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Improving representation of collective memory in socio-hydrological models and new insights into flood risk management

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Abstract

Collective memory plays a controlling role in adaptation to potential flood risks, by learning from past disasters. However, with little quantitative empirical data, previous socio-hydrological models have conceptualized the decaying process of flood memory in an oversimple approach. Here, based on survey data of 683 respondents on Ningxia Floodplain, we confirmed that flood memory decays overtime via two channels: oral communication (communicative memory) and physical recording of information (cultural memory). Using the Universal Decay Model (UDM) proposed by previous researchers provides better fitting of results to the decay of flooding memory (adjusted R^2 coefficient are 0.97, 0.90, 0.95 when data of all, rural or urban respondents used, respectively) compared with the original exponential model (adjusted R^2 coefficient are 0.91, 0.74, 0.59, corresponding). Then, significantly reduced losses for the same flood sequence predicted by integrating the UDM into a socio-hydrological model by 16% and the differences between different clusters (urban and rural respondents) can even reach 22.81%. These differences suggest that previous socio-hydrological models have been too simplistic in their conceptualizations of decaying processes associated with collective memory, which may have limited deeper insights into flood risk management.

KEYWORDS

collective memory, flood risk management, socio-hydrological models, floodplain

1 | INTRODUCTION

Collective memory (or social memory), a concept representing the collective perception of events and shared experiences (Assmann & Czaplicka, 1995), may determine the capacity of communities to maintain awareness of specific risks (Viglione et al., 2014). One of the significant consequences of future climate change is a predicted

increased incidence of flood hazards (Arnell & Gosling, 2016; Jaramillo & Destouni, 2015; Winsemius et al., 2016). In the face of increasing flood risks on the world's largest rivers and their floodplains, collective memory plays a controlling role on how society keeps awareness of flood risk, by learning from past disasters (Best, 2019; Blöschl et al., 2017; Fanta, Šálek, & Sklenicka, 2019).

Based on rich observations, previous studies had embedded collective memory in socio-hydrological models of the interplay between human and floods (Di Baldassarre et al., 2015; Viglione et al., 2014). With little quantitative empirical data, previous simulations suggest that adaptation to flooding can effectively increase resilience and reduce losses as collective memory accumulates (Ciullo, 2017; Di Baldassarre et al., 2017, 2015). However, these heuristic models use to oversimplified processes of collective memory, where remain a knowledge gap may limit further insights toward flood risk management. For instance, similar to the "forgetting" curve of individuals, previous models describe a constant decaying process of flooding memory by a simple exponential function (Kelley, Neath, & Surprenant, 2015; Rubin & Wenzel, 1996). However, there is a large body of literature suggesting that collective memory consists by more complex processes which combine two distinct channels (Assmann & Czaplicka, 1995; García-Gavilanes, Mollgaard, Tsvetkova, & Yasseri, 2017; Rubin, 2014a, 2014b): communicative memory (sustained by oral transmission) and cultural memory (sustained by physical records including texts and monuments). From this theory, a Universal Decay Model (UDM) of collective memory which offers better explanations and predictions, had been proposed (Candia, Jara-Figueroa, Rodriguez-Sickert, Barabási, & Hidalgo, 2019; Coman, 2019). By distinguishing two channels (communicative memory and cultural memory), the UDM assumes they decay independently while partial lost communicative memory can transform into cultural memory synchronously. Since it is still unclear whether it is more applicable to the flooding memory domain than the original exponential model, a logical next step is to identify collective memory models that can effectively explain socio-flood interplays and inspire flood risk management.

Based on a survey regarding five well-documented historical floods in Ningxia Floodplain, China, we test how flooding memory decays and integrate it into the socio-hydrological models. Then, by comparing different simulation results, we explore if any essential difference raised after reconstructing the society modules with the UDM. Lastly and more importantly, we give discussions on how these differences inspire further insights on flood risk managements.

2 | METHODS

2.1 | Research framework

Assuming flooding memory as an important partial, Di Baldassarre et al. (2013), Viglione et al. (2014), Di Baldassarre et al. (2015) raised models to capture the co-evolution of society and flood events. On the base of them, we proposed a substitution of the society module by the Universal Decay Model (UDM) of collective memory (Candia et al., 2019) as it provides a more explicit explanation of collective memory.

As all modules and their relationships illustrated in Figure 1, we choose the model by Di Baldassarre et al. (2015) as a basic version for substitution, where collective memory plays a controlling role. First of all, we select a typical floodplain (see Section 2.2) to do a survey regarding memory of major historical floods (see Section 2.3). Then, after processing the questionnaires in the survey, we use the datasets to fit memory decay rate under different alternatives of the society module (see Section 2.4). Finally, we do simulations with the socio-hydrological model (see Section 2.5) to test if any essential difference can be demonstrated.

2.2 | Study area

The Yellow River (Figure 2a) crosses the Ningxia Plain in the arid and semi-arid regions of China and is known for its huge sediment discharge and frequent historical floods (Wohlfart, Kuenzer, Chen, & Liu, 2016). The Ningxia Floodplain, a fault basin filled with sediment from the Yellow River, accounts for a majority (6,600 km^2) of the total area of the Ningxia Plain (Figure 2b). Since precipitation is scarce in this area (180–200 mm/year), irrigation is vital for agriculture, the dominant economic sector on the floodplain (Figure 2c). Moreover, floods caused by highly concentrated precipitation of summer months is a threat to the autumn grain harvest, the most important income source for farmers in the study area (Figure 2d,e).

We chose this study area for the following three reasons: (a) First, previous studies have shown that floods of the floodplain's mainstem and tributaries are essentially non-contemporaneous (Yuan & Tian, 2016), which reduces the possibility of respondents' memory confusion. (b) Because of the isolation of topography, distinguishing borders shaped the floodplain where kept a low emigration rate, which make it easier to inquire flooding memory (Yuan & Tian, 2016). (c) There is a wealth of historical materials of flooding events here, with recorded floods dating back to 1904. Taken together, the Ningxia Floodplain appears to be a region well suited for our survey.
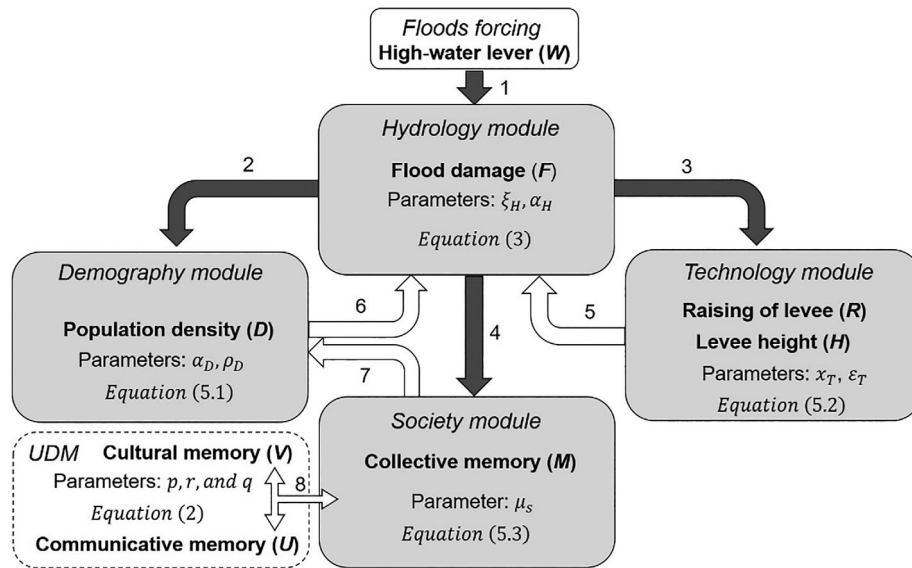
FIGURE 1 Model framework (adapted from Candia et al. (2019); Di Baldassarre et al. (2015)). The grey boxes are the main modules, and the white boxes are exogenous processes. The UDM (dashed box) is substituted for the *Society Module*. Black arrows indicate that output from one module directly causes an abrupt change in the target module, and white arrows indicate a gradual, coevolutionary relationship between the two connected modules. Arrow 1: Floods cause damages. Arrow 2: Flood damage leads to a sudden drop in relative population density. Arrow 3: Following its response strategies, the society chooses whether to heighten levees after flood damages. Arrow 4: The collective memory of flood damage accumulates abruptly. Arrow 5: The levee protects the society from floods with water levels lower than its height. Arrow 6: Greater relative population density means greater flood damage. Arrow 7: The population growth rate decreases in response to the collective memory of the floods. Arrow 8: In the UDM, collective memory consists of communicative memory and cultural memory and communicative memory is accumulated before cultural memory

2.3 | Data collection

To assess collective memory of the historical floods, we carried out a questionnaire survey (see Table 1) in the study area, collecting 391 online questionnaires and 338 offline questionnaires. Since the study area involves four prefecture-level cities: Shizui Shan (SZS), Yin Chuan (YC), Wu Zhong (WZ), and Zhong Wei (ZW), a stratified sample approach was applied according to the proportion of population in different prefectures. After screening, self-contradictory (e.g., the number of persons in a household is different from total members in each age group) and apparently haphazard responses (e.g., claiming to own a car in their home in 1904) were excluded as invalid data. A pre-processed dataset is open-access on Github (https://github.com/SongshGeo/Collective-Memory).

Some additional datasets were gathered for simulating with the socio-hydrological model. (a) High-water levels of the historical floods were provided by the Yellow River Conservancy Commission. (d) The demographic data and levee heights were retrieved from statistical yearbooks of government agencies (https://oversea.cnki.net/index/). (c) In order to calculate relative population density by the method from Di Baldassarre et al. (2017), the floodplain's maximum carrying capacity of population are set as 4–5 million by multiplying the number estimated from Zhao, Wang, and Wang (2008) and the area of the floodplain.

2.4 | Fitting of memory decay models

In our survey, respondents' memory to five well-documented major floods were collected. Once admitted to having memory to a certain historical flood, respondents must recall how they get known about it. Then, we labelled their answers by "heard of", "read about" or "experienced". Then, we assumed that the "heard of" label corresponds to communicative memory, the "read about" label corresponds to cultural memory, and the "experienced" label corresponds to that who initially influenced (Figure 3).

After that, we transferred the number of each catalogue into proportions. Considering five historical floods as observations, we applied least-squares fitting to estimate model parameters regarding memory decay rates. Our main concern was differences between two memory decaying models: the exponential-based model (Equation (1)) in the original socio-hydrological model and the UDM (Equations (2.1)–(2.3)). These alternatives
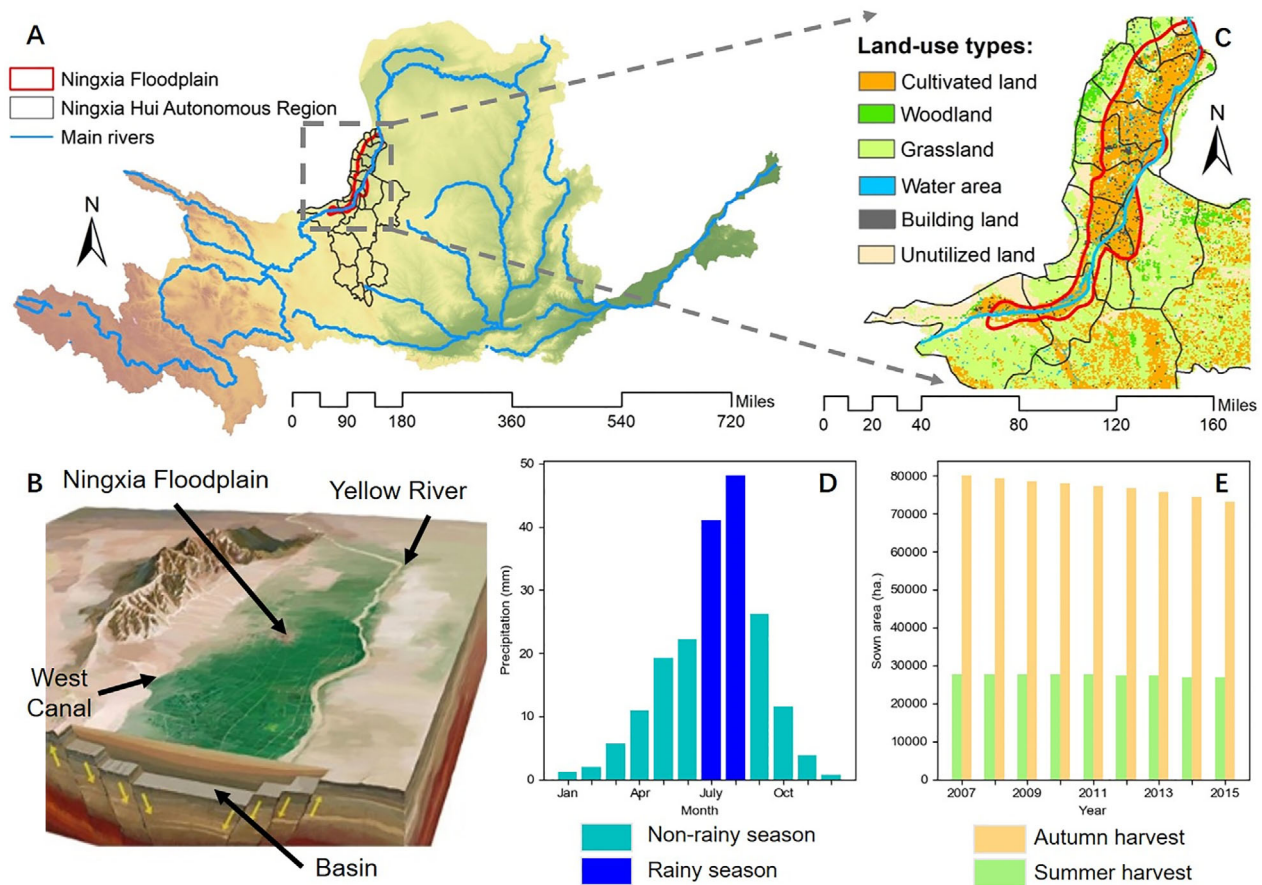
FIGURE 2 The study area. (A) Map of the Yellow River Basin showing the location of the Ningxia Floodplain. (B) Diagram showing the geography and tectonic structure of the Ningxia Floodplain, adapted from Chen (2010). (C) Land-use types of the Ningxia Floodplain. (D), Monthly precipitation in the study area. (E) Crop areas in the study area, 2007–2015

assume different memory decaying laws: while the exponential model only describes a single process of collective memory decaying (Figure 3A), the UDM splits collective memory into communicative memory and cultural memory, with conversions from the former to the latter (Figure 3B). Next, memory rates regarding historical floods are used in fitting the models and the results are assessed by the adjusted R^2. Since it can weaken impacts from various samples' size and degree of freedoms, the model with higher adjusted R^2 was considered as the more explanatory. Finally, we split the questionnaire dataset into different subsets according to household registration types (rural or urban) and refitted the model by above methods.

$$M_1 = n * e^{\mu_s * \Delta t} \tag{1}$$

$$M_2 = U + V \tag{2.1}$$

$$U = n * e^{-(p+r) * \Delta t} \tag{2.2}$$

$$V = \frac{n * r}{p + r - q} * e^{-q * \Delta t} - e^{-(p + r) * \Delta t} \tag{2.3}$$

where M_1 and M_2 refer collective memory, U and V refers communicative memory and cultural memory, respectively. Parameter n refers an initial value of memory, Δt is the time span from the beginning of decay. On the other hand, μ_s, p, r, and q are parameters related to decay rate (see Figure 3).

2.5 | Simulations by socio-hydrological models

In addition to the society module we focus on, there are another three main modules and an exogenous driving process in the socio-hydrological model (see Figure 1). (1) In the *Hydrology Module*, the relative flood damage (F, a proportion of loss ranging from 0 to 1) is a function of the flood's high-water level (W) and the current levee height (H). (2) In the *Technology Module*, the levee is

TABLE 1 Key questions in the questionnaire

Basic information:

Home address: _____, **Household registration type: Rural or Urban?** _____

Number of family members: _____, among them: <14___, 15-24___, 25-49____, 50-64____, 60 + _____

Education level: _____, **Income:** _____ (in a year)

Transportation and communication tools in: 1904_____, 1946_____, 1964____, 1981____, 2012_____.

Question 1: In which way did you learn about the following five floods? Please check the appropriate box (multiple selections are allowed)

	1904	1946	1964	1981	2012
Saw from books or other records	☐	☐	☐	☐	☐
Saw from a flood monument or historical marker	☐	☐	☐	☐	☐
Heard from others	☐	☐	☐	☐	☐
Friends who experienced it personally	**Impossible**	☐	☐	☐	☐
Do not know about it	☐	☐	☐	☐	☐
Personal experience	**Impossible**	☐	☐	☐	☐

Question 2: How much do you trust in the reliability of the levees of the Yellow River built by the government?

1(doubt)	2	3	4	5	6	7	8	9	10 (trust)

Question 3: How much do you trust in the accuracy of the flood predictions of the Yellow River by the government?

1(doubt)	2	3	4	5	6	7	8	9	10 (trust)

Question 4: How much do you trust in the ability of the government for emergency responses to floods?

1(doubt)	2	3	4	5	6	7	8	9	10 (trust)

raised by a factor (R) representing the response strategy the society takes. (3) In the *Demography Module*, the maximum growth rate of the population on the flood-plain decreases with the accumulation of collective memory or the occurrence of flood events. (4) The

driving process is *Floods Forcing*, which is an input as a time series of high-water levels (W) (Viglione et al., 2014). Taken together, the following equations (Di Baldassarre et al., 2015) are used in the model. The variables and parameters are defined in Tables 2 and 3, respectively.
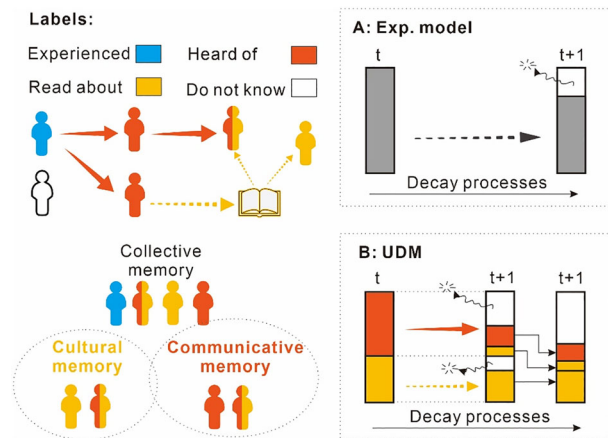
FIGURE 3 Respondent labels and their correspondence to different model variables. (A) Decay processes of collective memory according to an exponential model. (B) Decay processes of communicative memory and cultural memory, with part of communicative memory transfer into cultural one at the same time

$$F = 1 - e^{-\frac{W + \xi_H H_-}{\alpha_H}} \tag{3}$$

$$R = \begin{cases} \varepsilon_T \left(w + \xi_{H_-} - H_- \right) & \text{(Technological society)} \\ 0 & \text{(Green society)} \end{cases} \tag{4}$$

$$\begin{cases} \frac{dD}{dt} = \rho_D (1 - D(1 + \alpha_D M)) - \Delta(\psi(t)) \cdot FD_- & (5.1) \\ \frac{dH}{dt} = \Delta(\psi(t))R - x_T H & (5.2) \\ \frac{dM}{dt} = \Delta(\psi(t))FD_- - \mu_s M & (5.3) \end{cases}$$

Variables are indicated by capital letters, and a "minus" subscript indicates their current value. Parameters are indicated by Greek letters with subscripts that designate the module they apply to (i.e., H, F, R, S);

TABLE 2 Variables of the socio-hydrological model

Variable	Description	Position in the framework	Initial value
W	High-water level	Floods forcing	Time series of water levels
F	Relative flood damage	Hydrology module	0
H	Levee height	Technology module	0 m
R	Raising of levee	Technology module	0 m
D	Relative population density	Demography module	0.1
M	Collective memory	Society Module and the UDM	0
U	Communicative memory	UDM	0
V	Cultural memory	UDM	0

TABLE 3 Parameters of the socio-hydrological model

Parameter	Description	Unit	Module	Value
ξ_H	Proportion of additional high-water level relative to levee height		Hydrology	0
α_H	Relationship between floodwater levels and relative damage	L	Hydrology	84.5
ε_T	Safety factor for raising levees		Technology	0
κ_T	Rate of decay of levees	T^{-1}	Technology	0 year^{-1}
ρ_D	Maximum relative population growth rate	T^{-1}	Demography	0.03 year^{-1}
α_D	Ratio of preparedness to awareness		Demography	0.75
μ_s	Loss rate of collective memory	T^{-1}	Society	Fitted
p	Decay rate of communicative memory	T^{-1}	UDM	Fitted
r	Conversion rate from communicative to cultural memory	T^{-1}	UDM	Fitted
q	Decay rate of cultural memory	T^{-1}	UDM	Fitted

nonperiodic Dirac delta function ($\Delta(\psi(t))$) is always 0 except when $\psi(t) = 0$ (i.e., when flooding occurs), in which case it is 1. The main focus of this study is adaptation without considering the effects of levees, for which we set R as 0.

Next, we used data from the study area to estimate parameters. (1) For comparison with previous studies, the parameters related to levee effects (ξ_H, κ_T, and ε_T) were considered as zero, representing the hypothesis of no addition to high-water levels due to changes in levee height. (2) To estimate parameter α_H, we chose the high-water level of the flood event in 1904 ($W = 1{,}141.5$ m, $H = 1{,}135.3$ m, the biggest one ever) and calculated the percentage of the study area that would be inundated. According to (Yuan & Tian, 2016), this water level would affect 952.08 km^2 of the study area, which is 14.43% of the total area ($F = 0.1443$), i.e., $\alpha_H \approx 84.5$. (3) Our questionnaires scored the public's general perception of flooding risks in three respects (see Section 3.1):

reliability of levees (score = 7.31), flood prediction (score = 7.35), and emergency response (score = 7.54). Since the highest score is 10 (corresponding to $\alpha_D = 1$), we used these three scores as an estimation of the parameter for the public's risk awareness (i.e., $\alpha_D \approx 0.75$). (4) Since the model of increasing population in the study area appeared to be consistent with an exponential growth pattern, we adjusted the *Demography Module* by:

$$\frac{dD}{dt} = (D(\rho_D - \alpha_D M)) - \Delta(\psi(t)) \cdot FD_-, \qquad (6)$$

in which population growth is based on a Malthusian model with population growth rate in about 0.03 year^{-1}. (5) To the parameters related to collective memory decay (μ_s in exponential model, p, r, and q in UDM), the fitting results were used.

After then, we performed simulations under 100-year flooding sequence of forcing. We firstly compared the

UDM-based and the original exponential-based socio-hydrological model. Then, we further tested them under different memory decay parameters estimated from the "all respondents," "urban respondents," and "rural respondents" datasets, respectively. We repeat each test by simulating 100 times to ensure robustness of results and differences between them are evaluated by paired-samples T-test (significant when $p < .05$).

3 | RESULTS

3.1 | Survey results

There are 606 (88.86%) valid questionnaires after processing, whose distributions are similar to population ratio between different prefecture-level cities, compared with census data (Figure 4a). Furthermore, the proportion of respondents with rural household registration was 43.23%, with average gender ratio (male vs. female) of family members of 1.00, which are similar with 41.13% and 1.04 in census data. According to our survey, there are some differences between urban and rural respondents in channels of retaining flooding memory: only 21.02% flooding memory of rural respondents came from reading about, while it is 37.13% of urban respondents (Figure 4b). For five differ-magnitude historical floods, respondents' flooding memory mainly came from "hearing of," while the number of respondents who had known of each historical flooding by "reading about" is rather similar (Figure 4b). However, after proportional

scaling them by water levels, a clear trend shows that more respondents can memorize a more recent flood (Figure 4c). Finally, according to our survey of risk cognitions, there are few differences between dimensions of flooding risk awareness: trust to levee (mean score: 7.32), trust to disaster warnings (mean score: 7.36) and trust to government (mean score: 7.52) (Figure 4).

3.2 | Decay of collective flooding memory

The original exponential model and the UDM, based on different theories, result in different fitting results of flooding memory decay, respectively. According to the UDM, collective flooding memory estimated to have a rapid increment firstly then decreasing gradually (Figure 5a), consisting of the sum of communicative and cultural memory. On the other hand, the original exponential model estimates this process as a keeping decaying curve (Figure 5e), whose adjusted R^2 coefficient is 0.91 (Figure 5b), slightly below the UDM in 0.97 (Figure 5f). However, when fitting by different datasets catalogued by respondents' registration types, substantial gaps between two models were further revealed. For rural and urban respondents, respectively, the exponential decay model's adjusted R^2 decreases to 0.74 and 0.59 (Figure 5g,h). On the other hand, for all types of dataset, the UDM throughout provides effective fitting, as the adjusted R^2 remained above 0.9 (Figure 5c,d).
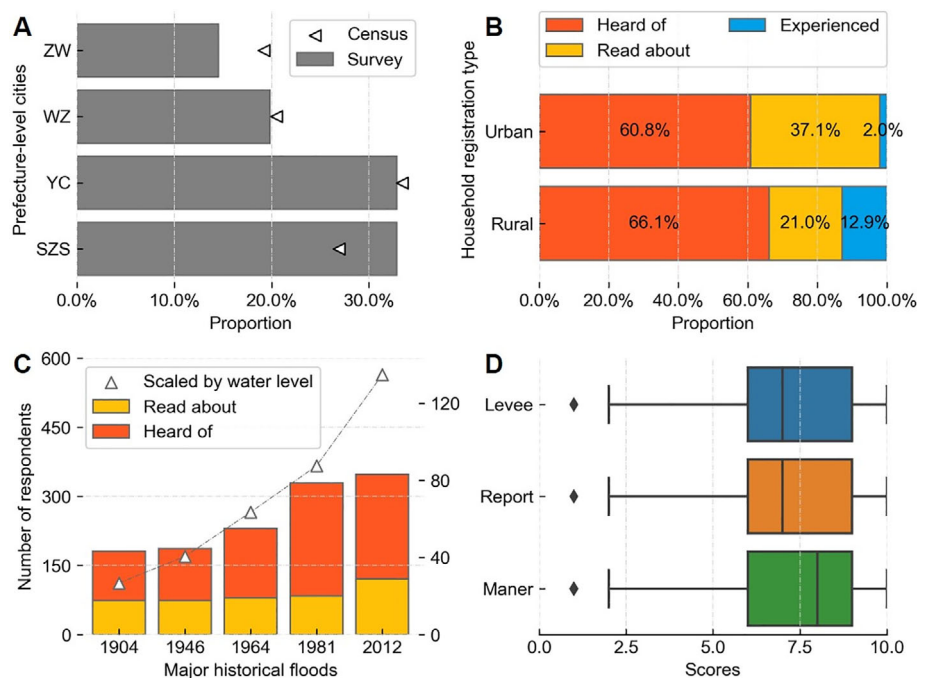
FIGURE 4 Main statistical results of the questionnaire. (A) Proportion of respondents from different prefecture-level cities. (B) Proportion of respondents' flood memory channels from different household registration types. (C) Number of respondents with memory regarding five major historical floods. (D) Perception scores of flood risks
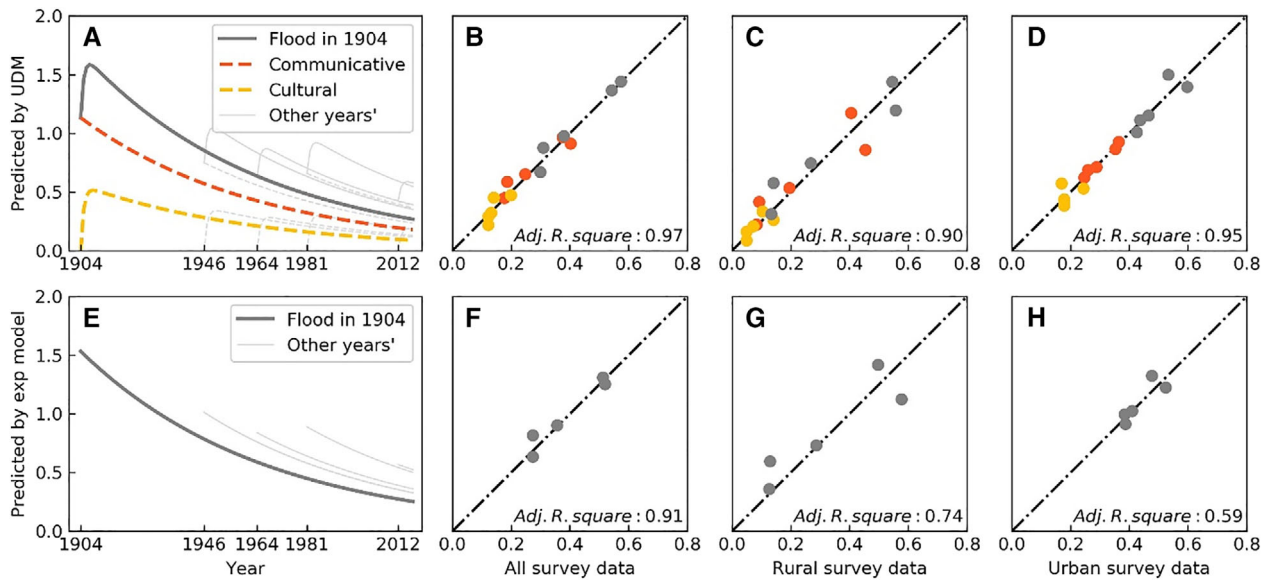
FIGURE 5 Fitting results by different collective memory decaying models. In the diagram of decay processes predicted by the UDM (A) and by the exp model (E), we only highlight the trend of flood in 1904 in order not to clutter. Others, Figures B, C and D show the relationship between the different survey data (all survey data, rural and urban survey data) results of flooding memory retention rate for each historical flood and of the predicted results by the UDM, while F, G, H correspondingly represent the exp model respectively

3.3 | Simulation results

After integrating the UDM as the society module of the socio-hydrological model, accumulations of flooding memory and simulations of flooding losses all differ from the original model. According to our results, since an accumulation of flooding memory simulated by the UDM-based model are faster, flooding losses significantly ($p < .01$) reduced over 16% within 100-year flooding sequence (Figure 6). Furthermore, some significant differences in the simulations of the socio-hydrological model also occur when the three different datasets are used to fit memory decay rates. Comparing with the base-case model whose parameters estimated by the dataset of all respondents, an average total flooding loss from the 100-times simulation within 100-year flooding sequences are (Figure 7A):
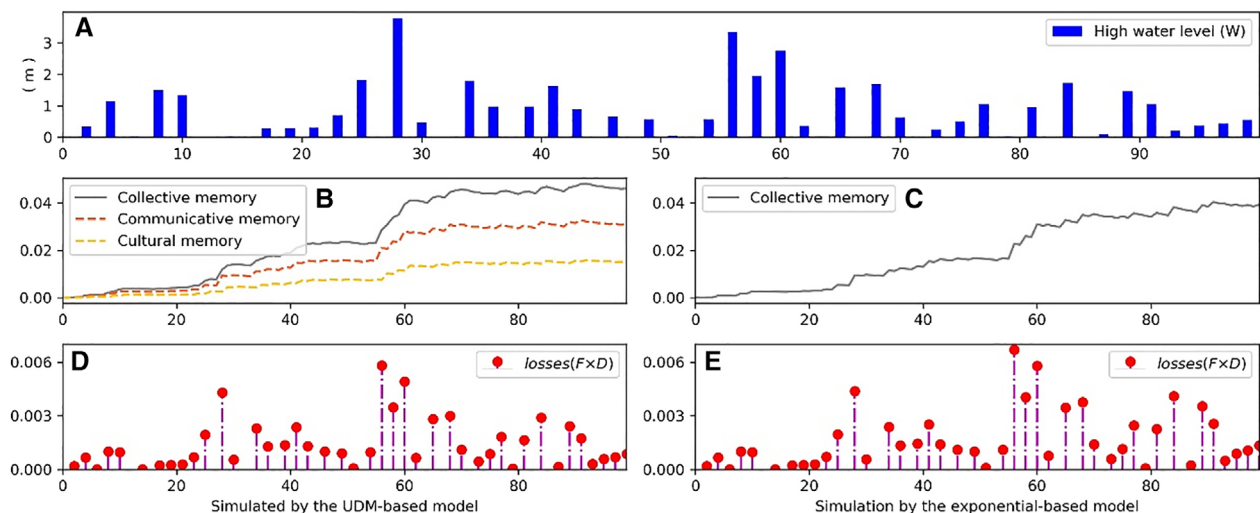
FIGURE 6 Losses simulation under a 100-year potential flood sequence. (A) Time series of random flood forcing. (B) Simulation of collective memory by the UDM as society module. (C) Simulation of collective memory by the exp model as society module. (D) Simulation of annual flooding loss by socio-hydrological model integrated the UDM. (E) Simulation of annual flooding loss by the original socio-hydrological model
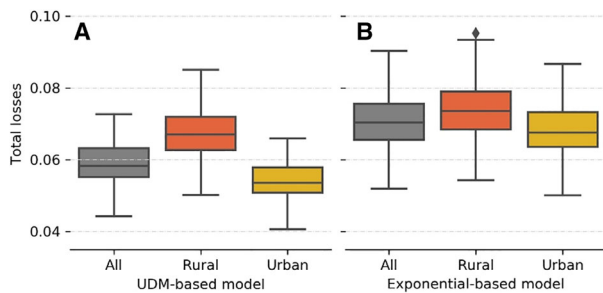
FIGURE 7 Total flooding losses simulated under a 100-year potential flood sequence by UDM-based (A) and exponential-based (B) socio-hydrological model (repeated 100 times of simulation), with parameters fitted by different dataset of respondents (all respondents, rural respondents, or urban respondents)

- Increased by 14.54% increased when parameters are evaluated from the rural dataset and
- Decreased by 8.27% decreased when parameters area evaluated from the urban dataset.

By way of contrast, these numbers are only 4.69% and 3.42% for the exponential-based model (Figure 7b). In addition, one of the simulations reveals that collective memory is accumulating more rapidly when the UDM-based model using parameters fitted by the urban dataset, and the flooding losses become progressively lower (Figure 8). However, when using parameters fitted by the rural dataset, the change of flooding memory is rather similar to that simulated by exponential-based ones, which have much slower processes for memory accumulation (Figure 8).

4 | DISCUSSION

### 4.1 | Why the UDM makes more sense

Based on rich empirical observations, collective memory, playing an important role on how societies keep

awareness to flood risks, has been embedded in socio-hydrological models to capture the interplay between human and floods (Ciullo, 2017; Di Baldassarre et al., 2015; Fanta et al., 2019; Viglione et al., 2014). Though flooding hazard leads to series of adaptative actions (fight or flight), potential losses increased as the memory decayed and awareness weakened, where flooding memory decay rates play a big part (Ciullo, 2017; Di Baldassarre et al., 2015). Our survey suggests people often forget the once devastating floods, since flooding memory shows an evident decreasing trend with time spans (Figure 4c), which is in line with the finding that "the memory of the flood will not last for generations" (Fanta et al., 2019).

On the base of flooding memory decaying hypothesis, studies on individual or collective memory also expand broad prospects in this realm. Many theories have depicted a general process of memory decaying, in which the newest and classic ones both point out that collective memory may consist of communicative memory (or living memory) and cultural memory (or distant memory) (Boyer & Wertsch, 2009; Hirst, Yamashiro, & Coman, 2018; Rubin, 2014a, 2014b). Again, our results are in line with this theory, based on following three reasons. (1) Firstly, for five surveyed historical floods, there is no significant correlation (see Figure 4c, $p > .1$) in flooding memory between two channels (communicative or cultural), which indicates that they may follow in different decaying processes. (2) Secondly, the UDM fit the flooding memory well (adjusted R^2 is 0.97, see Figure 5), while different memory channels (collective, communicative, or cultural) were all well predicted. (3) Thirdly, when tested by different subsets of survey data, the fitting results of UDM kept robust (adjusted R^2 is 0.90 and 0.95, by the rural or urban subsets, respectively). However, an exponential decaying model failed to capture diversities between rural and urban clusters, with the adjusted R^2 of fittings decrease rapidly (0.74 by rural dataset and 0.59 by urban dataset).

The above-mentioned differences may stem from underlying assumptions of memory decay. The original

FIGURE 8 Flooding memory simulation (A) and losses simulation (B) under a 100-year potential flood sequence (the same sequence as Figure 6), where different datasets or different memory-decay models (the UDM or the exponential model) were used
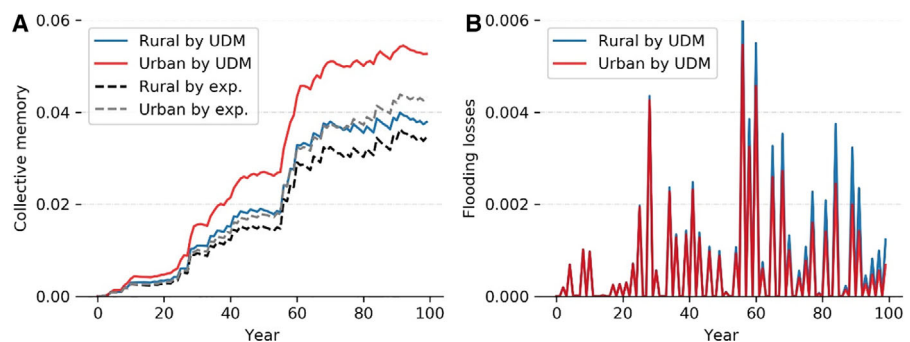
exponential model, also known as the "forgetting" curve, originally came from a famous psychological experiment in 1885 that explored the laws of individual memory (Psychology Wiki, 2020). However, a large body of literature suggests that collective memory following completely different laws from individual memory, as complex propagations and interactions play a role (Assmann & Czaplicka, 1995; Boyer & Wertsch, 2009; Candia et al., 2019). For example, cases show that collective memory contains a high level of attentions at the initial phase—often referred to as "opinion fermentation"—followed by a gradual but long-lasting period of forgetting (Candia et al., 2018; García-Gavilanes et al., 2017; Licata & Mercy, 2015). Again, our fitting results suggest the laws can be explained by the UDM, while the exponential model is rather a description of individuals' memory decay. For instance, differences between rural and urban subsets may reflect a fact that there are discrepancies in their flooding memory channels. While rural dwellers are influenced by communicative memory a lot, flooding memory is more accessible through cultural channels for urban dwellers (see Figure 4b). Since previous studies have pointed out that cultural memories often decay more slowly (Candia et al., 2018), urban respondents were able to accumulate flood memories faster (see Figure 8).

Taken together, our results suggest that while socio-hydrology has recognized the controlling role of collective flooding memory, an overly simplistic understanding of its decay may conceal some important features of this process.

4.2 | How can the UDM inspire insights of flood risk management

For following three reasons, we believe that the integration of UDM into the socio-hydrological model provides new insights into flood risk management.

Firstly, the improvement of the society module by the UDM contributes to further development of the related socio-hydrological models. Previous studies based on the original model have shown that it is paramount for floodplain societies to avoid potential flood risks by retaining flood memory (Ciullo, 2017; Di Baldassarre et al., 2015). Both empirical and simulation results suggest that adaptation comes with accumulation of collective memory as a powerful buffer against flood risk, while the adoption of structural measures (e.g., construction of levees) may lead to more catastrophic events (Ciullo, 2017; Fanta et al., 2019; Gober & Wheater, 2015). Since the memory decay laws serve as a key to understanding collective memory changes, the adoption of the UDM with more

general explanatory power helps further model developments, to deepen understanding of human–flood interactions.

Second, integration of the UDM helps in exploring differences between different clusters (e.g., rural and urban dwellers) that are prevalent in the face of flooding risks. Our results suggest that rural respondents, who had experienced floods in person (or heard from their around) (Figure 4b), are more likely to suffer larger total flooding losses than urban respondents, within a same flooding sequence (Figure 7). Urban dwellers can accumulate flood memory more quickly (Figure 8), which may be related to the fact that they often have higher levels of education, as their awareness of flood risk from cultural memory is higher than that of rural dwellers (Figure 4b). However, previous studies have shown that urban and rural flood risk management strategies are quite different (Morris, Beedell, & Hess, 2016; Twigger-Ross et al., 2005), for which it is necessary to set up different strategies to different clusters when confronted with flood hazard risk.

Finally, for policymakers, models should make practical sense to help in answering the question of how to maintain the flooding memory (Loucks, 2015; Troy, Pavao-Zuckerman, & Evans, 2015). With an improvement, the UDM introduces a parameter for the conversion rate of communicative memory to cultural memory (Candia et al., 2018). Since this parameter describes a social learning process of converting knowledge into a written record (regarding cultural memory), it can enlighten future policymakers on how to transmit flood memory to younger generations, in order to mitigate flooding risks. Thus, it responds to previous calls for exploration of flood memory transmission channels (Fanta et al., 2019).

Taken together, since the previous exponential model of flood memory is rigid and lacking in explanatory, a deeper understanding of flooding memory by distinguishing between two practicable channels (communicative memory and cultural memory) can inspire further flood risk management.

5 | CONCLUSION

Collective memory is often cited as an important variable in interplays between society and floods, but previous socio-hydrological models have conceptualized its decay too simply. We examined the real-life flooding memory through a survey and data were used to fit different models for the decay of flooding memory. Our results suggest that the Universal Decay Model (UDM), rather than the exponential model widely adopted in related

socio-hydrology models now, provides more consistent interpretations of flood memory. We then integrated the UDM into a socio-hydrological model for further simulations. Once again, results indicate that the UDM-based model successfully captured differences between clusters: Rural dwellers are more likely to suffer larger total flooding losses than urban respondents within a same flooding sequence as urban dwellers can accumulate flood memory more quickly. In summary, the exponential decay model widely used now lacks a sufficiently valid explanation of the social process associated with collective memory. On the other hand, supported by the results of survey, goodness of fit, and differences between models simulations, an integration of the UDM may well inspire us in generating deeper insights into flood risk management. We call for, therefore, a further exploration of socio-flood interactions based on the UDM as a society module in the future.

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DATA AVAILABILITY STATEMENT
The data that support the findings of this study are openly available in GitHub at https://github.com/SongshGeo/Collective-Memory.

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