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Forecast-based financing: an approach for catalyzing humanitarian action based on extreme weather and climate forecasts

E. Coughlan de Perez[1,2,3], B. van den Hurk[2,4], M. K. van Aalst[1,3], B. Jongman[1,2], T. Klose[5], and P. Suarez[1]

[1]Red Cross/Red Crescent Climate Centre, The Hague, the Netherlands
[2]Institute for Environmental Studies (IVM), VU University, Amsterdam, the Netherlands
[3]International Research Institute for Climate and Society, Earth Institute, Columbia University, Palisades, NY 10964-1000, USA
[4]Royal Netherlands Meteorological Institute, De Bilt, the Netherlands
[5]German Red Cross, Berlin, Germany

Correspondence to: E. Coughlan de Perez (coughlan@climatecentre.org)

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Abstract. Disaster risk reduction efforts traditionally focus on long-term preventative measures or post-disaster response. Outside of these, there are many short-term actions, such as evacuation, that can be implemented in the period of time between a warning and a potential disaster to reduce the risk of impacts. However, this precious window of opportunity is regularly overlooked in the case of climate and weather forecasts, which can indicate heightened risk of disaster but are rarely used to initiate preventative action. Barriers range from the protracted debate over the best strategy for intervention to the inherent uncomfortableness on the part of donors to invest in a situation that will likely arise but is not certain. In general, it is unclear what levels of forecast probability and magnitude are "worth" reacting to. Here, we propose a novel forecast-based financing system to automatically trigger action based on climate forecasts or observations. The system matches threshold forecast probabilities with appropriate actions, disburses required funding when threshold forecasts are issued, and develops standard operating procedures that contain the mandate to act when these threshold forecasts are issued. We detail the methods that can be used to establish such a system, and provide illustrations from several pilot cases. Ultimately, such a system can be scaled up in disaster-prone areas worldwide to improve effectiveness at reducing the risk of disaster.

1 Introduction

"Early warnings" of heightened risk, such as storm forecasts indicating enhanced risk of flooding, are often available at several lead times prior to an extreme weather event. These provide a window of time to reduce the potential societal consequences from such an event. Different types of action can be taken in this time window, such as evacuation, or distribution of water purification tablets. Each of these actions has its own level of cost, focus scope and preparation needs; a mixture of such actions can increase resilience to hazards, both prior to and during the immediate threat of a disaster. The majority of evaluations of preventative action demonstrate that avoided disaster losses can at least double or quadruple the investment in risk reduction (Mechler, 2005). However, the chance exists of a "false alarm" in which the most likely forecasted scenario does not materialize. What is the process by which stakeholder can select an appropriate action in the time frame allowed by an early warning, given this risk of acting in vain at a false alarm? Here, we offer a methodological approach to answer this question, addressing the gap that exists in the use of hydrometeorological early warning information to trigger disaster risk reduction actions in timescales of hours to months between a climate-based warning and a disaster.

Originally, humanitarian institutions were created with a mandate to respond to disasters only after they had occurred. Over the last few decades, the discourse has shifted to acknowledge disaster risks in long-term development projects and plans; particularly after the Hyogo Framework for Action was signed in 2005 (Manyena, 2012). Currently, disaster-related programming focuses on these two areas: post-disaster response and reconstruction, and long-term disaster risk reduction; the greater part of the latter has historically been invested in large flood prevention infrastructure projects (Kellett and Caravani, 2013).

However, there is a valuable window of time that exists after the issuance of science-based early warnings but before a potential disaster materializes. We argue here that the current humanitarian funding landscape does not make sufficient use of this window of heightened risk, in which a variety of short-term activities become worthwhile to implement and can provide a large return on investment. Opportunities range from reducing vulnerability, such as distributing mosquito nets before heavy rainfall, to preparedness for disaster response, such as training volunteer teams on first aid procedures or pre-positioning relief items before roads become impassable. However, according to a recent review of disaster-related financing by the Overseas Development Institute and the Global Facility for Disaster Reduction and Recovery, only about 12 % of funding in the last 20 years was invested in reducing the risk of disaster before it happens; the rest was spent on emergency response, reconstruction, and rehabilitation (Kellett and Carvani, 2013).

In this paper, we elaborate a method to invest a portion of this financing at times of heightened disaster risk, when triggered by forecast information. This framework quantifies the intuitive notion that many practitioners already have about when acting early may be worth it. This quantification also helps them make the case to donor agencies for such early action, which is currently often not implemented because the financing for it is not available. First, we review the context behind why forecast-based opportunities are routinely missed and discuss the use of short-term early warnings to trigger action. To operationalize this, we suggest a forecast-based financing model for the development of procedures to act based on probabilistic warnings, illustrated with a simple example from a surface water flooding alert in England and Wales. We then describe two pilot applications of the financing system in Togo and Uganda implemented with technical support from the German Red Cross and the Red Cross/Red Crescent Climate Centre. We conclude with further discussion of the concept and its potential for replication, as well as further research that will enable this to be applied widely.

2 Context

We will first explore types of decisions that can be funded to prepare for an unusually likely disaster event, followed by background on the types of warnings available. In the following section, we will present the concept of our proposed methodology to link these two.

2.1 Decisions

A variety of disaster risk reduction actions are available to be implemented in contexts of increased risk; the most frequent example is evacuation based on very short-term storm forecasts. For example, during Hurricane Sandy in New York City, 1000 patients were evacuated from two hospitals in Manhattan, and the Federal Emergency Management Authority (FEMA) pre-positioned urban search and rescue committees before the storm (Powell et al., 2012). In the 48 h before Cyclone Phailin hit India, as many as 800 000 people were evacuated based on weather forecasts (Ghosh et al., 2013). These actions are not viable in the context of long-term risk, but become appropriate in the context of a short-term warning of heightened disaster risk.

Similarly, there are a number of risk reduction actions that can be taken at the seasonal lead time to prevent disaster losses in coming months. In the International Federation of Red Cross and Red Crescent Societies' regional office in West Africa, disaster management supplies were sourced ahead of time based on a 2008 seasonal forecast of above-normal rainfall, which improved supply availability from about 40 days to 2 days when flooding did occur in the region (Braman et al., 2013). In other locations, volunteers have used information about heightened risk at seasonal time scales to fortify vulnerable structures, such as reinforcing latrines to reduce the risk of diarrheal disease outbreaks when above-normal rainfall is likely to occur (Red Cross/Red Crescent Climate Centre, 2013).

In contrast with these specific cases, the majority of forecast information does not routinely trigger early action in the humanitarian sector to reduce disaster risk. For example, the devastation from extreme flooding in Pakistan in 2010 affected 20 million people. Heavy rainfall had been predicted several days in advance, and if forecasts had been used to trigger action, the humanitarian sector could have averted many of the impacts (Webster et al., 2011). In the case of drought, the 2011 famine in southern Somalia was preceded by 11 months of early warning, including a specific famine warning 3 months before the event (Hillbruner and Moloney, 2012).

In all of the above situations, a warning was issued and a disaster situation followed; the distinction was whether action had been taken to prevent disaster effects. However, this is not always the case; warning information is probabilistic (expressed in terms of risk) rather than deterministic. Inevitably some early warnings are not followed by a hazard event, and some hazards are not preceded by a warning. In the former case, any action taken based on the early warning may be seen as action "in vain", and organizations often believe that money and time would have been better spent on other activities.

Such a situation had negative consequences in southern Africa when the drought anticipated due to the 1998 El Niño event did not materialize. Farmers reduced their cropping area, and public backlash after the event made it clear that many people had understood the seasonal forecast as a deterministic prediction of drought, rather than a forecast of increased chance of below-normal rainfall (Dilley, 2000). Similarly, in the Netherlands, about 200 000 people were evacuated in 1995, after which the dykes did not fail (Swinkels et al., 1998).

To evaluate the usefulness of an early warning system, both the number of disasters that are "hits" (a) and "false alarms" (b) are of interest, expressed in the 2×2 contingency table below, Table 1 (Suarez and Tall, 2010; Buizza et al., 1999). In this case, "forecast-based action" refers to whether or not there was a forecast of increased risk of the disaster in question that led to action being taken, and "disaster" refers to whether or not a disaster happened within the forecasted lead-time. We will come back to the elements in this table in later sections when discussing funding disbursements relative to the frequency of each of these categories.

Table 1. Contingency table depicting possible scenarios for forecast-based action.

	Yes disaster	No disaster
Yes forecast-based action	Hits a	False alarm b
No forecast-based action	Miss c	Correct rejection d

2.2 Warnings

For many actions, the risk of acting in vain is outweighed by the likely benefits of preventing or preparing for disaster; for example, if a life-threatening hurricane has an 80 % chance of making landfall, many people would choose to evacuate, even given the one in five chance of a false alarm. How can decision-makers navigate the attributes of forecast information, ranging from location to lead time to magnitude, and pair them with appropriate actions? Several major prerequisites to the use of early warning information for disaster risk reduction exist: warnings, opportunity for action, and mandate.

First, there must be a relevant early warning available. In this paper, we focus specifically on hydrometeorological disasters and the early warnings that are available through weather and climate forecasting. Rainfall and temperature forecasts for coming months, weeks, or days, exhibit some skill in many parts of the world (Hoskins, 2013). These forecasts, where available, can indicate heightened risk of disaster. According to a Foresight expert evaluation of forecasting capacity, current science has "medium to high" ability to produce reliable forecasts for the timing of storms and floods in a 6-day lead time in many locations (Foresight, 2012). At the seasonal level, research indicates that an increased probability of above-normal seasonal rainfall totals in standard forecasts is correlated with increases in the chances of heavy rainfall events (Hellmuth et al., 2011). Indices of the El Niño Southern Oscillation (ENSO), which are responsible for much of the predictability in seasonal forecasts, have also been linked to flooding frequencies in more than one third of the world's landmass (Ward et al., 2014). The Famine Early Warning System (FEWS) provides detailed forecasts using both short and long-term information in Africa and the Caribbean (Ross et al., 2009).

Secondly, the opportunity for early action is not always available within routine humanitarian operations; about 88 % of humanitarian financing is delivered only after disaster effects have already commenced (Kellett and Caravani, 2013). In the case of Somalia in 2011, the Consolidated Appeal Process for Somalia was funded at only 47 % during several months of urgent early warnings. In contrast, secured funding shot up to exceed 100 % of the original request within 2 months after famine was declared. Ultimately, the appeal was revised to nearly double the request for funding, because the situation had deteriorated so far (Maxwell and Fitzpatrick, 2012).

Lack of funding based on early warnings is attributed to protracted debate over the best strategy for intervention, inherent uncomfortableness on the part of donors to invest in a situation that will likely arise but is not certain, the high consequences of "acting in vain", and the lack of responsibility or accountability to act on early warnings (Ali and Gelsdorf, 2012; Hillbruner and Moloney, 2012; Lautze et al., 2012). Post-disaster evaluations of the humanitarian responses to this event call for mechanisms to trigger and incentivize consistent early action based on available early warning information, with responsible persons clearly designated (Bailey, 2013; Ali and Gelsdorf, 2012; Hillbruner and Moloney, 2012).

Thirdly, the mandate to take action based on early warning systems is not well-defined. It is often unclear who would be responsible for making this type of decision and what decision is appropriate based on the early warning. If the anticipated hazard does not materialize after the early action is taken, the decision-maker is considered culpable for his or her poor decision-making. This risk of "acting in vain" is inherent in probabilistic risk information; many employees are consequently reluctant to make decisions without 100 % certainty that the hazard will happen (Demeritt et al., 2007; Suarez and Patt, 2004).

Should someone be willing to assume the risk of acting based on an early warning, it is not clear at which threshold of forecasted probability it is worth taking action. Powell et al. (2012) conclude that many losses during Hurricane Sandy could have been averted had standard operating procedures (SOPs) been in place in more organizations, which designate specific duties and responsibilities for hypothetical situations.

Such SOPs would be based on thresholds of climate variables, similar to those calculated for post-disaster payments in index insurance programs (Leblois and Quirion, 2013; Hellmuth et al., 2011; Barnett and Mahul, 2007). In fact, forecast-based financing is informed by precedents that integrate seasonal forecasts into index insurance products. For example, Osgood et al. (2008) propose a mechanism to influence the amount of high- yield agricultural inputs given to farmers according to whether favourable or unfavourable rainfall conditions are expected for the season. An El Niño contingent insurance product was developed for the region of Piura (northern Peru): a business interruption insurance policy was designed to compensate for lost profits or extra costs likely to occur as a result of the catastrophic floods as predicted by a specific indicator of El Niño (known as "ENSO 1.2"). Indemnities were based on sea surface temperatures measured in November and December, which were taken as a forecast of flood losses that would occur a few months into the future (February to April). The insured entity chooses the amount to insure (which must not be larger than a maximum amount determined by an estimation of the largest plausible flood losses). Designers of this instrument specifically targeted risk aggregators: firms that provide services to numerous households or businesses exposed to El Niño and related floods, such as loan providers and the fertilizer sector. This is likely the first "forecast index insurance" product to receive regulatory approval (GlobalAgRisk Inc., 2010). For a comprehensive analysis of insurance-related instruments for disaster risk reduction, see Suarez and Linnerooth-Bayer (2011).

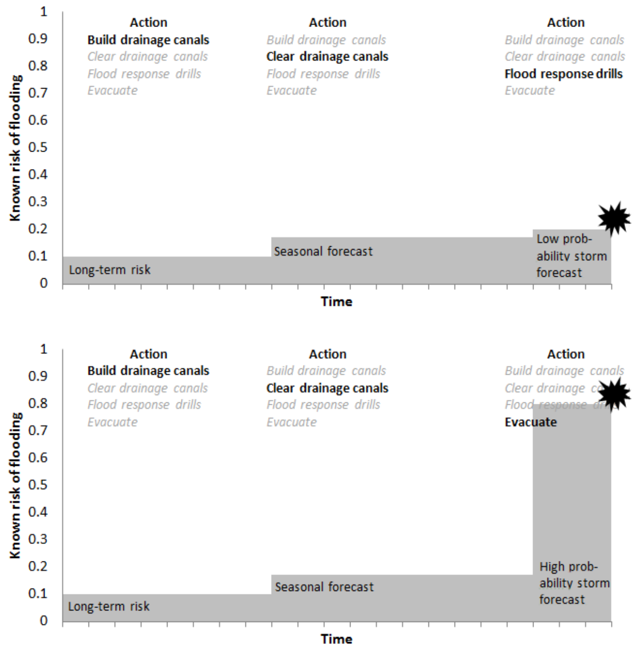

Figure 1. Idealized schematic depicting known risk of disaster impacts over time. Known risk of flooding increases when forecasts of rainfall are issued; the change in risk is a function of the probability of the forecasted event. Selected actions will be a function of both lead time (the difference between action based on long-term risk and seasonal risk) and the magnitude of flood risk (the difference between the far-right actions in both plots).

3 Concept

We address these barriers of opportunity and mandate by proposing a forecast-based financing mechanism coupled to risk-based operating procedures. Based on the successes and failures of previous efforts to act based on climate-based early warning information, we elaborate three components of a system for early warnings to become operational: (a) information about worthwhile actions, (b) available funding mechanisms, and (c) designated entities that are responsible for taking the pre-planned actions. A systematic forecast-based financing system integrates each of these three elements, contingent on the availability of (skillful) forecasts for the region in question. The case of a surface water flooding alert in England and Wales is used to demonstrate the application of this framework.

3.1 Matching forecasts with actions

Depending on the impacts in question, there are a number of actions that could be taken to prevent humanitarian outcomes (Fig. 1); however, only a subset of actions will be appropriate based on a specific piece of early warning information. Of all the possible actions, we undergo a matching process to select those that are most appropriate given the lead time and the probability of the forecast.

In the case of England and Wales, the surface water flooding warning service issues an alert based on the probability (p) of rainfall intensity exceeding a 1-in-30 year return period. Based on this, an extreme rainfall alert pilot was disseminated directly to professional emergency responders (Hurford et al., 2012). Of all the actions that could be taken by the recipients, not all are possible to complete given the lead-time of a specific forecast. From the larger list, actions will be eliminated if they cannot be completed in the available time frame before the anticipated disaster. For example, people are not able to build drainage canals based on a short-term forecast, but could create teams to clear existing drainage canals based on a seasonal forecast. In comparison, flood response drills could be carried out within a few hours or days of the forecasted disaster (Fig. 1). Many emergency responders receiving the pilot alert indicated that a lead time of more than two hours is necessary for most actions (Parker et al., 2011).

Subsequently, actions need to correspond to the strength of the specific forecast, such that high-regret actions are not taken based on a very small increase in disaster likelihood. For example, it would not make sense to evacuate based on a low probability forecast, but perhaps flood response drills would be appropriate as they can withstand "acting in vain" (Fig. 1). Assuming that action will be taken every time a forecast reaches probability p, how often will the actor take "worthy action", in which the action was followed by a disaster?

In the forecast-verification literature, there are a number of studies using Table 1 to evaluate forecasts for their likelihood of achieving "hits" for the variables that they are forecasting (i.e. mm of rainfall). In this paper, we consider this 2×2 table iteratively for each probability that could be issued by a single forecasting system to identify thresholds at which it is "worth" taking action (i.e. 10 % chance of 10mm of rainfall in the coming 24 h, vs. 20 % chance, etc.). Therefore, forecast-based action will be triggered (top row of Table 2) when the forecast issued shows a probability $>= p$; Table 1 therefore varies as a function of p. Using the results, we will determine threshold levels of p that can be used to trigger humanitarian action to reduce the risk of disaster. n is the sum of all boxes in the table, representing the total number of units (i.e. days) in which a forecast could be issued.

For a forecast lead time and probability p, we derive the variables in Table 1, to answer the following question: if we take action every time the forecast exceeds the threshold, how often our action be followed by a disaster, and therefore be worthwhile? To do this, we estimate the correct alarm ratio R(p) (fraction of all forecasts of probability p) as

$$R(p) = \frac{a(p)}{a(p) + b(p)} R(p) = \frac{a(p)}{a(p) + b(p)}. \quad (1)$$

In forecast-verification literature, this term is referred to alternatively as the "frequency of hits" (Doswell et al., 1990) and the "correct alarm ratio" (Mason and Graham, 2002). In the UK, emergency responders indicated that if the correct alarm ratio was less than 70 %, "awareness raising" would be the only feasible action (Parker et al., 2011).

In the case of advisory forecasts in the UK, 9 out of 36 advisories were followed by flooding in Hurford et al. (2012) case study areas. If action had been taken on the basis of each advisory, the correct alarm ratio is about 25 % (2011). The remaining 75 % ($1 - R(p)$) corresponds to the likelihood of acting "in vain".

Such actions will have economic consequences, which are given by Table 3 (Richardson, 2012). Costs are represented as C, and losses as L; they do not vary depending on the forecast probability. For the "act in vain" category, there is often a change to the original cost, ΔC, perhaps reputational risk or the need to dismantle preparations and move them back to storage. The additional cost, ΔC may be very significant; the reputational risk of a false alarm could outweigh (qualitatively) the benefits of a worthy action. This is, of course, a simplified representation of reality, not capturing, for example, the probability that an action will be successful at preventing the target loss. The cost of acting in vain might also be different than the cost of worthy action, given that supplies might need to be returned to warehouses, and efforts made to address the "cry wolf" effect.

Table 2. Contingency table based on a forecast threshold of p to trigger action.

	Yes disaster	No disaster
Yes forecast $>= p$	Hits $a(p)$	False alarm $b(p)$
No forecast $>= p$	Miss $c(p)$	Correct rejection $d(p)$

Table 3. Contingency table of costs and losses as outcomes of forecast-based action.

	Yes disaster	No disaster
Yes forecast-based action	C	$C + \Delta C$
No forecast-based action	L	0

The discount rate is not acknowledged here, as most of the actions take place on a timescale of less than a year. Time discounting would therefore have a fairly insignificant impact compared to the existing uncertainties. If the actions lasted for many years, it would be appropriate to include the discount rate, which could decrease the relative weight of the benefits, assuming that they occur less frequently than the costs. A more complicated version would also take into account the probability density function of different magnitudes of disaster, but the general principles outlined here will remain in effect.

Given this, we select actions for forecasted probability p in which the losses in a business-as-usual scenario (no forecast-based action at all) exceed the combined costs and losses in a scenario with forecast-based action. All worthwhile actions should satisfy the following:

$$L \cdot \frac{a+c}{n}(p) > C \cdot \frac{a+b}{n}(p) + \Delta C \cdot \frac{b}{n} + L \cdot \frac{c}{n}(p). \quad (2)$$

Not all disaster consequences can be expressed in economic terms, therefore this relationship will also need to be acceptable in qualitative terms by implementers. In addition, many of these actions will have long-term benefits, regardless of disaster incidence (i.e. educational interventions to promote hand-washing).

3.2 Funding mechanisms

The second component is a preparedness fund, a standard funding mechanism for forecast-based financing that is designated for use before potential disasters. Funding from this mechanism will be disbursed when a forecast is issued, supplying enough money to carry out the selected actions, with the understanding that occasionally funding will be spent to "act in vain". Financial procedures need to be in place to ensure the rapid disbursement of the fund when an early warning is issued, and accountability measures such that the funding is only used for designated early actions that correspond to that early warning.

The most basic method to determine how much funding is needed for this mechanism over a specified time period is to assume that all actions that were possible at the forecast lead time and also satisfied Eq. (2) are funded every time the corresponding forecast probability is issued. If C represents the cost of acting based on one warning, the total needed for the preparedness fund (T) would therefore be represented as

$$T = C \cdot \frac{a+b}{n}(p) + \Delta C \cdot \frac{b}{n}(p). \tag{3}$$

If there are several forecast probabilities, or several different types of forecasts, at which action is advisable, the total funding required would sum the funding needed for each of the individual forecasts. Note, however, that consecutively occurring forecasts do not need to repeatedly fund the same action, and stipulations need to be made for the autocorrelation of forecasts. In the UK, the emergency rainfall alert had three forecast levels: advisory, early, and imminent, that corresponded to 10, 20, and 40 % probabilities of exceeding the given rainfall threshold. Because each forecast should be matched with different actions based on lead time and probabilities, the preparedness fund should account for the likelihood of each probability being issued, as well as their correlation in time. If the forecast probability is defined as p, the total amount of funding needed to react to all possible forecast probabilities is represented as

$$T = \int_0^1 C \cdot \frac{a+b}{n}(p)\,\mathrm{d}p. \tag{4}$$

In operations such as the one from the example above, the equation is simplified to the sum of the costs to take action on each of the three categorical forecast alerts.

When disaster risk is substantially increased, $R(p)$ increases and more actions are eligible to be selected in Eq. (2) for that particular forecast, and therefore greater amounts of funding are disbursed when the chances of a disaster are higher. In practice, additional factors will be included to specify external drivers, such as the political repercussions of repeatedly acting in vain, and the interaction effect between actions. For example, if sand-bagging will prevent flooding for 3 months, then it is not eligible to be carried out again within 3 months of the original action, even if a "matching" forecast is issued in the interim. In other cases, certain actions are prerequisites for others; evacuation can only be carried out if evacuation shelters have been identified ahead of time.

In many cases, there might be a ceiling on the amount of money initially allocated (T) to pilot this mechanism over a specified amount of time. In this situation, the amount of funding in the preparedness fund must be distributed among the possible forecasts. Each forecast of probability p would have a corresponding disbursement amount (D) proportional to the probability of disaster conditional on that forecast, and this disbursement amount will need to be divided among all actions that could be implemented based on that forecast. If D is small, only the most priority actions will be implemented. Statistically, the D will be calculated such that T will be fully spent at the end of the allocated time period. This is represented as

$$T = \int_0^1 \frac{a+b}{n}(p) \cdot D(p)\,\mathrm{d}p, \tag{5}$$

where $D(p)/(\frac{a}{n}(p))$ should be equal for all values of p.

Using this method, there could be a number of categorical forecast probabilities (p) calculated to receive a very small disbursal amount, which might not suffice to carry out any selected actions. This could be the case for a very commonly forecasted event. Comparing the disbursal results to the cost of actions $C(p)$, we eliminate categories of p for which $D(p)<C(p)$. We then re-solve the above equations for the reduced number of probabilities (p) until all disbursements are greater than the cost of at least one of the actions that should be implemented at each remaining probability p.

This method assumes that funding should be allocated according to the likelihood of disaster, although this assumption could be replaced by other priorities, such as allocating funding according to the effectiveness of the actions. It would also be possible to set time-varying thresholds to be more conservative in spending at the beginning of available time period, and more free with spending the remaining amount as the end of the budget period draws near. When calibrating the system over a longer time period, we recognize that thresholds may vary to reflect progress in insights or changing drivers.

3.3 Responsibility

Once the forecast alert levels have been paired with appropriate actions, the actions must be taken every time the forecast alert is issued. In England and Wales, 86 % of emergency responders who received pilot extreme rainfall alerts in 2008–2009 said that the alerts were useful to them, but only 59 % reported that they took any action as a result of receiving the advisories. Organizational processes need to be defined to assign responsibility to act based on warnings; in this case, emergency responders indicated that they were still clarifying internal plans to react to these warnings (Parker et al., 2011).

In response to this, we propose the development of an organization-specific set of standard operating procedures that specify each selected forecast, the designated action, the cost, and the responsible party. Whenever the alert is issued, such as a forecast of a certain amount of rainfall, the designated action is taken by the responsible party, using funds from the financing mechanism that will be immediately made available. It is assumed that there will be instances of acting in vain. Based on the results of each action, stakeholders can continually evaluate and update the information used to create the SOPs, ensuring ongoing effectiveness of the mechanism.

4 Pilot applications

In Uganda and Togo, the National Red Cross Societies will be piloting this approach to quantify the relationship between forecast probability and resource disbursement with technical support from the German Red Cross and the Red Cross/Red Crescent Climate Centre from 2012 to 2018. Research and development of the standard operating procedures is funded by the German Federal Ministry for Economic Cooperation and Development (BMZ), complemented by project funding for long-term disaster risk reduction activities to address disaster risk at longer as well as short time scales.

In both countries, the pilot application of this preparedness fund will focus on flood disasters. In northeastern Uganda and along the Mono River in Togo, flooding disasters are recurrent and a major source of humanitarian losses. In five target districts of northeastern Uganda, flooding and extreme rain account for more than half of all disasters recorded in DesInventar databases (UNISDR et al., 2011). In Togo, the Red Cross has developed a set of colour-coded river gauges, such that communities upstream observing the river move to a "red" level volunteer to notify communities downstream that the water is on its way; the actions taken based on the existing information will form a basis for the larger variety of "early actions" that will be financed under the new system.

To assess possible actions that could be funded in anticipation of a flood, the Red Cross/Red Crescent Climate Centre designed a participatory game that can be played both with disaster-prone communities and with humanitarian staff; these types of "serious games" can be used to foster discussion and creativity in a collaborative setting (Mendler de Suarez et al., 2012; Maenzanise and Braman, 2012). The game begins with a brainstorm of actions to prevent specific disaster impacts, and designates a portion of the participants to represent a "flood", who penalize unrealistic actions and note which actions require funding. This panorama of possible actions ranges from planting a variety of crops to stocking water purification tablets; actions are grouped according to whether each one is possible to accomplish at specific lead times that correspond with available early warning information: observed rainfall, short-term rainfall forecasts, and seasonal rainfall forecasts (Fig. 2). Clearly, cropping decisions cannot be made with a lead time of days before a disaster, while purchasing medical supplies might be possible within 24 h.

For each possible threshold of early warning information, we evaluate the risk of flooding conditional on the forecast by using a coarse hydrological model to simulate the change in likelihood of inundation. In the participatory game, disaster managers and community members will be asked to describe the consequences of worthy action and acting in vain for each action that is suggested, in both qualitative and quantitative terms. In the case of purchasing water purification tablets, acting in vain will result in an opportunity cost relative to investment in other activities, but worthy action could prevent the loss of life in a cholera epidemic. Ultimately the assessment of whether consequences and likelihood of acting in vain outweigh the consequences and likelihood of worthy action (Eq. 2) will be a decision on the part of disaster managers based on economic and social assessments. Combining those results with the consequences elicited in the simulated flooding game, we will match forecast thresholds with relevant actions.

In comparison with the flood alert system from England and Wales that is described above, the actions developed for standard operating procedures in Uganda and Togo are likely to be somewhat different. In particular, the UK alert system focused on surface water flooding, while riverine flooding and water logging are likely to be of greater interest in Uganda and Togo. For the latter, longer lead-times can be expected for forecasts, although the forecasting skill might not be optimal for lack of observational data. This will likely allow for actions that target the spread of water-borne disease, for example, which are less of a problem in the UK. In addition, there are differences in forecast skill between the UK and equatorial Africa; the latter has less data available, but potentially larger skill at the seasonal level due to teleconnections with the El Niño Southern Oscillation.

Funding for this pilot mechanism has been provided by the German Red Cross, and a set amount is secured for each country (EUR 100 000 and 50 000 for Uganda and Togo, respectively) in a preparedness fund. Because the funding amount is pre-determined, this will be used as a constraint on how many of the eligible actions can be funded in a given year (Eq. 5). Matches of forecasts and actions will be reviewed and adjusted by disaster management staff familiar with the region. When a final product is acceptable to everyone, results will be codified in SOPs that indicate forecast levels of alert, corresponding actions, responsible parties, and the funding that will be released to ensure the actions are taken. The funding in this case is intended as a pilot, and is not a sustainable stream post-2018; mechanisms to refill and expand this pilot will be investigated.

With the methodology proposed here, specific actions can be selected that are worthwhile investments based on early warning information. While standard funding mechanisms and operating procedures are necessary to ensure consistent action based on forecasts, it is as of yet unclear what portion of total disaster funding should be allocated to such forecast-based financing operations. While results vary depending on the programme itself, positive benefit-cost ratios have been shown for a variety of long-term disaster risk reduction programmes (Mechler, 2005). Based on the initial results from pilots of this concept, a similar probabilistic benefit/cost ratio (B/C) can be assessed for this methodology, as in Eq. (6) (not corrected for discount rate).

$$\frac{B}{C} = \frac{\int_0^1 L \cdot \frac{a}{n}(p) - C \cdot \frac{a+b}{n}(p)\,\mathrm{d}p}{T}. \tag{6}$$

Comparing results to the B/C ratios for long-term disaster risk reduction will indicate the marginal benefit of additional funding spent in either category, thus reshaping the funding landscape for disaster risk reduction and preparedness and focusing on the most impactful actions at each timescale.

5 Discussion

As incentives emerge to use forecasts for disaster prevention and preparedness, forecasting capability will be a major constraint in maximizing the potential of such early warning systems. Individual cases of "missed events" could draw criticism to such investments in forecasting; it is key to weigh the investment in forecasting capacity or other aspects of an enabling environment for forecast-based financing with the possible benefit of such a system over time. Africa in particular has a lack of functional weather stations, including synoptic stations, which limit our ability to forecast meteorological events with skill (Rogers and Tsirkunov, 2013). Investments in both hardware and software in developing country meteorological and hydrological services is needed to address this gap. In the interim, recent research to merge existing sparse observations with satellite data can aid in developing more precise understandings of climate given the information available historically (Dinku et al., 2012). Any increase in the percent of disasters foreseen (also known as the hit rate) $a/a+c$ or an increase in the correct alarm ratio $a/a+b$ due to increase in forecast skill will directly increase our ability to prevent and prepare for disasters; this increase can be estimated directly using Eq. (7).

This framework quantifies the intuitive notion that many practitioners already have about when acting early may be worth it. This quantification also helps them make the case to donor agencies for such early action, which is currently often not implemented because the financing for it is not available.

Of course such quantification is not trivial – it does require context-specific analysis. In that analysis, the lack of historical disaster data will pose certain constraints. The impact of uncertainty in probability estimates, both of disaster impacts and of forecast probabilities, needs to be assessed, and thresholds of certainty established for identifying meaningful results. Local knowledge about the recurrence period and impact of extremes can be incorporated when calculating the fund, even if it carries inherent uncertainty.

In this vein, additional research will be required to achieve a large-scale application of forecast-based financing schemes. In particular, calculating the risk of hazards based on forecasted rainfall should be assessed and verified with hydrological estimates using statistical and dynamical techniques.

Most of the variables considered here, from action options to forecast skill, vary sharply between regions, and therefore forecast-based financing systems must be designed for a specific hazard at a specific geographical scale. Standard operating procedures developed in one area are unlikely to have value if applied indiscriminately elsewhere. Further research should study the effect of varying each of these parameters, and the resulting differences in forecast-based financing potential across regions and hazards.

Calibrating cost and benefit estimates will be difficult. For example, the cost of acting or the cost of acting in vain might need to be estimated iteratively, based on whether the actor had recently acted in vain, and would therefore be reluctant to take a risk again. Similarly, a "miss" by the system could cause a lack of confidence in the system itself. The equations here could be extended with a "risk perception" factor that changes in response to false alarms or successful interventions. This would be calibrated with information from the practitioners. All cost estimates should undergo sensitivity analyses in order to assess the robustness of the value of this funding mechanism; if we perturb our estimates of probabilities and costs in the above equations, how does this affect the results? At what point does uncertainty in these values greatly influence the selection of actions and the estimation of their benefits? In addition, there will be interaction effects between short-term and long-term investments, the latter often constraining the ability to make decisions in the short-term.

6 Conclusions

Climate information presented as early warnings are only as valuable as the actions that are taken in response to the information, even if the information is a perfect warning of future events. While weather and climate forecasts do not exhibit perfect skill, tailoring of forecast information to the operational contexts of the humanitarian sector can dramatically increase the uptake of existing forecast products.

In this light, innovations need to lead to improved tailoring of the information itself to better serve the needs of the target decision-makers sector, rather than simply tweaking the visual display of existing information (Rodó et al., 2013; Johnston et al., 2004). Currently many disaster warnings issued by established early warning systems in developed countries go unheeded for lack of standard plans for forecast-based action (Kolen et al., 2013). At the seasonal level, standard forecasts provide little information on the likelihood of extreme events. The Global Framework for Climate Services has made disaster risk reduction a thematic priority area, and seeks to encourage dialogue between forecast producers and users to better identify opportunities and needs for tailoring this information (Hewitt et al., 2012).

Forecast-based financing systems are an excellent opportunity to foster and operationalize such dialogues. The system outlined above makes use of existing forecast-verification methods in conjunction with user-defined information on risk reduction costs and disaster losses. When housed in such a system, this information can break down the barriers of opportunity and mandate that currently prevent the systematic use of forecasts in the humanitarian sector, and develop SOPs that ensure ongoing return on investment. The net benefit of such a system will only be clear in the long term, as the hits and false alarms begin to accumulate and converge on their true frequency.

Ultimately, the value of forecast-based financing systems will be greater than simply the losses avoided when the fund is released. If such a system is in place, actors in that region will be aware that many disaster effects are likely to be prevented due to forecast-based action. Because of this, actors can focus on development investments with less concern that a disaster event will suddenly demolish their investment. Further pilots and research to quantify the value added of forecast-based financing schemes is needed to provide the evidence base for forecast-based funding and the widespread development of climate-based SOPs.

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