A Value Chain Approach to Optimising Early Warning Systems

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1. Background: weather-related disasters and the value of warnings

In 2017, weather-related disasters killed nearly 10,000 people and affected 100 million people, causing damage of over $300bn (CRED, 2018). Whereas the number killed has exhibited a downward trend over the past half century, the cost of damage has steadily increased. Those affected may suffer serious injury or debilitating illness, loss of personal wealth, raised food prices, or temporary loss of electric power or road access. Cost of damage is largely deduced from insurance claims, which are often the only data available, but these represent only a fraction of the full economic impact. Poor economies may suffer a long term setback to development following major or repeated disasters (Mochizuki et al., 2014).

A weather-related disaster occurs when hazardous weather impacts the lives, wealth or livelihoods of people so as to cause serious disruption of the functioning of their community, requiring outside help for recovery (UNISDR, 2016). A disaster may be prevented or mitigated by reducing the hazard (only generally possible if human activity contributes to the hazard, e.g. pollution emissions, or deforestation), reducing the community's exposure (e.g. by evacuation or land use zoning), or reducing their vulnerability (e.g. by building hazard-resistant buildings or by improving nutrition). These responses all require policy decisions based on accurate and detailed information about hazard, exposure and vulnerability. Early warning systems are a key policy option that can reduce the risk from hazards for which other protection is unavailable or unaffordable.

Effective weather-related disaster warnings highlight periods of increased risk, whether due to enhanced hazard likelihood (e.g. the approach of a storm), high levels of exposure (e.g. crowds gathering in a hazardous location for a festival) or high vulnerability (e.g. a health hazard during a flu outbreak). They depend on accurate monitoring and prediction of the weather and its related hazards, such as flood, landslide, excess heat or cold, wildfire and road icing, together with detailed knowledge of the exposure and vulnerability of communities in the affected area.

The development of computer weather forecasting has been one of the most spectacularly successful applications of science in the past half-century (Bauer et al., 2015). Figure 1 illustrates, quantitatively, the improvement in the accuracy of surface pressure predictions over that period. Comparison of curves at different lead times shows that a lead-time gain of about 24 hours per decade has been sustained for the past 40 years. The curve for persistence (i.e. using today's observed conditions as the 3-day forecast) indicates no significant change in natural variability that might bias the results. The results imply a commensurate qualitative improvement in the prediction of the travelling weather systems with which most mid-latitude weather hazards are associated. These advances have been achieved through a combination of improved monitoring, especially by satellite earth observation, improved computing power and improved modelling of atmospheric processes.

Direct prediction of the hazard itself has been more challenging, since hazardous conditions are often extreme and may be highly sensitive to small changes in atmospheric conditions. The last decade has seen a breakthrough in capability to predict small-scale weather variability through the introduction of convection-permitting prediction models (Clark et al., 2016). Uncertainty associated with such small-scale weather forecasts depends on the availability and effective use of good quality observations to initiate the forecast, and grows rapidly with lead time. Confidence in the forecast therefore needs to be quantified if the forecast is to be useful, such as by using ensemble prediction systems (Clark et al., 2016, Golding et al., 2016). Novel methods of verification are also needed to represent the skill of these forecasts; for example, figure 2 shows the spatial scale over which UK nowcasts (which are a blend of 1.5km model forecasts and radar-based extrapolation) have useful skill at 3 hours ahead (Bowler et al., 2006, Roberts and Lean, 2008) – a critical time horizon for resource mobilisation for flash floods in the UK.

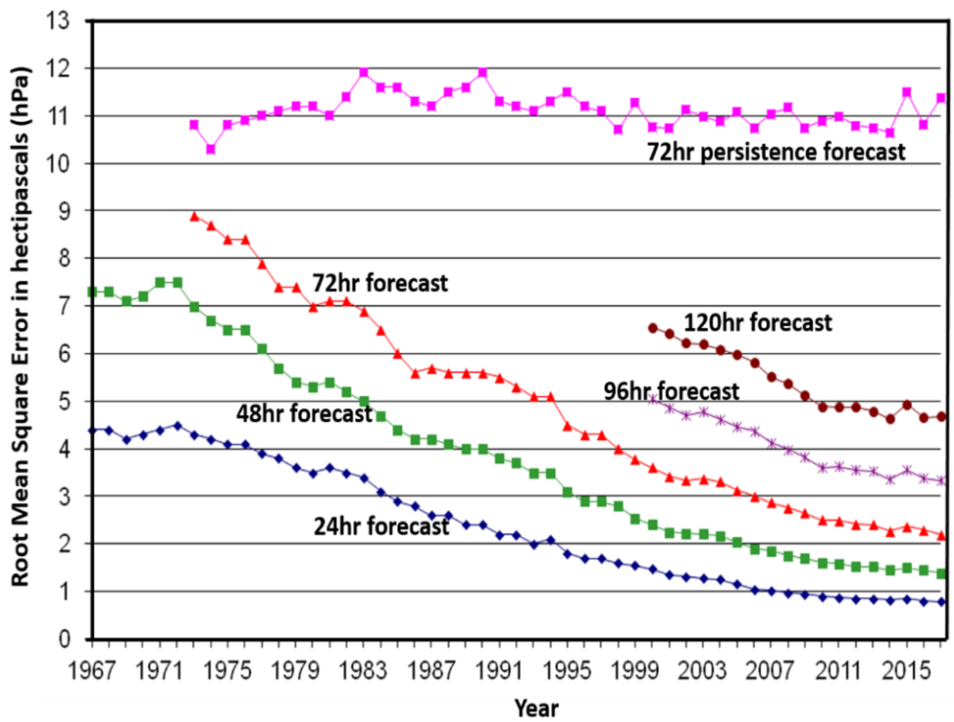


Figure 1. Time series 1967-2017 of annual root mean square error of mean sea level pressure predictions for the North Atlantic and NW Europe from the UK Met Office global numerical weather prediction model, illustrating the gain in accuracy over this period. © British Crown Copyright

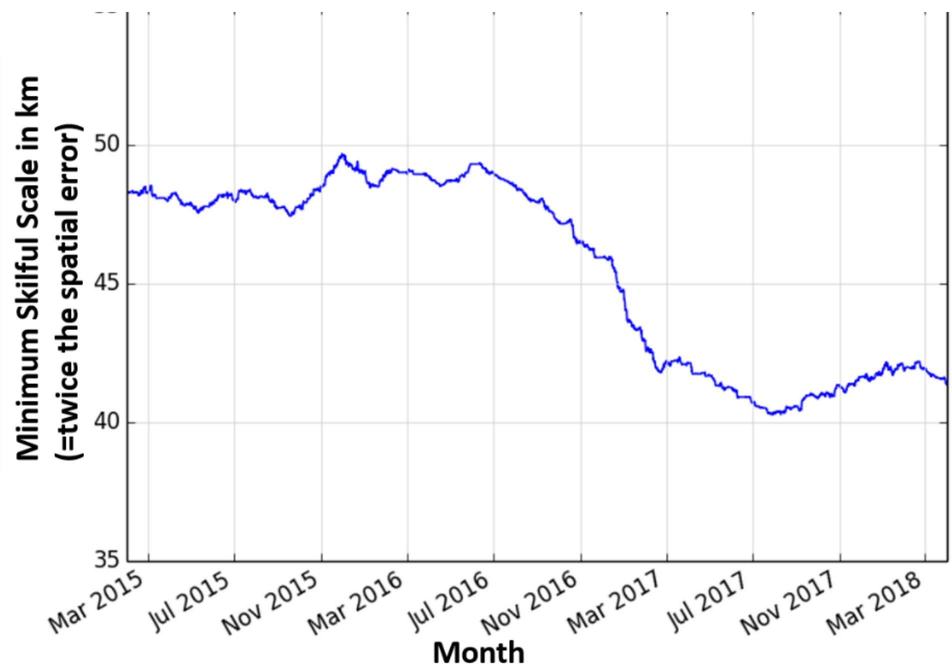


Figure 2. 36-month running mean, from March 2015 to June 2017, of the monthly skilful spatial scale of 3hr forecasts of hourly precipitation accumulations exceeding the 90th percentile. Skilful spatial scale is double the average spatial error. © British Crown Copyright

Advances in environmental hazard prediction have followed those in weather forecasting with coupled ocean wave (Rogers et al., 2005), storm surge (Flowerdew et al., 2013), river flow (Smith et al., 2016), and wildfire risk (Dowdy et al., 2010) models all well established in hydro-meteorological services. Current trends are towards closer coupling to enable more effective tuning, faster forecast delivery and to enable feedbacks among the different geophysical variables (Lewis et al., 2018).

However, forecasting the likelihood of the hazard is only the first part of the warning process. To be successful, the warning must enable its recipients to take the right decisions to protect themselves and their communities (Taylor et al., 2018). This means that they must receive the information they need in a form that they understand. Warnings that include the likely impact of the hazard and recommend actions to be taken are most effective (WMO, 2015b). Information on hazard impact is often based on past experience, but advances in information technology are enabling the creation of tools that combine hazard, exposure and vulnerability information automatically to predict impacts. Hazard mapping tools enable probabilistic hazard forecasts to be overlaid with exposure and vulnerability data, such as population density, roads and hospitals, to provide a visual assessment of risk. Quantitative estimation of the risk of socioeconomic impacts requires integrated modelling of the relationship between the hazard, vulnerability and exposure. While this is well established for a few specific applications, such as aviation or shipping, the complexities of modelling the diverse impacts on the public remain very challenging. The Natural Hazards Partnership in the UK has developed a framework for such models and is in the process of developing operational capabilities in surface water flood impact, strong wind impact and landslide (Hemingway & Gunawan, 2018). Modelling the impacts of multi-hazard events such as the wind, rain, and storm surge associated with a tropical cyclone, or the extreme heat, air pollution and wildfires associated with a heat wave, is an especial challenge. However, new techniques based on the application of machine learning to historical databases, are beginning to deliver useful results in this area.

Although the response to a warning is assumed to be an action, giving the warning a yes/no character, in reality warnings are always perceived as a risk (Eiser et al., 2012) to which users apply their own interpretation of how much uncertainty they attach to the source of the warning & how serious the impact will be.

To complicate the picture, hazards are rarely the result of weather alone. For instance, the issue of a flood warning requires a weather forecast first, which is then used to predict flood levels, which then informs the issue of the warning. The local vulnerability assessment may then be added by local disaster management officials, who may then order evacuations. Thus, there is typically a chain of organisations, with different objectives and responsibilities, and with different areas of expertise expressed in different technical language, communicating with each other to enable a final warning to be issued to the public. Not only are the expertise and technical language likely to be different, but each expert may choose to substitute other sources of information, including personal experience and indigenous knowledge, in preference to the "official" information stream. Such differences can make successful communication between these bodies as much of a challenge as is communication with the end user. Thus, the warning process may be represented as a chain of peaks of expertise, separated by communication gulfs between the different languages and cultures of expertise, each of which may be bridged, more or less effectively, by procedures, information formats, training etc.

Ideally, investment in improving warnings should be targeted so as to maximise the beneficial outcome. In this paper we use the economic concept of a value chain (Lazo et al., 2009) to explore the extended warning production chain shown in figure 3. Our thesis is that by focussing on the chain as a whole, and on its connectivity represented by the bridges over the "valleys of death", we can contribute to the development and implementation of more effective warning systems that will build resilience to weather-related hazards.

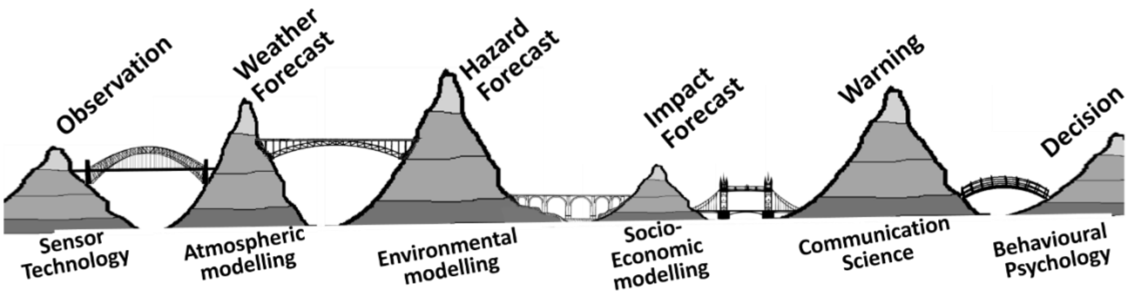


Figure 3. The peaks of expertise, valleys of death and bridges of communication between them, in a conceptual value chain for a weather-related hazard warning. Each peak adds value to the process, but value is lost in each valley and the value of warning lead time is lost at every stage of the process. © British Crown Copyright

2. Method: Sources of information used in this study

The study was carried out in the context of an international 10-year project, HIWeather, of the World Meteorological Organisation's World Weather Research Programme (WMO, 2017). The objective of HIWeather is to increase resilience to high impact weather through research to improve weather-related early warning systems. Firmly linked to the early warnings objective of the Sendai Framework (Aitsi-Selmi, et al., 2016), it has identified gaps in capability across the scientific spectrum from basic meteorological understanding and monitoring, through prediction of hazard and impact, to the communication of warnings, with about half of its activities falling in each of the physical and social sciences. Five task teams are working on these gaps, both through promotion of linked national and international research programmes and through collaborative activities such as workshops and best-practice reviews (WMO, 2017). Together, the task teams have identified the concept of the warning value chain as an important integrating feature. During 2017, two workshops on the value chain were held: the first in Berlin, Germany in May, was attended mainly by academic experts associated with HIWeather; the second in Melbourne, Australia in September was attended mainly by operational managers from the Australian Bureau of Meteorology.

In addition to the HIWeather workshops, this paper draws on expertise from a U.K. Met Office internal network on Socio-Economic Benefit assessment. This network was formed in response to increasing demands for justification of major investments in the UK weather service through formal cost-benefit appraisals. The network draws together expertise from many parts of the Met Office for use in future investment proposals and in assessing the benefits of previous investment, an increasing requirement of government. The most recent benefit case studies were conducted as part of the procurement of the current supercomputer. A major report on the value of the Met Office as a whole (London Economics, 2016) then re-framed and re-used these benefit case studies, some of which used value chain approaches to estimate the value of weather information to specific users. In the case of flood warnings, one of the challenges in doing so, was to attribute benefits separately to investment in the Met Office or in the Environment Agency (the flood management authority for England).

Expert knowledge from the HIWeather workshops and Met Office network together with references in three key reports (NAS (2018a), WMO (2015a) and London Economics (2016)) were used to identify key papers that identify metrics of warning accuracy, skill or value and/or that relate outcomes to measurable characteristics of the warnings. The results presented below summarise the information drawn from these papers, in the context of contributing to the evaluation and optimisation of the warning chain.

3. Results: characterising and evaluating a warning system as a value chain

3.1 The warning system

3.1.1 Characterising risk

Before a warning system can be designed it is necessary to clarify the risk that is to be addressed. Since the consequences depend on both the severity of the hazard and the vulnerability of those affected, a mapping exercise is required. Hazard maps have traditionally been based on historical observations. However, with the increasing realism of models, the sparsity of historical observations in many parts of the world, and the need to project forwards in a changing climate, the use of models is increasing, especially for hazards associated with larger scale weather systems. Care must be taken, however, to calibrate results using those historical data that are available.

The literature on weather-related impacts – taken to include death, injury, disease, cost of damage, loss of business and loss of economic capacity - is voluminous, especially in the context of changing frequencies of severe events due to climate change. However, assigning a cost to these impacts is highly contested. Typically, damage is based on insurance records, which cover far less in developing countries than in developed countries. The cost of a life can be highly distorting, as it varies by an order of magnitude between countries, while the cost of injury or disease is usually excluded, except perhaps for any direct impact on health service costs. Impact is most easily monetised when there is a protection system already in use, as in winter road maintenance (Joslyn and LeClerc, 2011). The cost of protection may then be used as lower bound for the cost of impact of the hazard.

The economic impact of weather variability in the USA was investigated by Lazo et al. (2011). They used an historical regression approach to estimate the weather sensitivity of the annual GDP of eleven economic sectors to heating degree days (a measure of the coldness of the winter), cooling degree days (a measure of the heat of summer), total precipitation and precipitation variance over the period 1976-2000. They found that most sectors in most states were weather sensitive when tested at the 10% significance level, but that the sensitivity varied in both magnitude and sign across different sectors. In 2008 prices they estimated the total US weather sensitivity to be US$485 billion per year (NOAA, 2011) contains a collection of estimates of the economic impact of specific weather hazards in the USA.

Nagy et al. (2018) investigated the relationship between vulnerability and weather-related hazard impacts on health and well-being in Latin America. The highest impacts in all of these countries were from floods, storms, droughts & landslides. The authors found generally positive relationships between development indices and numbers of fatalities, but with several outliers.

3.1.2 Warning design

Having identified the impact of hazards in the current or projected climate, policy responses need to be identified, of which an early warning system should be one. In developed countries, communities are generally protected against frequently recurring hazards and warned against less frequent ones, but it may be more effective to warn when people can easily avoid the impact of the hazard, or to protect when protection is easy and cheap to construct. For an undeveloped country, the level of protection will often be low and the budget for increased protection will be small, so early warnings may offer the only option for disaster mitigation. The efficacy of an early warning depends on what mitigating actions can be taken within the existing social and cultural environment, as well as what is possible and practicable given available science and technology (Eiser et al., 2012).

Any warning system must contain at least a monitoring capability and a means of communicating information to emergency responders. Such a warning enables early response. An early warning must also include a prediction element, though this can vary from a general indication of raised probability of the hazard, to a definite statement of specific intensity, time and location. More generally, the prediction system should produce a probability distribution of intensity, time and location. An early warning system enables protective action to be taken before hazardous conditions occur.

Aparicio-Effen et al. (2018) describe an early warning system for heavy rain and landslides, developed for La Paz, Bolivia, following a major landslide disaster in 2002. In this case the hazard is the product of both the geological situation of the city and its climate. Extensive building on hazardous slopes has created a high-risk environment in the city. Following the 2002 disaster, an early warning system for heavy rain was put in place. The Municipality of La Paz created an Early Warning Operations Centre (EWOC) within the Special Office for the Integrated Management of Risks (DEGIR) to issue early warnings for coordinated action by municipal authorities and emergency response personnel. While the EWOC cannot predict specific landslides, it was able to trigger preparedness activities, leading to effective disaster management that prevented loss of life when another major landslide occurred in 2011.

3.1.3 Warning delivery

Having identified a set of potential actions to mitigate the hazard, and a means of generating the information required for their activation, a system needs to be put in place to communicate the information to decision makers, including the public. Typically, a warning to evacuate or take cover will come from emergency managers, who will most likely source their information from the state weather service. The media will be an important channel of information and may also be constrained to use the national authoritative source. On the other hand, individual members of the public may obtain information from a plethora of different public and private agencies, potentially leading to confusion. In this situation, clear identification of the information source is critical.

In developing countries, the absence of fixed communication infrastructure may constrain the ability to deliver any warning information to large parts of the population. This is increasingly being overcome by the use of mobile phone technology. Van Vark (2012) highlights the strong penetration of mobile phones in Africa and India, and the benefits of its use for delivering weather and climate information, not just because of its extensive reach, but also because it enables delivery by trusted entities, such as NGOs with local knowledge.

Given an authoritative source and a means of delivery, the chain of communication by which weather monitoring and forecasting information is translated into a protective response may look something like the conceptual chain in figure 3. At each stage of this chain, the responsible organisation will have measures of its own success, but these measures rarely enable a direct connection with any measure of success in impact mitigation at the end of the chain. Yet optimisation of the warning system, and effectiveness of the investment, rely on being able to identify which elements, or combinations of elements, of the chain contribute most to disaster risk reduction.

3.2 Modelling the value chain

3.2.1 Measuring producer skill

There are many approaches to measuring the skill of weather forecasts, but some basic principles have been identified that help to make the results consistent with the subjective concept of skill (Wilks, 2011). For smoothly varying quantities like temperature or pressure, such approaches are based on the application of elementary statistical theory. Figure 1 shows the application of the root mean square error to assessing the accuracy of surface pressure forecasts in a global prediction model for the European region. While skill can be derived relative to a null forecast, such as persistence of climatology, it is the trends with lead time and with historical year that best illustrate the advances achieved. Thus, a 2-day forecast today is of similar skill to a 1-day forecast, 10 years ago.

For quantities like rainfall, with more complex distributions, such techniques do not provide an adequate assessment of skill, especially as the resolution of the predictions improves, so new methods have had to be developed that focus on the accuracy of the spatio-temporal pattern, rather than of point values (Gilleland et al., 2010). This difficulty is magnified when the assessment is restricted to extreme values, such as might cause a disaster, due to their isolation in time and space, to the poor sampling of the observations, and to the lack of statistical significance in the small samples available for evaluation. As described earlier, figure 2 illustrates the use of a spatial assessment technique to estimate the average length scale over which hourly precipitation accumulation nowcasts are deemed to have useful skill. To evaluate these nowcasts each hour the exceedance threshold is set to the top 10% of the hourly distribution (e.g. Mittermaier et al. (2013)). Based on the 36-month mean, the scale has decreased substantially over the past few years given improvements in the forecast algorithms. However, the 90th percentile is not high-impact most of the time, so whilst the use of percentiles enables an examination of the tail of the distribution, these results cannot be seen as truly capturing the skill for high-impact events. For this purpose, evaluation needs to be couched in probabilistic, rather than deterministic, terms. The introduction of ensemble weather prediction systems has facilitated this move (Golding, 2016).

Assessing the quality of a forecast for hazard impacts is complicated by the difficulty in measuring the impacts. Damage surveys are often conducted in the aftermath of high impact weather events, but these generally do not cover the full extent of damage and impact, and the data that are collected may not be sufficiently detailed or quantitative to evaluate the vulnerability-damage relationships used in the impact modelling. Understanding impacts on human health requires access to anonymised medical and hospital admissions data. Partnerships between warning providers and relevant response agencies is crucial to being able to measure the accuracy of impact forecasts.

Crowdsourcing is becoming an increasingly popular method of data gathering for many purposes (Muller et al., 2015). TAHMO (2019) describes an initiative that aims to provide dense rainfall monitoring across Africa, by installing low cost instruments in schools then collecting and disseminating the data freely. Typhoon Haiyan brought the value of crowdsourcing for post-event damage assessment to public attention (Butler, 2013). In this case, groups around the world used before and after satellite imagery to create damage maps for use in the recovery process. There is increasing evidence that coupling early warning services and crowdsourcing activities could better assist warning decision making (Bielski et al., 2017). It is nowadays possible to monitor social media (search through keywords/languages/locations), to detect events based on social media streams and to do informative classification of social media content e.g. distinguish between related information that is informative to warnings and the information that is related but not informative (Rossi et al., 2018). This includes for example mobile devices sending geolocated real-time in-field observations, using gamified crowdsourcing to meet data quality standards and ensure source trustworthiness, using machine learning to automatically extract relevant information in real time from social media on generic hazard-related data streams, as well as during a warning (Frisiello et al., 2017, Nguyen et al., 2017).

Evaluating the skill of the information in a warning adds an additional level of complexity. If there is a well-defined process behind the issue of the warning, it should be possible to apply many of the above approaches to estimate the accuracy of the factual content. Since most warnings are based on a binary forecast of exceedance of a threshold, binary scores such as those discussed by Wilks (2011) can be applied, provided adequate observations are available. However, this ignores the possible misunderstanding of the content due to inappropriate use of technical language, poorly designed graphics, poor choices of geographical cues, etc. It also ignores the possibility of "grades of success", for instance in a near-miss situation, or when the spatial or temporal extent is only slightly in error (Sharpe, 2016). It is further complicated if an impact-based approach to warning is used, when the level of vulnerability must be accounted for in deciding whether the warning was correct or not. Finally, if the warning results in successful mitigation actions, the forecast impacts will not, in any case, take place, and the warning can no longer be successfully verified. For example, in the case of road icing, observations of road state will not show that the road is covered in ice if it has been treated in advance, though the temperature may still show the road surface to be below freezing. In this instance the meteorological trigger for the hazard (sub-zero temperature) is verifiable but the hazard itself (slippery road) is not. In this situation, the absence of impacts would be an indicator of success.

Examples of studies that address specific forecast thresholds of relevance to warning production include skill scores for aviation Terminal Aerodrome Forecasts, which contain safety thresholds for civil aircraft (Mahringer, 2008), 99th and 99.9th percentile rainfall threshold forecasts, with relevance to flood prediction (Sukovich et al., 2014), and tornado predictions (Brotzge et al., 2013).

3.2.2 Estimating losses and benefits

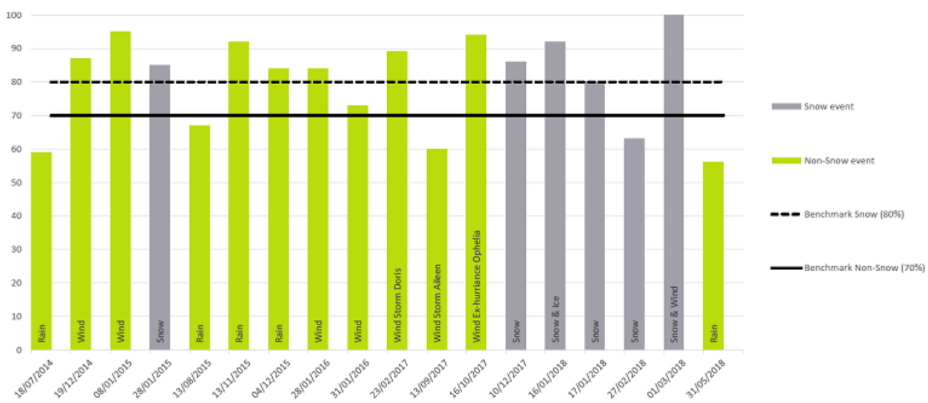
The basic metrics for disaster impact are loss of life, number of people affected and cost of damage, as used in the Sendai framework reporting. Cost is usually based on insured losses, since these are often the only conveniently aggregated figures available. However, such figures exclude the loss of uninsured wealth – such as the stock of subsistence farmers or government-owned infrastructure in many countries. In developed countries it may be assumed that uninsured losses are correlated with insured losses and case study data can be used to estimate the size of the uninsured contribution. This is unlikely to be as successful for less developed countries and, in any case, reliable case studies do not yet exist for most of the world.

For investment purposes, loss of life may be incorporated into a monetary value by applying a “value of life” to each fatality (Department of Transport, 2007). The “cost” of “people affected” is widely ignored in investment studies, yet long term disablement from injury or chronic disease, including from mental health impacts such as Post-Traumatic Stress Disorder, can have major impacts on the economic productivity of a community. The use of DALYs (disability-adjusted life years) or QALYs (quality-adjusted life years) is an approach to addressing this issue that has not yet been widely applied in disaster impact evaluation (Marseille et al., 2015). Users often have their own approaches to impact measurement based on their own monitoring activities. Thus, electricity distribution companies may have detailed records of weather-induced faults, the cost of rectifying them, and the resulting number of households that lost access to power. Based on past experience, humanitarian aid bodies can estimate the cost of some disasters from their type and scale. Epidemiological studies can be used to estimate the impact on health or mortality of weather events.

Having measured the losses due to disasters, which are really residual losses, contingent on existing mitigation measures, the evaluation of a warning system requires assessment of the reduction in loss due to any disaster management measures that might be applied as a result of the warning. A protective action produces a benefit by reducing the lives lost, people affected or cost of damage. On an annual basis, this is the Annual Avoidable Loss. For fixed protection, such as flood levees, this can be estimated by modelling the protected area and the frequency and magnitude of flood damage to each property in that area, calibrated using historical case studies. As well as its use in valuing future investment, this calculation can be used for ongoing estimation of the losses avoided by existing protection, and to correct the annual residual loss to an estimate of the annual loss that would have occurred in the absence of protection.

Economic analysis of the value of protection is usually based on a cost-loss model. Investment in protection is worthwhile if the aggregate benefit from all occasions when action is taken outweighs the total cost of protection. For a rational decision maker, protective action will be undertaken whenever a warning is received, whereas the reduction in loss will occur only when the hazard both occurs and is warned. If action is taken when it is not needed, due to a false alarm warning, the cost of protection is wasted. If action is not taken when needed, due to a missed warning, there is no benefit. Since different actions will have different costs relative to their benefits, analysis of value will show that optimal decisions require a different balance of false alarms and misses for each action. An overall optimal warning system should therefore be probabilistic so that the decision maker can choose the probability level at which to take each action, depending on the ratio of cost to loss. Palmer (2002) contrasts the situation of predicting precipitation thresholds of 1mm per day or 20mm per day. For the former, the event takes place frequently and the loss is small relative to the cost of protection, so the optimum strategy is to protect at rather a high probability of occurrence. By contrast, for the high threshold, the event is rare but loss is high, so the optimum strategy is to protect at a low probability.

Since real users are rarely "rational decision makers", assessing the real value of a warning requires additional measures, which can only be estimated from surveys and interviews. For an investment decision, these will normally be pre-disaster and will measure what people say they would do, given a set of scenarios. Thus Rollins & Shaykewich (2007) estimated the price that a sample of Canadians said they were prepared to pay for a forecast service using a contingent valuation approach. For ongoing monitoring, post-event surveys capture what people say they actually did and how effective they felt the information was in helping them to protect themselves. The UK Met Office routinely surveys affected communities after warnings. Figure 5a-b shows the proportion who received a warning and who felt it enabled them to take useful action, for the more severe warnings issued in 2014-8 (Met Office, 2018). It is clear from the annotations on the graph that the type of hazard affects the number of people who remembered receiving a warning, as well as their response to it.



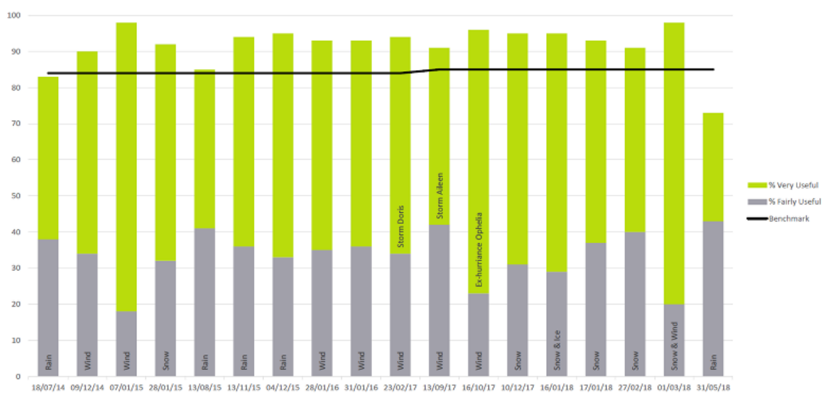


Figure 4. Results of public surveys carried out by the UK Met Office following amber or red warnings (i.e. moderate to high impact and/or likelihood) during 2014-2018. The type of hazard is annotated on each bar. (a) % of respondents who recall seeing or hearing a warning of this event. (b) % of respondents who found the warning of this event fairly useful or very useful. © British Crown Copyright

Heatwaves are the most deadly of natural hazards in Australia, killing an estimated 1000 people over the age of 65 each year (McMichael et al., 2003). While the cost of emergency and health services can be quantified, wider economic costs are not as easily accounted for. The establishment of Australia's heatwave service (BoM, 2018) was partly driven by a business need to minimise economic impacts (Nairn and Fawcett, 2013). Surveys of small to medium size businesses in 2017 found that most respondents received and understood the warnings, but that affordability of energy for cooling was a barrier to community preparedness. Business owners reported losses from staff absences and reduced productivity. Most were satisfied with the warnings, but many called for more information on expected impacts and what to do during a heatwave (Tofa and Gissing, 2017).

3.2.3 Measuring the response

The simple cost-loss model assumes a user who will always take the best decision in cost-benefit terms. In reality, the connection between warning and response is much more complex - a variety of constraints prevent an optimal response by the decision maker, including failure to receive the warning, failure to understand it, and insufficient time or ability to respond.

Nurmi et al. (2013) investigated these factors to create a value chain in their evaluation of weather information for transport in Finland and Europe. Their figure 5 shows the factors influencing the value of warnings in reducing the cost of traffic accidents in Finland: accuracy, customer orientation of message, access, comprehension, ability to respond and effectiveness of response. The biggest reduction in value comes from lack of ability to respond – hence the emphasis that we place here on identifying feasible responses before even considering the design of a warning service.

Environment Agency (2015) used a similar approach to estimate the value of flood warnings in England in reducing damage to property. For each of a number of possible actions to be taken in response to a flood warning, including flood defences, watercourse management, property protection and movement of valuables, they estimated the effectiveness of the response based on evidence of the availability and impact of these responses, warning lead time, access to warnings, and the likelihood of a response. They report detailed case studies of the use of this approach.

Results of such studies can be compared with estimates of revealed behaviour – either from post-event surveys or from observation, e.g. of numbers that evacuate when ordered to, so as to calibrate the model. The individual inhibitors, represented by the reduction factor, are sensitive to the behavioural responses of information users and therefore vary with make-up of the population affected, such as their gender, educational status, first language, cultural background, age, health status, etc. Research is increasingly identifying aspects of the warning communication process that impede a wide response, so that the effectiveness of warnings systems can be improved. For instance, surveys indicate that people understand the warning and perceive the risks better if the warning describes the expected impact (Weyrich et al., 2018). This is especially true when behavioural recommendations are added to the warnings (Figure 5). The same research has shown that people are more likely to engage in risk-minimising actions when given this additional information.

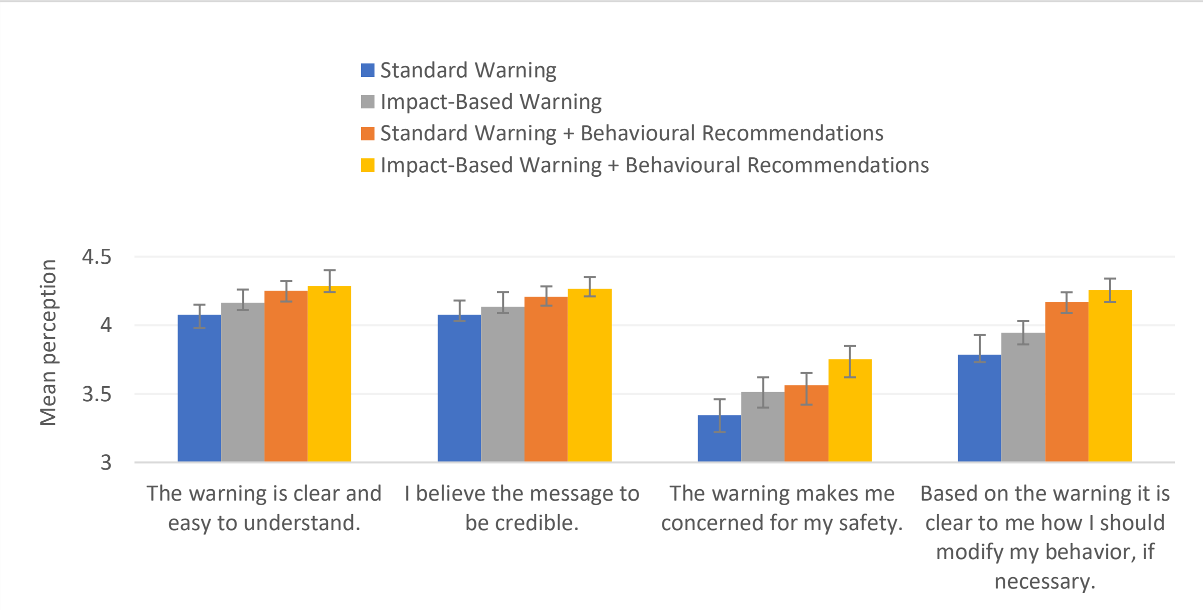


Figure 5. Perception of warning information for four warning types (standard or impact based, with or without behavioral recommendations). Bars indicate how much participants agreed or disagreed on a five-point Likert scale from 'totally disagree' to 'totally agree' with each of the five perception attributes. Error bars indicate the 95% confidence interval.

Research on warning communication is also increasingly addressing the new challenges posed by the wide proliferation of the Internet, new technologies (such as smartphone applications) and data crowdsourcing, which has revolutionised the ways that users collect, obtain, interpret and respond to information (NAS, 2018).

Relating the skill of the information in the warning to the reduction in loss is straightforward for the simple cost-loss calculation of potential benefit. It is also straightforward if the reduction factor resulting from imperfect communication is fixed and independent of skill. However, several of the inhibiting factors are likely to be dependent on skill – not least the time available to take action which impacts on the ability to respond. In addition, the likelihood of a user acting on a warning depends heavily on trust in the information provider and that trust is largely built on past experience. If the user perceives that skill has improved, the level of trust may increase, leading to a more effective response. This, potentially, makes the problem of modelling the response to warnings intractable. A possible solution is to explore the dependencies with a view to identifying a dominant one that can be used to relate skill to response. Lead time is one such factor, as it limits the actions that can be taken, both to confirm the warning and to respond to it. Thus, whereas forecast skill is typically calculated as a function of lead time, this approach suggests that lead time for a given level of skill may be a more useful guide to effectiveness of response.

An additional complication not normally taken into account, except as a potential inhibitor, is alternative sources of information available to the decision maker and to the public. These are, of course, crucial in the event of a breakdown in the primary information supply. In many countries, the front-line emergency management authority may have its own observing networks, independent of the weather service. At a less formal level, communications among family members and friends living in more or less exposed locations, may be used to reinforce or replace official data, while in less developed countries, indigenous knowledge provides a powerful background to any response (UNISDR, 2008)

In the context of figure 3, the warning chain consists of not just one producer–user link, but of several. At each link, producer skill, user response and communication effectiveness need to be considered. Moreover, each user has a different set of objectives, resources and constraints that frame the use and transfer of information. As described above, there may also be user redundancy in each link of the chain, and these alternative sources may even have their own subsidiary value chains. No research has been undertaken to address this extended value chain as a coherent system, let alone to propose a method of optimising it. However, some of the tools that have been used in more simplified approaches may help.

Each communication reduces the amount of information passed on. For example, although weather observing sensors are continuously exposed, weather reports are typically provided hourly or less frequently, which means that a report of exceedance of a warning threshold may be delayed by up to an hour – reducing the lead time for action. Each step in the chain takes time to gather information, process it, create new information, interpret it and formulate the information to pass on. This can make the information more useful and useable but further reduces the lead time for action. Some links in the chain may be available 24x7 while others may only operate business hours, potentially causing considerable delay unless earlier information has enabled on-call arrangements to be activated. It is in such circumstances that the emergency responder or member of the public may be reduced to trawling social media for information.

3.3 Example of the UK National Severe Weather Warning Service

The UK National Severe Weather Warning Service has been under development for 30 years. Its development was triggered by the review of the disastrous storm on October 16th 1987 (Met Office, 1987). The key development incorporated in its initial form was a move from warning based on monitoring (with a lead time of 0-3 hours) to warning based on forecasting. The improved forecasting capability that enabled this change had been developed over the preceding decade, but it took this major disaster to prompt the required change in the governance of the warning system (Houghton, 1988).

Subsequently the service evolved to a hazard risk-based warning service, with categories of warning related to the severity of the hazard and to the probability of its occurrence. This enabled the lead time of the initial warning to be extended substantially, as it could be associated with a low likelihood. While this might be ignored by many users, it could be critical information for users that would be seriously impacted.

Finally, in the last decade, the service has further evolved to be impact-based, with risk now related to the expected impact, taking account of variations in exposure and vulnerability across the country, in time, and according to the occurrence of public events. In parallel, communication of the warnings has evolved to take advantage of increased flexibility in telecommunications. A warning is therefore now typically supported by social media posts, a blog and a press release, as well as commanding the dominant part of any TV and radio weather broadcasts.

The service will continue to evolve to take advantage of improving forecast capability, advances in monitoring capability, and the continuing evolution of mobile communications. At present it is restricted to the direct impacts of weather, mainly on property and transport, though following the review of the 2007 floods (Pitt, 2008), UK flood warnings have also become forecast-based, using the same structure and formats, facilitated by the very close relationship between the Met Office and the Environment Agency for England, Natural Resources Wales and the Scottish Environmental Protection Agency. Health impacts are currently dealt with by separate warning systems for air quality, pollen, UV radiation, heat and cold, developed in collaboration with Public Health England. Other hazards, such as wildfires, are similarly dealt with through bilateral arrangements with relevant authorities. There are clear opportunities for benefit from further integration, both in impact forecasting and in communication, but the challenges posed by the different response actions and their timescales are great.

4. Conclusions

The impact of weather-related hazards continues to be a major cause of human and economic loss in the world. Reducing those losses requires a combination of policies that protect, avoid and facilitate recovery. Early warnings are a key contributor, especially in countries without the governance structures and resources to provide permanent protection or avoidance. Advances in weather modelling, earth observation from space, and hazard reporting by citizens, provide a solid baseline for hazard mapping; however, this needs to be matched by comparable mapping of the (time-dependent) exposure and vulnerability of people, buildings and infrastructure, and by the development of response capability especially in risk hot-spots.

Recent developments in weather forecasting have enabled early warnings of weather-related hazards to be produced at longer lead times, with greater precision, and with reference to their likely impacts, enabling more effective preparatory actions to be taken. At the same time, the explosion of communications technology has enabled warnings to be delivered more quickly, to targeted audiences, and in more flexible formats. Development of innovative evaluation techniques has enabled increasing forecast skill to be quantified but more work is needed to enable reliable quantification of skill for extremes, for many hazards and for their impacts. Quantitative assessment of the response to warnings is undertaken routinely in some countries through surveys, and research shows the benefit of communicating warnings based on the impact of the hazard rather than on the weather. The potential value of warnings has been evaluated using economic cost-loss models. Modification of these models to incorporate the value chain connecting producer and user has been demonstrated using a cascade of inhibiting factors that degrade the potential value. Such models are used to justify investment and to monitor performance, but fail to capture the complexity of the institutional chain that connects contributors to production of the warning with the decision maker. Nevertheless, they offer a starting point for the development of more sophisticated value chain models.

In the light of these findings, we offer the following conceptual outline of good practice for designing a new warning system, bearing in mind that user input (co-design) is required in most of the steps described below.

i. Map the hazard risk using monitoring data, space-based earth observation data, field surveys, census data, indigenous knowledge, etc. How does the hazard vary, spatially and temporally? What are the exposure and vulnerabilities of the population to this hazard, both directly and through dependence on infrastructure? Where does higher vulnerability intersect with higher hazard? Which areas are already protected?

ii. Identify potential beneficial responses to early warning. What is already done? What could be done with earlier or better warnings? What is the capacity for doing more if warnings were available? What would be the benefit if perfect information was available?

iii. Identify capability. What technologies/expertise are needed, what are available and what could they deliver? Who should deliver the warning – who do people listen to? Who is able to produce the information needed? What would it cost? What are the institutional constraints and how can they be minimised? How can responsibilities be allocated to maximise value?

iv. How much of the potential benefit could be realised with available capability? Drawing on previous value chain work, how much is likely to be realised? Is a warning system affordable and would it be cost effective, bearing in mind that there is a cost of response for false alarms as well as for correct warnings? If not, can the chain be re-engineered to make it cheaper or more effective?

v. Quantify the links in the chain using measures of skill and value. Is there a single metric (such as "gain in lead time") that can be used through the whole chain? Calibrate the measures using case studies. Use to justify the investment and to set standards for performance of the value chain components.

vi. Evaluate the warning chain when in use. Identify the links that are falling short of the expected contribution and work to improve or replace them. Use the value chain model to target improvements in the links that will provide most gain in overall value. Identify where information from outside the chain (e.g. indigenous knowledge) is beneficial to the final outcome and incorporate it into the model, modifying the existing chain as necessary.

By using a value chain approach to the design of warning systems, the centrality of two key requirements is established and maintained, i.e. that the information delivered must be defined by the needs of the decision maker (whether emergency manager or member of the public) and that the method of delivery must enable the decision maker to act on the information. These requirements apply, not just at the end of the chain, where public media may be involved, but at each and every step of the chain from basic monitoring to hazard prediction to warning and to response. Value is only created when a protective decision is made, so each link in the chain only contributes value in relation to its role in enabling better decisions to be made.

Consideration of the challenges in delivering such a warning system, highlights priorities for research in the formulation of forecasts and warnings which are being progressed or promoted through the HIWeather project (WMO, 2017), including a focus on the accurate monitoring and prediction of extremes, coupled modelling of weather-related hazards and of their socio-economic impacts, formulation and design of warning messages, and clarification of the role of culture and trust in the response to warnings. Above this, however, we identify the need for a systems approach to modelling the multi-organisation value chain to enable better evaluation of the contributions of each actor in the chain, and hence to optimise investment.

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Acknowledgements

The authors are grateful to the members of the HIWeather task teams for their support in preparing this paper.

Particular thanks must go to Philippe Weyrich for his contribution on perceptions of risk and for providing figure 5.

We are also grateful to the reviewers for suggested changes which have much improved the paper.