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1 **Mapping territorial vulnerability to wildfires: a participative multi-criteria**
2 **analysis**

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12
13 **Highlights**

- 14 • Analytical Hierarchy Process proves a flexible method to assess vulnerability and risk
15 • Risk experience, wildland-urban interface and tree traits drive vulnerability
16 • Considering socio-economic drivers and several assets broadens the analysis
17 • Stakeholders confirmed the relevance of participative assessments using MCDA
18 • We identify vulnerable locations not yet subject to hazard

19
20 **Abstract**

21 The Mediterranean region is routinely affected by forest fires, with adverse consequences on
22 ecological, infrastructural, and socioeconomic assets. In a context of climate change, it is

23 crucial for fire prevention and suppression to be able to identify locations where assets are most
24 at risk, due to environmental, physical or socio-economic reasons. Besides, this knowledge
25 needs to be developed conjunctly with operational services and field experts to ensure their
26 application. So far, fire risk research has largely focused on fire behavior, effects, and model
27 simulation. In this article, we show how the concept of vulnerability can provide a flexible and
28 relevant framework for assessing fire risk and be evaluated using a spatial multicriteria decision
29 analysis method (MCDA) - the Analytical Hierarchy Process (AHP)- based on both
30 quantitative data and expert judgment gathered through a participative approach. We focus on
31 South-Eastern France, a region characterized by high economic and environmental stakes and
32 heavily affected by wildfires. We develop a series of spatialized indicators using ecological,
33 land-use and sociodemographic data which we aggregate to produce vulnerability maps for
34 three categories of assets: population, ecosystems and infrastructures. An ex-post workshop
35 was organized with field experts to put both the approach and results into discussion. Results
36 reveal significant differences in indicators' perceived contributions to risk and vulnerability
37 and enable appraising the contribution of sociodemographic factors, often overlooked in the
38 literature. We also reveal differences in spatial patterns across both vulnerability
39 subcomponents and exposed assets, helping identify primary and secondary vulnerability
40 hotspots and underlying drivers. Consideration of multiple subcomponents of risk and
41 vulnerability may help local decision makers prioritize how and where measures should be
42 implemented, while the use of MCDA favors experience and knowledge sharing and among
43 stakeholders while providing a basis of discussion.

44 **Keywords**

45 AHP, GIS-MCDA, wildfire, vulnerability, risk assessment, forest

46 1. Introduction

47 Human societies derive benefits from well-functioning ecosystems through the services they
48 provide (Diaz et al., 2019). Hazards such as storms, fires and pest outbreaks are natural
49 ecosystem features whose regimes (i.e. patterns of occurrence and intensity) are expected to be
50 affected by global changes (IPCC, 2021; Seidl et al., 2017). Wildfires, or forest fires, are one
51 of the commonest disturbances to affect vegetated ecosystems (Bowman et al., 2020) and can
52 negatively affect environmental, socio-economic, and infrastructural assets (Gill et al., 2013;
53 J. C. Liu et al., 2015). Their occurrence and behavior have environmental determinants such as
54 weather and fuel moisture, as well as anthropogenic determinants such as land-use patterns and
55 the presence of nearby activities (Bowman et al., 2020; Ganteaume et al., 2013). Most of these
56 are dependent on the local context, e.g. wildfires are known to be prevalent in locations with
57 high wildland-urban interface (Radeloff et al., 2018). As a result, there is a need to discuss and
58 prepare fire risk management policy locally with stakeholders, especially in regions where
59 wildfire regimes are expected to worsen, such as the Mediterranean (Dupuy et al., 2020; Pimont
60 et al., 2022).

61 As a field of study, wildfire risk assessment is concerned with the integrative evaluation of fire
62 likelihood and impacts (Oliveira et al., 2021). Wildfire risk is often defined as the resultant of
63 three characteristics: *fire occurrence* and *behavior* - their resultant being *fire likelihood*, i.e. the
64 probability that a fire will happen - and *fire effects* on values-at-risk (Finney, 2005; Thompson
65 et al., 2013). The evaluation of fire risk and its components have been made possible by the
66 development of sophisticated wildfire simulators alongside fire effects models (Costafreda-
67 Aumedes et al., 2017; O'Brien et al., 2018; Xi et al., 2019). Despite the existence of this
68 “technical” definition of wildfire risk, a large part of the literature either uses unclear
69 definitions or puts a strong emphasis on fire hazard, i.e. the physical phenomenon, through

70 metrics such as burn probability and fire intensity (Johnston et al., 2020), ignoring the impact
71 on values-at-risk.

72 The natural hazards literature, especially that related to climate change (e.g. Füssel & Klein,
73 2006; Metzger et al., 2006) adopts a broader definition of risk as “*the potential for*
74 *consequences where something of value is at stake and where the outcome is uncertain*” (IPCC,
75 2019). Within this framework, vulnerability refers to “*the propensity or predisposition to be*
76 *adversely affected by a hazard, including sensitivity or susceptibility to harm and lack of*
77 *capacity to cope and adapt*”. Applications of this framework, despite shifting contours, share
78 a common point in the consideration of four key aspects: hazard, exposure of assets, their
79 susceptibility (or sensitivity) and adaptive capacity (also, coping capacity or resilience) (Comte
80 et al., 2019). Despite their similarities, this latter conceptualization is more encompassing than
81 the traditional view of wildfire risk due to the clear distinction made between exposure of assets
82 and hazard likelihood, the explicit inclusion of adaptive capacity and the consideration of social
83 and economic dynamics. Besides, clearer boundaries are set to vulnerability, while the term
84 can be found in the fire risk literature with a meaning akin to sensitivity (Johnston et al., 2020;
85 Liu et al., 2012). While some recent studies have adopted this broader view (Ghorbanzadeh et
86 al., 2019; Lecina-Diaz, Martínez-Vilalta, Alvarez, Vayreda, et al., 2021; Oliveira et al., 2018,
87 2020; Thorne et al., 2010), the general framework has only recently been formally adapted to
88 the case of forest-related natural hazards (Lecina-Diaz, Martínez-Vilalta, Alvarez, Banqué, et
89 al., 2021; Oliveira et al., 2018; Vaillant et al., 2016).

90 Many fire risk assessments use model simulations, raising questions of model integration, the
91 use of a common (often monetary) metric, and, given model complexity, the difficulty to
92 transfer knowledge to local decision makers. Model-based assessments also tend to overlook
93 or simplify human and social dimensions, even though recent advances have been made

94 regarding e.g. citizen involvement and behavioral aspects (Johnston et al., 2020; Oliveira et al.,
95 2021). This can be addressed with multiple-criteria decision analysis (MCDA), which relates
96 to an ensemble of methods that propose a structured and formal framework for assessing
97 complex problems considering several dimensions. MCDA methods can integrate data of
98 mixed natures, including expert knowledge, and foster collaborative decision making by
99 providing focus to discussions. MCDA is particularly well-suited for natural resources
100 management issues, especially at local scales (Mendoza & Martins, 2006). Their further
101 integration into Geographic Information Systems (GIS) enables the combination of spatial data
102 and value judgements to create visual information supporting decision making. GIS-MCDA
103 methodologies have proven to be powerful, comprehensive and convenient tools in
104 environmental planning when spatial drivers are significant (Malczewski, 2007; Malczewski
105 & Rinner, 2015), including applications to hazard risk assessment for e.g. floods, earthquakes
106 and explosions (Duzgun et al., 2011; Fernandez et al., 2015; Ghajari et al., 2017; Le Cozannet
107 et al., 2013; Nyimbili et al., 2018; Pham et al., 2021). Owing to the emphasis on the physical
108 phenomenon and model simulation, similar examples are scarcer in the fire risk literature.
109 Ghorbanzadeh et al. (2019) use GIS-MCDA to assess social and infrastructural vulnerability
110 based on census, land-use and economic data. They subsequently demonstrate the coupling of
111 vulnerability maps to hazard maps generated with machine learning models to assess overall
112 fire risk. Oliveira et al. (2020) focus on risk to populations and jointly assess hazard exposure
113 and vulnerability using a fire spread simulator and a clustering algorithm on sociodemographic
114 and geographic data. They also show how their model could be used to inform policy planning
115 by evaluating overall risk under various scenarios of land management policy. Another
116 example is given by Thompson et al. (2013), which consider several exposed assets and expert
117 knowledge in their assessment of vulnerability.

118 In this article, our objective is to perform an encompassing assessment of fire risk based on the
119 vulnerability concept, using field knowledge from experts with direct experience with wildfires
120 and considering three assets of different natures important at the territorial scale: population,
121 ecosystems and infrastructures. A secondary objective is to explore and confirm the potential
122 of a MCDA participative approach to foster discussion between experts that do not usually
123 engage in dialogue, in a field where model-based evaluations by academics constitutes the main
124 research methodology. As a result, our approach is exploratory and is not a predictive
125 assessment: the research process is as important as results, which are themselves (e.g. maps)
126 tools to foster discussion and the emergence of collaborative knowledge.

127 Vulnerability is decomposed into a hierarchical problem and its subcomponents – exposure,
128 sensitivity and adaptive capacity – are assessed by integrating quantitative land-use, economic
129 and sociodemographic data as well as expert knowledge and simulation results using the
130 Analytic Hierarchy Process (Saaty, 2004), a MCDA method based on stakeholder participation
131 and expert judgment. This approach of vulnerability is furthermore combined with probabilistic
132 modelling of fire activity (Pimont et al. 2021) to assess fire hazard, hence resulting in an
133 integrated multidisciplinary approach to wildfire risk. We focus on South-Eastern France, a
134 fire prone area with contrasted land-use patterns which influence fire activities (Castel-Clavera
135 et al., 2022) and where fire regimes are expected to worsen through significant intensification
136 of fire activities, an expansion of the fire-prone region and a lengthening of the summer fire
137 season (Pimont et al. 2022).

138 We aim to develop a methodology suited to our biophysical and institutional context and to
139 provide synthetic, visual and interpretable results at the meso scale. The availability of such
140 resources can have implications for local stakeholders engaged in fire risk management,
141 helping them identify vulnerability hotspots and underlying drivers, and to select measures to

142 be implemented locally. These latter aspects were discussed in an ex-post workshop with field
143 experts.

144 **2. Material and methods**

145 **2.1. General framework**

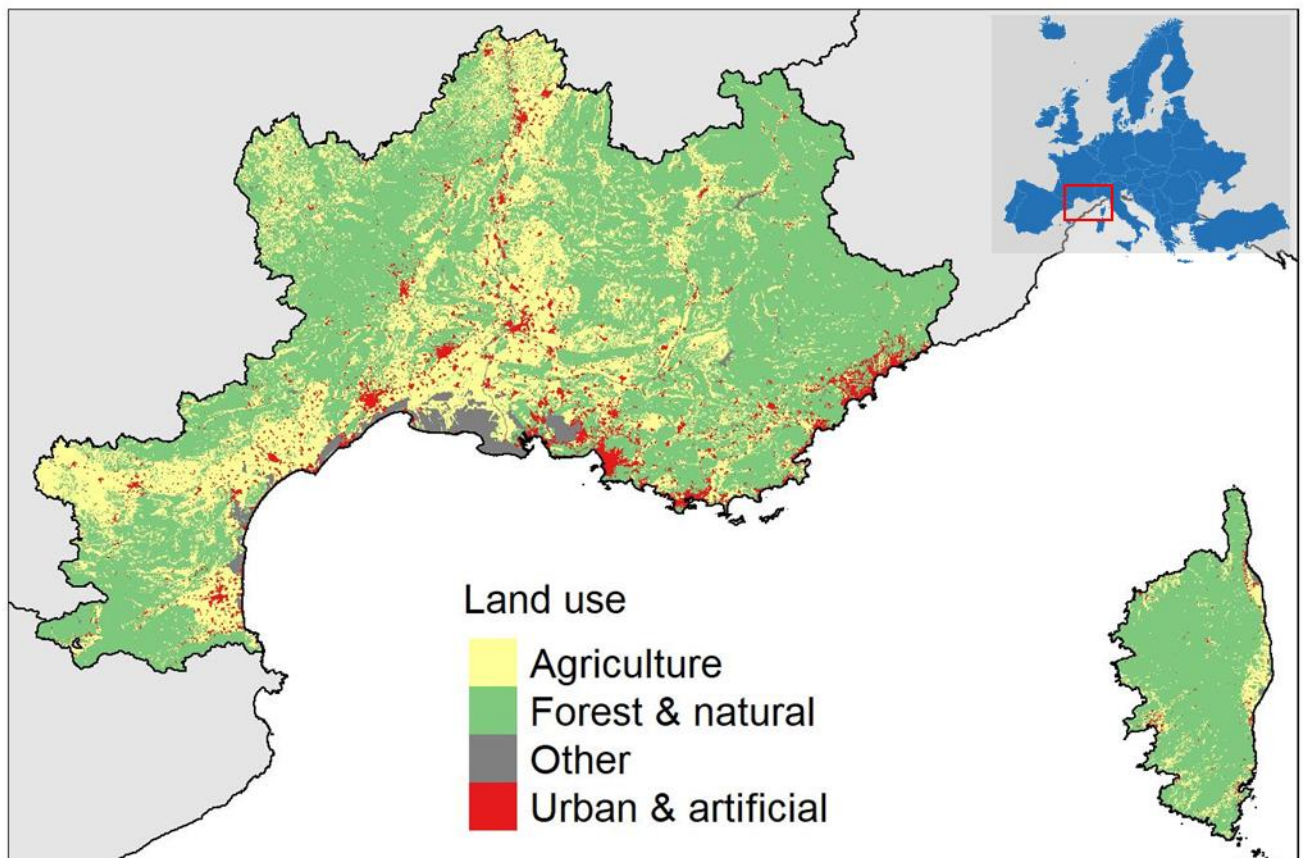
146 **2.1.1. Presentation of the study area**

147 We focus on South-Eastern France (Fig. 1), namely the area known as *Prométhée* after the fire
148 observation database covering it (<https://www.promethee.com/>). The region is mostly
149 Mediterranean but displays varied topographic conditions with coastal plains, the Rhône river
150 valley and several mountainous areas (e.g. the Alps¹). It also includes the mountainous and
151 highly forested Corsica island. Forests cover 30% of land area, agriculture 49% and artificial
152 land uses 5% (Figure 1). Fires in the area are very numerous and an average of 9000 ha have
153 burned yearly over in the period 2011-2021, representing 80% of the national total. Most fires
154 occur over the summer (May-October) and are largely human-caused, voluntarily or
155 accidentally. They tend to occur close to population centers, in areas with high wildland-urban
156 or wildland-agriculture interfaces, and in locations with touristic frequentation (Ganteaume et
157 al., 2013; Ruffault & Mouillot, 2017). Over the decades to come, fire danger is expected to
158 increase significantly owing to increases in temperatures and changes in precipitation patterns
159 (Dupuy et al., 2020; Fargeon et al., 2020). Climate change could induce an increase in the
160 number of large fires (>100ha) by up to +180% for a +4°C warming, a doubling of fire-prone
161 areas and a large symmetrical lengthening of the summer fire season (Pimont et al. 2022).
162 Stakes in terms of exposed assets are high. There are over 9 million inhabitants in the area
163 (14% of France's population), most of which are located in the lowlands, which also includes
164 large economic and industrial centers. The region comprises 5 national parks and more than 15

¹ An annotated map of the study area is provided in Appendix B.

165 regional parks with valuable habitats, as well as numerous reserves. Owing to the mountainous
166 nature of many locations, in addition to classical ecosystem services (e.g. wood production,
167 carbon storage), forests also provide important regulation services (e.g. erosion and flood
168 control), as well as aesthetic and cultural services due to touristic frequentation, which is very
169 high in the summer along the coast and in the mountains. These Land-Use and Land-Cover
170 factors affect spatial patterns of fire activity (Castel-Clavera et al., 2022).

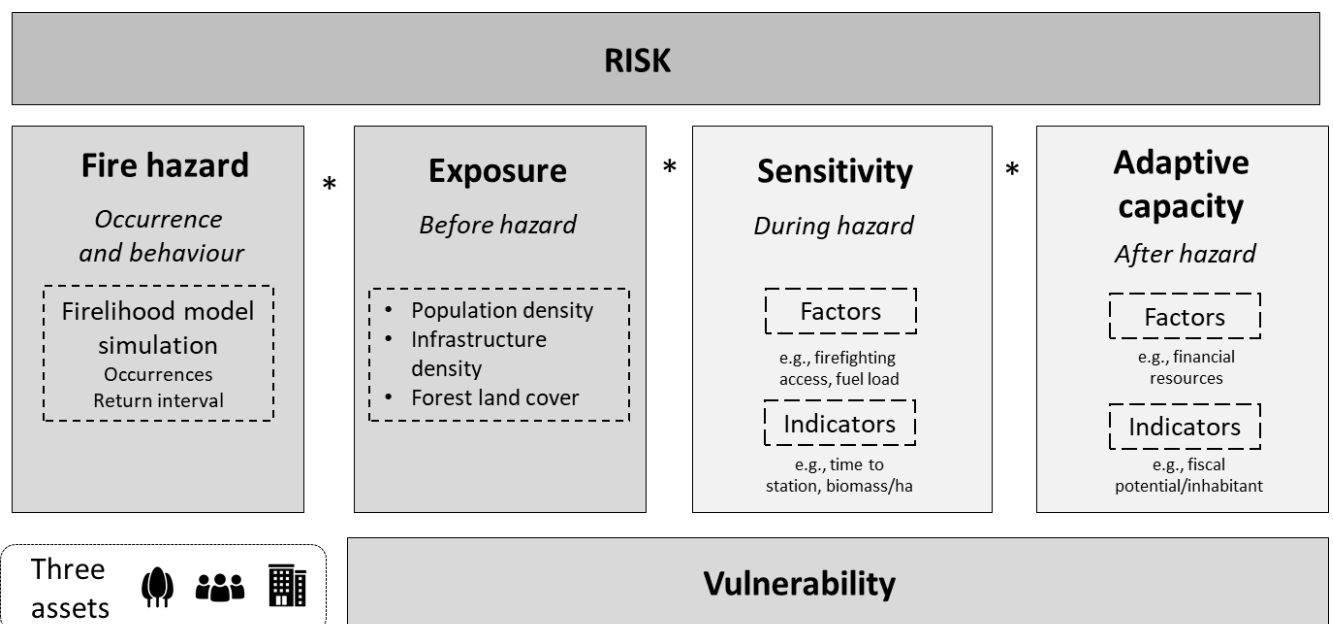
171



172 *Figure 1 – Location and land-use in the study area. “Other” land-uses include wetlands,*
173 *water bodies and open spaces with little to no vegetation in the Corine Landcover*
174 *Classification.*

175 **2.1.2. Conceptual framework on vulnerability**

176 We conceptualize fire risk and vulnerability following frameworks developed by Lecina-Diaz
 177 et al. (2021) and Oliveira et al. (2018) for forest disturbances and forest fires respectively
 178 (Figure 2). Risk and vulnerability are defined with regards to *exposed assets* (or values-at-risk)
 179 that contribute to wellbeing in societies and may be damaged. *Exposure* is defined as the
 180 presence of valuable assets before the hazard occurs. *Sensitivity* refers to the asset's
 181 susceptibility to sustain damage during or immediately after the hazard's occurrence. *Adaptive*
 182 *capacity* (AC) is defined as the asset's ability to cope with damage that has been sustained and
 183 to recover after the hazard has occurred. Both sensitivity and AC depend on *intrinsic factors*
 184 (e.g. bark thickness, housing density) and *extrinsic factors* (e.g. silvicultural practices, financial
 185 resources). *Vulnerability* then refers to the assets' propensity to be adversely affected by the
 186 hazard, to cope and recover from it, and is the resultant of exposure, sensitivity and AC. In
 187 turn, *risk* is defined as the potential for negative consequences for an asset due to a hazard that
 188 may occur. It is the resultant of vulnerability and *hazard*, which refers to the physical fire
 189 phenomenon (occurrence and behavior).



191 *Figure 2 - Risk and vulnerability framework used in the assessment, adapted from Oliveira*
192 *et al. (2018) and Lecina-Diaz et al. (2021)*

193 **2.1.3. The Analytical hierarchy process**

194 The Analytical Hierarchy Process (AHP, Saaty 2004) is a weighted additive MCDA method
195 based on problem decomposition and the subsequent aggregation of indicators, where weights
196 are attributed to individual indicators through a binary comparison process involving expert
197 judgment. Within a GIS environment, AHP is used to compute weights attributed to layers of
198 spatial data representing criteria and to produce synthetic maps (Malczewski & Rinner, 2015).

199 For each indicator pair, relative preference is quantified by experts using the verbal scale by
200 Saaty (2004), to which an underlying 1-9 scale is associated². Scores are then compiled in a
201 matrix of order n , where c_{jk} is the pairwise comparison score between factors j and k , and n is
202 the number of factors. The matrix is reciprocal and scores on the diagonal are equal to 1, hence
203 only $n * (n - 1)/2$ comparisons are required. The relative importance of factors, or weights,
204 are given by the principal eigenvector of the matrix. These are computed as $w_k = \sum_{k=1}^n c_{jk}^*/n$,
205 where w_k are the computed weights for factors and c_{jk}^* are the matrix's coefficients normalized
206 over columns. A consistency ratio CR is computed to assess the level of inconsistency in expert
207 judgments. It is computed as $(\lambda_{max} - n)/(RI * (n - 1))$, where λ_{max} is the maximum
208 eigenvalue of the matrix and RI , or random index, is the consistency ratio of randomly
209 generated matrices.

210 Aggregation of individual judgements is performed using the geometric mean as it preserves
211 the AHP axioms and matrices' properties and dampens the effects of extreme judgements.
212 Given a large enough sample size, consistency of the aggregated matrix will tend towards 1,

² See Appendix A.

213 e.g. a 20 sample size is enough to reach 90% consistency for matrices of order 3 or more (Aull-
214 Hyde et al., 2006; Bernasconi et al., 2013). Once weights are computed, a score for the
215 objective higher up in the hierarchy (e.g. sensitivity of population) is calculated using weighted
216 summation. Within the GIS environment, scores are calculated by combining weights with
217 layers of spatial data for each indicator and location.

218 **2.2. Application to fire vulnerability**

219 ***2.2.1. Problem decomposition and choice of indicators***

220 We adopt a hierarchy with three levels (Fig. 2). The first level comprises the two concepts
221 assessed in the study: risk and vulnerability. The second level corresponds to subcomponents
222 of the two concepts: hazard, exposure, sensitivity and adaptive capacity (AC). The third level
223 refers to factors, i.e. reasons why an asset may be more or less vulnerable, and indicators, i.e.
224 variables developed to quantify factors. Factors are therefore defined by a rationale (e.g. a place
225 that is easily accessible to firefighters is less sensitive), while indicators are measurable and
226 characterized by values (e.g. distance to the nearest fire station).

227 **Hazard**

228 Hazard refers to the likelihood of fires, including both occurrence probability and fire spread.
229 At the regional scale, fire activity can be represented through emergent properties, in particular
230 burned areas. Hazard was quantified using simulations with Firelihood, a probabilistic fire
231 activity model developed for Southern France and estimated in a Bayesian framework using
232 the Fire Weather Index (Van Wagner, 1987) and forest area as predictors (Pimont et al., 2021).
233 It represents fire activity as a Poisson point process and comprises two sub-models: one
234 determining fire occurrence probability and one determining fire sizes for fires larger than 1ha.
235 The sequential use of the two enables the simulation of fire occurrences and their subsequent

236 spread, yielding a spatialized account of burned areas at the 8km pixel and daily scales. We
237 used the mean annual burned area computed from a set of 1000 stochastic replications as the
238 indicator for fire hazard.

239 *Vulnerability*

240 For exposure, one indicator was developed per asset: population density, land-use share of
241 forest ecosystems and infrastructural building density. For sensitivity and adaptive capacity,
242 the choice of factors and indicators was based on a review of the specialized literature. Factors
243 also needed to be relevant at the regional study scale and quantifiable at the 1km pixel scale
244 using publicly available data. For this reason, factors such as building materials were discarded
245 while date of construction was preferred. We give a brief overview of the reasoning behind
246 such choices below (Table 1).

247 Three factors for population's sensitivity relate to ease of evacuation (Table 1): the presence of
248 collective housing and the presence of large or single-adult households, who are harder to
249 evacuate, and the presence of young and elderly people who may require assistance.
250 Unemployment level and household wealth were selected as they relate to access to resources,
251 highlighted, contributing to social vulnerability (Emrich et al., n.d.; Geomatics et al., 2017;
252 Nguyen et al., 2017). Geographic isolation contributes to increased sensitivity by making
253 evacuation more complex while also relating to lower access to resources (services). Several
254 of these also relate to ease of defending the property (e.g. harder with children, easier when
255 better equipped). Factors for population's AC relate to their ability to recover over the medium
256 term by having access to various forms of community-level support (e.g. financial, social),
257 information and health services. Recent experience of fire events is also considered to
258 contribute to better AC (Edgeley et al., n.d.; Paveglio et al., 2009).

259 Three factors for ecosystem sensitivity were based on firefighting services' capacity to monitor,
260 access and defend the area. Two other factors were based on forests' intrinsic characteristics:
261 fuel load, known to favor fire activity and intensity, and the intrinsic sensitivity of tree species.
262 Three factors for AC were based on extrinsic features, two of which are shared with other assets
263 (risk experience and city-level financial resources). Besides, we considered public forests to
264 have better AC given their active monitoring and management by authorities, while private
265 forest owners, especially in fragmented and remote areas, can be absentee (Lindner et al.,
266 2010). Two factors account for ecological features: tree species' intrinsic AC and fire return
267 interval, estimated from the Firelihood model (Pimont et al., 2021).

268 Factors for the sensitivity of infrastructures relate to the buildings' capacity to withstand
269 damage (recent buildings are designed for better evacuation and resistance), to ease of access
270 for firefighting services as well as to the presence of sensitive industrial compounds nearby
271 that may aggravate potential damages. We also took into account the presence of wildland-
272 urban interface, i.e. intermingled vegetation and urban land-uses, which is known to favor fire
273 activity (Ganteaume & Jappiot, 2013; Radeloff et al., 2018). Factors for the AC of
274 infrastructures largely relate to the coping capacity of their owners, occupants and of local
275 authorities, and we use the same factors as for populations, except access to health services and
276 social isolation, which are specific to people.

277 **2.2.2. Computation and aggregation**

278 All indicators were computed on GIS software QGIS (<https://qgis.org>) at the scale of 1km wide
279 pixels. They were computed from publicly available sociodemographic, economic and land-
280 use data from the Geographic National Institute (IGN), the National Institute for Statistics and
281 Economic Analysis (INSEE), the French Observatory of Territories, and the French Forest
282 Agency (ONF) databases. Most were natively at the pixel size (no treatment) or at larger pixel

283 and municipality scales and were downscaled to 1km pixel size. Cover shares for land-use data
284 were computed using QGIS's overlay and buffer tools, and distances using the nearest neighbor
285 tool. Fuel load was directly taken from the raster map by the EU Joint Research Center
286 (Avitabile & Camia, 2018) and computed with the raster calculator. Intrinsic sensitivity had
287 been previously assessed for dominant tree species of the national high-resolution forest cover
288 database (BD Forêt) by experts of the French Forest Agency (ONF) and was kindly provided
289 as a raster map for this study.

Component	Factor	Indicator	Weight	CR
Asset 1 - Population				
Exposure	Resident population	Population density (people/km ²) *	1	-
Sensitivity	Geographic isolation	Average access time to intermediate-level-services (min) •	0,42	1,40%
	Age	People under 10 and over 65 years old (%) *	0,18	
	Housing type	Households in collective housing (%) *	0,14	
	Household composition	Households with only one adult or 3 or more children (%) *	0,12	
	Unemployment	Unemployed people (%) *	0,07	
	Household wealth	Winsorised household wealth (€) *	0,06	
AC	Risk experience	Burned area over the past 10 years (ha, www.promethee.com)	0,30	1,90%
	Financial resources	Fiscal potential per inhabitant at city level (€) •	0,19	
	Access to health	Localised potential accessibility to doctors•	0,12	
	Social isolation	People either unemployed or over 75 years old (%) •	0,14	
	Geographic isolation	Average access time to intermediate-level-services (min) •	0,14	
	Education level	People with higher education (%) •	0,11	
Asset 2 - Ecosystems				
Exposure	Presence of forests	Pixel area covered by forests (%) †	1	-
Sensitivity	Intrinsic sensitivity	Pixel area with sensitivity classes 4-5 (% , ONF)	0,29	1,90%
	Fuel load	Biomass per hectare (Mt/ha, JRC Avitabile et al. 2020)	0,23	
	Surveillance	Pixel area covered by surveillance and patrol zones (% , ONF)	0,22	
	Defendability	Pixel area within 200m of roads and water points (% , ONF)	0,19	
	Firefighting access	Distance to nearest station (km) †	0,07	
AC	Intrinsic adaptive capacity	Pixel area with adaptive capacity classes 4-5 (% , ONF)	0,43	0,80%
	Fire return interval	Fire return interval (years, firelihood model simulations Pimont et al. 2021)	0,29	
	Risk experience	Burned area over the past 10 years (ha, www.promethee.com)	0,10	
	Financial resources	Fiscal potential per inhabitant at city level (€) •	0,10	

	Property regime	Pixel area of publicly owned forests (% , www.data.gouv.fr)	0,07	
Asset 3 - Infrastructure				
		Pixel area covered by commercial, residential and industrial buildings (%) †	1	-
Exposure	Presence of buildings			
	Wildland-Urban Interface (WUI)	Pixel area within 200m of both forest and urban land-uses (% , CORINE Landcover)	0,50	
Sensitivity	Building use	Distance to closest Classified Installation of Environmental Protection ICPE (km, www.data.gouv.fr)	0,24	0.50%
	Firefighting access	Distance to nearest station (km) †	0,18	
	Age of building	Number of buildings built before 1990 (%)*	0,08	
	Financial resources	Fiscal potential per inhabitant at city level (€) •	0,54	
AC	Risk experience	Burned area over the past 10 years (ha, www.promethee.com)	0,23	2,10%
	Education level	People with higher education (%) •	0,12	
	Geographic isolation	Average access time to intermediate-level-services (min) •	0,11	
Fire Hazard				
Hazard	Mean annual burned area	Mean annual burned area (ha) over 1000 simulations with the fire model Firelihood (Pimont et al. 2021).	1	-

291 *Table 1 – List of factors and indicators for risk and vulnerability components: exposure,*
292 *sensitivity and adaptive capacity (AC). Indicators are presented by order of decreasing*
293 *importance following the Analytical Hierarchy Process. Data was retrieved from publicly*
294 *available databases from INSEE (*), Observatoire des Territoires (*) and IGN (+), unless*
295 *indicated otherwise.*

296 Indicators use different units and scales and were standardized before summation using the
297 score range procedure, yielding unitless values between 0 and 1 (Malczewski, 1999). Most
298 were right-skewed and were winsorized between their 95% and 100% quantiles prior to
299 standardization. This procedure ensures that post-aggregation results use a large range of
300 values, facilitating map interpretation by experts in workshops. It amounts to assuming that the
301 contribution of any given indicator to vulnerability becomes marginal for very high values at
302 the right end of the distribution (e.g., that an extremely wealthy community is as vulnerable as
303 a very wealthy community).

304 After the weighted summation of indicators, vulnerability was obtained by multiplication of
305 exposure, sensitivity and AC. Risk was computed by multiplying vulnerability with hazard. All
306 metrics computed were represented on maps using the Jenks natural breaks algorithm, a
307 clustering procedure which minimizes variance within classes and maximizes variance across
308 classes and is particularly well suited for representing data on choropleth maps.

309 **2.3. Expert selection, interviews and discussion workshop**

310 Given, the objective of bridging the gap between science and field knowledge, experts were
311 primarily drawn from local agencies working with wildfires and selected based on experience
312 rather than academic background. We interviewed policy officers from the French agencies of
313 the environment and agriculture and members of firefighting forces. We also included scientists
314 conducting research on fire risk. 48 experts were contacted and 22 agreed to be interviewed

315 (Table 2). Interviews lasted between 1 and 2 hours each and, given restrictions due to the Covid
 316 pandemic, were conducted through videoconference. The project’s general objective and
 317 methods were explained to interviewees, examples of pairwise comparisons were given for
 318 training, and factors were explained beforehand.

Institution	Contacted	Interviewed
French forest agency	6	4
Firefighting and prevention	9	5
Public agencies	22	9
Scientists	7	3
Private sector	4	1
Total	48	22

319 **Table 2 – Breakdown of experts interviewed.**

320 The last step of the process was the organization of a workshop with the same pool of experts.
 321 As mapping constitutes a modified representation of a spatial phenomenon (Malczewski &
 322 Rinner, 2015; Palsky, 2013), resulting conclusions must be discussed by stakeholders to ensure
 323 results appropriation and to contribute to local risk management. this constitutes an *ex-post*
 324 validation of result where maps are considered as visualization and dialogue tools. We
 325 specifically discussed the geographical implications of results through a three steps process:
 326 (1) redefining key concepts, (2) collective appropriation of results, issue identification and (3)
 327 discussion on key messages and limitations for decision makers and practitioners. Inspired by
 328 participatory research approaches in a pandemic context (Hall et al., 2021), workshops were

329 conducted using the online collaborative workspace MURAL (<https://www.mural.co/>). This
330 allowed participants to freely navigate through the maps and tables in an interactive manner
331 while discussing results and writing down personal observations.

332 **3. Results**

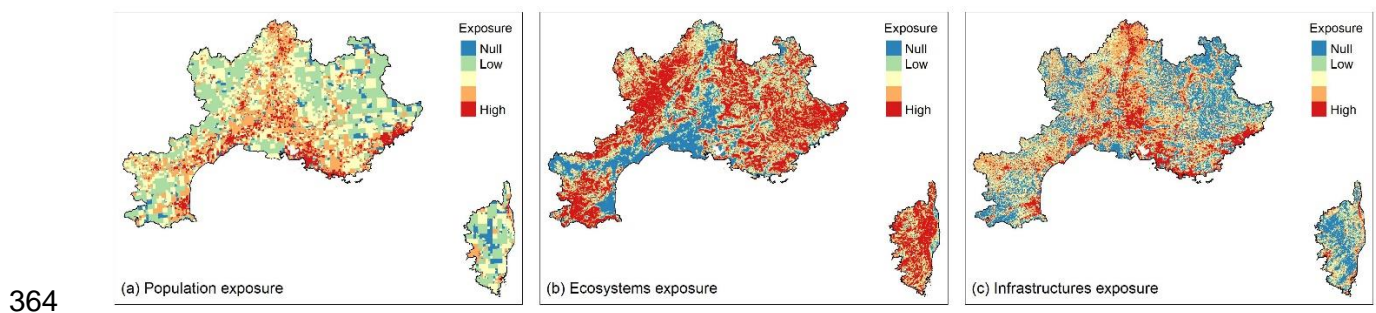
333 **3.1. AHP results and aggregation**

334 AHP results show that experts considered geographic isolation to be the main factor
335 contributing to population's sensitivity (42% weight) while all three factors related to ease of
336 evacuation had intermediate weights (12-18%, total 43%). Access to resources (wealth,
337 unemployment) was judged not to be as important (6-7%). Results for AC display moderate
338 contributions for all factors (11-30%), among which past experience with fire hazard was
339 judged most important (30%), followed by financial resources (19%). Experts judged that
340 ecosystem sensitivity was primarily dependent on intrinsic forest characteristics - intrinsic tree
341 sensitivity (29%) and fuel load (23%). As for factors related to firefighting, surveillance (22%)
342 and defendability (19%) were deemed more important than ease of access (7%). AC was judged
343 to be mainly determined by ecological factors, namely tree species' intrinsic adaptive capacity
344 (43%) and fire return interval (29%), while socio-economic factors were deemed less relevant
345 (7-10%). All matrices showed high levels of consistency with consistency indices below 5%.
346 For infrastructures, sensitivity was judged by experts to be overwhelmingly dominated by the
347 presence of WUI (50%). The presence of firefighting access, a mitigating factor, and that of
348 sensitive industrial sites nearby, an aggravating factor, were also deemed important (18% and
349 24% respectively), while building age, an intrinsic characteristic, was not (8%). AC was judged
350 to be mostly determined by financial resources (54%) and experience of risk (23%).

351 **3.2. Vulnerability maps for individual assets**

352 **3.2.1. Population**

353 Densely populated urban areas are mostly located along the coast and in the Rhône valley (Fig.
354 3a). In mountainous areas (e.g. the Alps), the most exposed areas are concentrated in valleys,
355 while exposure is more homogeneous in the plains. Sparsely populated areas such as Corsica
356 are little exposed. Sensitivity (Fig 4) is higher in the North-East and North-West of the study
357 area as well as in Corsica. This corresponds to the most remote locations (largely mountainous),
358 which are characterized by a high share of people with reduced mobility (esp. elderly) and the
359 most distant to public and rescue services. Given the relatively low importance given to access
360 to financial resources by experts, the South-West area, despite high unemployment and low
361 wealth, appears as moderately sensitive. On the other hand, local clusters of intermediate
362 sensitivity appear in well-connected urban centers (e.g. Narbonne, Marseille) owing in part to
363 the high proportion of shared housing and large households³.



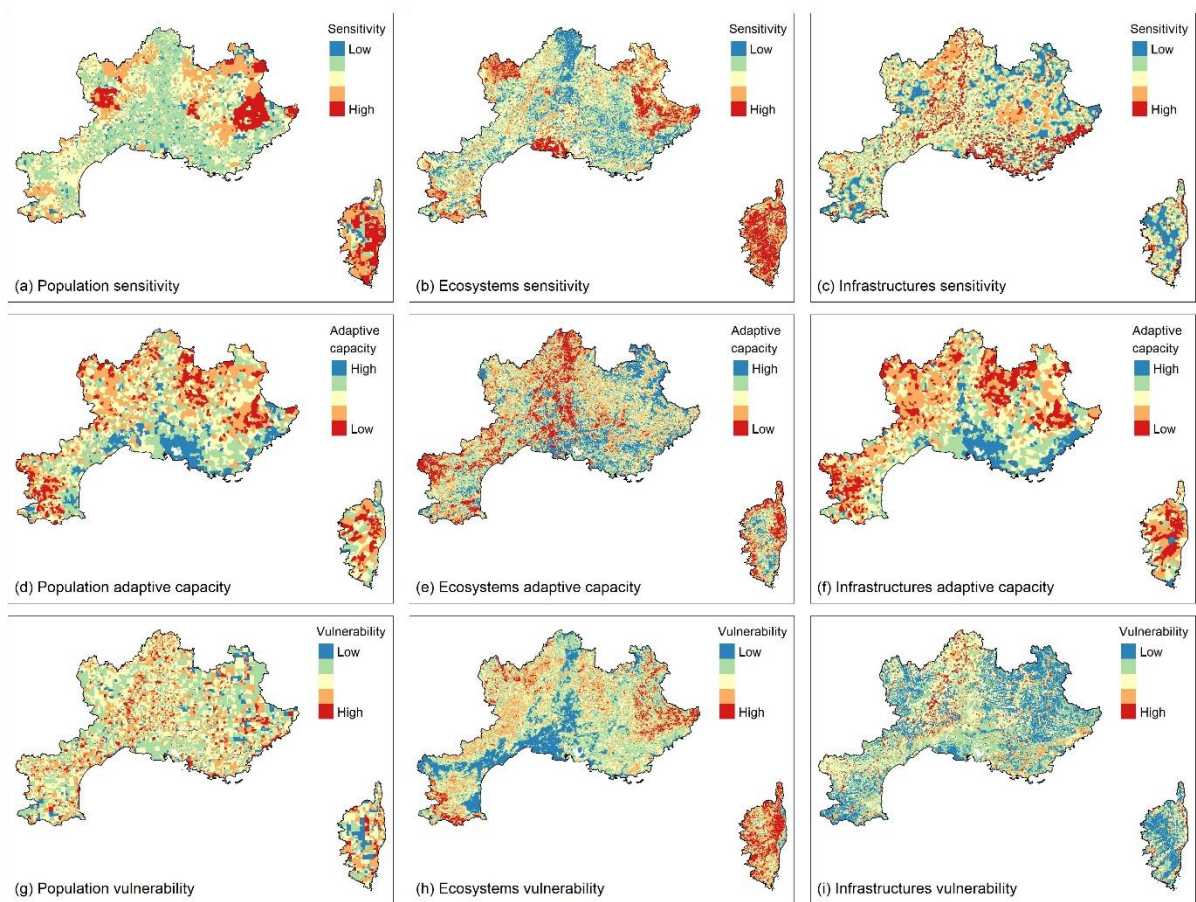
365 **Figure 3 - Maps of exposure for the three assets studied: population (a), ecosystems (b) and**
366 **infrastructures (c). Red areas indicate strong contribution to vulnerability (i.e. high**
367 **exposure, cf. Table 1).**

368 AC mostly follows the spatial patterns of risk experience and financial resources, with high
369 values (i.e. low contribution to vulnerability, blue-green on maps) on cities on the eastern coast
370 where both indicators display high values. Urban areas along the Rhône valley and the south-
371 western coast display slightly lower AC due to only financial potential or risk experience being

³ Maps for individual indicators' contribution of vulnerability components are available as an Electronic Supplementary Material on the journal's website.

372 very strong respectively. Large urban areas (i.e. Marseille, Montpellier) display among the
373 highest values for AC and are also characterized by high levels of education and access to
374 health services. Lowest AC is found in the mountainous hinterland, where not only risk
375 experience and financial resources are low, but also access to services, while social isolation is
376 stronger. Despite low levels of social isolation and relatively high financial resources, the
377 Northern Rhône and Alpine valleys display intermediate AC owing to the low importance
378 given by experts to the factor, their low levels of risk experience and, for the latter, lower access
379 to services.

380 Owing to low exposure despite high sensitivity and low AC, vulnerability is low or null in the
381 hinterland and mountainous areas. On the contrary, urban areas along the Rhône valley and the
382 coast, while strongly exposed, show limited vulnerability due to low sensitivity and higher AC.
383 Areas where populations are most vulnerable are located at the margin between large urban
384 centers and the hinterland, around secondary cities and along the Alps valleys, where sensitivity
385 is high, AC low and exposure at an intermediate level. Figure 5 displays differences in
386 vulnerability when using AHP weights instead of equal weights. Using expert knowledge
387 increases vulnerability in remote areas (strong isolation), and decreases it along major
388 population axes, to a limited extent.



389

390 **Figure 4 - Maps of sensitivity, adaptive capacity and vulnerability for the three assets studied:**
 391 **population (a, d and g), ecosystems (b, e and h) and infrastructures (c, f and i). Red areas**
 392 **indicate strong contribution to vulnerability (i.e. high sensitivity, low AC). Larger maps with**
 393 **higher resolution can be found in electronic supplementary materials.**

394

3.2.2. Ecosystems

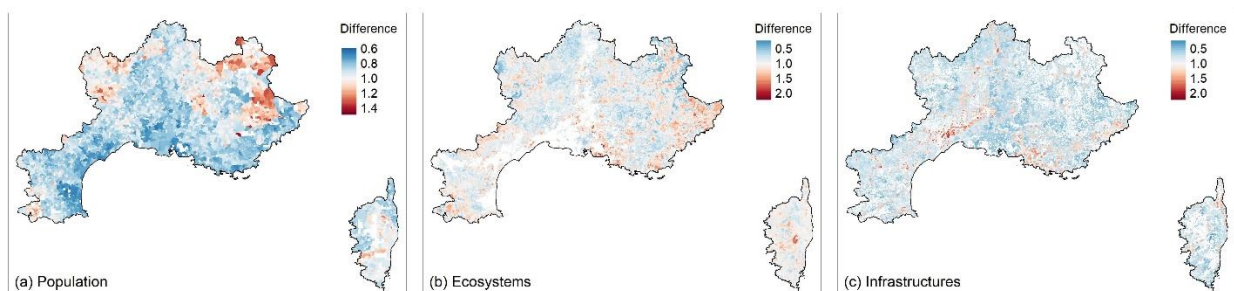
395 Ecosystem exposure matches the “forest and natural” type of land-use and therefore is highest
 396 in hilly and mountainous areas located further away from urban centers, agricultural land and
 397 vineyards.

398 Sensitivity is highest in areas that are both less surveilled and have high fuel loads, e.g. remote
 399 mountainous locations to the North-East and North-West, but also in surveilled locations with
 400 high fuel load and a strong presence of intrinsically sensitive forests, e.g., the Ardèche,

401 Cévennes and Vercors areas. Many areas with high intrinsic sensitivity, especially along the
402 coast and its immediate hinterland, display moderate sensitivity values owing to lower levels
403 of fuel load, surveillance of the area and proximity to fire stations. The moderating influence
404 of defensible areas can be witnessed locally, e.g. in Corsica where their presence results in
405 sensitivity values one or two classes lower than in similar, non-defensible locations. AC
406 follows the general patterns of forests' intrinsic AC, even though some of these display low to
407 moderate levels of AC owing to the influence of fire return interval, e.g. along the South-
408 Western coast. Risk experience and financial resources intervene as aggravating or moderating
409 factors locally.

410 Vulnerability is determined for low values by exposure, i.e., areas with little to no forests,
411 including locations with low AC or high sensitivity (e.g. Rhône Valley). The highest values for
412 vulnerability are found in elevated mountainous areas at the margins of the study area, where
413 both exposure and sensitivity are strong while AC displays low to intermediate values. Hilly to
414 mountainous areas along the Rhône river and along the South-Eastern coast display
415 intermediate to high vulnerability due to a conjunction of AC and sensitivity. Within these
416 areas, vulnerability hotspots (e.g. within the Ardèche and Cévennes) are driven by locally high
417 values for sensitivity rather than low AC. The use of AHP weights leads to null or moderate
418 decreases in assessed vulnerability in many locations, and moderate to strong increases in
419 remaining locations, owing to complex interplays between indicators.

420



421 *Figure 5 – Difference in vulnerability when using AHP weights compared to using equal*
422 *weights for indicators. A value above a 1 means a higher vulnerability when using AHP*
423 *weights (e.g. 1.5 means +50%).*

424 3.2.3. Infrastructures

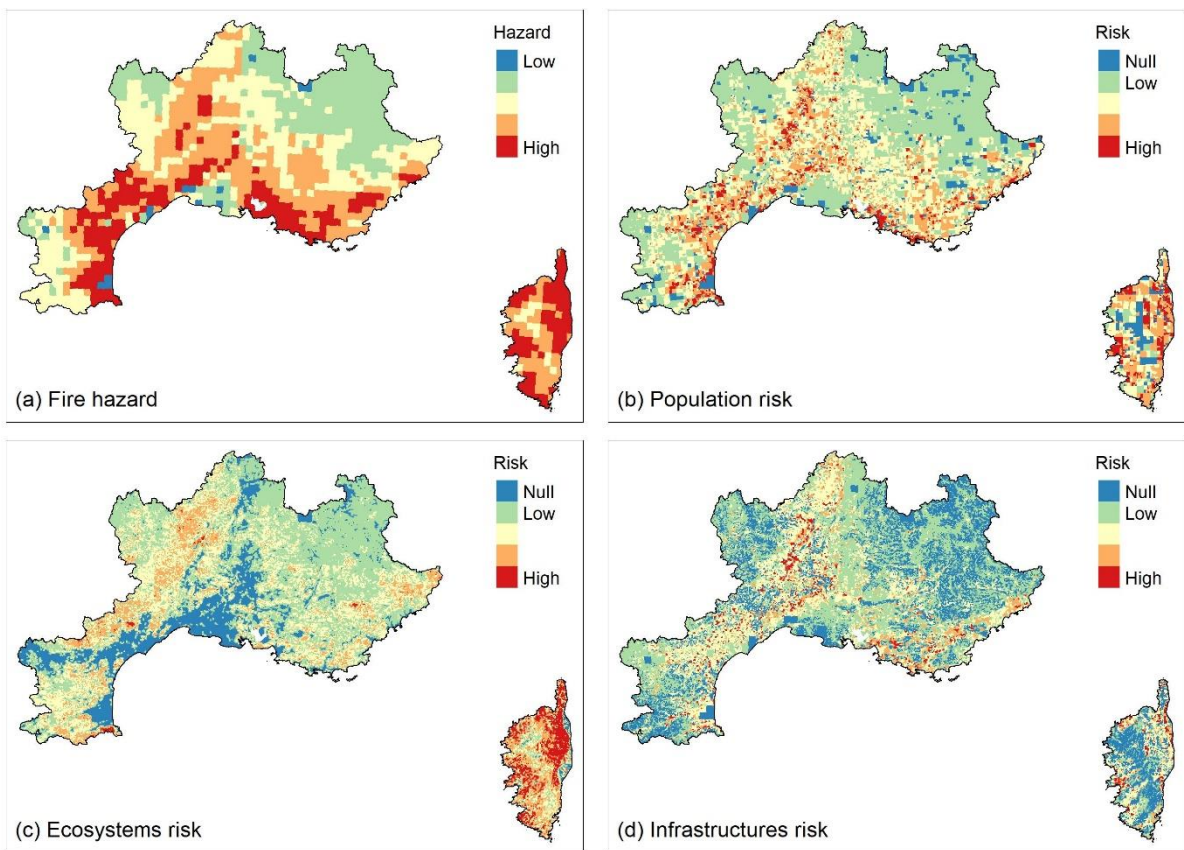
425 Exposure of infrastructures displays spatial patterns similar to that of population, i.e. high
426 values along urban axes and a large share of pixels with null to very low values. However, it
427 appears less concentrated as infrastructures may be encountered in rural areas despite low
428 population rates for historical reasons (de-industrialization, rural exodus).

429 Sensitivity is highest along the Rhône valley and around the cities of Marseille and Nice, where
430 it is driven by the presence of significant WUI, especially for the latter. Other locations with
431 high sensitivity correspond to those close to industrial sites and located further away from fire
432 stations (e.g. Ardèche, South-Western Alps, Western Languedoc). These locations also display
433 a very high share of older buildings. Low sensitivity values are found locally in relatively
434 isolated locations across the study area, where exposure is low.

435 AC is highest in southern Rhône Valley and along the South-Eastern coast owing to a
436 conjunction of abundant financial resources and, to a lesser degree, high risk experience and
437 education (Montpellier, Marseille). Low to intermediate AC values are found in rural areas
438 with low financial resources. In such locations, high risk experience can be a moderating factor
439 (e.g. Cévennes, Corsica) and low access to services an aggravating factor (e.g. southern Alps).
440 AHP weights contribute to increasing assessed vulnerability in two types of locations: first
441 around large urban centers of the South-Eastern coast (high WUI), second around sensitive
442 industrial sites to the West of the Rhône valley, where financial resources are also lower while
443 WUI is high.

444 **3.3. Hazard and risk**

445 Figure 6 (a) displays average burned areas from 1000 simulations with the Firelihood model as
446 a metric for hazard. We observe hazard to be highest to the South of the study area, especially
447 along the coast, in the Southern Rhône valley, the Cevennes area and Corsica, while
448 mountainous locations are much less concerned.



449 **Figure 6 - Maps for (a) hazard (Firelihood model simulations), (b) population risk, (c)**
450 **ecosystems risk and (d) infrastructures risk. Red areas indicate high risk.**

452 Risk maps show that once hazard is considered, some areas display low risk levels despite
453 being vulnerable owing to lower hazard levels. For ecosystems, this is the case of the
454 mountainous Alps (north-east) and Pyrenees areas (south-west), and also in Aubrac (north-
455 west, mostly due to sensitivity). While these locations tend not to be highly vulnerable for

456 population and infrastructures due to their relative isolation, this moderating influence of
457 hazard is striking for ecosystems. In the end, ecosystems risk is highest in the Ardèche and
458 especially Cevennes and South-Eastern coastal areas. Corsica displays high levels of both
459 vulnerability and risk for ecosystems.

460 Similarly, due to low hazard levels, the center of urban areas (e.g., the cities of Montpellier and
461 Perpignan) have low levels of risk. While vulnerability tends to already be null or low for such
462 locations for ecosystems (no exposure) and infrastructures (no industrial site), the moderating
463 influence on risk is higher for populations.

464

465 4. Discussion

466 4.1. *Spatial patterns of vulnerability and risk and policy response*

467 Our study provides a basis for discussing with stakeholders how to identify vulnerable regions,
468 causative factors, and prioritize prevention and suppression measures. Besides, the separate
469 consideration of population, ecosystems and infrastructures helps planning differentiated
470 responses according to the importance given to each asset. A map-based approach may also
471 improve how choices are made spatially and help choosing appropriate measures in different
472 locations.

473 For example, while locations with highest vulnerability levels correspond to those already
474 known to public authorities (e.g., coastline, Languedoc and Cevennes), our work suggests the
475 existence of secondary vulnerability hotspots, often very localized, specific to one asset and
476 caused by a limited number of factors. Besides, some areas also call for particular attention,
477 such as Corsica, which appears to be very exposed but with a low adaptive capacity despite
478 populations' strong experience of risk. This is a first step in identifying where more detailed
479 assessments should be carried out with local services, or where specific policies (e.g. risk
480 prevention) may be the preferred course of action

481 Results also showed that risk was moderate-to-low in some locations with high vulnerability
482 but low hazard values. Given that fire regimes are expected to aggravate and reach new areas
483 (Pimont et al., 2022, Dupuy et al., 2020), the assessment of exposure, sensitivity, adaptive
484 capacity and their underlying factors in such locations is needed. Areas without past experience
485 will become exposed, which represents a challenge for the implementation of public policies
486 adapted not only to the characteristics of the territory but also to those of the populations.

487 4.2. *Stakeholder participation and feedback*

488 Our work also highlights the potential advantages of using expert knowledge in vulnerability
489 studies applied to wildfire risk. Indeed, using the AHP aggregation also enabled us to get a
490 quantified understanding of how sociodemographic and economic factors (e.g., risk
491 experience, isolation), often overlooked in integrated assessments but known to be important
492 in the specialized literature, compare to commonly found land-use, ecological and physical
493 factors.

494 The method itself was highly appreciated by stakeholders, who emphasized the importance of
495 including field-experts in applied research. Feedback stressed benefits both from a scientific
496 point of view, as well as in terms of the actors' ability to reflect on their professional activity:
497 *“This is very beneficial because it gives us an opportunity to think and pushes us out of our*
498 *comfort zone. It makes us consider other types of indicators and wonder: what are the major*
499 *factors to consider? It's interesting because it is questioning⁴”. MCDA became part of the*
500 *knowledge creation process and gave birth to discussions on e.g. data availability and missing*
501 *indicators to develop, several participants insisting on the potential value of long-term*
502 *collaboration. Future endeavors could raise the question of integrating collective knowledge*
503 *and local populations as well, probably at finer geographical scales (e.g. landscape level).*

504 Regarding future evolution as well, experts underline the importance of the participatory
505 approach for the exploration of subjects with little hindsight: *“Being associated is very*
506 *important because there is little collaboration between operational services and research. This*
507 *work brings technical and scientific evidence in a context of change where we do not always*
508 *have straightforward answers⁵”. Our work contributes to it by helping identify vulnerable*
509 *areas even in the absence of hazard, and by inducing discussions on underlying factors.*

⁴ Stakeholder's feedback from the workshop

⁵ Stakeholder's feedback from the workshop

510 4.3. *Limitations and further research*

511 South-eastern France is heavily frequented by tourists during the fire season. Tourists are
512 particularly sensitive owing to their lower experience, harder access to information and harder
513 evacuation in heavily frequented locations. They were omitted owing to the difficulty of
514 deriving a simple indicator and of aggregating it to resident population numbers. Besides,
515 people are mobile and many casualties happen while fleeing, but we conceptualized exposure
516 as “before fire”, our exposure metric was based on the town of residency, and proxies for
517 evacuation were independent of the fire event (e.g. housing type). Further work should strive
518 to consider evacuation in a dynamic manner, which may be easier at a finer geographical scale,
519 to include tourists. The inclusion of indicators related to ease of defense of a property could
520 also be improved, given that some people prefer to stay rather than flee (McLennan et al.,
521 2012).

522 While the conceptual framework derived from previous studies proved flexible for a
523 hierarchical MCDA approach, boundaries between the several components of risk and
524 vulnerability remain unclear. This is the case e.g. for factors such as defendability, firefighting
525 access or landscape structure, which were considered to contribute to sensitivity but may also
526 affect how fires ignite and behave, i.e., hazard. Setting boundaries remains necessary for
527 practical purposes, but choices made must be remembered when analyzing and communicating
528 about results. Besides, we followed several authors and computed vulnerability as a product of
529 its sub-components, with the rationale that when an asset is e.g. not present, or does not sustain
530 damage, it is not vulnerable. Others have adopted an additive approach to vulnerability
531 (Oliveira et al., 2018). This seems to remain a debated question in the conceptual literature.

532 While the participative and exploratory objectives of our work were attained, its non-predictive
533 nature hinders further applied uses. While vulnerability maps provide powerful discussion

534 tools, confidence in underlying values remains limited. Discussion-based subjective validation
535 (e.g. interviews, workshops) may be enough for our purposes, but a more objective validation
536 based on comparisons with external datasets would be necessary for prediction purposes.
537 Besides, even though the AHP's consistency ratios were small enough, results remain
538 contingent on experts interviewed, the choice of which can induce bias, and the small sample
539 size hinders further analysis. To our knowledge, published vulnerability assessments do not
540 exist for our study area, only evaluations of hazard and exposure, the former of which we
541 already included. Besides, comparisons between model-based vulnerability values and
542 composite indicators would be methodologically challenging owing to their distinct natures.

543 A subsequent and more ambitious effort would include a larger amount of field experts
544 throughout the research project, from indicator selection to ex-post discussion. They could be
545 drawn from several Mediterranean regions and professional backgrounds, enabling cross-
546 comparisons across locations, expert profiles, and validation of indicators weights by
547 comparing similar but independent expert groups. Methods such as fuzzy set theory could be
548 used to decrease uncertainty arising from experts' interpretation of the AHP's linguistic
549 elements, increasing confidence in indicator weights (Donevska et al., 2012). Other world
550 regions subject to wildfire risk could also be studied (e.g. Australia, South America).
551 Quantitative fire hazard evaluations are already performed there: applications of a participative
552 methods would widen the scope of research conducted and provide insights on how territorial
553 vulnerability is perceived and defined based on different local experience, environmental and
554 socio-economic contexts.

555 Finally, our assessment was conducted at the regional scale and assets were considered as the
556 aggregation of many individual units. Some locations with a low number of sensitive and non-
557 resilient assets may appear as not vulnerable owing to a low exposure while, taken individually,

558 assets would be considered vulnerable (e.g. pixels with very few but isolated and precarious
559 elderly inhabitants). Our results should be taken as an assessment of vulnerability at a collective
560 level, helpful for decision makers to prioritize the allocation of means, but not as an absolute
561 evaluation. Other works should strive to develop a better understanding of vulnerability
562 dynamics at the individual level, e.g. individual people's behaviors and factors of resilience.

563 **5. Conclusion**

564 In this article, we developed a participative approach to assessing and mapping territorial
565 vulnerability to wildfires in South-Eastern France, distinguishing between several components
566 of vulnerability: exposure, sensitivity and adaptive capacity, and three assets (populations,
567 ecosystems and infrastructures), thus providing an encompassing overview of the issue at stake.
568 This hierarchical framework was coupled to the Analytical Hierarchy Process to prioritize and
569 spatially aggregate indicators taken from the specialized literature, which proved a relevant and
570 flexible way to integrate expert knowledge. Besides, model simulation data was used to derive
571 an indicator of fire hazard, demonstrating how classical approaches to fire risk assessment
572 could be used conjunctly to multi-criteria decision-making approaches. Results helped identify
573 vulnerable locations overall and for each asset individually. We were also able to highlight
574 major causative factors, and e.g. confirmed the importance of the wildland-urban interface and
575 of experience with past fires. Secondary vulnerability hotspots were revealed, as well as
576 vulnerable locations not yet confronted to hazard but where prevention efforts may be needed
577 with respect to climate change. The participative approach also proved a successful manner of
578 engaging stakeholder discussion. Interviews with experts, even during the covid pandemic,
579 enabled discussions to take place, and an ex-post workshop was organized to put results into
580 perspective and get feedback on the process. Field experts were in particular pleased with the
581 introduction of the adaptive capacity concept and the inclusion of socio-economic and

582 demographic data, which, according to them, encouraged novel ways of thinking. Further
583 research should include several fire-prone regions and a larger number of experts, enabling
584 comparisons across expert groups, locations, and the external validation of indicator weights
585 to allow for more applied uses.

586 **Credit author statement**

587 **Miguel Rivière:** Conceptualization, Methodology, Formal analysis, Data curation, Writing –
588 Original draft, Writing – review & editing, Visualization, Supervision, Project administration,
589 Funding acquisition

590 **Jonathan Lenglet:** Conceptualization, Methodology, Writing – Original draft, Writing –
591 review & editing, Visualization, Supervision, Project administration, Funding acquisition

592 **Adrien Noirault:** Formal analysis, Investigation, Data curation, Visualization

593 **François Pimont :** Methodology, Software, Writing – review & editing

594 **Jean-Luc Dupuy :** Methodology, Software, Writing – review & editing

595

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600

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Appendix A

780 *Table A.1 – Scale used for pairwise comparison of factors (from Saaty 2004)*

Score	Definition
1	Equal importance
3	Moderate importance of one over the other
5	Essential or strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate values between two adjacent judgements
Reciprocals	If factor i has one of the score assigned to it when compared with factor j, then j has the reciprocal score assigned to it when compared to factor i.

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783 *Figure B.1 – Annotated land-use maps of the study area*

