A Bayesian network approach to assessing wildfire consequences

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ABSTRACT: Wildfire risk is a function of hazard occurrence probability and potential consequences. Wildfire consequences in turn are a function of the vulnerability and exposure of the biotic and abiotic systems affected by the fire. These include among others human lives, property, infrastructure, biodiversity, soil and air quality, and agriculture production. This study focuses on the development of a wildfire building damage consequences assessment system at the meso scale, i.e. at a 1km^2 resolution. We achieve this with the construction of a Bayesian network (BN), due to its ability to facilitate the explicit modeling of the relevant parameters, their causal relationships and the associated uncertainties. Probability distributions are obtained both from observations and literature (e.g. for property values) and expert knowledge (e.g. for fire suppression performance). Numerical investigations are made with spatial datasets for the Mediterranean island of Cyprus. Results of the estimated building damage cost for given fire type are shown in maps. The presented model can be attached to a wildfire hazard model to determine wildfire risk in a spatially explicit manner.

1 INTRODUCTION

Wildland fires are a common phenomenon in regions with wet, vegetation-growing winters and hot long, fuel drying periods, such as the Mediterranean. Fire occurrences are caused both naturally (e.g. by lightning) and by humans (e.g. through negligence or arson) (Moreno et al. 1998; Pausas 1999; Leone et al. 2009).

Under favoring topographic and weather conditions, such as steep slopes, high wind speeds with changing directions and heat waves, wildland fire events can develop into uncontrollable wildfires with severe consequences to humans and the environment. Wildfires threaten public health, safety and welfare, and can result in damages both to humans and the environment, including fatalities and injuries, property damage, agricultural losses, natural habitat degradation (Lynch 2004; Munich RE 2012). Studies predict more weather extremes in the future leading to more frequent uncontrollable fire events (Moritz et al. 2012).

Wildfire risk prediction can support adequate prevention and mitigation planning and thus increase site resilience (Finney 2005). Wildfire risk assessments documented in the literature vary strongly depending on risk, vulnerability and cost definitions of study field. Wildfire cost analysis often focus on detailed documentation of case studies but do not result in generalized models, which would allow performing cost assessments in other sites with similar conditions (Butry et al. 2001; Lynch 2004; Snider et al. 2006). Reports on community wildfire protection plans use point systems to assess wildfire occurrence danger and consequences (Ohlson et al. 2003; Oregon Department of Forestry 2004; ECONorthwest 2007). Rating systems are often used to evaluate the susceptibility of items at risk and the degree of loss on the basis of expert knowledge (Tutsch et al. 2010).

Natural hazard risk assessments typically require interdisciplinary efforts (e.g. involving natural hazard modeling, statistical modeling, economic and environmental impact assessments). The Bayesian Networks (BN) model framework is ideally suited to combine interdisciplinary domain knowledge and models (Straub & Der Kiureghian 2010). BN have been used to assess natural hazard risks, e.g. due to rock-fall hazard (Straub 2005), avalanches (Grêt-Regamey & Straub 2006), seismic hazard (Bayraktarli et al. 2005) and wildfire danger (Dlamini 2009). These models combine human expertise with quantitative models and data, and account for the interdependencies between the involved processes (Grêt-Regamey & Straub 2006). BN can easily be extended to include potential mitigation actions or can be modified when additional information is available (Straub 2005). For these reasons, they appear to be an ideal modeling framework for a quantitative hazard consequence assessment system.

This study develops a wildfire consequences assessment system at the meso scale, i.e. at a 1km^2 resolution. Exemplarily, the system focuses on damages to buildings. It is based on a BN model, which includes variables expressing hazard characteristics, people and objects at risk and their susceptibility. As a case study, the proposed BN is applied to Cyprus. The BN is combined with a GIS and maps are provided to illustrate the results.

2 METHODOLOGY

2.1 *Vulnerability and exposure indicators*

Wildfire risk can be estimated as a function of occurrence probability and consequences. Wildfire consequences are a function of vulnerability and exposure of the affected biotic and abiotic systems (e.g. human lives and properties, infrastructure, soil and air quality). Vulnerability describes the degree of expected damage as a function of hazard intensity (UNDRO 1991; Thywissen 2006). Exposure refers to the items at risk, such as people and property. Risk is the expected consequences of wildfires.

Based on the above definitions, the risk R can be formulated as a function of the hazard H, the resulting damages D and the consequences C as

$$R = \mathrm{E}_{H,D}[C] = \int_H \Pr(H) \int_D \Pr(D|H) C(D,H) dD\, dH \quad (1)$$

$\mathrm{E}_{H,D}$ denotes the expected value with respect to H and D. $\Pr(D|H)$ is the probability of damage D conditional on the hazard H, i.e. it describes the vulnerability, and $C(D,H)$ is the cost as a function of damage and hazard.

The inner integral in Eq. (1) describes the expected consequences for given hazard:

$$\mathrm{E}_D[C \mid H] = \int_D \Pr(D|H)\, C(D,H) dD \quad (2)$$

Consequences can be classified based on their ability to be measured by market values as either tangible (e.g. building damage) or intangible (e.g. cultural heritage losses). Consequences can furthermore be classified according to whether they are direct (e.g. life/property losses) or indirect (e.g. erosion on slopes following the destruction of a stabilizing forest). Tangible direct damages can be measured by the costs of repairing or replacing damaged items, whereas intangible direct damages may be measured in terms of number of affected items (Paul 2011).

In order to quantify consequences, vulnerability and exposure indicator are identified, which are related to the degree of loss and the items at risk. Selecting the appropriate indicators is crucial for an accurate assessment of vulnerability and exposure. Indicators should be relevant, measurable, easy to interpret, analytically and statistically sound (Birkmann 2006).

2.2 *Bayesian Networks*

Bayesian Networks (BN) are directed acyclic graphs and consist of nodes, arcs and probability tables attached to the nodes (Jensen, Nielsen 2007). In a discrete BN considered here, each node represents a discrete random variable, whose sample space consists of a finite set of mutually exclusive states. The arcs describe the assumed dependence structure among the random variables.

A conditional probability table (CPT) is attached to each of the nodes, defining the probability distribution of the variable conditional on its parents. If we consider a BN with discrete random variables $\mathbf{X} = [X_1, \dots, X_\mathrm{n}]$, then the full (joint) probabilistic model of these variables is the joint Probability Mass Function (PMF), $p(\mathbf{x}) = p(x_1, \dots, x_n)$, which can be specified with the help of the chain rule:

$$p(\mathbf{x}) = p(x_n|x_{n-1}, \dots, x_1) p(x_{n-1}|x_{n-2}, \dots, x_1) \dots p(x_2|x_1) p(x_1) \quad (3)$$

By making use of the independence assumptions encoded in the graphical structure of the BN, this chain rule reduces to:

$$p(\mathbf{x}) = \prod_{i=1}^{n} p(x_i|pa(x_i)) \quad (4)$$

wherein $pa(x_i)$, are realizations of the parents of X_i. In other words, the joint probability mass function (PMF) of all random variables in the BN is simply the product of the conditional PMFs of each individual random variable given its parents. Therefore, the graphical structure of the BN, together with the conditional PMFs $\Pr(x_i|pa(x_i))$, are sufficient for specifying the full (joint) probabilistic model of $\mathbf{X} = [X_1, \dots, X_n]$.

Inference in the BN model is performed through updating. When one or several variables are observed or fixed, this information (evidence $\mathbf{e}$) is propagated through the network and the joint prior probability of all nodes is updated to its posterior. The posterior joint probability of a set of variables $\mathbf{y}$ in the network given the evidence $\mathbf{e}$ is:

$$p(\mathbf{y}|\mathbf{e}) = \frac{p(\mathbf{y}, \mathbf{e})}{p(\mathbf{e})} \quad (5)$$

The joint probabilities $p(\mathbf{y}, \mathbf{e})$ and $p(\mathbf{e})$ are computed following Eq. (4). Efficient algorithms for performing these computations exist, which are implemented in software such as GeNIe (Decision Systems Laboratory 2013) or Hugin (HUGIN EXPERT 2012).

In the context of wildfire consequence assessments, the advantage of the BN is not its computational effectiveness but that it facilitates the combination of information from various sources in a single model.

2.3 *BN for building damage consequences due to wildfires*

Figure 1 introduces a BN for assessing consequences to buildings caused by wildfires. The BN includes variables that correspond to hazard, exposure, vulnerability and costs. Connecting arcs show the causal relationships among the variables. The BN serves to model the probabilistic relation between damage D and cost C for given hazard H, allowing the computation of expected cost (risk) for given hazard following Eq. 2.

White nodes in the BN of Figure 1 represent the hazard. Wildfire hazard is characterized by the resulting *Burnt area* and the *Fire intensity*. Fire intensity is defined through the rate of energy or heat release per unit length of fire front [kW/m] (Byram 1959; Alexander 1982). Wildfire severity is here expressed by the resulting burnt area. The variables describing the fire hazard should be a function of further variables that are part of a fire hazard model (e.g. Papakosta & Straub 2013; Zwirglmaier et al. 2013). However, since our interest in this study is only in the expected consequence conditional on the hazard, $\mathrm{E}_D[C \mid H]$, these models need not be included here. Note that the burnt area of wildfires is recorded in databases, but not fire intensity. Therefore, the conditional probability distribution of fire intensity is here determined based on expert knowledge, conditional on the burnt area. This is contrary to the causal relationship between these variables, as higher fire intensities relate to longer fire flame lengths, typical for crown fires, which are difficult to suppress and can result in large burnt areas (Rothermel et al. 1980).

Light grey nodes in the BN describe the exposure of the system (items at risk). *Land cover type* discriminates urban from rural areas, which influences the building density [building/km²] and the building stock. *Building stock* describes the combination of building types in 1km², which include single houses,

Figure 1: Bayesian network for building damage cost due to wildfires

semi-detached/row houses, and apartments. The building stock classification influences the costs of rebuilding, which is here taken as the construction value of the buildings in monetary terms. *Construction type* describes the combination of the building portfolio in the 1 km² cell. *Distance to fire station* describes the smallest distance of each location (cell center) to the next fire station. *Road density* expresses the accessibility inside a cell. These two nodes have an impact on the response time and consequently on the fire suppression performance. This neglects airborne fire suppression.

The dark grey node *Building damage* represents the degree of damage, i.e. the vulnerability of the building portfolio in the cell. The vulnerability is influenced by fire intensity, fire suppression performance, construction type and building stock. It is expressed as percentage of damage of the building construction relative to the whole building.

The node *Building damage costs* (BDC) in Figure 1 expresses the building damage cost in the 1 km² cell as a product of the building damage, the construction value, the building density and the burnt area. BDC is expressed in monetary terms [€].

2.4 *Coupling of BN and GIS*

BN can be coupled with a GIS as illustrated in Figure 2. Spatial feature groups, such as points, lines and polygons are processed, stored and managed in a GIS database. Georeferenced spatial features are projected on a grid with 1 km² cell size, which will serve as the spatial resolution of the model. In each cell, a copy of the BN of represents the wildfire consequence. Spatial dependence is represented through the dependence of the observed indicator variables, but not through the BN itself. ArcGIS 10.1 is used for geospatial analysis and mapping (ESRI 2012).

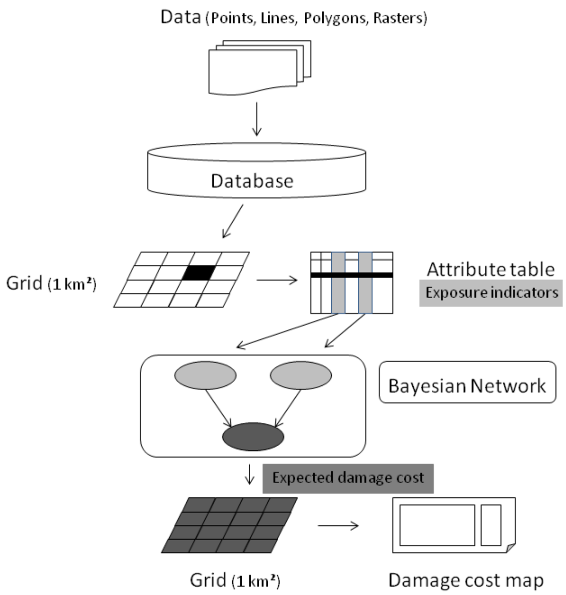

Figure 2: Coupling of BN and GIS

3 NUMERICAL IMPLEMENTATION

The proposed BN of Figure 1 for modeling building damage costs due to wildfires is implemented for a test-bed area. This BN will be expanded in the future to additionally include consequences related to human safety, agricultural capital or natural habitat damage.

3.1 *Test-bed area*

The parameters of the proposed model are learnt for Cyprus. The case study covers 5285 km² and the dominating natural vegetation is coniferous forests (e.g. *pinus brutia*). Due to Mediterranean climate and the mosaic landscape formed by humans, Cyprus is prone to fires. Fires occur with an annual mean occurrence rate of $5.5 \cdot 10^{-5}$ (Papakosta & Straub 2013). The average annual burnt area during 2000-2009 was 29 km² (Joint Research Center (IES) 2010). Besides safety risks to the population, the main assets at risk on Cyprus are buildings, protected natural habitats and agricultural areas.

3.2 *Variables and data sources*

Table 1 summarizes the modeling of the BN variables for the test-bed area. The definitions of the discrete states of the variables are provided as well as the sources for the conditional probabilities defining the variables. It is reminded that the spatial resolution of the model is 1 km², which is of relevance in the definition of the variables. Figure 3a shows the test-bed area with its administrative borders and Figure 3b the fire events registered during the period 2006-2010.

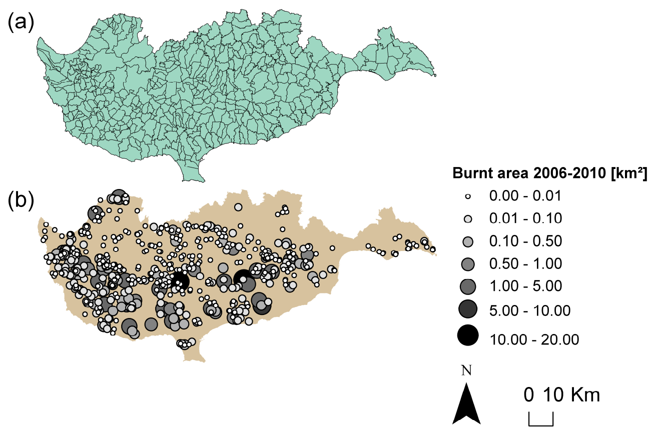

Figure 3: Cyprus test-bed area: (a) Municipalities, (b) Fire events during 2006-2010 classified by the burnt area [km²]

Figure 4 shows selected exposure indicators of the test-bed area.

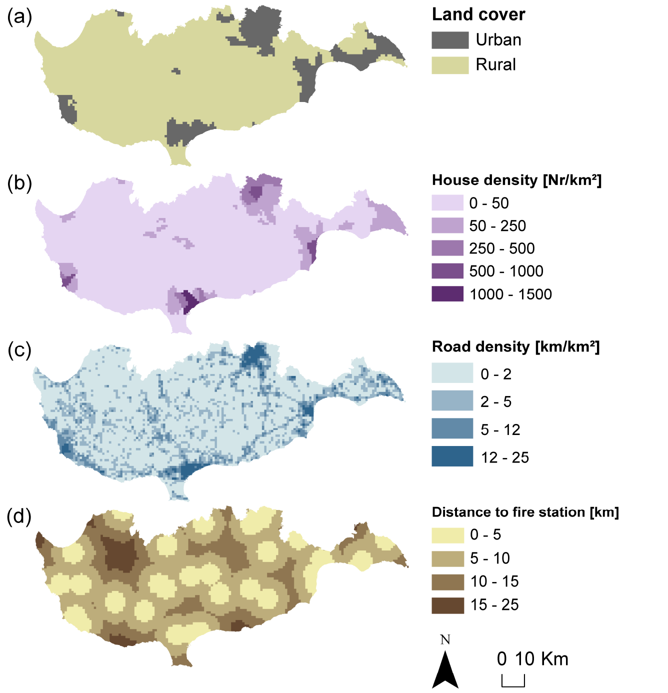

Figure 4: Exposure indicators (a) land cover types (b) house (dwelling) density [Nr. dwellings/km²] (c) road density [km/km²] (d) distance to fire stations [km] on Cyprus case study

4 RESULTS

4.1 *Building Damage Cost (BDC)*

Figure 9 illustrates the BN estimate of the building damage cost conditional on the lowest hazard conditions, i.e. with burnt area $0-0.01$ km² and fire intensity $0-346$ kW/m. In each node, the posterior marginal distribution of the variable is shown together with the expected cost given the corresponding state. In this example, even variables that are known for a given location are considered as random, such as land use. The results are therefore representative for an average cell in the test-bed area. Note that since burnt area states $0-0.01$ and $0.01-0.1$ [km²] are only associated with fire intensity states $0-346$ and $346-1730$ [kW/m], the expected BDC cost for fire intensity >1730 [kW/m] is zero.

Figure 5 - Figure 7 show the computed expected BDC in an average cell, with given evidence in the variable. Figure 5 shows the BDC for different states of burnt area. As expected, the cost increases with increasing burnt area. Burnt area > 1 [km^2] exceeds the area of the cell, and in these cases the cost in an average cell is overestimated. The neighboring cells are then assumed to have similar characteristics with the cell, where fire occurs. For burnt area $10-20$ km² the cost is $2.28 \cdot 10^8$ [€].

Figure 6 shows expected building damage cost conditional on fire intensity. Fire intensities higher than 1730 kW/m are associated with crown fires and are therefore expected to result in higher costs.

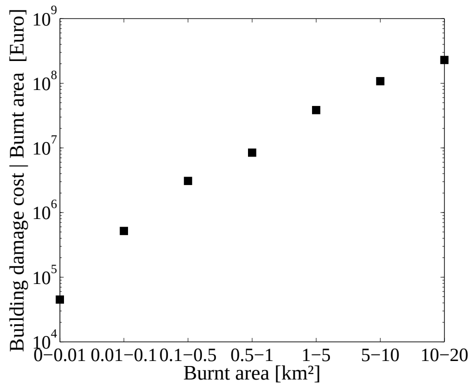

Figure 5: Building damage cost [€] conditional on burnt area [km²]

Building damage is modeled to increases exponentially with higher fire intensity to express vulnerability to crown fires.

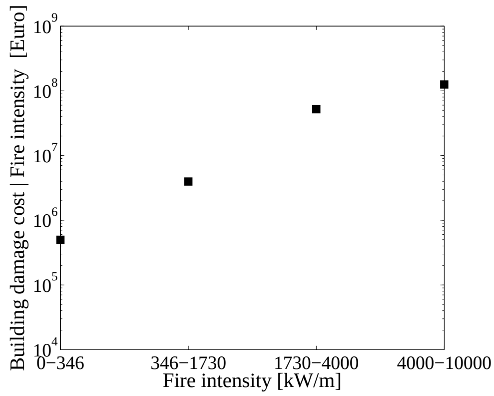

Figure 6: Building damage cost [€] conditional on fire intensity [kW/m]

Figure 7 shows expected building damage cost conditional on house density. Cells with high house density (urban areas) are expected to register higher building damage cost when affected by wildfires.

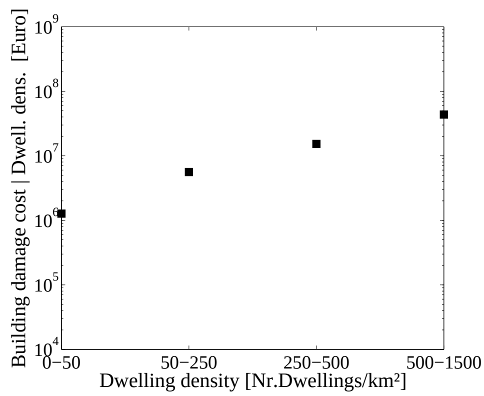

Figure 7: Building damage cost [€] conditional on dwelling density [Nr. Dwellings/km²]

Figure 8 shows the estimated building damage cost [x 10^3 €] for each cell under two different hazard conditions. The maps result from the coupling of the BN with the GIS. Figure 8a shows expected damage cost conditional on burnt area $= 0-0.01$ km² and fire intensity $= 0-346$ kW/m.

Table 1: Description of BN variables and data sources for the definition of conditional probability tables

Variable	#states	States	Source of probability distribution
Fire intensity [kW/m]	4	0-346 346-1730 1730-4000 >4000	Classification based on (Sugihara et al. 2006), p.63 (Box 4.1, 4.2 'Heinselman's fire regimes') and p.68, (Ryan et al. 2012), p.56, Table A-1 ('Representative ranges for fire behavior characteristics') (Ryan 2002)
Burnt area [km²]	6	0-0.01 0.01-0.1 0.1-0.5 0.5-1 1-5 5-10 10-20	Historical fire events (2006-2010) Data source: Department of Forest, Ministry of Agriculture Cyprus
Road density [km/km²]	3	0-2 2-5 5-15	Edited from road map Data source: Open Street Map
Distance to next fire station [km]	3	0-5 5-10 10-30	Edited from fire station locations Data source: Cyprus Fire Service
Fire suppression	3	poor medium effective	Conditional on fire intensity based on: (Smith 2011) p.18, Table 4 ('Fire intensity limits for various suppression options') Conditional on road density and distance to fire station based on fire response times: (ECONorthwest 2007), Appendix C, page C-5
Land cover	2	Urban/Rural	Edited from Corine Land Cover map (version 13) Data source: European Environmental Agency
Building Stock	2	40s_25r_35a 70s_20r_10a	s: single houses r: row houses a: apartments (% percentage) Edited from data from (Cyprus Statistical Service 2010)
Construction Type	2	5t_15s_80i 10t_25s_65i	t: traditional house, stone/mud wall s: single brick wall/flat roof house i: insulated brick/inclined roof (% percentage) Edited from (Statistical Service Cyprus 2012) (Florides et al. 2001), p. 228 (Nemry, Uihlein 2008), p.A147 (Cyprus Statistical Service 2010)
Building density [Nr.dwelings/km²]	5	0-50 50-250 250-500 500-1000 >1000	Based on Nr.dwellings (houses) statistics and municipality borders Data source: Statistical Service Cyprus
Building damage	2	minor major	minor: 20% major: 80% Conditional on fire intensity based on fire severity evaluation of different fire intensities: (Sugihara et al. 2006), p.68 assumed minor for fire intensities<346 kW/m Conditional on construction type based on scoring from: (Oregon Department of Forestry 2004), p.11-12 (ECONorthwest 2007), Appendix C, page C-8 Conditional on building stock (defensible space) based on scores from: (Long, Randall 2004), p.6-7 (Oregon Department of Forestry 2004), p.11-12
Construction value [x 10³ €]	4	0-100 100-200 200-500 500-1500	Customized to Building Stock based on mean value and range for each building type, data from: (Cyprus Statistical Service 2010), p. 160 (Table 14: Building permits authorized by type of project 2010)

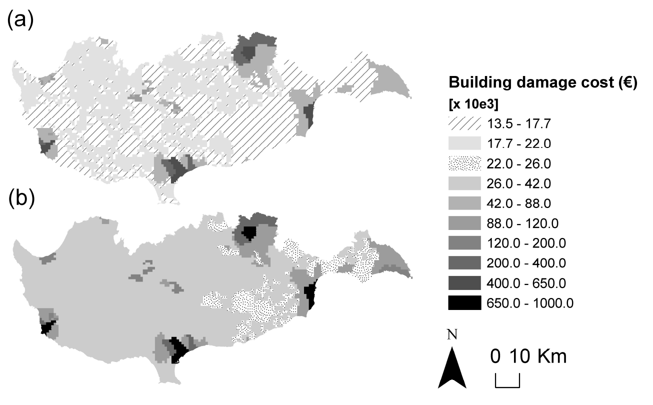

Figure 8: Expected building damage cost [x 10^3 €] conditional on burnt area = 0-0.01 km², and (a) fire intensity= 0-346 kW/m and (b) fire intensity= 346-1730 kW/m

Figure 8b shows expected damage cost conditional on burnt area $= 0 - 0.01$ km² and fire intensity = $346 - 1730$ kW/m. As expected, the building damage cost under higher fire intensity (Figure 8b) is higher than under lower fire intensity (Figure 8a). The highest values of building damage cost are estimated, as expected, in urban areas (see also Figure 4a), due to their higher house densities.

5 DISCUSSION

Research on wildfire consequence estimation has made limited progress, comparing to model development for wildfire probability estimation (Tutsch et al. 2010), hindering wildfire risk assessment. The consequence estimation may be facilitated by BNs, which, as demonstrated in this paper, allow modeling the building damage cost of wildfires in the meso scale with respect to different hazard characteristics. The meso scale modeling requires that the indicators are representative for a 1 km² spatial unit. This makes the modeling more demanding, as it is necessary to identify representative states not of individual buildings, but rather of portfolios of buildings, e.g. building stock, construction type. This introduces uncertainties in building damage estimation at the meso scale. In this study, airborne fire suppression is neglected. When included, airborne fire suppression is expected to reduce the resulting cost of wildfire events with high fire intensity (> 1730 kW/m). The further steps of this study include sensitivity analysis of the results, validation of the model with published data and an extension of the model to assess consequences related to human safety and habitat losses.

6 CONCLUSION

A BN model was developed to quantify building damage cost caused by wildfires at the meso scale. The model was applied to the Mediterranean island of Cyprus. Coupling of BN and GIS resulted in maps providing the expected building damage cost for different hazard intensities.

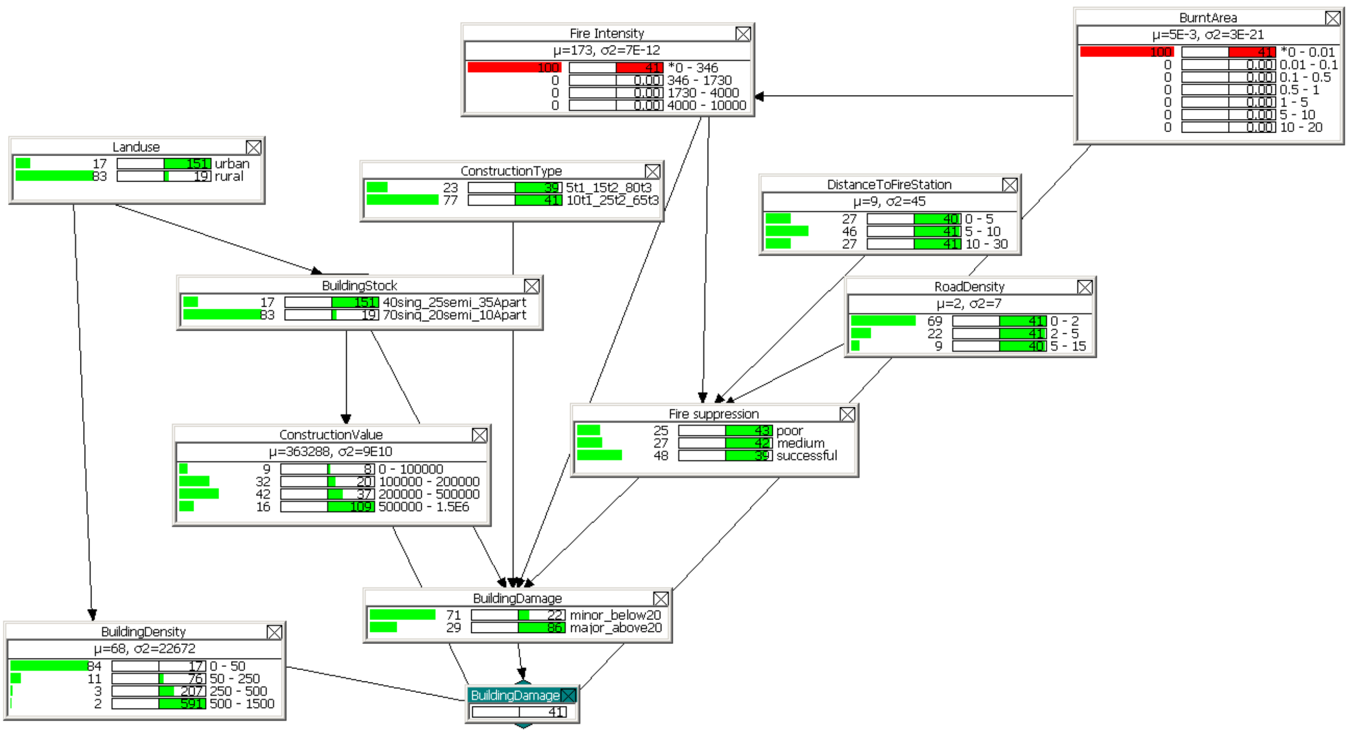

Figure 9: Expected building damage cost [x 10^3 €] for average cell, estimated for burnt area 0-0.01 [km²] and fire intensity 0-346 [kW/m]. Screenshot from Hugin EXPERT (2012).

REFERENCES

Alexander, M.E. 1982. Calculating and interpreting forest fire intensities. *Canadian Journal of Botany* 60(4): 349-357.

Bayraktarli, Y.Y., Ulfkjaer, J., Yazgan, U., Faber, M.H. 2006. On the application of Bayesian probabilistic networks for earthquake risk management. *Proc. ICOSSAR 2005*, Rome, Italy.

Birkmann, J. 2006. Indicators and criteria for measuring vulnerability: Theoretical bases and requirements. In J. Birkmann (ed.) *Measuring vulnerability to natural hazards. Towards disaster resilient societies*, United Nations University Press, Tokyo, Japan.

Butry, D.T, Mercer, D.E., Prestemon, J.P, Pye, J.M, Holmes, T.P. 2001. The price of wildfires. *Journal of Forestry* 99(11): 9-17.

Byram, G.M. 1959. Combustion of forest fuels. In K.P. Davis (ed.) *Forest fire: control and use*, McGraw-Hill, NY, US: 61-89.

Cyprus Statistical Service 2010. *Construction and housing statistics*. Statistical service report, Republic of Cyprus.

Decision Systems Laboratory 2013. *GeNie 2.0* Online available, http://genie.sis.pitt.edu/

Dlamini, W.M. 2009. A Bayesian belief network analysis of factors influencing wildfire occurrence in Swaziland. *Environmental Modelling & Software* 25(2): 199-208.

ESRI (Environmental Systems Resource Institute) (2012). *ArcGIS 10.1*. ESRI, Redlands, California, US.

Finney, M. A. 2005. The challenge of quantitative risk analysis for wildlife fire. *Forest Ecology and Management* 211(1-2): 97-108.

Florides, G.A., Tassou, S.A., Kalogirou, S.A., Wrobel, L.C. 2001. Evolution of domestic dwellings in Cyprus and energy analysis. *Renewable energy* 23(6): 219-234.

Grêt-Regamey, A., Straub, D. 2006. Spatially explicit avalanche risk assessment linking Bayesian networks to a GIS. *Natural hazards and Earth System Sciences* 6: 911-926.

HUGIN EXPERT 2012. *Hugin 7.7*. HUGIN EXPERT, Aalborg, Denmark. Available at: http://www.hugin.com

Jensen, F.V., Nielsen, T. D. 2007. *Bayesian Networks and Decision Graphs*. Springer (Information Science & Statistics), NY, USA.

Joint Research Center (JRC-IES) 2010. *Forest Fires in Europe 2009*. Report No10, JRC Scientific and Technical Reports, European Commission, Land Management and Natural Hazards Unit, Ispra, Italy.

Leduc, A., Juntunen, K., Mitchell, K. 2007. *Linn County Community Wildfire Protection Plan*. ECONorthwest, Portland, Oregon, US.

Leone, V., Lovreglio, R., Martín, M.P., Martínez, J., Vilar, L. 2009. Human Factors of Fire Occurrence in the Mediterranean. In E. Chuvieco (ed.) *Earth Observation of Wildland Fires in the Mediterranean Ecosystems*, Springer: 149-170.

Long, A., Randall, C. 2004. *Wildfire Risk Assessment Guide for Homeowners in the Southern United States*. Report of School of Forest Resources and Conservation, University of Florida (IFAS), Gainesville, Florida, US.

Lynch, D. L. 2004. What do forest fires really cost? *Journal of Forestry* 102(6): 42–49.

Moreno, J.M., Vázquez, A., Vélez, R. 1998. Recent history of forest fires in Spain. In J.M Moreno (ed.) *Large Fires*. Backhuys Publishers, Leiden, The Netherlands.

Moritz, M.A., Parisien, M.A., Battlori, E., Krawchuk, M.E, van Dorn, J. 2012. Climate change and disruptions to global fire activity. *Ecosphere* 3(6), ESA Journals, Article 49.

Munich RE 2012. Geo Topics 2011. Natural catastrophes 2011. Analyses, assessments, positions. Munich, Germany

Nemry, F. Uihlein, A. 2008. *Environmental Improvement Potentials of Residential Buildings (IMPRO-Building)*. Report of Joint Research Center, Institute for Prospective Technological Studies, EU, Luxembourg.

Ohlson, D.W, Blykwell, B.A, Hawkes, B.C, Bonin, D. 2003. A wildfire risk management system - an evolution of the wildfire threat rating system. *Proc. 3rd International Wildland Fire Conference and Exhibition*, Sydney, Australia.

Oregon Department of Forestry 2004. *Identifying and assessment of communitites at risk in Oregon. Draft Version 4.0.*, Report draft, Wildfire Risk Explorer. Available at http://oregonexplorer.info/wildfire

Papakosta, P., Straub, D. 2013. Probabilistic prediction of fire occurrence in the Mediterranean. *International Journal of Wildland Fires*, under review.

Paul, B.K. 2011. *Environmental Hazards and Disasters. Contexts, Perspectives and Management*. Wiley-Blackwell, John Wiley & Sons.

Pausas, J.G., Vallejo V.R. 1999. The role of fire in European Mediterranean Ecosystems. In E. Chuvieco (ed.) *Remote sensing of large wildfires in the European Mediterranean basin*, Springer: 3-16.

Rothermel, R.C., Deeming, J.E. 1980. *Measuring and interpreting fire behavior for correlation with fire effects*. USDA Forest Service General Technical Report INT-93.

Ryan, K.C 2002. Dynamic interactions between forest structure and fire behavior in boreal ecosystems. *Silva Fennica* 36(1): 13-39.

Ryan, K.C, Jones, A.T, Koerner, C.L, Lee, K.M 2012. *Wildland Fire in Ecosystems: Effects of Fire on Cultural Resources and Archaeology*. USDA Forest Service General Technical Report RMRS-GTR-42-vol.3.

Smith, R. 2011. *Investigation of the house losses in the Rolleystone/Kelmscott bushfire 6 February 2011 - Final report.* Fire and Emergency Services Authority of Western Australia (FESA).

Snider, G., Daugherty, P.J, Wood, D. 2006. The irrationality of continued fire suppression: An avoided cost analysis of fire hazard reduction treatments versus no treatment. *Journal of Forestry* 104(8): 431–437.

Statistical Service Cyprus 2012. *Conventional dwellings enumerated by year of construction (completion).* Report table statistics 2012, Republic of Cyprus.

Straub, D. 2005. Natural hazards risk assessment using Bayesian networks. *Proc. ICOSSAR 2005*, Rome, Italy.

Straub, D., Der Kiureghian, A. 2010. Bayesian network enhanced with structural reliability methods. Part A: Theory. *Journal of Engineering Mechanics* 136(10): 1248-1258.

Sugihara, N.G., van Wagtendonk, J.W, Fites-Kaufman, J. 2006. Fire as an ecological process. In N. G Sugihara (ed.) *Fire in California's ecosystems*. University of California Press, Berkeley, US.

Thywissen, K. 2006. Core terminology of disaster reduction: A comparative glossary. In Birkmann, J. (ed.) *Measuring vulnerability to natural hazards. Towards disaster resilient societies*. United Nations University Press Tokyo, Japan.

Tutsch, M., Haider, W., Beardmore, B., Lertzman, K., Cooper, A.B., Walker, R.C. 2010. Estimating the consequences of wildfire for wildfire risk assessment, a case study in the southern Gulf Islands, British Columbia, Canada. *Canadian Journal of Forest Research* 40(11): 2104–2114.

UNDRO - Office of the United Nations Disaster Relief Co-Ordinator 1991. *Mitigating natural disasters: phenomena, effects and options. A manual for policy makers and planners*. UNDRO, Geneva, Switzerland.

van Wagner, C.E., Stocks, B.J., Lawson, B.D. 1992. *Development and Structure of the Canadian Forest Fire Behavior Prediction System*. Information Report ST-X-3. Forestry Canada Fire Danger Group, Ottawa, Canada.

Zwirglmaier, K., Papakosta, P., Straub, D. 2013. Learning a Bayesian network model for predicting wildfire behavior. *Proc. ICOSSAR 2013*, NY, US.