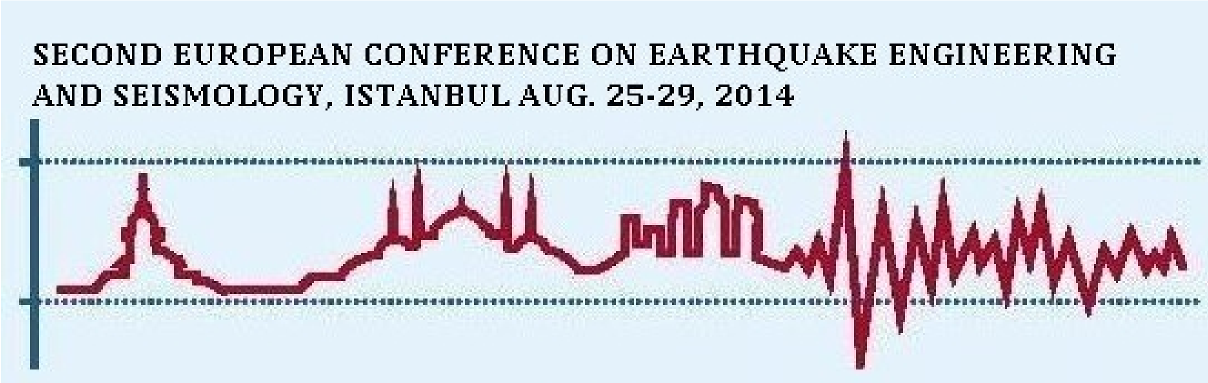

THE POTENTIAL OF BAYESIAN NETWORKS FOR NATURAL HAZARD VULNERABILITY STUDIES

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Natural hazard vulnerability studies are characterized by several uncertainties that arise form our lack of knowledge, called *epistemic uncertainty* (limited process understanding, sparse and/or error-prone data, etc.) or the intrinsic randomness of the underlying process, called *aleatoric uncertainty*. The complex nature of social and environmental systems limits the reducibility of the associated uncertainty. Thus our ability to predict future damage caused by natural disasters will never be complete, even after a great deal of research (Berkes 2007). In this manner it is crucial to capture and quantify uncertainties in vulnerability studies for reliable natural hazard assessments. Moreover we face the challenge to express and communicate uncertainties in an intuitive way. Decision-makers, who often find it difficult to deal with uncertainties, might otherwise return to familiar (mostly deterministic) proceedings.

We present the probabilistic framework of Bayesian networks as a flexible tool to not only quantify uncertainties in vulnerability studies, but also to learn about the underlying processes. The great potential of Bayesian networks for natural hazard assessments is already pointed out by Straub (2005), underlining their intuitive format: The (in-)dependences between the considered variables are translated into a graph structure that provides direct insights into the relationships and workings of the system. Further, Bayesian Networks capture the joint probability of all variables and thus implicitly contain each conditional distribution of interest. This allows for a reasoning into all directions, e.g. we could ask for the effect of certain precautionary measures on building damages.

To illustrate the working of Bayesian networks textbooks often refer to the burglary alarm scenario (Pearl, 1998), where the alarm of your home is not only sensitive to burglary, but also to earthquakes and an earthquake has a chance to be reported in the news. Figure 1 shows the Bayesian network that captures the (in-)dependence relations of the considered variables. Now, imagine you get a call from your neighbor notifying you that the alarm went off. Supposing the alarm was triggered by burglary you drive home. On your way home the radio reports a nearby earthquake. Even though burglaries and earthquakes may be assumed to occur independently, the radio announcement changes your belief in the burglary, as the earthquake "explains away" the alarm. Bayesian network offer a mathematically consistent framework to conduct and specify reasonings of such kind.

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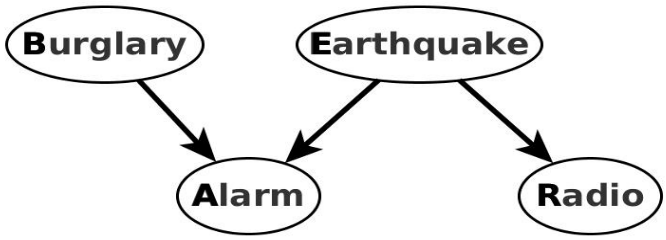

Figure 1. The figure shows the Bayesian network for the burglary example. The graph structure illustrates the dependence relations of the involved variables: The alarm can be triggered by a burglary or earthquake. An earthquake might be reported in the radio newscast (Vogel et al. 2013).

The graph structure of a network can either be defined based on expert knowledge or learned based on observational data (or a combination of both is applied). A graph learned from data may reveal unknown dependence relations or identify the most relevant dependences and thus provide information about the underlying process and identify driving forces.

In recent studies we applied the Bayesian network learning approach amongst others in a flood damage assessment (Vogel et al. 2013). Along the way we tackled practical problems that typically arise when Bayesian networks are learned from real-world data. The major focus is placed on the handling of continuous variables and incomplete observations. We present the results of the flood damage assessment to illustrate the benefits of Bayesian networks for vulnerability studies. As our proceeding is completely data driven it can easily be transferred to applications in other natural hazard domains, i.e. earthquakes.

World-wide statistics indicate an increase in the damage caused by flood events over the last decades. Apparently this development is due to economic grows and changes in society, and it is likely to continue, since flood prone areas are still evolving (Barredo 2009). Today flood damages are responsible for approximately one-third of the economic losses caused by natural disasters in Europe (Moel and Aerts 2011). A future increase in the occurrence rate and magnitudes of flood events might be caused by climate change. Recent extreme flood events in Central Europe, i.e. in 2002 and 2013, have raised public concerns and awareness, but we are far from understanding the damage driving forces and the effects of precautionary measures in detail.

For an efficient flood management it is crucial to not only consider the hydrological hazard, but also the flood vulnerability. The potential damage depends on a variety of factors not limited to flooding characteristics, but including exposure and susceptibility indicators as well (Messner and Meyer 2006). Still, commonly used flood damage models are simple and determine the expected damage based only on the type of the element of risk and the water depth. More recently developed models take additional factors as contamination, building quality and precautionary measures into account (Thieken et al. 2008). We make use of same data set as used by Thieken et al. The data were collected after the 2002 and 2005/2006 flood events in the Elbe and Danube catchments and contain variables that describe not only the flooding situation, but also building characteristics, precautionary measures, warning situations and socio-economic factors.

Learning the network structure from the data the algorithm requires no prior domain knowledge, rather the learned graph structure reveals information about the underlying process. The learned network is shown in Figure 2 and displays direct dependence relations between the building damage and a variety of factors from different domains. The single and joint impact of the predictors on the building damage can be inferred from the joint distribution, that is captured by the Bayesian network. Allowing for inference Bayesian networks enable detailed examinations of specific scenarios and may thus contribute to an improved communication between scientist and public authorities and further provide a valuable decision support.

Comparisons of the learned network with a modern classification approach (Thieken et al. 2008) show a similar performance in terms of building damage prediction with the advantage of Bayesian networks to capture the associated uncertainties. Moreover, allow Bayesian networks for a prediction based on incomplete observations and thus enable predictions at an early stage of an event. Via inference missing values are estimated based on the observations of neighboring variables. The prediction can be updated as soon as new information arises.

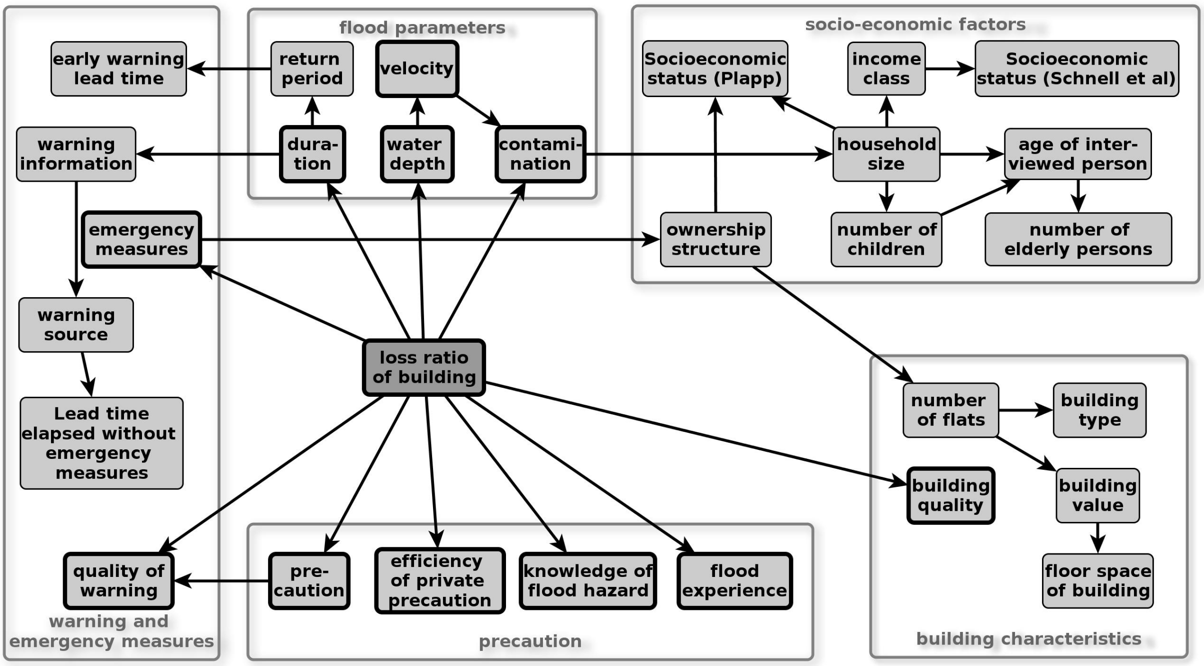

Figure 2: Bayesian network learned for a flood damage assessment based on the data collected after the 2002 and 2005/2006 flood events in the Elbe and Danube catchments (Vogel et al. 2013).

Thus, detecting (in-)dependences, capturing uncertainties, allowing for a handling of incomplete observations and for investigations of specific situations we believe Bayesian networks to be a valuable tool for vulnerability studies in natural hazard assessments.

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