Quantifying the Effect of Early Warning Systems on Natural Hazard Risk

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ABSTRACT: Risk to persons caused by gravitationally driven site-specific natural hazards along traffic routes is frequently reduced with Early Warning Systems (EWS). To identify an optimal risk reduction strategy, decision-makers should be able to quantify the effectiveness and costs achieved with EWS and compare both to alternative mitigation measures. A recognized framework approach for quantifying the effectiveness of EWS is currently lacking. We provide such a framework approach, which includes six steps that enable a structured quantification of the effectiveness, from the reliability of the EWS. To this end, site specific EWS are distinguished in two classes and the reliability analyses are conducted according to specific needs with Bayesian Networks (BN).

1. INTRODUCTION

Damages to infrastructures and fatalities caused by natural disasters are on the rise (SwissRe, 2014). It is expected that climate change, economic growth and social shifts will reinforce this development in the future (Lall & Deichmann, 2011). The damages caused by hurricanes, tornados and tsunamis will continue to increase as long as populations and assets in coastal regions grow. In mountain regions, climate change will in many locations lead to more intense precipitation, melting permafrost and deglaciation, fostering gravitationally driven hazard processes such as flash floods, debris flows, snow avalanches and rockfall.

Associated losses due to business interruptions and shortages of supply can be large even for small events. Recently, a 3000m^3 rockfall at Gurtnellen caused one casualty, the closure of a major Swiss railway line for one month and losses between 10-20 Millions CHF (Tagesanzeiger, 2012).

To protect persons, buildings and transport routes from natural hazards, structural and design related risk mitigation measures are frequently applied and building codes have been established in civil engineering. For the management of natural hazards, framework approaches have been established to support decision-makers in identifying optimal mitigation measures (Dai et al., 2002, Fell et al., 2005, Bründl et al., 2009, Safeland, 2011). These frameworks focus on the evaluation of the risk reduction achieved with structural mitigation measures such as dams, galleries and nets installed to protect against floods and mass movements.

During the last decade, Early Warning Systems (EWS) have undergone a rapid technical development and are applied as cost-effective measure to reduce natural hazard risks (ISDR, 2007). They provide timely information and allow to take preventive measures that avoid damage (UNISDR, 2007). Site-specify EWS are installed to reduce the exposure probability of persons on endangered transport route sections or in infrastructure facilities. However, their effect on risk reduction is rarely quantified and an acknowledged framework approach is lacking.

In the present contribution, we provide a framework approach and associated methods for quantifying the effectiveness of site-specific EWS. First, a generic classification for site-specific EWS is presented, enabling a structured identification of factors influencing the effectiveness. Second, a framework approach for quantifying the effectiveness based on reliability analysis of site-specific EWS is presented. Methods used in the framework approach were tested on active systems of each class in two case studies.

2. CLASSIFICATION

Site-specific EWS for natural hazards can be classified into warning and alarm systems (Sättele et al., 2012). The assignment of an EWS to one of these classes depends on the underlying monitoring strategy, which determines the available lead time and the system design.

2.1. Monitoring strategies

In general, EWS can monitor either precursors or parameters that can be measured after the start of the natural hazard process (Fig. 1). Precursors can be events that trigger the hazard, such as intense rainfall or other associated changes in the disposition.

If the EWS monitors process parameters of already ongoing hazard events, the information content of the measured data is high, but the associated lead time is short. EWS that detect already ongoing events are classified as *alarm systems* and are mainly installed to detect spontaneous events such as flash floods, debris flows, snow avalanches, spontaneously triggered slope failures, earthquakes and tsunamis.

Other EWS monitor precursors before a hazard event starts. Here, the information content of the monitored data is lower, but the lead time is extended. Systems installed to predict hazard events before they start are classified as *warning systems* and are operated for processes that evolve slowly such as static river floods, slope failures such as mid- and high-magnitude rockfalls/-slides and deep-seated landslides.

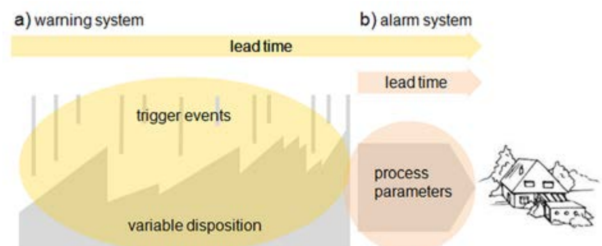

Figure 1: Monitoring strategies: a) Warning systems monitor precursors and provide longer lead times. b) Alarm systems monitor processes parameters and provide short lead times.

2.2. System design

The design of an EWS depends on the class and can be described with three main units: monitoring, interpretation and dissemination unit (Sättele et al., 2012). Fig. 2 summarizes essential components of alarm and warning systems grouped into these units. In practice, EWS include additional components for power supply, data storage, analyses and control.

To deal with short lead times, *alarm systems* are fully automated. The sensors monitor process parameters close to the release area. The alarm decision is based on predefined thresholds and associated intervention measures are taken automatically, e.g. in form of optical signals or sirens.

The extended lead times provided by *warning systems* allow a partly-automated data interpretation in two levels. Sensors monitor precursors to detect relevant changes in advance. At the first level, thresholds are used to generate automated and timely information. At the second level, experts and decision-makers apply models to predict the event magnitude and timing. The intervention of warning systems is mainly based on organized evacuations and/or closures of e.g. roads and railway sections.

A generic framework approach for quantifying the effectiveness of site-specific EWS has to deal with varying characteristics and needs associated with each system class. The effectiveness of an alarm system depends mainly on the threshold and the availability of automated technical procedures. Warning systems are subject to additional uncertainties caused by models and human decision-making.

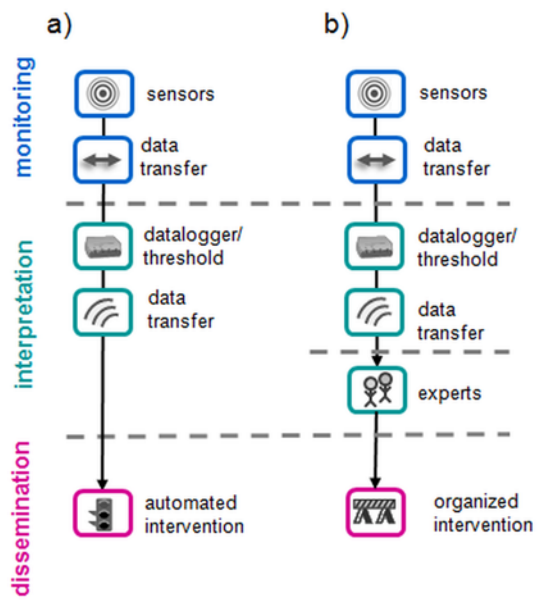

Figure 2: Essential system components. a) Alarm systems are automated and incorporate one decision level; b) Warning systems are partly automated and include two decision levels.

3. FRAMEWORK

To compare EWS in cost-benefit analyses with alternative measures for risk reduction, their effects on risk and system life cycle costs have to be compared (Penning-Rowsell E., 2005, SafeLand, 2012, Špačková & Straub, in print). If the costs associated with the hazard and its consequences are not explicitly measured in monetary terms, the effectiveness of EWS can be used as an evaluation criterion.

In our framework approach, the effectiveness is quantified as the reduced exposure probability of persons in a hazard scenario and is determined based on reliability analyses (Fig. 3). The effects of EWS on the risks to assets are typically small for gravitational hazards, hence they are not considered.

Within the present framework approach, complex human decision-making and the accuracy of models are not addressed. Therefore, automated alarm systems can be evaluated entirely and warning systems up to the point when experts receive automated information by the system.

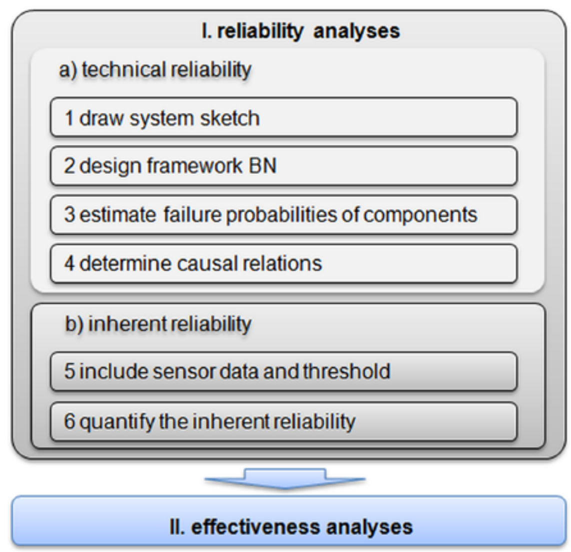

Figure 3: The reliability is quantified in six steps.

3.1. Reliability analysis

An EWS is reliable, if it detects dangerous events timely and leads to measures that prevent damage. In reliability analyses, both the technical and the inherent reliability should be addressed. The technical reliability of an EWS depends on failure probabilities of system components and their configuration within the system. The inherent reliability is the general ability of the EWS to distinguish between hazard and noise, in analogy to the signal-to-noise ratio of classical signal detection theory (Swets, 1996). It is common practice to quantify the reliability of EWS through the Probability of Detection (POD) of a hazard event and the Probability of False Alarms (PFA) (Sättele et al., under review).

Our framework approach includes six steps to quantify the reliability (Fig. 3). The first four steps are associated with the quantification of the technical reliability. In the last two steps sensor data and thresholds are integrated to assess the inherent reliability. Within the framework approach the reliability is probabilistically modeled with Bayesian Networks (BN) that may be implemented using free software programs such as Genie [DSL, 2014].

3.1.1. Draw system sketch

A system sketch is an essential basis to understand the system design and the dependencies among the components. It can be constructed according to the three main units of an EWS: monitoring, data interpretation, information dissemination.

Fig. 4 illustrates an exemplary system sketch describing the essential components of an alarm system for snow avalanches.

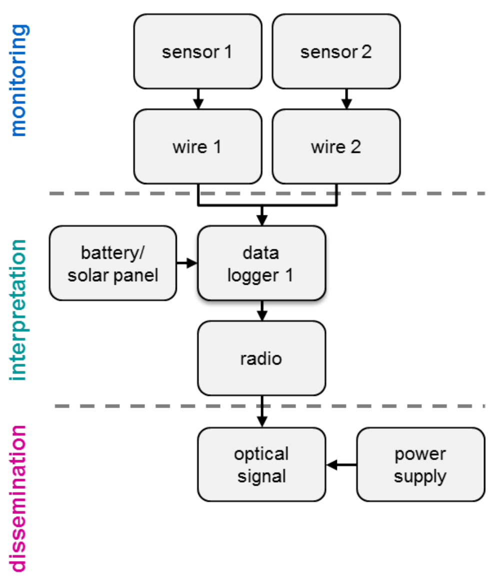

Figure 4: System sketch of an alarm system for avalanche detection.

The alarm system for snow avalanches includes two redundant sensors, here trigger lines. The data logger controls the sensors, issues an alarm when at least one trigger line is pulled-out and is powered by a battery charged from a solar panel. Alarm information is transmitted via radio connection and used to activate an optical signal supplied by the power network.

Similar system sketches can be constructed for warning systems. Typically, they end in the interpretation unit, where the warning information is transmitted to decision-makers.

3.1.2. Design Framework BN

The framework BN is constructed according to the system sketch and consists of arcs and three different node types, shown as black, white and grey in Fig. 5.

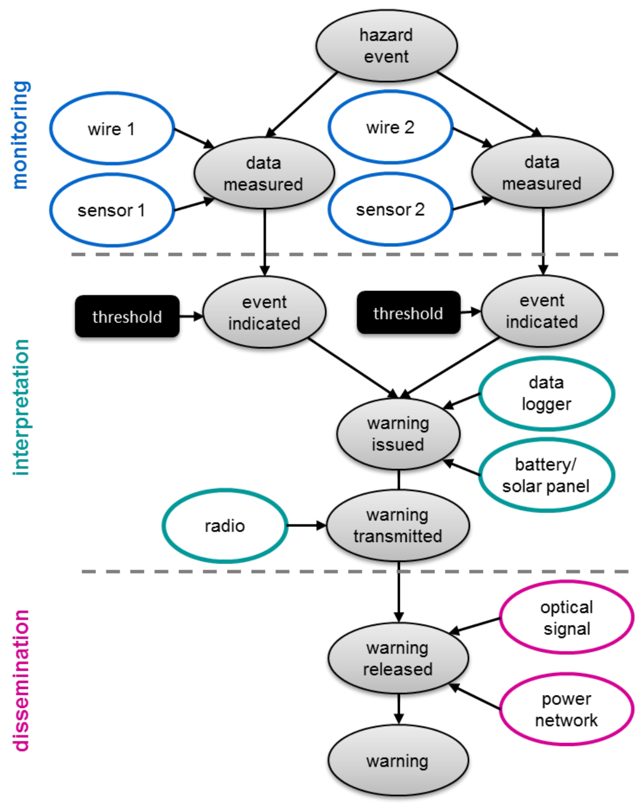

Figure 5: The BN of an alarm system for avalanche detection consists of three node types.

Grey nodes describe the causal chain from the hazard event to the warning. The node "warning" is used to model the reliability of the EWS, as a measure of POD and PFA (details see Chapter 3.1.6). Dependencies between the nodes are described by the arcs and in the Conditional Probability Tables (CPTs) of grey nodes (details see Chapter 3.1.4). Redundant system parts, which are duplications in the form of identical or different system components fulfilling the same function, require redundant nodes in the causal chain. *Black decision nodes* are added in the causal chain to incorporate the inherent reliability into the BN (details see Chapter 3.1.5). The technical failure probabilities of individual components are specified in the CPTs of *white nodes* (details see Chapter 3.1.3).

3.1.3. Incorporate technical failure probability

The CPTs of *white nodes* describe binary random variables, i.e. the component performance that can be either "functioning" or "failed" with associated probabilities (Table 1).

Table 1: CPT of white nodes include probabilities to specify component performance (functioning/ fail).

sensor	functioning	0.9995
	failure	0.0005

The probability of failure for individual components at time *t* can be calculated following (Straub, 2012):

$$Pr(F(t)) = \lambda \times E[T] \qquad (1)$$

where λ is the failure rate of the system component and $E[T]$ is the expected time it takes to detect and repair a failure. Eq. (1) is an approximation that is valid for small $\Pr(F(t))$, as they are commonly found in EWS. The failure rate includes both the internal failure rate and the rate of failures caused by external influences such as lightning, animals, extreme temperatures and humidity. Usually, the internal failure rate can be adopted from specified mean time to failure (MTTF) and mean time between failure (MTBF) values. External failure rates are derived from repair records or estimated by experts.

3.1.4. Determine causal relation of components

Dependencies among individual system components are specified with arcs and in the CPTs of grey BN nodes. They are typically modeled deterministically as AND or OR relations.

OR relations are used to model redundancies. E.g. the avalanche alarm system will issue a warning when either trigger line 1 or 2 are pulled out (Table 2a).

AND relations are used to specify serial connections in which the failure of a single component leads to a failure in the subsequent child node and to an overall system failure in non-redundant system parts. E.g. a warning can only be released by the avalanche alarm system if the power supply and the optical signal in the non-redundant dissemination unit are both functioning (Table 2b).

Table 2: System configurations of EWS can include a) parallel (OR) and b) serial (AND) connections.

a)

event indicated		yes		no	
event indicated		yes	no	yes	no
warning issued	yes	1	1	1	0
	no	0	0	0	1

b)

optical signal		yes		no	
power network		yes	no	yes	no
warning released	yes	1	0	0	0
	no	0	1	1	1

3.1.5. Incorporate sensor data and threshold

Black decision nodes, named "threshold" in Fig. 5, are added in the BN to model the ability of each sensor to distinguish between hazard and noise. To this end, black decision nodes are added to the "event indicated" nodes.

In the CPT of nodes "data measured" one specifies the probabilities of sensor signal exceeding the alarm threshold, conditional on whether or not an event occurs during that day

(Table 3). These probabilities are first described as Probability Density Functions (PDFs). To obtain PDFs conditional on an event occurring, probability distributions are fitted to data measured on days with events. Similar fits are generated for sensor data measured on days without events. To include the probabilities in the CPT, they are discretized according to the threshold.

The example avalanche system is equipped with trigger lines. Their outcome space is binary, as they can either be pulled out or not. In this case, the probability of a pull-out conditional on the occurrence of an event is specified in the CPT of the node "data measured" (Fig. 5).

Table 3: CPT of node "data measured" includes probabilities for a pull-out conditional on the occurrence of an event.

hazard event		
data measured	not pulled-out	0.9995
	pulled-out	0.0005

In many instances measured sensor data are not available, e.g. during the design phase of an EWS. In this case, data from similar sites and/or expert estimates can be used to determine the probabilities conditional on the thresholds.

3.1.6. Quantify reliability with BN

In the last step, the BN is operated to probabilistically model the reliability. Values for POD and PFA can be obtained by changing the status of the top node and running the BN. To compute the POD in the node "warning", the top node "hazard event" can be set to the state "true"; likewise, the PFA is obtained by setting the top node to the state " false".

The same BN allows one to model the technical or inherent reliability separately. The technical reliability can be modeled if the status of all nodes "event indicated" is set to "yes"; the inherent reliability is modeled if the status of all white nodes describing "technical components" is set to the state "functioning".

3.2. Effectiveness of EWS

The risk reduction achieved with an EWS is referred to as the effectiveness E_w. The effectiveness can be calculated in terms of the relative reduction of the overall risk. With R being the overall risk without the warning system and $R^{(S)}$ the risk with the warning system installed, the effectiveness is defined as (Sättele et al., under review):

$$E_w = 1 - \frac{R^{(S)}}{R} \tag{2}$$

For the case where EWS only reduce the presence probability of exposed persons, the effectiveness of Eq. (2) can be calculated as a function of POD and Probability of Compliance (POC) alone, following Eq. 3 (Sättele et al., under review):

$$E_w = POD \times POC \tag{3}$$

The POC, i.e. the degree to which alarms are followed in practice, is strongly dependent on the PFA. A high number of false alarms reduces the POC to an issued warning, due to a loss of trust that is known as the cry-wolf syndrome (Breznitz, 1989, Dejoy et al., 2006). In Sättele et al. (under review), we calculate the POC as a result of a basic compliance probability and a compliance reduction factor due to false alarms. Others address the available lead time, when quantifying the effectiveness (Paté-Cornell, 1986). The lead time must be long enough that those willing to comply are able to comply.

4. CONCLUSION

The presented framework approach allows the quantification of the effectiveness of automated site-specific EWS. This framework can support decision-makers in evaluating and optimizing EWS. BN can easily be used to assess the effectiveness of alternative designs. Moreover, decision-makers can compare EWS with alternative measures to identify cost-effective strategies for the protection of persons and mobile objects.

The present framework approach is not able to cover all factors that influence the reliability of warning systems. The prediction accuracy and human decision-making (second decision level) are not considered here, although they do have a significant influence on the effectiveness and cost associated with EWS. Wrong predictions of the event timing can e.g. create unnecessary long evacuation periods. Nevertheless, the presented framework approach allows quantifying the ability of the warning system to inform experts about relevant changes and contributes significantly to decision-making critical for safety.

5. ACKNOWLEDGEMENT

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