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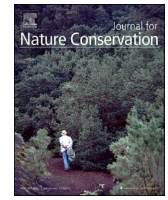

Mapping human- and bear-centered perspectives on coexistence using a participatory Bayesian framework

Paula Mayer [a,*], Adrienne Grêt-Regamey [a], Paolo Ciucci [b], Nicolas Salliou [a], Ana Stritih [c]

[a] *Department of Civil, Environmental and Geomatic Engineering, IRL, Planning of Landscape and Urban Systems (PLUS), ETH Zürich, CH-8093 Zürich, Switzerland*
[b] *Department of Biology and Biotechnologies, University of Rome La Sapienza, 00185 Roma, Italy*
[c] *Ecosystem Dynamics and Forest Management Group, Technical University of Munich, Hans-Carl-von-Carlowitz-Platz 2, 85354 Freising, Germany*

A R T I C L E I N F O

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A B S T R A C T

Coexistence with wildlife is becoming a key challenge in Europe as populations of large carnivores recover in human-dominated landscapes. Modeling the spatial distribution of conditions for human-bear coexistence can help support conservation by identifying priority areas and measures to support coexistence, but existing models often only address risks either to humans or to large carnivores. In this study, we developed a participatory modeling process that incorporates both human-centered and large carnivore-centered perspectives on coexistence and applied it to a case study of coexistence between humans and the endangered Apennine brown bears (*Ursus arctos marsicanus*) in Italy. Local and expert knowledge, as well as available data on bear habitats and land use, were integrated into a spatially explicit Bayesian network. This model is used to predict and map the tolerance to bears from the human perspective and the risk of fitness loss from the bear perspective. We found that conditions for human-bear coexistence vary between human communities and are spatially heterogeneous at the local scale, depending on ecological factors, social factors influencing the level of tolerance in community, such as people's emotions and knowledge, economic factors, such as livelihoods, and policies such as damage compensation. The participatory modeling approach allowed us to integrate perceptions of local people, expert assessments, and spatial data, and can help bridge the gap between science and conservation practice. The resulting coexistence maps can inform conservation decisions, and can be updated as new information becomes available. Our modeling approach could help to efficiently target measures for improving human-large carnivore coexistence in different settings in a site-specific manner.

1. Introduction

Coexistence between people and wildlife is a major challenge of our time (Henle et al., 2008; Redpath et al., 2013), with human-large carnivore interactions posing particular challenges for both humans and predators (Treves and Karanth, 2003; Graham et al., 2005; Athreya et al., 2013; Van Eeden et al., 2018). Forming the top of the trophic cascades, large carnivores are rarer than other wildlife (Hatton et al., 2015) and depend on an abundance of large prey and extensive habitat (Wolf and Ripple, 2016; Wolf and Ripple, 2017). Large carnivores can, on the one hand, significantly affect ecosystem dynamics (Ritchie and Johnson, 2009; Beschta and Ripple, 2009; Estes et al., 2011). On the other hand, they provide important socio-economic benefits to society (Sillero-Subiri and Laurenson, 2001; Rode et al., 2021). However, they can pose both direct and indirect risks to humans by threatening livestock, livelihoods, and human safety, which is why they have been hunted to total or near extinction in many parts of the world (Ripple et al., 2014). In Europe, most large carnivore populations are currently rebounding from their restricted ranges (Kaczensky et al., 2012; Chapron et al., 2014). The recent recovery of large carnivore populations is a result of legal protection, forest regrowth, recovery of wild prey populations, and increased human tolerance towards wildlife (Boitani and Linnell, 2015). A majority of the European countries implement national compensation schemes for large carnivore damage to human property, with annual damage compensation costs in Europe estimated at around 28.5 million Euros (estimated for 2005–2012, (Bautista et al., 2019)). Yet, in many regions, the return of large carnivores is still poorly accepted by local communities as human tolerance depends not only on

Abbreviations: BN, Bayesian network; HBC, human-bear coexistence.

* Corresponding author.
E-mail address: mayerpa@ethz.ch (P. Mayer).

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economic costs and benefits, but is grounded in the social context (Dickman, 2010; Linnell and Boitani, 2012). Communities with experience in human-large carnivore coexistence have been found to tolerate these species more than communities where large carnivores are currently returning to (Kaczensky et al., 2004; Majić and Bath, 2010).

Human-wildlife interactions are commonly described as the temporal and spatial co-occurrence of wildlife and human activities mutually influencing each other (Peterson et al., 2010; Lischka et al., 2018). These vary on a range from positive to negative impacts, low to severe intensity, and rare to high frequency (Nyhus, 2016). From a human perspective, the impacts of human-wildlife interactions include tangible and intangible effects such as economic costs and benefits, attitudes, emotions and group dynamics on the individual and societal level (Dickman, 2010; Bruskotter and Wilson, 2014; Kansky et al., 2016; Marino et al., 2021). Taking a wildlife perspective, we can assume that human-wildlife interactions influence the behavior as well as the health and reproductive status of individuals and populations (Ciuti et al., 2012; Lischka et al., 2018; Goumas et al., 2020). An ideal form of human-wildlife interactions is coexistence, where neither wildlife nor humans are affected by each other in a negative way (Marchini et al., 2021), ensuring long-term wildlife survival, social legitimacy and tolerable risk levels (Carter and Linnell, 2016). Although the concept of coexistence is gaining traction in conservation science, a conflict-oriented view of human-wildlife interactions still prevails (Nyhus, 2016; König et al., 2020; Pooley et al., 2021). If human-wildlife interactions have negative impacts on wildlife or humans, these are often referred to as human-wildlife conflicts (Conover, 2001; Madden, 2004; IUCN, 2021). Many studies of human-large carnivore conflict take an anthropocentric view, considering the behavior of large carnivores as potentially harmful to human safety, livelihood, and recreation (Morehouse and Boyce, 2017; Lozano et al., 2019; Krofel et al., 2020). Other studies stress impacts on wildlife, such as human disturbance and influence on predator mortality (e.g. (Martin et al., 2010; Liberg et al., 2012; Basille et al., 2013; Wynn-Grant et al., 2018). While modeling human-wildlife interactions can help inform decision-making in conservation (Lischka et al., 2018), both the anthropocentric and wildlife-centered perspectives on human-wildlife conflicts and coexistence are rarely combined in social-ecological models.

Models that combine social and ecological drivers of human-large carnivore interactions have the potential to support decisions and define priorities in conservation actions (Behr et al., 2017; Struebig et al., 2018; Gálvez et al., 2018). Since local people's experiences, knowledge, emotions and risk perceptions are key components of human-wildlife coexistence, they need to be considered in such decision-support models (Kansky et al., 2016; Inskip et al., 2013). Social-ecological models coupled with a participatory approach are a useful tool, as stakeholders can support the modeling process with local knowledge and their perceptions of risk (Calheiros et al., 2000; De Dominicis et al., 2015). Participatory approaches are particularly recommended to tackle complex issues characterized by high stakes, high levels of uncertainty and conflicting values among stakeholders (Funtowicz and Ravetz, 1994; Voinov and Bousquet, 2010), where it is important that any decision-support models are interpretable and transparent (Rudin, 2019). Participatory modeling increases the transparency and credibility of modeling results, and supports communication and learning among participants (Jakeman et al., 2006; Voinov and Bousquet, 2010).

Bayesian networks (BNs) are commonly used in participatory modeling because of their graphical, transparent structure, and their capacity to integrate qualitative and quantitative data (Celio et al., 2014; Gonzalez-Redin et al., 2016; Salliou et al., 2017). Moreover, co-creation of BNs enables discussion between experts and stakeholders (Barton et al., 2012; Henriksen et al., 2012). Due to their probabilistic nature, and their capacity to model various scenarios and continuously update probabilities, BNs also have a high potential for communicating risk and uncertainty (Barton et al., 2012; Ahmadi et al., 2015; Grêt-Regamey et al., 2013; Stritih et al., 2019; Kaikkonen et al., 2021). In conservation, BNs have been used to model species' distributions, especially when access to occurrence data is rare and expert knowledge must be incorporated (Smith et al., 2007; Tantipisanuh et al., 2014; Hamilton et al., 2015), but they have rarely been used to address human-carnivore interactions. Some studies have employed BNs to analyze the effects of social, political, and ecological factors on the survival of predator populations (Amstrup et al., 2008; Atwood et al., 2015; Fortin et al., 2016; Davis et al., 2020). However, to our knowledge, no such study exists that assesses the risks to human-large carnivore coexistence from both the human and wildlife perspective within their shared landscapes.

In order to help local conservationists and administrations identify priority areas and measures to foster coexistence between people and large carnivores, we developed a modeling process that integrates human and animal dimensions of human-large carnivore coexistence in a spatially explicit way. The resulting maps of the probability of coexistence can support real-world decisions about where to invest in what type of coexistence measures. Using a participatory approach involving experts and locals, we illustrate this modeling process for human-bear coexistence (HBC) in a case study area in Italy.

2. Methods

2.1. Case study context and area

The mountainous landscapes of the Central Apennines are home to a variety of wildlife species and habitats preserved within a dense network of protected areas. The "Parco Nazionale d'Abruzzo, Lazio e Molise" (Abruzzo National Park) and adjacent areas are the core range of a small source population of Apennine brown bears (*Ursus arctos marsicanus*, about 50–60 individuals, (Ciucci et al., 2015)), which is under severe risk of extinction (Ciucci and Boitani, 2008; Gervasi and Ciucci, 2018) and classified as critically endangered by the IUCN (McLellan et al., 2016). Long-term isolation from other populations has resulted in genetic, morphological, and behavioral characteristics that distinguish the Apennine brown bear from other European brown bears (Ciucci and Boitani, 2008; Colangelo et al., 2012; Benazzo et al., 2017). Genomic analyses indicate that Apennine brown bears, originally distributed over greater part of the Apennines, became separated from other brown bear populations during Neolithic periods of intense forest clearing and have lost genes coding for aggressive behavior through genetic drift (Benazzo et al., 2017). The population is approaching the carrying capacity of its core distribution area, which is mainly located in the Abruzzo National Park (Ciucci et al., 2015; Ciucci et al., 2017). However, surrounding areas across the Central Apennines could host four to five times the existing number of bears if connectivity between habitat patches was maintained and enhanced (Maiorano et al., 2019). Indeed, in recent years an increasing number of bears, including reproductive females, are dispersing beyond their core range (Morini et al., 2017; Gervasi et al., 2017; Penteriani et al., 2020). Especially in the north of the Abruzzo National Park, towards the Sirente e Velino Regional Park, and in the east, towards the Majella National Park, bears have been recently monitored more frequently in recent years (Gils et al., 2014; Ciucci et al., 2017; Morini et al., 2017). In these zones between protected areas, bears find densely populated areas where most of the people still rely on rural livelihoods, in contrast to communities within the Abruzzo National Park, which additionally benefit from tourism related to bears. Very few bears (i.e., <5) regularly approach settlement areas to date and have become conditioned to human food resources (PNALM, 2021). Two local non-governmental organizations (NGOs), Rewilding Apennines and Salviamo l'Orso, supported by the European organization Rewilding Europe, are developing so-called "coexistence corridors" defined according to landscape modeling procedures (Maiorano et al., 2019). In these zones, which include and connect suitable bear habitat, they seek to both minimize human-bear conflict and develop economic

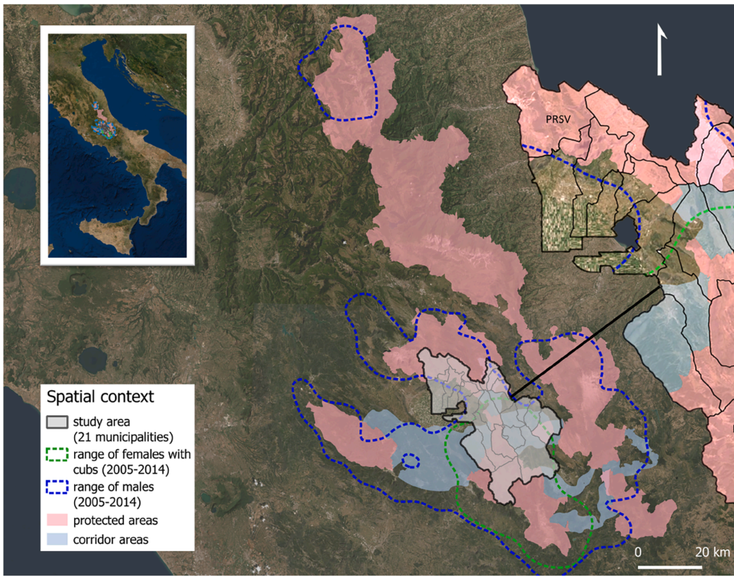

Fig. 1. Spatial context of the case study. The study area is located in the Central Apennine mountain range. The core distribution range of the Apennine brown bear population (visible in the distribution of females with cubs, (Ciucci et al., 2017)) lays mainly within the Abruzzo, Lazio and Molise National Park (PNALM). Some individuals (cf. distribution of males, (Ciucci et al., 2017)) inhabit surrounding areas. In the study area (grey area; zoom-in), we find core home range, as well as modeled corridor zones for bears (Maiorano et al., 2019). These can be cultivated or left unmanaged as protected areas (PNALM, Sirente-Velino Regional Park PRSV, Monte Genzana Alto Gizio Nature Reserve MGAGNR).

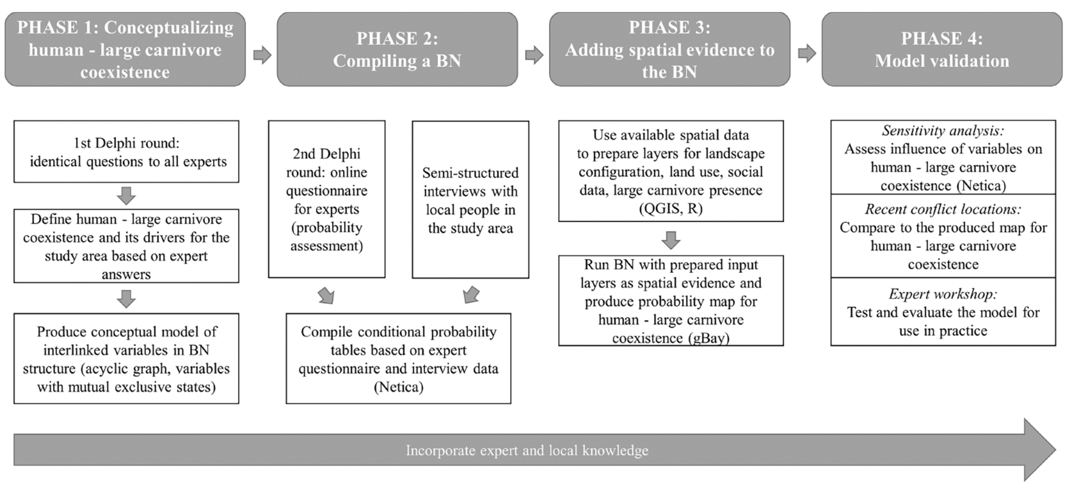

Fig. 2. Four phases of a participatory process to develop maps for human-large carnivore coexistence.

opportunities such as wildlife tourism and product labeling (Rewilding Apennines, 2022).

This study is aimed to develop a model to support the decisions of local NGOs and administrations about prioritizing coexistence measures. To do so, we focused on an area in which we find a range of bear abundance and different social attitudes towards bears. Covering an area of 1006 km^2 of the Abruzzo region, the study area consists of 21 municipalities with a population density of 34 people per km^2 (ISTAT, 2021). It includes the northern part of the Abruzzo National Park, the two described connecting corridors to the north and east, the southern portion of Sirente-Velino Regional Park, the Monte Genzana Alto Gizio Nature Reserve, as well as parts with intensive agriculture (Fig. 1). While people in the Abruzzo National Park have been used to bear presence for decades, human-bear coexistence has become an issue in the nature reserve and in agricultural areas directly adjacent to the national park only in the last decade. In some villages of the agricultural lowlands, bears were sighted in 2021 for the first time in modern times. Hence, human knowledge of best practices for coexisting with these opportunistic omnivores varies widely, as does access to human food sources for bears.

2.2. Bayesian network approach

We used a BN approach to model the probability of HBC. BNs are probabilistic multivariate models for a set of variables, that combine qualitative and quantitative components (Aguilera et al., 2011; Kjaerulff and Madsen, 2013). Variables are linked as nodes (X) of a directed, acyclic graph and have a set of mutually exclusive states (x_i). The links between the nodes represent causal relationships (e.g. X→ Y), while nodes can be connected to multiple other nodes. Conditional probability tables display the probability distributions for each node's state given each combination of states of the parent nodes. The probability that node Y is in a particular state y_1 is calculated by marginalization, i.e. the summing of conditional probabilities over the states of its parent nodes (Kjaerulff and Madsen, 2013): $P(Y = y_1) = \sum_{x_i} P(Y = y_1 \middle| X = x_i) \times P(X = x_i)$.

The modeling process of selecting and linking variables and their states, as well as defining their conditional probability tables, can be based on empirical data or guided by expert or stakeholder knowledge, or a combination of both (Marcot, 2012). By adding new evidence to the BN, the nodes' findings can be updated. The software gBay allows for the integration of spatial data as evidence, resulting in a spatially explicit

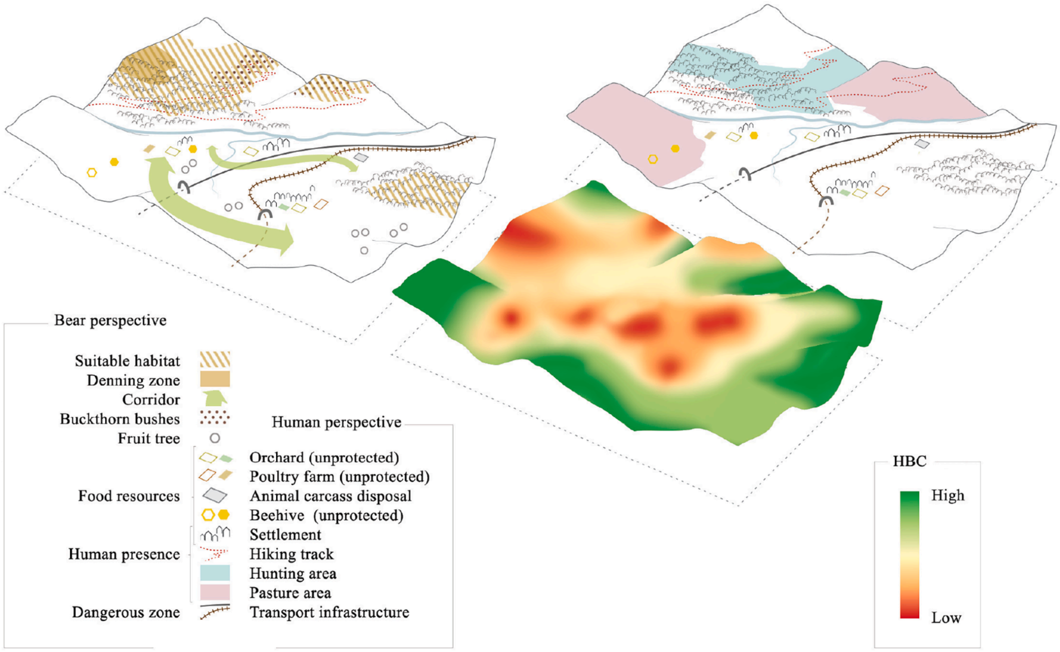

Fig. 3. Humans and bears have different perspectives on the landscape, shaped by their use of territory and resources as well as their past experiences which results in areas of higher and lower probability of HBC. This is an hypothetical example for illustrative purposes.

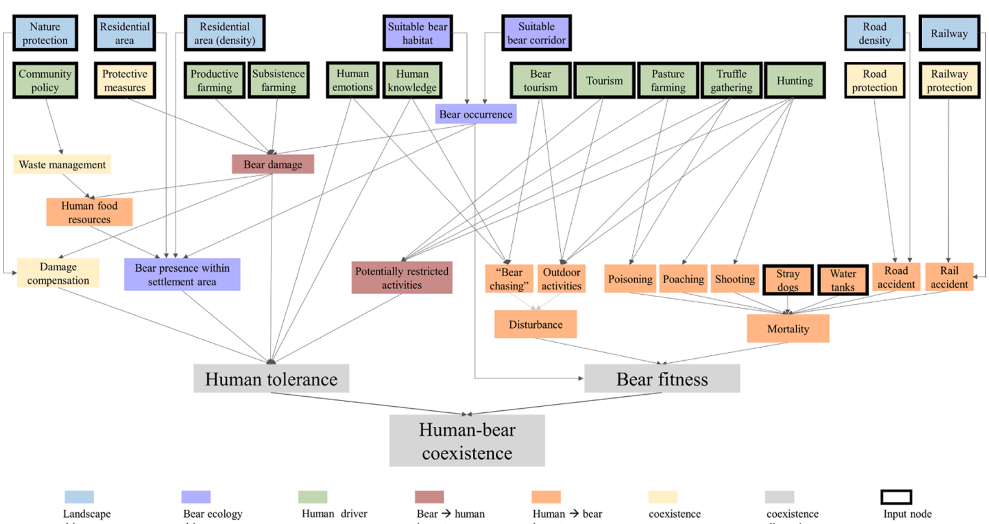

Fig. 4. BN resulting from the participatory modeling process. Gray boxes represent HBC and its human and bear dimensions. Green boxes depict human drivers, while purple boxes belong to bear-ecology drivers of HBC. Landscape drivers are shown in light blue boxes. Human impacts on bears are illustrated in orange, while bear impacts on humans are illustrated in red. The beige boxes belong to measures for improving HBC. Input nodes are shown with a bold outline. Note that all arrows indicate causal relations, except for the final weighting of the HBC dimensions.

visualization of the posterior probability distribution of the target node (Stritih et al., 2020).

2.3. Participatory Bayesian network modeling

Throughout the process, we actively collaborated with experts and locals in the study area to incorporate their knowledge into the model. In a four-step participatory process (Fig. 2), we collaborated with 16 experts on human-bear coexistence from academia (seven experts), practice (nine), and tourism (five), with five experts involved in more than one of the sectors to combine scientific and local ecological knowledge (Bélisle et al., 2018). We conducted a Delphi approach (Mukherjee et al., 2015) consisting of two main rounds of questions and 20 one-on-one discussions with six experts interested in providing feedback. First, we jointly created a conceptual model of HBC, its drivers and impacts (Phase 1). Then, we used expert and local knowledge to assess the probabilities of HBC dynamics and to compile a BN (Phase 2). In Phase 3, spatial data was added to the BN, and in Phase 4, the model was validated.

2.3.1. Phase 1: Conceptualizing human - large carnivore coexistence

In the first Delphi round, we invited 16 experts via email to answer seven general questions regarding HBC in the Central Apennines (see supplementary material). We then synthesized the insights gained from the responses into an initial conceptual model for a fictitious community in the Central Apennines, which we iteratively refined by incorporating feedback from the experts. The experts defined relevant types of human-bear conflicts that pose a risk to coexistence, their components, underlying drivers and impacts, and their causal relationships. From the beginning, we tried to make the diagram BN-compliant (directed, acyclic graph; variables defined in sets of mutually exclusive states, 2.2).

Key *dimensions of coexistence* identified by the experts include the human-centered perspective (i.e. the human tolerance of bears) and the bear-centered perspective (i.e. bears' fitness) as illustrated in Fig. 3.

From an anthropocentric perspective, tolerance of bears can be negatively influenced by bears damaging human property (such as livestock) and causing restrictions to human activities, and positively influenced by activities such as bear-related tourism. Activities such as hunting, truffle gathering, pasture and tourism might be restricted due to the bears' conservation status in case of bear presence. From a bear perspective, negative human impacts on bears include mortality threats, such as from traffic accidents, poisoning, or poaching, as well as the loss of fitness due to disturbance (e.g. by tourists). Both the human- and bear-centered dimensions of HBC are thus result of interacting social and ecological factors, such as bear habitat suitability, dispersal corridors and landscape configuration. Underlying social and economic drivers of HBC include various human livelihoods and activities, as well as people's experience and emotions towards bears. The Italian expression "cultura dell'orso", used in our case area, describes people's cultural relationship with bears, formed by shared narratives, direct experience, and education. People within a community strongly influence each other in this regard by exchanging stories and experiences. Furthermore, HBC can be influenced by measures for bear damage prevention and compensation.

2.3.2. Phase 2: Compiling a Bayesian network

In the second phase, we transformed the conceptual model into a BN using the Norsys software Netica 6.09 (Fig. 4). In Table A1 of the Appendix, all nodes and their respective states are described in detail. To fill in the conditional probability tables, we included both expert and local knowledge. In a first step, we composed an online questionnaire with 41 questions regarding the links between the variables of the conceptual model set in Phase 1. Experts could weight the probabilities of certain events under given circumstances (e.g. *If there is truffle gathering in an area, how likely is the use of poison?*, see Fig. D1 in the Appendix). The probabilities elicited from different experts were averaged in the final model.

Since the number of probabilities in a conditional probability table grows exponentially with the number of parent nodes, filling these tables can lead to boredom and fatigue for participating experts (Das, 2004). For example, the node of bear mortality risk is connected to 6 parent nodes (*poisoning, poaching, accidental shots, railway accidents, car accidents, open water wells, stray dogs*, Fig. 4). An expert might be able to weight the probability of mortality given the state of an individual parent node (e.g. *There is poisoning in a zone frequented by bears. How likely is it that a bear will die?*), but may not be able to weight the probability of elevated mortality for each combination of several parent nodes (e.g *There is no poisoning, but poaching and a high speed road in a zone frequented by bears. How likely is it that a bear will die?*). To facilitate this process, we therefore used the Noisy-OR operator, and its generalization, the Noisy-MAX (Zagorecki and Druzdzel, 2013) to combine the probabilities of independent parent nodes.

Local knowledge was incorporated to calibrate conditional probability tables of all nodes influenced by human experiences and emotions. To this end, we conducted a total of 315 semi-structured interviews with local people in the 21 municipalities of the study area (15+- 5 per community) taking an approach of active participation (Spradley, 2016; Johnson et al., 2006). For these open-ended interviews, we visited each of the municipalities and conducted convenience sampling (Etikan et al., 2016) by approaching people at common village meeting places. In addition, we conducted a purposive snowball sampling (Johnson, 2014) by actively reaching out to people who had experienced bear damage to their properties in the past or who wanted to protect them as a preventative measure. These latter open-ended interviews were carried out while we accompanied the respondents in their daily rural activities. In contrast to the expert elicitation, we were not asking the interviewees to weight probabilities of certain events but to share their personal experiences, knowledge and emotions (e.g., *Has a bear ever damaged your property? Has there been any kind of information event in your community about coexisting with bears? How do you feel about the bear that recently came to your village?*). Based on the interview data, we derived conditional probabilities relating circumstances such as community policy or nature protection status and respondents' experiences to their level of knowledge, and attitude towards bears (e.g. $P(knowledge = yes|nature\ protection = nature\ reserve)$.

All nodes in the network directly or indirectly influence the two modeled *coexistence dimensions*, *human tolerance* (can be either in a "positive" or "negative" state) and *bear fitness* ("baseline" or "reduced"). Their probability distributions are conditional on other nodes in the network and defined through expert elicitation. The final target node, *HBC*, combines these two nodes by weighing the human and bear dimension of HBC (see Table A2 in the Appendix, here, we used 1-to-1 weights). Hence, varying the probability table for *HBC* allows for decisions on which perspective - that of the local people or that of the bears - should be accentuated in the spatial modeling.

2.3.3. Phase 3: Adding spatial evidence to the Bayesian network

The HBC map becomes more precise with more spatially explicit information incorporated into the model. In Phase 3, we prepared a total of 22 spatially explicit input layers on potential bear presence, landscape configuration, human-induced threats to bears, social data and land use for use as spatial evidence in the BN. We were able to utilize monitoring data from Salviamo l'Orso and Rewilding Apennines, spatial knowledge of experts and locals, open data such as from OpenStreetMap, and an existing habitat suitability model (see details in Table B1 in the Appendix). The suitability models for bear habitat and corridors have been based on bear occurrence data over a study period from 2004 to 2015 related to environmental (e.g slope, land cover types) and anthropogenic variables (population density, distance to paved and non-paved roads) (Maiorano et al., 2019). Corridors connecting suitable bear habitats were modeled based on a dataset of Global Positioning System (GPS) trajectories of female bears and potential bear habitat, and corridors were predicted for the whole mountain range of the Central Apennines (Maiorano et al., 2019).

All of the input layers were converted into 100x100m grids in order to run the BN spatially in gBay (Stritih et al., 2020). This resolution corresponds to the smallest cell-size the habitat suitability and corridors models can be run at (Maiorano et al., 2019) and was chosen to capture the small-scale heterogeneity of the landscape and important landscape features, such as roads and small settlements. Most of the spatial inputs were used as "hard evidence" (e.g., truffle gathering within a pixel cell has a probability distributions of 100% Yes, 0% No). "Soft evidence" was used for some nodes where the state is not known with certainty, such as habitat suitability (e.g., a pixel cell has a probability distributions of 75% suitable and 25% unsuitable, with the most suitable pixel cell in the research area considered as being 100% suitable) or local people's emotions (e.g., in a pixel cell you can meet a person whose emotion towards bears has a probability distribution of 60% anger, 30% fear, 10% admiration). Importantly, we assigned probability distributions of local people's emotions, knowledge and community policy at the municipality level, meaning that each pixel cell within a municipality's boundaries has the same probability distribution for these variables. Using the resulting HBC map, we compared the spatial distribution of the probability of HBC across pixels between different municipalities.

2.3.4. Phase 4: Model validation

During the participatory modeling process, the experts had already validated the model at its various intermediate stages during Phase 1 and 2, when we were iteratively adapting the BN based on their feedback. For a final validation of the model and its spatial outputs, we performed three validation steps including a sensitivity analysis (1), a comparison of the HBC map with locations of human-bear conflicts and anthropogenic threats to bears found in recent years (2) and a workshop as feedback session with experts who are actively engaged in HBC promotion in the study area (3).

First, we ran a sensitivity analysis on the target node *HBC* to analyze

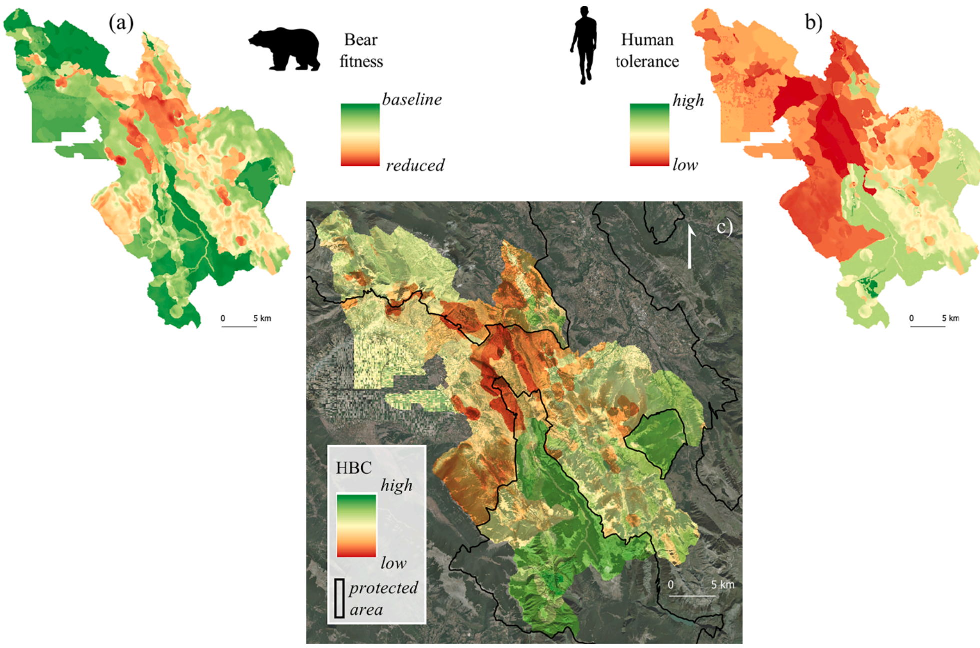

Fig. 5. HBC is spatially heterogeneous across the landscape as probabilities of HBC vary with landscape configuration, social and ecological factors (c). The mapped HBC is a weighing of a bear-centered perspective (bear fitness, a) and a human-centered perspective (human tolerance, b). For bears, probability of HBC is low where it is likely that they might be disturbed or even killed by human activities in their natural habitats (fitness loss, a). For local people, probability of HBC is low where bears have negative impacts on their livelihoods, resulting in lower tolerance of bears (b). This may be the case in settlement, agricultural, or hunting areas. In contrast, we often find high tolerance in hotspots of bear tourism.

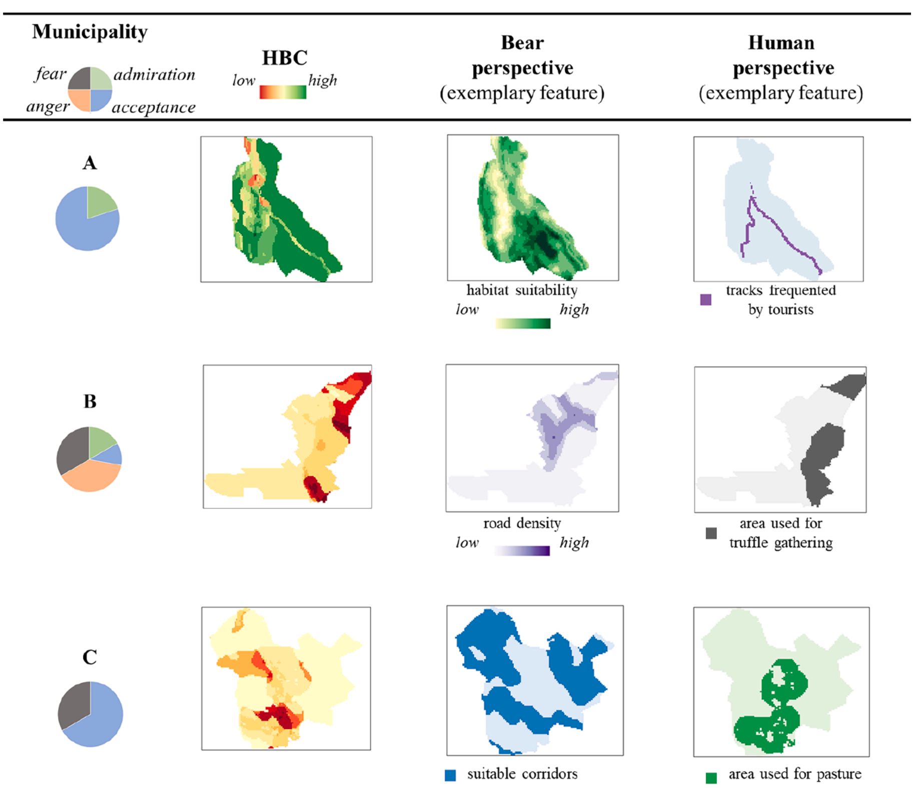

Fig. 6. Spatially explicit distribution of probabilities for human-bear-coexistence in three municipalities. The first column depicts the communities with the distribution of human emotions towards bears obtained from the interviews in Phase 2. The second column shows the HBC combining both human and bear perspectives, while the third and fourth columns each display an input layer that represents a particular human or bear perspective on the landscape and explains part of the spatial distribution of HBC.

its most influential variables. Sensitivity analysis in BN modeling refers to determining the extent to which uncertainty in posterior probability distributions of a node of interest can be reduced by new findings on other nodes (Marcot, 2012), and is calculated as entropy reduction ("mutual information", MI) (Kjaerulff and Madsen, 2013). Second, we compared the map of HBC to locations of real cases of negative human-bear interactions in the study area monitored over the past two years, which were expected to occur in areas with a low probability of HBC. We had intentionally not used these data (monitored poison and snares, bear occurrence in residential areas and on heavily trafficked roads, dataset of 37 locations) for model calibration in order to use these cases in model validation. The final step was to validate the model for use in practice. To this end, we invited experts who engage in HBC promotion in the area and who had also participated in the Delphi question rounds to an online workshop. We reviewed the BN in Netica by running different scenarios and examined spatial distributions of the input layers and resulting probability of HBC in the QGIS environment. Furthermore, we discussed the results of the sensitivity analysis and recent human-bear interactions in the study area. The feedback was used to refine the model for its applicability in practice.

3. Results

3.1. Spatially explicit probability of human-bear coexistence

The first two phases of participatory BN modeling resulted in a BN with 41 nodes encompassing landscape configuration, socio-economic factors and bear ecology, as well as mutual impacts of humans and bears and measures for promoting HBC, which ultimately influence HBC (Fig. 4). The overall HBC map (Fig. 5) shows much lower probability of HBC in the central part of the study area, where people depend on rural livelihoods, than in the southern and extreme northern regions. The southern part of the study area is within the core range of the Apennine brown bear population in the Abruzzo National Park and has a generally high probability of HBC. Here, reduced probability of HBC is primarily concentrated in settlement zones, around connecting roads, and areas frequented by tourists. Towards the center of the study area, probability of HBC decreases sharply and is distributed over larger areas. In these areas, people use the landscape for hunting, truffle gathering, and agriculture, some of which overlap with suitable bear habitats or corridors. In the south-eastern part, a generally higher HBC probability is projected, especially within the Genzana nature reserve (small polygon in the east, Fig. 5). There is a medium HBC probability with spots of lower HBC in the Sagittario valley between the national park and the nature reserve, where bears find suitable habitat and people depend on both rural livelihoods and tourism. In the northernmost part of the research area, which is generally less suitable bear habitat, the HBC probability increases, except in individual locations where potential bear corridors overlap with high road density, high building dispersal or ski tourism.

3.2. Differences among municipalities

At the municipality level, we observe local differences in HBC both in municipality averages and their spatial distributions. For instance, in Fig. 6, we zoom into three municipalities which lie on a north–south line in the study area and are representative of the 21 studied municipalities (average population size 1634, max: 10474, min: 200 (ISTAT, 2021)). The model predicts a generally high probability of HBC for municipality A (mean = 77.7%) with zones of medium HBC around the main road and pastures and along the main hiking trails. For municipality B, the model predicts on average a medium HBC probability (mean = 47.7%) with lower probability of HBC on the eastern hillsides adjacent to the village. In municipality C, we find a medium HBC probability (mean = 54.8%) with zones of low probability of HBC in the southern mountain slopes as well as around the settlement area and in a ski resort. These differences between the municipalities are a result of differences in the landscape configuration, current and past land use, as well as local social attitudes towards bears.

Municipality A, consisting of two small villages within a total area of 46.42 km^2, is located in the national park within the core area of current bear distribution. The residents (200 total, average age 59.5 years, (ISTAT, 2021)) are retired or commute to work in distant regions. Many cultivate gardens and practice small farming. There is some tourism, mainly day tourism during the summer months as A is a starting point for several hiking and wildlife watching tours. In the past, the valley was intensively cultivated, but today there are only four cattle farms. Bears sometimes pass by the villages, which are surrounded by dense broadleaf forests, a very suitable bear habitat. In recent years bears have occasionally damaged human properties. In general, the municipality is in favour of human-bear coexistence, information is provided and best practices are promoted. People have become accustomed to bear presence, use bear-resistant electric fences and receive financial compensation in case of bear damage. Sometimes, when news of a bear near the settlement makes the rounds, people crowd into watch.

Municipality B covers 48.63 km^2 and is located on the edge of the cultivated Fucino plain, less than 20 km from A. Many of the 3.866 inhabitants (average age = 47, (ISTAT, 2021)) work nearby or in the next city. In the last decade, the town has grown out of its old center in a highly dispersed manner. In the lowlands, intensive agriculture is practiced, while along the surrounding mountain slopes are used for pasture and apiaries. Many residents, especially those living on the outskirts of the village, grow their own orchards and keep some poultry. The shrubland next to the village is used for wild boar and hare hunting as well as for truffle gathering. Around the town and in the surrounding mountains, a structured pack of semi-wild dogs has established its territory. Tourism has not entered this village, which is located outside any protected area next to a busy highway and a railroad line connecting Rome and Pescara. During the interview period in May 2021, a habituated female bear and her cubs caused some minor damage to local farmers' beehives and poultry. This was the first time in modern times that a bear entered this densely populated and fragmented area. At first, the bear's arrival was an issue only for some farmers, who mostly accepted it after NGOs constructed bear-resistant fences. Two weeks later, the same mother bear ran through the town centre and crossed the crowded main square, causing both fear and fascination among inhabitants.

Municipality C, 61.19 km^2 in area, is the most northern of the research area. It is located another 15 km north of B, in the Sirente-Velino Regional Park. It is one of the few southern Italian centers of ski tourism, which is the municipality's main source of income. The 1.176 inhabitants (average age 49, (ISTAT, 2021)) practice almost no subsistence farming, but some farmers use the adjacent plateau as pasture land. The mountain ranges south and north of the village represent suitable bear habitat and in particular corridor zones according to the suitability models (Maiorano et al., 2019). However, the interviewed residents have never sighted a bear there and many believe that bears only inhabit the Abruzzo national park. So far, there are neither prevention measures for bear damages nor information for the population about appropriate behavior in case of bear encounters in C. In principle, the interviewees acknowledge bears, while some people are afraid of them.

3.3. Model validation

We performed three validation steps including a sensitivity analysis (1), a comparison of the HBC map with locations of actual cases of human-bear interactions in the study area (2) and a workshop with experts (3).

Influence of the variables on HBC probability are presented in the Appendix, with *potentially restricted activities* (MI = 23.4%) slightly more influential on overall HBC probability than *bear occurrence* (MI = 23.35%), see C1 in the Appendix). The bear→ human impacts *bear damage* and *bear damage compensation* (both MI = 6.27%) were slightly more influential than bear-ecological factors *habitat suitability* (MI = 5.42%), and *corridor suitability* (MI = 5.04%). *Bear presence within settlement areas* (MI = 3.12%) and *human emotions* (MI = 2.97%) were similarly important.

When comparing observed negative human-bear interactions to the modelled probability of HBC, we found that 72% of the observed cases of bears entering residential areas (and, in most cases, damaging human property and livestock) took place in areas of low (below 50%) HBC probability. All monitored cases of poisoned or trapped wildlife and bears passing or killed on roads occurred in areas of low HBC probability.

The third validation step was a final workshop with five experts from practice, who had participated in the Delphi rounds. They recognized the potential of this model for practical application as a tool for monitoring HBC and prioritizing measures to improve coexistence, both in the study area and over a wider area in the Central Apennines. They also

Table A1
Description of the BN nodes and their states based on expert elicitation in Phase 1 of the modeling process.

Name & *category*	Type	Description	States
human-wildlife coexistence			
human-bear coexistence	target node	state where neither bears nor humans are affected by each other in a significant negative way ensuring long-term bear survival, social legitimacy and tolerable risk levels	high/ low
human tolerance	coexistence dimension	local people's tolerance towards bears	positive/ negative
bear fitness	coexistence dimension	fitness of the Apennine brown bear population	baseline/ reduced
Potential bear presence			
suitable bear habitat	bear-ecology driver	landscape suitability for bear habitat	suitable/ unsuitable
suitable bear corridor	bear-ecology driver	landscape suitability for bear movement	yes/ no
bear occurrence	bear-ecology driver	occurrence of bears	yes/ no
bear presence within settlement area	bear-ecology driver	regular bear presence within an inhabited area	yes/ no
landscape configuration			
residential area	landscape driver	occurrence of human settlement area	yes/ no
residential area (density)	landscape driver	density of inhabited buildings	high/ low
railway	landscape driver	occurrence of railroad lines	yes/ no
railway protection	coexistence measure	protection of railroad lines to prevent wildlife accidents	not protected/ protected/ no railway
road density	landscape driver	density of roads with high risk of wildlife accidents	low/ medium/ high/ no roads
road protection	coexistence measure	protection of roads to prevent wildlife accidents	no/ some/ much road protection/ no roads
local livelihoods			
subsistence farming	social driver	occurrence of households keeping a small number of chickens or sheep or cultivating an orchard for their own use	yes/ no
productive farming	social driver	occurrence of farms with poultry or sheep breeding and apiaries	yes/ no
pasture farming	social driver	occurrence of pasture farms	yes/ no
damage	impact bear→ human	occurrence of bear damage to livestock/ properties/ apiaries/ crops	yes/ no
damage compensation	impact bear→ human	occurrence and timing of financial compensation for bear damage from institutions in charge	yes/ late/ no/ not necessary
protective measures	coexistence measure	density of preventive measures to protect livestock/ properties/ apiaries/ crops from bear damage.	high/ low
waste management	coexistence measure	the community's waste management regarding the accessibility of food resources for bears	yes/ no

Table A1 (*continued*)

Name & *category*	Type	Description	States
human food resources	impact human→ bear	accessibility of human food resources for bears	yes/ no
hunting	social driver	practice of hunting	yes/ no
truffle gathering	social driver	practice of truffle gathering	yes/ no
tourism	social driver	occurrence of tourist infrastructures and activities not related to bears	nothing/ some/ much
potentially restricted activities	impact bear→ human	number of human activities (hunting, truffle gathering, pasture, tourism) that could be subject to restrictions due to the presence of bears	0/ 1/ 2/ 3/ 4
bear tourism	social driver	occurrence of tourism infrastructures and activities related to bears	nothing/ some/ much
"bear culture"			
community policy	social driver	orientation of the community's policy regarding human-bear coexistence	neutral/ pro coexistence
human emotions	social driver	community members' short-term emotions towards bears	fear/ anger/ acceptance/ admiration/ neutral
human knowledge	social driver	community members' awareness of bears in general and of the appropriate behavior when encountering a bear	yes/ no
bear mortality and disturbance			
mortality	human→ bear impact	risk of human-induced bear mortality	natural/ elevated
disturbance	human→ bear impact	risk of human-induced bear disturbance	baseline/ elevated
poisoning	impact human→ bear	occurrence of poison baits	yes/ no
poaching	impact human→ bear	occurrence of poaching (illegal shooting, trapping)	yes/ no
shooting	impact human→ bear	occurrence of intentional and accidental shooting of bears	yes/ no
road accidents	impact human→ bear	collisions between bears and motorized vehicles	yes/ no
railway accidents	impact human→ bear	collisions between bears and trains	yes/ no
stray dogs	impact human→ bear	occurrence of semi-wild dog packs that could transmit pathogens or attack bear cubs	yes/ no
water tanks	impact human→ bear	occurrence of unprotected water tanks in which bears could drown	yes/ no
outdoor activities	impact human→ bear	practice of outdoor activities that might disturb bears (e.g. off-roading, hiking, truffle gathering etc.)	yes/ no
"bear chasing"	impact human→ bear	deliberate persecution of bears out of curiosity or with negative intention	yes/ no

Table A2
Probability table for the target node *human-bear coexistence* in the BN. The HBC can be *low* or *high* with the defined probability distribution given the states of the two coexistence dimensions. In contrast to all other nodes, the probability table of the target node *human-bear coexistence* does not include expert- or interview-based conditional probabilities but is used to weigh the human and wildlife dimension of HBC. This allows for decisions on which coexistence dimension to accentuate in the spatial modeling.

Coexistence dimensions		Human-bear coexistence	
human tolerance	*bear fitness*	*high(%)*	*low(%)*
low	natural	50	50
low	reduced	0	100
high	natural	100	0
high	reduced	50	50

highlighted the importance of HBC maps for visualizing the urgency of HBC measures. In particular, the experts saw the advantage of the model for use in practice in its ability to link monitored point data, such as poison baits or non-bear-resistant farms, with species distribution models as well as human social context data. For application to other areas, they suggested further social surveys, as the model shows how strongly the probability of HBC influenced by local attitudes in different communities.

4. Discussion

We present a participatory modeling approach to map human-large carnivore coexistence and apply it on human-bear interactions in the Central Appennines. Here, we discuss the model findings related to the spatial pattern and drivers of HBC, the implications of these results for conservation practice in the study area and in the broader context of human-large carnivore coexistence, as well as the potential for further improvements.

4.1. Spatial variability and drivers of human-bear coexistence

We found diverse, intertwined influences on HBC, related to shared territories, agricultural land use and human culture. In the southern part of the research area, which belongs to the Abruzzo National Park, bears are more numerous and people derive economic benefits from their presence as tourist attractions. In the center of the study area, bears find suitable habitat and corridors, while many people depend on agriculture and use the surrounding landscapes for hunting and truffle gathering, and bear damage and fear of restrictions due to bear presence often lead to low human tolerance of bears. In the northern part of study area, human-bear interactions have been very rare so far and people are generally neutral towards bears, although occurrence data and models indicate that bears are increasingly roaming these areas (Morini et al., 2017; Ciucci et al., 2017). Other studies in the study area support our findings of local variability in both human tolerance towards bears (Glikman et al., 2019; Marino et al., 2021) and human-induced bear mortality (Ciucci and Boitani, 2008; Maiorano et al., 2019).

From a human perspective, local variability in conditions for human-wildlife coexistence is often related to economic costs and benefits, as well as restrictions due to wildlife presence (Inskip et al., 2013; Chen et al., 2013; Mateo-Tomás et al., 2012; Sharma et al., 2020). In our case study, people's attitudes are affected by direct interactions with bears (e.g. encounters, damage) and often differ substantially among municipalities. HBC is challenged by bear presence in human settlement areas, which can be exacerbated by habituation of bears to urban areas and conditioning to human food resources (McCullough, 1982; Herrero et al., 2005; Marley et al., 2017). However, this effect interacts with social factors, and human attitudes can be mutually reinforced within communities (Scherer and Cho, 2003). For example, a female bear and her four cubs have regularly frequented settlement areas in the study area in recent years. In communities with tourism infrastructure, residents' admiration for these bears predominates, while in communities depending on subsistence farming, anger about bear damage prevails.

Moreover, people are affected by indirect interactions with bears, such as potential territorial restrictions and financial damage compensation. Poorly functioning compensation programs with ineffective and unreliable processes may foster negative attitudes towards large predators (Boitani et al., 2010; Dickman et al., 2011). Interestingly, in our model, the influence of financial compensation for bear damage on human tolerance is as high as the influence of damage itself. This indicates that (in) tolerance towards bears is related to the discrepancy between local people's expectations of institutions and reality. Indeed, human-wildlife conflicts may sometimes actually be human–human conflicts (Madden, 2004; Redpath et al., 2013). In the case of the brown bear, most national administrations in the EU routinely compensate for bear damage, while only half of the countries systematically subsidize preventive measures (Bautista et al., 2019). In our study area, there is substantial local variation among communities in terms of success of human-bear coexistence, often depending on the prevention of human impacts on bears and bear impacts on humans, public information, and economic benefits to communities. Investments in human-large carnivore coexistence appear to be critical for both the persistence of rural communities and for the survival of (threatened) large carnivore populations.

From the bear-centered perspective, poisoning, (accidental) shooting and car accidents are the most influential factors of bear fitness loss in our model. In fact, these three factors have been the most frequent human-induced mortality causes in Abruzzo over the last 50 years (PNALM, 2021) and pose major threats to bears in other regions (Kaczensky et al., 2003; Mörner et al., 2005; Reljić et al., 2012; Lamb et al., 2020). If human-caused mortality were significantly reduced, it could have a major impact on bear population survival and growth (Gantchoff et al., 2020). In particular, unintentional killing is a major threat to Apennine brown bears. For example, truffle gatherers who put out poison bait to kill their competitors' dogs are not intentionally trying to kill bears, but may be unaware of the potentially lethal effects on wildlife. "Bear chasing", where people increasingly track bears in order to record them, can also cause stress and potentially reducing bear fitness. This behavior can be exacerbated by social media (Otsuka and Yamakoshi, 2020), and can reinforce both positive and negative emotions (Cloutier et al., 2020; Lenzi et al., 2020; Otsuka and Yamakoshi, 2020), cause stress for both humans and wildlife (Pagel et al., 2020; Lenzi et al., 2020), and can trigger human–human conflicts via social media discussions. Updating spatial models, such as the one presented here, with information from social media, could help identify high risk locations for such conflicts, which may drastically reduce human-wildlife coexistence, for monitoring, providing public information on these sites, or temporarily restricting human access(Mateo-Tomás et al., 2012; Stewart et al., 2012).

4.2. Informing practice through participatory and spatially-explicit modeling of human-large carnivore coexistence

Spatial data related to conservation are not always readily available (Rissman et al., 2017), so combining knowledge from the field and research is critical (Sunderland et al., 2009; Cook et al., 2013). Particularly in the context of human-carnivore coexistence, mapping and communicating locations with a high risk of conflicts can increase the effectiveness of measures to reduce livelihood losses, reduce mortality (Nayeri et al., 2022) and enhance carnivore conservation (Behdarvand et al., 2014; Miller, 2015). Local conservation practitioners recognized the participatory BN model and maps developed in this study as a useful tool. Since resources for conservation are limited, the model outputs are helping practitioners identify priorities for conservation activities at two levels - among municipalities as well as within municipalities. Among communities, those with a current low probability of HBC, especially

Table B1
Input layers for BN produced in Phase 3. For each input layer, the table shows the source, the preparation process, and the type of evidence and format used for the model run in gBay. Hard evidence indicates that the node state is known with certainty (100%), while soft evidence indicates that a probability distribution is used as the input. SLO/RA refers to the organizations Salviamo l'Orso and Rewilding Apennines. PNALM refers to the National Park Abruzzo, Lazio and Molise.

Name & *category*	Source	preparation process	Evidence	Format
Potential bear presence				
suitable bear habitat	(Ciucci et al., 2016)	The continous model (resolution 100x100m) was masked to the study area and rescaled to a raster with values ranging from 0 to 100 (with 100 being assigned to the most suitable grid cell in the study area). A second band with inverse scale was added.	soft	Multi band raster with Band 1: suitable (0–100%), Band 2: unsuitable (0–100%)
suitable bear corridor	(Ciucci et al., 2016)	The binary corridor model (resolution 100x100m) was masked to the study area and rasterized.	hard	Single band raster with values 1 (corridor) or 2 (no corridor)
landscape configuration				
residential area	Facebook High Resolution Settlement Layer (Facebook, 2016)	The Italian population density layer (resolution 30x30m) was aggregated to 100x100m resolution, masked to the study area were assigned to all cells containing population/building data.	hard	Single band raster with values 1 (residence) or 2 (no residence)
residential area (density)	Facebook High Resolution Settlement Layer (Facebook, 2016)	The Italian population density layer (resolution 30x30m) was aggregated to 100x100m resolution, masked to the study area and rescaled to a raster with values ranging from 0 to 100 (with 100 being assigned to the most densely populated grid cell in the study area). A second band with inverse scale was added.	soft	Multi band raster with Band 1: high (0–100%), Band 2: low (0–100%)
railway	OpenStreetMap (OSM, 2021)	OSM data with key "railway" was downloaded, viaducts and tunnels were excluded. The lines were buffered (r = 200 m) and rasterized.	hard	Single band raster with values 1 (railway) or 2 (no railway)
railway protection	SLO/RA database, expert judgment	Values were assigned to *railway* layer based on knowledge of protection status.	hard	Single band raster with values 1 (not protected), 2 (protected) or 3 (no railway)
road density	OpenStreetMap (OSM 2021), SLO/RA database, expert judgment	OSM data with key "roads" was downloaded, viaducts and tunnels were excluded. Most risky roads for human-wildlife collisions were selected. After a line density analysis (r = 500 m), the grid was categorized into four states.	hard	Single band raster with values 1 (low), 2 (medium), 3 (high) road density or 4 (no roads)
road protection	SLO/RA database, expert judgment	Values were assigned to *road density* layer based on knowledge of protection status.	hard	Single band raster with values 1 (nothing), 2 (some), 3 (much) road protection or 4 (no roads)
nature protection	Web Map service: "VI Official List of protected areas" (Geoportale, 2019)	Layer of Italian protected area polygons was masked to research area, rasterized and values were assigned based on the protection status.	hard	Single band raster with values 1 (not protected), 2 (nature reserve), 3 (regional park) or 4 (national park)
local livelihoods				
subsistence farming	SLO/RA database, interviews with local people	Based on interviews, zones of residential areas with occuring subsistence farming were mapped in *residential area* layer and rasterized.	hard	Single band raster with values 1 (subsistence farming) or 2 (no subsistence farming)
productive farming	Web Map Service "active farms" (Geoportale, 2018), interviews with local people	Point layers with active poultry, sheep and goat farm locations were redrawn in QGIS and merged with additional point coordinates obtained from interviews. The layer was rasterized by assigning a value = 1 if a cell at least contained one farm.	hard	Single band raster with values 1 (farm) or 2 (no farm)
pasture farming	Web Map Service "active farms" (Geoportale, 2018), interviews with local people	Point layers with active cattle and horse farm locations were redrawn in QGIS and merged with additional point coordinates obtained from interviews. Points were buffered (r = 1 km) and rasterized.	hard	Single band raster with values 1 (pasture) or 2 (no pasture)
protective measures	SLO/RA and PNALM database	Kernel Density was calculated from prevention point coordinates (QGIS: Heatmap, r = 500 m), rescaled to a raster with values ranging from 0 to 100 (with 100 being assigned to the grid cell with the most prevention measures in the study area). A second band with inverse scale was added.	soft	Multi band raster with Band 1: high (0–100%), Band 2: low (0–100%)
hunting	Web Map service: "VI Official List of protected areas" (Geoportale, 2019), interviews with local people	All pixel cells of *nature protection* layer with value = 1 (not protected ≙ hunting is allowed) were selected and some illegal hunting areas mapped during interviews were rasterized and added.	hard	Single band raster with values 1 (hunting) or 2 (no hunting)
truffle gathering	Web Map Service "truffle suitability" (Geoportale, 2018), satellite imagery, interviews with local people	The truffle suitability layer for Tuber magnatum abundance was redrawn in QGIS and frequented truffle zones mapped during interviews were added. The combined polygons were rasterized.	hard	Single band raster with values 1 (truffle gathering) or 2 (no truffle gathering)
tourism	expert judgment, satellite imagery	Together with tourism experts frequented tourism zones (e.g ski areas, highly frequented hiking tracks) were mapped and then rasterized.	hard	Single band raster with values 1 (no tourism), 2 (some tourism) or 3 (much tourism)
bear tourism	expert judgment, satellite imagery	Together with tourism experts frequented bear tourism zones (e.g villages with "bear" marketing, frequented bear observation spots) were mapped and then rasterized.	hard	Single band raster with values 1 (no bear tourism), 2 (some bear tourism) or 3 (much bear tourism)
bear culture				

(*continued on next page*)

Table B1 (*continued*)

Name & *category*	Source	preparation process	Evidence	Format
community policy	interviews with local people	Interview data was allocated per municipality and rasterized.	hard	Single band raster with values 1 (pro coexistence) or 2 (neutral)
human emotions	interviews with local people	Interview data was allocated per municipality and rasterized. A layer with five bands was produced.	soft	Multi band raster with Band 1: fear (0–100%), Band 2: anger (0–100%), Band 3: acceptance (0–100%), Band 4: admiration(0–100%), Band 5: neutral (0–100%)
human knowledge	interviews with local people	Interview data was allocated per municipality and rasterized.	hard	Single band raster with values 1 (no knowledge) or 2 (knowledge)
bear mortality				
dogs	SLO/RA database	Polygons from occurrence areas of monitored semi-wild dog packs were drawn and rasterized.	hard	Single band raster with values 1 (dogs) or 2 (no dogs)
water tanks	SLO/RA and PNALM database	Monitored point coordinates were rasterized by assigning a value = 1 if a cell at least contained one unprotected water tank.	hard	Single band raster with values 1 (unprotected water tank), 2 (no water tank)

Table C1
Results of sensitivity analysis for HBC of the target node, with respective node group and mutual information (MI) values indicated. The MI values indicate how much the entropy (uncertainty) about the target node would be reduced by a finding on each node. All nodes with MI⩾ 0 are listed.

node	node group	MI (%)
potentially restricted activities	bear→ human impact	23.396
bear occurrence	bear ecology	23.351
bear damage compensation	coexistence measure	6.27
bear damage	bear→ human impact	6.266
bear presence in settlement areas	bear ecology	5.419
habitat suitability	bear ecology	5.044
corridor suitability	bear ecology	3.1222
emotions	social driver	2.97
mortality risk bears	human→ bear impact	0.94
human food resources	human→ bear impact	0.866
disturbance risk bears	human→ bear impact	0.808
”bear chasing”	human→ bear impact	0.499
outdoor activities	social driver	0.174
knowledge	social driver	0.162
poisoning	human→ bear impact	0.122
hunting	social driver	0.108
accidental shots	human→ bear impact	0.097
truffle gathering	social driver	0.059
car accidents	human→ bear impact	0.034
bear tourism	social driver	0.032
pasture farming	social driver	0.031
protective measures	coexistence measure	0.024
poaching	human→ bear impact	0.022
tourism	social driver	0.021
stray dogs	human→ bear impact	0.018
road density	landscape driver	0.014
water tanks	human→ bear impact	0.012
subsistence farming	social driver	0.01
residential area	landscape driver	0.008
railway accidents	human→ bear impact	0.007
productive farming	social driver	0.003
road protection	coexistence measure	0.001
railway	landscape driver	0.001
railway protection	coexistence measure	0.001
residential area (density)	landscape driver	0.001

due to their reliance on agriculture and lack of experience with bears, should be prioritized through early information campaigns and the long-term establishment of livestock conservation measures. Within municipalities, the probability of HBC is spatially heterogeneous, so mapping this distribution can help identify specific priority locations, such as road sections or unprotected livestock shelters, for coexistence measures. Since different spatial drivers are more or less important in different communities (Fig. 6), different types of conservation actions can be prioritized in each municipality. For example, in municipality A, measures should focus on information and guidance for tourists (Penteriani et al., 2017; Dybsand, 2020), while in municipality B, communication with truffle hunters and regular poison control, e.g. by detection dogs (Badia-Boher et al., 2019; Deak et al., 2021), and planning of different road protection measures (Graves et al., 2006; Glista et al., 2009; St Clair et al., 2020), would be more important in the short term. In community C, which relies on ski tourism, information campaigns and livestock protection measures would be currently required, with a priority for pastures that overlap with bear corridors (Treves et al., 2004; Miller, 2015), while a concept for responsible wildlife tourism should be developed in the coming years (Fortin et al., 2016; Choi et al., 2017).

Although the model developed here is specific to the context of the Central Apennines, this type of model combining different perspectives is also relevant for conservation practice more broadly. As large carnivores regain new habitats across Europe, mapping the probabilities of human-large carnivore coexistence based on expert knowledge and openly available spatial data could help identify priorities for improving the conditions for coexistence before conflicts occur, preventing negative effects on both human tolerance and wildlife fitness. To best support conservation decisions, the model would need to be adapted to the local context, and the weighing of each perspective should be adapted to local priorities. In the Apennine context, our model does not include direct risks to human safety due to the bears' non-aggressive behavior (Benazzo et al., 2017), and bear fitness is of high priority given the small and strictly protected Apennine bear population. In other regions, these components may be weighed differently, although the drivers related to territorial constraints and rural livelihoods are similar for bears and other large predators such as wolves and lynx in many European areas (Bautista et al., 2019).

The participatory BN approach allowed us to combine openly available spatial data with specific local perspectives, while accounting for uncertainty. Habitat suitability models are often used to predict species' occurrence, but are associated with some uncertainty, and when using such a model as an input to the BN, this uncertainty is propagated to the BN output. Further uncertainty arises from different people's subjective perceptions of risk, which are shaped within social networks and environmental conditions (Skjong and Wentworth, 2001; Scherer and Cho, 2003; Baird et al., 2009; De Dominicis et al., 2015; Inskip et al., 2013), and often driven by emotions (Slovic and Peters, 2006), in the context of large carnivores especially by fears (Røskaft et al., 2003; Johansson and Karlsson, 2011; Johansson et al., 2012). Indeed, the interviewees' perceptions of bear-related risks were shaped by both their own experiences and shared stories within communities, and were always highly emotionally charged. The local people's emotional and economic dependence on agricultural livelihoods clearly affected their risk perceptions (Bruskotter and Wilson, 2014; Carter et al., 2020; Inskip et al., 2013). For example, people living solely from subsistence farming were concerned about bear damage, while people living from both subsistence agriculture and bear tourism were not. The experts involved may also be biased in their risk assessments (Skjong and Wentworth, 2001; Anthony Cox, 2008), and might overestimate human-induced

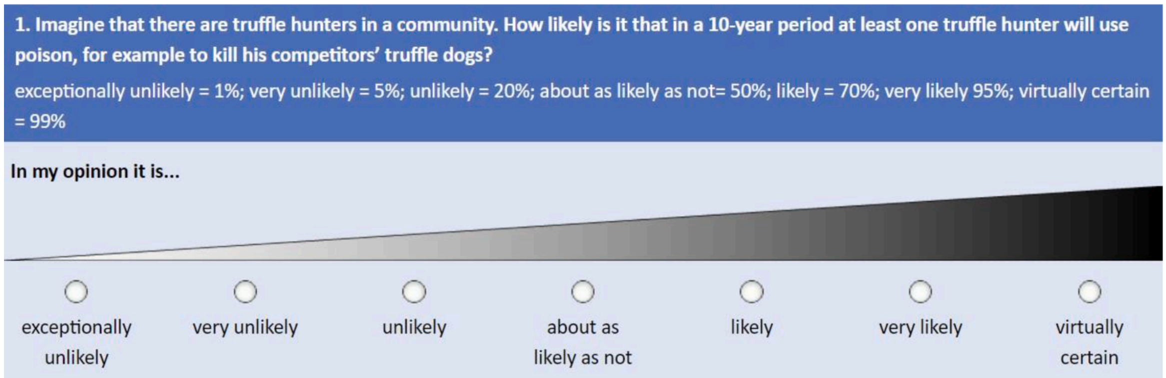

Fig. D1. An example question from the online questionnaire used to fill the conditional probability tables in Phase 2. As conditional probabilities can be difficult to imagine, the experts were asked to assign probabilities to fictitious situations. The questions are based on the variables and their linkages in the conceptual model. A clear definition on probability levels was provided, so that participants could click on specific levels on a probability scale. All questions can be find in the supplementary material.

mortality and disturbance risks due to the Apennine bears' endangered status. Although we here combined different expert assessments into one operational model, the BN could also be used as a tool to specifically study the differences in perspectives among experts or stakeholders (Salliou et al., 2017).

Since HBC is an issue with different perspectives and high stakes for many of the stakeholders involved, it is essential to bring these different viewpoints together into dialogue (Funtowicz and Ravetz, 1994; Salvatori et al., 2021). Involving local people in the modeling process (Sandker et al., 2010; Voinov and Bousquet, 2010), or at least in interviews (Calheiros et al., 2000), provides an opportunity to engage them in coexistence projects. The resulting maps can serve as communication tools to demonstrate perceived risks from stakeholders, potential threats to wildlife, and ultimately, the need for measures to improve coexistence. Since results of models that are created together with local practitioners are more likely to be used by them as decision-support (Jakeman et al., 2006), such participatory models can help make modeling efforts more directly useful for conservation practice.

4.3. Model limitations and potential for further development

The model developed in this study is static, although human-wildlife interactions are dynamic and change throughout the year (Linkie et al., 2007; Goswami et al., 2015; Zarzo-Arias et al., 2021). For example, the bears' diet varies throughout the year, as do their movement ranges due to both their specific nutritional requirements before and after hibernation and the temporal availability of food (Ciucci et al., 2014; Swenson et al., 2020). Some Apennine brown bears approach settlement areas during summer months when fruits ripen in the orchards. Bears conditioned to human food resources enter settlement areas particularly at the time of increased feeding activity before hibernation. In winter, during hibernation, and in spring, female bears raising cubs are especially vulnerable to human disturbance (Swenson et al., 1997; Ordiz et al., 2013; Fortin et al., 2016; Linnell et al., 2000). Likewise, human land use practices and tourism activities often vary seasonally. Although bears are an extreme case of these seasonal feeding and movement variations, many large carnivores change their predation patterns throughout the year (Metz et al., 2012; Bianchi et al., 2014; Koziarski et al., 2016), which influences both their impacts on humans as well as their vulnerability to human threats. The current model does not capture seasonal variability or the potential changes in HBC over time. However, the BN approach allows new evidence to be added at different points in time (Landuyt et al., 2013; Hamilton et al., 2015), so that the resulting maps could be updated to show a time series of HBC.

Another point that was not explicitly considered in our model and was questioned in the final expert workshop is the financial value of bear presence with its potential positive impact on HBC. We only implicitly considered the bears' economic value through the variables of damage, damage compensation, restricted activities, and tourism related to bears, all of which influence human tolerance of bears (Dickman, 2010; Linnell and Boitani, 2012; Glikman et al., 2019). In addition, to limit model complexity, we did not include policy changes at the regional, national, and EU levels that could affect community policies. In future, new nodes could be added to the BN and evidences could be updated to incorporate these changes.

In this work, we made use of an existing habitat suitability model for bears (Ciucci et al., 2016; Maiorano et al., 2019), assuming that habitat and corridor suitability are conditioning factors of bear occurrence throughout the study area. However, probabilities of bear presence differ between zones where bears already occur and those beyond the current distribution range. Furthermore, human population density was used as a negative predictor of bear habitat suitability (Maiorano et al., 2019), although this is not true for bears conditioned to human food resources, which are the main cause of conflicts in settlement areas. In further research, it would therefore be important to include a habitat suitability model for conditioned bears that incorporates areas with high accessibility to human food resources as habitat predictors.

Modeling coexistence from the perspective of animals relies on the assumption that wild animals seek to maximize their individual fitness, and therefore human disturbance poses a threat to them. However, this might actually be a conservationist perspective. Getting closer to a wildlife perspective would require a better understanding of animals' mechanisms for adaptive decision-making in natural environments (Budaev et al., 2019), the effects of individual behavior on population dynamics (Maspons et al., 2019) and, for example, to assess stress levels and behavioral responses to human presence (Ellenberg et al., 2007; Ciuti et al., 2012).

5. Conclusion

Human-large carnivore coexistence is influenced by a variety of human, wildlife, and landscape factors. The modeling process developed in this study considers both human and large carnivore perspectives on coexistence, as well as the spatial variability of conditions for coexistence in the landscape. In the case study presented in the Central Apennines, human-bear coexistence is spatially heterogeneous with strong differences between municipalities, as its probabilities vary with landscape configuration, social-economic factors, and bear ecology, as well as with the mutual impacts of humans and bears and the implementation of measures promoting coexistence. The spatially explicit BN produced in this study can help prioritize both human-centered and bear-centered conservation efforts in areas with a low probability of human-bear coexistence. Facilitating human-bear coexistence can support both the conservation of the endangered Apennine brown bear population and the maintenance of local livelihoods. Our case study demonstrates how a participatory modeling process that takes into account local people's perceptions, experts' assessments, and spatial data, resulting in up-to-date coexistence maps, can be a valuable tool for conservation practice. This modeling approach can be used in a variety of settings with human-large carnivore interactions, and may be particularly useful in areas where large carnivores are currently returning and where humans lack experience in coexistence with predators.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A

Bayesian network nodes

Appendix B

Input layers for spatial-explicit Bayesian network

Appendix C

Sensitivity analysis of Bayesian network run

Appendix D

Example question from the online questionnaire conducted in the 2nd Delphi round

Appendix E. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jnc.2023.126387.

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