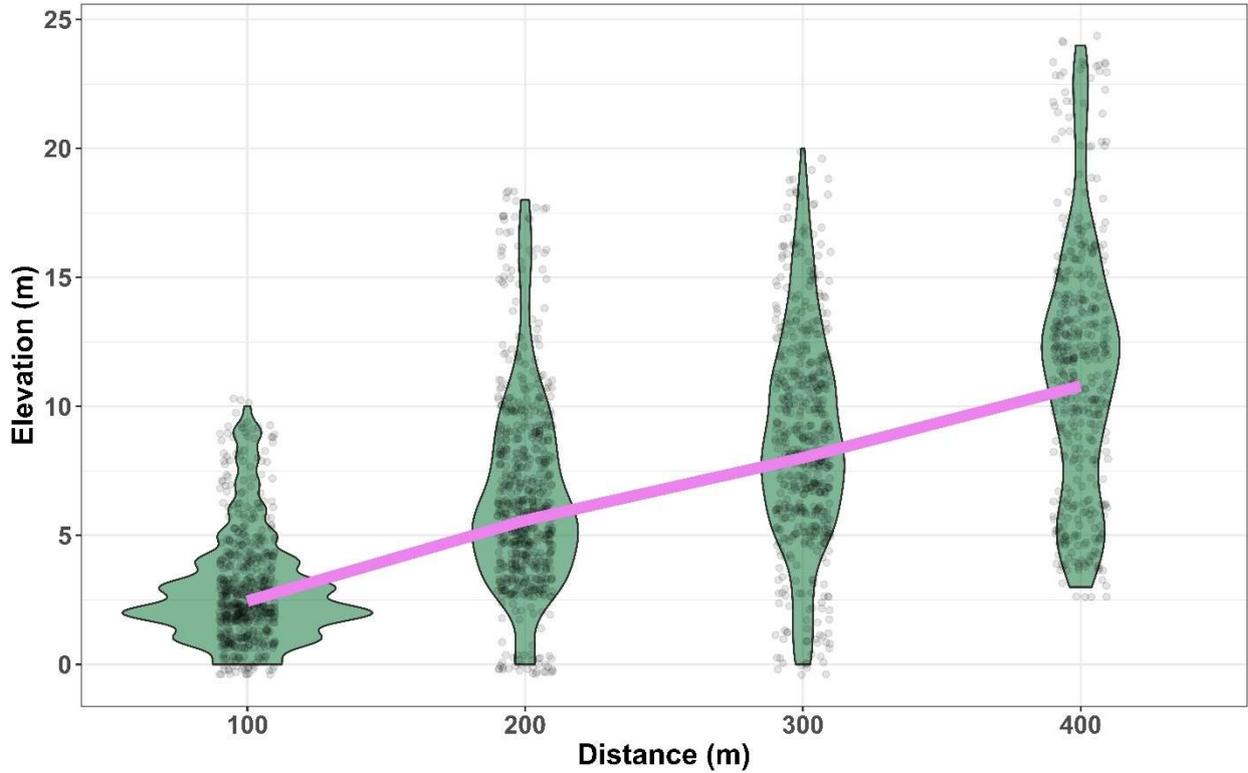
713 resolution radar precipitation product would usually entail a re-engineering of the model
714 and associated variables. However, we show here that a process based, spatially
715 distributed model can capture the dynamics due to their mechanistic description of the
716 flow system (conserving both the energy and mass balances). Moreover, as we show in
717 Section 4.1, we are more interested in the temporal soil moisture variability rather than
718 the absolute values predicted by the models. Hence, we expect very less model bias due
719 to the choice of the reanalysis product.

720 One argument frequently put against the use of process-based models in flash flood
721 modelling and forecast strategies is their higher computational times. In the current
722 attempt, we reiterate that by employing a representative approach which spatially
723 averages along the main driving gradient of flow, we can preserve the total flow potential
724 of the catchment without significant computational effort (For reference, the spin-up
725 phase for the entire year had run time of less than 10 minutes while the event simulation
726 for each catchment took around 2 minutes, in a normal Windows PC with 32GB RAM
727 only).

728 **Conclusions**

729 The method of modeling flash floods in data-scarce, small headwaters using
730 representative hillslopes, supplemented by climate reanalysis products, appears to be a
731 viable pathway for achieving dependable rainfall-runoff simulations during high
732 intensity storm events. By ensuring that these representative hillslopes align with the
733 principles of thermodynamic conservation, we strike a balance between the intricacies
734 required by physically based models and the desired simplicity rooted in parsimony
735 considerations. Integrating with global climate reanalysis products effectively addresses
736 the persistent challenges of data availability, a crucial aspect when modeling extreme
737 events in data-limited regions globally. The findings indicate that the modeled
738 hydrograph aligns well with the observed flood curve, derived from reservoir gauge level
739 measurements, in three of the four studied catchments. While the approach
740 demonstrated limitations in one of the region's larger catchments, further exploration
741 and research, as outlined in the subsequent text, could provide more insights into
742 modeling elongated catchments, especially those with urban developments.

743 **Appendix - A** (Energy considerations in the derivation of the representative hillslope
 744 catena)



745 Figure A1 Plots showing the distribution of elevation values of each cell within four distinct
 746 distance classes from Fig 3B. The pink line denotes the representative hillslope profile derived
 747 from the mean elevation values using the approach detailed in Section 3.1.

748 From Newtonian mechanics, flow potential at a relative elevation (h) is defined as

$$E = m \times g \times h \quad (A1)$$

749 Where E is the potential energy of the water on the hillslope (J), m is its mass (kg), g
 750 represents the gravitational acceleration (m s^{-2}), and h is the relative height of the water
 751 above a reference (m).

752 For each class (say $x = l$ m), the average flow potential due to elevation values is related
 753 to the sum of the individual flow potential of all the cells ($j: 1$ to n) within the class

$$E_{avg}^{x=l} = \frac{E_{total}^{x=l}}{n} = \frac{\sum_{j=1}^n E_j^{x=l}}{n} \quad (A2)$$

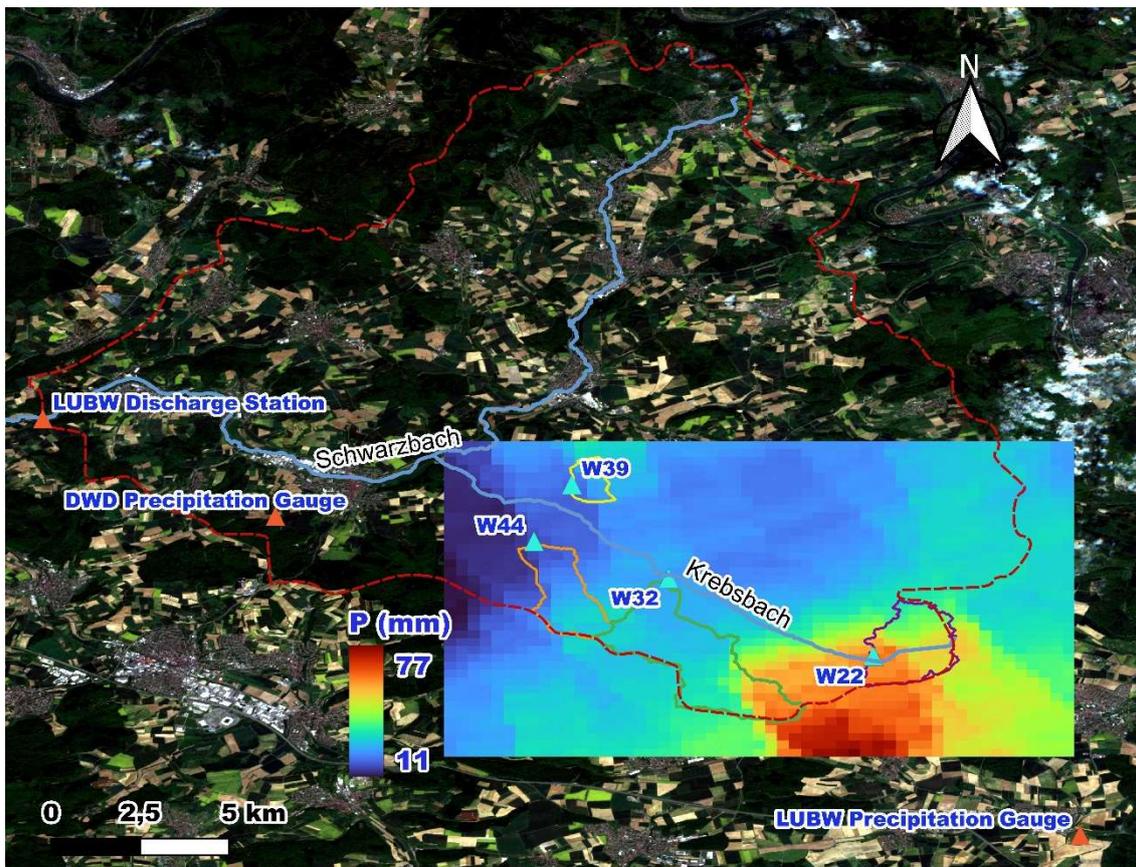
754 The flow potential in the representative hillslope element at $x = l$ m is given by:

$$\bar{E}^{x=l} = \bar{m} \times g \times \bar{h} \quad (A3)$$

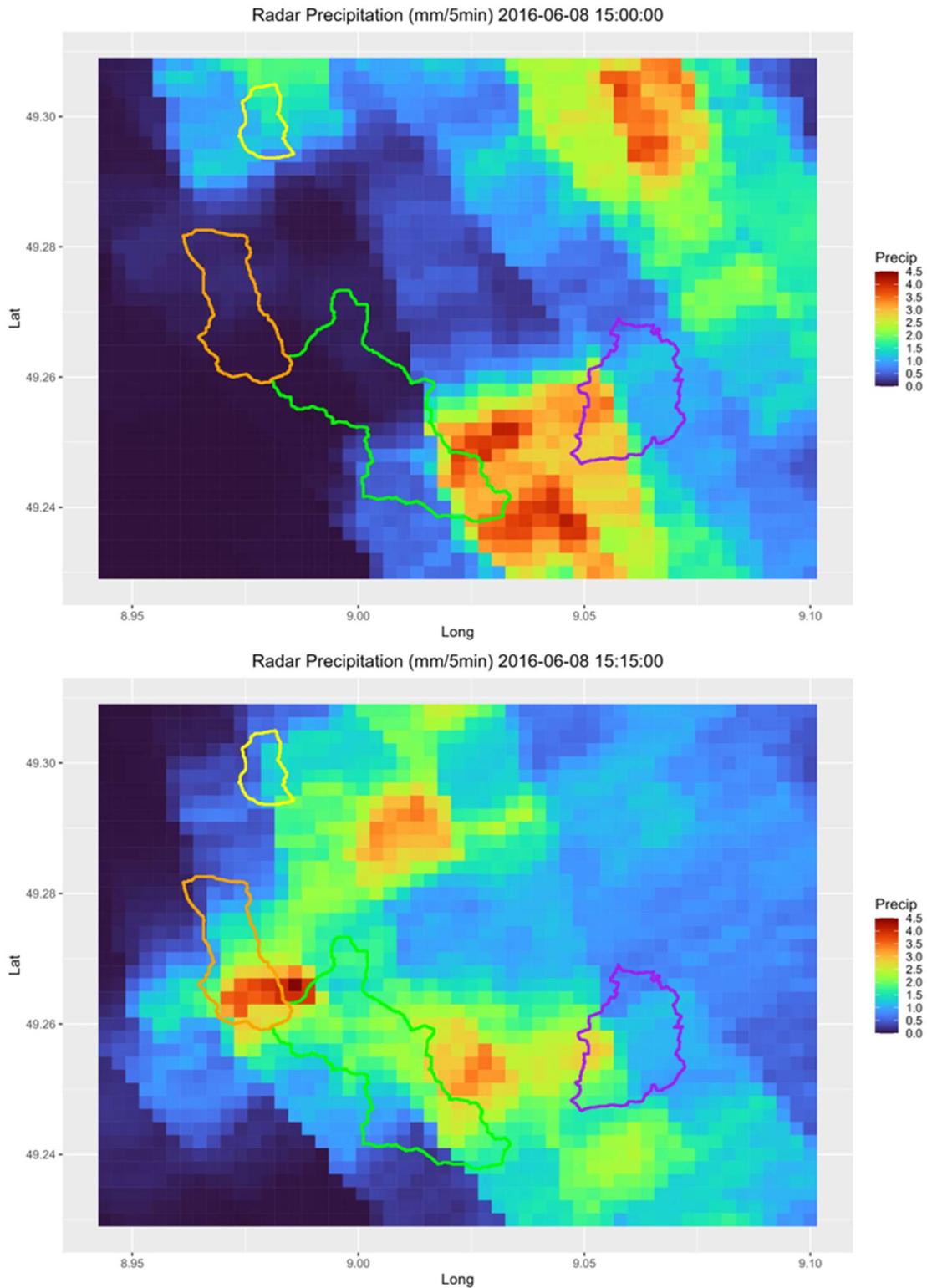
755 Where \bar{h} is the estimate of weighted mean elevation for a class at distance l , calculated
 756 using Eqn. 3.1 in Section 3.1. Table A1 shows these different energies for all the four
 757 classes illustrated in Fig A1. On average, the relative errors between flow potential in the
 758 classes and in the derived representative catena are seen to decrease as the distance from
 759 the stream increases.

760 Table A1 The difference between the total flow potential in each class (Figure A1) and in the
 761 derived representative hillslope in terms of density, ρ and gravitational acceleration, g .

Classes	$l = 100 \text{ m}$	$l = 200 \text{ m}$	$l = 300 \text{ m}$	$l = 400 \text{ m}$
<i>Energy in class, $E_{avg}^{x=l}$</i>	$301\rho g$	$660\rho g$	$877\rho g$	$1152\rho g$
<i>Energy in profile, $\bar{E}^{x=l}$</i>	$245\rho g$	$558\rho g$	$801\rho g$	$1079\rho g$
Relative Error (%)	-22.8	-18.28	-9.4	-6.7



763 Figure B1 Overview of the Schwarzbach catchment till the LUBW streamflow station at
764 Eschelbronn. In addition, the total accumulated precipitation (in mm) during the event is depicted
765 as an overlay layer over the four catchments. Also, shown are the DWD and LUBW precipitation
766 gauges.



767 Figure B2 Evolution of the convective storm event on 08.06.2016 over the Krebsbach as captured
 768 in the chosen radar based precipitation product (Kachelmannwetter, n.d.).



769
770

Figure B3 Impact of flash floods on 08.06.2016 over Catchment W22. (Zweckverband
Hochwasserschutz Elsenz-Schwarzbach)

771 **Appendix – C** (Flood estimation using reservoir mass balance)

772 Mass conservation has long been the foundation of hydrological modeling. This basic
773 physical law is usually expressed (for hydrological systems) in the form of:

$$\frac{dS}{dt} = I(t) - O(t) \quad (C1)$$

774 where the change of a system's mass storage (S) with respect to time (t) is equal to total
775 mass input, $I(t)$ minus total mass output, $O(t)$. This represents one of the most basic
776 physical constraints placed on the functioning of any hydrological system.

777 Considering the mass balance of the downstream flood reservoirs in the four catchments
778 (Fig 1 and B1) as shown in Fig C1, the storage in the reservoir at any time t being a
779 function of the level (h). An automatic recorder measures the water level in the reservoir
780 as shown in Fig C1. The outflow being again a function of the water level in the reservoir.
781 Having knowledge of the reservoir geometry relations ($S = f(h)$) and the stage-
782 discharge relationship of the outlet ($O = g(h)$), we now need to estimate the inflow to
783 the reservoir from the catchment due to the convective storm activity. Again, from Eq C1:

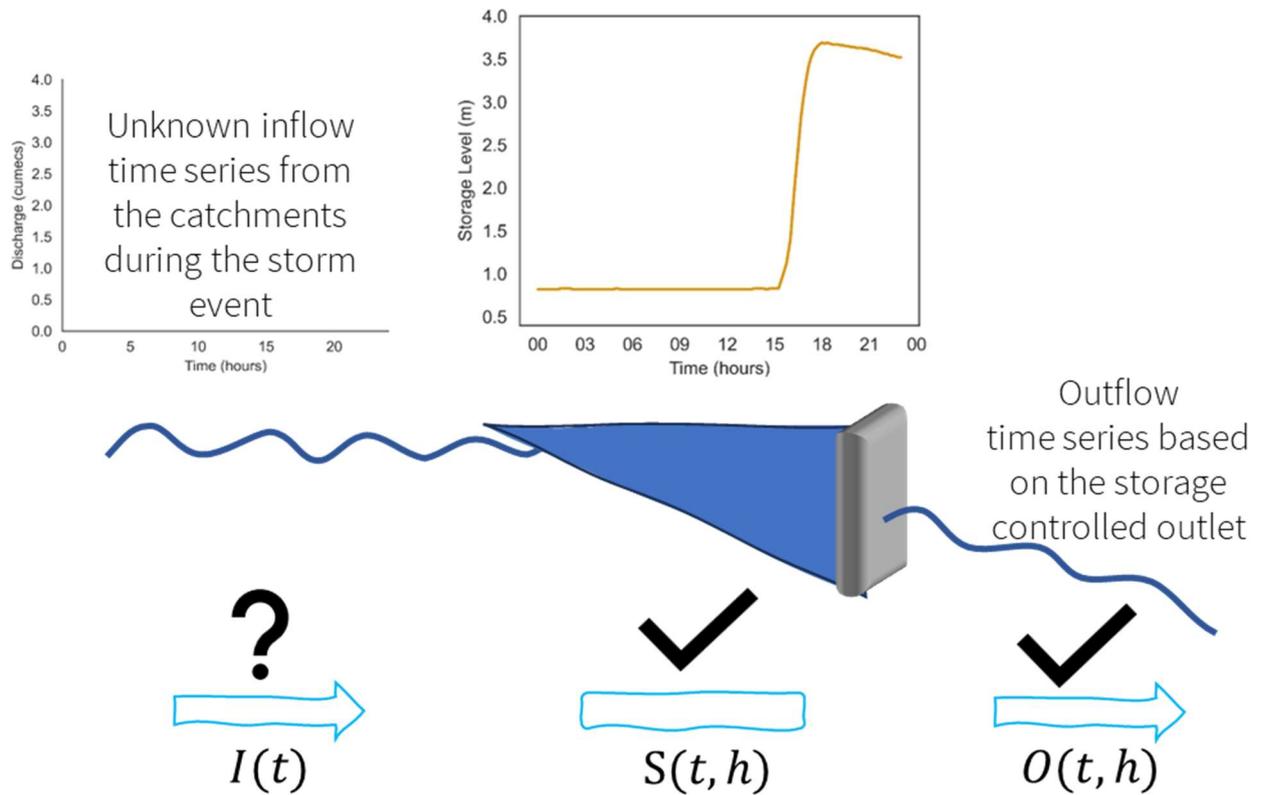
$$\frac{dS}{dt} = I(t) - O(t) \quad (C1)$$

$$\frac{S(t + \Delta t, h + \Delta h) - S(t, h)}{\Delta t} = I(t) - O(t) \quad (C2)$$

784 Hence, the inflow is given by,

$$I(t) = \frac{S(t + \Delta t, h + \Delta h) - S(t, h)}{\Delta t} + O(t) \quad (C3)$$

785 Now for the uncertainty analysis, we consider a relative error of 5% in the reservoir level
786 measurements and again calculate the inflows using Eq. C3. The inflow hydrograph
787 obtained, and calculations are further shown for catchment W22 in Fig C2 and Table C1
788 respectively.



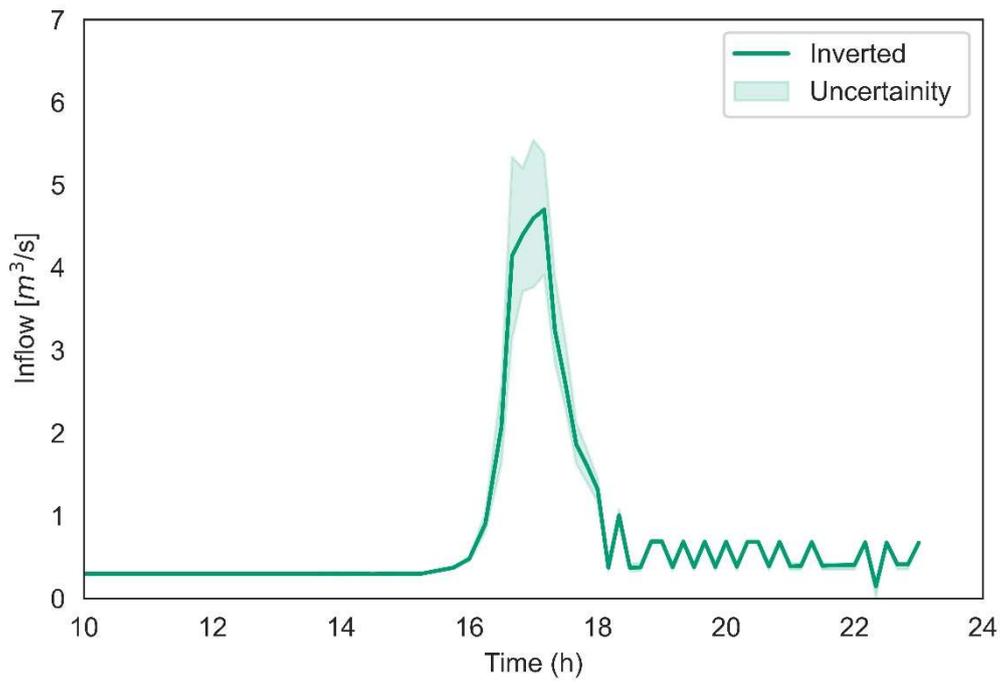
789

Figure C1 Schematic representation of the reservoir mass balance inversion

790

Table 2 Reservoir mass balance calculations for catchment W22

S No	Time	Level (m)	Storage (m ³)	Change in Storage (m ³)	Outflow (m ³ /s)	Dt	Inflow (m ³ /s)
63	08-06-2016 15:45	1.12	41.94883	16.42903	0.354373	900	0.372627
64	08-06-2016 16:00	1.4	107.4919	65.54307	0.407547	900	0.480373
65	08-06-2016 16:15	1.98	471.3575	363.8656	0.500051	900	0.904346
66	08-06-2016 16:30	2.48	1828.668	1357.311	0.565968	900	2.074091
67	08-06-2016 16:40	2.82	3952.833	2124.165	0.605154	600	4.145429
68	08-06-2016 16:50	3.06	6215.17	2262.337	0.631057	600	4.401619
69	08-06-2016 17:00	3.26	8583.66	2368.49	0.651033	600	4.598516
70	08-06-2016 17:10	3.43	11005.15	2421.491	0.666923	600	4.702742
71	08-06-2016 17:20	3.53	12547.01	1541.86	0.676144	600	3.245911
72	08-06-2016 17:30	3.6	13690.94	1143.932	0.68265	600	2.589203



791

Figure C2 Reconstructed inflow time series for catchment W22. All times in CET.

792 **Data Availability Statement**

793 The ERA5 Land hourly data is freely available and can be accessed via the Copernicus
794 Climate Change Services (C3S) Climate Data Store
795 (<https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=overview>).
796 The simulation results can be found in Zenodo at
797 (<https://doi.org/10.5281/zenodo.8376684>). All other data and codes used in this study
798 are available on request from the corresponding author, Ashish Manoj J
799 (ashish.jaseetha@kit.edu).

800 **CRedit Author Contribution Statement**

801 Ashish Manoj J: Data curation, Formal analysis, Investigation, Methodology,
802 Conceptualization, Resources, Software, Validation, Visualization, Writing - original draft,
803 review & editing. Ralf Loritz - Methodology, Resources, Validation, Supervision, Writing
804 – review & editing. Franziska Villinger - Methodology, Conceptualization, Resources,
805 Writing - review & editing. Mirko Mälicke – Software, Resources, Writing – review &
806 editing. Mehdi Koopaeidar - Conceptualization, Writing – review & editing. Hans Göppert
807 – Methodology, Conceptualization, Writing – review & editing. Erwin Zehe - Funding
808 acquisition, Methodology, Conceptualization, Project administration, Supervision,
809 Writing – review & editing.

810 **Declaration of Competing Interest**

811 The authors declare that they have no known competing financial interests or personal
812 relationships that could have influenced the work reported in this paper.

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