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Probabilistic prediction of wildfire economic losses to housing in Cyprus using Bayesian Network analysis

6   Papakosta P.[1], Xanthopoulos G.[2], Straub D.[1]

7   [1] Engineering Risk Analysis Group, Technische Universitaet München, Munich, Germany

8   [2] Hellenic Agricultural Organization "Demeter", Institute of Mediterranean Forest Ecosystems,

9   Athens, Greece

10 Corresponding author: Panagiota Papakosta (patty.papakosta@gmail.com)

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Abstract

13 Loss prediction models are an important part of wildfire risk assessment, but have received only

14 limited attention in the scientific literature. Such models can support decision making on

15 preventive measures targeting fuels (e.g. thinning, pruning, mechanical treatments) or potential

16 ignition sources (e.g. public behaviour), on fire suppression (e.g. firefighting crew allocation),

17 on mitigation of consequences (e.g. property insurance, education of the citizens to make their

18 homes fire resistant) and on effective allocation of funds. This paper presents a probabilistic

19 model for predicting wildfire housing loss at mesoscale (1 km^2) using Bayesian network (BN)

20 analysis. The BN enables the construction of an integrated model based on the causal

21 relationships among the influencing parameters jointly with the associated uncertainties. Input

22 data and models are gathered from literature and expert knowledge, to overcome the lack of

23   housing loss data in the study area. Numerical investigations are carried out with spatio-

24   temporal datasets for the Mediterranean island of Cyprus. The BN is coupled with a GIS and

25   the resulting estimated house damages for given fire hazard are shown in maps. The BN model

26   can be attached to a wildfire hazard model to determine wildfire risk in a spatially explicit

27   manner. The developed model is specific to areas with house characteristics similar to those

28   found in Cyprus, but the general methodology is transferable to any other area, as well as other

29   damages.

30   Keywords: wildfire damages, vulnerability, Bayesian networks, Mediterranean

31   **Introduction**

32   Wildfire risk prediction is an important tool for fire management planning because it can justify

33   and guide fire risk management measures, including preventive measures targeting fuels (e.g.

34   thinning, pruning, mechanical treatments, prescribed burning) (Mason et al. 2006; Ager et al.

35   2010) or elimination of potential ignition sources (e.g. activities of the public), fire suppression

36   (e.g. firefighting crew allocation), and mitigation of consequences (e.g. property insurance,

37   education of the citizens to make their homes fire resistant). Wildfire risk is commonly defined

38   as the expected net value loss in a particular geographic area and time period (Finney 2005). In

39   recent years, significant effort has been devoted to fire risk analysis across wildlands leading to

40   methodological advances and the development of advanced tools (Finney 2006; Miller and

41   Ager 2013).

42   In most forest landscapes, the highest wildfire risks are associated with houses damaged by

43   forest fires. Therefore, the development of a method for assessing housing losses is an important

44   step towards improved decision support for the authorities and private owners. Significant

45   research efforts are devoted to improved prediction of housing losses due to wildfires. Studies

focus on the analysis of past house losses, either concentrating on the documentation of the events (Lynch 2004;Xanthopoulos 2008) or providing in-depth analysis and discussion (Gibbons *et al.* 2012; Syphard et al. 2012). Other studies use spatial simulation of fires (Ager et al. 2010;Salis et al. 2013;Mitsopoulos et al. 2015;Platanianaki et al. 2015). Only few studies compare model predictions to real world data (Cohen 2000, Cohen 2004).

In general, it has been found that house losses due to wildfires are mainly influenced by fire characteristics (fire intensity, spread rate, burning ember density), by house location, surroundings (defensible space, distance from forest, fuel accumulation), design and construction materials, and by fire suppression effectiveness. The fire impact may be at various intensity levels and may include convective heating or direct contact of the flames, radiant heat flux from nearby flames and airborne firebrands (Cohen 2000;Koo *et al.* 2010;Mell *et al.* 2010). Focusing on the effect of meteorology on fire characteristics, Blanchi et al. (2010) analyzed the relationship between house loss and the fire weather under which it occurred and found that virtually all of the loss occurred under extreme conditions. Harris et al. (2012) considered a measure of the power of the fire (PWR), calculated as the product of Byram's fireline intensity (Byram 1959) with a portion of the length of the fire perimeter, and showed the existence of a strong relationship between community loss and PWR. Gibbons *et al.* (2012) examined the effectiveness of fuel management on decreasing house losses and found that all fuel treatments were more effective when undertaken closer to houses.

The vulnerability of a house is usually determined by its weakest point (Xanthopoulos 2004). In most cases, houses either survive a fire or are totally destroyed; partial damages are less common (Blong 2003). Structure flammability depends on exterior construction materials (e.g. roof type and roof material influence the ignition by firebrands (Koo *et al.* 2010;Gibbons *et al.* 2012) and construction design (e.g. number, size and characteristics of openings). Fire resistant roof materials are, for example, metal, clay tile and asphalt shingles (FSBC 2003). In addition,

71 houses are not only a loss potential, but also serve as potential fuels (Cohen 2000). Therefore,

72 building density is also included in studies of house losses due to wildfires (Gibbons *et al.*

73 2012;Syphard *et al.* 2012). However, for areas where houses are built with less flammable

74 materials than those in Northern America and Australia, such as the Mediterranean region, this

75 may be of less relevance (Xanthopoulos et al. 2012). Poor firefighter access may explain why

76 housing clusters with fewer roads are more vulnerable (Cohen and Butler 1998). Finally, there

77 is significant variability in the behavior under fire even for houses with the same characteristics.

78 Occasionally, houses with low ignitability can be destroyed even during low intensity fire

79 events, whereas houses with high ignitability can sometimes survive high intensity fires (Cohen

80 2000).

81 Despite the insights into wildfire-related housing loss that is provided by these studies, there is

82 currently no broadly accepted generalized predictive model that would allow performing cost

83 assessments at sites other that the ones for which studies have been carried out. Reports on

84 community wildfire protection plans use damage rating systems to assess consequences

85 (Ohlson *et al.* 2003;OFD 2004;ECONorthwest 2007). Rating systems are also often used to

86 evaluate the vulnerability of items at risk on the basis of expert knowledge (Tutsch *et al.*

87 2010;Penman *et al.* 2013).

88 The interdisciplinary domain knowledge needed to predict house loss requires model

89 frameworks that can account for the interdependencies among the involved processes. BNs are

90 well suited to combine interdisciplinary models (Straub and Der Kiureghian 2010). They

91 combine expert knowledge with quantitative models and data and can be modified when

92 additional information is available. For these reasons, BNs are an ideal modeling framework

93 for a quantitative system for the assessment of the consequences of a natural hazard. For

94 example they have been used in assessing volcano hazard (Aspinall *et al.* 2003), rock-fall

95 hazard (Straub 2005), seismic hazard (Bayraktarli *et al.* 2005;Li *et al.* 2012; Bensi *et al.* 2014),

96 avalanches (Grêt-Regamey and Straub 2006), floods (Vogel *et al.* 2013), tsunami (Blaser *et al.*

97 2009) and landslides (Song *et al.* 2012). Applications of BNs to wildfires include the prediction

98 and assessment of wildfire occurrence and burn severity (Dlamini 2009;Sunderman and

99 Weisberg 2012;Papakosta *et al.* 2013;Zwirglmaier *et al.* 2013), wildfire spread (Dahmani and

100 Hamri 2011), effectiveness of wildfire management measures such as fuel treatment and fire

101 suppression (Penman *et al.* 2012;Penman *et al.* 2014), ecological consequences from wildfires

102 (Howes *et al.* 2010), risk of human fatality from fire in buildings (Hanea and Ale 2009), fire

103 spread in buildings (Cheng and Hadjisophocleous 2009) and wildfire causes (Biedermann *et al.*

104 2005).

105 In this study, we propose a methodology to quantify economic loss to housing at a resolution

106 of 1 km^2. This methodology accounts for the lack of data and the variability among data types

107 and sources, and facilitates incorporation of expert knowledge. It is based on a BN model, which

108 includes variables expressing hazard characteristics, houses at risk and their susceptibility, and

109 fire suppression.

110 As a case study, the proposed BN is applied to Cyprus. The parameters of the model (initial

111 probability distributions) are learnt with both data and expert knowledge. Past wildfire disaster

112 events in Cyprus from the period 2006-2010 are chosen to demonstrate the model's ability to

113 predict housing economic loss [€]. For given hazard characteristics, the information is

114 propagated through the Bayesian network and the model predicts expected housing economic

115 loss. We examine the influence of the model parameters (including fire management options)

116 on housing economic loss. The BN is coupled with a Geographic Information System (GIS)

117 and maps of expected economic losses for given wildfires are provided to illustrate the results.

118 The predictions are compared with the damages registered in the NatCatSERVICE database of

119 the reinsurance company Munich Re. The presented model can potentially be transferred to

120 other regions with similar hazard and house characteristics.

Methodology

Study area

The parameters of the proposed BN model are learnt for the Mediterranean island Cyprus. The study area covers 5285 km². The State forests of Cyprus are made up of the following plant communities: *Pinus brutia* (accounting for more than 80% coverage), *Pinus nigra, mixed Pinus brutia-nigra, Cedrus brevifolia, mixed Cedrus brevifolia-Pinus brutia, Quercus alnifolia, mixed Pinus brutia-Quercus alnifolia, Eucalyptus sp.* and Riverine communities. The private forests in Cyprus, in addition to Pinus brutia also include stands of *Cupressus sempervirens, Ceratonia siliqua, Olea europaea*, *Juniperus phoenicia,* and *Quercus infectoria*. Furthermore, there is significant coverage of maquis and garrigue vegetation which is found mainly on private land (Department of Forests 2006).

The topography of the island is dominated by the densely forested Troodos range with Mount Olympus, at 1.953 meters being its highest peak; to its north lies the central Messaoria plain while many coastal valleys surround it along the southern coast.

Due to its Mediterranean climate Cyprus is prone to fires. In the 2006-2010 period, the annual mean occurrence rate of fires was $5.5 \cdot 10^{-5} \frac{\text{Fires}}{\text{day·km²}}$ and the average total burnt area was 21 km²/year (Papakosta and Straub 2015). Fires of all sizes were recorded, with 10% of recorded fires being less than 0.01 ha. The total number of recorded fires in 2006-2010 was 616, which corresponds to a mean annual number of fire occurrences of 123 (Fig. 1). The mean burnt area [km²] of the fires is 0.17 km² and the standard deviation is 0.92 km². The maximum burnt area recorded in 2006-2010 is 13.62 km² (Papakosta 2015).

143   Besides human safety, the main assets at risk on Cyprus are buildings, protected natural habitats

144   and agricultural areas (Fig. 2).

145   *Risk assessment framework*

146   In risk assessment for natural hazards, varying conventions are applied, and the terminology is

147   not unified even within the forestry world (Hardy 2005). We therefore briefly summarize the

148   risk concept and terminology as used in this paper.

149   In many areas of natural hazard risk assessment, it is common to express risk as a function of

150   *hazard*, *vulnerability* and *exposure*; the latter is also known as value at risk, and characterizes

151   the damage potential. Vulnerability describes the response of the affected system to the hazard,

152   e.g. the probability of a house being destroyed by a specific fire. This framework dates back to

153   (UNDRO 1980) and is common practice in earthquake (Carreño *et al.* 2007), flood (Kron 2002)

154   or landslide (Guzzetti et al 2005) risk assessments; it has also been adopted by the International

155   Panel on Climate Change (IPCC) (Cardona *et al.* 2012).

156   The hazard H describes the hazard process in probabilistic terms, e.g. by means of occurrence

157   probabilities for different types and magnitudes of events. Therefore, fire hazard in this study

158   refers to both the occurrence and intensity of the phenomenon. This is similar to Scott et al.

159   (2012) who characterized wildfire hazard with burn probability, fireline intensity and a

160   composite index. It is, however, in disagreement with the common approach of tying hazard

161   only to the contribution of the forest fuels to fire danger (Hardy 2005, Miller and Ager 2013).

162   In spite of these differences, it is commonly agreed that risk is the expectation of losses

163   (UNDRO 1980, Finney 2005). Utilizing the above definitions, the risk of an asset (or resource)

164   *j* is mathematically expressed as

$$Risk_j = \int\limits_{\substack{Hazard \\ scenarios\ h}} p_H(h) \int\limits_{\substack{damage \\ scenarios\ d}} p_{D_j|H}(d|h)\, C_j(d,h)\, \mathrm{d}d\, \mathrm{d}h \tag{1}$$

165 wherein $p_H(h)$ is the probability (density) of a particular wildfire hazard event. $p_{D_j|H}(d|h)$ is the

166 vulnerability of asset j, which describes the probability of a damage d conditional on a hazard

167 event h. $C(d,h)$ is the economic loss associated with the hazard and the damage scenario, it is

168 a measure of exposure.

169 Wildfire risk has previously been defined as (Finney 2005; Miller and Ager 2013):

$$Risk_j = \sum_i \Pr(F_i)\, RF_j(F_i) \tag{1}$$

170 where $\Pr(F_i)$ is the probability of a fire at intensity level i and RF_j is the response function of

171 resource j as a function of fire intensity level j (Miller and Ager 2013). $\Pr(F_i)$ corresponds to

172 $p_H(h)$, with the difference that the hazard (a fire at a specific intensity level) is modeled by a

173 discrete number of scenarios, hence the integral in Eq. (1) is replaced by the summation. The

174 inner integral in Eq. 1 corresponds to the response function:

$$RF_j = \int_D f_{D_j|H}(d|h)\, C(d,h)\mathrm{d}d \tag{2}$$

175 This integral considers that a fire with a given intensity level h can lead to different responses,

176 depending on which damages d occur. In this study, this response function is developed for

177 damages to housing.

178 Consequences can be classified based on their ability to be measured by market values as either

179 tangible (e.g. house damage) or intangible (e.g. cultural heritage losses). Consequences can

180 furthermore be classified according to whether they are direct (e.g. house damage) or indirect

181   (e.g. erosion on slopes following the destruction of a stabilizing forest). Tangible direct

182   damages can be measured by the costs of repairing or replacing damaged assets, whereas

183   intangible direct damages may often be measured in terms of number of affected items (Paul

184   2011).

185   In order to quantify consequences, vulnerability and exposure indicators are identified, which

186   are related to the degree of loss and the items at risk by means of a BN model. Selecting the

187   appropriate indicators is crucial for an accurate assessment of vulnerability and exposure.

188   Indicators should be relevant, measurable, easy to interpret, analytically and statistically sound

189   (Birkmann 2006).

190

191   *Bayesian Network (BN)*

192   BNs are directed acyclic graphs and consist of nodes, arcs and probability tables attached to the

193   nodes (Jensen and Nielsen 2007). In a discrete BN considered here, each node represents a

194   discrete random variable whose sample space consists of a finite set of mutually exclusive

195   states. The arcs describe the dependence structure among the random variables.

196   A conditional probability table (CPT) is attached to each of the nodes, defining the probability

197   distribution of the random variable conditional on its parents. The full (joint) probabilistic

198   model of the random variables $\mathbf{X} = [X_1, \ldots, X_n]$ in the BN is the joint Probability Mass Function

199   (PMF), $p(\mathbf{x}) = p(x_1, \ldots, x_n)$. By making use of the independence assumptions encoded in the

200   graphical structure of the BN, this joint PMF is equal to the product of the conditional

201   probabilities (Kjaerulff and Madsen 2013):

$$p(\mathbf{x}) = \prod_{i=1}^{n} p(x_i | pa(x_i)) \tag{3}$$

202 wherein $pa(x_i)$ are realizations of the parents of X_i. Eq. (3) states that the joint PMF of all

203 random variables in the BN is simply the product of the conditional PMFs of each individual

204 random variable given its parents. Therefore, the graphical structure of the BN and the

205 conditional PMFs $\Pr(x_i|pa(x_i))$ specify the full probabilistic model of $\mathbf{X} = [X_1, \ldots, X_n]$.

206 Inference in BNs is performed by computing the conditional probabilities of selected variables

207 given the available data on other variables. Efficient algorithms for performing these

208 computations are implemented in software such as GeNIe (Decision Systems Laboratory 2013)

209 or HUGIN (HUGIN EXPERT 2012). The latter is employed in this study. However, in the

210 context of wildfire consequence assessments, the advantage of the BN is not its computational

211 effectiveness but that it facilitates the combination of information from various sources in a

212 single model.

213 We propose the BN model of Fig. 3 for assessing consequences to houses caused by wildfires.

214 Houses are here defined as separate households contained within a multi-unit apartment

215 building (dwelling unit) (Service 2010). The BN structure is based on phenomenological

216 reasoning, the authors' experiences and existing models, such as a fire containment model. The

217 present version of the model reflects the availability of data that can be used for defining and

218 learning the model parameters, and may be modified if additional data becomes available. Table

219 1 summarizes the definitions of the variables and the corresponding data sources. It is reminded

220 that the spatial resolution of the model is 1km², which is of relevance for the definition of the

221 variables.

222 The BN includes variables that correspond to (a) hazard, (b) exposure, (c) vulnerability and (d)

223 costs (Fig. 3). Connecting arcs show the causal relationships among the variables. It models the

224 probabilistic relation between the Hazard H, damage D and cost C, for computing the response

225   function to a given wildfire hazard following Eq. (3). The BN thereby automatically performs

226   the integration (or summation) over the possible damage states d.

227   (a) Wildfire hazard H is characterized by the variables *Fire type, Burnt area* and the Fire

228   Weather Index (*FWI*) of the Canadian Forest Fire Weather Index System, a numeric rating of

229   fire intensity, used as a general index of fire danger as influenced by weather conditions

230   (Lawson and Armitage 2008). In the BN applied here, *FWI* influences only the result of the

231   suppression effectiveness. No link from FWI to the *Burnt area* and the *Fire type* is included.

232   The reason for this omission is that in this study we account for specific hazard characteristics

233   and are not interested in modeling the hazard itself. However, in a full risk analysis these links

234   must be included, as shown in Papakosta *et al.* 2014). *Fire type* distinguishes among a surface

235   fire with flame length <3.5m, a surface fire with flame length >3.5m and a crown fire (Table

236   1). *Burnt area* represents the extent of the wildfire. Through the link to *Fire type*, the variable

237   *Burnt area* also provides information on wildfire severity, since it influences the posterior

238   probability distribution of the variable *Fire type*. The variables describing the fire hazard

239   typically result from a fire hazard model (Papakosta and Straub 2013;Zwirglmaier *et al.* 2013).

240   Since our interest in the present study is in the response to a given hazard h according to Eq. 3,

241   these models need not be included here (the hazard characteristics h are provided as an input to

242   the consequence model).

243   As a rule, more intense wildfires, i.e. those with longer flame lengths, are more difficult to

244   extinguish and thus result in larger burnt areas (Rothermel and Deeming 1980). In the proposed

245   model, there is an arc from *Burnt area* to *Fire type*, which is contrary to the causality among

246   these two variables. Such a contra-causal connection is possible in BNs, but care is needed to

247   ensure that the overall dependence structure among variables is consistent with reality (Straub

248   and Der Kiureghian 2010). The arc is introduced here in view of an extension to a larger BN,

249   which includes fire size prediction, i.e. a model that predicts *Burnt area* (Papakosta *et al.* 2014).

250 The variable *Fire type* and its probabilities conditional on *Burnt area* are ideally defined based

251 on data. Since no data on *Fire type* are available for Cyprus, a data set is used that includes the

252 *Fire type*, the resulting *Burnt area* and the *House damages* of 195 fire events that took place in

253 the Wildland Urban Interface (WUI) in Greece in the 1981-2003 period. These fire events

254 resulted in 442 heavily damaged structures. Wildfire conditions in Greece are generally

255 considered similar to those in Cyprus, as both countries have Mediterranean climate and similar

256 forest vegetation. Fig. 4 shows a boxplot of the fire type versus the resulting burnt area for the

257 Greece data used to learn the CPT of *Fire type*.

258 (b) Exposure nodes in the BN describe the exposure of the system (items at risk). *Urban/Rural*

259 discriminates urban from rural areas, which influences *House density* [house/km²] and *House*

260 *stock*. *House stock* accounts for the house type portfolio in the meso-scale. It describes the

261 relative distribution of house types in 1km², which include single houses, semi-detached/row

262 houses, and apartments. Specifically for the study area, *House stock* can be in one of two states:

263 40s_25r_35a, meaning that 40% of the houses are single houses, 25 % row houses and 35%

264 apartments and 70s_20r_10a, meaning 70% single houses, 20% row houses, 10% apartments

265 (Table 1). The definition of House stock should be adjusted when modeling at different scales

266 and for other regions. The vulnerability of *House stock* classes (single houses, row houses,

267 apartments) based on the possible flammability of their surroundings is considered to be high

268 for single houses, medium for row houses and low for apartments (Long and Randall 2004;

269 OFD 2004). The house stock classification influences

270 the costs of rebuilding, which is here taken as the construction value of the houses in monetary

271 terms. The above variables were chosen to represent the exposure of the houses based on their

272 arrangement and surrounding conditions. At the applied meso-scale level, the portfolio of the

273 variable *House stock* is the combination of house types in each 1 km² spatial unit and is defined

274 specifically for the study area. Fig. 2 shows selected exposure indicators of the study area.

275 (c) *Fire containment in 24hrs* and *Construction type* are vulnerability nodes. The parents to the

276 vulnerability variable *Fire containment in 24 hrs* are chosen based on (Plucinski *et al.* (2012)),

277 where a logistic regression analysis is performed to determine the effect of multiple variables

278 on fire containment. The probability of successful *Fire containment in 24hrs* is modeled as

$$\Pr(Fire\ Containment\ in\ 24hrs)$$
$$= b_0 + b_1 \times F(G)FDI + b_2 \times Time\ for\ ground\ attack + b_3 \times Air\ time \qquad (6)$$

279 *FFDI* is the Forest Fire Danger Index and *GFDI* is the Grass Fire Danger Index that were

280 developed for Australia (McArthur 1967). Which of the two should be used depends on the

281 Vegetation type (forest/shrub/grass). Here, F(G)FDI is adapted to the *FWI* according to Dowdy

282 *et al.* (2010).

283 *Time for ground attack* and *Air time* is the time needed by ground and air suppression crews to

284 reach the fire. In the BN, *Time for ground attack* [min] is modeled as a function of the *Distance*

285 *to next fire station* [km], which describes the shortest distance to the next fire station. The

286 response time of the ground firefighting group is defined as 5 min. The mean vehicle velocity

287 is assumed to be 70km/hr. The response time of the air firefighting group is 10 min with a mean

288 aircraft travel time of 190 mph (306 km/hr). *Land cover types* refer to the Corine 2006 land

289 cover type nomenclature and influences the variable *Vegetation type*. *Vegetation type* can be

290 grass, forest, shrub and non-burnable. *Air suppression* can be either present or absent (yes/no).

291 The above variables are chosen to express the suppression result and how it influences the house

292 damages.).

293 *Construction type* categorizes the houses based on the construction materials and roof type. It

294 represents a portfolio of construction types found in the 1 km² cell, and includes construction

295 materials such as stone/mud, single/insulated brick, and roof types such as flat concrete or

296 inclined roof with tiles (Table 1). The definition of *Construction type* may be modified when

297 modeling at different scales and for different areas. The vulnerability node *House damages*

298 represents the degree of damage to the house portfolio in the cell. The vulnerability is influenced

299 by *Fire type*, *Fire containment in 24 hrs*, *Construction type* and *House stock*. It is expressed as

300 percentage of houses totally destroyed in 1 km². Since *House damages* refers to the portfolio in

301 the cell, it is expressed as the percentage of destroyed houses (Table 1). The definition of the

302 CPT of *House damages* can vary based on the modeling scale and the available data set. Here,

303 the CPT of *House damages* results as a normalized summation of the individual contributions

304 to the damage from each of the influencing variables. The influence of *Fire type* on *House*

305 *damages* is quantified using the Greek dataset. The failure of *Fire containment* is assumed to

306 lead to minor *House damages* with 60% probability and major *House damages* with 40%

307 probability. The *Construction type* of houses in Cyprus includes mainly three types of

308 structures. Traditional houses, mostly built in the period prior to 1945 with stone or mud walls

309 and roofs with punky wood parts (Nemry and Uihlein 2008), are considered the most

310 vulnerable. The vulnerability of houses built with single brick walls and flat reinforced concrete

311 roofs in the period $1946 - 1970$ (Nemry and Uihlein 2008) is considered to be lower, and

312 newer houses with insulated brick walls and inclined roofs with ceramic tiles are the most fire

313 resistant.

314 (d) The node *Housing economic loss* (HDC) in Fig. 3 expresses the housing economic loss in

315 the 1km² cell as the product of *House damage*, *Construction value*, *House density* and *Burnt*

316 *area*. HDC is expressed in monetary terms [€].

Coupling with GIS

318 The BN model is coupled with a GIS for both parameter learning and output mapping. GIS

319 layers are used as inputs for some BN nodes and the spatially referenced output of the BN is

320 returned and visualized in the GIS. First, the spatial information is managed in a Geodatabase

14

321 (and attached to a 1 km² grid. The CPTs of the BN model are trained with the attribute table of

322 the grid, which combines the attributes of the GIS layers. After the learning process, the BN

323 model is applied to additional spatial datasets for predictions. The new dataset is initiated as

324 evidence on the BN nodes and the target node is updated via inference based on the trained

325 CPTs. The output of these calculations is the expected losses (in €) in each 1 km² cell of the

326 study area. The evidence propagation is conducted as batch propagation within the BN software

327 shell (HUGIN).

328 The BN is run separately for each of the grid cells. Note, that spatial dependence between cells

329 is represented through the dependence of the observed indicator variables, but not through the

330 BN itself.

331

Results

333 The expected housing economic loss (HDC) estimated by the BN model for an average cell of

334 the study area conditional on a fire occurring is 18635 €. To obtain this results, the BN is

335 evaluated without any information, i.e. all influencing variables are represented by their

336 probability distributions reflecting an average $1km^2$ area on Cyprus.

337 Fig. 5 illustrates the BN estimate of the HDC conditional on a fire with the lowest hazard

338 conditions, i.e. with a burnt area < 0.01 km² and of fire type 1 (surface fire with flame length <

339 3.5m). The average HDC in a $1km^2$ cell over the study area is 331 €. In each node of Fig. 5 the

340 posterior marginal distribution of the variable is shown together with the expected housing

341 economic loss, given the corresponding state. As an example, were the FWI fixed to its largest

342 state 60-120, with all other parameters left unaltered, the expected HDC would increase to 580

343 €. For different land cover types, the expected HDC varies from 0 (for urban areas and

344 wetlands) to 588€ (for forested areas). Areas with forests (land cover type: 5) are expected to

15

345   have the highest housing economic loss, followed by shrubs (land cover type: 6) and permanent

346   crops (land cover type: 3).

347   As expected, HDC increases proportionally to burnt area (Fig. 6). When burnt area > 1km², it

348   exceeds the total area of the cell. In such a case, if burnt area would be visualized as a circle

349   buffer zone from the cell where fire occurred, this burnt area circle would intersect also with

350   neighboring cells. In this case, and since we still want to include bigger burnt areas in the study,

351   for simplification purpose the neighboring cells are assumed to have similar characteristics with

352   the "fire" cell (where fire occurs) and would result in similar losses. The losses for the "fire"

353   cell when burnt area > 1km² are thus over-estimated, since they include losses that are expected

354   in neighboring cells, if they are similar to the "fire" cell. The effect of *Fire type* can be studied

355   by fixing this variable while leaving all others without evidence; the expected HDC varies

356   between $7.6 \cdot 10^3$ € (*Fire type* = 1) and $57.0 \cdot 10^3$ € (*Fire type* = 3).

357   To assess the sensitivity of HDC to the model variables and their variability, we compute the

358   variance (and standard deviation) of HDC with respect to each individual variable. This

359   variance-based sensitivity analysis is global, i.e. it accounts for the interaction among the input

360   variables and the non-linearity of the model (Saltelli *et al.* 2008). The highest influence on

361   housing economic loss have the variables (in decreasing order) *House damage*, *Burnt area, Fire*

362   *containment in 24 hrs*, *House density*, *Urban/rural*, *House stock*, *Construction value*, *Fire type,*

363   *Air suppression*, *Vegetation type*, *Land cover*, *FWI*, *Construction value*, *Time for ground attack*

364   and *Distance to next fire station* (Fig. 7). The variable *House stock* is deterministically related

365   to the variable *Urban/rural*, and hence their effect on HDC is the same.

366   Two examples of past fire periods are selected to compare the estimated HDC to available

367   observations (Fig. 8). Based on the hazard characteristics (Burnt area and FWI) and the

368   exposure and vulnerability indicators, the model estimates the expected HDC for each cell

369   (1km²) in which a fire occurred. The results vary from 0 to $570 \cdot 10^3$ €. The aggregated

370 expected housing economic loss from all fire events in the periods are also provided. The BN

371 model gives results that are in agreement with actual recorded losses (Table 2). However, the

372 NatCatSERVICE database (Munich Re) gives information on the number of houses damaged,

373 and not on the resulting housing economic loss, which hinders a direct verification of the BN

374 results. It is also noted that the BN model provides expected (mean) values, which do not have

375 to coincide with the actual observed losses for a single event.

376 On the assumption of a specific fire occurring throughout the entire study area, it is possible to

377 get estimates of the HDC in maps (Fig. 9). The specifics of the assumption (Burnt area, Fire

378 type and FWI) are based on data for the prefectures of East Attica, West Attica, Corinthia and

379 Viotia as reported by Xanthopoulos *et al.* (2014). As expected, the HDC under more destructive

380 fire (*Burnt area* $= 0.4$ km², *Fire type* $= 1 - 3$) and dryer vegetation conditions (FWI $= 60$) is

381 higher than under less destructive and easier to contain fires (*Burnt area* $= 0.003$ km², *Fire*

382 *type* $= 1$) and humid vegetation conditions. Urban areas have the lowest conditional HDC, due

383 to the lack of flammable vegetation and a higher probability of fire containment. The peri-urban

384 areas, which represent the coexistence of residential areas and natural vegetation, have the

385 highest expected HDC values for given fire hazard. Forested areas also exhibit an above-

386 average expected HDC (see also Fig. 2c).

387

Discussion

389 Predictive models for quantitatively estimating consequences to houses are an important

390 component of wildfire risk assessment. Our aim is to present a methodology than can be used

391 in assessing different types of damages and can be useful in case of variable data sources or

392 even lack of data. The model should be able to incorporate other existing models. Moreover,

393 we are interested in evaluating the influence of different variables on the damage economic

394   loss. The model should be able to predict damage economic loss for given fire characteristics

395   in monetary values in 1 km² spatial resolution.

396   The model shows that the wildland-urban interface is expected to experience the highest

397   damages, a result which agrees with previous studies (Mozumder *et al.* 2009; Gibbons *et al.*

398   2012;Syphard *et al.* 2012). Moreover, the influence of higher fire danger conditions (*FWI* =

399   60) on the expected house losses shows that the majority of losses are expected to occur on

400   days with adverse fire weather conditions, as found in other studies as well (Blanchi *et al.* 2010).

401   While such results are potentially useful and can serve as a plausibility check, they are not the

402   main aim of this study. Instead, the goal is to develop a predictive model for wildfire

403   consequences based on readily available spatially and temporally variable indicators that are

404   known to have an effect on wildfire risk.

405   Although the proposed model has shown to give plausible and useful results and can be applied

406   to other areas with similar characteristics, there are limitations that should be addressed. The

407   meso-scale modeling requires that the indicators are representative for a 1 km² spatial unit. This

408   introduces uncertainties into the model, as it is necessary to identify representative states not of

409   individual houses, but of portfolios of houses, e.g. house stock, construction type. These must

410   be adjusted when the model is transferred to other regions. The resulting BN includes the

411   Australian model from Plucinski (2012) on fire suppression. Clearly, the conditions are

412   different in the Mediterranean, but we believe that the model is still valuable as the variables

413   influencing the probability of fire containment are similar in both regions. Furthermore, the

414   approach is flexible. As we demonstrate, the BN can easily incorporate existing models, in this

415   case a linear regression model, and with the same ease, the models can be replaced. The CPTs

416   of the corresponding variables are to simply change when a similar model calibrated with data

417   from the Mediterranean is available. We have also demonstrated the ability of the model to

418 incorporate expert knowledge, but in case of missing data, care is needed when incorporating

419 such information.

420 The proposed model should be seen as an initial step towards a comprehensive consequence

421 analysis for wildfires. Besides extending it to consequences other than house damage, the model

422 should include additional factors known to influence wildfire consequences. The flexibility of

423 the BN framework facilitates such an extension of the model. Additional influencing variables

424 that could be added to increase the model accuracy include the adjacent vegetation influencing

425 house damages, evacuation plans and a distinction between permanent and non-permanent

426 house use to account for the suppression attempts of residents, the existence of fire protection

427 plans at the community level to account for the preparedness of residents to protect their houses

428 from fire, and the existence of house insurance against fire, which also influences residents'

429 behavior in case of fire. These (and other) parameters can be included in the BN model by

430 adding them as nodes, together with the appropriate links. Their inclusion does however require

431 that quantitative models of their influence on the house damage, or on other variables of the

432 BN, are available.

433 Finally, data on actual house damages and fire characteristics would be valuable for model

434 calibration and validation. While databases on fires are available, it is difficult to obtain reliable

435 statistics on the consequences of fires. In the absence of such data, the BN enables the

436 combination of the limited available data with expert knowledge and models.

437

438 **Conclusions**

439 A Bayesian Network (BN) model for estimating housing economic loss at the meso-scale is

440 developed and applied to the Mediterranean island of Cyprus. The coupling of BN with GIS

441 results in maps providing the expected building damage economic loss for different hazard

442   types. The model is flexible and can be extended to include additional indicators and to assess

443   consequences related to human safety, habitat and agricultural losses.

444

Acknowledgements

452

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679

680   **Table 1. Description of BN variables and data sources for the definition of the conditional probability tables.**

681   **Discretization varies based on data (e.g. Fire type) or established classification (e.g. FWI).**

Variable	#states	States	Source of probability distribution and additional information
Fire type	3	1	1: surface fire with flame length < 3.5m
		2	2: surface fire with flame length >3.5m
		3	3: crown fire
			Classification based on fire events in WUI Greece 1993-2003
Burnt area [km²]	7	0-1e-12	Historical fire events (2006-2010)
		1e-12-0.01	
		0.01-0.1	
		0.1-1	Data source:
		1-3	Department of Forest, Ministry of Agriculture Cyprus
		3-10	
		10-30	
Distance to next fire station [km]	3	0-5	Edited from fire station locations
		5-10	
		10-30	Data source: Cyprus Fire Service
Time for ground attack [min]	4	5-10	Ground troop response time assumed to be 5 min.
		10-15	Conditional on distance to next fire station.
		15-20	Vehicle travel velocity assumed 70 km/h
		20-25	
FWI	4	0-10	FWI calculated from interpolated weather data from 5 weather stations
		10-30	
		30-60	Source: Deutscher Wetterdienst (DWD),
		60-120	Cyprus Meteorological Service (Papakosta and Straub 2015)
Land cover	7	1: Urban/Wetland/Pastures	Edited from Corine Land Cover map (version 13)
		2: Arable land	Data source: European Environmental Agency
		3: Permanent crops	
		4: Heterogeneous agriculture	
		5: Forests	
		6: Shrubs/Herbaceous vegetation	
		7: Open spaces	

Vegetation type	4	Grass	Conditional on Land cover types
		Forest	
		Shrub	
		No burn	Edited from Corine Land Cover map (version 13)
			Data source: European Environmental Agency
Air suppression	2	no	no: 50%
		yes	yes: 50%
			(initial probability that air suppression will be performed, assumed)
Fire Containment in 24 hrs		yes	Conditional on Vegetation type, FWI, Air suppression, Time for ground attack
		no	
			Probabilities calculated based on regression models from Plucinski *et al.* 2012
Urban/Rural	2	Urban	Classified based on population density values
		Rural	Urban >120 residents/km²
			Rural <120 residents/km²
House Stock	2	40s_25r_35a	s: single houses
		70s_20r_10a	r: row houses
			a: apartments
			(% percentage)
			Probabilities from data from Service 2010
Construction Type	2	5t_15s_80i	t: traditional house, stone/mud wall
		10t_25s_65i	s: single brick wall/flat roof house
			i: insulated brick/inclined roof
			(% percentage)
			Edited from Service 2012
			Florides *et al.* 2001 p. 228
			Nemry and Uihlein 2008, p.A147
			Probabilities from data (Service 2010)

House density [Nr.Houses/km²]	6	0-3	Based on Nr. dwellings (houses) statistics and municipality borders
		3-10	
		10-30	
		30-100	Data source:
		100-300	Statistical Service Cyprus
		300-1000	
		1000-3000	
Construction value [x 10³ €]	4	0-10	Customized to House stock based on mean value and range for each building type, data from:
		10-50	
		50-100	
		100-500	Service 2010, p. 160 (Table 14: Building permits authorized by type of project 2010)
House damages	2	no damage	Conditional on fire type based on fire events in WUI Greece 1993-2003
		minor: <20%	
		major: >20%	
			Conditional on fire containment assumed 60% minor, 40% major
			Conditional on construction type based on scores from: OFD 2004, p.11-12 ECONorthwest 2007, Appendix C, page C-8
			Conditional on house stock (defensible space) based on scores: OFD 2004, p.11-12

682

683 **Table 2. Aggregated expected housing economic loss (HDC) [€] compared to registered losses**

684 **(NatCatSERVICE) for two past fire periods in 2007 and 2008 on Cyprus**

Fire Period	Aggregated Burnt Area [km²]	Aggregated estimated expected HD economic loss [€]	Losses as recorded in NatCatSERVICE Service	Estimated Losses [€] *
20 June 2007- 16 July 2007	34	$1.11 \cdot 10^6$	several buildings	n.a.
June 2008	19.54	$761 \cdot 10^3$	5 houses	$728 \cdot 10^3$

685 * Estimated Losses= NatCatSERVICE service x Mean House construction value (145684 €)

686

(a)

(b)

Burnt area 2006-2010 [km²]
∘ 0.00 - 0.01
∘ 0.01 - 0.10
● 0.10 - 1.00
● 1.00 - 3.00
● 3.00 - 6.00
● 6.00 - 10.00
● 10.00 - 15.00

N

0 10 Km

687
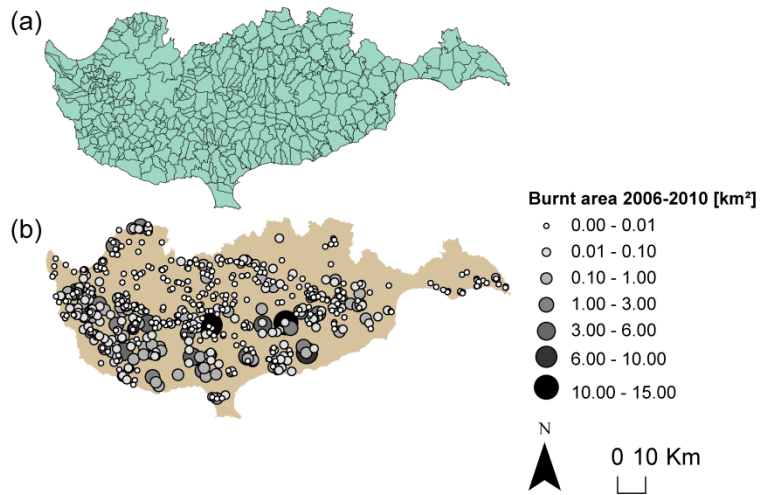
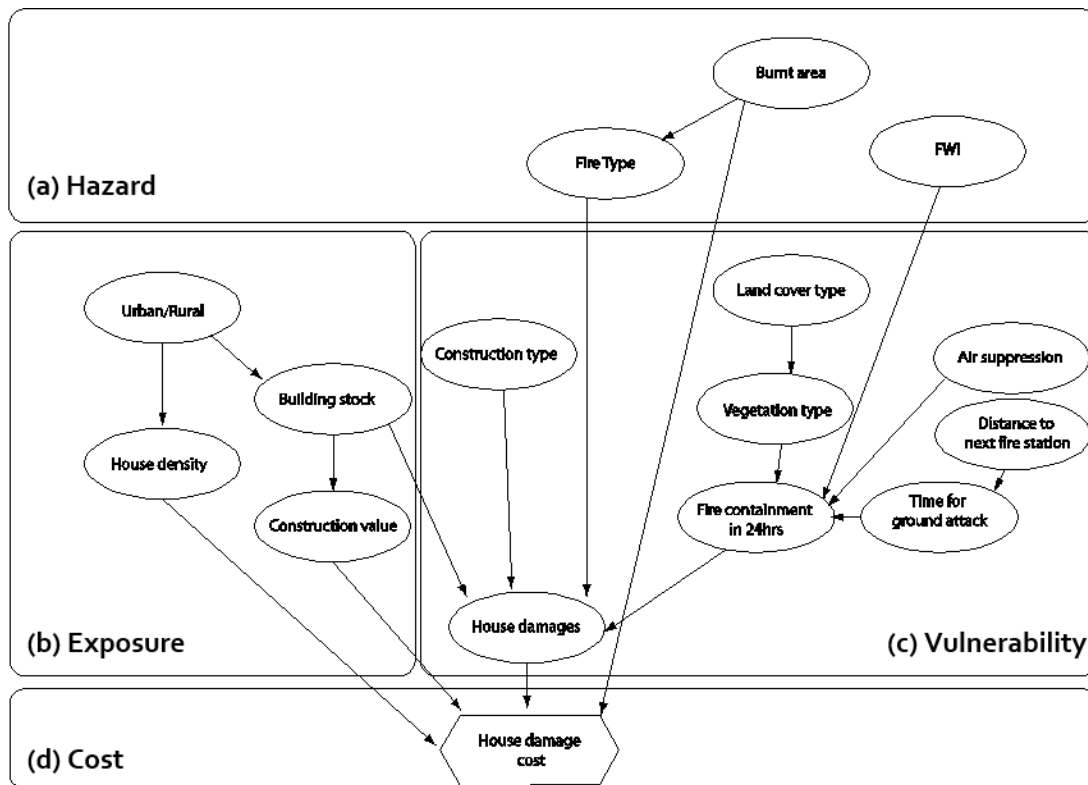**Fig. 1. Cyprus study area: (a) Municipalities, (b) Fire events during 2006-2010 classified by burnt area [km²].**

690
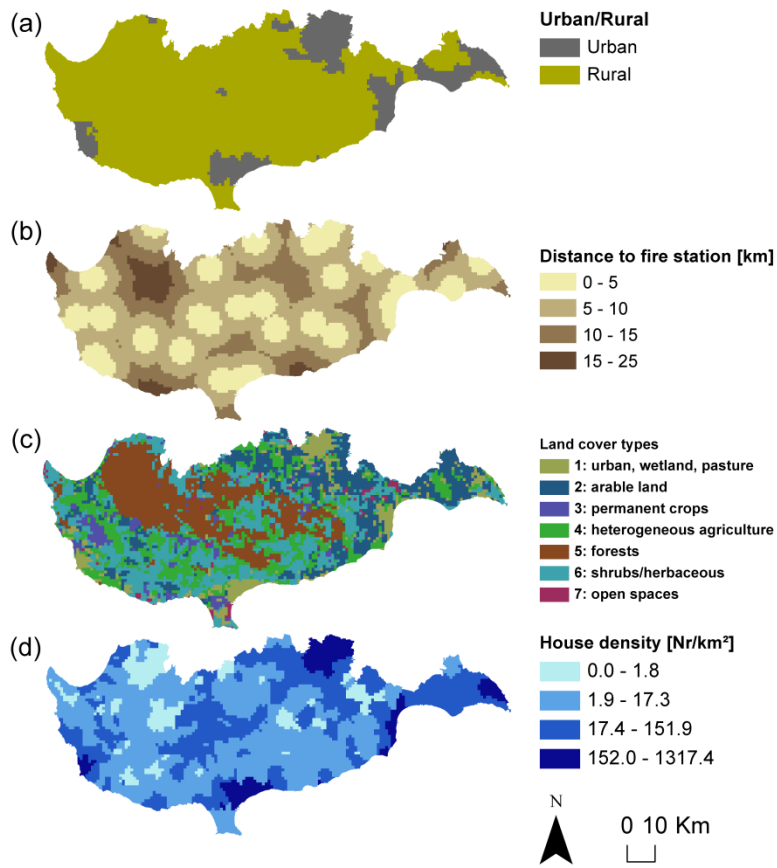
Fig. 2. Exposure indicators for Cyprus study area: (a) urban/rural land, (b) distance to next fire station [km], (c) land cover types, (d) house density [Nr. Houses/km²].
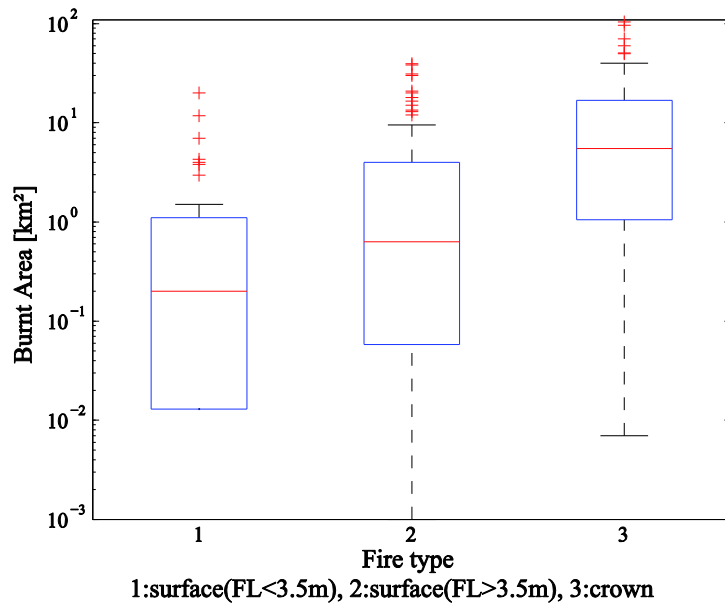
693

Fig. 3: Bayesian Network (BN) for consequences to houses caused by wildfires. Influencing variables are classified in hazard, exposure, vulnerability and economic loss variables. The BN estimates Housing economic loss in 1 km².
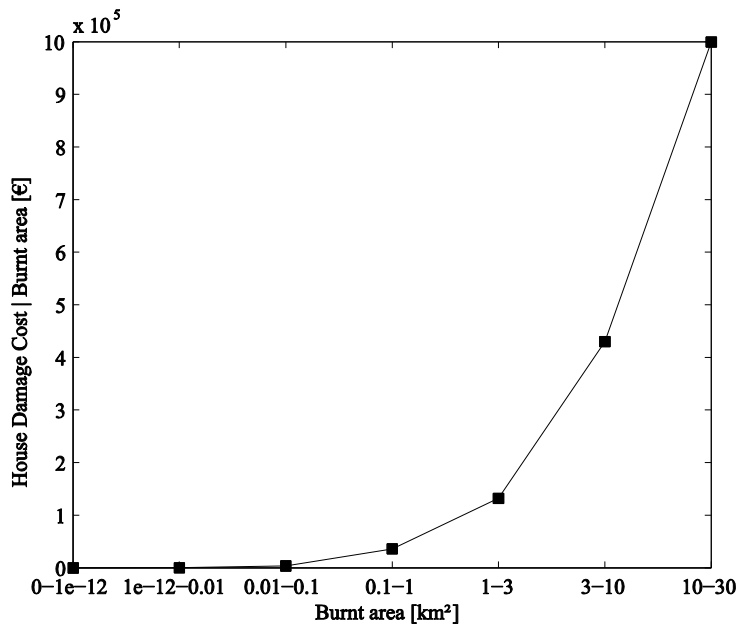
697

Fig. 4. Boxplot of Burnt area [km²] versus Fire type in WUI areas of Greece (1993-2003).

Fire types: 1= surface fire (flame length<3.5m), 2= surface fire (flame length>3.5m), 3= crown fire

700
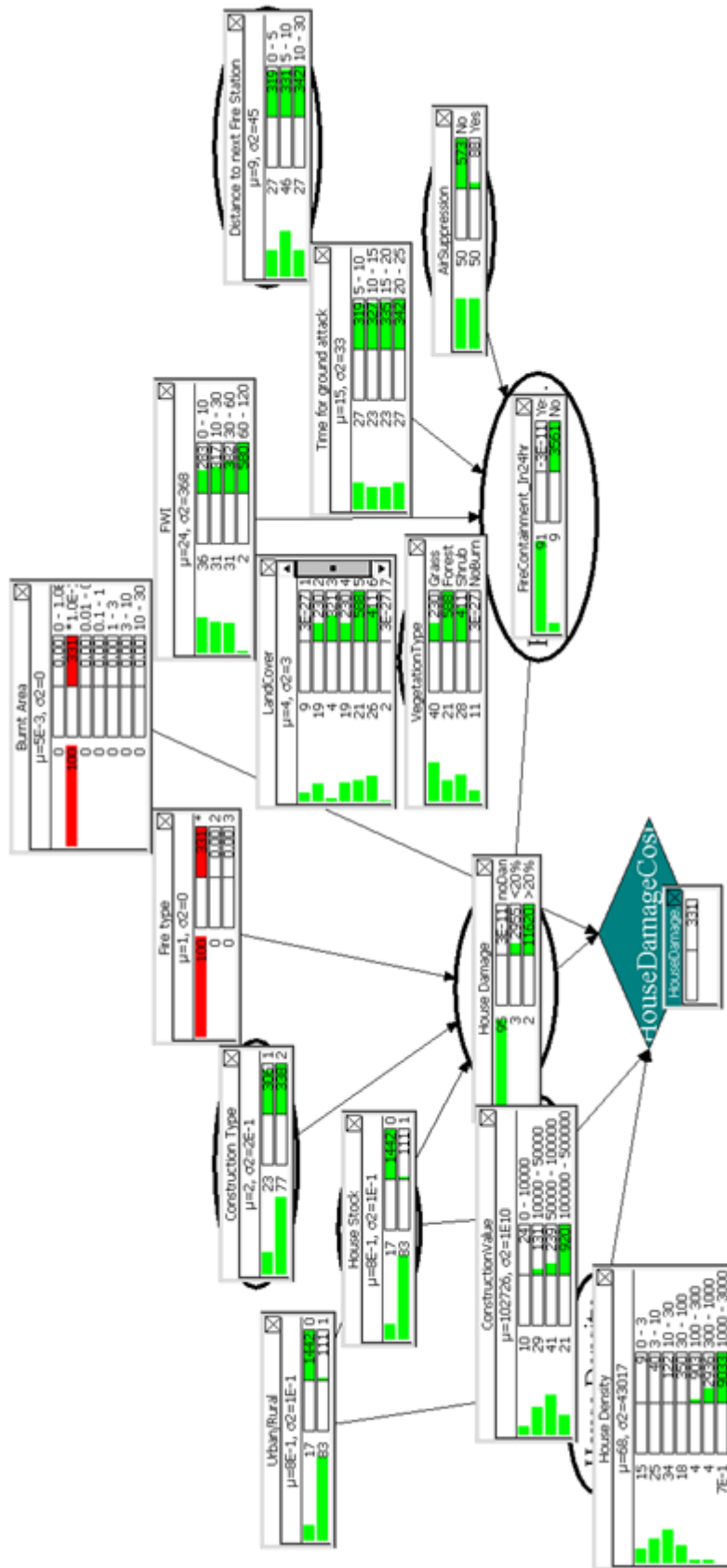
Fig. 5. Expected housing economic loss for average cell, estimated for burnt area <0.01 [km²] and fire type

701

702   **1 (screenshot from HUGIN).**

703

Fig. 6. Housing economic loss [€] conditional on burnt area [km²] estimated by the proposed Bayesian
network.

706
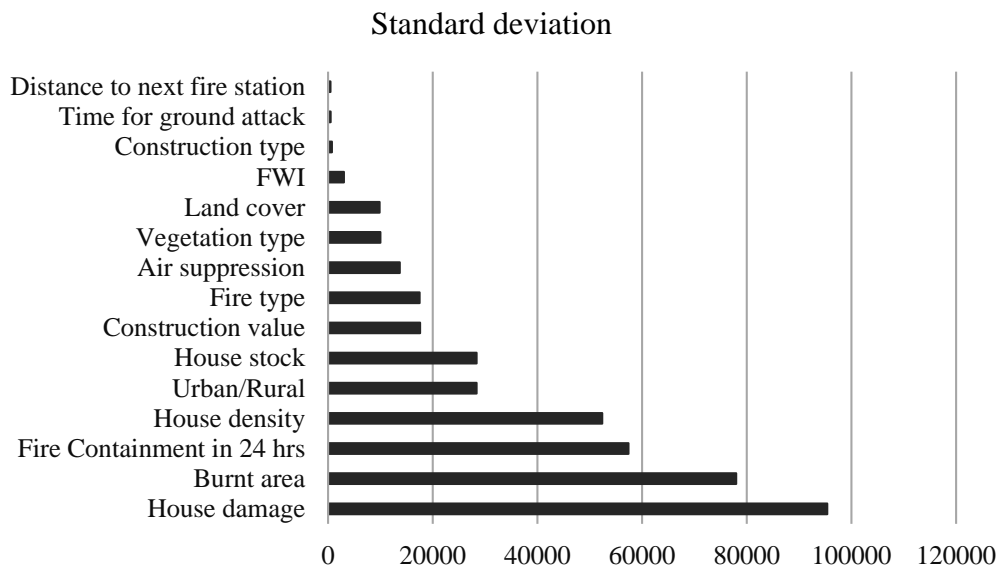
Fig. 7. Global sensitivity of housing economic loss to individual variables, as expressed by the individual

contribution of each variable on the standard deviation of HDC (Table S1 in supplementary material).

710

711

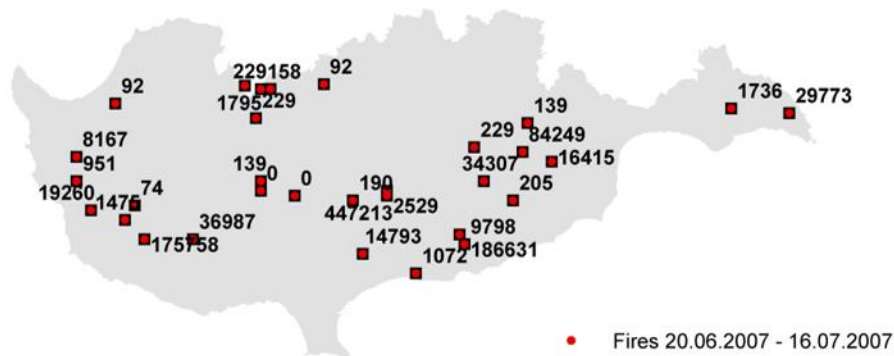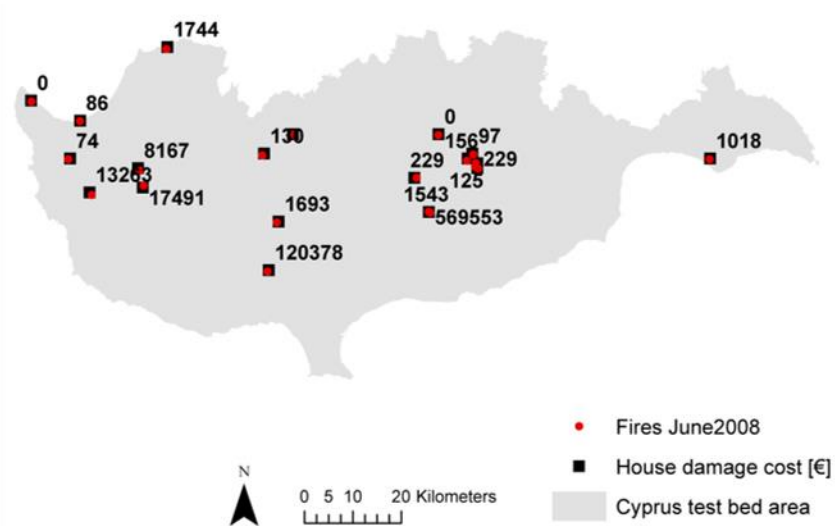Fig. 8. Expected housing economic loss [€] for days and locations where fires occurred in the period (a) 20. June 2007-16. July 2007 and (b) June 2008 on Cyprus study area.

716

(a) Burnt Area = 0.003 km², Fire Type = 1, FWI = 3

(b) Burnt Area = 0.4 km², Fire Type = 1-3, FWI = 60

Expected House Damage [€]
- 0 - 100
- 100 - 300
- 300 - 1'000
- 1'000 - 3'000
- 3'000 - 10'000
- 10'000 - 30'000
- 30'000 - 100'000
- 100'000 - 300'000
- 300'000 - 1'000'000
- 1'000'000 - 3'000'000
- 3'000'000 - 10'000'000

N

0 5 10   20 Kilometers

717
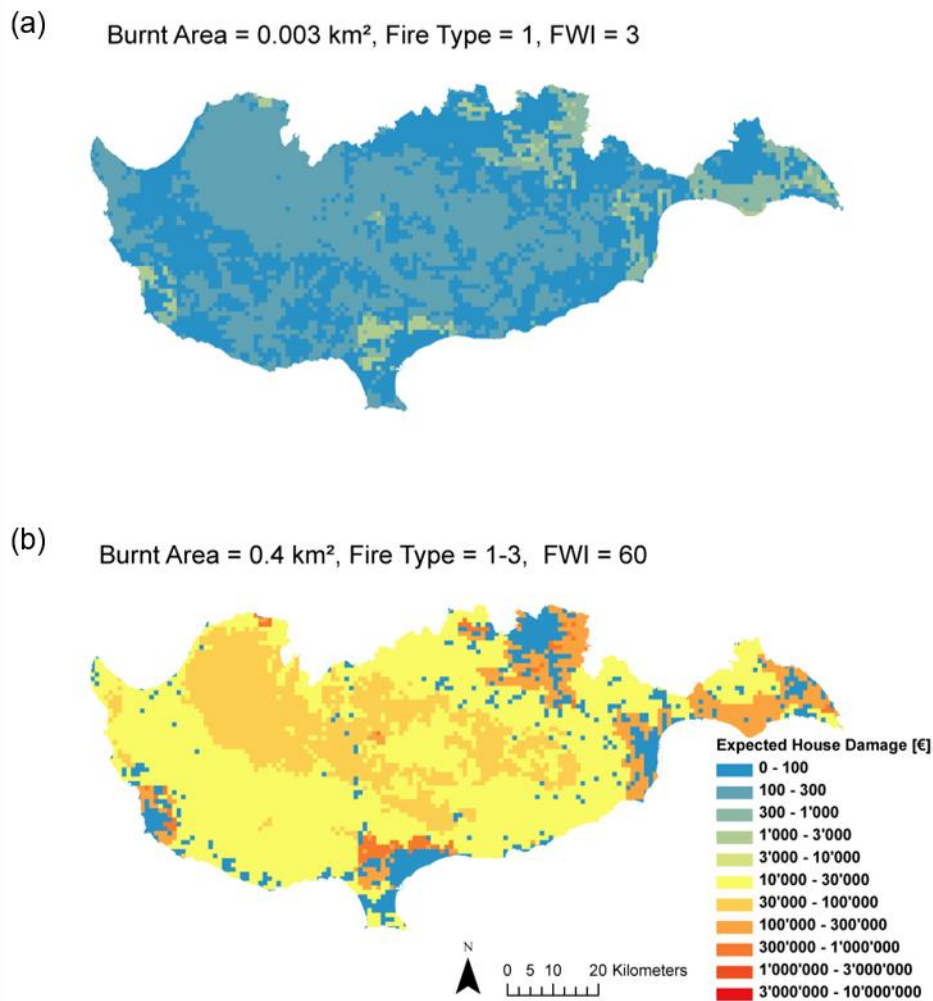
Fig. 9. Expected housing economic loss [€] conditional on (a) Burnt area = 0.003 km², Fire type = 1 and

FWI=3 and (b) Burnt area = 0.4 km², fire type = 1-3 and FWI=60 on Cyprus study area.

720

Note that in (b) for forested areas Fire type $=$ **3**, for shrubs Fire type $=$ **2** and for the rest land cover types Fire

type $=$ **1**, to account for realistic assumptions of the fire occurring (e.g. Fire type $=$ **3** refers to a crown fire

relevant only to forested areas).

725 Table S1. Effect of influencing variables on housing economic loss (HDC) in the BN. HDC is estimated after

726 giving evidence on each state of the variables.

Variable	States of the variable	Probability of variable being in the state $p(v)$	Expected value of HDC conditional for given value of the variable v [€] $E[HDC\|v]$	$(E[HDC\|v] - E[HDC])^2 \cdot p(v)$ Expected value of HDC: $E[HDC] = 18635 €$	Variance $\sum(E[HDC\|v] - E[HDC])^2 \cdot p(v)$	Standard deviation $\sqrt{\textbf{Variance}}$
Burnt area	0	0.11	0	$3.82 \cdot 10^7$	$6.08 \cdot 10^9$	$7.80 \cdot 10^4$
	< 0.01	0.42	327	$1.41 \cdot 10^8$		
	0.01-0.1	0.31	3606	$7.00 \cdot 10^7$		
	0.1-1	0.12	36178	$3.69 \cdot 10^7$		
	1-3	0.02	132109	$2.58 \cdot 10^8$		
	3-10	0.01	430013	$1.69 \cdot 10^9$		
	10-30	4e-3	10^6	$3.85 \cdot 10^9$		
Fire type	1	0.33	7556	$4.05 \cdot 10^7$	$3.05 \cdot 10^8$	$1.75 \cdot 10^4$
	2	0.50	13199	$1.47 \cdot 10^7$		
	3	0.17	56988	$2.50 \cdot 10^8$		
Construction type	5t_15s_80i	0.23	17263	$4.33 \cdot 10^5$	$5.63 \cdot 10^5$	$7.50 \cdot 10^2$
	10t_25s_65i	0.77	19046	$1.30 \cdot 10^5$		
Urban/Rural	urban	0.17	81258	$6.67 \cdot 10^8$	$7.95 \cdot 10^8$	$2.82 \cdot 10^4$
	rural	0.83	6229	$1.28 \cdot 10^8$		
House stock	40s_25r_35a	0.17	81258	$6.67 \cdot 10^8$	$7.95 \cdot 10^8$	$2.82 \cdot 10^4$
	70s_20r_10a	0.83	6229	$1.28 \cdot 10^8$		
Construction value	0-10,000	0.10	1353	$2.99 \cdot 10^7$	$3.09 \cdot 10^8$	$1.76 \cdot 10^4$
	10,000-50,000	0.29	7382	$3.67 \cdot 10^7$		
	50,000-100,000	0.41	13472	$1.09 \cdot 10^7$		
	100,000-500,000	0.21	51817	$2.31 \cdot 10^8$		

House density	0-3	0.15	515	$4.93 \cdot 10^7$	$2.75 \cdot 10^9$	$5.24 \cdot 10^4$
	3-10	0.25	2232	$6.73 \cdot 10^7$		
	10-30	0.34	6868	$4.71 \cdot 10^7$		
	30-100	0.18	19736	$2.18 \cdot 10^5$		
	100-300	0.04	50898	$4.16 \cdot 10^7$		
	300-1,000	0.04	165419	$8.62 \cdot 10^8$		
	1,000-3,000	7e-3	508982	$1.68 \cdot 10^9$		
House damage	no damage	0.95	0	$3.30 \cdot 10^8$	$9.06 \cdot 10^9$	$9.52 \cdot 10^4$
	minor	0.03	172405	$7.09 \cdot 10^8$		
	major	0.02	651701	$8.02 \cdot 10^9$		
FWI	0-10	0.36	15923	$2.65 \cdot 10^6$	$9.32 \cdot 10^6$	$3.05 \cdot 10^3$
	10-30	0.31	17838	$1.97 \cdot 10^5$		
	30-60	0.31	21542	$2.62 \cdot 10^6$		
	60-120	0.02	32667	$3.94 \cdot 10^6$		
Distance to next fire station	0-5	0.27	18001	$1.09 \cdot 10^5$	$2.24 \cdot 10^5$	$4.73 \cdot 10^2$
	5-10	0.46	18632	4.14		
	10-30	0.27	19287	$1.15 \cdot 10^5$		
Time for ground attack	5-10	0.27	18001	$1.09 \cdot 10^5$	$2.45 \cdot 10^5$	$4.95 \cdot 10^2$
	10-15	0.23	18419	$1.07 \cdot 10^4$		
	15-20	0.23	18848	$1.04 \cdot 10^4$		
	20-25	0.27	19287	$1.15 \cdot 10^5$		
Air suppression	no	0.50	32286	$9.32 \cdot 10^7$	$1.86 \cdot 10^8$	$1.37 \cdot 10^4$
	yes	0.50	4984	$9.32 \cdot 10^7$		
Fire Containment in 24 hrs	yes	0.91	0	$3.16 \cdot 10^8$	$3.30 \cdot 10^9$	$5.74 \cdot 10^4$
	no	0.09	200635	$2.98 \cdot 10^9$		
Land cover	1	0.09	0	$3.13 \cdot 10^7$	$9.70 \cdot 10^7$	$9.85 \cdot 10^3$
	2	0.10	12987	$3.19 \cdot 10^6$		
	3	0.04	18082	$1.22 \cdot 10^4$		
	4	0.19	12987	$6.06 \cdot 10^6$		
	5	0.21	33119	$4.41 \cdot 10^7$		
	6	0.26	23177	$5.36 \cdot 10^6$		
	7	0.02	0	$6.95 \cdot 10^6$		

Vegetation type	Grass	0.40	12987	$1.28 \cdot 10^7$	$1.01 \cdot 10^8$	$1.00 \cdot 10^4$
	Forest	0.21	33119	$4.41 \cdot 10^7$		
	Shrub	0.28	23177	$5.78 \cdot 10^6$		
	No vegetation	0.11	0	$3.82 \cdot 10^7$		

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728