

Special Series

Causal Bayesian networks in assessments of wildfire risks: Opportunities for ecological risk assessment and management

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EDITOR'S NOTE:

This article is part of the special series “Ecological consequences of wildfires.” The series documents the impacts of large-scale wildfires in many areas of the globe on biodiversity and ecosystem condition in both terrestrial and aquatic ecosystems, the capacity for systems to recover, and management practices needed to prevent such destruction in the future.

Abstract

Wildfire risks and losses have increased over the last 100 years, associated with population expansion, land use and management practices, and global climate change. While there have been extensive efforts at modeling the probability and severity of wildfires, there have been fewer efforts to examine causal linkages from wildfires to impacts on ecological receptors and critical habitats. Bayesian networks are probabilistic tools for graphing and evaluating causal knowledge and uncertainties in complex systems that have seen only limited application to the quantitative assessment of ecological risks and impacts of wildfires. Here, we explore opportunities for using Bayesian networks for assessing wildfire impacts to ecological systems through levels of causal representation and scenario examination. Ultimately, Bayesian networks may facilitate understanding the factors contributing to ecological impacts, and the prediction and assessment of wildfire risks to ecosystems. *Integr Environ Assess Manag* 2021;17:1168–1178. Published 2021. This article is a U.S. Government work and is in the public domain in the USA.

KEYWORDS: Assessment, Avian ecology, Bayesian belief networks, Causal modelling, Decision model

INTRODUCTION

Wildfire risks and losses have increased over the last 100 years, associated with population expansion, land use practices, and global climate change, with more than 30% of the global land surface experiencing increased fire frequency (Abatzoglou & Williams, 2016; Bowman et al., 2017; Chuvieco et al., 2008; H. A. Kramer et al., 2018, 2019; Pechony & Shindell, 2010; Radeloff et al., 2018). The devastating consequences of catastrophic wildfires have caused unprecedented individual, family, community and societal impacts, displacement and costs that will increase in the future as environmental conditions become drier and hotter. In the western United States, increases in frequency and duration of fires and fire seasons over the last three decades have been ascribed to raised temperatures, earlier snow melt, and accumulated fuels from fire suppression practices (Andrews et al., 2007; Westerling et al., 2006). Wildfires can

have large-scale landscape, human health, and socio-economic impacts that are predicted to increase with climate change-driven increases in the number of days with extreme fire conditions (Gedalof et al., 2005; Goss et al., 2020). For example, the November 2016 wildfires in the southeastern United States contributed an estimated 45% of fine particulate matter (PM_{2.5}) and affected the air quality for millions of people (Guan et al., 2020). Large-scale impacts from smoke from the 2017–2018 wildfires in California included degraded air quality, public health emergencies, and the closure of thousands of schools and businesses (Goss et al., 2020). Estimates of California state fire suppression costs from the 2017–2018 wildfires exceeded \$1.6 billion USD and economic losses were estimated to exceed \$40 billion USD (Goss et al., 2020).

Wildfires have also had extensive ecological impacts including direct effects in burnt regions and indirect effects from runoff and water quality that have affected resources used by humans and ecological communities (e.g., K. D. Hyde et al., 2016; Rhoades et al., 2017). For example, the recent (2019–2020) wildfires in Australia burnt 7.2 million hectares of land and caused large-scale mortality of wildlife and aquatic biota (Silva et al., 2020). In forest ecosystems,

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TABLE 1 Illustrative set of applications of Bayesian networks in a variety of wildfire problem contexts

Problem context	Example variables/nodes	Reference(s)
Fire occurrence prediction	Population, distance from roads, distance from settlements, topography, temperature, precipitation, land cover	Bashari et al. (2016); Dlamini (2010); Sevinc et al. (2020)
Fire behavior modeling	Wind direction, fire weather, forest canopy characteristics, fuel model	Norman et al. (2010)
Housing loss prediction	Fire behavior, fire weather, burned area, distance to fire station, land cover, housing type and construction, housing density	Papakosta et al. (2017)
Wildlife habitat characteristics and vulnerability	Habitat suitability, fire size, fire likelihood, time since fire, recolonization potential, genetic risk, population demographics, vegetation cover, predator occurrence	Falke et al. (2015); Hradsky et al. (2017); Zeigler et al. (2019)
Vegetation response to wildfire	Fire frequency, vegetation type	Loftin et al. (2018)
Reduced risk to homes and infrastructure due to fuel mitigation	Housing density, vegetation type, fire weather, fire size, presence of fuel breaks, fuel treatment rate, fire danger index, suppression response	Cirulis et al. (2020); Penman and Cirulis (2020); Penman et al. (2014, 2015, 2020)

wildfires have caused a multitude of effects on soils and watershed processes that affect ecological systems leading to sedimentation, elevated stream temperatures, and nutrient concentrations (Ice et al., 2004; Moody et al., 2013). There is growing awareness of and concern over the adverse ecological impacts of wildfire, especially associated with increases in burned area and increasing high-severity patch size (i.e., increasing size of contiguous areas burned at high severity; Collins et al., 2017; Parks & Abatzoglou, 2020; Stevens et al., 2017). Impacts have included declining resilience of forests, inhibited post-fire regeneration, and threat of forest loss (e.g., Coop et al., 2020; Davis et al., 2019, 2020; Stevens-Rumann et al., 2018), degraded wildlife habitat (e.g., Barber et al., 2018; Roerick et al., 2019; Stephens et al., 2016), post-fire debris flows (e.g., S. H. Cannon et al., 2010; Wall et al., 2020), and loss of carbon stability (e.g., Bowman et al., 2020; Hurteau & Brooks, 2011). Wildfires can also affect vegetation condition and distribution of successional states (e.g., Scott et al., 2014). The current article provides a brief review, perspectives, and opportunities for incorporating causal Bayesian networks (BNs) in assessments of ecological risks and impacts of wildfires.

CAUSATION IN WILDFIRE ECOLOGICAL IMPACTS

Understanding causal linkages between wildfires and drivers of the cascading effects on ecological systems remains a critical need in fire management and impact assessment. However, causal associations between wildfire effects and landscape, climate change, and forest management practices have been difficult to quantify and predict (Silva et al., 2020). Challenges of observation and measurement, core gaps in understanding fire science and interconnections of wildfire effects, and integration of fire effects into risk assessment have led to limited focus on causal mechanisms in fire ecology research (K. Hyde et al.,

2013; Keane et al., 2009; O'Brien et al., 2018). Recently Qiu et al. (2018) qualitatively showed causal linkages between wildfire management practices and resulting risks to humans and ecological services, but quantitative models have generally been limited.

BNS IN WILDFIRE AND ENVIRONMENTAL RISK ANALYSIS

One option for developing and applying quantitative models for assessing causal linkages in the ecological effects of wildfires is BNs. Bayesian networks are probabilistic graphical models of variables and their dependencies that can be used to make the assumptions for causal assessments and decision-making explicit (Moe et al., 2021). Their usefulness in causal modeling comes from their intuitive graphical depiction of cause-effect linkages and the capabilities for including the uncertainties in these linkages. A recent systematic review found that BNs have been used in environmental modeling and ecological risk assessments but have had only limited application in quantitatively assessing the ecological impacts of wildfires (Kaikkonen et al., 2021).

Table 1 presents an illustrative set of BN applications, organized according to problem context and with examples of variables included in the BN models. Bayesian networks have been used in modeling general fire occurrence and fire behavior, a precursor to risk analysis (e.g., Bashari et al., 2016; Dlamini, 2010; Sevinc et al., 2020), in predicting potential home loss (Papakosta et al. (2017)), in assessing the influence of fire regime on woody vegetation in tropical savannahs (Liedloff & Smith, 2010), and in considering fire risks and effects on salmonid habitat (Falke et al., 2015; Zeigler et al., 2019). Bayesian networks have also been used in assessing fire as a driver of habitat structure and terrestrial fauna distributions (Hradsky et al. 2017), and fire and vegetation dynamics in protected wetlands (Loftin et al., 2018).

Ayre and Landis (2012) developed a risk-based BN model that examined the influence of wildfires and other factors and management practices on forest resources and habitat.

In addition to assessment, BNs have also been used in decision-oriented frameworks to evaluate alternative management scenarios. For example, Penman et al., (2014, 2015) developed BNs focused on property and housing loss and fuel management decisions. Similarly, BNs were developed for a comprehensive risk assessment and comparison of alternative fire management approaches in Australia (Penman & Cirulis, 2020), and to quantify the effectiveness of preventative and suppression strategies on avoiding loss in a multicriteria analysis including housing loss, carbon release, and powerline damages (Penman et al., 2020).

In summary, some BN studies with ecological endpoints include fire as a causal variable but with limited consideration of factors influencing fire activity or management actions to alter fire activity. Some studies instead focus on factors influencing fire activity or management actions to alter fire activity, but with a limited focus on ecological endpoints. This paper is in part an attempt to bridge that gap, while also emphasizing the broader envelope of insights that causal modeling and inquiry with BN frameworks can provide.

LADDER OF CAUSATION

In the remainder of this article, we discuss the ladder of causation (Pearl & Mackenzie, 2018) and the opportunity for using BNs to model causal linkages in wildfire impacts on ecological systems. Recently, Pearl and Mackenzie (2018) constructed a ladder of causation for benchmarking the causal knowledge embedded in models. The ladder of causation provides a framework for the type of causal questions being addressed for a problem domain (Figure 1). The first rung of the ladder is the lowest in terms of causal information and is designated as “seeing.” This rung examines questions from an observation from a causal process (“After X happens, I am more likely to observe Y”). The seeing level is where most standard questions in classical and Bayesian statistics are examined and a causal model is not required for addressing seeing questions, just non-spurious correlations. The next two rungs are where explicit causal structures are required. Rung 2 (Intervening) assumes some type of manipulation (simulated or actual) of a system variable from an intervention to examine the causal implications (“If X is changed to x, what will happen to Y?”) and Rung 3 (Imagining) requires changes to a causal system that did not happen given what did (“Imagine if x had not occurred, would y also still have happened?”). These rungs will be examined more fully in terms of ecological impacts to a wildland system from fire regimes but they provide a useful way of separating causal modeling types for assessment or decision-making. However, most models, even most causal BNs have not surpassed Rung 1 in terms of causal modeling.

Although purely associational models are classified at the lowest levels, a higher-level model does not imply a better model for every task. As will be illustrated below, observational models are better equipped to answer certain

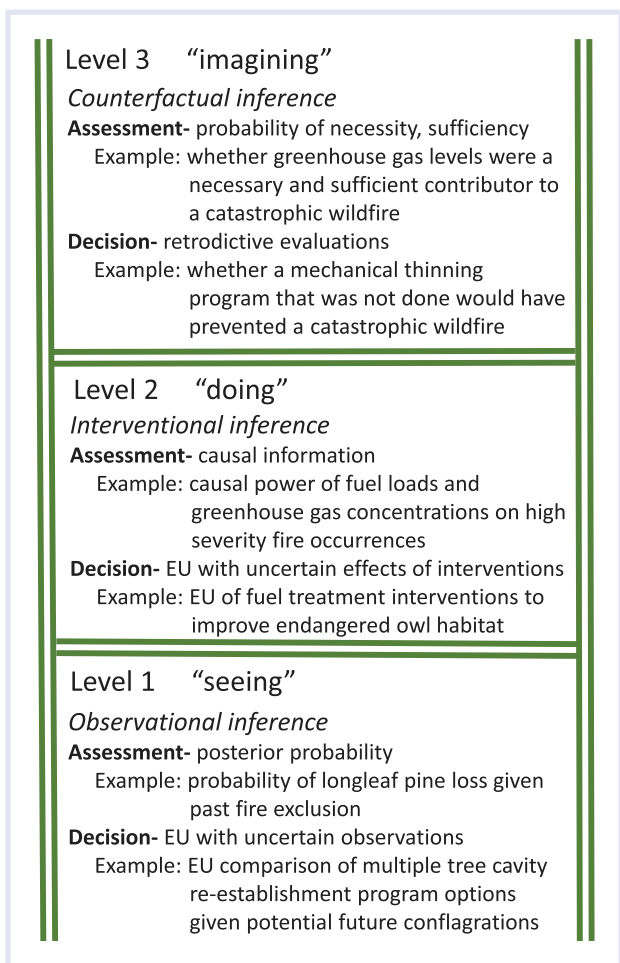


FIGURE 1 Assessment and decision-making modeling inference types under different rungs of Pearl's ladder of causation (Pearl & Mackenzie, 2018). EU, expected utility

questions than models at the highest levels. However, Pearl and Mackenzie's (2018) ladder is a useful way to establish the questions that can be addressed and the information and calculus that are necessary. We assume for each of the levels that a causal model is used. However, some models may be developed that utilize causal assumptions without using causal connections among variables. This is an active area of research in machine learning and can be insightful with complex multivariate data sets (Conrady & Jouffe, 2015). The sections below will examine the ladder in terms of assessment and decision models. Assessment models are ones that examine states of the world and are mostly found at Rung 1. Decision models are ones that examine the outcomes from decision and are mostly found at Rung 2. However, both model types are found at all levels based on the types of questions being asked. A recent paper by Landis (2020) discussed the ladder of causation and the potential for its use in better preparing for future emerging risks. The discussion by Landis (2020) was an impetus for this work and the ideas explored herein.

As motivating examples, we consider two avian species of conservation concern: the red-cockaded woodpecker (RCW;

Picoides borealis) and the California spotted owl (CSO; *Strix occidentalis occidentalis*). Both the RCW and CSO exist in forests historically adapted to frequent, low- to moderate-intensity fire regimes, but forest conditions have been impacted by a legacy of logging and fire exclusion, among other factors (Stephens et al., 2019). In the case of the RCW, application of prescribed burning has helped to restore longleaf pine habitat, but reintroduction of fire after extended periods of fire exclusion presents a risk of excessive overstory mortality due in part to smoldering combustion of accumulated duff on the forest floor (Cox et al., 2020; Hiers et al., 2020; O'Brien et al., 2010; Varner et al., 2007; Williams et al., 2006). In the case of the CSO, application of prescribed burning has been limited, surface and ladder fuel loads are high, and habitat characterized by tall tree cover is at risk of large, stand-replacing wildfires (G. M. Jones et al., 2016, 2020; A. Kramer et al., 2021; North et al., 2017; Schofield et al., 2020).

In the sections below, we briefly illustrate with stylized examples how causal models can inform assessments and decision questions related to wildland fire and wildlife habitat management, using the ladder of causation hierarchy as a guidepost. For brevity, we avoid detailed descriptions of data available to parameterize such models, although as alluded to in the above section, there is a wide range of sources to turn to such as fire occurrence and burn severity databases (e.g., Eidenshink et al., 2007; Short, 2017), geospatial layers on vegetation and fuel and topography (e.g., Rollins, 2009), fire weather history and downscaled climate projections (e.g., Abatzoglou & Brown, 2012; Vejmela et al., 2016), past management actions such as fuel treatments (e.g., Forest Service Activity Tracking System [FACTS]; <https://data.fs.usda.gov/geodata/edw/datasets.php?xmlKeyword>), and aforementioned studies of wildlife observations.

Rung 1—"Seeing"

The first level in the ladder of causation is purely observational. It is for addressing problems of the type, "Given that one thing occurs, this is what is also more or less likely." Rung 1 integrates background observations with observable measurements to address association-type questions (Pearl & Mackenzie, 2018). On a standard resolution for most models, "seeing" says that raising the probability of one or more variables changes the probability of one or more other variables. Examining the total effects of relationships among variables for predictive models is a "seeing" inference (Conrady & Jouffe, 2015). The "seeing" questions are most often usefully supported with statistical and exploratory analysis but the knowledge of causal interactions can be important to incorporate for addressing many "seeing" questions and this is the focus here.

An example of a "seeing" problem may be found in the RCW habitat restoration for longleaf pine systems in the southeastern United States. The RCW requires suitable cavity tree density habitat to maintain populations. Fire exclusion can increase hardwood growth, shrub cover, and

accumulation of organic matter on the forest floor (Varner et al., 2005). This understory growth and duff accumulation provide fuel for a severe and ecologically damaging wildfire to the pine trees if an unplanned fire occurs. In addition to fuel and forest characteristics, burn severity is influenced by fire weather characteristics (i.e., wind, relative humidity) and a host of other variables (e.g., topography) not included here for the economy of presentation. In this example, an assessment is needed for predicting the risk of a severe and damaging fire to the habitat in regions of interest for the RCW. The probabilistic model for such an assessment would consider the uncertainties related to the prediction of longleaf pine losses from a future fire event. The assessor considers the influence of fire exclusion (time since fire) and the uncertainties on a future fire event to the longleaf pine and the habitat provided for RCWs with an explicit or implicit causal model linking the variables (Figure 2A). The "seeing" questions can also benefit from a causal model to make diagnostic inferences. Diagnostic inferences are from an observed effect to an unobserved cause. An assessment may ask, for example, "Given that a large fire occurred, what were the likely states of the fuel accumulation levels and the pine density prior to this event?"

A decision model may still be associated with a Rung 1 model when it requires knowing about, and not intervening on, the events in a system. Continuing with the same example, a habitat restoration decision model may be used for choosing whether to artificially create cavities, which notably would not affect the underlying dynamics of the fire regime and forest conditions, and which would be based on predicting the amount of large, mature trees suitable for cavity nesting (Figure 2B). The information needed to support the decision of interest would be concerned with the characteristics of the longleaf pine. Although prescribed burning and other treatments can maintain the conditions to support longleaf pine systems, it may take decades for the trees to mature into the appropriate size and age class RCW typically nest in, such that artificial cavities create an interim solution if a significant mortality event from a fire occurs. The utility node would include a value scale with the trade-offs of the cost of establishing a program to restore cavity density if the cavity tree density is or is not suitable for the RCW after a fire event.

Rung 2—"Doing"

The second level moves from the realm of observation to action or "doing." The doing level addresses "what would happen if we do this?" and "How can this be done?" questions (Pearl & Mackenzie, 2018). Second rung inferences refer to changing the world through actively changing a causal process. This level is where the notion of interventions comes into play and requires that causal understanding is incorporated into the development of and inferences from the models. Interventions can have a potential real-world counterpart or be simulated (Korb et al., 2009). Simulated interventions are useful for assessment models to examine the strength of causal pathways

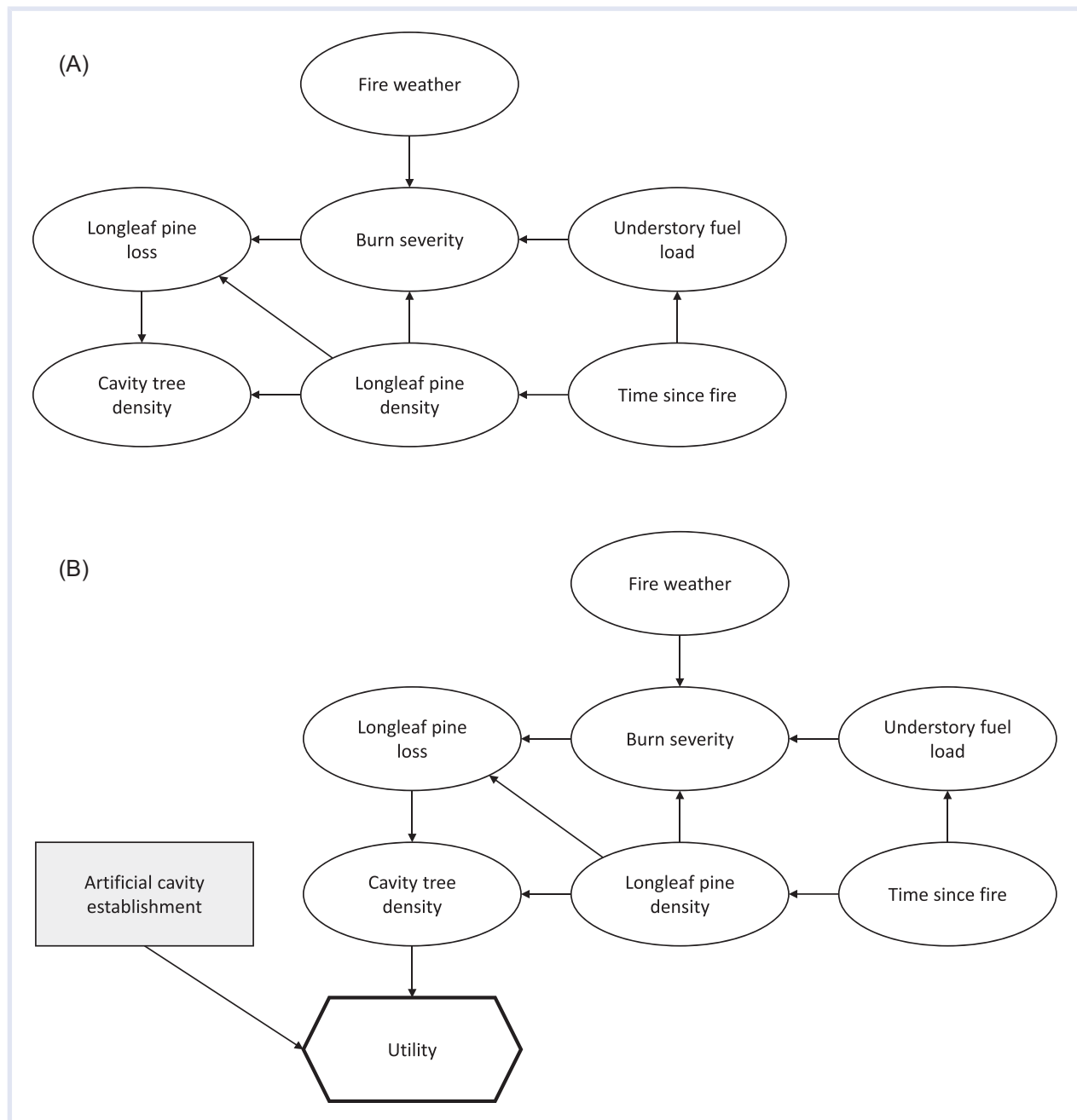


FIGURE 2 Stylized causal model of red-cockaded woodpecker habitat restoration for assessment (A) and for decision making on the need for re-establishing cavity trees for woodpecker habitat (B). Ovals are chance nodes (random variables), grey boxes are decision nodes, and bolded hexagons are utility nodes

(Carriger et al., 2016). An intervention would be a type of decision that would explicitly change a node's value or probability distribution. One of the contributions from Judea Pearl is the capability for qualitatively and quantitatively examining causal pathways with interventions on a causal structural model (Pearl & Mackenzie, 2018). Causal questions related to the power of one variable to influence another are addressed in the doing level. Korb et al. (2009) developed the notion of causal power. Causal power is used for questions about the strength of the causal relationship between causes and effects. Causal power between causes and effects can be quantitatively provided through

manipulating causal variables through simulated interventions and applying information theory measures (Shannon, 1949) to calculate the impacts from the manipulation on an effect (Korb et al., 2009).

For the second and third rungs, we turn to a slightly more complicated example causal model of wildfire impacts on CSO habitat. Wildfire can degrade CSO habitat directly through the mortality of tall trees that owls prefer, and indirectly through large areas burned at high severity that owls tend to avoid. The total area burned at high severity is influenced by among other factors fuel loads (i.e., volume of flammable vegetation) and fire weather (Penman et al.,

2020), the latter of which is also driven by a changing climate (Abatzoglou & Williams, 2016; Jolly et al., 2015), and high-severity patch size is additionally influenced by the continuity of fuels (i.e., the horizontal and vertical spacing of flammable vegetation) across the landscape (J. B. Cannon et al., 2020). More complex models could also evaluate the near-term impacts of harvesting on habitat use (Ganey et al., 2017; Irwin et al., 2015) or could capture additional detail in spatial patterns of fuels and burned areas (Collins et al., 2017; Stevens et al., 2017).

In this case, one potential “what would happen” question relates to the assessment of the role of climate change from greenhouse gas concentration scenarios on wildfire risk to

owl habitat. One study, for example, identified a trend of increasing habitat area burned at high severity and projected that high-severity fire could pose a substantial threat to CSO persistence in the next 75 years (Stephens et al., 2016). A causal assessment model could examine the causal power of alternative global climate model scenarios (e.g., Riley & Loehman, 2016) on changes to habitat variables or owl abundance under an assumed causal structure (Figure 3A). Similarly, analyses could project climate change impacts on fire activity and habitat suitability (e.g., Stephens et al., 2020; Wan et al., 2019).

The doing level is where the decision models that intervene on a system to achieve objectives are found

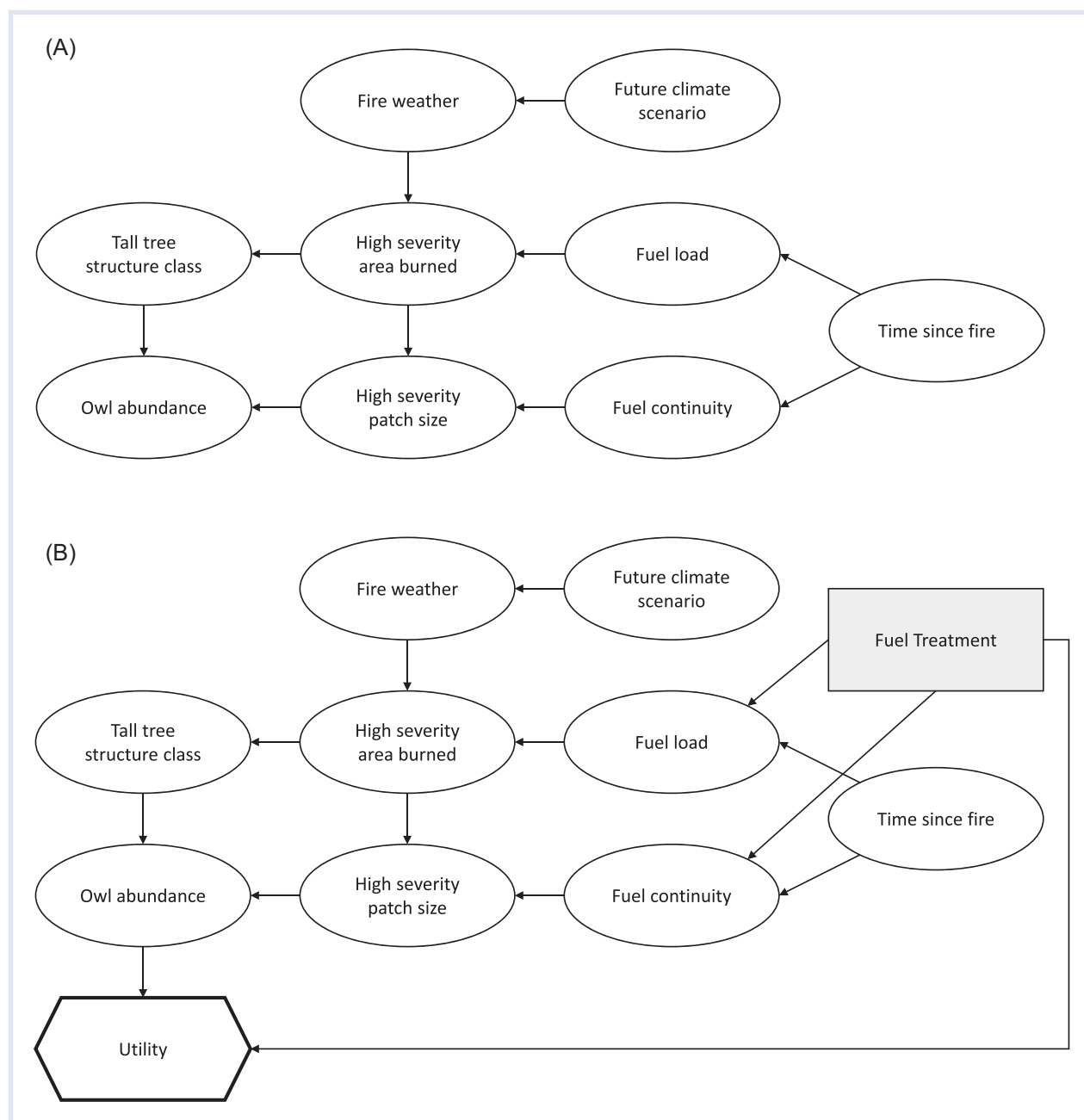


FIGURE 3 Stylized causal model of California spotted owl habitat protection for assessment (A) and decision making (B). Ovals are chance nodes (random variables), grey boxes are decision nodes, and bolded hexagons are utility nodes

(Carriger et al., 2018). These types of questions can be addressed through examining the power of an intervention directly or indirectly on a target variable of interest. Incorporating values and value-based trade-offs for outcomes can be used to examine the impacts of a decision by the costs and benefits of the outcome with the uncertainties from the management actions. Another “what would happen” question relates to the decision problem of designing fuel treatment strategies to mitigate wildfire risk to CSO habitat (Figure 3B). Reducing fuel loads can reduce localized burn severity and can also interrupt fire spread pathways, both of which can, in turn, reduce high-severity patch size. Furthermore, strategic placement of treatments can create gaps and openings that reduce fuel continuity and promote low- to moderate-severity fire and thereby reduce the size of patches that burn with high severity. Examining the influence of alternative strategies based on treatment location and extent is a longstanding issue in wildfire risk mitigation (Ager et al., 2007, 2010; Penman et al., 2020). The expected utility would be based on the uncertainties of the future abundance predictions for the CSOs and the trade-offs between owl abundance outcomes and decision costs.

Rung 3—“Imagining”

Rung 3 is the highest level and addresses “what would have happened?” questions by examining different counterfactual worlds (Pearl & Mackenzie, 2018). As seen in our examples, Rung 2 requires counterfactual thinking for constructing the network but the questions addressed in Rung 3 address problems and require calculations of a more detailed nature to consider two possible worlds in one estimation (Pearl et al., 2016). Rung 3 allows the estimation of an outcome from a path not taken given the outcome that occurred from a path taken; it allows us to imagine another world. Counterfactuals examine if any of the precursors to an event that occurred were different, would the outcome have been different (Sloman, 2005)? If a catastrophic wildfire occurs over a season, it is natural to wonder what conditions contributed to this fire and what would have occurred if they were different. Counterfactual assessments would examine the reason for an occurrence and would be required to fully address this problem. Thompson et al. (2016) estimated the probable growth of the Las Conchas Fire had it not burned into the Cerro Grande Fire. Here, a counterfactual assessment could evaluate how wildfire activity would have affected CSO habitat under a different, unrealized climate scenario.

Other important aspects of Rung 3 causal assessments are *necessary*, *sufficient*, and *necessary and sufficient* causation as described for climate change in Pearl and Mackenzie (2018) and summarized from their discussion below. Necessary causation is useful in attribution to address such problems as to whether greenhouse gas levels were a necessary cause of a wildfire that caused the loss of tree habitat. Sufficiency is useful for long-term considerations such as whether greenhouse gas levels provide sufficient conditions

for causing a wildfire that destroys tree habitat. The two together imply that an effect can only occur with a cause and without the cause, there is no effect. If the greenhouse gas levels exceed a certain point, a highly destructive wildfire will surely follow but one will not if the greenhouse gas levels stay below this level if the greenhouse gas levels are necessary and sufficient for this highly destructive wildfire. The probability of necessary, sufficient, and necessary and sufficient causality can be derived from the probability an effect does not occur without a cause given that the two did occur, the probability an effect would occur with a cause given both did not occur, and the probability that an effect would occur due to a cause and the probability it would not occur without the cause, respectively (Hannart et al., 2016).

For decision making, Rung 3 is necessary to answer important questions about what the world would be like if a different decision were made or if some conditions were different (Pearl & Mackenzie, 2018). Counterfactuals are needed to fully examine the effectiveness of past decisions. To claim another decision would have been more effective requires a counterfactual assessment. A decision model could ask what would have happened had a different fuels treatment strategy been implemented prior to a wildfire that occurred under another fuels treatment regime? Counterfactuals currently play an important role in understanding the role of past fuel treatments and wildfire in affecting future fire activity. As one example, Cochrane et al. (2012) estimated probable spatial burning patterns had previously treated landscapes not been treated. Counterfactuals also play an important role in exploring the legacy of historical management actions and how forest conditions and habitat risk would differ had past management practices been different. For instance, one could ask whether habitat risk would be lower in the absence of decades of fire exclusion and can use that information to design wildfire management strategies moving forward (A. Kramer et al., 2021). The formal theory developed for counterfactual analysis would benefit these types of assessments in the future.

DISCUSSION

Causal models with BNs can provide powerful tools for evaluating causal questions in assessment and decision models for wildfire ecological risks (Landis, 2021). Many studies have relied on ecological risk assessments to inform mitigation planning and prioritization (e.g., Ager et al., 2007, 2010; Kreidler et al., 2020; O’Laughlin, 2005; Stockdale et al., 2019) and have developed decision analytic structures with application to natural resource decisions (e.g., Brown & Ferguson, 2019; Keane et al., 2019; Marcot et al., 2012; Thompson et al., 2015). Risk assessments with BNs will be conducive to representing the causal knowledge of the problem through the structure of the network and evaluating how uncertainties propagate through the causal network to assessment endpoints and expected utilities for the alternatives.

Bayesian networks are flexible modeling structures that have some use for qualitative and quantitative decision

support for narrow contexts found in Rung 1 to broader comprehensive assessments that support broader decisions. The structure can be used to incorporate the information and the uncertainties in the information from measurement inaccuracies and variability and weigh the impacts on the decision. Development of the structure and probabilities should follow formal processes with review by subject matter experts for important assessments and decisions (Marcot et al., 2006). One future opportunity is the adaptation of probabilistic fire spread (e.g., Parisien et al., 2020) or state-and-transition simulation (e.g., Taylor et al., 2013, 2015) to parameterize networks considering the role of wildfire in causing abrupt changes in ecosystem state. Value of information is a natural extension for decision models and can examine the potential for new information on an ecosystem variable or forecast report to improve the decision. An adaptive management process with BNs can be developed to better support the knowledge used to develop the structure and the probabilities of the BNs (Nyberg et al., 2006).

Although several applications were demonstrated here, the case studies were necessarily simplified and limited to similar domains with avian species habitat protection and restoration. Additional application areas where BNs could be useful include modeling interacting disturbances such as fires and storms with critical causal cascades from post-fire debris flows (e.g., Staley et al., 2018) and extreme erosion events (e.g., O. D. Jones et al., 2014). Hurricane and storms not only have the potential to degrade habitat but could lead to dramatically altered fuel complexes (St Peter et al., 2020; Zampieri et al., 2020) and may have long-term benefits to habitat through succession or renewal. Interacting disturbances such as beetle impacts and fire are another opportunity for examining ecological risks and management opportunities (Moriarty et al., 2019; Page et al., 2013).

The ladder of causation provides powerful tools that can be used to examine the implications of wildfire management decisions and the contribution of risk factors to ecological risk outcomes. Counterfactual thinking could be applied to the assessment of the role of past hazardous fuel reduction and forest restoration treatments and burned areas in preventing or enhancing severe wildfires. Case studies by Cochrane et al. (2012) and Thompson et al. (2016) examined how historical fire impacts could have been different had the fires not burned into previously burned or treated areas. Other questions include the potential for interacting disturbance such as extreme erosion after fires in the presence or absence of storms, considering fire activity in the presence or absence of ignition prevention programs, home loss as a function of differential home ignition zone characteristics, fuel break effectiveness in the presence or absence of suppression resources, and examining the contribution of specific fire events to climate change. Incorporating the influence of climate change will be critical in developing causal models

of wildfire impacts. For example in western US forests, anthropogenic climate change has been estimated to have caused over half of the increases in fuel aridity and forest fire area over the last several decades, and is expected to continue to enhance forest fire activity (Abatzoglou & Williams, 2016). Development and application of causal BNs should facilitate understanding the factors contributing to fire susceptibility and resilience, and the prediction and assessment of wildfire risks to and impacts on fire-affected ecosystems.

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