Weather and Climate Extremes xxx (2017) 100167

Contents lists available at ScienceDirect

Weather and Climate Extremes

journal homepage: www.elsevier.com/locate/wace

Bridging forecast verification and humanitarian decisions: A valuation approach for setting up action-oriented early warnings

Ana Lopez [a,b,*], Erin Coughlan de Perez [c,d,e], Juan Bazo [c,g], Pablo Suarez [c], Bart van den Hurk [d,f], Marteen van Aalst [c,e]

[a] University of Oxford, Atmospheric, Oceanic and Planetary Physics, Clarendon Laboratory, Oxford, OX1 3PU, UK
[b] University College, Oxford, OX1 4BH, UK
[c] Red Cross/Red Crescent Climate Centre, The Hague, The Netherlands
[d] Institute for Environmental Studies (IVM), VU University, Amsterdam, The Netherlands
[e] International Research Institute for Climate and Society, Palisades, NY, USA
[f] Royal Netherlands Meteorological Institute, De Bilt, The Netherlands
[g] Technological University of Peru (UTP), Lima, Peru

ABSTRACT

Empirical evidence shows that acting on early warnings can help humanitarian organizations reduce losses, damages and suffering while reducing costs. Available forecasts of extreme events can provide the information required to automatically trigger preparedness measures, while 'value of information' approaches can, in principle, guide the selection of forecast thresholds that make early action preferable to inaction.

We acknowledge here that, for real-world humanitarian situations, the value of information approach accurately estimates the value of forecasts only if key factors relevant for the humanitarian sector are taken into account. First, the negative consequences of acting in vain are significant and must be factored in. Secondly, the "most valuable" forecast thresholds depend on criteria beyond expenses reduction, and this choice must be explicitly considered in funding mechanisms for early warning products and services. Two options to guide this selection are examined: a maximizing criterion for cost effectiveness, and a satisficing criterion for loss avoidance. Third, decision-makers must be able to confidently assess whether the forecast threshold they are selecting is robust to all possible cost/loss structures for the action in question.

Based on these considerations, we explore the application of the valuation approach to select which forecasts (magnitude, probability and lead time) should trigger humanitarian actions. Using a basic example of ensemble precipitation forecast to prepare for potential floods, we discuss how the valuation approach can be used to select probability thresholds that trigger early action, and some of the generalisations required to make this applicable to a wider range of humanitarian situations.

1. Introduction

Extreme events lead to disasters only when they hit exposed, vulnerable people and assets and no timely measures are taken to avoid damages and losses. Empirical evidence shows that acting on early warnings can help humanitarian organizations to achieve their aims of reducing suffering and, at the same time, reduce costs. For example, early action based on seasonal forecasts of unusually wet conditions in West Africa allowed regional and local Red Cross workers to implement flood preparedness measures, from evacuation plans at the community level to prepositioning relief items - resulting in flood response that was weeks faster and substantially cheaper than in other similar occasions when no early action was taken (Braman, 2013). Based on evaluations post disaster, some authors have argued that early humanitarian action can be far more effective than late disaster response after the extreme event has materialized, even when taking into consideration the possibility of early action followed by no extreme event. (Cabot Venton, 2012; Oenone Chadburn, 2013; Webster et al., 2010; Knowlton et al., 2014).

However, for many humanitarian organizations, implementing preventive actions in response to a forecast is usually not possible, as financing mechanisms are available only *during and after* an extreme event (i.e. emergency appeals for disaster response and reconstruction) or for measures not linked to actual extreme events occurring (i.e. annual appeals for general disaster risk reduction) (Suarez, 2009; Hillbruner and Moloney, 2012).

As a way to overcome this limitation, the idea of forecast based financing (FbF) for disaster preparedness is being trialled in a series of pilot studies in different countries. The FbF approach aims to pre-agree on early humanitarian actions, science based triggers and earmarked funding before the early warning is issued (Coughlan de Perez et al.,

* Corresponding author. PO Box 28120, 2502 KC, The Hague, The Netherlands.
E-mail address: lopez.m.ana@gmail.com (A. Lopez).

https://doi.org/10.1016/j.wace.2018.03.006
Received 15 April 2016; Accepted 20 March 2018
Available online xxxx

2014, 2015). After these are agreed, funding is automatically disbursed when the forecast trigger arrives; ensuring action is taken before a potential extreme event. While in traditional humanitarian interventions, the response and disbursement of funds are done once the disaster has occurred; the goal of early actions based on forecasts is to respond before the potential event using hydro-meteorological forecasts.

The FbF approach is currently being piloted in Peru, Mozambique, Bangladesh and 12 other countries around the world.[1] In five of these countries (Guatemala, Niger, Sudan, Philippines and Zimbabwe), the World Food Programme developed a FbF mechanism as part of their Food Security Climate Resilience Facility (FoodSECuRE) ,[2] which is a financial and programmatic tool that uses seasonal climate forecasts to trigger actions for community resilience-building and for preparedness to reduce the impacts of climate disasters before they occur. Climate variability is one of its key drivers of food and nutrition security in vulnerable regions around the world, and the ability to anticipate extreme events before they happen can help avoid food insecurity at the household level.

To implement the FbF approach, given a forecast of the hydro-meteorological extreme event that could cause a disaster, the humanitarian worker must select the forecast attributes that should trigger her actions. These include the lead time, the minimum magnitude of the extreme event that causes damage (hereafter "danger level"), and for ensemble forecasts, the forecast probability threshold (hereafter "trigger").

Forecasters have developed a "value of information" approach whereby user actions and associated avoidable losses are introduced, and forecasts are evaluated in terms of their potential to reduce expected losses, as opposed to evaluating them uniquely in terms of forecast skill (see for instance Murphy et al. (1985), Mylne (2002), Katz and Murphy (1997), Jolliffe and Stephenson (2003)). From the point of view of the forecaster, this approach is useful to assign value to the forecasting system. In reality, such valuation statistics are rarely (if ever) [3] used to trigger action in the humanitarian sector, in part because some of the assumptions of the approach do not hold. Firstly, the current prevailing humanitarian model is simply to not act on the forecast but act after the extreme event,[4] affording the losses when the disaster has already occurred. Moreover, traditional forecast valuation techniques assume that the decision-maker will minimize the average expense when acting on a forecast, calculated over a series of events and actions. However, when assessing "value" in the context of disaster risk reduction, criteria beyond optimising expenses are decidedly relevant. Finally, the potential consequences of "acting in vain" are an important part of the valuation of the forecast for the humanitarian actor. The forecast valuation approach usually assumes the cost of early action to be constant whether or not the extreme event occurs[5]; whereas humanitarian organizations see the consequences of actions "in vain" as different in nature than the cost of "worthy actions" (Coughlan de Perez et al., 2014, 2015).

By adapting the 'value of information' approach to the particular context of humanitarian interventions, in this work we identify the attributes of the forecasts that can support a forecast based approach to financing disaster preparedness and propose an analytical framework for decision criteria, establishing thresholds linking early warning information to early humanitarian action.

The paper is organised as follows. In section 2 we describe the basic elements required to support forecast based financing of disasters, e.g., early actions, early warnings and the decision criteria to trigger actions. In section 3 we describe the methodology to identify the forecasts attributes to trigger action, and in section 4 we illustrate this approach with precipitation forecasts for flood preparedness in Peru. Section 5 is devoted to the discussion.

2. Early warnings for forecast based financing

When implementing the forecast based approach to financing disaster preparedness, the humanitarian actor has to consider three key elements: (1) the set of **early actions** (or action plan) to be triggered by the forecasts, and whose aim is to avoid losses and damages if extreme event materialises, (2) the **early warning information** derived from forecasts that triggers the early actions, and (3) the **decision criteria** chosen to define whether or not it is worthwhile to act based on the available information. It is helpful to discuss the main properties of each of these elements with some detail.

(1) Action is motion with purpose. In terms of the **early actions** worth considering prior to an extreme event, the humanitarian actor should select a menu of pre-determined actions to be triggered by different forecasts of the extreme event at different lead-time. For each of the actions, she needs to estimate, the time required for implementation, how long the action will last, and the cost of taking the action. This includes the cost of acting in vain if no extreme event materialises.

Clearly some of these parameters are not static; for instance the cost of acting in vain might increase over time if the forecasting system has several false alarms in a row. Moreover, estimating some of these parameters is not trivial, particularly when the decisions to act depend on collaboration of individuals and organizations, such as voluntary evacuation.

(2) The **early warning information** can be provided by (skilful) numerical weather model forecasts, or combinations of these models' output and statistical models (some times useful to improve skill or to interpret model output for the location of interest (see for instance Webster et al. (2010))). The lead time and spatial scale of the forecasts has to match the lead time and spatial reach of the actions.

For some events such as slow onset flooding, an impacts model that translates the meteorological information (extreme precipitation) into the impacts variable (inundation area) will be necessary to issue a flood forecast.

In some cases an (observed) "index" to trigger action could be more appropriate than a forecast. For instance, observed rainfall deficits that precede crop failure could be used to trigger actions to prevent drought losses .[6]

(3) Lastly, a forecast-based financing system requires a **decision criteria** to select the forecast probability or trigger that will

[1] http://www.climatecentre.org/downloads/files/Stephens%20et%20al.%20Forecast-based%20Action%20SHEAR%20Final%20Report.pdf.

[2] http://documents.wfp.org/stellent/groups/public/documents/communications/wfp279583.pdf?_ga=1.133895053.2057468830.1444162287.

[3] To our knowledge, there are no reports of real-world humanitarian action triggered by a probabilistic forecast based on thresholds determined by the 'value of information'.

[4] With the exception of tropical cyclone forecasts and some resilience programmes aimed at reducing the baseline risk, the default for the humanitarian user is not to act.

[5] The false alarm or 'cry-wolf' effect has been taken into account through, for instance the incorporation of the users' rate of compliance in the valuation approach (Roulston and Smith (2004)). Roulston et al. show that adopting a probabilistic approach to forecasting avoids making implicit assumptions about users' attitudes towards false alarms. Furthermore, communicating the forecast uncertainty improves weather related decisions (Joslyn and LeClerc (2012)).

[6] This approach requires robustly quantifying the relationship between the observed index and the hazard occurrence. In drought-prone regions it has been used to implement index-based insurance (see for instance African Risk Capacity: http://www.africanriskcapacity.org/documents/350251/371107/ARC_Overview_Brief_EN.pdf, and Suarez and Linnerooth-Bayer (2011)). Note however that while the aim of index based insurance is to compensate for losses and damages after the hazard, FbF intends to take preventative actions to avoid the losses and damages.

trigger worthwhile actions (Coughlan de Perez, 2014). The question faced by the humanitarian actor with a specific budget is the following. Should she act given any arbitrary forecast probability of an extreme event? This will of course cost a lot of money, but ensure that the region under her watch will have very few damages and losses if the extreme event materialises. Alternatively, should she use the forecasts to try to economise on spending, and only act on the forecasts that ensure a better chance of preventing disasters?

Two methods, each representing different priorities relevant to the humanitarian sector, could be used to address these questions – these represent a divergence from the assumptions of value maximization inherent in traditional value of information approaches.

Prevented event maximization: For a given early action, the humanitarian actor selects the forecast thresholds or triggers in such a way that the maximum possible number of extreme events is preceded by the preventive action, under the constraint that expenses incurred by triggering this action are not larger than expected expenses and losses assuming no early action. This is a satisficing approach, more appropriate for organizations with a fixed budget for a specific location; they would use the same amount (or less) of funding for pre-disaster preparedness measures as would have been spent for post-disaster relief measures, but would drastically reduce the avoidable losses in the target area.

Expense minimization: For a given early action, the humanitarian actor selects the forecast thresholds or triggers that minimize expected *expenses relative to* the expected losses post-disaster that could be avoided if the preventative action is implemented. This is a maximization approach, potentially relevant for organizations that are trying to reach the largest geographical coverage possible; they would use this method to minimize expenses for a specific location and then spend the available budget on as many locations as could be covered – or on actions other than disaster preparedness.

The early actions, early warning information and decision criteria described above are all required to develop approaches that aim to use meteorological forecasts of extreme events to trigger actions that could prevent a disaster. The risk of disaster however, results as a combination of the probability of the hazard or extreme event, and the exposure and vulnerability of the population at risk. Therefore the use of meteorological forecasts to trigger early action assumes that when the extreme event occurs, the impacts are high enough to cause a disaster. This requires the determination of the event threshold or *danger level*, i.e., the magnitude and persistence of the hydro-meteorological event that is linked to the occurrence of avoidable and unavoidable losses and damages (which, if large, leads to disaster).

Based on the experience of public weather services and some humanitarian organizations, the determination of the danger levels can be done in several ways depending on the availability of data:

- Using empirical evidence linking hydrometeorology with disaster. For heat waves for instance, the temperature threshold for an increased risk of morbidity and mortality can be determined based on epidemiological studies (Kovats and Hajat, 2007; Ebi et al., 2004; Public Health England, 2015), or through surveys in the populations at risk (Knowlton et al., 2014).
- Based on how frequently the decision maker is willing or able to act. For instance, cold weather alerts could be issued based on the number of alerts that health and social services are able to act upon during the winter (Public Health England, 2014)
- Combining observational data and listings of historical disasters sourced from databases such as EM-DAT (http://www.emdat.be) and media outlets, to identify the magnitude of extreme meteorological events that preceded disasters (and did not occur very frequently with no disaster following) (Coughlan de Perez et al. (2016)). In this case, care has to be taken to develop reliable damage functions, especially when combining databases, since these could be based on different impact assessment methods used at country level.
- Combining the experience of local community members and the expertise of the local hydro-meteorological services to identify critical thresholds of meteorological events that have led to local impacts in the past (Han et al., 2010). This is not different from the construction of disaster profiles based on expert panel discussions and insights provided by customers, a common approach in places where weather alerts and warnings are standard part of the meteorological services (Ambhul, 2010).

In the FbF pilots currently being developed around the world, danger levels describe the hydro-meteorological conditions that cause impact on the people living in a particular area. To formulate danger levels, conversations are held between technical and scientific entities, community representatives, government actors, and local non-governmental entities to determine what weather or climate conditions have caused impact in the past. These levels are validated through a field study in some communities, to ensure that the actions are adapted to the local context, as the danger level will vary across regions. Danger levels can be expressed as a return period of the event, related to how frequently the humanitarian actor would like to take preparatory action. This can be a political decision, also dependent on the funding availability for action.

In the FoodSEcurRE pilots, the WFP together with the International Research Institute for Climate and Society (IRI) has worked to identify the climate shocks that tend to impact on food security. Indicators such as the number of wet days in a season that are needed to grow crops define the danger level. When this danger level is forecasted to be reached, and taking into account background information such as other non climatic factors that impact on food security, disaster managers can take action, well before the crops have failed and food security has declined. For example, when planning interventions related to an El Niño event that potentially increases the likelihood of drought in a given region, the WFP might call a high level meeting at the first sign of the event. When the event is confirmed, a drought forecast and monitoring plan might be developed and agricultural extension officers contacted. If the forecast confidence increases and dry conditions start to appear the WFP will then access the FbF fund to prepare for food crisis interventions.

Fig. 1 summarizes the three pieces of information required to support FbF of disasters: actions, forecasts and decision criteria, and their links

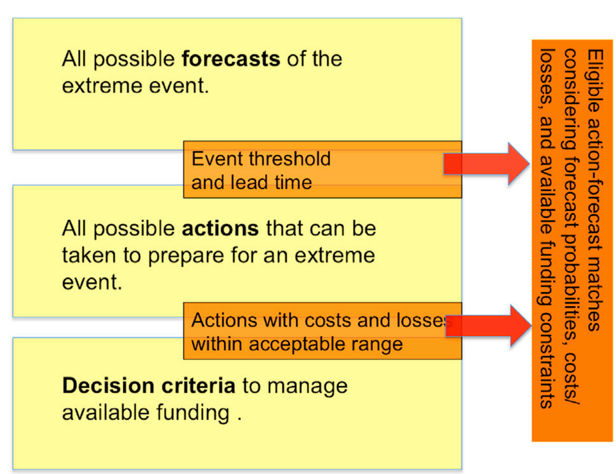

Fig. 1. Summary of the information supporting the forecast based financing approach. The yellow boxes represent the three components: actions, forecasts and decision criteria. The orange boxes include information that combines two or more of these components. For instance, event threshold or danger level is common to the forecasts and the actions in that a forecast of a particular danger level will trigger actions that protect if the danger level is overcome. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

trough the determination of forecasts attributes and actions' cost-loss structure.

3. Choosing the triggers for action

While the extreme event magnitude that causes impact can be determined a priori, the trigger or forecast probability threshold that should be used to trigger an action depends on the action itself.

There are three prerequisites to the application of the simple valuation approach:

First, the meteorological or hydrological conditions that lead to avoidable losses are well defined (thus the work to identify the danger level has already been done), and an early action is available. Given the meteorological parameter that has the potential to cause the disaster (for instance the accumulated precipitation, or the river discharge defined by both a magnitude and a duration or time scale), we can then define that the (binary) event occurs when the meteorological variable (Q) is above *its danger level or critical value* (Q_{crit})*, and it does not occur otherwise.*

Second, we assume that the forecast-based financing system will automatically trigger action when the forecast probability of exceeding Q_{crit} is larger than a trigger p_{th}; no action is taken otherwise.

To optimally determine the trigger, information about the past performance of the forecast system is required. So the third prerequisite is that a set of forecasts and the corresponding observations (or verifications) for the meteorological event of interest is available. In the case of pluvial floods for instance, this will entail the precipitation forecasts of the extreme event and their corresponding verifications over a period of time long enough to be of climatological relevance. This might be a problem in places where the observational records are short or incomplete, or when using new forecasting systems that do not have long enough reforecasts (Coughlan de Perez et al., 2016).

Given the set of forecasts and verification pairs over a period with n discrete event intervals (i.e., days over a series of rainy seasons), they can be summarized in a contingency table as follows.

In this table $n = a + b + c + d$ is the total number of forecast-observation pairs (for instance the number of days in the record for daily precipitation forecasts). The sample estimate of the climatological probability of the extreme event is $s = (a + c)/n$. The variables a, b, and c will take different values when different triggers p_{th} are chosen, and can be used to define two key parameters: the Hit Rate and the False Alarm Ratio.

Hit Rate: $H = a/(a+c)$. H is the sample estimate of the likelihood that an early action was triggered given that the event occurred, and estimates the fraction of prevented disasters (i.e. humanitarian measures implemented, losses avoided).

False Alarm Ratio: $FAR = b/(a + b)$. FAR is the sample estimate of the probability of the event not happening given that the forecast probability p exceeded p_{th} and the early action was triggered. FAR estimates the fraction of early actions that would end up being in vain.

These statistics assume that the benefit of an early action does not outlive the duration of the disaster, consequently every time there is a new warning the action will be triggered again. That is clearly not the case for actions that last longer than any individual disaster. For instance, in the case of a village prone to become isolated by pluvial floods, water or food storage units deployed just before an extreme precipitation forecast, will be in use for much longer than that individual flood. The generalization of this approach for long lived actions is discussed in the Supplementary Information (SI).

In order to establish what forecast probability threshold or triggers should trigger early action, the disaster manager (DM) should consider the expenses (i.e. costs and losses) associated with taking or not a particular early action based on an early warning. These are.

- If the early warning is issued and the disaster occurs, for any particular action the total cost for the DM will be the sum of the cost of acting C, and the unavoidable losses L_{ua} (losses that cannot be reduced by the action taken, such as crop loss due to inundation).
- If the early warning is issued and the disaster does not happen, then the cost for the DM is C plus any additional cost of acting in vain C_{av}. The difference between C and C_{av} is that the former is a cost incurred regardless of whether the action proves worthy or in vain, while C_{av} is incurred only if the extreme event does not materialize after taking early action. For example, the additional cost of transporting back to headquarters non perishable food that had been prepositioned, would be an additional cost of acting in vain that would not have been incurred if the extreme event had occurred. However, C_{av} could be negative, if for instance stocks that had been purchased are sold to recuperate some of their value if the extreme event did not occur.
- If the extreme event is not forecast but it does happen, the cost is the sum of the avoidable and the unavoidable losses, $L = L_a + L_{ua}$. Note that L_a are the avoidable losses for the particular action (or actions) for which the cost is C. These include the savings in potentially more costly responsive actions after the disaster if no preventive action was taken, and also the losses that will not be incurred by the disaster-impacted population had the action been taken.
- If the event is not forecast and the disaster does not happen, there is no cost to the DM.

Table 1
Contingency table summarizing the number of instances when each of the four scenarios linking actions and extreme events materialized over the evaluation period.

		Occurrence of Event	
		T_{crit} exceeded: Extreme Event	T_{crit} not exceeded: No Extreme Event
Humanitarian Action	p_{th} is exceeded **Early Action**	*a* *Worthy action* *Losses avoided*	*b* *Action in vain* *Unnecessary expenses*
	p_{th} is not exceeded **No Early Action**	*c* *Fail to act* *Losses not avoided*	*d* *Worthy inaction*

This information is summarized in Table 2.

By multiplying the entries in Table 1 (expressed as the fraction of times the early action is taken (or not) according to the issuing (or not) of the early warning) by the entries in Table 2 (i.e., the costs and losses associated with taking or not taking early action), the *expected value of the expense incurred* when linking early warning and early action based on the trigger p_{th}, E_{EW} can be derived:

$$E_{EW} = \frac{a}{n}(C + L_{va}) + \frac{b}{n}(C + L_{av}) + \frac{c}{n}L \tag{1}$$

When writing this expression, we are assuming that the early actions triggered by the early warning are not correlated in time (or space); and that expenses can be averaged over a large sample (space and/or time) implicitly assuming that actions are equally effective every time they are taken, and their cost loss structure does not change. In some cases this might not be true, for example if over a given season the cost of taking the action a second time is smaller than when taking it for the first time. These limitations can be addressed by applying generalisations of the simple valuation approach such as sequential decision making (Katz and Murphy, 1997; Murphy et al., 1985).

To evaluate the potential savings when using the early warning, E_{EW} has to be compared with the expected expenses in the absence of an early warning: $E_{no\_EW} = sL$ (i.e. the sample estimate of the climatological

Table 2
Structure of costs and losses for each scenario.

	T_{crit} exceeded: Extreme Event	T_{crit} not exceeded: No Extreme Event
p_{th} is exceeded **Early Action**	$C + L_{ua}$ *Worthy action* *Losses avoided*	$C + C_{av}$ *Action in vain* *Unnecessary expenses*
p_{th} is not exceeded **No Early Action**	$L = L_a + L_{ua}$ *Fail to act* *Losses not avoided*	0 *Worthy inaction*

probability of the extreme event multiplied by the sum of avoidable and unavoidable losses).

Taking early action based on the early warning is worthwhile if the expected value of the expenses is reduced, i.e., if E_{no_EW}-E_{EW} >0.[7]

A useful metric to evaluate the effectiveness of the early warning based action is the *relative expense reduction* $0 < V_{rel} < 1$, that expresses the saved expenses relative to the expenses incurred when not using an early warning. Using the expressions for *a,b* and *c* in terms of *H* and *FAR*, we can write

$$V_{rel} = \frac{E_{no\_EW} - E_{EW}}{E_{no\_EW}} = \frac{H}{1 - FAR}\left[1 - \frac{C}{L_a} - FAR\left(1 + \frac{C_{av}}{L_a}\right)\right] \tag{2}$$

The larger V_{rel} the larger the proportion of E_{no_EW} saved, or equivalently, the smaller the expenses E_{EW} that mitigate the loss L_a. It is clear that $V_{rel} > 0$ whenever the bracket in equation (2) is positive, and this is a necessary condition for acting on the forecast (otherwise it would be cheaper not to act). While the condition for V_{rel} being positive only depends on *FAR*, the maximum value of V_{rel}, i.e. the minimum expense for acting on the forecast for a particular action, depends on *H* and is achieved for smaller *FAR*.

If the DM knows the cost-loss structure of the actions (Table 2), and has the forecast-verification statistics to build the contingency table (Table 1), then she can use either the expense minimization or the prevented events maximization method to choose the optimal trigger p^*_{th}.

The resulting system would state that, whenever a forecast of precipitation, or river discharge exceeding Q_{crit} is issued with a probability *p* larger than the optimal threshold or trigger p^*_{th}, the DM should take preventive early action.

How does the decision process work in a generic case?

Whether or not the inequality $E_{no\_EW} - E_{EW} > 0$ is satisfied depends on the action through the cost and loss values in Table 2; and on the choice of trigger p_{th} through the values of *a,b,c,d* in Table 1 (or equivalently the values of *H, FAR*). Therefore, by varying the probability threshold (or equivalently varying *a,b,c,d*) it is possible to find the optimal value of the trigger p^*_{th} for which the inequality holds for a given action (or cost-loss structure). For those cases (if they exist), the DM can systematically reduce her expected expenses if she takes early action whenever the forecast probability is equal or larger than p^*_{th}. Fig. 2 displays the information needed to choose this optimal threshold or trigger.

For expense minimization, the DM aims to make V_{rel} as large as possible (red in the diagram), thus reducing the expected expenses when acting on the early warning. She will search for triggers that are closer to red in the underlying colour shading. Following this method the DM will choose $p^*_{th} = p_2$.

For event maximization (highest possible number of extreme events is preceded by the preventive early action), the DM aims to maximize the Hit Rate *H* under the constraint that $V_{rel} > 0$. She will then select triggers located as high as possible on the vertical, but with a valid background colour ($V_{rel} > 0$). In this case the DM will choose $p^*_{th} = p_1$.

Given a probabilistic forecast and its forecast-verification statistics, a Disaster Manager can use the contingency table to calculate the values of *H* and *FAR* for different forecast probabilities and plot them in the figure. These are indicated as p_1, p_2, and p_3 with p_1 the smallest and p_3 the largest value. The grey shading represents an estimate of the sampling error in the determination of *H* and *FAR* for each trigger.

Reducing the value of the danger level Q_{crit} or the lead time, and/or increasing the skill of the forecasting system will in general decrease *FAR* and increase *H*, therefore moving the position of p_1, p_2, and p_3 towards the top left corner of the figure, where V_{rel} is larger.

Lower triggers have larger values of *H* and *FAR* (p_1), while larger triggers have smaller *H* and *FAR* (p_3).

4. Choosing triggers for action for flood preparation in Peru

In the previous section, we used a generic example (Fig. 2) to illustrate how the forecast trigger can be defined based on the value of information approach. In this section we concentrate on one of the Forecast-based Financing pilot projects currently being implemented by the Peruvian Red Cross.[8] This pilot aims to implement preventative actions to reduce losses and damages associated with floods in the North West of Perú.

In this region, the rainy season extends between January and April (Bazo, 2013), and pluvial and fluvial floods are particularly severe during El Niño events (Lagos et al., 2008). Peru was seriously affected during the last two extraordinary El Niño in 1982-83 and 1997-98, when the country's economic losses amounted to 4.5% of the GDP (CAF, 2001). In particular, the losses in the agricultural sector reached 612 millions of dollars (17% of the total losses). Food production was negatively affected by the inundation of arable land, the destruction of irrigation infrastructure due to extreme precipitation, floods and landslides, and the proliferation of pests in rice and maize (CAF, 2001).

Since October 2015, the Peruvian and German Red Cross have been collaborating to develop the early warnings products required to support the implementation of preventative actions in anticipation of extreme precipitation and floods linked with the possibility of a strong coastal El Niño event. Data from previous events show that, at the community level, a strong El Niño has a great impact on health, drinking water, food security and housing.[9]

Early action protocols have been developed that include actions to be triggered by a series of different lead times forecasts. The selection of actions was based on the needs identified in the vulnerable communities and the availability of adequate forecast products. Some of the forecasts that are being considered include sea surface temperature forecasts over the El Niño 1 + 2 region 2 or 3 months out, monthly precipitation forecasts, and medium range precipitation and river discharge forecasts. The actions include volunteer training, awareness campaigns, the purchase and supply of relief items for safe drinking water, training to improve health and hygiene, and strengthening of houses.

For our illustration, the forecast information was obtained from the ECMWF medium range ensemble forecasting system of daily total accumulated precipitation (Molteni, 1996). We focus the analysis on the regions of Piura and Lambayeque in North West Peru, and pool together the rainy seasons (January to April) of a series of consecutive years

[7] Equation (1) and this inequality assume that cost and losses can be monetised and all the terms in the equations are commensurable. This might be problematic if for a particular decision maker, the losses involve only life lost, whereas costs are only monetary (the funding needed to save that life with an early action triggered by the early warning). This can lead to the potentially unacceptable need of establishing a monetary value for a statistical life.

[8] The project is supported technically by the German Red Cross and the Red Cross Red Crescent Climate Centre, and funded by the German Federal Foreign Ministry.

[9] http://climatecentre.org/downloads/files/NotaTecnicaFEN%20-%20Ingles%2020set2016.pdf.

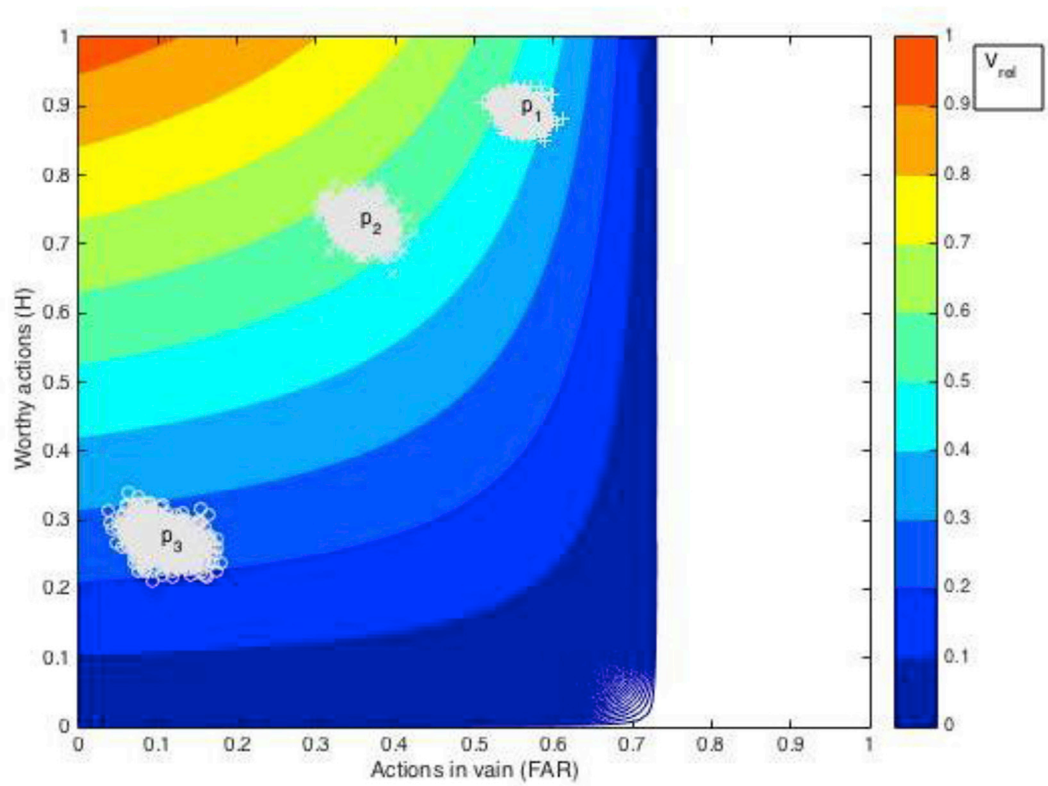

Fig. 2. For a given early action (with associated, fixed values of C/L_a and C_{av}/L_a), the relative cost gain V_{rel} that can be obtained by linking actions to forecasts is a function of the proportion of actions in vain (*FAR*, in the horizontal) and proportion of worthy actions (*H*, in the vertical). The possible values of V_{rel} are represented by the background colour shading (with indicated legend), with white shading indicating $V_{rel} < 0$ for high *FAR* values. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

(2009–2015) to obtain a sample large enough to be climatologically relevant. We consider consecutive years to ensure as far as possible that the skill of the forecasting system is similar from year to year.

In order to build the statistics depicted in Table 1 for different choices of the probability threshold p_{th}, we use as verification the station data provided by the Peruvian National Meteorological Service (SENHAMI) and compare it with the nearest grid point in the ECMWF forecasting model.

Fig. 3 illustrates the selection of triggers for the extreme precipitation forecast for Chulucanas, a station situated in one of two regions chosen to intervene. We show the results for the 7-day lead-time forecasts for the 85% extreme event, i.e., when the danger level corresponds to daily precipitation exceeding the 85% percentile of the climatological distribution for the region. The dependence of the valuation of the early warning information on choosing alternative danger levels or forecast lead-time is discussed in the SI.

To estimate the sampling uncertainty of the values of *H* and *FAR* and their resulting V_{rel} (for each particular action), we use a bootstrapping resampling approach (Jollife, 2007). This uncertainty might be significant in situations where the records available to compute the statistics are short; in these cases there might not be enough information to identify the optimal trigger.

Approaches to measure avoidable and unavoidable losses, as well as quantifiable and unquantifiable losses, are being developed by the FbF pilot projects to advance the understanding of early actions. This includes traditional quantitative cost-benefit studies as well as more qualitative discussions of costs and benefits within a project team. In particular, the estimation of the cost-loss structure of the preventative actions included in the protocols developed by the Peruvian Red Cross is work under progress. Therefore, for illustrative purposes and to test the sensitivity of the triggers to the cost-loss structure of the actions, we choose a range of values of C/L_a (0.03 and 0.3).

Fig. 3 shows the information required to select the optimal triggers for the Chulucanas forecast. It is clear when comparing the different panels that the inclusion of a cost of "acting in vain" will affect the trigger selected for action. For an action whose cost is about 3% of the avoidable losses ($C/L_a = 0.03$ in the top panels) minimization of expenses (or maximization of V_{rel}) leads to choosing $p^*_{th} = 10\%$ when the cost of acting in vain is negligible ($C_{av}/L_a = 0$ in the top left panel), or $p^*_{th} = 30\%$ if the cost of acting in vain is 30% of the avoidable losses ($C_{av}/L_a = 0.3$ in the top right panel). A higher trigger in the later case makes sense, since increasing the cost of acting in vain increases the expenses of acting more often (and then risking acting in vain). On the other hand, if the DM aims to achieve as many worthy actions as possible without overspending, in both cases she will choose $p^*_{th} = 10\%$ which corresponds to the largest number of worthy actions. However, for negligible cost of acting in vain ($C_{av}/L_a = 0$) the relative reduction in expenses is 70% (top left panel) while the relative reduction in expenses for $C_{av}/L_a = 0.3$ is just 30% (top right panel). This must be considered when estimating the number of times the DM can act in vain without negative consequences.

When the cost of action increases relative to the avoidable losses (bottom panels), the potential reduction in expenses V_{rel} decreases (darker colour shading in both panels). Moreover, it becomes negative for some choices of trigger, such as for $p^*_{th} = 10\%$ in the bottom right pane, eliminating the possibility of choosing the lower trigger. As expected, the larger the relative costs, the larger the trigger required for the expenses to be reduced when acting on the forecast.

V_{rel} is shown, as in Fig. 2, as a function of H and *FAR* for the cost-loss structure indicated in each panel. Notice that the cost of acting in vain increases from the left to right in each row of panels, and the cost of the action increasing from top to bottom in each column.

Given the probabilistic forecast of extreme precipitation ($Q_{crit} = 85\%$ event), the values of *H* and *FAR* are computed for triggers 10%, 30%, and 50% and indicated in each of the panels, with the surrounding grey

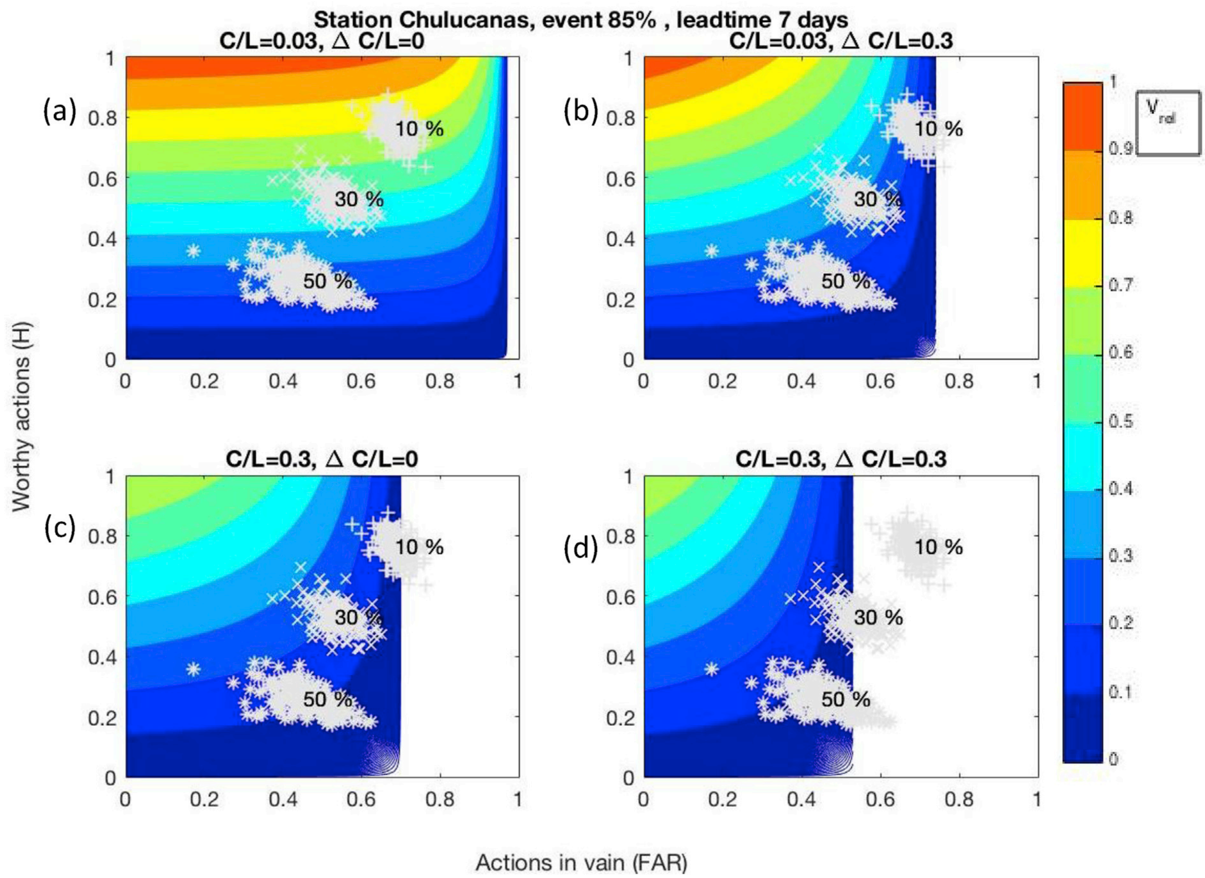

Fig. 3. Decision process for the 7-day lead time precipitation forecasts at Chulucanas.

markers representing the sampling uncertainty. Note that the probabilistic forecast is the same in all panels; so the position of the grey symbols indicating sampling uncertainty remains the same.

5. Discussion

In this work we adapted existing valuation approaches to illustrate how probabilistic weather forecasts can be selected to trigger an action for FbF of disasters. Given a specific early action, we described an approach to identify under which circumstances it is valuable to trigger it (if at all) with the forecast product under consideration, and discussed assumptions and trade-offs when selecting thresholds for action (and limitations of the approach).

Our work suggests the following best practices:

Forecast value must be determined in collaboration with actors

Skilful forecasts of hydro meteorological events per se are not necessarily valuable to humanitarians. An understanding of extreme events that cause impact (danger level) and the associated early actions that can help avoid losses and damages is required. In order to understand the value of specific early warning thresholds, local meteorological services should work with disaster responders and local communities to identify the characteristics of the hazards and the humanitarian decision challenges. For instance, as we illustrated in the flooding example, adding the cost of acting in vain can dramatically change the choice of triggers or forecast thresholds that have the most value; in one case, considering the cost of acting in vain cause the once-optimal warning trigger to have *negative value*. Collaborating to identify possible early actions is critical to define appropriate action triggers in early warnings.

Collaboration between development and humanitarian donors

Depending on the desired impact of the funding invested, actors will select different decision-rules, which substantially impacts the choice of p^*_{th}. Donors wishing to support the establishment of an early warnings for FbF need to consider the merits of investing a specific amount of funding in a specific location (minimize suffering in that location by spending all the funding available) or maximizing the effectiveness of their work by maximizing V_{rel} and acting in as many locations as possible.

While this assumes that a single investor is considering the costs of early action and the costs of response from a single budgetary standpoint, in reality this is rarely the case, as investments often originate from different entities. The proposed approach enables transparency in assumptions and priorities, thus encouraging greater strategic collaboration between the two sides.

Too many instances of acting in vain can lead to 'crying wolf' perceptions, desensitizing people and organizations to take action based on early warnings. However, if *FAR* is large and at the same time V_{rel} is large for actions with a low cost-loss ratio, then those actions could be incorporated into a basic preparedness plan that could be put in place before the floods or heat wave season for instance. Securing funding for this type of plans could guarantee long term commitment to DRR as well as to blending DRR measures into development strategies (Glantz et al., 2013).

It is also up to humanitarian policies to select between the expense minimization and event maximization criteria described above. As illustrated in this paper, the optimal trigger depends on this choice, and there are a number of options in between that all have some sort of value.

Valuation as one of many criteria for developing early warnings

The valuation approach for the selection of thresholds to trigger preventative actions assumes that the cost and losses for each preventative action can be quantified. In real situations this can be a barrier since a wide range of cost-loss ratios can be obtained depending on the underlying assumptions. At the same time, changing the cost-loss ratio can change the optimal forecast threshold for action. Therefore decision-makers will need to be confident that – for the range of cost-loss ratios that could possibly apply to their action, they are picking a trigger that is robust (will have value in all/most of the cases) (Lempert et al., 2006). In the above analysis, increasing the cost/loss ratio by a factor of 10 still resulted in options for a "valuable" trigger.

As shown, the valuation approach allows for some flexibility in the choice of forecast attributes and allows for some margin of error in the choice of triggers.

However, the valuation, or economic case, for the selection of thresholds for a forecast-based financing early warning is a key component, but not the only necessary consideration. Even though humanitarian organizations have to work under the constraints of a finite budget, considerations other than minimization of expenses must be taken into account. While equations (1) and (2) assume that cost and losses can be monetised and all the terms in the equations are commensurable, in the humanitarian context losses and costs are likely to be incommensurable (e.g. money for C, lives lost for L, reputational damage for C_{av}). In this case, and/or when the cost-loss data is not available, the humanitarians will select the triggers using qualitative approaches that take into consideration their subjective situation, including institutional constraints and reputational risks, by addressing questions such as how often do they feel comfortable with taking FbF action, how many times they can access FbF funding, what are the non-climatic factors that contribute to the risk of impacts, etc.

There is some evidence suggesting that disaster risk reduction enhances the potential for communities to develop by for instance reducing the negative impacts of disasters on economic growth (Mochizuki et al., 2014). Developing a FbF mechanism (Coughlan de Perez, 2014) that, based on early warnings, provides the institutional and funding arrangements that allow humanitarian actors to carry out pre disaster activities to reduce potential losses and damages, effectively bridges the humanitarian and the development sectors. The valuation approach detailed here can be used in collaborations between forecasters and humanitarians to establish such a mechanism, contributing to effectively bridge this gap.

Acknowledgements

The authors of this paper would like to extend their gratitude to the donors who have made the Forecast-based Financing pilots possible. In addition, the German Federal Foreign Office has developed an Action Plan for humanitarian adaptation to climate change, and has invested in Forecast-based Financing in several other countries around the world. AL was supported by the Oxford Martin School, University of Oxford.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.wace.2018.03.006.

References

Ambhul, J., 2010. Customer Oriented Warning Systems. MateoScheiz, Zurich.
Bazo, J., de las Nieves Lorenzo, María, da Rocha, Rosmeri Porfirio, 2013. Relationship between monthly rainfall in NW Peru and tropical sea surface temperature. Adv. Meteorol. 2013, 152875 https://doi.org/10.1155/2013/152875, 9 pages.
Braman, L.M., van Aalst, M., Mason, S.J., Suarez, P., Ait-Chellouche, Y., Tall, A., 2013. Climate forecasts in disaster management: red Cross flood operations in West Africa 2008. Disasters 37 (1), 144–164.
Cabot Venton, C.F., 2012. The Economics of Early Response and Disaster Resilience: Lessons from Kenya and Ethiopia. DFID, London.
CAF, 2001. El fenomeno el niño 1997-1998 Memoria, retos y soluciones, Comision Andina de Fomentao available at: http://scioteca.caf.com/bitstream/handle/123456789/676/Las%20lecciones%20de%20El%20Niño.Perú.pdf?sequence=1.
Coughlan de Perez, E., Monaso, F., van Aalst, M., Suarez, P., 2014. Science to prevent disasters. Nat. Geosci. 7 (2), 78–79.
Coughlan de Perez, B. v, 2014. Forecast based financing: an approach for catalysing humanitarian action based on extreme weather and climate forecasts. Nat. Haz. Earth Syst. Sci. Dis. 2, 3193–3218.
Coughlan de Perez, E., van den Hurk, B., van Aalst, M.K., Jongman, B., Klose, T., Suarez, P., 2015. Forecast-based financing: an approach for catalyzing humanitarian action based on extreme weather and climate forecasts. Nat. Hazards Earth Syst. Sci. 15, 895–904. https://doi.org/10.5194/nhess-15-895-2015.
Coughlan de Perez, E., van den Hurk, B., van Aalst, M., Amuron, I., Bamanya, D., Hauser, T., Jongman, B., Lopez, A., Mason, S., Mendler de Suarez, J., Pappenberger, F., Rueth, A., Stephens, E., Suarez, P., Wagemaker, J., Zsoter, E., 2016. Action based flood forecasting for triggering humanitarian action. Hydrol. Earth Syst. Sci. Discuss. https://doi.org/10.5194/hess-2016-163.
Ebi, K.L., Tesiberg, T.J., Kalkstein, L.S., Robinson, L., Weiher, R.F., 2004. Heat watch/warning system save lives: estimated costs and benefits in Philadelphia 1995-98. Bull. Am. Meteorol. Soc. 85 (8), 1067–1073.
Glantz, M., Baudoin, M.-A., de la Poterie, A.T., Naranjo, L., Pierce, G., Pradhananga, G., et al., 2013. Working with a Changing Climate, Not against it. Hydro-meteorological Disaster Risk Reduction: a Survey of Lessons Learned for Resilience Adaptation to a Changing Climate. USAID. University of Colorado, Boulder.
Han, J., Ye, Q., Yan, Z., Jiao, M., Xia, J., 2010. Conceptual study on incorporating user information into forecasting systems. Front. Environ. Sci. Eng. China 5 (4), 533–542.
Hillbruner, C., Moloney, G., 2012. When early warning is not enough - lessons learned from the 2011 Somalia Famine. Global Food Secur. 1, 20–28.
Jollife, I.T., 2007. Uncertainty and inference for verification measures. Weather Forecast. 637–650.
Jolliffe, I.T., Stephenson, D.B., 2003. Forecast Verification: a Practitioner's Guide in Atmospheric Science. Wiley, Chichester, England.
Joslyn, S.L., LeClerc, J.E., 2012. Uncertainty forecasts improve weather-related decisions and attenuate the effects of forecast error. J. Exp. Psychol. Appl. 18, 126–140.
Katz, R.W., Murphy, A.H., 1997. Economic Value of Weather and Climate Forecasts. Cambridge, UK.
Knowlton, K., Kulkarni, S.P., Mavalankar, D., Jaiswal, A., Connolly, M., Nori-Sarma, A., et al., 2014. Development and implementation of South Asia's first heat-health action plan in Ahmedabad (Gujarat, India). Int. J. Environ. Res. Publ. Health 11 (4), 3473–3492.
Kovats, R.S., Hajat, S., 2007. Heat stress and public health: a critical review. Annu. Rev. Publ. Health 29, 41–55.
Lagos, P., Silva, Y., Nickl, E., Mosquera, K., 2008. El Niño, climate variability and precipitation extremes in Perú. Adv. Geosci. 14, 231–237.
Lempert, R.J., Groves, D., Popper, S.W., Bankes, S., 2006. A general analytic method for generating robust strategies and narrative scenarios. Manag. Sci. 52, 514–528.
Mochizuki, J., Mechler, R., Hochrainer-Stigler, S., Keating, A., 2014. Revisiting the 'disaster and development' debate - toward a broader understanding of macroeconomic risk and resilience. Clim. Risk. Manage. 3, 39–54.
Molteni, F.B., 1996. The ECMWF ensemble prediction system:methodology and validation. Quart. J. Roy. Meteor. Soc. 122, 73–199.
Murphy, A.H., Katz, R.W., Winkler, R.L., Hsu, W.-R., 1985. Repetitive decision making and the value of forecasts in the cost-loss ratio situation: a dynamical model. Mon. Weather Rev. 113, 801–813.
Mylne, K.R., 2002. Decision making from probability forecast based on forecast value. Meteorol. Appl. 9, 307–315.
Oenone Chadburn, C.A., 2013. Applying Cost Benefit Analysis at a Community Level, a Review of its Use for Community Based Climate and Disaster Risk Managment. Oxfam Research Reports, Oxfam. Oxford.
Public Health England, 2014. Cold Weather PLan for England 2014. Protecting Health Annd Reducing Harm from Cold Weather. NHS England, Public Health England. London.
Public Health England, 2015. Heatwave Plan for England. Protecting Health and Reducing Harm from Severe Heat and Heatwaves. NHS England, London.
Roulston, M.S., Smith, L.A., 2004. The boy who cried wolf revisited: the impact of false alarm intolerance on cost–loss scenarios. Weather Forecast. 19, 391.
Suarez, P., 2009. Linking Climate Knowledge and Decisions: Humanitarian Challenges. Boston University, Boston.
Suarez, P., Linnerooth-Bayer, J., 2011. Insurance Related Instruments for Disaster Risk Reduction. Contribution to the Global Assessment Report on Disaster Risk Reduction. United Nations International Strategy for Disaster Reduction. UNISDR, Geeva.
Webster, P.J., Jian, J., Hopson, T.M., Hoyos, C.D., Agudelo, P.A., Chang, H.-R., et al., 2010. Extended range probabilistic forecasts of Ganges and Brahmaputra floods in Bangladesh. Bull. Am. Meteorol. Soc. 91, 1493–1514.