

Assessing the Economic Value of Early Warning Systems

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ABSTRACT

As of today, investments into early warning systems are, to a large extent, politically motivated and “disaster-driven”. This means that investments tend to increase significantly if a disaster strikes, but are often quickly reduced in the following disaster-free years. Such investment patterns make the continuous operation, maintenance and development of the early warning infrastructure a challenging task and may lead to sub-optimal investment decisions. The paper presented here proposes an economic assessment model for the tangible economic impact of early warning systems. The model places a focus on the false alert problematic and goes beyond previous approaches by incorporating some socio-cultural factors (qualitatively estimated as of now). By doing so, it supports policymakers (but also private investors) in their investment decisions related to early warning applications.

Keywords

Disaster management, early warning systems, investment decisions, assessment model.

INTRODUCTION

Modern societies are increasingly threatened by a wide range of hazards. Natural hazards are on the rise due to the effects of climate change. The introduction of critical technologies (e.g., nuclear power plants, chemical plants) came along with new types of contamination risks, and even more recently, the rise in terrorist activities has raised the threat level for people everywhere in the world. One way to enable populations to cope with all these potential disasters more efficiently is the use of modern early warning systems (EWS). Recent advances in information and communication technology now allow for the implementation of systems which can warn a large number of users within a very short time frame over a wide range of communication channels (SMS, cell-broadcast, pager, internet, satellite-based broadcast, etc.). These communication channels significantly extend classical warning methods via TV, radio and sirens towards more targeted localized or personalized alerts. It can be expected that ICT progress both on the sensor and communication side will enhance EWS effectiveness. However, implementing such modern systems requires quite significant investments, which raises the question if and when these are justified. Graymen and Males, 2002, observed that the public tends to invest heavily into EWS soon after a disaster struck, but that funding then rapidly decreases in disaster-free years. Such investment patterns make sustainable system development and maintenance difficult, and the underlying question whether investing in a particular EWS creates added value remains unanswered. As Graymen and Males state, there is a lack of methods for assessing and justifying the economics of early warning systems. The United Nations Inter-Agency Secretariat of the International Strategy for Disaster Reduction (UNISDR) underlines the importance of developing cost-benefit models for EWS (United Nations, 2006). This paper intends to close this gap by proposing an investment decision model for early

Reviewing Statement: This full paper has been fully double-blind peer reviewed for clarity, relevance, significance, validity and originality.

warning systems that address people¹. The paper is organized as follows: the next section discusses existing approaches to assess the value of EWS; thereafter, factors influencing the effectiveness of EWS are analyzed. Subsequently, an assessment model for EWS is developed, and the paper concludes with a discussion and outlook.

EXISTING APPROACHES TO ASSES THE VALUE OF EARLY WARNING SYSTEMS

Two main approaches have been discussed to assess the value of earth observation / early warning systems: contingent valuation and cost avoidance calculations (Fritz, Scholes, Obersteiner, Bousma and Reyners, 2008). Contingent valuation tries to assess the value of a system by analyzing its users' willingness to pay. The total amount that users are willing to pay finally determines the value of the system. The cost avoidance approach uses statistical analyses and cost estimations to determine the amount of damage that can be prevented if a warning system is in place, and compares these benefits with the investments needed to build and operate the system. In the latter, we can distinguish top-down approaches that estimate overall costs on a macro-economic level and bottom-up approaches that calculate costs based on single response actions.

Although being frequently used for the evaluation of public goods like EWS, the contingent valuation approach is somewhat problematic because it has a tendency to generate biased results. Respondents may, for example, wilfully misrepresent their willingness to pay for strategic reasons. This refers to the classic "free rider problem of public goods" where respondents systematically understate their willingness to pay because they hope that this will actually reduce the price they finally have to pay. Some other respondents ("Yea-sayers") may, to the contrary, overstate their willingness to pay just to please the interviewer. In the worst case, people are even unable to identify well-defined preferences for a public good (Carson, 2000). A second source of bias is the setting of the survey itself, which may temporarily distort the psychometric perceptions of the subject (Green, Jacowitz, Kahneman and McFadden, 1998). Contingency valuation can be further distorted by embedding effects, which arise from the failure of respondents to consider their budget constraints in hypothetical settings (Diamond and Hausman, 1994). As a result, Diamond and Hausman even go so far to conclude that "contingent valuations do not have much information to contribute to informed policy-making" (p. 46).

Therefore, the cost avoidance approach should be preferred for the assessment of EWS wherever feasible (i.e., where the necessary input data is available in sufficient quality). A few cost-avoidance models for the assessment of EWS have been discussed. Meissen and Voisard, 2008, for example, developed an initial model for EWS assessment based upon the parameters event frequency, warning accuracy, response, prevention and damage costs. They focus on weather-related disasters and use data provided by the insurance industry to calculate EWS benefits. Their model is a good starting point for the economic evaluation of EWS, but it does not include behavioural / psychological effects of system use, and does not fully account for the false alert problematic and the possibility to detect adverse weather conditions in time even without an IT-based early warning system. Another model presented by Wenzel, Baur, Fiedrich, Ionescu and Oncescu, 2001 does include costs caused by false alerts, but omits any human factor because the authors look into earthquake warnings with their extremely short lead times (in the range of seconds), where only automated protective actions can be initiated.

A completely different approach to assess the effectiveness of early warning systems was proposed by Grayman and Males, 2002, who used Monte Carlo simulations to assess the impact of an EWS for pollution accidents on rivers. The EWS was evaluated in terms of its effects on population exposure, and its effects on water treatment facilities downstream. Graymen and Males' approach does provide valuable insights in the potential benefits of the particular

¹ This has to be seen in contrast to EWS targeting technical actuators that trigger protective actions automatically. In this case, the model would have to be modified by replacing or deleting some behavioural variables.

EWS under analysis. However, their simulation is only applicable to a limited scenario (here: effects of pollutions on one single river). For every other application case, the model needs to be altered / redesigned and simulations need to be performed anew. As a result, the approach does not appear to be practical for a wide-scale assessment of EWS due to the high evaluation effort.

In general, assessments of EWS are characterized by difficulties in obtaining sufficiently accurate cost-benefit predictions. Therefore, Fritz et al., 2008, recommend to follow a benefit chain concept before considering the implementation of an EWS. This concept comprises at least the following 2 steps: (1) showing that improved observation / information has an impact on decision-making, and (2) showing that the resulting decisions improve well-being. Additionally, decision-makers should use order-of-magnitude approaches in the decision making process to take the high inaccuracies of cost-benefit predictions into account.

As can be seen from the discussion above, very few suitable methods for assessing the value of early warning systems exist, and the existing solutions still have some shortcomings which leave room for additional improvements. The goal of this paper is to provide an evaluation approach which helps to obtain a more precise and complete view on the costs and benefits of EWS than the existing approaches, and to provide a formal evaluation model that supports systematic EWS assessment.

FACTORS INFLUENCING THE EFFECTIVENESS OF EARLY WARNING SYSTEMS

The effectiveness of an early warning system is influenced by a wide range of factors, which can be classified into the following groups: (1) personal and cultural factors, (2) prediction-related factors, and (3) dissemination-related factors.

Personal and cultural factors influence how a warning is processed by the recipients and if and how the warning is then translated into protective actions. According to the United Nations, an individual's response to an early warning is influenced by his or her capability to

- understand
- believe
- verify and
- personalize

the warning message (United Nations, 2006). Even if the warning is noticed, understood, believed and personalized, this still is no guarantee that protective actions are taken, as these actions largely depend on how the underlying risk is perceived, which is in turn influenced by

- familiarity with the risk and previous exposure (Plapp and Werner, 2006),
- gender and race (Flynn, Slovic and Mertz, 1994),
- culture (e.g., Heine and Lehman, 1995), and
- current context (Meissen and Voisard, 2008)

In order to translate an acknowledged and relevant risk into protective actions, more hurdles need to be overcome. The individual has to believe in his or her mitigation capabilities (Plapp et al., 2006), so that he / she can be in control of the situation (Rachman, 1990). Personal mitigation capabilities are, in turn, a result of previous risk exposure and the degree of training, as "people are more likely to heed and act upon warnings when they have prepared warning-reaction plans" (United Nations, 2006). Additionally, people have to believe that the recommended mitigation activity is worth the effort. As an example, Table 1 provides an overview of response patterns in case of meteorological warnings in Germany.

Type of protective action	Willingness to respond
Close the window	~100%
Secure loose items outside	97.6%
Drive the car into a garage	92.9%
Check backwater valves in storm-water drainage systems	66.7%
Stay indoors	57.3%
Switch off electronic devices in the house	51.2%
Shield windows / glass surfaces	29.8%

Table 1. Willingness to respond to appeals for protective actions (in case of meteorological warnings in Germany)

Prediction-related factors which affect the economic impact of early warning systems comprise (a) the *prediction accuracy* of the disaster and (b) resulting *lead times* of disaster warnings (Jacks and Ferree, 2007).

Prediction accuracy is key in every early warning process. With regard to prediction accuracy, two types of errors have to be considered: type one errors refer to missing alerts, and type two errors refer to false alerts. These errors can also be referred to as false-negatives and false-positives. While the relevance of missing alerts is obvious, the impact of false alerts should not be underestimated. Fritz et al., 2008, for example, emphasize the economic importance of type 2 errors in the case of algal blooms. Reliable algal bloom alerts are of great importance to the fishing industry, as fishing vessels are usually taken out of duty or rerouted in case of bloom incidents. Due to the huge economic impact of these protective actions, the authors found that the economic value of warning information already becomes negative if more than 20% of warnings are false. Additionally, false alerts undermine the credibility of all warnings (“crying wolf syndrome”, Bennighaus, Bennighaus and Renn, 2005) and thus have a negative long-term impact on the compliance with recommended mitigation activities.

Lead times (i.e., time gap between issuing a warning and the appearance of the disaster) have an influence on the scope and complexity of protective actions that can be taken by warning recipients. Table 2 (adapted from National Science and Technology Council Committee on Environment and Natural Resources 2000; Wenzel et al., 2001; Klafft, Kräntzer, Meissen, Voisard 2009) outlines warning accuracy and lead times for different disaster types.

Disaster type	Accuracy	Typical lead times of acute warnings
Tornado	74%	~15 min
Heavy thunderstorm	89%	~23-24 min
Flash flood	89%	~13-58 min
Extreme snow	72%	> several hours
Earthquake	10% (?)	max. 75 seconds
Tsunami	n/a	20-60 min
Volcano eruption	n/a	days to hours
Hurricane	n/a	days

Table 2. Estimated prediction accuracy and typical lead times for warnings

As can be seen from the table, typical lead times are often in the range of one hour or less, thus leaving little time to take protective actions. 25 minutes may be enough to seek shelter and save lives, but not sufficient for actions to protect, e.g., personal property. The additional value of such short-notice warnings may also be limited if alert recipients could have detected the approaching disaster visually within a similar time span anyway. This points

towards a general dilemma in the early warning domain: the high warning accuracies of today's warning systems can often only be achieved at the expense of rather limited lead times (Bennighaus et al., 2005).

Dissemination-related factors influence the likelihood that recipients of early warnings are correctly notified and actually take notice of the warning in time.

In order to leverage the dissemination impact of warnings, modern EWS address a plethora of communication channels ranging from short messaging services (SMS, e-mail, fax, RSS feeds, TV set top boxes (Klaft, Krüntzer, Meissen and Voisard, 2008)) to dedicated paging devices. This multi-channel approach increases the notification capabilities and makes EWS less vulnerable to breakdowns or congestions of specific communication means. Nevertheless, surveys conducted in the framework of the SAFE project ("Sensor-actuator-based early warning systems for extreme weather conditions") revealed that survey participants could be reached and were able to take protective actions during approx. 7 hours during a whole day. This means in practice that, on average, about 29% of warning messages will be noticed in due time and can potentially be translated into an appropriate response. Observe that, in case of breakdowns in the communication systems, this number may be even be further reduced. Another dissemination-related factor addresses the amount of information that can be transported over different communication media. Some communication channels like SMS and paging systems can only carry a limited amount of characters, so that the alert is basically restricted to the disaster type and does not contain any instructions for recipients how to protect themselves and their property. Here, the training level of the population becomes again a key factor while translating warnings into appropriate mitigation actions.

AN ASSESSMENT MODEL FOR THE ECONOMIC VALUE OF EARLY WARNING SYSTEMS

In this section, a mathematical model for assessing the economic value of early warning systems is proposed, based upon personal and cultural factors, prediction-related factors, dissemination related factors and more general variables related to disaster types, system parameters and the area under consideration. In a first step, the economic impact of early warnings is assessed. Note that for reasons of clarity and simplicity, just one (atomic) warning area is considered in the following section. In case that the early warning system can address different warning areas / zones, the benefit calculation needs to be repeated for each zone in order to obtain the aggregate benefit. Figure 1 displays the overall process of assessing the economic impact of an early warning.

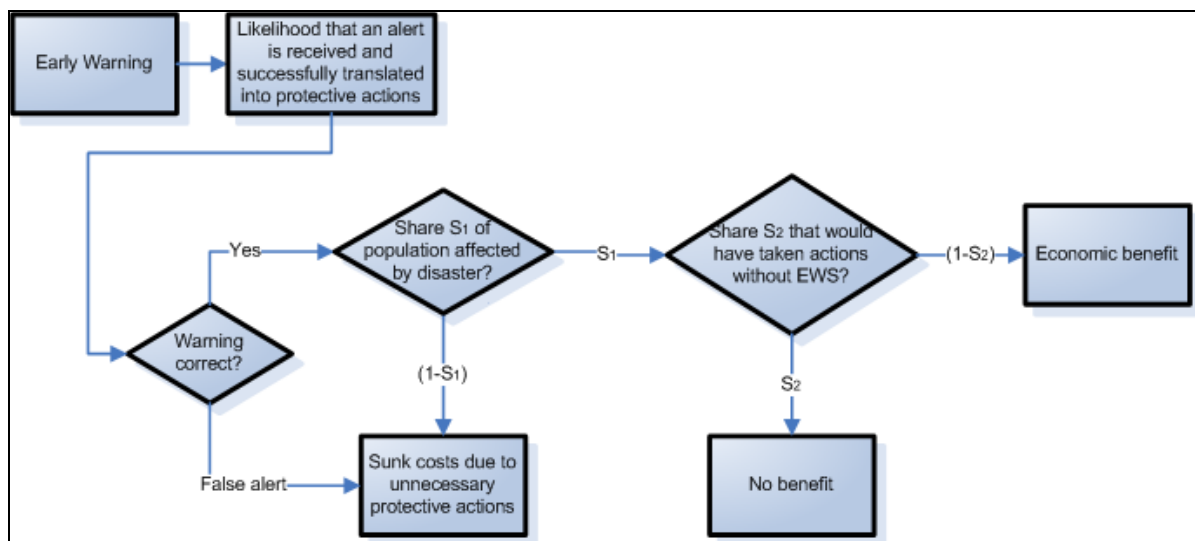


Figure 1. Assessing the economic impact of an early warning

In order to be able to formally describe the different elements of the impact assessment model, the following set of variables is introduced. Please note that variables on disaster occurrence, prediction accuracy and damage potential are available from insurance industry data bases. Determining the impact of socio-cultural variables, however, is an issue of ongoing research and can, as of now, only be intuitively estimated. We propose to use Hofstede's model of cultural dimensions (Hofstede, 2001) in this assessment process because his model is, to our knowledge, the one that has been analyzed for the largest number of cultures and countries and therefore allows a widespread application of the EWS assessment approach presented in this paper.

General variables:

D_i	: disaster of type i
$P(D_i)$: probability of occurrence of a type i disaster per time unit in the warning area
N	: number of people living in the warning area
S_i	: share of the population in the area under consideration typically struck by a disaster of type i , with $0 < S_i \leq 1$
k	: protective response action of type k
$R_{i,k}$: Relevance of protective action k in case of a disaster of type i , with $R_{i,k} \in [0;1]$
$\text{cost}_{\text{prot},k}$: average cost of a protective action of type k
$\text{cost}_{\text{prot},\text{total}}$: overall costs for additional protective actions induced by the EWS
$\text{bfit}_{\text{prot},k,i}$: average monetary benefit of one protective action of type k in case that a disaster of type i strikes
bfit	: total system benefit caused by additional successful protective actions
$f_k(T)$: function describing the likelihood that a protective action of type k can be implemented as a function of time between noticing a warning and impact of the disaster
t	: time span of economic assessment (EWS life cycle time)
I	: investment needed to establish the EWS
E	: energy costs per time unit to operate the EWS
Tr	: training costs for the personnel operating the EWS
Mat_{op}	: costs for operating and expendable materials for the EWS per time unit
C_m	: communication costs per recipient for one early warning via communication channel m
W	: wages per time unit for the operational personnel of the EWS
V	: direct (tangible) economic value of the EWS
$\text{cost}_{\text{sys},\text{total}}$: costs for installing and operating the EWS over its life cycle t

Personal and cultural factors:

$S_{G,c}$: shares of socio-culturally distinctive groups c among the target population, $0 \leq S_{G,c} \leq 1$
PD	: power distance of the target population (score according to Hofstede 2001)
UAV	: uncertainty avoidance of the target population (score according to Hofstede 2001)
$\text{LHood}_{\text{able},k}$: likelihood that a person is able to perform protective action k
$\text{LHood}_{\text{willing},k,i}$: likelihood that a recipient is willing to perform protective action k in case of an early warning for disaster type i

Prediction-related factors:

$P_{\text{Pred}}(D_i)$: probability that a disaster of type i is (correctly) predicted
$P_{\text{False}}(D_i)$: probability [per time unit] that a false alert for a disaster of type i is issued
$T_{\text{Lead,EWS}}(D_i)$: typical lead time for an EWS warning for a disaster of type i
$T_{\text{Lead,human}}(D_i)$: typical lead time in which humans can detect upcoming disasters of type i without EWS

Dissemination-related factors

- $LHood_{subscr,m}$: likelihood that a person uses communication channel m
 $LHood_{notice,m}$: likelihood that a person notices an incoming warning message via communication channel m
 $LHood_{outage,m,i}$: likelihood that communication channel m is inoperational (e.g., due to adverse effects of the disaster of type i)
 $T_{lag,notice,m}$: average time lag between receiving and noticing a warning communicated via communication channel m (if noticed at all)

Calculation of the economic impact

In a first step of the impact calculation, the likelihood that a warning is received and translated into a protective action is considered. Please note that, in the following, it is assumed for reasons of simplicity and clarity that each individual did not subscribe to more than one communication channel.²

The likelihood $LHood_{action,m,k,i}$ that a warning is translated into a protective action of type k in case of a disaster of type i can then be described as:

$$LHood_{action,m,k,i} = LHood_{subscr,m} \cdot (1 - LHood_{outage,m,i}) \cdot LHood_{notice,m} \cdot LHood_{willing,k,i}(PD, UAI, S_{G,C}, R_{i,k}) \cdot LHood_{able,k} \quad (1.)$$

Equation (1.) includes factors like the reachability as a matter of communication channel subscriptions ($LHood_{subscr,m}$), possible communication loss ($LHood_{outage,m,i}$), attention (i.e., noticing a warning message, $LHood_{notice,m}$), and the willingness ($LHood_{willing,k,i}$) and ability ($LHood_{able,k}$) of the population to take relevant protective actions in case of an early warning.

A sample calculation for equation (1.) may look as follows (referring to a severe thunderstorm warning via SMS in Germany requesting people to secure loose items outside their home):

- $LHood_{subscr,m}$: in Germany, max. 1% of households are subscribed to an SMS based severe weather warning system
 $LHood_{notice,m}$: SMS-based alerts are likely to be read during daytime but are rarely noticed at night when the recipients are asleep – so the likelihood that such an alert is noticed is around 60%.
 $LHood_{outage,m,i}$: in Germany, occasional breakdowns of the mobile phone networks during thunderstorms have been reported. Complete network failures, however, are rare and can be estimated at max. 5%.
 $LHood_{willing,k,i}$: for Germany, questionnaire-based studies show that the willingness to secure loose items outside one's own home is very high (97.6 %) in case of meteorological alerts
 $LHood_{able,k}$: the likelihood that one member of the household is at home during the upcoming thunderstorm and can actually perform the protective action (securing loose items) is set around 50%.

Thus, the likelihood that an SMS based thunderstorm warning induces a household in Germany to secure loose items outside can currently be set at:

$$LHood_{action,m,k,i} = 0,01 * (1-0,05) * 0,6 * 0,976 * 0,5 = 0,0028 \sim 0,3\%$$

² An acceptable simplification, because experiences with the EWS "WIND" (Weather Information on Demand) show that, e.g., less than 15% of recipients in Austria and less than 5% in Eastern Europe subscribed to more than one communication channel.

In equation (1.), the compliance factor $LHood_{willing,k,i}$ is not ubiquitously constant but has to be adjusted regionally as a function of socio-cultural factors $S_{G,c}$, PD and UAV . $LHood_{willing,k,i}$ is, for example, strictly increasing with PD as power distance improves the compliance with instructions from the authorities. It also strictly increases with uncertainty avoidance (UAV) as protective actions are a measure to reduce the uncertainty emerging from upcoming disasters. Additionally, people are only willing to take protective actions if these are relevant ($R_{i,k}$) for the type of disaster under consideration. Thus, the functional relationship between $LHood_{willing,k,i}$ and its determinants can be characterized as:

$$LHood_{willing,k,i} = f_{LH}(S_{G,c}, PD, UAV) \cdot R_{i,k} \quad \text{with} \quad \frac{df_{LH}}{dPD} > 0; \quad \frac{df_{LH}}{dUAV} > 0 \quad (2.)$$

Costs and benefits resulting from protective actions depend to a large extent on the alert accuracy and the disaster frequency. Considering the life cycle time t of a multi-channel multi-hazard early warning system, the benefit (bfit) created by additional protective actions initiated by an EWS can be calculated as:

$$bfit = \sum_i \left[t \cdot P(D_i) \cdot P_{Pred}(D_i) \cdot \sum_k \sum_m LHood_{action,m,k,i} \cdot bfit_{prot,k,i} \cdot N \cdot S_i \cdot inc_{prot,m,k,i} \right] \quad (3.)$$

(3.) summarizes the benefits ($bfit_{prot,k,i}$) of all types of additional ($inc_{prot,m,k,i}$) protective actions k taken by people in the area under consideration ($LHood_{action,m,k,i}$, N) as a result of warnings distributed over different communication channels m . Of course, benefits only materialize with those people who have actually been struck by a disaster (S_i), and in case of disasters that have been correctly predicted ($P(D_i)$, $P(P_{Pred}(D_i))$) over the EWS life cycle time t .

Within (3.), “ $inc_{prot,m,k,i}$ ” describes the increased likelihood that protective actions k will be completed due to an EWS-generated warning. Here, the term “additional likelihood” refers to the fact that some people might have taken the same protective action k even without an EWS (e.g., because they notice an upcoming thunderstorm visually). Key aspect is the time frame available for protective measures. In case of the EWS, this timeframe consists of the lead time of the warning minus the time lag until the recipient actually notices an incoming alert, the difference of which should be longer than the “lead time” of humans in the field in order to create added value.

Thus, the formal definition of “ $inc_{prot,m,k,i}$ ” is:

$$inc_{prot,m,k,i} = f_k(T_{lead,EWS}(D_i) - T_{lag,notice_m}) - f_k(T_{lead,human}(D_i)) \quad (4.)$$

After calculating the overall positive impact bfit of the early warning system (3.) by considering the increased likelihood of protective actions (4.), this impact needs to be set into relation to system-induced costs, which consist of the costs of all protective actions initiated by the system and the operational costs of the system itself.

Costs for protective actions initiated by the system: Overall protection costs $cost_{prot,total}$ include both efforts for additional protective actions in case of correctly issued early warnings and efforts for unnecessary actions in case of false alerts (5.).

$$cost_{prot,total} = \sum_i \left[t \cdot P(D_i) \cdot P_{Pred}(D_i) \cdot \sum_k \sum_m LHood_{action,m,k,i} \cdot cost_{prot,k} \cdot N \cdot inc_{prot,m,k,i} \right] + \sum_i \left[t \cdot P_{False}(D_i) \cdot \sum_k \sum_m LHood_{action,m,k,i} \cdot cost_{prot,k} \cdot N \right]$$

Costs of the EWS: When assessing the overall costs for an early warning system ($\text{cost}_{\text{sys},\text{total}}$), the following cost drivers need to be taken into consideration:

One-time investments:

- investments for the early warning system (I)
- initial training costs of the personnel (Tr)

Variable costs:

- wages of the system operators per time unit (W)
- maintenance costs per time unit (M)
- costs for operating / expendable materials per time unit (Mat_{op})
- energy costs per time unit (E)
- communication costs (C_m) per recipient and warning over communication channel m

Thus, the life cycle costs of the early warning system can be summarized as:

$$\text{cost}_{\text{sys},\text{total}} = I + Tr + t \cdot \left(W + M + \text{Mat}_{\text{op}} + E + (P(D_i) \cdot P_{\text{Pred}}(D_i) + P_{\text{False}}(D_i)) \cdot N \cdot \sum_m L_{\text{Hood}_{\text{subscrm}}} \cdot C_m \right) \quad (6.)$$

In order to complete the economic assessment of the EWS, system benefits need to be set into relation to system costs. The tangible economic value V of an EWS can then be calculated as:

$$V = \text{bfit} - \text{cost}_{\text{prot},\text{total}} - \text{cost}_{\text{sys},\text{total}} \quad (7.)$$

Please note that the value calculated in accordance with (7.) only assesses the tangible economic value of the system. Intangible factors such as an improved quality of life, a general feeling of security among the population, or ethical factors (particularly important in case of potentially fatal disasters) need to be taken into account separately using multi-dimensional assessment methods in light of the precise goals of the EWS investment under consideration.

CONCLUSION AND OUTLOOK

In this paper, we presented a model for the evaluation of tangible economic costs and benefits of early warning systems. By doing so, we outlined a framework that can be used to assess and justify EWS investment decisions. As a result, decision-making processes can be improved, which may lead to more continuous and systematic spending on EWS in the years to come. Nevertheless, a lot of work still needs to be done. Although some of the input variables discussed in the model are already well-researched (such as communication range or lead times), some other factors are in urgent need of more in-depth analysis. This is, in particular, true for the functional relationship between socio-cultural variables and EWS effectiveness, which, at the moment, still have to be intuitively estimated. However, ongoing research projects such as “*BeSeCu - Human behaviour in crisis situations: A cross-cultural investigation in order to tailor security-related communication*” or “*Opti-Alert: enhancing the efficiency of alerting systems through personalized, culturally-sensitive multi-channel communication*” are trying to close this knowledge gap. If successful, their results will allow for even more precise and context-specific EWS evaluations, lead to well-informed investment decisions and thus create an added value for the public.

ACKNOWLEDGEMENTS

Some parts of this work were funded by the German Federal Ministry of Education and Research (BMBF) through the SAFE project grant.

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