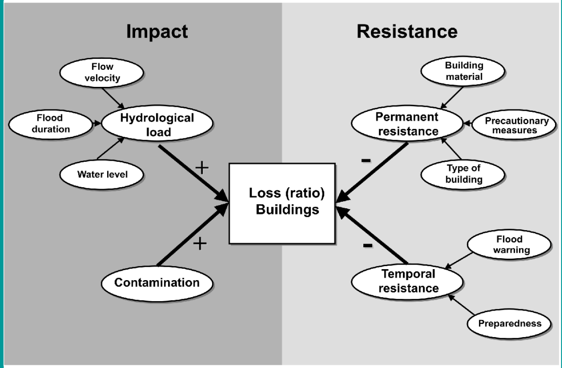
Capturing changes in flood risk with Bayesian approaches for flood damage assessment

K. Vogel, K. Schröter, H. Kreibich, A. Thieken, M. Müller, T. Sieg, J. Laudan, S. Kienzler, L. Weise, B. Merz, F. Scherbaum

Motivation

Damages caused to buildings **by flood events** depend on a **variety of factors**:



Thieken, A. H., Müller, M., Kreibich, H., & Merz, B. (2005) *Flood damage and influencing factors: New insights from the August 2002 flood in Germany.* Water Resources Research, 41.

More over, many of those factors are under change over space and time. Yet, existing flood damage models are comparatively simple.

A **complex dataset**, that comprises hazard, exposure and vulnerability related variables of **recent flood events in Germany**, was collected over the last 15 years. It offers a unique data mining opportunity to **improve our understanding of the damaging processes**.

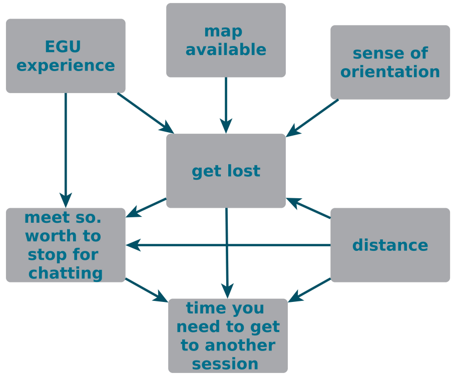
Kienzler, et al. (2015) *NHESS 15, 505-526*

Bayesian networks: Properties & Advantages

Vogel, K., C. Riggelsen, O. Korup, & F. Scherbaum. (2014) *Bayesian network learning for natural hazard analyses* Natural Hazards and Earth System Science, 14(9), 2605–2626

Properties

- **multivariate** models
- **probabilistic** approach: considers involved parameters as random variables
- **graphical representation**: variables are represented as nodes in a network; (missing) edges between the nodes represent (in)dependencies
- structure and parameters can be defined by experts or **learned from data**



Example for a Bayesian network, that considers the time you need to get to another EGU session.

Advantages

- **capture uncertainty**
  → provide probability distribution instead of point estimate
- reveal insight into underlying systems
  → **improve understanding**
- inference: consideration of different scenarios and courses of action possible
  → valuable **decision support**
- allow for handling of incomplete observations
  → **predictions** can be made **based on incomplete observations**

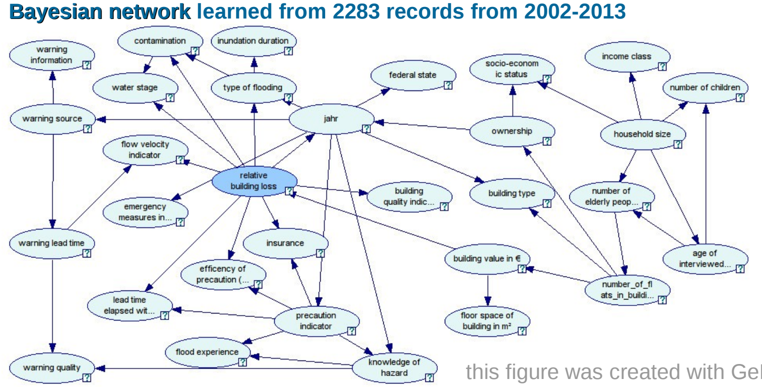
Application: private sector

Number of records with observed relative building loss:

2002	2005	2006	2010	2011	2013
947	127	62	242	103	803

Challenges for Bayesian network learning:
- handling of continuous data
- incomplete observations

Bayesian network learned from 2283 records from 2002-2013



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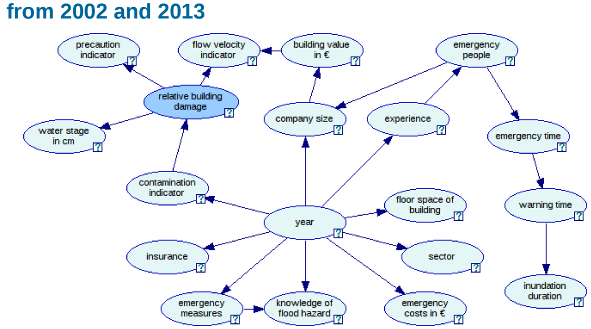
Application: company sector

Number of records with observed relative building loss:

2002	2013
113	221

Challenges for Bayesian network learning:
- handling of continuous data
- incomplete observations
- sparse and heterogeneous dataset

Bayesian network learned from 334 records from 2002 and 2013



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http://www.natriskchange.de/

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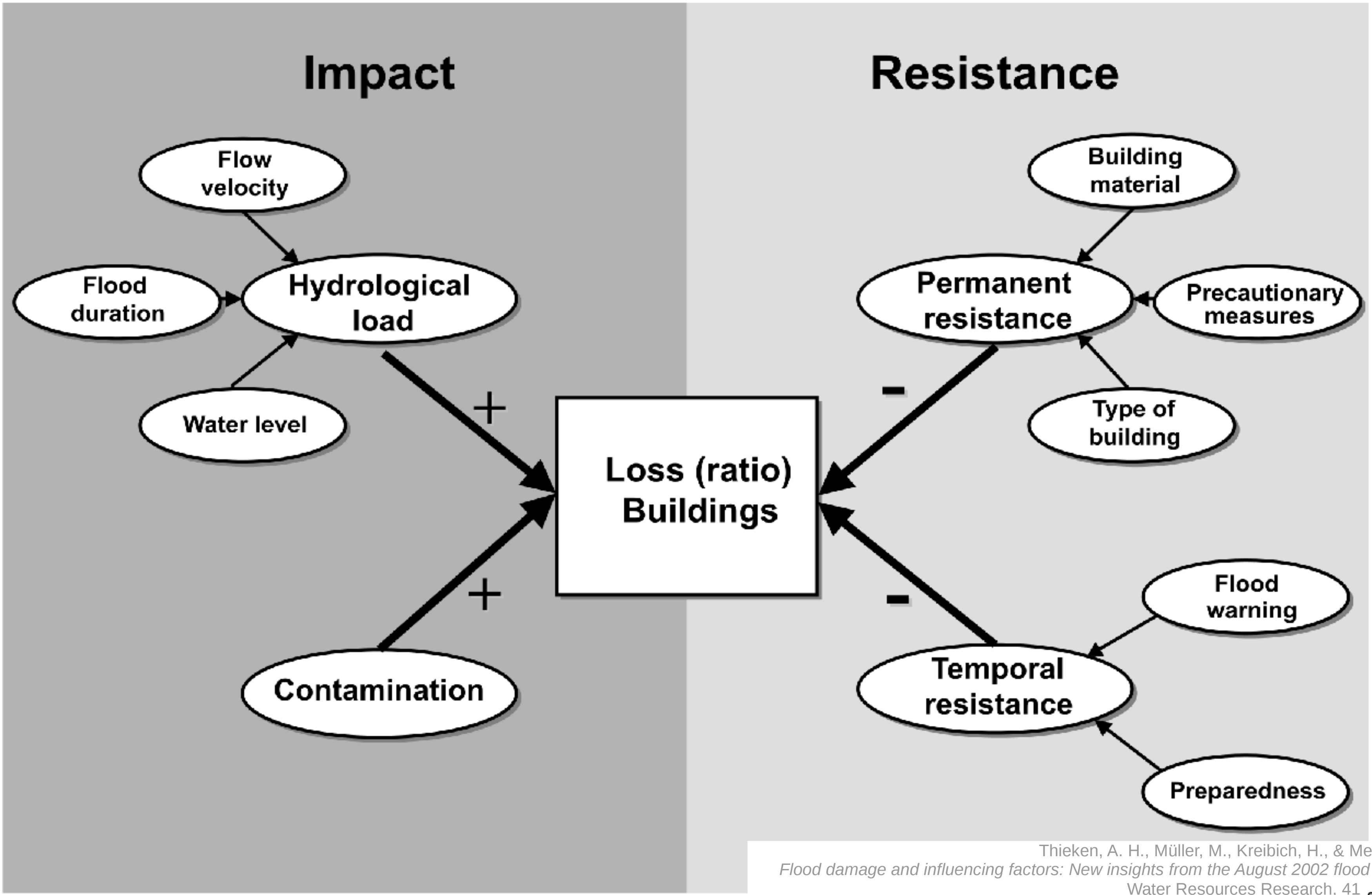
A variety of factors affects the damage that is caused by flood events



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Water Resources Research, 41

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Recorded variables for the private sector

Year (2002, 2005, 2006, 2010, 2011, 2013)
Federal state

flood parameters

Water stage (C: 248 cm below ground to 670 cm above ground)
Inundation duration (C: 1 to 1440 h)
Flow velocity indicator (O: 0=still to 6=high velocity)
Contamination indicator (O: 0=no contamination to 2=heavy contamination)
Type of flooding (N: 1=crevasse, 2=river flood, 3=flash flood, 4=basic stage flood)

warning and emergency measures

Early warning lead time (C: 0 to 336 h)
Quality of warning (O: 1=receiver of warning knew exactly what to do to 6=receiver of warning had no idea what to do)
Indicator of flood warning source (N: 0=no warning to 4=official warning through authorities)
Indicator of flood warning information (O: 0=no helpful information to 16=many helpful information)
Lead time period elapsed without using it for emergency measures (C: 0 to 335 h)
Emergency measures indicator (O: 1=no measures undertaken to 17=many measures undertaken)

precaution

Precautionary measures indicator (O: 0=no measures undertaken to 2=many, efficient measures undertaken)
Perception of efficiency of private precaution (O: 1=very efficient to 6=not efficient at all)
Flood experience indicator (O: 0=no experience to 9=recent flood experience)
Knowledge of flood hazard (N: yes / no)
Building insurance (N: yes / no)

building characteristics

Building type (N: 1=multifamily house, 2= semidetached house, 3=one-family house)
Number of flats in building (C: 1 to 45 flats)
Floor space of building (C: 45 to 18000 m²)
Building quality (O: 1=very good to 6=very bad)
Building value (C: 92244 € to 3718677 €)

socio-economic factors

Age of the interviewed person (C: 16 to 95 yrs)
Household size, i.e. number of persons (C: 1 to 20 people)
Number of children (< 14 years) in household (C: 0 to 6)
Number of elderly persons (> 65 years) in household (C: 0 to 4)
Ownership structure (N: 1=tenant; 2=owner of flat; 3=owner of building)
Monthly net income in classes (O: 11=below 500 to 16=3000 and more)
Socioeconomic status according to Plapp (2003) (O: 1=lower class to 4=upper class)

damage

loss ratio of residential building (C: 0 = no damage to 1 = total damage)

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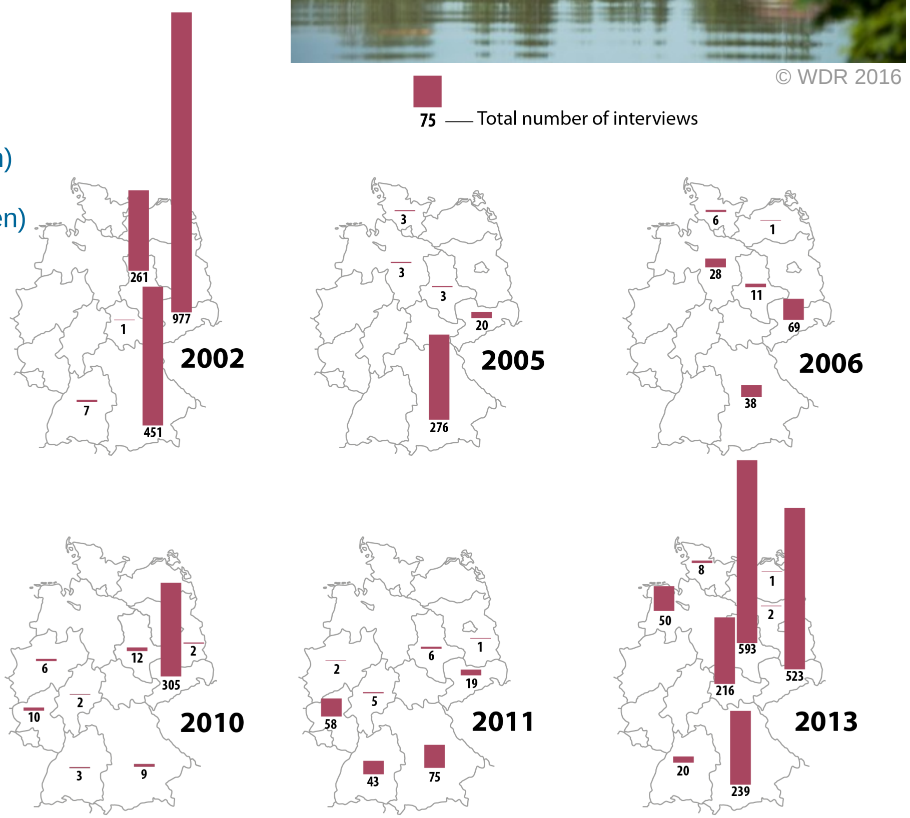

Kienzler S., I. Pech, H. Kreibich, M. Müller, A.H. Thieken (2015): *After the extreme flood in 2002: changes in preparedness, response and recovery of flood-affected residents in Germany between 2005 and 2011.* NHESS 15: p. 505-526
DKKV (Hrsg., 2015): *Das Hochwasser im Juni 2013: Bewährungsprobe für das Hochwasserrisikomanagement in Deutschland.* DKKV-Schriftenreihe Nr. 53, Bonn, ISBN 978-3-933181-62-6, p. 207.

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Recorded variables for the company sector

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Year (2002, 2013)

flood parameters
Water stage (C: 0 - 1000 cm)
Inundation duration (C: 1 to 1440 h)
Flow velocity indicator
(O: 0=still to 6=high velocity)
Contamination indicator
(O: 0=no contamination to
2=heavy contamination)

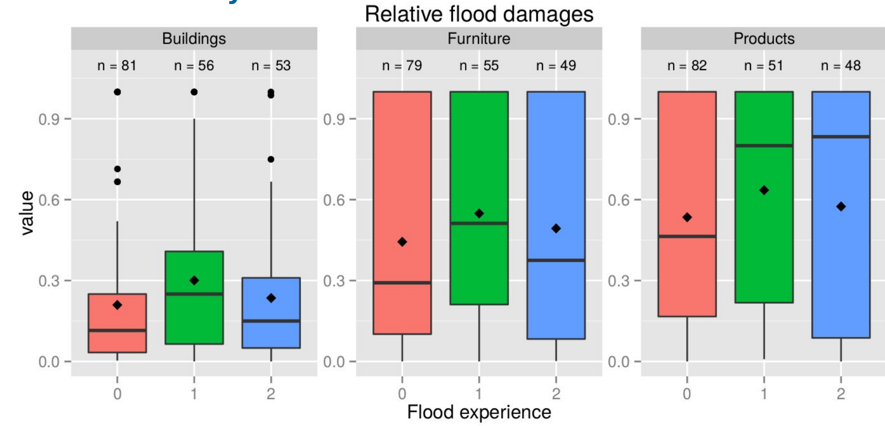
warning and emergency measures
Early warning lead time (C: 0 to 336 h)
Emergency measures (N: yes / no)
Emergency people (O: number of people needed for measures)
Emergency time (O: time needed for measures: 0 to 336 h)
Emergency costs (O: 0 to 1,000,000 €)

precaution
Precautionary measures indicator (O: 0=no measures to 48=many, efficient measures)
Flood experience (O: 0 to 5 flood events experienced before)
Knowledge of flood hazard (N: yes / no)
Insurance (N: yes / no)

company characteristics
Sector (N: 1 = agriculture, forestry, fishing; 2 = manufactor;
3 = trade, hotel & restaurant, traffic; 4 = finance, leasing, corporate services;
5 = public & private services)
Size (O: number of employees 1 - 500)
Floor space of building (C: 60 to 100,000 m²)
Building value (C: 10,000 € to 135,000,000 €)

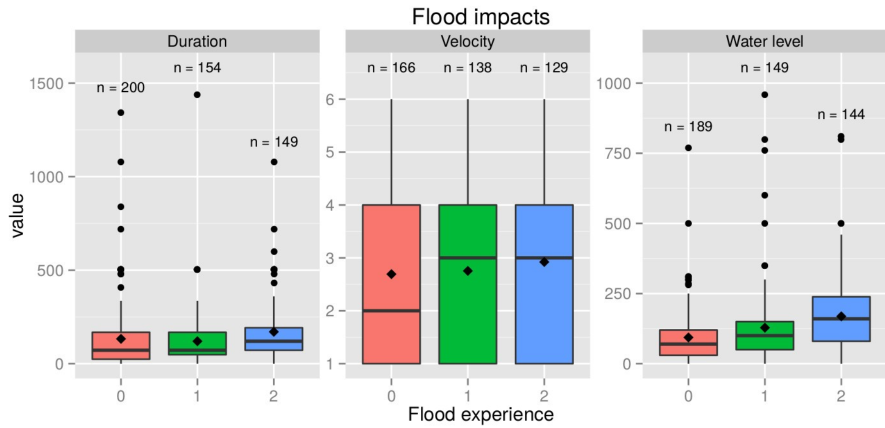
damage
Loss ratio of building (C: 0 = no damage to 1 = total damage)
Damage to furniture
Damage to products
Duration of business interruption
Duration until business is back to normal

Univariate analysis



The box plot shows the relative damage for the 2013 flood event for 3 groups with different experience (0: no experience; 1: experienced 1 flood event; experienced at least 2 flood events)

Apparently the group with 1 previously experienced flood event suffers the most damage. Why?



impacts for the different group. Group 1 and 2 experience stronger impacts than group 0 and consequently might experience more damage. Yet, group 2 might be better prepared and less vulnerable.

Multivariate analyses are required for a better understanding of the damage driving processes.

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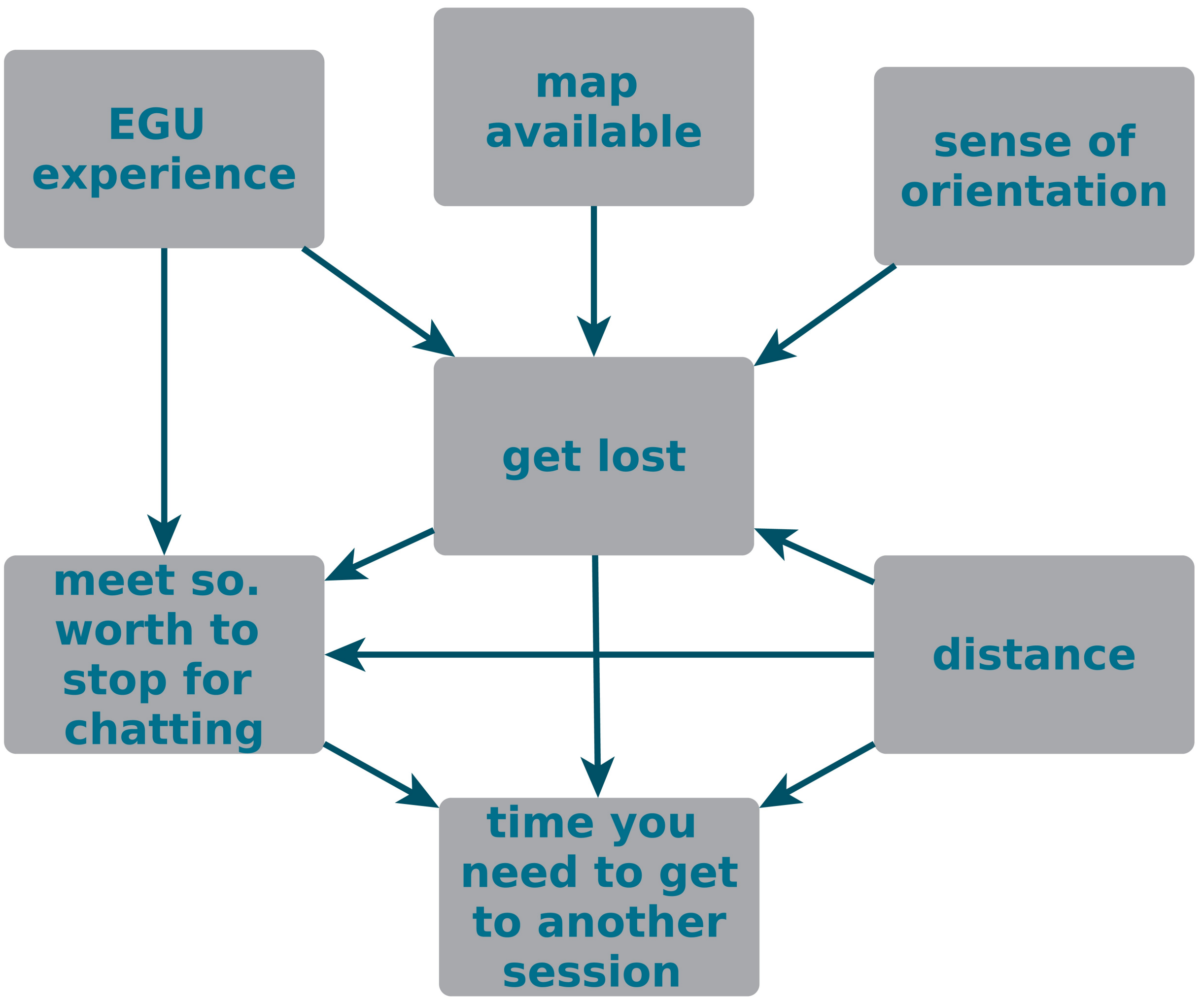
Bayesian network example



Example for a Bayesian network, that considers the time you need to get to another EGU session.

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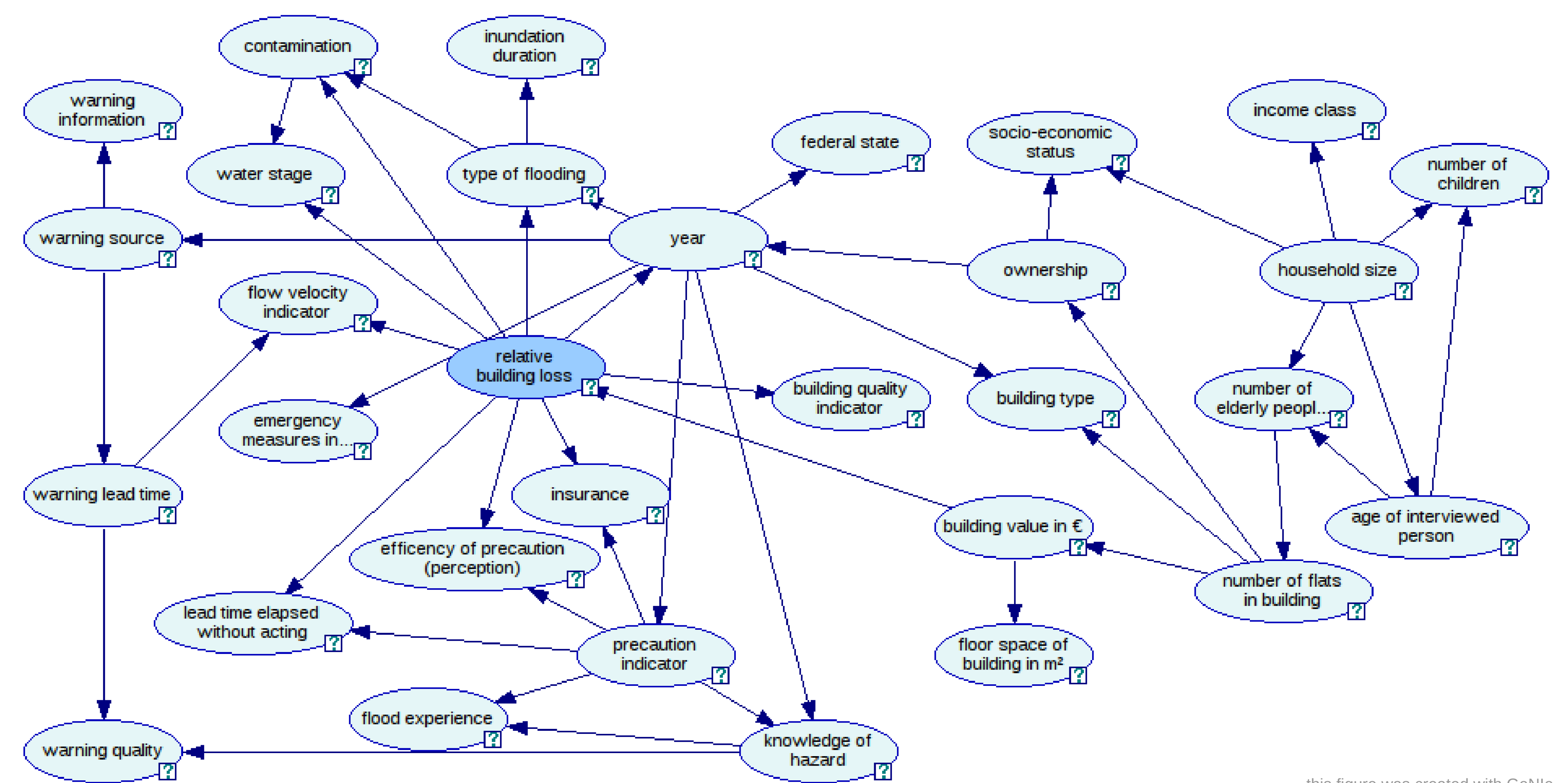
Bayesian network for damages caused to residential buildings



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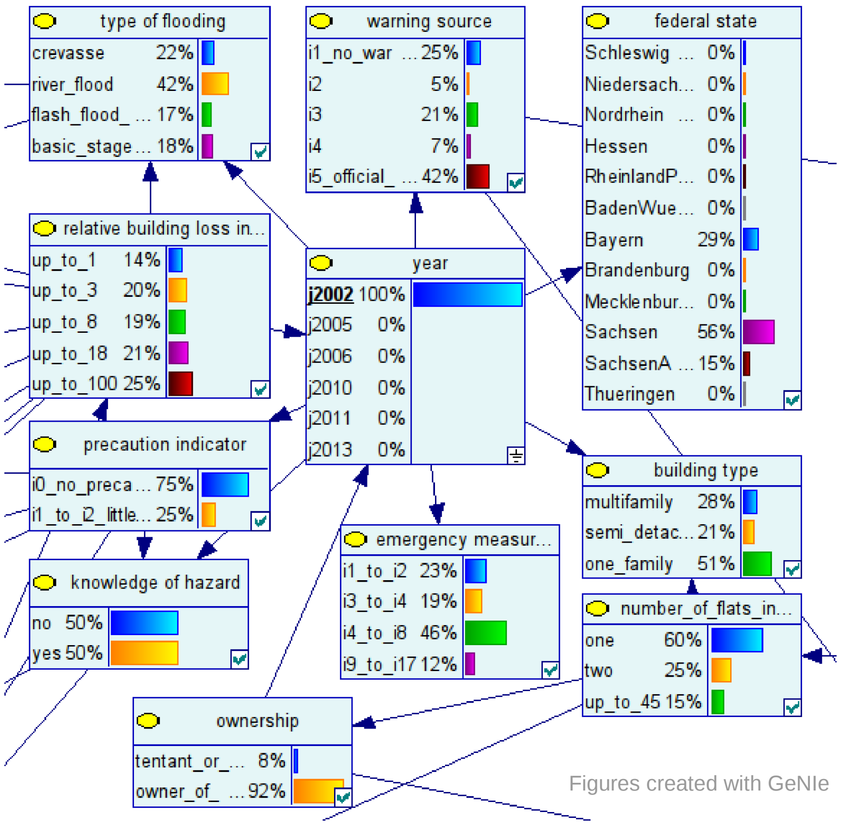
Improve process understanding with Bayesian networks

Consider the changing conditions for the two events in

2002 and **2013**



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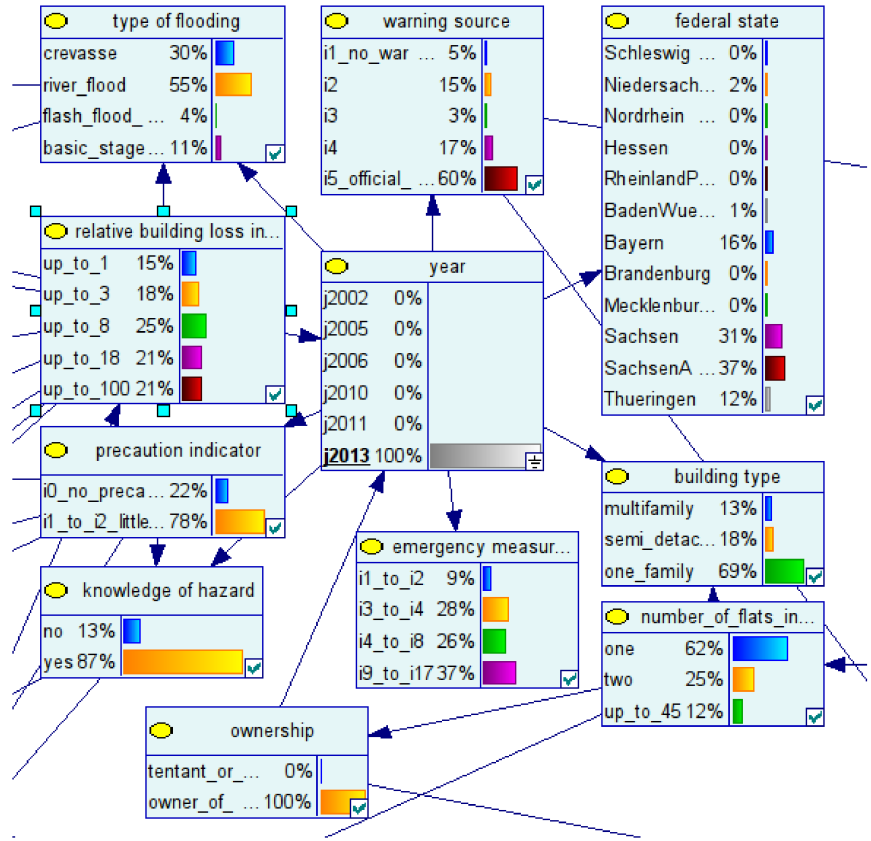

Precaution, knowledge of hazard and type of flooding, differ considerably for the 2002 and 2013 event.

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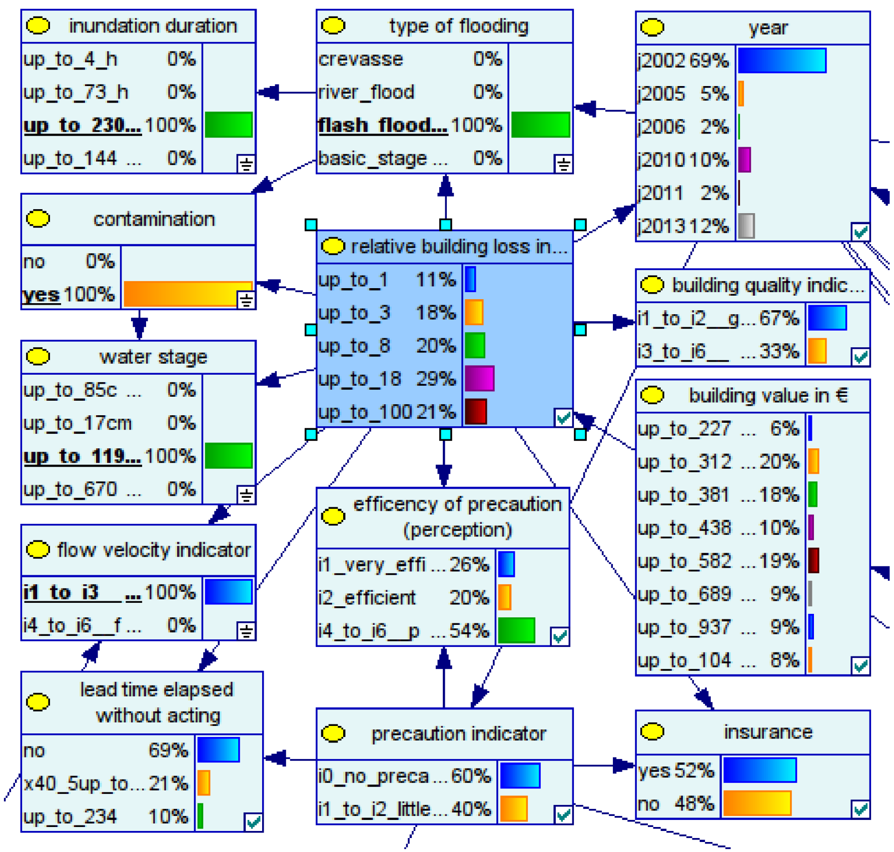
Study specific case scenarios and different courses of action

Study specific case scenarios

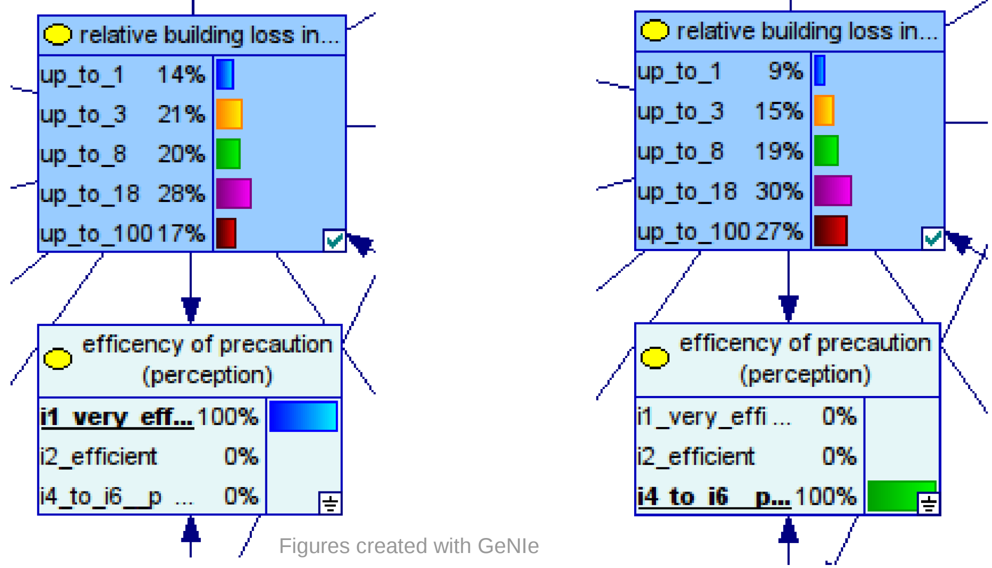


The probabilities of damages to residential buildings are calculated for a specific case scenario.

- BNs return probability distributions instead of point estimates
- missing values of not given variables can be handled (precaution, building characteristics, etc.)
  → predictions can be made at an early stage of an event, before all values are observed

Use Bayesian networks to support decision processes

Compare the probabilities for building damages for an **efficient precaution** and a **non-efficient precaution**.



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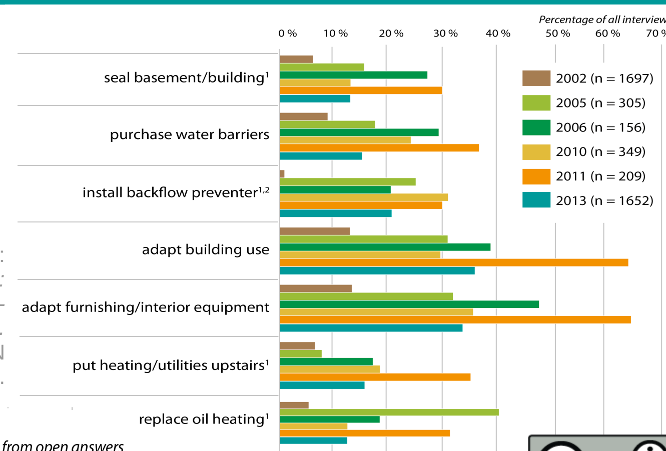
Future perspective:

Identify efficiency of specific precautionary measures



Kienzler et al. (2015) NHESS 15, 505-526

DKKV (Hrsg., 2015): *Das Hochwasser im Juni 2013: Bewährungsprobe für das Hochwasser-risikomanagement in Deutschland.* DKKV-Schriftenreihe Nr. 53, Bonn, ISBN 978-3-933181-62-6, p. 207.

[1] *measures were only given to homeowners*
[2] *measures were not explicitly requested in 2002, but deduced from open answers*

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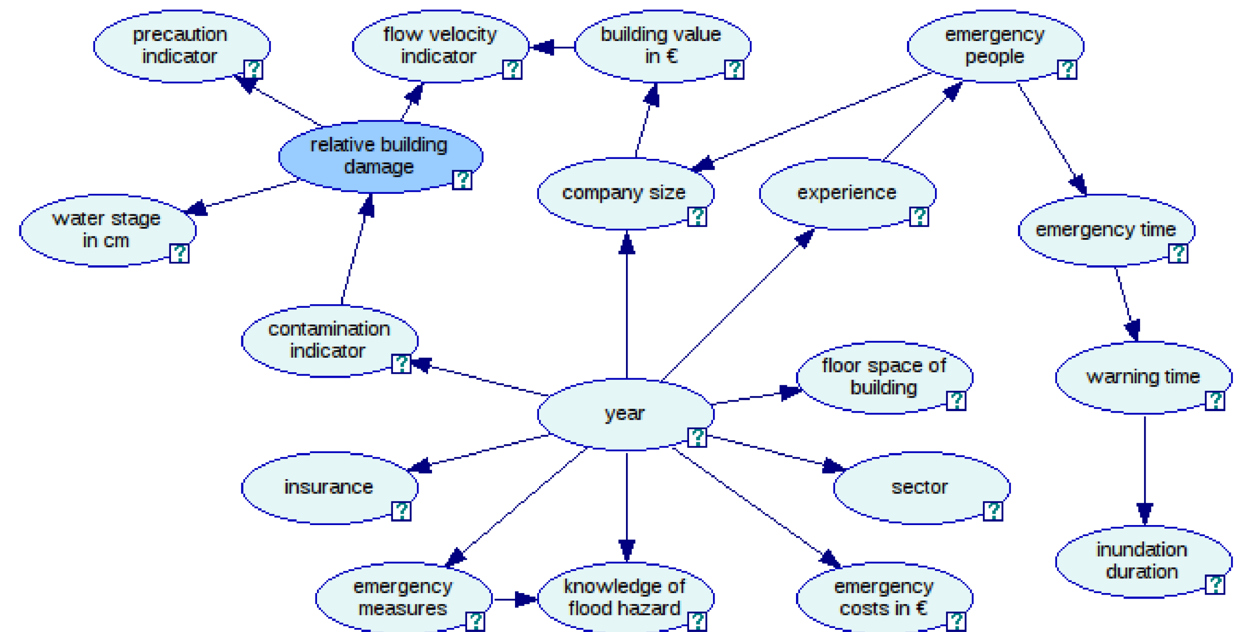
Bayesian networks learned for the company sector

Bayesian network learned with 334 records from 2002 and 2013



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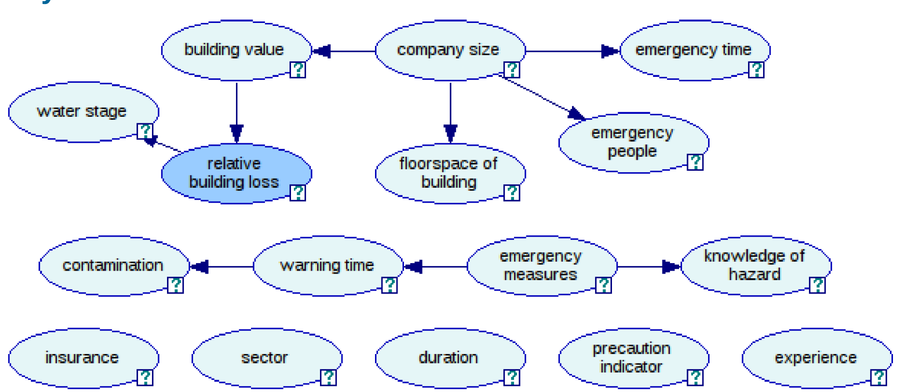
Future perspectives

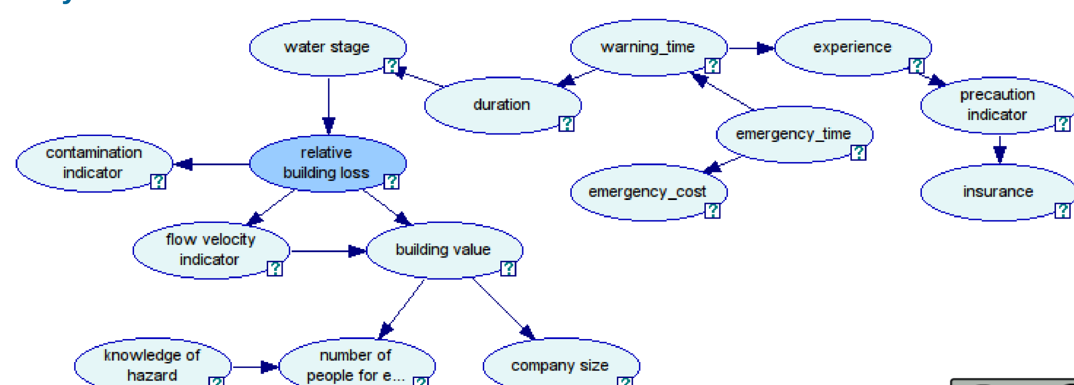
- learn Bayesian networks that focus on variables close to building loss (so called Markov Blanket) to compensate for sparse data
- learn Bayesian networks for
  - damage to furniture
  - damage to products
  - duration of business interruption
  - duration until back to normal business

Investigate differences in damaging processes with Respect to the object of consideration

Bayesian network learned with 113 records from 2002



Bayesian network learned with 221 records from 2013



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