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Key Points:

- We develop a simple stylized model linking social preparedness with flood warning outcomes
- We explore how preparedness decay rates affect the efficiency of early warning systems
- We find that preserving social preparedness can significantly contribute to reduced disaster losses

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Impact of social preparedness on flood early warning systems

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Abstract Flood early warning systems play a major role in the disaster risk reduction paradigm as cost-effective methods to mitigate flood disaster damage. The connections and feedbacks between the hydrological and social spheres of early warning systems are increasingly being considered as key aspects for successful flood mitigation. The behavior of the public and first responders during flood situations, determined by their preparedness, is heavily influenced by many behavioral traits such as perceived benefits, risk awareness, or even denial. In this study, we use the recency of flood experiences as a proxy for social preparedness to assess its impact on the efficiency of flood early warning systems through a simple stylized model and implemented this model using a simple mathematical description. The main findings, which are based on synthetic data, point to the importance of social preparedness for flood loss mitigation, especially in circumstances where the technical forecasting and warning capabilities are limited. Furthermore, we found that efforts to promote and preserve social preparedness may help to reduce disaster-induced losses by almost one half. The findings provide important insights into the role of social preparedness that may help guide decision-making in the field of flood early warning systems.

1. Introduction

The concept of flood risk management has evolved from being a set of strictly technical procedures focusing on flood defense to integrating all relevant actions and actors in flood crisis situations into what is now referred to as the disaster risk reduction framework [*Basher*, 2006; *United Nations International Strategy for Disaster Reduction* (*UNISDR*), 2007, 2015]. Even so, the limited understanding of the interactions and feedbacks between the physical and social systems means that, in practice, most flood management operations and research still cannot make use of the full potential of this framework [*Jongman et al.*, 2015; *Winsemius et al.*, 2015]. This, however, is beginning to change as both researchers and practitioners are realizing the importance of integrating social, environmental, and economic aspects of flood risk management in order to improve flood risk reduction and mitigation actions [*Buchecker et al.*, 2013; *Sivapalan et al.*, 2012]. This transition is exemplified by the IAHS *Panta Rhei* Scientific Decade 2013–2022 [*Montanari et al.*, 2013].

Flood Early Warning Systems (FEWS) are among the most widely used tools for flood risk management [*Cloke and Pappenberger*, 2009]. FEWS not only contribute to mitigate disaster damage and casualties and foster economic benefits through the optimization of flood-sensitive economic activities, but they also have a high benefit to cost ratio [*Hallegate*, 2012]. FEWS are however also constrained by an insufficient emphasis on the social, economic, and environmental vulnerabilities; among other issues [*United Nations* (*UN*), 2006]. In this context, many studies have focused on improving individual components of FEWS such as forecasts [*Alfieri et al.*, 2011] or social vulnerability [*Balica et al.*, 2012], and even the overall system [*Ambühl*, 2010; *Krzysztofowicz and Davis*, 1983].

A key element conditioning the efficiency of FEWS is preparedness. This term refers to the knowledge and capacities of different stakeholders to anticipate, prepare themselves, and respond to an imminent or ongoing disaster [*UNISDR*, 2009]. According to the previous definition, preparedness may refer to different social groups such as decision-makers, first responders, or the general public; each with its own set of relevant factors [*Christoplos et al.*, 2001]. Social preparedness, in particular, is strongly affected by human behavioral traits such as risk awareness, recency of flood experience—related to memory—trust in the authorities, or the interactions between society and the environment [*Ejeta et al.*, 2015; *Terpstra*, 2011; *Viglione et al.*, 2014]. Additionally, social disengagement when efficient risk reduction services are in place, perceived responsibilities, effectiveness, and costs of mitigation measures, or even media coverage, gender, fatalism, and denial also play an important role in individual flood mitigation behavior [*Bohensky and Leitch*, 2014; *Bubeck et al.*, 2012; *Grothmann and Reusswig*, 2006; *Parker et al.*, 2009; *Scolobig et al.*, 2012; *Zaalberg et al.*, 2009]. Overall, improving the understanding of the way people behave during a flood crisis situation may also improve the usage of the available technological capabilities [*Parker et al.*, 2009] and reduce the casualties and damages from flooding events [*Brilly and Polic*, 2005].

Quantifying social dynamics such as social preparedness toward flood disasters is a challenging task due to the complex nature of these processes [*Di Baldassarre et al.*, 2015; *Oki and Kanae*, 2006]. Consequently, most studies in this field need to rely on qualitative, context dependent data such as those obtained by interviews or surveys [*Erikson*, 1976; *Kreibich et al.*, 2011; *Mishra et al.*, 2010]. While these data and methodologies provide accurate depictions of the specific case studies [*Burningham et al.*, 2008; *Knowles and Kunreuther*, 2014; *Takao et al.*, 2004], results from different studies are difficult to compare and their explanatory power outside the specific case study is limited [*Kellens et al.*, 2013]. A number of alternative approaches have been recently developed that aim to capture broad trends across different settings, at the expense of simplifying the complexities of sociohydrological systems [*Blair and Buytaert*, 2016]. Recent examples include, but are not restricted to, modeling interactions and feedbacks mechanisms between agriculture development and environmental health [*van Emmerik et al.*, 2014] or between social vulnerability and floods [*Di Baldassarre et al.*, 2013].

In this study, we aim to assess and quantify the impact of social preparedness on the efficiency of FEWS. Due to the complexity and variety of factors affecting preparedness, and following the reasoning exposed in the previous paragraph, some simplifications and assumptions need to be made in order to provide quantitative estimations that may be valid for different settings. For this purpose, we considered the recency of flood events to be the main driver of preparedness, while neglecting other factors. This assumption implies that the willingness to take precautionary actions toward potential flood events—both by first responders and the general public—is primarily dependent on the damage associated to the last flood event and the time elapsed since that event. This behavior is not only intuitive but has also been observed, for instance, in peaking flood insurance coverages after a major flood and subsequent decreases over time [*Hanak et al.*, 2011]. To achieve the aims of the study, we developed a simple stylized model of a hypothetical sociohydrological system as a tool to quantify the impacts of social preparedness on the efficiency of FEWS and provide insights into possible enhancements. In addition we also performed a sensitivity analysis of this model to assess its robustness and usefulness for further studies.

2. Methodology

In the following sections, we present the data, model structure, and the efficiency measures used in this study and we outline the analysis. Due to the exploratory nature of this study, we constrained ourselves to synthetic data and simplified relationships between the different components of the model. Nevertheless we made an effort to keep the model realistic by using observations extracted from the literature to constrain our hypotheses and parameters, where feasible.

2.1. Data Set

We used a synthetic time series of discharge data to test the model. This approach allowed us to avoid the limitations of experimental time series such as a limited time span or a reduced number of registered extreme events [*Brown et al.*, 2000]. The adequate characterization of the variability of hydrometeorological events has been the object of many studies and different probability distributions have been proposed to explain these dynamics [*Kelly and Krzysztofowicz*, 1994]. Some relevant examples include lognormal [*Yue*, 2000], Gumbel [*Yue et al.*, 1999], Two-Component Extreme Value (TCEV) [*Rossi et al.*, 1984], and the Generalized Extreme Value (GEV) [*Morrison and Smith*, 2002] distributions. For the present study, we used a simple bivariate gamma, Γ, distribution based on *Yue* [2001] in order to generate a long—1000 years—time series of maximum annual flows, Q, covering an adequate number of extreme events (Figure 1). This probability distribution is characterized by shape, κ_C, and scale, θ_C, parameters (equation (1)). The maximum flow for a given year was assumed to be independent from the maximum flows of the previous years.

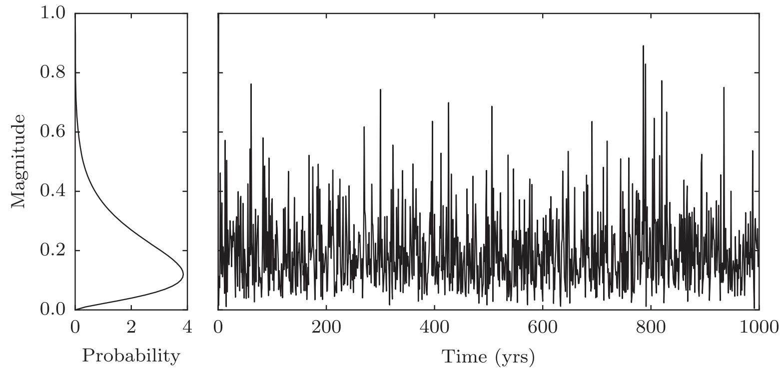

Figure 1. Synthetic data series used in this study. (left) Bivariate gamma distribution—normalized between 0 and 1—used to generate the time series. (right) Time series of maximum annual flows for a predefined period of 1000 years.

$$Q \sim \Gamma(\kappa_C, \theta_C) \tag{1}$$

2.2. Model Description

The stylized model we developed to assess the impact of social preparedness on the efficiency of FEWS is introduced in the following sections together with the main assumptions and simplifications that we made. The model draws from previous work in the fields of flood management, forecasting, and warning; most notably from *Ambühl* [2010], *Di Baldassarre et al.* [2013], *Nester et al.* [2012], and *Verkade and Werner* [2011]. Furthermore, unlike previous studies we normalized site-specific model parameters such as reference damage or cost of mitigation actions to ensure that results from different settings remain comparable.

The model consists of four different routines. First, flow magnitude is input into the *flood forecasting system routine*, which generates a corresponding probabilistic forecast. The forecast and subsequent warning are evaluated by the *forecasting and warning evaluation routine* by comparing the forecast probability distribution function with the actual flow magnitude. The economic consequences related to the warning outcome and social preparedness level are then calculated by the *consequences estimation routine*. Finally, the social preparedness level is updated based on the warning output and flood damage by the *preparedness routine*. The different variables and parameters used in the model are summarized in Tables 1 and 2 respectively.

2.2.1. Flood Forecasting System

This routine is responsible for generating probabilistic forecasts based on the input flow magnitude. Probabilistic flood forecasts have been preferred over deterministic ones for many years as they take into account forecasting uncertainties, provide tools for taking risk into account, and help making rational decisions [*Krzysztofowicz*, 2001]. In this model, we used a random probabilistic forecast generator based on *Ambühl* [2010] (equation (2)). This way, the forecast probability distribution function, F, takes the shape of a normal distribution with the accuracy being determined by a second normal probability distribution and the precision being determined by a gamma probability distribution. The parameters controlling the accuracy (μ, σ^2) and precision (κ_F, θ_F) of the forecasts can be used to represent the technical capabilities of different forecasting systems. For this study these parameters were determined based on *Nester et al.* [2012]. Forecast lead-time, which is an important variable affecting the performance of forecasts [*Todini*, 2004], is not explicitly taken into account for this study. Even so, it can easily be incorporated by modifying the forecasting accuracy and precision parameters.

Table 1. Variables of the Coupled Flood Warning and Response Model and Their Initial Conditions

	Description	Equation	Initial Condition
C	Cost of mitigation actions		
D	Flood damage	(3, 4, 5)	0.00
E	Social preparedness	(5, 6)	0.50
O	Warning outcome		
P	Probability of exceedance		0.00
Q	Normalized maximum annual flow magnitude	(1, 2, 3)	0.00
R	Residual flood damage	(4, 5)	0.00

$$F \sim N(Q+N(\mu, \sigma^2), \Gamma(\kappa_F, \theta_F)) \tag{2}$$

2.2.2. Forecasting and Warning Evaluation

Once a forecast is available, if the probability of exceedance, P, exceeds a predefined probability threshold, π, a warning is automatically issued. A

Table 2. Parameters of the Coupled Flood Warning and Response Model and the Range of Values Used in This Study

	Description	Equation	Values
α	Residual damage fraction	(4, 5)	0.10–0.90
β	Shape parameter of the damage function	(3)	0.10–0.50
δ	Damage threshold	(3)	0.35
η	Mitigation cost proportionality factor		0.10
θ_F	Forecast precision scale	(2)	0.01–1.00
κ_F	Forecast precision shape	(2)	0.01–1.00
λ	Social preparedness decay rate	(6, 7)	Dependent on τ
μ	Forecast accuracy mean	(2)	−1.00 to 1.00
ξ	Magnitude threshold		0.35–0.80
π	Probability threshold		0.20–0.80
σ^2	Forecast accuracy variance	(2)	0.01–1.00
τ	Social preparedness decreased half-life	(7)	1.00–100.00
χ	Shock magnitude	(6)	1.00

strong simplification is done here as forecasts are usually meticulously assessed by flood warners before issuing a warning. Decisions are then made based on the likelihood of the warning but also on previous experience [*Ramos et al*., 2010].

Warning outcomes, *O*, are thereafter evaluated based on a simple contingency table (Table 3). Contingency tables are a common tool for decision making and are widely used for early warning systems [*Alfonso et al*., 2016; *Choo*, 2009]. Outcomes are dependent on two conditions: first, whether the magnitude of the forecasted event is above a certain magnitude threshold, ξ, and therefore likely to cause damage; and second, whether the forecasted likelihood of that event causing damage is above a predefined probability threshold, π. The interplay of the two conditions produces the following outcomes: *true positive (successful alarm)*, *false positive (false alarm)*, *false negative (missed event)*, and *true negative*.

2.2.3. Consequences: Costs and Damages

Each warning outcome has specific costs and damages associated with it (Table 3). Costs, *C*, include all the expenses related to operating the forecasting, warning, and response actions. Some of these costs are fixed, such as those related to running the flood forecasting and warning service; while others are dependent on the magnitude of the forecasted flood event. Costs related to response and mitigation actions are placed under this category. In this study, we made the assumption that fixed costs are small compared to those arising from mitigation and protection actions and that the total costs are therefore proportional to the magnitude of the forecasted flood event through the parameter η. Structural flood damage, D_Q, is usually considered to be dependent on the magnitude of the event. Many theoretical and experimental damage curves relating the magnitude of a hazard to its associated consequences have been proposed [*Jongman et al*., 2012]. In this study, we used a simple exponential function (equation (3)) based on *Di Baldassarre et al*. [2013]. Following this equation, flood damage is negligible below a predefined damage threshold, δ, and increases above it, asymptotically approaching the reference damage, which was normalized to 1 in this study (Figure 2). The curvature of the damage function is controlled by the β parameter.

$$D_Q = \begin{cases} 0 & \text{for } Q < \delta \\ 1 - e^{-\frac{Q-\delta}{\beta}} & \text{for } Q \geq \delta \end{cases} \tag{3}$$

The residual damages (or unavoidable damages), R_Q, are the fraction, α, of the potential damages, D_Q, caused by a certain event that cannot be eliminated through damage mitigation actions triggered by the flood early warning system (equation (4)).

$$R_Q = \alpha D_Q \tag{4}$$

Table 3. Contingency Table Defining the Possible Outcomes of the Flood Early Warning System[a]

	$Q < \xi$	$Q \geq \xi$
$P < \pi$	True negative *0*	False negative (missed event) *Damage*
$P \geq \pi$	False positive (False alarm) *Cost*	True positive (Successful alarm) *Cost + residual damage*

[a]Costs and damages associated with each of the outcomes are highlighted in italics.

Previous studies have attempted to estimate the unavoidable damage in several settings [*Carsell et al*., 2004; *Gocht et al*., 2009; *Penning-Rowsell and Green*, 2000]. Residual damages are usually reported to oscillate between 40 and 80% of the total disaster damages, depending on the forecast lead-time, level of preparedness, and setting. For this study, we used a simple exponential function to represent

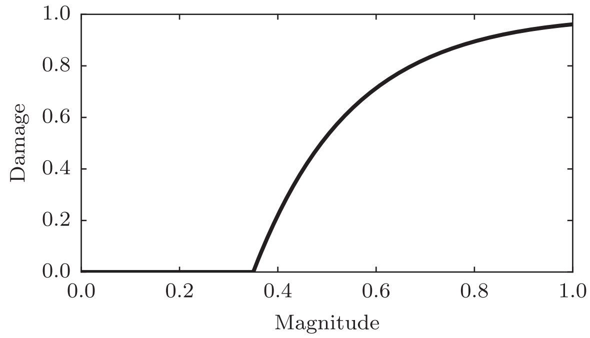

Figure 2. Normalized flood damage as a function of the magnitude of any given flood event. Damages are negligible for events with magnitudes below a predefined damage threshold (δ=0.35) and increase logarithmically thereafter.

the link between preparedness and residual damage (Figure 3).

Following the main assumption that social preparedness can be estimated using the recency of flood experience, increased vulnerability and subsequent higher residual damage produced by suboptimal decisions would be related to long periods without flood disasters. The residual damage, $R_{Q,E}$, is thus given by an exponential decay function by setting social preparedness, E, as the independent variable, and α_0 as the minimum possible residual damage (equation (5)).

$$R_{Q,E}=D_Q e^{\ln\left(\frac{1}{\alpha_0}\right)E} \tag{5}$$

2.2.4. Preparedness: Recency of Flood Experience

Social preparedness not only influences the damage produced by a given flood event but is also influenced by it. By assuming that recency of flood experience is the primary driver of social preparedness, the willingness of people to take precautionary measures is increased immediately after a flood event through a shock, χ, and exponentially decays over time at a certain decay rate, λ [*Di Baldassarre et al.*, 2013; *Parker et al.*, 2009] (equation (6)). Social preparedness is set at a neutral initial value of 50%. Figure 4 illustrates the variability of social preparedness in conjunction with damaging flood events.

$$E_t=\begin{cases} E_{t-1}-\lambda E_{t-1} & \text{for } R_{Q,E}=0 \\ E_{t-1}+\chi & \text{for } R_{Q,E}>0 \end{cases} \tag{6}$$

Instead of using the social preparedness level decay rate directly we used the half-life, τ, expressing the time it would take for the social preparedness level to become half of the starting value (equation (7)). Through this transformation, it is possible to get a more intuitive notion of the rate at which social preparedness fades.

$$\tau=\frac{\ln(2)}{\lambda} \tag{7}$$

2.3. Efficiency Measure

The aim of FEWS is to reduce the losses—i.e., the sum of flood damage and mitigation costs—experienced by society as a consequence of floods. For this reason, and to ensure comparability among different settings, we used normalized disaster losses as efficiency measure in this study. Different approaches to normalize disaster losses have been proposed in the literature [*Neumayer and Barthel*, 2011]. In this case, we used the relative loss measure (equation (8)). The relative loss, L_r, is the ratio between the losses incurred after damage mitigation measures have been taken, L_w, with respect to the losses incurred when no warning system is in place, i.e., the damages dependent only on the climatic variability, L_c. Using the climatic losses as a reference point to calculate, the relative loss allowed us to estimate the actual benefits of (i) having an early warning system in place, and (ii) comparing different configurations of the model. This way, efficient early warning systems would translate into low relative loss values. Conversely, inefficient warning systems could

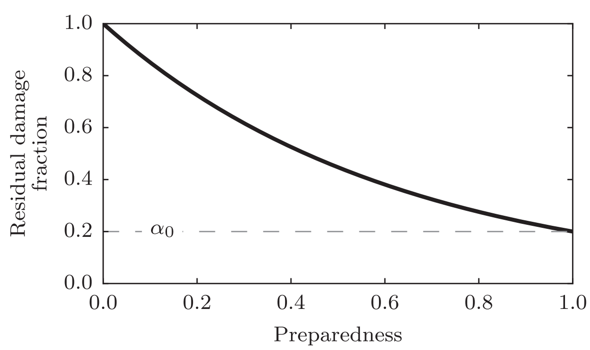

Figure 3. Residual damage fraction as a function of the level of social preparedness. The dashed line, α_0, represents the baseline residual damage fraction, which is a model parameter.

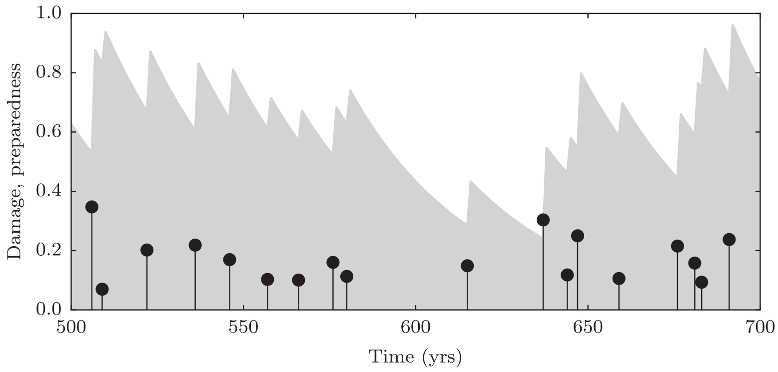

Figure 4. Detail of the evolution of social preparedness along the time series maximum annual flows (shaded area) as a function of the (lack of) occurrence of damaging flood events (black dots). Social preparedness increases immediately after damage occurs and decreases exponentially thereafter if nothing happens.

bring the relative loss over 1 by adding the costs of operation on top of the unmitigated damages from flood events.

$$L_r = \frac{L_w}{L_c} \tag{8}$$

In addition to the relative losses, we also used the hit rate and false alarm ratio measures to evaluate the performance of the forecasting and warning system. The *hit rate* is the ratio between the total number of true positive warning outcomes, O_{TP}, over the total number of positive events, $O_{TP}+O_{FN}$ (equation (9)). The *false alarm ratio*, in contrast, expresses the ratio between false positive warning outcomes, O_{FP}, over the total number of positive warnings, $O_{FP}+O_{TP}$ (equation (10)).

$$\text{Hit rate} = \frac{O_{TP}}{O_{TP}+O_{FN}} \tag{9}$$

$$\text{False alarm ratio} = \frac{O_{FP}}{O_{FP}+O_{TP}} \tag{10}$$

2.4. Analysis

The first step in the analysis was to perform a sensitivity analysis of the model. This procedure allowed us to get a first overview of the impact of social preparedness on the FEWS but also to get insights on other possible relationships involving other model parameters. We performed the analysis based on 100,000 Monte Carlo model runs with random parameter values within given ranges (Table 2). Some parameters were kept constant as they represent boundary conditions (e.g., damage threshold or the mitigation cost proportionality factor), which are dependent on the setting in which the model is applied. Additionally, we investigated the impact of social preparedness on relevant individual parameters such as warning decision thresholds and model components such as flood forecasting performance to investigate possible connections and feedbacks.

Thereafter we tested the impact of social preparedness on a range of scenarios representing different flow magnitude distributions. We tested the model for a total of four scenarios—including the scenario we used to perform the sensitivity analysis on, hereafter referred to as *default scenario*—covering a range of flood return periods and likelihood of extreme events. *Scenario 1* is characterized by a lower average maximum annual flow and less frequent extreme events than the *default scenario* (where an extreme event is defined as being equal to or larger than the damage threshold δ) while

Table 4. Average Normalized Flow Magnitude ($\bar{Q}$) and Probability of Occurrence of Extreme Flow Events—Events Larger Than the Predefined Damage Threshold δ—for the Different Hydrological Regime Scenarios Considered in the Analysis

	Scenario 1	Default Scenario	Scenario 2	Scenario 3
$\bar{Q}$	0.12	0.20	0.28	0.36
$P(Q \geq \delta)$	0.03	0.12	0.27	0.46

Scenario 2 and *Scenario 3* present increasingly larger average maximum annual flow magnitudes and higher likelihood of extreme events (Table 4).

3. Results

3.1. Sensitivity Analysis

We performed a sensitivity analysis on the model parameters (Figure 5). Out of the 13 model parameters, we allowed 9 of them to vary within predefined ranges and we kept the remaining 4 parameters constant (Table 2). In section 2.4, we provide further description on the sensitivity analysis.

We found the model to be sensitive to four of the nine parameters that we tested: the forecast accuracy mean, magnitude threshold, residual damage fraction, and social preparedness half-life. A distinct peak can be observed for the forecast accuracy mean while model efficiency decreases for increasing magnitude threshold and residual damage fraction values. Conversely, model efficiency increases for decreasing social preparedness half-life. The model is also moderately sensitive to the forecast accuracy variance and the damage function shape parameter. For both cases the model efficiency also decreases for increasing parameter values. The other parameters have little impact on the model efficiency.

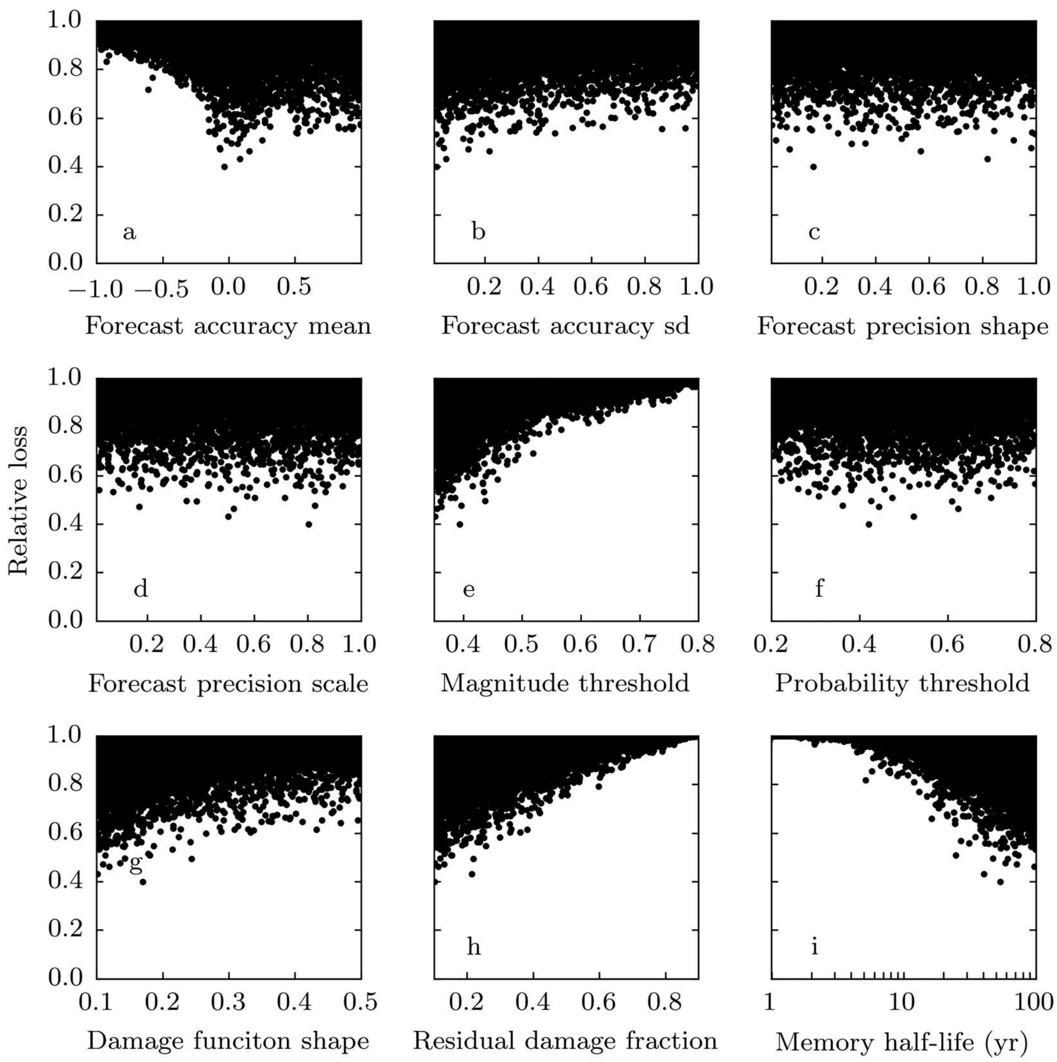

Figure 5. Sensitivity analysis of the model to relevant model parameters. (a–d) Parameters controlling the accuracy and precision of flood forecasts; (e and f) threshold parameters for the flood warning evaluation; (g and h) parameters governing the damage functions; and (i) social preparedness half-life parameter.

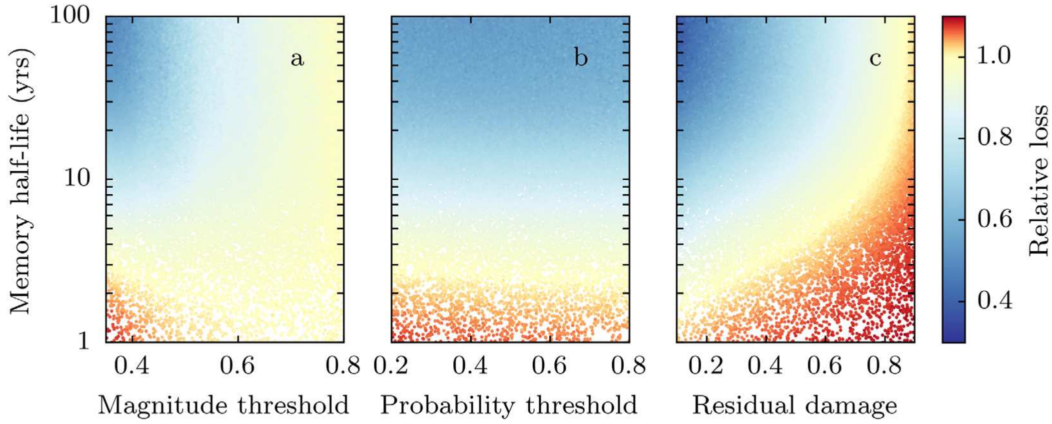

Figure 6. Model efficiency (relative loss) for combinations of social preparedness half-life and (a) magnitude threshold, (b) probability threshold, and (c) residual damage fraction parameters.

Thereafter we studied the impact of combinations of social preparedness half-life and one other parameter on the model efficiency in order to get insights into possible connections. First we tested the warning thresholds: magnitude threshold (Figure 6a) and probability threshold (Figure 6b). For the combination of social preparedness half-life and probability threshold the trend is approximately horizontal, with the steepest gradient at around 10 years. The case involving the magnitude threshold parameter is more complex and the model efficiency increases toward the second quadrant meaning that combinations of long social preparedness half-life and low magnitude thresholds produce the minimum relative losses. A comparable behavior arises for the combination of social preparedness half-life and residual damage fraction (Figure 6c). In this case, however, the efficiency gradients are larger than for the combination of social preparedness half-life and magnitude threshold.

Additionally, we tested the impact of social preparedness half-life on the flood forecasting module of the model. Four model parameters control the accuracy (μ, σ) and precision (κ_F, θ_F) of the forecasting system thus defining its performance. In this case, we tested the impact of social preparedness half-life on the forecasting system performance as defined by the hit rate and false alarm ratio measures (Figure 7). Warning efficiency, as expressed by the relative loss measure, decreases for decreasing forecasting system performance, as given by a reduced hit rate but most notably by an increased false alarm ratio. Larger social preparedness half-life values produce an increase of the performance range of forecasting systems keeping relative losses below one. Furthermore, the magnitudes of the relative losses for a given forecasting performance also decrease.

3.2. Hydrological Variability

The following step was to test the impact of the social preparedness half-life parameter on the model by using input data with different annual maximum flow distributions (Figure 8). Relative losses as a function of the social preparedness half-life decrease for scenarios with an increasing proportion of medium and high magnitude maximum annual flows, both in terms of the minimum relative losses magnitude as well as in the social preparedness half-life value required for a specific relative loss magnitude.

In order to get better understandings of the processes linking social preparedness half-life, residual loss and hydrological variability we calculated a number of statistics for each scenario such as the return period of floods, the hit rate and false alarm ratio, and the average social preparedness level along the analysis period (Table 5). The obtained results show that a higher proportion of medium to large magnitude maximum annual flows leads to shorter return periods for flooding events, lower false alarm ratios, and higher average social preparedness levels.

4. Discussion

We developed a simple stylized model to study the impact of social preparedness—as estimated by the recency of flood experience—on the efficiency of FEWS. Quantifying complex processes, such as

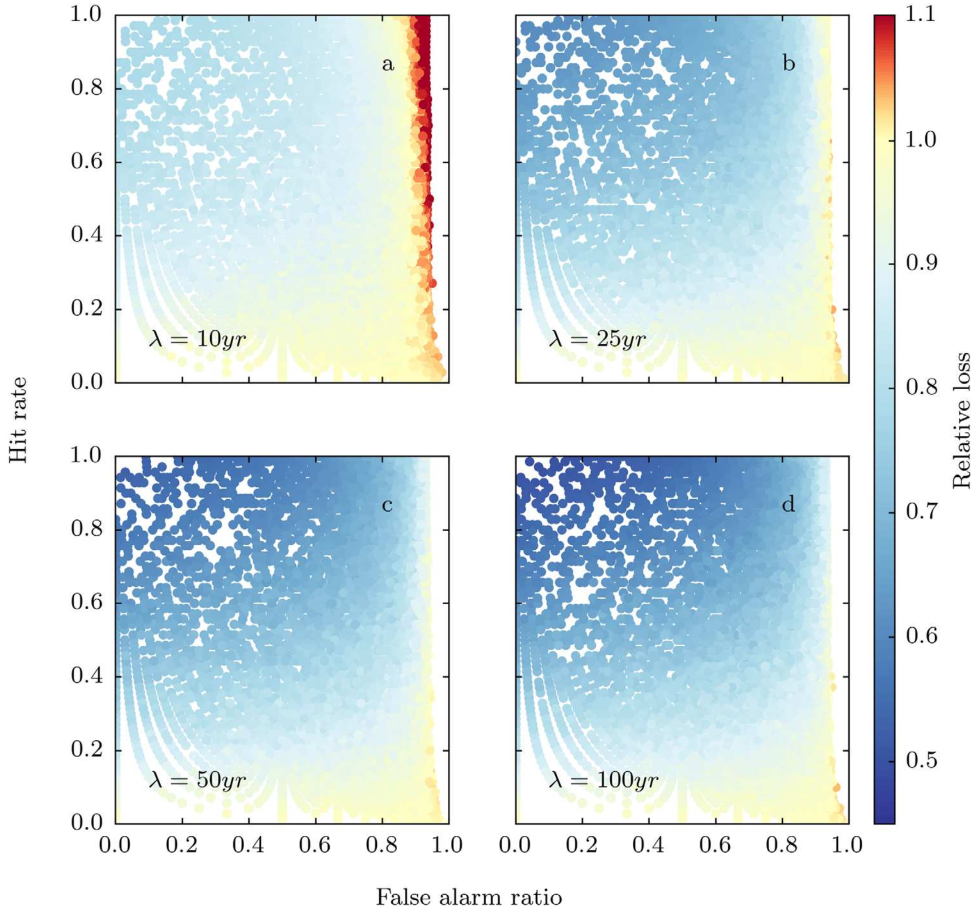

Figure 7. Model efficiency (relative loss) for different flood forecasting performances as given by the hit rates and false alarm ratios, and social preparedness half-life values: (a) 10 years (b) 25 years (c) 50 years, and (d) 100 years.

preparedness, is extremely challenging and requires a number of assumptions and simplifications to be made. Additionally, the exploratory nature of this study, which uses synthetic data to replace limited observations, generates further uncertainties and inaccuracies. Overall the results obtained in this study as well as the interpretations that are made need to be taken with caution. Nevertheless, most assumptions concerning the model as well as the parameter ranges and values are based on well-established knowledge so the outcome of this study might provide valuable insights and guidance for future research on the topic.

The sensitivity analysis (Figure 5) reveals that the model is robust and that the number and choice of parameters is adequate for its purpose. When designing the model, an effort was made to keep it simple so as to avoid problems such as overparametrization [*Young*, 2002]. Another potential problem lies in overconditioning the model to produce results that would fit the hypothesis [*Beven*, 2008]. While this is a risk whenever a stylized model is developed we did our best to constrain the model with well-established, peer-reviewed knowledge.

Looking closely at the model parameters (Figure 5), the parameters controlling the accuracy and precision of the forecasting system show very different behavior on one side, both the accuracy mean and the accuracy variance parameters present a large, nonsymmetrical impact on the model efficiency. On the other side, both precision parameters seem to have very little impact on the efficiency of the model. The accuracy mean and variance parameters control whether the forecast is biased, and to which extent; while the precision parameters control the spread of the range of possible values. The conceptualization of probabilistic forecasts (equation (2)) and the subsequent warning evaluation procedure used in this study tends to favor accuracy over precision, i.e., getting the approximate magnitude of the event is more important than having a smaller uncertainty on the actual value. Even if in reality both components are related, these results

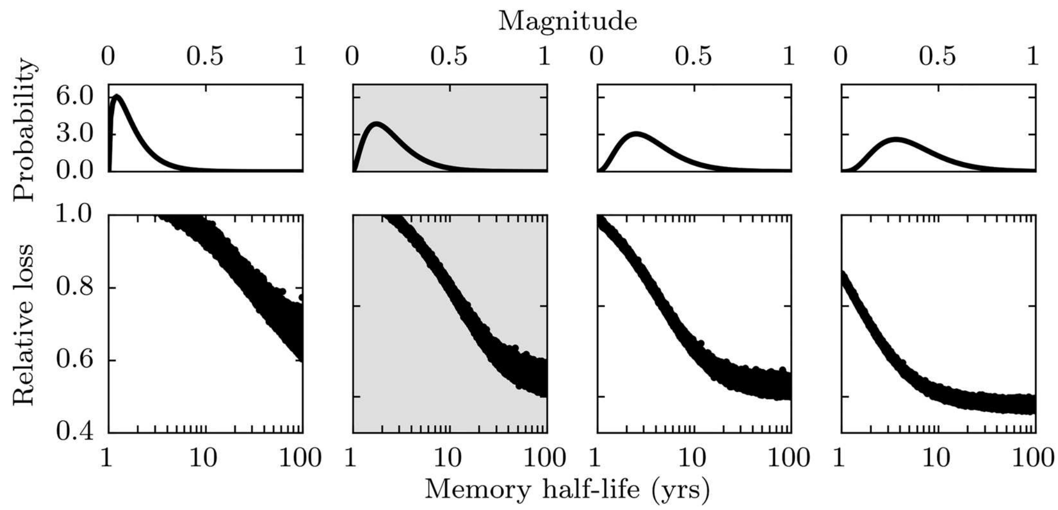

Figure 8. (bottom row) Model efficiency sensitivity to the social preparedness half-life parameter (top row) for the different hydrological regime scenarios. The scenario used for the sensitivity analysis—*default scenario*—is highlighted.

suggest that focusing on enhanced forecasting accuracies might produce better results in terms of reduced overall losses.

The warning threshold parameters also shown distinct patterns; the decision on the magnitude threshold for issuing warnings is likely to have a larger impact on the efficiency of those warnings than the decision on the probability threshold of the warnings (Figure 5). For instance, by increasing the magnitude threshold, many events causing damage (Figure 2) have no warning issued for, causing relative losses to rapidly increase. Conversely, the required degree of confidence for issuing warnings appears to have a smaller influence on the warning efficiency.

The recency of flood experience, which we used in order to estimate social preparedness, appears to have a large influence on the efficiency of the model (Figure 5). Quickly decaying preparedness—as given by short half-life values—is related to high relative losses, which rapidly decrease for increasingly long half-life values. A difference of 10 years in the half-life variable produces a striking reduction of the relative losses of the order of 50%. This is especially important for societies that have lost a generation of knowledge concerning the hazard itself but also about how to respond to it [*UN*, 2006]. A similar behavior can be observed when relating half-life to other model parameters (Figure 6). This way poor forecasting system performances or even high residual damages can be compensated by high half-life values. In practice this implies that, even if the technical capabilities of the FEWS are limited, a high social preparedness level, given by the temporal proximity to the previous flood, can help mitigate disaster losses to a significant extent.

Scenarios with more frequent medium and large magnitude maximum annual flows also present lower relative losses for identical preparedness decrease half-life values (Figure 8). This behavior is explained by the relative magnitudes of flood frequency and preparedness decrease rate (Table 5): short return periods—compared to the preparedness decrease rate—contribute to maintaining preparedness levels high, and consequently reducing relative losses. This phenomenon resembles that of the so-called Green Society [*Viglione et al.*, 2014], in which disaster damages are kept low by taking a proactive attitude to flood management.

Table 5. Flood Warning Outcome and Social Preparedness Statistics for the Different Hydrological Regime Scenarios Considered in the Analysis

	Return Period (years)	Hit Rate	False Alarm Ratio	Average Preparedness
Scenario 1	53	0.86	0.30	0.47
Default scenario	14	0.86	0.21	0.79
Scenario 2	6	0.84	0.18	0.90
Scenario 3	3	0.89	0.12	0.96

Overall, disaster preparedness as estimated by the recency of flood experience is found to be a relevant factor for flood risk reduction. Longer social preparedness decay half-life values are consistently related to lower relative damages, even in challenging circumstances. Relevant examples include limited technical capabilities (represented by low forecasting accuracy and precision), low-probability, high-impact events (given by high magnitude threshold values), and high residual damages. Furthermore, exploring different hydrological variability scenarios shows that, contrary to popular belief, a certain degree of familiarity with floods may enhance preparedness levels and ultimately effectively mitigate flood-related losses.

The conceptualization done for this study is obviously a large simplification of the actual relationship between flood warnings and society. Other important factors driving this connection were purposely left aside in order to keep the model simple and to avoid confusing results arising from the interaction of different factors. Trust in the official FEWS has been shown to have a large impact on the efficiency of response actions [*Molinari and Handmer*, 2011]. Trust is especially relevant when false alarms and missed events occur, undermining the confidence of the public in the warnings issued and therefore decreasing the likelihood that adequate precautionary actions will be taken. Furthermore, trust in the competent authorities is largely divergent for different societies and cultures. Other factors can promote preparedness, such as risk awareness campaigns and activities to preserve the memory of past flood events [*Berkes*, 2007; *UNISDR*, 2015]. To unravel the role of these additional aspects, e.g., trust and social memory, both theoretical and empirical researches are needed. In particular, stylized models like the one presented here can complement case studies and ethnographic field work carried out by disaster sociologists and anthropologists over the past decades [*Colten and Sumpter*, 2009; *Bhattacharya-Mis and Lamond*, 2014; *Erikson*, 1976; *Folke et al*., 2005; *Siegrist and Gutscher*, 2008; *Tschakert et al*., 2010].

5. Conclusions

In this study, we present an exploration of the impact of disaster preparedness on the efficiency of flood early warning systems. For this purpose, we used the recency of flood experience as a proxy for preparedness and we developed a simple stylized model to perform the analysis. Even if results need to be tested with experimental data the following conclusions can be drawn from this study:

1. The model, which we developed, is robust and the choice of parameters is meaningful for achieving the objectives of the study.
2. An accurate estimation of the flood event magnitude was found to be more important for producing a correct forecast than a smaller uncertainty on the actual magnitude of the event.
3. A high social preparedness level contributes to mitigation of flood-related losses even if the forecasting technical capabilities are limited, residual damages are high or warnings need to be issued for low-probability, high-impact events.
4. Social preparedness contributes to mitigation of flood losses especially for situations where flood return periods are shorter than the social preparedness decrease half-life.
5. Efforts to preserve and promote social preparedness such as memory-raising campaigns may have a large impact in mitigating future flood-related damages.

Overall, these findings provide important insights into the behavior and influence of the recency of flood experience on social preparedness and its associated benefits, and may help guide decision-making within flood early warning systems.

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