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# A review of single and multi-hazard risk assessment approaches for critical infrastructures protection

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## CRITICAL INFRASTRCUTURE (CI)

A system which must be constantly monitored because its destruction or interruption of service brings to a weakening of the efficiency of a city or of an entire country

**is subject to**

## NATURAL HAZARDS

Dangers whose origin becomes from nature. Examples of natural hazards are hurricanes, floods, landslides, etc.

## MAN-MADE HAZARDS

Dangers whose origin is anthropogenic. Examples of man-made hazards are terroristic attacks, crimes, etc.


## Data Collection

**brings to**

### POOR DATA

Data must be integrated thanks to **expert judgment**.

This subjective knowledge is supported by:

- *Bayes' theorem*
- *Probability bound analysis*

### RICH DATA

Data can be objectively stored thanks to **triplets**:

$$\langle s_i; p_i; x_i \rangle$$

- $s_i \rightarrow$ $i$-th scenario;
- $p_i \rightarrow$ probability of $i$-th scenario;
- $x_i \rightarrow$ effect of the $i$-th scenario.

## Multi-Hazard Interactions

**split into**

### INDEPENDENT EVENTS

Considering the events as **independent** is less complex, but brings to underestimate risk. The method used is the total exceedance probability:

$$P(L_j)_{TOT} = 1 - \prod (1 - P_i(L_j))$$

### CORRELATED EVENTS

Considering the events as **correlated** is more accurate, but the cases to consider are a lot:

- *Unidirectional* vs. *bidirectional* hazards
- *Triggering* vs. *increased probability* vs. *catalysis or impedance*

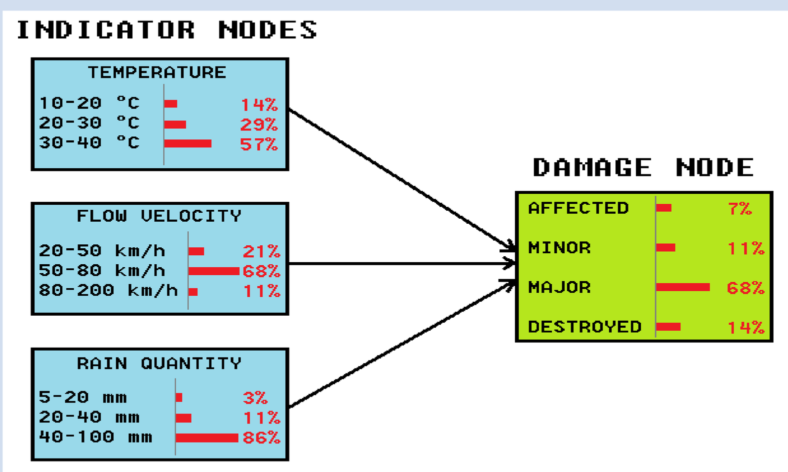
**Conditional probability** is then used

***Depending on the quantity of data available and on the type of interactions, it is possible choosing the best methodology to use for the single or multi-hazard problem faced***

# Methodologies

## MATHEMATICAL AND STATISTICAL METHODS

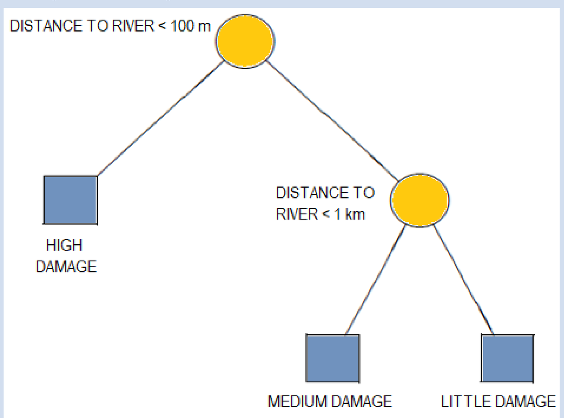
- **Bayesian Belief Network (BBN)**




- Logarithmic regression
- Early warning index calculation

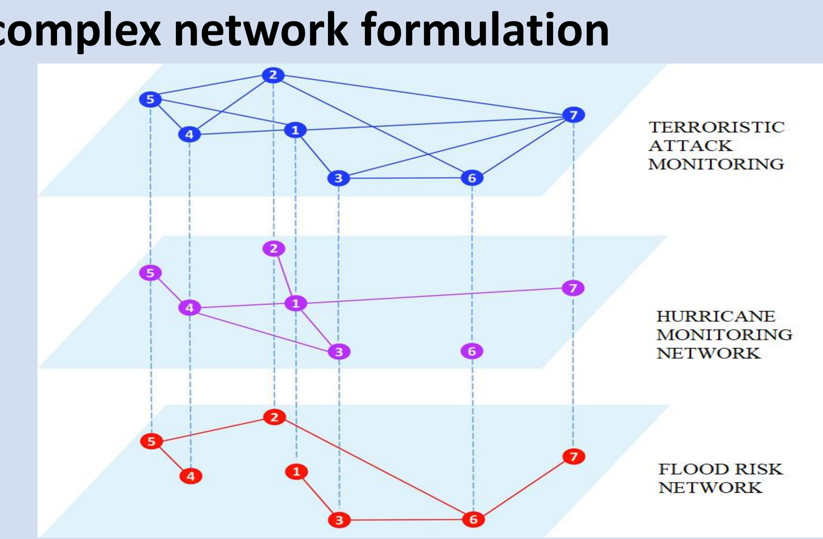
## MACHINE LEARNING TECHNIQUES

- Artificial Neural Network (ANN)
- Support Vector Machine (SVM)
- Boosted Regression Tree (BRT)
- Generalized Additive Model (GAM)
- Genetic Algorithm Rule-Set Production (GARP)
- **Quick Unbiased Efficient Statistical Tree (QUEST)**




## GRAPHS AND NETWORKS APPROACH

- Game theory technique
- Classical complex networks methodology
- **Multi-level complex network formulation**




# Pros & Cons

## MATHEMATICAL AND STATISTICAL METHODS

**Pros**

- *BBNs* work well with few data and capture the dependencies among variables
- The *logarithmic regression* gives good results even with poor data accompanied by expert opinions
- The *early warning index* highlights well the correlations among variables

**Cons**

- The more complex a *BBN*, the more data are required
- The *logarithmic regression* does not capture well the interdependencies among variables
- The *early warning index* calculation requires lots of data

## MACHINE LEARNING TECHNIQUES

**Pros**

- *ANNs* find amazing results also with poor data and are very good for evaluating correlations
- *SVM, BRT* and *GAM* sometimes show good performance for the hazards predicted
- *GARP* and *QUEST* requires a little quantity of data and are very quick methodologies

**Cons**

- *ANNs* perform badly with too many variables and are able to predict one hazard at a time
- *SVM, BRT* and *GAM* can consider one hazard at a time and can show weak results for the hazards predicted
- *GARP* and *QUEST* deals with one hazard at a time

## GRAPHS AND NETWORKS APPROACH

**Pros**

- *Game theory* model is easy to build and can be used for more hazards together
- *Classical complex network* requires few data
- *Multi-level complex network* performs well both with small and with large data sets and is able to deal with interdependencies among different hazards

**Cons**

- *Game theory* needs expert judgement
- *Classical complex network* works with one hazard at a time
- *Multi-level complex network* is used only with time series with the same number of elements

## References

[1] Chatterjee, S., & Abkowitz, M. D. (2011). A methodology for modeling regional terrorism risk. Risk Analysis: An International Journal, 31(7), 1133-1140.
[2] Liu, Z., Nadim, F., Garcia-Aristizabal, A., Mignan, A., Fleming, K., & Luna, B. Q. (2015). A three-level framework for multi-risk assessment. Georisk: Assessment and management of risk for engineered systems and geohazards, 9(2), 59-74.
[3] Major, J. A. (2002). Advanced techniques for modeling terrorism risk. Journal of Risk Finance, 4(1), 15-24.
[4] Ferson, S., & Ginzburg, L. R. (1996). Different methods are needed to propagate ignorance and variability. Reliability Engineering & System Safety, 54(2-3), 133-144.
[5] Daskalaki, E., Spiliotis, K., Siettos, C., Minadakis, G., & Papadopoulos, G. A. (2016). Foreshocks and short-term hazard assessment of large earthquakes using complex networks: the case of the 2009 L'Aquila earthquake. Nonlinear Processes Geophys, 23(4), 241-256.
[6] Fleming, K., Parolai, S., Garcia-Aristizabal, A., Tyagunov, S., Vorogushyn, S., Kreibich, H., & Mahlke, H. (2016). Harmonizing and comparing single-type natural hazard risk estimations. Annals of Geophysics, 59(2), 0216.
[7] Gill, J. C., & Malamud, B. D. (2016). Hazard interactions and interaction networks (cascades) within multi-hazard methodologies. Earth System Dynamics, 7(3), 659.
[8] Van Verseveld, H. C. W., Van Dongeren, A. R., Plant, N. G., Jäger, W. S., & Den Heijer, C. (2015). Modelling multi-hazard hurricane damages on an urbanized coast with a Bayesian Network approach. Coastal Engineering, 103, 1-14.
[9] Rahmati, O., Yousefi, S., Kalantari, Z., Uuemaa, E., Teimurian, T., Keesstra, S., ... & Tien Bui, D. (2019). Multi-hazard exposure mapping using machine learning techniques: A case study from Iran. Remote Sensing, 11(16), 1943.
[10] Reed, D. A., Friedland, C. J., Wang, S., & Massarra, C. C. (2016). Multi-hazard system-level logit fragility functions. Engineering Structures, 122, 14-23.
[11] Lacasa, L., Nicosia, V., & Latora, V. (2015). Network structure of multivariate time series. Scientific reports, 5, 15508.
[12] Aven, T. (2010). On the need for restricting the probabilistic analysis in risk assessments to variability. Risk Analysis: An International Journal, 30(3), 354-360.
[13] Kaplan, S., & Garrick, B. J. (1981). On the quantitative definition of risk. Risk analysis, 1(1), 11-27.
[14] Dubois, D. (2010). Representation, propagation, and decision issues in risk analysis under incomplete probabilistic information. Risk Analysis: An International Journal, 30(3), 361-368.
[15] Aven, T. (2015). The concept of antifragility and its implications for the practice of risk analysis. Risk analysis, 35(3), 476-483.
[16] Darabi, H., Choubin, B., Rahmati, O., Haghighi, A. T., Pradhan, B., & Kløve, B. (2019). Urban flood risk mapping using the GARP and QUEST models: A comparative study of machine learning techniques. Journal of hydrology, 569, 142-154.
[17] Pilkington, S. F., & Mahmoud, H. N. (2016). Using artificial neural networks to forecast economic impact of multi-hazard hurricane-based events. Sustainable and Resilient Infrastructure, 1(1-2), 63-83.
[18] Hamadeh, N., Karouni, A., Daya, B., & Chauvet, P. (2017). Using correlative data analysis to develop weather index that estimates the risk of forest fires in Lebanon & Mediterranean: Assessment versus prevalent meteorological indices. Case Studies in Fire Safety, 7, 8-22.

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